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ABSTRACT

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Abstract

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1 Introduction

In a "post-truth" world of "alternative facts," different media outlets present diverging, and often conflicting, perspectives on reality. Americans are increasingly divided, not only by their political preferences but also by their dramatically different beliefs about *objective facts* (Alesina et al., 2018, 2020).

A growing literature uses information provision experiments to study the determinants and behavioral consequences of beliefs (Barrera et al., 2020; Cantoni et al., 2019; Cruces et al., 2013; Perez-Truglia and Cruces, 2017), sometimes focusing specifically on the role of news media (Chen and Yang, 2019; Nyhan et al., 2020). Yet identifying the causal effect of information on behavior in natural settings is challenging for several reasons. Most importantly, ruling out alternative explanations for differences in behavior among consumers of different media sources — such as different prior beliefs, different ideologies, or different preferences — generally requires a setting in which two media sources 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.

In this paper, we examine a setting in which high-stakes outcomes depend on viewers holding accurate beliefs: the onset of the COVID-19 pandemic in the United States, a period characterized by considerable uncertainty about the extent of the virus' severity. Misinformation in this setting is particularly concerning given the large externalities inherent to contagious diseases (Miguel and Kremer, 2004): it may have harmful effects far beyond those who are directly exposed, if it leads the exposed to take actions which affect disease trajectories in the broader population.

To overcome the aforementioned empirical challenges, we examine the two most popular cable news shows in the United States: *Hannity* and *Tucker Carlson Tonight*. These shows are aired back-to-back on the same network (Fox News) and had relatively similar content prior to January 2020, yet differed sharply in their coverage of the COVID-19 pandemic. Focusing on two shows *within the same network* enables us to compare two *ex ante* similar viewer populations, allowing us to examine how exposure to different informational content drives beliefs, behavior, and downstream health outcomes.[1]

We first document how the two shows diverged as the coronavirus began to spread beyond China using qualitative evidence, text-analysis methods, and human coding of the shows' scripts. Carlson warned viewers that the coronavirus might pose a serious threat from early February, while Hannity first ignored the topic on his show and then dismissed the risks associated with the virus, claiming that it was less concerning than the common flu and insisting that Democrats were using it as a political weapon to undermine the president. We also show that Hannity began to moderate his tone in early March, and that the two shows had largely converged in their coverage of the coronavirus by mid-March.

Radical behavioral changes, such as stay-at-home behavior, did not become widespread until mid-to-late March by which time coverage of the pandemic on the two shows had mostly converged. To shed light on the timing of more subtle behavioral adjustments at the early stages of the pandemic (such as washing hands more often, cancelling travel plans, and maintaining physical distance from others), we fielded a survey among 1,045 Fox News viewers aged 55 or older. Consistent with a persuasive effect of content on behavior, we find that viewership of *Hannity* is associated with changing behavior four days later than other Fox News

[1]By using the term "misinformation," we mean statements that *ex post* turned out to be false. We do not claim that figures who made these statements were intentionally misrepresenting the facts, nor that these statements were unreasonable given the data available at the time.

viewers; while viewership of *Tucker Carlson Tonight* is associated with changing behavior three days earlier (controlling for demographics and viewership of other shows and networks). Given the critical importance of early preventive measures (Bootsma and Ferguson, 2007; Markel et al., 2007), these differences in the timing of adoption of cautious behavior may have significant consequences for health outcomes. For example, Pei et al. (2020) estimate that approximately half of all COVID-19 deaths in the United States at the early stages of the pandemic could have been prevented had non-pharmaceutical interventions (NPIs) such as mandated social distancing and stay-at-home orders been implemented one week earlier. While the behavioral changes our survey respondents report are likely not as extreme, and our survey is representative only of Republicans over the age of 55, this evidence nonetheless suggests that these differences in timing may have directly affected the spread of the pandemic.

Motivated by our survey evidence of persuasive content, we examine disease trajectories in the broader population using county-level data on COVID-19 cases and deaths. In our primary analysis, we focus on health outcomes during the early stages of the pandemic where we would expect first-order effects of treatment – late February to mid-April – though in additional analyses we report our main outcomes until the time of writing.[2] 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. In a set of permutation tests across socio-economic, demographic, political, and health-related covariates, as well as across geographical fixed effects accounting for unobservable factors, we show that the established relationship is highly robust.[3]

Even so, it is likely that areas where people prefer Hannity over Carlson might differ on a number of unobservable dimensions that could independently affect the spread of the virus. Thus, to identify our effect of interest, we employ an instrumental variable approach that shifts relative viewership of the two shows, yet is plausibly orthogonal to local preferences for the two shows 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 idea 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.[4] We show that, conditional on a minimal set of controls and the main effects, the interaction term is uncorrelated with any among a larger number of variables that might independently affect the local spread of the coronavirus. We then show 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. Our results

[2]In principle, there could be second-order effects due to behavioral adjustments and policy responses when local infections and deaths rise sharply due to the treatment. To estimate these endogenous dynamic effects is beyond the scope of the paper, which is why we focus on the early time period.

[3]Indeed, an exercise following Oster (2019) to estimate the bias generated by omitted variables suggests that our estimated coefficients are *negatively* biased.

[4]Leaving out Fox News from the first term and *Hannity* and *Tucker Carlson Tonight* from the second allows us to ensure that the variation we exploit is driven by general preferences for when to watch TV and general preferences for watching Fox News, rather than specific, potentially endogenous, preferences for the two shows.

indicate that a one standard deviation increase in relative viewership of *Hannity* relative to *Tucker Carlson Tonight* is associated with approximately 34 percent more COVID-19 cases on March 14 and approximately 24 percent more COVID-19 deaths on March 28. 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 two weeks later.[5] Our results survive a large number of robustness checks and two alternative instrumental variables strategies designed to rule out further endogeneity concerns by *predicting* TV viewership in each timeslot based upon variation in local sunset times. We also use a multi-group epidemiological model from Acemoglu et al. (2020) to show that the delay in the adoption of cautious behaviors that we document in the survey can generate treatment effects similar in magnitude to those we estimate. The model suggests that the persuasive effect of show content on the relatively small fraction of viewers generates significant externalities within the broader population, particularly in the early stages of the pandemic.

The timing of the estimated effects suggests an important role of the informational content of the two shows in explaining health outcomes. We construct two indices: a "pandemic coverage gap" quantifying the day-by-day differential coverage of the pandemic on *Tucker Carlson Tonight* and *Hannity*, based on the shows' content; and a "behavioral change gap" quantifying the day-by-day correlation between show viewership and behavioral change, based on our survey. The "behavioral change gap" lags the "pandemic coverage gap" by approximately two weeks, and trajectories of cases and deaths follow with an additional lag. The timing of effects is thus inconsistent with alternative potential drivers of our estimated treatment effects, such as time-invariant unobservables correlated with our instrument and differential effects of exposure to the shows that are unrelated to their reporting about COVID-19. Instead, these findings suggest that the documented effects on health outcomes are driven by the differences in how the two shows covered the pandemic in February and early March.

We also allow for potential spillover effects of viewership of *Hannity* and *Tucker Carlson Tonight* onto other Fox News evening shows. We investigate the information provision mechanism in greater depth, allowing for arbitrary spillovers and generalizing our analysis to *all* Fox News evening shows. We combine detailed information on local viewership shares of different Fox News shows with a measure of how seriously each show portrayed the threat of the coronavirus on each day, based on independent coding of episode scripts. We show that our instrumental variable for the relative viewership between *Hannity* and *Tucker Carlson Tonight* strongly increases predicted exposure to coverage downplaying the threat of the virus, as measured by our index. We also show that our index strongly predicts case and death trajectories.

Our work contributes to the literature on the effects of media and propaganda on political behavior and health outcomes (Durante and Zhuravskaya, 2018; Eisensee and Strmberg, 2007; La Ferrara, 2016; Banerjee et al., 2019a; DellaVigna and La Ferrara, 2015; La Ferrara et al., 2012; Bursztyn et al., 2019; Jensen and Oster, 2009; Chiang and Knight, 2011; Martinez-Bravo and Stegmann, 2017). Previous work has shown that media exposure can influence mass killings (Yanagizawa-Drott, 2014); it can also affect domestic violence (Card and Dahl, 2011; Banerjee et al., 2019b), fertility choices (La Ferrara et al., 2012; Kearney and Levine, 2015), and responses to natural disasters (Long et al., 2019). More closely related to our paper, prior work has highlighted that Fox News causally affects voting choices (DellaVigna and

[5] It is important to note that we cannot account for county to county externalities: riskier behavior by individuals in one area may expose other people in different areas to the virus.

Kaplan, 2007; Martin and Yurukoglu, 2017).[6] Relating to the literature on the effects of biased media, we show that even short-term variation in content can affect high-stakes outcomes: our approach holds fixed important mechanisms that may operate through exposure to biased media over an extended period of time, such as increased partisanship or lower trust in science.[7] We are thus able to identify a mechanism of contemporaneous information as the driver of the treatment effects by exploiting variation in informational content. Our analysis also highlights the quantitatively important role of externalities in the propagation of misinformation, though we cannot empirically separate the role of informational spillovers (as studied by Banerjee et al. 2020) from the behavioral externalities in our setting. Thus, while viewers may select into slanted media for ideological and/or partisan reasons (Gentzkow and Shapiro, 2010), we show that slanted media can have significant consequences for the broader population.

We also contribute to the literature studying the role of information in shaping people's behaviors and beliefs (Alsan et al., 2020; Banerjee et al., 2020; Cruces et al., 2013; Perez-Truglia and Cruces, 2017; Alesina et al., 2018; Stantcheva, 2020; Fetzer et al., 2020). For example, Barrera et al. (2020) examine how effective fact checking is in countervailing "alternative facts," i.e., misleading statements by politicians. In the context of health behaviors, Nyhan and Reifler (2015) and Nyhan et al. (2014) study the effects of information about vaccines. Banerjee et al. (2020) show that messaging on COVID-19 prevention in India increased symptoms reporting and adherence to preventive behaviors among 25 million recipients, with similar effects on non-recipient members of their communities, highlighting an important role of behavioral and informational spillovers. Our work contributes to this literature by examining how viewers' exposure to differing information sets within a natural setting affects high-stakes behavior.

Related to our study is contemporaneous work studying correlations between political ideology and responses to the coronavirus. A number of studies find that areas with higher Republican vote shares practice less social distancing, as measured by cell phone GPS data (Allcott et al., 2020b; Barrios and Hochberg, 2020; Andersen, 2020; Wright et al., 2020). Allcott et al. (2020b) additionally present survey evidence documenting substantial partisan differences in individual beliefs about personal risk and pandemic severity, while Barrios and Hochberg (2020) find that more Republican areas perceive lower risk, as measured by internet searches. Adolph et al. (2020) show that both governors from states with more Trump supporters and Republican governors were slower to implement social distancing policies such as stay-at-home orders and school and business closures.[8] Analyzing Brazil's case, Ajzenman et al. (2020) and Mariani et al. (2020) show that following public speeches of the president opposing social isolation policies, social distancing immediately fell in municipalities with higher support for the president. Egorov et al. (2020) show that areas with greater levels of xenophobia and ethnic fractionalization show the greatest reductions in mobility following the first local COVID-19 case. Besley and Dray (2020) consider cross-country variation and investigate the role of the media in shaping governments' reporting on and response to the COVID-19 pandemic.

Recent studies (Simonov et al., 2020; Ash et al., 2020; Ananyev et al., 2020) use the channel numbers instrument developed by Martin and Yurukoglu (2017) to establish a causal effect of exposure to Fox News on mobility. We complement these findings through our analysis of COVID-19 cases and deaths (in addition

[6]Our identification strategy also relates to a literature on *inattention* to particular news events (Eisensee and Strmberg, 2007; Durante and Zhuravskaya, 2018).

[7]Our work thus relates to a small literature focusing on the content of specific TV shows (Banerjee et al., 2019a; Kearney and Levine, 2015).

[8]Taken together, this evidence is consistent with a broader literature finding that Republicans and Democrats hold different beliefs about objective facts (e.g. Alesina et al. 2020).

to stay-at-home behavior, the primary outcome studied in these papers) and our use of 2020 rather than 2015 viewership data (albeit at a coarser geographical level). More importantly, our work differs by identifying the role of a specific mechanism — contemporaneous exposure to slanted information — through a novel instrument that compares two relatively similar populations: counties that disproportionately watch *Tucker Carlson Tonight* vs. counties that disproportionately watch *Hannity*. In contrast, the channel number of Fox News has been relatively stable since the channel's 1996 rollout; long-term exposure to Fox News has been shown to causally affect Republican vote share (Martin and Yurukoglu, 2017) and may influence stay-at-home behavior through a number of additional mechanisms, including ideology and partisanship, trust in science, and health investments.[9] Our work also complements these papers through its focus on the early stages of the pandemic; the coverage gap between *Hannity* and *Tucker Carlson Tonight* had closed before stay-at-home behavior became widespread, and we present evidence that slanted coverage affected COVID-19 outcomes by influencing other, less-extreme, forms of behavior: hand-washing, physical distancing, and cancelling planned trips.

The remainder of this paper proceeds as follows. In Section 2, we provide a brief overview of media coverage of the coronavirus, with a particular focus on the differences in coverage between *Hannity* and *Tucker Carlson Tonight*. In Section 3, we present our survey results relating viewership of different Fox News shows to behavioral change in response to coronavirus. In Section 4, we describe our primary datasets. In Section 5, we present OLS estimates of the effects of differential viewership of *Hannity* and *Tucker Carlson Tonight* on health outcomes. In Section 6, we introduce an instrumental variable approach, and present results. In Section 7, we conduct a number of exercises to examine the robustness of our estimates. In Section 8, we assess effect sizes through the lens of an epidemiological model. In Section 9, we provide evidence on mechanisms by combining information from the scripts of the shows with local day-by-day viewership shares. Section 10 concludes.

2 Setting

2.1 The early stages of the coronavirus pandemic in the US

The rapid spread of COVID-19 (Zhu et al., 2020; Li et al., 2020) has fundamentally disrupted the modern world. The first confirmed case in the United States was reported on January 21, 2020 (Holshue et al., 2020). A few days later, the World Health Organization declared a global public health emergency.[10] Throughout most of February, there remained uncertainty about the extent of the coronavirus outbreak and the threat it posed; on February 25, the Centers for Disease Control and Prevention warned the US public that the virus was likely to spread rapidly in the United States (Jernigan, 2020). On March 11, the WHO declared the COVID-19 outbreak a pandemic; two days later, President Donald Trump declared a national emergency (Cucinotta and Vanelli, 2020). By late March, the US had 186,082 cases, the highest number of confirmed COVID-19 cases in the world, and at least 3,806 COVID-19-related deaths (Dong et al., 2020). By April 7,

[9] For example, Hmielowski et al. (2014) find that viewership of Fox News decreases trust in scientists, and Brzezinski et al. (2020) find that counties with lower trust in science (as measured by the prevalence of climate change skepticism) practice less social distancing.

[10] "Statement on the second meeting of the International Health Regulations (2005) Emergency Committee regarding the outbreak of novel coronavirus (2019-nCoV). *World Health Organization*, January 30, 2020.

95 percent of the US population were under stay-at-home orders banning them from leaving their places of residence for all but "essential reasons."[11]

2.2 Media coverage of COVID-19 on Fox News

Fox News is the most watched cable network in the United States, 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).[12] Moreover, the median age of primetime Fox News viewers is 68, substantially higher than that of CNN and MSNBC viewers.[13] 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 (Martin and Yurukoglu, 2017).

Primetime shows on Fox News There are seven different news shows on Fox News running between 5pm and 11pm across the four major time zones in the continental US: *The Five* (5pm-6pm ET); *Special Report with Bret Baier* (6pm-7pm ET); *The Story with Martha MacCallum* (7pm-8pm ET); *Tucker Carlson Tonight* (8pm-9pm ET); *Hannity* (9pm-10pm ET); *The Ingraham Angle* (10pm-11pm ET); and *Fox News at Night* (11pm-12pm ET). Most of our paper focuses on the two most widely-viewed news shows on Fox News — indeed, in the United States: *Hannity* and *Tucker Carlson Tonight* — with an average of 4.2 million and 4 million daily viewers in the first quarter of 2020, respectively.[14] Before the coronavirus began to spread 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. Yet as we document using qualitative evidence, text-analysis methods, and human coding of the shows' scripts, the two shows differed sharply in coverage of the coronavirus.

Qualitative evidence: Carlson vs. Hannity 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 was unlikely to be a serious threat to the country.[15] Many observers have identified Sean Hannity of Fox News as advancing a particularly dismissive narrative toward the virus.[16] Tucker Carlson, on the other hand, stood out not only among his colleagues at Fox News, but also among anchors across the ideological spectrum, for his insistence as early as the beginning of February that the coronavirus posed a serious threat to the United States.[17] For example, on January 28 — 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:

[11] "Coronavirus: These US states refuse to issue stay-at-home orders." *Al Jazeera*, April 15, 2020.
[12] "Fox News Channel ratings for first quarter of 2020 are the highest in network history." *Fox News*, March 31, 2020.
[13] "Half of Fox News' Viewers are 68 and Older." *The Atlantic*, January 27, 2014.
[14] Authors' calculations based upon Nielsen data.
[15] See "What went wrong with the media's coronavirus coverage?" *Vox*, April 13, 2020.
[16] See, for example, "Fox News has succeeded – in misinforming millions of Americans." *The Washington Post*, April 1, 2020; "Fox's Fake News Contagion." *The New York Times*, March 31, 2020.
[17] See, for example, "His colleagues at Fox News called coronavirus a 'hoax' and 'scam.' Why Tucker Carlson saw it differently." *The LA Times*, March 23.

> All of a sudden the Chinese coronavirus is looking like a real threat, that could be a global epidemic or even a pandemic. It's impossible to know. But, it's the kind of thing that could be very serious – very serious.

On February 5, Carlson emphasized the large death toll due to COVID-19 in China and the emergence of COVID-19 cases in the US:

> The Chinese coronavirus continues to spread tonight. The death toll now exceeding 500, that's the official number. In the United States, there are now 12 confirmed cases of it. Meanwhile, alarming videos trickling out of China indicate the virus is far from under control.

On February 25, Carlson warned his viewers about the deadly consequences of the coronavirus:

> Currently, the coronavirus appears to kill about two percent of the people who have it. So let's be generous for a moment and imagine that asymptomatic carriers are not detected and the real death rate is only say half a percent — that would be one quarter of the current estimates. Even under that scenario, there would still be 27 million deaths from coronavirus globally. In this country, more than a million would die.

In contrast, Hannity covered the coronavirus and its consequences substantially less than Carlson and other Fox shows — particularly in February, when the virus was first beginning to spread in the United States. Even after he began discussing it more prominently in February, he downplayed the threat the virus posed. For example, in his show on February 27, Hannity stated:

> And today, thankfully, zero people in the United States of America have died from the coronavirus. Zero. Now, let's put this in perspective. In 2017, 61,000 people in this country died from influenza, the flu. Common flu. Around 100 people die every single day from car wrecks.

In his show on March 2, Hannity strongly emphasized that Democrats were politicizing the virus, claiming that "[Democrats] are now using the natural fear of a virus as a political weapon. And we have all the evidence to prove it, a shameful politicizing, weaponizing of, yes, the coronavirus." While he began in early March to discuss the mortality statistics in more detail, he continued to emphasize that the virus still posed a relatively minor threat to US citizens. For example, on March 10, Hannity stated:

> So far in the United States, there has been around 30 deaths, most of which came from one nursing home in the state of Washington. Healthy people, generally, 99 percent recover very fast, even if they contract it. Twenty six people were shot in Chicago alone over the weekend. You notice there's no widespread hysteria about violence in Chicago.

By mid-March, after President Trump declared a national emergency in response to the coronavirus, Hannity's coverage had converged to that of Carlson and other Fox News shows, emphasizing the seriousness of the situation and broadcasting CDC guidelines:

> If you feel sick, stay at home. If your kids feel sick, don't send them to school or day care. If someone in your household has tested positive for coronavirus, please self-quarantine your entire household. Keep them at home. If you are an older person or an individual with underlying

> medical conditions, a compromised immune system, maybe you are receiving chemotherapy, radiation, have autoimmune issues, whatever the underlying diseases are, please stay away, almost quarantine yourself from other people.

Taken together, the qualitative evidence highlights that (i) Carlson warned his viewers early on about the potential threat posed by the coronavirus; and (ii) Hannity did not cover the coronavirus throughout most of February, and he downplayed its seriousness until as late as mid-March. To more systematically evaluate differences in the extensive margin of coverage between primetime Fox News shows, we turn to a simple word-counting procedure.

Word counts: Carlson vs. Hannity For each of the seven shows on Fox News airing between 5pm and 11pm local time across the four major time zones, we download episode transcripts from LexisNexis. 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 Panel A of Figure 1.[18] In particular, the y-axis of the panel displays the log of one plus the word count on each day.

Compared to the other three primetime shows, both *Hannity* and *Tucker Carlson Tonight* stand out. Both anchors first discussed the coronavirus 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 three shows fell somewhere between these two extremes. By early March, the word counts of all shows had converged.[19]

However, this simple procedure does not entirely capture differences in how shows discussed the coronavirus. The qualitative evidence above suggests that while Hannity discussed the coronavirus 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.

Mechanical Turk script validation Between April 2 and April 6, we recruited workers on Amazon Mechanical Turk to assess how seriously each of the seven shows portrayed the threat of the coronavirus 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 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.[20]

Panel B of Figure 1 displays one-week rolling means of this variable for Carlson, Hannity, and the other four shows. Throughout almost the entire period, MTurk workers rate Carlson as portraying the threat of

[18] The words are "coronavirus", "virus," "covid," "influenza", and "flu."

[19] 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 the coronavirus (see Appendix Figure A22); this also holds for .

[20] 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).

the coronavirus more seriously than the other three 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.

Together, our evidence suggests that coverage of the coronavirus differed enormously between *Tucker Carlson Tonight* and *Hannity*. We next present survey evidence that these differences may have affected viewers' behavior during the period of initial spread of the coronavirus in the United States.

3 Survey

In this section, we present correlations between viewership of different primetime Fox news shows and viewers' self-reported timing of behavioral change in response to the coronavirus. Radical behavioral changes, such as stay-at-home behavior, did not become widespread until mid-to-late March, when the pandemic coverage gap between *Hannity* and *Tucker Carlson Tonight* had already closed.[21] Indeed, using data from SafeGraph, a GPS-based location vendor widely used by studies examining stay-at-home behavior, we find no significant association between viewership and stay-at-home behavior at the Designated Media Market (DMA) level during the period when stay-at-home behavior became more widespread. Thus, to capture other behavioral changes that may have occurred in February and March, and to shed light on which types of behavioral change were most common, we fielded a survey on April 3, 2020.

Our survey targeted a representative sample of approximately 1500 Republicans aged 55 or older in cooperation with Luc.id, a survey provider widely used in social science research (Wood and Porter, 2019). We focused on this subsample both because such individuals are more likely to watch Fox News and because the elderly are at increased risk from the coronavirus.[22] As we show in Appendix Table A1, our sample is broadly representative of Republicans aged above 55 and older. All survey materials are available in Appendix E.

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. 1045 individuals reported that they watched 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 primetime 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 behavior in response to the coronavirus outbreak. First, we ask whether they have changed any of their behaviors (e.g., canceling travel plans, practicing social distancing, or washing hands more often) in response to the coronavirus. For those respondents who answer that they have changed behavior, we elicit the date on which they did so. Finally, we ask an open-ended question asking respondents to describe which behaviors they changed.

Sample characteristics Of viewers in our sample who regularly watch *Hannity*, approximately 69 percent also regularly watch *Tucker Carlson Tonight*; of viewers who regularly watch *Tucker Carlson Tonight*,

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

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

approximately 77 percent also regularly watch *Hannity*.[23] In Table 1, we plot demographic characteristics of exclusive *Tucker Carlson Tonight* and *Hannity* viewers. *Hannity* viewers are somewhat more likely to be white, somewhat more likely to be male, somewhat more likely to be working full-time, and more likely to watch CNN and MSNBC. However, taken together, the observable differences between the two groups appear to be modest.

Results To examine the correlation between viewership of different news shows and the timing of behavioral 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 February 1, 2020 on which the respondent reported having significantly changed any of their behaviors in response to the coronavirus, 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.[24] The dependent variable for respondents who report that they have not changed any of their behaviors 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.

Panel A of Figure 2 plots the smoothed density function of the reported date of behavioral 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 behavior four to five days later than viewers of other shows ($p < 0.001$), while viewers of *Tucker Carlson Tonight* changed their behavior three to four days earlier than viewers of other shows ($p < 0.01$); the difference in coefficients is also highly statistically significant ($p < 0.01$).[25] Column 2 reports a linear probability model in which the dependent variable is an indicator for whether the respondent reported changing behavior 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 behavior before March 1 than viewers of other Fox shows.[26] We estimate identical linear probability models for each day between February 1 and April 3 (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

[23] Our survey focuses on the population aged 55 or older, which also consumes the most television in general. Thus, the extent of the overlap between viewers of the two shows in our sample likely overstates the overlap for viewers as a whole.

[24] The elements of S_i are neither mutually exclusive nor jointly exhaustive; 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.

[25] In independent work, Ash et al. (2020) 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*.

[26] To benchmark the plausibility of the estimated effects, we calculate the *persuasion rate* of viewership on the outcome of changing behavior by March 1, 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 percent, well within the range of comparable estimates; for example, Martin and Yurukoglu (2017) find a Fox News persuasion rate on voting behavior of 58 percent in 2000, 27 percent in 2004, and 28 percent in 2008; Adena et al. (2015) finds a persuasion rate of up to 36.8 percent; and Enikolopov et al. (2011) finds persuasion rates rating from 7 to 66 percent. 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.

Panel B of Figure 2. By this measure, the difference between the two anchors peaks around March 1, then declines. The difference between the coefficients are significant at the one percent level throughout most of mid-February through mid-March; the individual coefficients are also significantly different from the one percent level throughout most of this period. To ensure that our results are robust to different specification choices, in Appendix Figure A1, we report a "coefficient stability plot" (Rao, 2020) displaying specifications under every possible combination of demographic controls, with and without state fixed effects. In every specification, the difference between the two coefficients is significant at the one percent level; and in almost all specifications, the individual coefficients are significantly different from 0 at the five percent level.

We also examine the timing of specific margins of behavioral adjustment by manually coding the open-ended responses to the question of which behaviors respondents changed. Figure 3 highlights that increased hand washing and physical distancing are the most frequently mentioned behavioral changes, particularly in February, the period during which the differences in show content were largest. Canceling travel plans and staying at home are also frequently mentioned, though primarily in mid and late March.[27]

Our survey suggests that show content may have affected individual behaviors relevant for the spread of the coronavirus. However, the correlations might be driven by omitted variable bias or reverse causality: viewers who did not want to believe that the coronavirus was a serious problem or viewers less inclined to changing their behavior 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 behavior earlier or later than they actually did. To address these issues, we turn to outcome data on COVID-19 cases and deaths, and later turn to an instrumental variable strategy shifting relative viewership of *Hannity* and *Tucker Carlson Tonight*.

4 Overview of Data Sources

Aside from our survey and the show transcripts we use in our previously-described content validation, we employ six primary categories of data in our observational analysis: (1) show viewership data provided by Nielsen at the day-by-show-by-Designated Market Area (DMA) level; (2) COVID-19 cases and deaths data from the Johns Hopkins Coronavirus Research Center at the county-by-day level; (3) county-level demographics from a variety of sources; (4) county-level data on 2016 Republican vote share from the MIT Election Lab; (5) measures of health system capacity from the Dartmouth Atlas of Health Care; and (6) data on sunset timing from `www.timeanddate.com`.

Viewership data Our show viewership data is provided by Nielsen. Nielsen reports viewership at the Designated Market Area (DMA) level, of which there are 210 in the US.[28] We focus on the continental

[27] The responses highlight the importance of distinguishing between two types of social distancing. Following the Federal Reserve, we distinguish *stay-at-home behavior* — remaining at home for all or a substantial part of the day — from *physical distancing* — continuing with day-to-day activities, but keeping a distance (e.g. of six feet) from others. While stay-at-home behavior becomes widespread only in mid-to-late March (see, e.g. Allcott et al. 2020b), our survey responses suggest that physical distancing was widespread even in February, at least among the population we survey.

[28] Comprehensive viewership data is not available at more granular levels after 2015. It is possible to approximate ZIP-level (and thus county-level) viewership in 2015 or earlier, as in Simonov et al. (2020). This approximation involves aggregating "headends," or cable systems, to ZIP codes, a procedure that requires discarding all but the largest headend in each ZIP code; (Simonov et al. 2020 find that 47% of ZIP codes have more than one headend, though the largest headend accounts for at least half of subscribers in the vast majority. Aside from this measurement error and the possibility that the change in

United States, excluding the two DMAs in Alaska (Anchorage and Fairbanks) and the single DMA in Hawaii (Honolulu).[29] Our dataset contains viewership data between 5pm and 11pm (local time) at the DMA-by-timeslot-by-day level (i.e. hourly ratings). 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. To avoid using variation based on *Hannity* and *Tucker Carlson Tonight*, these market shares are calculated based on evening time slots outside of those two shows. 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 January 1 through March 8 (the beginning of Daylight Savings Time, a natural stopping point given the structure of our identification strategy).

COVID-19 cases and deaths data We use publicly-available county-level data on *confirmed* COVID-19 cases and deaths from Johns Hopkins University (Dong et al., 2020). The data is a panel at the day-by-county level, with data sourced from a variety of agencies, including the World Health Organization, the Centers for Disease Control, state health departments, and local media reports. Throughout our main analyses, we take the logarithm of one plus the cumulative number of cases and deaths, both to correct for outliers with a large number of cases and because the exponential nature by which a virus spreads makes the logarithm normalization natural. However, our results are qualitatively identical and quantitatively extremely similar if we instead transform cases and deaths by the inverse hyperbolic sine (IHS) rather than the natural logarithm. Appendix D displays all our main results under the IHS transformation.

Data on COVID-19 cases are potentially subject to both classical and non-classical measurement error. For example, many COVID-19 cases are unreported (Lachmann, 2020; Stock et al., 2020), 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. Data on COVID-19 deaths is far less subject to both classical and non-classical measurement error.

In our primary analysis, we focus on outcomes during the early stages of the pandemic — from late February to April 15 — given that stay-at-home orders were widely enacted in late March and the estimated 1-3 week lag between infections and deaths.[30] However, in Appendix A.8, we report our main outcomes up

viewership between 2015 and 2020 is endogenous, we use 2020 DMA-level data for two reasons: first, because we are interested in the effects of *contemporaneous* exposure to misinformation on pandemic outcomes and thus require viewership data from the period of interest; and second, because *Tucker Carlson Tonight* first aired in 2016, and thus constructing accurate ZIP-code level estimates of differential viewership is not feasible using currently-available data.

[29] We also exclude Palm Springs, CA; this DMA is so small that it does not contain a county centroid, and thus we are unable to consistently map any counties to Palm Springs.

[30] The earliest stay-at-home order was enacted in California on March 19; other states followed suit between March 20 and April 7. While our primary specification is estimated separately for each day and employs state fixed effects, thus controlling for any state-specific policies, it is possible that the timing of regional stay-at-home orders (e.g. at the municipal, county, or DMA level) are directly influenced by coverage of the pandemic on Fox News, though such effects are likely of limited quantitative significance. It is, however, likely that the timing of regional stay-at-home orders were affected by the trajectories of cases and deaths in the county, which, as we show, are themselves affected by Fox News coverage; we view this as a mechanism.

until the time of writing.[31]

Demographics We collect demographic data at the county level from a wide variety of sources. Our data on age, racial composition, and household income and educational attainment is drawn from the 2018 round of the American Community Survey. We use data on county rurality from the 2010 Census and data on population drawing from the Annual Estimates of the Resident Population for Counties in the United States provided by the U.S. Census Bureau. Our measures of poverty and health insurance are provided by the US Census Bureau under the 2018 Small Area Income and Poverty Estimates (SAIPE) and 2018 Small Area Health Insurance Estimates (SAHIE) programs. Our data on unemployment is from the US Bureau of Labor Statistics' 2019 Local Area Unemployment Statistics (LAUS). Finally, our data on physical health is from the CDC's Behavioral Risk Factor Surveillance System (BRFSS).

2016 Republican vote share We obtain county-level voting data for the 2016 US Presidential election from the MIT Election Lab, which contains the total number of votes cast and the number of votes cast for each of the major parties.

Health system capacity We use standard measures of health capacity from the Dartmouth Atlas of Health Care's Hospital and Physician Capacity dataset. Data are at the Hospital Referral Region level, defined by the Atlas as "regional health care markets for tertiary care"; we use the most recent version of the dataset (2012). We include all three measures included in the data — the number of nurses, hospital personnel, and hospital beds — and divide by population to construct per capita measures.

Sunset timing Our data on sunset timing is drawn from `www.timeanddate.com`. We extract sunset times for every day from January 1, 2020 to March 1, 2020 for all counties based on their centroids, and we construct the sunset time of each DMA for each day as the population-weighted mean sunset time on that day of all counties in that DMA.

5 OLS Estimates on Health Outcomes

In this section, we first discuss the empirical challenge in identifying causal effects. We then present OLS evidence on the effects of differential viewership of the two shows on COVID-19 cases and deaths.

5.1 Empirical challenge

Obviously, show viewership is not randomly assigned: people self-select into television shows that they like to watch. For example, it is well known that Fox News viewers are over-represented among older individuals and that age is a determinant of COVID-19 mortality. Our object of interest, though, is not to understand the effect of watching Fox News *per se*, but to understand the role of differential information spread by the different shows. Since selection into viewership of *Hannity* and *Tucker Carlson Tonight* is less well known, we begin by examining county-level correlates of their relative popularity. As Appendix Figure A2 displays,

[31]In addition to the larger confidence intervals, interpretation of these results is complicated by the fact that treatment effects on cases and deaths are endogenous to earlier trajectories, motivating our choice to focus on results until April 15.

counties with a relative preference for *Hannity* differ from counties with a relative preference for *Tucker Carlson Tonight* on a number of *observable* dimensions, including racial composition and education. For example, a high share of blacks is positively correlated with popularity of *Hannity*, while a high share of Hispanics is negatively correlated. Rural areas, areas with less education and with less health insurance coverage tend to favor *Hannity* over *Tucker Carlson Tonight*. In contrast, the relative popularity of the two shows is not strongly associated with the share of people over the age of sixty five.[32]

Together, these patterns suggest that a simple OLS estimate may be biased. The *direction* of this bias, however, is unclear. For example, COVID-19 has severely affected African-American communities, for many reasons beyond *Hannity*'s relative popularity, which would positively bias our coefficient. On the other hand, *Hannity* is also more popular in areas with greater local health capacity, suggesting a negative bias.

In what follows, we will show in a transparent manner how OLS estimates evolve under various combinations of county-level controls and fixed effects. We will then present an instrumental variable approach aimed at addressing any lingering concerns.

5.2 OLS estimates

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 standardize this variable to take mean zero and a standard deviation of 1 for ease of interpretation. In our primary analysis, we estimate the following specification separately for each day between February 24 and April 15 (for cases) and between March 1 and April 15 (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 of *Hannity* and *Tucker Carlson Tonight*, and X_{mc} is a vector of county-level controls.

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 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 $f_{mc,h}$. Letting $h \in \{H, T\}$ represent viewership during *Hannity* and *Tucker Carlson Tonight*, respectively, we plot the distribution of $s_{mc,H}$ and $s_{mc,T}$ across DMAs, along with the distribution of $s_{mc,H} - s_{mc,T}$ across DMAs, in Figure 4.

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

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

[32] Differences are reduced, though not eliminated entirely, when we include state fixed effects (our preferred empirical specification, as described below).

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

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

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 (observable or 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 8pm to 11pm 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 will arguably 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 to us which way the bias would go, given that we are comparing differential exposure to two shows on the same network.) For example, *Hannity* goes live at 9pm locally in the Eastern time zone, 8pm local time in the Central time zone, 7pm in the Mountain time zone and 6pm in the Pacific time zone. *Tucker Carlson Tonight* goes live an hour earlier. To address concerns about local preferences for watching TV *per se* 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 8pm and 11pm Eastern Time (three variables, each capturing one hour): $s_{mc,8-9pm}$, $s_{mc,9-10pm}$, $s_{mc,10-11pm}$. These controls will arguably 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. Obviously, including additional *observable* characteristics as control variables is informative and desirable. For example, since we study the early stages of the COVID-19 pandemic and initial outbreaks occurred around metropolitan hot spots (e.g., Seattle, New York City and the Bay Area), one concern may be that viewership patterns across the two shows correlate with such hot spot locations. For this reason, we will 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 will 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 sixty-five); *economic* factors (the share under the federal poverty line, log median household income, the unemployment rate); *health* factors (the share lacking health insurance, 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); and *political* factors (Republican vote share and the log total number of votes cast in the 2016 Presidential election). To see the spatial distribution of the remaining variation when all covariates are included, Figure 5 displays the values of D_{mc} across the U.S., residualized by the controls described above. To account for additional *unobservable* determinants of health outcomes that differ across localities, we will 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 preferable in that it helps rule out a whole host of concerns beyond the ones explicitly outlined above – will include state fixed effects and a full set of control variables.

To capture the effects in a transparent manner over time, our preferred approach is to 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.[33]

Results We report day-by-day results for cases and deaths in Figure 6, 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; at the time of writing, the coefficient on deaths follows with a two weak lag, consistent with the approximately two-to-three week lag between the appearance of COVID-19 symptoms and deaths (Wu et al., 2020). Effects on cases are statistically significant at the 5 percent level throughout the majority of the period, while effects on deaths are only statistically significant at the 5 percent level in late March and April. 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 approximately 2 percent more cases on March 7 ($p < 0.05$), 5 percent more cases on March 14 ($p < 0.01$), and 10 percent more cases on March 21 ($p < 0.01$). A one standard deviation greater viewership difference is associated with 2 percent more deaths on March 21, 4 percent more deaths on March 28, and 9 percent more deaths on April 11.[34] We report these results at weekly intervals in regression table form in Table 3.

Robustness To probe the robustness of our estimates, we choose a single day for cases — March 14, two weeks into March — and a single day for deaths — March 28, two 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 eight sets of county-level controls (population density and rurality, race, age, economic, education, health, health capacity, politics) and our three levels of fixed effects (no fixed effects, census division fixed effects, and state fixed effects). Panel A of Appendix Figure A4 reports coefficient estimates for each of these 768 models for cases as of March 14; Panel A of Figure 7 reports the analogous estimates for deaths as of March 28. The majority of coefficient estimates on cases and deaths are statistically significant at the 1 percent

[33]Our results are also statistically significant if we instead cluster at the state level, as we show in Appendix Figure A3.

[34]In Appendix Figure A19, we report day-by-day results for cases and deaths extending until the time of writing. Point estimates remain positive; effects on cases increase slightly, while effects on deaths decrease slightly. However, these coefficients are less precisely estimated, and we cannot rule out null effects on deaths past late April.

level. Almost all coefficient estimates from specifications including state fixed effects, our most demanding and most precisely estimated specifications, are significant at the 1 percent level. Moreover, our coefficient estimates are relatively stable.[35] Appendix Figure A5 shows a generally positive correlation between the R^2 of each model and the coefficient estimate, suggestive evidence that omitted variable bias seems to be downward biasing our coefficients of interest. 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.[36]

To ensure that our results are not driven by a small number of outliers, we residualize our outcome variables and the standardized difference in viewership by our controls and fixed effects, then plot the residuals of our outcome variables against the residuals of the viewership difference in Appendix Figure A6; the positive relationship between relative viewership and cases and deaths appears consistent throughout the distribution of residuals. To further ensure that counties with a large number of cases or deaths are not driving our results, in Appendix Figure A7, we estimate our time series figures leaving out *entire states* containing prominent COVID-19 hotspots: California, Massachusetts, New Jersey, New York, Washington, and all five states. Our estimates remain qualitatively identical and quantitatively similar in each case.

A limitation of the OLS approach is that, ultimately, it requires an assumption based on selection-on-observables. We may still be concerned about unobservable factors driving both viewership preferences for *Hannity* over *Tucker Carlson Tonight* and COVID-19 outcomes. To address this concern, we develop an instrumental variables strategy to isolate plausibly exogenous variation in relative viewership.

6 Instrumental Variables Estimates on Health Outcomes

To address concerns about unobservables biasing our estimates, we need an instrument that shifts relative viewership of *Hannity* and *Tucker Carlson Tonight*, yet is orthogonal to (i) underlying *preferences* for the shows and (ii) any socioeconomic and demographic factors relevant for the spread of coronavirus or for coronavirus mortality, such as income, racial composition, and health system capacity. In this section, we describe our approach to generate plausibly exogenous variation in relative viewership of these two shows. For now, we will leave aside potential spillover effects onto viewership of other evening shows on Fox News beyond *Hannity* and *Tucker Carlson Tonight*. However, in Section 9, where we investigate mechanisms more in depth, we will allow for arbitrary spillovers and generalize our analysis to *all* Fox News evening shows.

6.1 Leave-out IV

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

[35] We repeat this exercise for every date between February 24 and April 15 for cases and between March 1 and April 15 for deaths (768 regressions per day). 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).

[36] 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.

unobservable determinants. 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 Fox News viewers that primarily favor *Hannity* over other Fox News shows, such as *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.[37]

The logic of the instrument is as follows. We know that the share of households regularly watching *Hannity* is determined by the interaction of *timing preferences* and *channel preferences*, $s_{mc,H} \times f_{mc,H}$. The OLS estimations already flexibly control for the tendency to watch TV *per se* at certain hours in the evening. Under the assumption of generic timing preferences that 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 around 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 while leaving out households that watch Fox News.

We use an analogous approach for *channel preferences*, i.e. for the other factor in the interaction term. 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 not biased. However, we cannot rule out that such a correlation structure exists. For example, 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, *Tucker Carlson Tonight* is on, the OLS estimates would be (negatively) biased. To purge the treatment variable D_{mc} from such variation, 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 8-10pm 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:

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

The 2SLS strategy is therefore based on two identifying assumptions. First, that there is a cross-sectional *first stage* relationship: $\beta_1 > 0$. Second, the *exclusion restriction* assumes that conditional on the main effects of the individual leave-out variables, $\tilde{s}_{mc,H}$ and $\tilde{f}_{mc,-HT}$, the interaction term Z_{mc} only affects outcomes through D_{mc}. The intuition is as follows: the interaction terms shifts viewers not only into Fox News in general, but in particular into the timeslot when *Hannity* airs, as opposed to slots when other Fox News shows, such as *Tucker Carlson Tonight*, air (resulting in $\beta_1 > 0$). The variation is driven by the purged

[37] The logic of the leave-out approach is discussed in Goldsmith-Pinkham et al. (2020) and Burchardi et al. (2019).

interaction of timing preferences *unrelated to Fox News viewership* and channel preferences for Fox News *unrelated to viewership of Hannity or Tucker Carlson Tonight*. In short, it is driven by local habits to turn on the TV during certain time-slots – habits not specific to regular Fox News viewers – together with a preference to watch Fox News whenever the TV is turned on (but not specific to the time slots of interest). This interaction should push people into watching *Hannity* over *Tucker Carlson Tonight*.

We will also show robustness of the 2SLS estimates when two instruments are included (see Section 7.3.3): the instrument for *Hannity* as specified above and an analogously constructed instrument for *Tucker Carlson Tonight*, $\tilde{s}_{mc,T} \times \tilde{f}_{mc,-HT}$. In this case, the two instruments identify a causal effect using a similar logic as above, provided the first stage relationship is sufficiently strong.[38]

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 turns on peaks. For example, *Hannity* airs one hour after the prime time in EST, while it airs two hours 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.

Correlation with pre-determined characteristics To illustrate the spatial distribution of the induced variation, Figure 8 maps the residuals of our instrument, where the instrument has been residualized according to the specification above with the baseline controls. In Appendix Figure A9, we report regressions using each county-level covariate as an outcome, scaled to a standard normal distribution to facilitate interpretation, on our instrument. Only one coefficient is significantly different from zero at the 5 percent level, and coefficient magnitudes are generally small.[39] This lends credibility to the identification strategy. Nevertheless, as in the OLS approach, we will show in a transparent manner the extent to which results are robust to permutations across all possible combinations of the groups of covariates.

Exclusion restriction Our approach is motivated by the fact that (1) *Hannity* and *Tucker Carlson Tonight* are the most-viewed shows in the United States, and by the fact that (2) the differences in coronavirus coverage were greatest between Hannity and Carlson, with the divergence emerging in early February and lasting for several weeks until eventual convergence by mid-March. In this sense, the instrument variable approach is designed to shift exposure to misinformation in the early stages of the pandemic through its effects on the two most popular and most relevant shows on Fox News. At a first-order approximation, this seems reasonable. However, as we will discuss more thoroughly in Section 9, even if our instrument is relevant so that $\beta_1 > 0$ in Equation (3), it is important to consider potential violations of a more narrowly defined

[38]While instrumenting D_{mc} using both $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$ and $\tilde{s}_{mc,T} \times \tilde{f}_{mc,-HT}$ makes sense conceptually, one concern is that because the instruments imply using variation in timing preferences in adjacent timeslots, the two instruments are highly correlated, potentially leading to weak instrument problems. Indeed, as we report in Appendix Table A2, the first-stage Kleibergen-Paap F-statistic is significantly lower when we use both instruments, even though the resulting 2SLS coefficients are extremely similar in magnitude and statistical significance. As there remains uncertainty in how to test for and overcome weak instruments in over-identified models, as opposed to in simpler just-identified settings (see Andrews et al. 2019 for a discussion), our primary specification uses only the instrument for *Hannity*'s timeslot.

[39]Indeed, the coefficient that is significantly different from zero is the percentage uninsured, which is *lower* in areas with a high value of our instrument — suggesting that any bias should work against finding an effect.

exclusion restriction and how such violations influence the interpretations of our results. In particular, if one assumes 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 – then one would also have to assume that our instrument does not have any spillovers, negative or positive, onto other shows. This is, of course, a strong assumption. For example, it may be that our instrument pushes Fox viewers into regularly watching more *Hannity* and less *Tucker Carlson Tonight*; but this in turn could make them less (or more) interested in watching some other Fox News show. Such spillovers could be very complex, as they would depend on underlying preferences – how shows are complements and substitutes. Patterns of complementarity or substitution between relative viewership of *Hannity* versus *Tucker Carlson Tonight* and viewership of other shows would then violate that exclusion restriction and complicate interpretation of the two-stage least squares regressions.

For these reasons, while we will proceed in this section under the assumption that the exclusion restriction described above holds, it is important to keep in mind the aforementioned limitations of the approach. In Section 9, we will relax the exclusion restriction assumption and employ a more general approach allowing for arbitrary spillovers across Fox News programs, while still allowing us to investigate the hypothesized mechanism of exposure to differential coverage of the coronavirus crisis.

Instrument relevance As we show in Table 4, our instrument strongly predicts viewership of *Hannity* relative to *Tucker Carlson Tonight*. The first-stage F-statistic of our preferred specification (Column 6) is substantially higher than 10, and 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. For consistency and transparency, we will show 2SLS results across all specifications in Appendix Table 4, as well as permutations across all of the additional combinations.

6.2 Results on COVID-19 cases and deaths

We next turn to our instrumental variable estimates on downstream health outcomes: COVID-19 cases and deaths.

Figure 9, which for consistency and ease of comparison mirrors the OLS specification of Figure 6 (that is, 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. As in the OLS specification, we cluster standard errors at the DMA level.[40] Effects on cases start to rise in early March and peak in mid-March before gradually declining, consistent with Hannity's changing position on the coronavirus. Consistent with estimated lags between case and death reporting, effects on deaths start emerging approximately three weeks after cases.[41] A one standard deviation higher viewership of *Hannity* relative to *Tucker Carlson Tonight* is associated with approximately 15 percent more cases on March 7 ($p < 0.001$), 34 percent more cases on March 14 ($p < 0.001$), and 29 percent more cases on March 21

[40]The analogous results with standard errors clustered at the state level are reported in Appendix Figure A10.
[41]See, e.g., "A Second Coronavirus Death Surge is Coming." *The Atlantic*, July 15, 2020.

($p < 0.05$); the effect then declines to a statistically-insignificant 7 percent more cases on April 4. A one standard deviation greater viewership of *Hannity* relative to *Tucker Carlson Tonight* is associated with 24 percent more deaths on March 28 ($p < 0.01$), 35 percent more deaths on April 4 ($p < 0.05$), and 30 percent more deaths on April 11 ($p < 0.10$).[42] The initial divergence and eventual plateauing of effects on COVID-19 cases are consistent with our proposed mechanism that differential reporting between Hannity and Carlson about the coronavirus throughout February and early March are driving our results, as we will explore more fully in the next subsection and in Section 6.3.[43] We report reduced-form and 2SLS results at weekly intervals in regression table form in Table 5.

6.3 Mechanism: differential coverage

Taken together, our evidence suggests that higher viewership of *Hannity* relative to *Tucker Carlson Tonight* is associated with a greater number of COVID-19 cases and deaths during the early onset of the coronavirus pandemic. Given the qualitative evidence highlighted in Section 2, the timing of these effects on cases and deaths already suggests an important role of differences in information content between the two shows in driving results. We now examine the timing of deaths and cases relative to the timing of differences in content of the two shows more closely.

We construct two indices measuring differences between the two shows. First, to construct the Carlson-Hannity "pandemic coverage gap", we use our Mechanical Turk coding results from Section 2.2. 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 the coronavirus 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 "behavioral change gap," we return to our survey results from Section 3. In particular, for each day, the gap is defined as the associated Hannity coefficient minus the same-day Carlson coefficient from Panel B of Figure 2 — that is, the difference between the marginal effects of viewership of these two shows on the event that the respondent had changed their behavior to act more cautiously in response to the coronavirus by the date in question. Thus, we should expect the behavioral change gap to lag the pandemic coverage gap, since viewers react to the differences in information sets presented on the two shows.

Figure 10 plots the pandemic coverage gap and the behavioral change gap in tan diamonds and green squares, respectively. To facilitate plotting on the same figure, we rescale the pandemic coverage and behavioral change gaps by dividing each series' coefficients by the maximum coefficient value over the series, such that the maximum value is 1. Figure 10 also plots the 2SLS estimates of the Hannity-Carlson viewership gap (instrumented by Z_{mc}) on log one plus cases and log one plus deaths in gray circles and red triangles, respectively (as previously reported in Figure 9).

The pandemic coverage gap peaks in mid-February, a period during which there was no discussion of the coronavirus on *Hannity* and during which *Tucker Carlson Tonight* discussed the topic on virtually every

[42]In Panel B of Appendix Figure A20, we report day-by-day results for cases and deaths extending until the time of writing, as discussed in Footnote 43.

[43]In Appendix Figure A20, we report day-by-day results for cases and deaths extending until the time of writing. Like the OLS results, point estimates remain positive; effects on both cases and deaths increase, though these coefficients are imprecisely estimated, and we cannot rule out null effects.

episode, before declining to zero by mid-March. The behavioral change gap follows a similar shape with a two-week lag, peaking in early March before declining. The trend in coefficient estimates on cases closely mirrors the trend in the pandemic coverage gap (with a lag of approximately one month) and the trend on the pandemic coverage gap (with a lag of approximately two weeks), while the trend in coefficient estimates on deaths follows with an additional two 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.

It is important to note that as of the time of writing, effects on cases and deaths have not reverted to zero (see Section A.8). As we show in Section 8.2, a simple epidemiological model can, with reasonable parameters, match the approximate magnitude of treatment effects throughout both our primary period of focus (late February through mid-April) and our extended period of focus (late February through the time of writing in August).

7 Robustness

In this section, we conduct a number of exercises to probe the robustness of our estimates.

7.1 Robustness to choice of controls, zero values, and outliers

Robustness to choice of specification As in Section 5.2, we run our specifications under every possible combination of our eight sets of county-level controls (population density and rurality, race, age, economic, education, health, health capacity, politics) and our three levels of fixed effects (no fixed effects, Census division fixed effects, and state fixed effects). We again focus on March 14 for cases and March 28 for deaths. Panel B of Appendix Figure A4 reports coefficient estimates for each of these 768 models for cases as of March 14; Panel B of Figure 7 reports the analogous estimates for deaths as of March 28. 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 percent 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 OLS estimates can thus be interpreted as a plausible lower bound on the true causal effect of differential viewership on COVID-19 trajectories; indeed, correcting the OLS coefficients for omitted variables bias by the method proposed in Oster (2019) yields estimates very similar to our IV estimates.

[44]We repeat this exercise for every date between February 24 and April 15 for cases and between March 1 and April 15 for deaths (768 regressions per day). 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).

Robustness to outliers and COVID-19 hotspots One potential concern is that COVID-19 hotspots with a 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 Appendix Figure A11. 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 Appendix Figure A12, we estimate our time series figures leaving out entire states containing prominent COVID-19 hotspots. In general, our estimates remain quantitatively and qualitatively similar; if anything, point estimates are slightly *higher*, suggesting the mechanism that we study is less relevant in explaining the trajectories of cases and deaths in these states. However, these coefficients are less precisely estimated.

Robustness to zero values To ensure that our results are not driven by zero values, we construct an unbalanced panel wherein a county only enters the panel once it has a COVID-19 case. In Appendix Figure A13, we report 2SLS estimates. Because relatively few counties had a non-zero number of cases during early March, our main specification (which includes a rich set of county-level controls, along with state fixed effects) results in a singular or close-to-singular matrix until mid-March, and even afterward, confidence intervals are relatively large. Nonetheless, our estimates are qualitatively similar (though quantitatively smaller), and our estimates on deaths are statistically significant at the five percent level between mid-March and early April. The somewhat smaller effects sizes are consistent with an important role of movements in both the intensive and extensive margins in shaping our results. Estimates on cases are not statistically significant at the five percent level.

7.2 Resampling inference

Finally, we conduct a number of resampling exercises to further probe the robustness of our estimates. We conduct each exercise with 1000 repetitions.

Bootstrap To address sampling error, in Appendix Figure A14, we calculate our standard errors via a block bootstrap procedure, randomly sampling DMAs with replacement and estimating counterfactual treatment effects for each day. We employ a conservative approach to calculating standard errors: rather than ex ante fixing the set of counties between the 0.025-quantile and the 0.975-quantile of *average* treatment effects, we compute confidence intervals separately by day, using the 0.025-quantile and the 0.975-quantile of the estimated treatments effects *on each day* as the upper and lower bounds on our confidence intervals, respectively. Our bootstrapped standard errors are larger and thus our effects are statistically significant for a somewhat shorter period of time: effects on cases are statistically significant from early-to-mid March, while effects on deaths are statistically significant from mid-March to late April. However, our findings remain qualitatively unchanged.

Randomization inference To address error arising from treatment variation (including spatial autocorrelation), in Appendix Figure A15, we employ a randomization inference approach (Athey and Imbens, 2017), permuting the plausibly exogenous "shift" ($\tilde{s}_{mc,H}$) across DMAs while leaving the "shares" ($\tilde{f}_{mc,-HT}$), the county-level covariates, and cases and deaths unchanged. For each repetition, we then regenerate our instrument as the interaction of the placebo $\tilde{s}_{mc,H}$ with $\tilde{f}_{mc,-HT}$, then estimate placebo treatment effects as before. Under this approach, we find that our effects on cases and deaths are statistically significant at the 5% level throughout essentially the same period as described above.

Permutation test To ensure that our results are not driven by statistical artifacts, in Appendix Figure A16 we randomly permute the joint tuple of case and death counts across counties and estimate counterfactual treatment effects. The resulting distribution of estimates is centered around zero; and once more, our true estimates for cases exceed the 0.975-quantile of counterfactual estimates from early to mid March, while our true estimates for deaths exceed the 0.975-quantile of counterfactual estimates from late March to mid-April.

7.3 Robustness to alternative IV strategies

7.3.1 Predicted DMA level viewership curve

A key source of variation driving variation in our main leave-out instrument, Z_{mc}, is differing preferences across localities for when to watch TV. The use of leave-outs to generate cleaner and plausibly exogenous variation in differential exposure to the two shows has the limitation that it is somewhat unclear what remaining underlying factors are driving the residual variation in timing preferences. In particular, the concern would be some confounding determinant of health outcomes still covarying with preferences for the time slot of the respective shows, in ways which interact with the market share of Fox News. While this possibility seems somewhat remote, it cannot be ruled out. By contrast, in an ideal experiment, one would randomly assign Fox viewers to different timeslots, exposing some areas more to *Hannity* and other areas more to *Tucker Carlson Tonight*. To get closer to this ideal, we now consider an extension of the instrument which more explicitly exploits variation in timing preferences.

Specifically, we show – and empirically exploit – important systematic patterns that drive TV viewership over the course of the evening, in ways that are highly unlikely to interact with the leave-out Fox News market share to drive health outcomes. In particular, DMAs across the country exhibit a relatively consistent *inverse-U shaped* relationship between the time since sunset and total TV viewership. Panel A of Figure B1 plots a non-parametric local polynomial fitting the relationship between time since sunset and the fraction of TVs tuned to non-Fox channels. On average across the country, TV viewership peaks 2.5 hours after sunset and then declines smoothly. Panel A also shows a histogram depicting, at each twelve-minute interval relative to sunset, the number of DMAs in which *Tucker Carlson Tonight* begins in that interval (blue) and in which *Hannity* begins in that interval (purple). Because both shows are broadcast live — *Tucker Carlson Tonight* at 8pm Eastern Time and *Hannity* at 9pm Eastern Time — both shows are aired much earlier and closer to sunset in more Western time zones (e.g. 5pm and 6pm Pacific Time, respectively). Yet as Panel B of Figure B1 highlights, even holding constant what (clock) time shows air, there remains substantial variation in start time relative to sunset. [45] While DMAs differ in the precise shape of their viewership curve over the course of the evening, the vast majority exhibit a clear inverted-U pattern.[46] For example, on February

[45] Appendix Figure A8 highlights this phenomenon across the continental United States, plotting sunset times in each county on February 1, 2020.

[46] Episodes of *Tucker Carlson Tonight* and *Hannity* are generally re-run three hours after they first air, and because our data spans 5pm to 11pm, we observe repeats in more western time zones but not in Eastern Time. In order to avoid making

1, 2020, the sun set at 6:05pm in Louisville, KY, whereas it set at 5:19pm in Philadelphia, PA — nearly an hour earlier. Thus, predicted viewership during *Hannity*'s timeslot is larger in Louisville, as "prime time" is at approximately 8:30pm, only 30 minutes before *Hannity* airs. Predicted viewership during *Hannity*'s timeslot is lower in Philadelphia, where the local prime time of TV consumption is forty five minutes earlier.

Our identification strategy exploits cross-DMA variation in sunset timing and viewership preferences alongside timezone-specific variation in local airtimes of *Hannity* and *Tucker Carlson Tonight*, such that cross-DMA variation in the predicted amount of total TV viewership during Hannity's timeslot — or more precisely, total non-Fox TV viewership during this timeslot — generates variation in relative viewership of *Tucker Carlson Tonight* vs. *Hannity*.

Let $\widehat{\mathrm{s}}_{mc,H}$ denote the *predicted* fraction of TVs turned on in DMA d at the time slot of *Hannity*, leaving out TVs watching Fox News (i.e. leaving out TVs watching *Hannity*).[47] We predict $\mathrm{s}_{mc,H}$ parametrically for each DMA using a second-degree polynomial. Denoting by n_{mt} the sunset time in DMA m on day t, we have:

$$\mathrm{s}_{mc,H} = \alpha_m + \delta_{m1}(s - n_{mt}) + \delta_{m2}(s - n_{mt})^2 + \epsilon_{dst} \tag{4}$$

As before, letting f_{mc} denote the viewership share of Fox News in DMA m, leaving out *Hannity* and *Tucker Carlson Tonight*, the modified instrument is given by $\widehat{\mathrm{s}}_{mc,H} \times \tilde{f}_{mc,-HT}$. The underlying logic for this modified version is the instrument is simple: if people like to turn on their TVs to watch *something* when *Hannity* happens to be on rather than when another Fox show happens to be on, simply as a function of when shows air relative to when it gets dark locally (and not just what official time it is locally), the number of viewers shifted into watching *Hannity* is disproportionately large in areas where Fox News is popular in general, for arguably exogenous reasons. As before, conditional upon the small set of controls accounting for local viewership patterns, this instrument is not significantly correlated with demographic characteristics (Appendix Figure B2) and has a strong first stage on viewership (Columns 3-4 of Appendix Table A2). In Appendix B, we replicate all of our analysis with this alternative instrument and find qualitatively identical and quantitatively similar results.

7.3.2 Division-level viewership curve

One possible concern with both our main instrument and our sunset instrument is that they might rely excessively on local preferences (that is, DMA-specific preferences) for watching TV over the course of the evening. We now consider a prediction of the share of TVs turned on during *Hannity* and *Tucker Carlson Tonight* using *Census division-wide*, rather than DMA-specific, preferences for TV viewership over the course of the evening. Thus, our identifying variation is driven by the interaction of the viewership curve *at the division level* with DMA-specific market shares of Fox News, controlling for the main effects at the DMA level. To allow DMAs to differ in their *absolute* preference for TV viewership while keeping our identifying variation — the viewership curve over the course of the evening — constant, we allow the level and scale of the viewership curve to differ between DMAs within a division but hold the shape of the curve fixed. In

assumptions about viewership patterns in western time zones relative to Eastern Time by failing to include Eastern Time viewership that falls outside of the window covered by our data, we simply set viewership to the average viewership across both airings in DMAs in which we observe re-runs. However, our results are robust to only using viewership of the live broadcasts.

[47] As mentioned above, we leave out TVs watching Fox News in order to capture a general DMA preference for TV viewership at a given time rather than specific preferences for Fox News. The logic is analogous to the logic of the leave-one-out estimator used in Bartik instruments (Bartik, 1991).

particular, we estimate the following first-stage regression separately for each of the nine Census divisions in the United States:

$$\log(\mathrm{s}_{mc,H}) = \alpha_m + \delta_1(s - n_m) + \delta_2(s - n_m)^2 + \epsilon_{ms},$$

where the DMA-specific fixed effect α_m allows the level of the curve to vary between DMAs and the log transformation of $\mathrm{s}_{mc,H}$ allows the scale of the curve to vary between DMAs. We re-define $\widehat{\mathrm{s}_{mc,H}} = \exp(\widehat{\log \mathrm{s}_{mc,H}})$ and, as before, construct our instrument based on the interaction of $\widehat{\mathrm{s}_{mc,H}}$ with the viewership share of Fox News in DMA m, leaving out *Hannity* and *Tucker Carlson Tonight*. Our first-stage specifications are otherwise identical to those in Section 6.1.

Like our main instrument, conditional upon the small set of controls accounting for local viewership patterns, this alternative instrument is not significantly correlated with demographic characteristics (Appendix Figure C1), and it has a first stage on viewership (Columns 5-6 of Appendix Table A2), though the relationship is weaker than that which we find with our main instrument or the DMA-based sunset prediction. In Appendix C, we replicate our analysis with this alternative instrument and find qualitatively identical and quantitatively similar results. Although our confidence intervals are wider due to a weaker first stage, there still remain approximately 2-week intervals in mid-March and in late March to early April where cases and deaths, respectively, are statistically significant at the 5% level across all randomization exercises.

7.3.3 Two instruments

Table A2 shows robustness of the 2SLS estimates when two instruments are included, the one for *Hannity* as specified in Section 6 and an analogously constructed instrument for *Tucker Carlson Tonight*, $\tilde{s}_{mc,T} * \tilde{f}_{mc,-HT}$. Two-stage least squares estimates are similar in magnitude and statistical significance, but — as might be expected given the correlation between the two instruments — the first stage F-statistic is smaller and below the generally-accepted threshold of 10, suggesting that including both instruments may induce a weak instruments problem and bias both our coefficients and standard errors. As there remains uncertainty in how to test for and overcome weak instruments in over-identified models, as opposed to in simpler just-identified settings (see Andrews et al. 2019 for a discussion), our primary specification uses only the instrument for *Hannity*'s timeslot.

8 Assessing Effect Sizes

8.1 Assessing magnitudes along the COVID-19 curve

How should one interpret the magnitudes of the coefficients, given that they are estimated at different moments in time as the pandemic spreads? To illustrate, we perform a simple back-of-the-envelope calculation using information on actual COVID-19 case trajectories across counties combined with the estimated effects of viewership reported in Figure 9. By construction, the 2SLS coefficient for any given day will capture the percent increase in cases from a one standard deviation greater viewership difference between *Hannity* and *Tucker Carlson Tonight*. We use this information by first taking the actual mean cases for each day

— effectively capturing the COVID-19 trajectory for a 'representative' county — and adding the implied percent increase as given by the estimated coefficient for that day. We then plot the logarithmic trajectory for actual cases, together with the calculated counterfactual trajectory. We then conduct the same exercise using the data and estimates on COVID-19 deaths.

Panel A of Figure 11 plots the trajectories for cases: (i) log one plus cases for a representative county (in black) and (ii) the implied counterfactual log one plus cases for counties with a one standard deviation higher viewership of *Hannity* versus *Tucker Carlson Tonight* (in gray). The *relative* magnitude peaks around March 15 at slightly above 0.3 log points, corresponding to approximately a 30 percent increase from the base. However, given the logarithmic scale, the implied magnitude on cases keeps growing in economic importance as the pandemic expands, before slowly converging and turning statistically insignificant. The evidence is therefore consistent with differential viewership of *Hannity* over *Tucker Carlson Tonight* having induced a steeper curve early on in the pandemic, in opposition to efforts aimed at "flattening the curve."

Panel B of Figure 11 plots the trajectories for estimated deaths. Similar patterns emerge, except they arise approximately two weeks later. Here, the estimated coefficient of the relative effect peaks in the first week of April, at around 0.4 log points, as Figure 9 also shows clearly, before starting to decline and turning statistically insignificant.[48]

8.2 Assessing treatment effects through an epidemiological model

We now assess the effect sizes documented in Section 8.1 through a simple epidemiological model. The key behavioral foundation is that *Hannity* and *Tucker Carlson Tonight* influence the behavior of viewers by changing their beliefs about the threat posed by the coronavirus, thus influencing the extent to which they take precautionary measures (such as washing hands or disinfecting more frequently) and in turn affect the disease transmission rate among viewers.[49]

Our model allows us to estimate the extent to which the shows would need to affect transmissibility among viewers in order to generate treatment effects similar in magnitude to those we estimate. Our goal is not to point-identify structural parameters of the model: estimating models of the COVID-19's spread is notoriously difficult (as evidenced by the wide variance in model predictions from different sources over the course of the pandemic) and there may be multiple parameters that ; and moreover, our identification strategy does not allow us to account for inter-county externalities, a crucial element in explaining the virus' spread (Kuchler et al., 2020). Instead, we view our exercise as a back-of-the-envelope calculation to demonstrate that our observed treatment effects on deaths are consistent with reasonable changes in disease transmissibility.

Basic SIR (Susceptible-Infected-Removed) models, or most standard variants thereof, do not allow for heterogeneous groups that differ in their mortality or transmission rates. We wish to account for heterogeneity in age, since the elderly both have elevated COVID-19 fatality rates and are disproportionately likely to

[48]In Appendix Figure A17, we present results from an equivalent exercise using the OLS estimates. The magnitudes of the estimated effects are in general smaller. In Appendix Figure A21, we extend the figure with treatment effects estimated until the time of writing, as discussed in Footnote 43.

[49]Viewership of *Hannity* and *Tucker Carlson Tonight* may also affect transmissibility through indirect channels. For example, these shows might change social norms associated with behavior such as wearing masks, temporarily closing businesses, and providing employees with sick leave (Shadmehr and de Mesquita, 2020), or, relatedly, viewers might share the information they learned on the shows with others. For simplicity, we do not model these channels.

watch Fox News. We also wish to account for heterogeneity in viewership of *Tucker Carlson Tonight* and *Hannity*, since only a fraction of the population are exposed to these shows and an even smaller fraction are "treated" (in the sense of being shifted into watching more *Hannity* relative to *Tucker Carlson Tonight* by our instrument inducing a one standard deviation increase in relative viewership).

We thus adapt the multi-group SIR model introduced in Acemoglu et al. (2020) to model four groups: the "untreated" population between 25 and 64 (of size N_{yu}); the "treated" population between 25 and 64 (of size N_{yt}); the "untreated" population aged 65 and older (of size N_{ou}); and the "treated" population aged 65 and older (of size N_{ot}). We calibrate N_j using ACS data on the age distribution of the US population alongside our Nielsen data on daily viewership and our survey data on viewership frequency.[50] Following Acemoglu et al. (2020), we normalize the total population size $N = \sum_j N_j$ to 1. [51] We assume that death and recovery rates are invariant to time and the number of patients. To capture differential interaction patterns — the fact that young agents are more likely to interact with other young agents (e.g. through the workplace) while old agents are more likely to interact with old agents (e.g. in nursing homes), we calibrate the interaction matrix ρ using the intergenerational interaction matrix from Akbarpour et al. (2020).[52] While age affects the probability of interaction between groups, treatment status does not: conditional on age, a treated person is equally likely to interact with another treated person as with an untreated person. Following Allcott et al. (2020a), we model the effect of cautious behaviors such as washing hands, wearing face masks, or social distancing — and thus, the effect of differential viewership of *Hannity* and *Tucker Carlson Tonight* — by assuming that they directly affect the transmission rate β_j.[53]

Denoting the susceptible, infected, recovered, and dead populations by S, I, R, and D, respectively, the model is characterized by the following system of differential equations:

$$\begin{aligned}
\dot{I}_j &= S_j \left(\sum_k c(\beta_j, \beta_k) \rho_{jk} I_k \right) - \gamma_j I_j - \delta_j I_j \\
\dot{R}_j &= \gamma_j I_j \\
\dot{D}_j &= \delta_j I_j \\
\dot{S}_j &= -\dot{I}_j - \dot{R}_j - \dot{D}_j
\end{aligned}$$

To fix notation, let $\bar{X}$ denote the value of variable X in a representative county with a mean viewership of *Hannity* relative to *Tucker Carlson Tonight*, and let X^+ denote the value of X in a representative

[50] As in our survey analysis, we include "occasional" viewers (those who watch the shows between one and three times per week) alongside "regular" viewers (those who watch four or five times per week).

[51] We make a number of additional parameter assumptions to make the model more tractable. In particular, we assume $\alpha = 2$ (quadratic matching in transmission, which most closely matches the dynamics of a standard SIR model); and we abstract away from healthcare capacity constraints by assuming that $\iota = 1$.

[52] The matrix is based on data provided by Replica, which uses anonymized cellphone GPS data to simulate a "synthetic population" that "closely approximates both age and industry distributions from the Census ACS, as well as granular ground-truth data on mobility patterns from a variety of different sources" (Akbarpour et al., 2020).

[53] Thus, in contrast to Acemoglu et al. (2020), there is no single transmission rate β governing the probability by which a susceptible agent will be infected when they come into contact with an infected agent; this rate is an increasing function c in the β_j parameters of the infected agent and the susceptible agent. To our knowledge, there are no estimates of $c(\cdot, \cdot)$ for COVID-19. For tractability, we assume that when agents from groups a and b with $\beta_a \neq \beta_b$ come into contact, the "effective transmission rate" is given by $c(\beta_a, \beta_b) = \max\{\beta_a, \beta_b\}^2$, intuitively capturing the intuition that it is the less cautious agent that drives the transmission probability. (For example, the primary benefit of face masks is that they help prevent infected people from spreading COVID-19 to others; they are less effective in protecting the wearer against contracting COVID-19 from others Bai (2020). However, our results are qualitatively similar if we instead assume $c(\beta_a, \beta_b) = \beta_a \beta_b$.

county with a one standard deviation higher viewership of *Hannity* relative to *Tucker Carlson Tonight*. By construction, there is no "treated" population in the county with mean relative viewership: $\bar{N}_{yt} = \bar{N}_{ot} = 0$, $\bar{N}_{yu} = N^+_{yu} + N^+_{yt}$, $\bar{N}_{ou} = N^+_{ou} + N^+_{ot}$. Also by construction, transmissibility in the county with mean relative viewership is always equal to transmissibility among untreated in the county with a one standard deviation higher relative viewership: $\bar{\beta}_{yu}(t) = \bar{\beta}_{ou}(t) = \beta^+_{yu}(t) = \beta^+_{ou}(t)$, for all t. To ease notation, we write $\bar{\beta} := \bar{\beta}_{yu} = \bar{\beta}_{ou}$, $\beta^+_u := \beta^+_{yu} = \beta^+_{ou}$, $\beta^+_t := \beta^+_{yt} = \beta^+_{ot}$. We report all parameter values in Table 6.

We take the timing of behavioral changes in response to the coronavirus from our survey, which are presented in Panel B of Figure 2, as primitives in our model. The treatment effect of *Hannity* viewership relative to *Tucker Carlson Tonight* viewership on the total number of people who report having changed their behavior to act more cautiously in response to the coronavirus is approximately 0 on February 1, increases to peak on March 1, and then decreases. The difference had not yet returned to zero by the date of the survey, but assuming the observed trend continued, we would expect it to return to zero by mid-April. We thus fix $\bar{\beta}(t) = \beta^+_n(t) = \beta^+_c(t)$ for $t =$ Feb 1 and $t \geq$ Apr 15. Since, in our survey, both the increase in estimated treatment effects between February 1 and March 1 and the decrease between March 1 and April 3 are approximately linear, we linearly interpolate values of β between February 1 and March 1 and between March 1 and April 15. Informed by recent epidemiological estimates (e.g., Unwin et al. 2020), we allow the transmission rate to decline linearly from April 15 to May 1. This leaves us with five parameters to estimate: $\bar{\beta}(\text{Feb } 1) = \beta^+_u(\text{Feb } 1) = \beta^+_t(\text{Feb } 1)$, $\bar{\beta}(\text{Mar } 1) = \beta^+_u(\text{Mar } 1)$, $\beta^+_t(\text{Mar } 1)$, $\bar{\beta}(\text{Apr } 15) = \beta^+_u(\text{Apr } 15) = \beta^+_t(\text{Apr } 15)$, and $\bar{\beta}(\text{May } 1) = \beta^+_u(\text{May } 1) = \beta^+_t(\text{May } 1)$.

COVID-19 cases are vastly underreported with some preliminary estimates suggesting that as many as 93% of cases may be undetected (Stock et al., 2020). This is particularly true in the United States, which continues to suffer from testing shortages at the time of writing.[54] As a result, we focus on fitting the trajectories of *deaths* estimated in Section 8.1. We proceed by simulating death trajectories under different values of parameters, selecting the combination that minimizes a loss function based on the sum of squared residuals between the 2SLS estimates and the simulated trajectories.[55]

Panel A of Figure 12 plots the fitted trajectories of β for the untreated (which comprise the entire county with a mean viewership difference and the vast majority of the county with a one standard deviation higher viewership difference) and for the treated (the remaining fraction of the county with a one standard deviation higher viewership difference).[56] The peak difference in $\bar{\beta}$ and β^+_t on March 1 is approximately 27%.[57] The estimated paths imply that the treated population did not adjust their behavior at all throughout most of February and only began doing so in March, while the non-treated population gradually adjusted behavior throughout the period before the April 15 convergence. For ease of comparison with other studies, we can also calculate the trajectories of the effective reproduction number R_t: the expected number of susceptible individuals an individual infected at time t will him or herself infect. At $t = 0$, this is approximated by $R_0 \approx \frac{\beta^2}{\gamma} = 3.18$; R_t falls to approximately 1.81 by April 15 among the untreated and approximately

[54]See, for example, "Why America's coronavirus testing barely improved in April", *The New York Times*, May 1, 2020.

[55]We begin our simulations on February 1, five days before the day of the first confirmed COVID-19-related death in the US (see "First Known U.S. COVID-19 Death Was Weeks Earlier Than Previously Thought", *NPR*, April 22, 2020.)

[56]We repeat this exercise for our OLS estimates; the results are reported in Appendix Figure A18.

[57]This difference is approximately equal to the March 1 persuasion rate we identify from the survey data (24.1%), though the two estimates are of course not directly comparable. Weighting by the size of each group, the maximum difference in the *average* beta in the county with a mean viewership difference vs. the county with a 1 SD higher viewership difference is around 2%.

1.15 among both groups by May 1. These values are broadly similar to recent estimates of the effective reproduction rate, e.g. Atkeson et al. (2020).

Panel B of Figure 12 plots the implied simulated trajectories of deaths (dashed line) and the trajectories of deaths implied by our 2SLS estimates (solid line) for a representative county with a mean *Hannity-Tucker Carlson Tonight* viewership difference and for a representative county with a one standard deviation higher viewership difference. Panel C of Figure 12 plots the simulated treatment effect, i.e. the difference between the two dashed lines, and the 2SLS treatment effects, i.e. the difference between the solid lines. Our model fits the estimated treatment effects fairly well.[58]

Our model also allows us to examine what fraction of people who died were members of the treated group, i.e. the group whose transmissibility was affected by a one standard deviation increase in relative viewership. We estimate that approximately 5% of the additional deaths occur in the treated group, with the additional deaths occurring in the untreated group. Since there is substantial uncertainty about the true values of the exogenously taken input parameters of the model, and since our model fails to capture important features such as county-to-county spillovers, we should be cautious when interpreting this estimate. Nonetheless, the model highlights the relevance of externalities in generating our estimated treatment effects.[59] Taken together, our results suggest that behavioral responses among viewers early on in a pandemic – due to differential media coverage of the virus – can give rise to modest but meaningful differences in transmissibility among the broader population, which ultimately translate into effect sizes of roughly the same magnitude as those we estimate.

9 Generalized Exposure across Fox News Shows

Our previous estimates focused on the effects of our instrument on differential viewership of *Hannity* and *Tucker Carlson Tonight*. These two shows were the largest outliers on Fox News in their coverage of the coronavirus (in opposite directions), and are the most widely-watched programs on the network and in the United States, suggesting that the viewership gap between the two shows alone had effects on cases and deaths. Yet as we discuss in Section 6.1, differences in viewership across those two Fox News shows may, through various spillovers, also correlate with viewership of many other shows. Specifically, for any given DMA, regular viewership of *Tucker Carlson Tonight* (airing 8pm-9pm ET) and *Hannity* (airing 9pm-10pm ET) could lead to positive or negative selection into various combinations of: *The Five* (5pm-6pm ET); *Special Report with Bret Baier* (6pm-7pm ET); *The Story with Martha MacCallum* (7pm-8pm ET); *The Ingraham Angle* (10pm-11pm ET); and *Fox News at Night* (11pm-12pm ET).[60] Despite the fact that the other evening shows are neither as widely watched as *Hannity* and *Tucker Carlson Tonight* nor as extreme

[58]Adding additional degrees of freedom by modeling agent heterogeneity, "super-spreader" events, and network structure would allow us to better fit the shape of estimated treatment effects (McGee, 2020), but these are beyond the scope of our exercise.

[59]Our results are in line with those of Banerjee et al. (2020), which also finds large spillovers in the context of health behaviors during the COVID-19 pandemic.

[60]Of course, there might also be spillovers to day-time Fox News shows, but such selection would arguably be less significant given that TV is primarily viewed between 5pm and 11pm. Cross-network spillovers are also possible. Such spillovers are likely minor given that viewers tend to favor shows within the same network; indeed, in the survey discussed in Section 3, 73 percent of respondents report that Fox News is the only cable TV network they watch at least once a week. Moreover, as we show in Appendix Figure A22, the other two dominant cable TV networks, CNN and MSNBC, featured far less variation between shows in their coverage of COVID-19, limiting the extent that spillovers might bias our results.

in their coverage, their content may also have influenced COVID-19 outcomes. In this case, the narrow exclusion restriction, which requires that effects operate through viewership of *Hannity* or *Tucker Carlson Tonight*, would be violated. Thus, we now turn to a more general approach to capture viewers' (predicted) exposure to misinformation on Fox News.

Specifically, for each DMA, we first calculate a measure of local exposure to information about the pandemic across *all* evening-time shows on Fox News, allowing us to consider the broad information set to which Fox News viewers were exposed. We combine our data on viewership shares of the different shows at the DMA-by-day level with our Mechanical Turk episode coding results to construct a measure of information exposure, the *pandemic coverage index*, as the average of the degree to which each episode portrayed the coronavirus as a serious threat to the United States, weighted by viewership of that episode within the DMA. More formally, we define r_{st} to be the average seriousness rating of show s on day t and m_{sdt} to be the average viewership share of episde s in DMA d among all Fox News evening-time episodes on day t. Then the *daily exposure* e_{dt} of a DMA is given by:

$$e_{dt} := \frac{1}{|S_d|} \sum_{s \in S_d} r_{st} m_{sdt}.$$

where S_d is the menu of shows between 5pm and 11pm in DMA d. We then construct the pandemic coverage index for DMA d as the sum of $\tilde{e}_{dt}$ throughout the months of January and February:

$$PCI_d := \sum_{t \in \text{Jan, Feb}} \tilde{e}_{dt}.$$

The index therefore captures an (inverse) local "stock" of exposure to news on Fox News underplaying the pandemic threat throughout February relative to the mean exposure across DMAs in the same period. For ease of interpretation, we scale the index to a standard normal distribution. Because we are broadly interested in the effects of misinformation, and to be consistent with our previous figures, we use the inverse of our pandemic coverage index, $-1 \times PCI_d$ throughout the rest of this section.

Columns 1 and 2 of Table 7 highlight that our measure of viewership of *Hannity* relative to *Tucker Carlson Tonight* strongly predicts the pandemic coverage index ($p < 0.001$), whether we include only the minimum set of controls to capture local viewership patterns or we condition on the full set of controls employed in Section 6. Next, we examine the extent to which our instrument, Z_{mc}, is associated with the pandemic coverage index. Columns 3 and 4 of Table 7 show that our instrument is strongly and significantly associated with the pandemic coverage index, again whether we include only the minimum set of controls or we condition on the full set of county characteristics. Finally, in Columns 5 and 6 of Table 7, we examine the relationship between the pandemic coverage index and COVID-19 cases and deaths through 2SLS. We follow the approach from Section 6, but we use the pandemic coverage gap as the endogenous variable instead of the standardized difference in viewership of *Hannity* versus *Tucker Carlson Tonight*, allowing us to fully capture spillovers between shows on Fox News. Our results suggest that a one percentage point increase in the inverse of the pandemic coverage index increases the number of cases by 3.96 percent on March 14 ($p < 0.001$) and the number of deaths by 2.83 percent by March 28 ($p < 0.001$).

In Appendix Figure A23, we estimate the same 2SLS specifications separately for each day, allowing us to examine the relationship between the inverse pandemic coverage index and health outcomes over time. The effect of the inverse pandemic coverage index on cases peaks in mid-March and then begins to decline, while effects on deaths appear to level off in early April.

10 Conclusion

How can diverging media coverage influence beliefs and behavior? Examining this question is particularly important during a pandemic, given the large externalities involved and the significant consequences of misinformed behavior for individuals' health and for the health care system as a whole. In this paper, we show that differential exposure to information broadcast on mass media significantly affected behavior and downstream health outcomes in the context of the COVID-19 pandemic.

We examine the two most popular cable news shows in the United States: *Hannity* and *Tucker Carlson Tonight*. These shows are aired back-to-back on the same network (Fox News) and had relatively similar content prior to January 2020, yet differed sharply in their coverage of the COVID-19 pandemic. We validate differences in content with independent coding of shows' transcripts and present new survey evidence that, consistent with these content differences, viewers of *Hannity* changed behavior in response to the virus later than other Fox News viewers, while viewers of *Tucker Carlson Tonight* changed behavior 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 the number of total cases and deaths in the initial stages of the coronavirus pandemic. A standard epidemiological model matches the approximate magnitude of our measured treatment effects and highlights the relevance of externalities. Finally, we also provide additional evidence that contemporaneous information exposure is an important mechanism driving the effects in the data. Together, our results indicate that misinformation on mass media can have significant social consequences.

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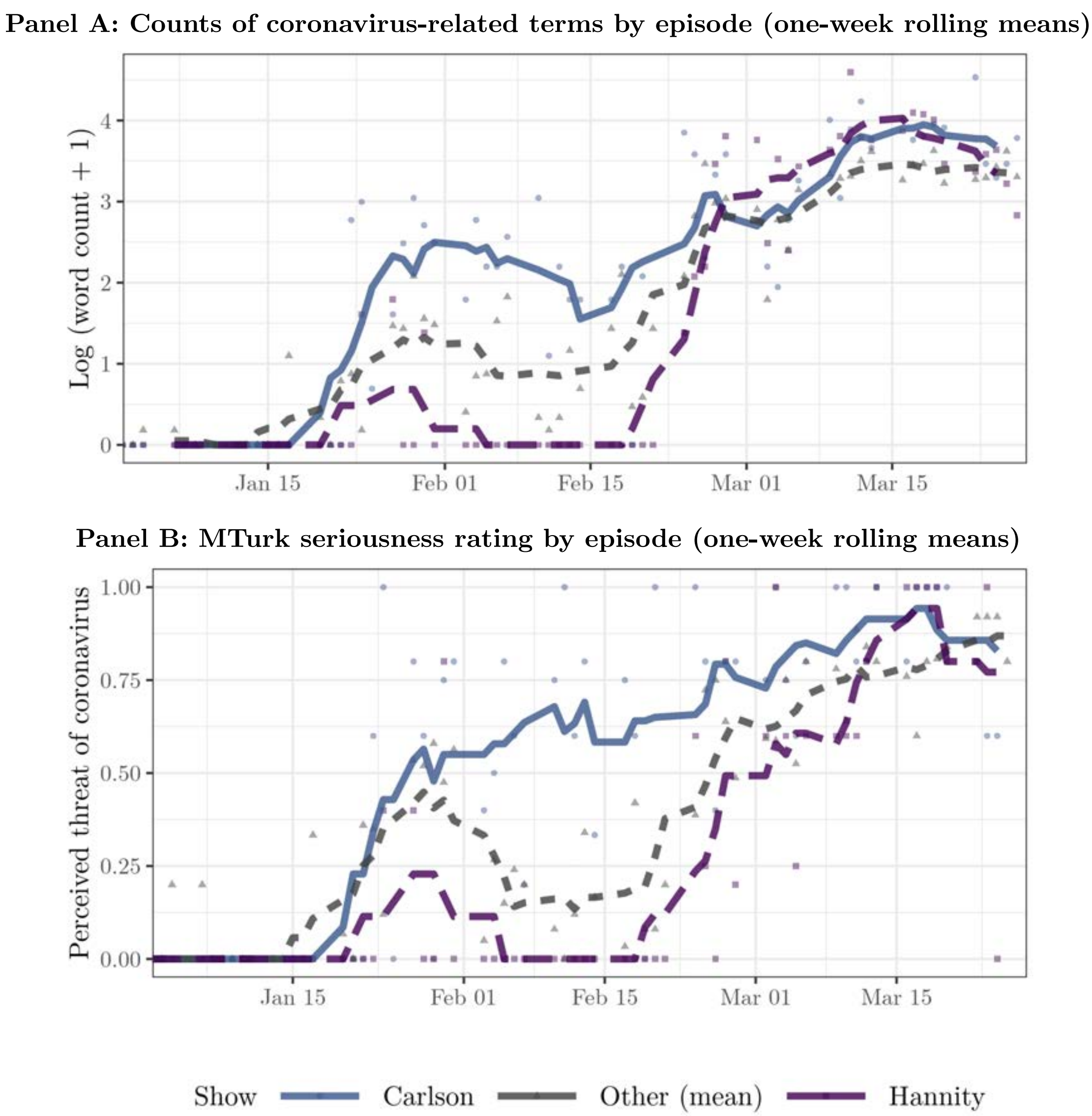
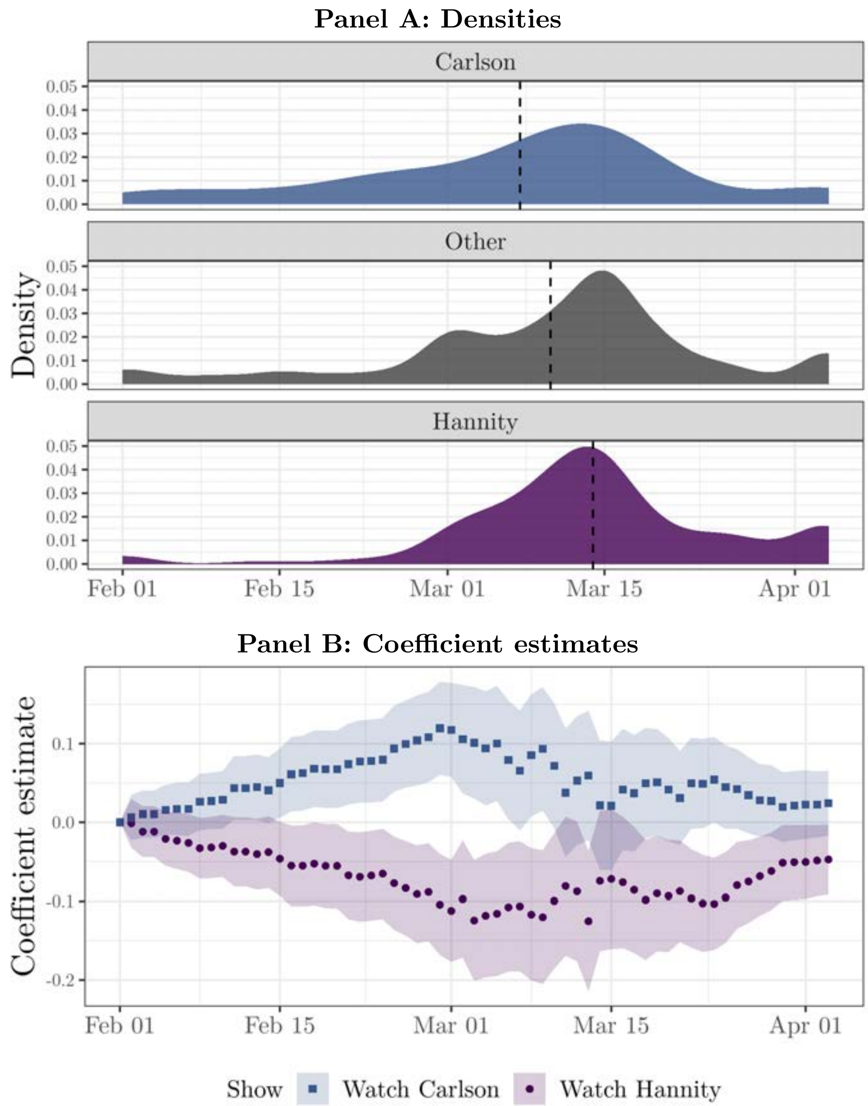
Figures

Figure 1: Show content validation



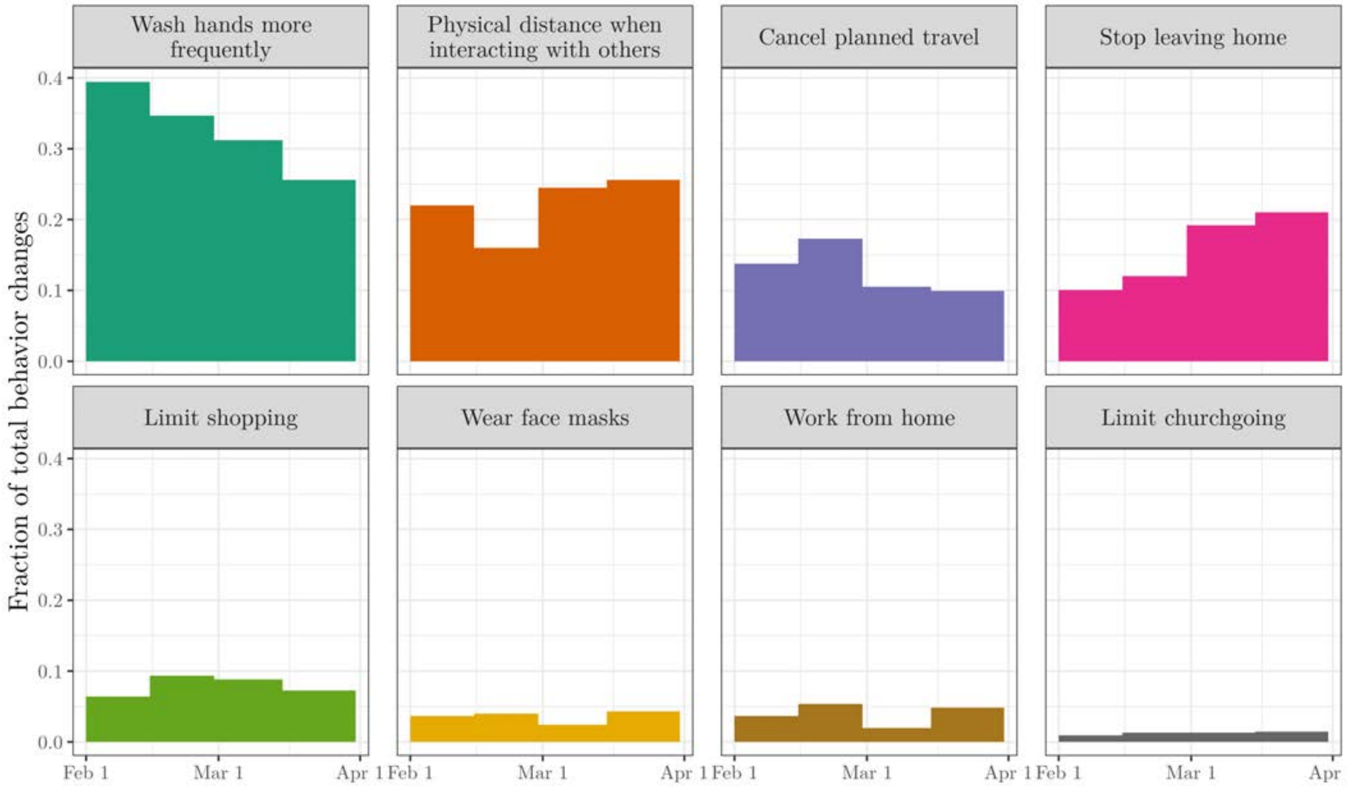
Notes: Panel A shows counts of coronavirus-related terms (coronavirus, COVID, virus, influenza, and flu) separately for *Hannity*, *Tucker Carlson Tonight*, and the other Fox News shows aired on Fox News between 5pm and 11pm local time across all four major time zones in the continental US (*The Five*, *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.

Figure 2: Timing of behavioral change by show viewership



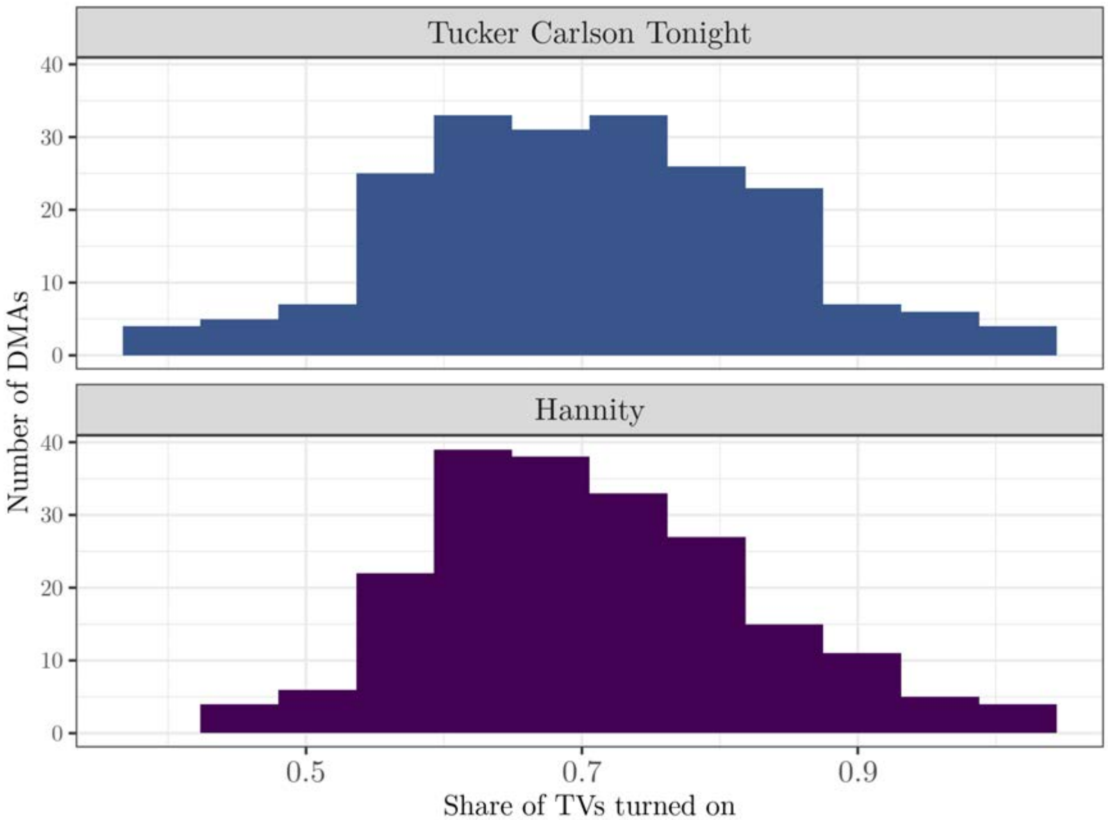
Notes: Panel A of Figure 2 displays the density function of viewers' reported day of behavior change in response to the coronavirus. For respondents who report that they have not changed any of their behaviors by the date of the survey, we impute the date of the survey (April 3). The dashed line indicates the mean date of behavior 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 behavior 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.

Figure 3: Margins of behavioral adjustment



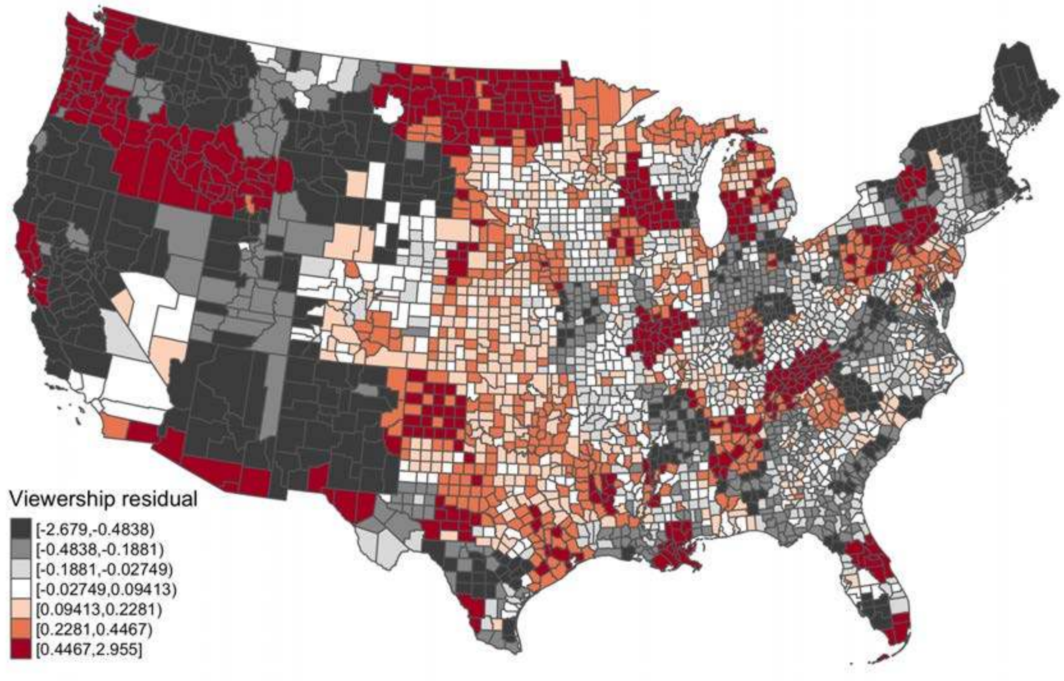
Notes: For each two-week interval between February 1 and April 1, Figure 3 shows the fraction of reported behavioral changes falling under each category. Behaviors were coded based upon responses to the following open-ended question from our survey: "When did you first significantly change any of your behaviors (for example, cancelling travel plans, washing hands or disinfecting significantly more than often, staying six feet away from others, asking to work from home, etc.) in response to the coronavirus? How did you change your behavior? Why did you change your behavior?"

Figure 4: Total TV viewership during *Hannity* and *Tucker Carlson Tonight*



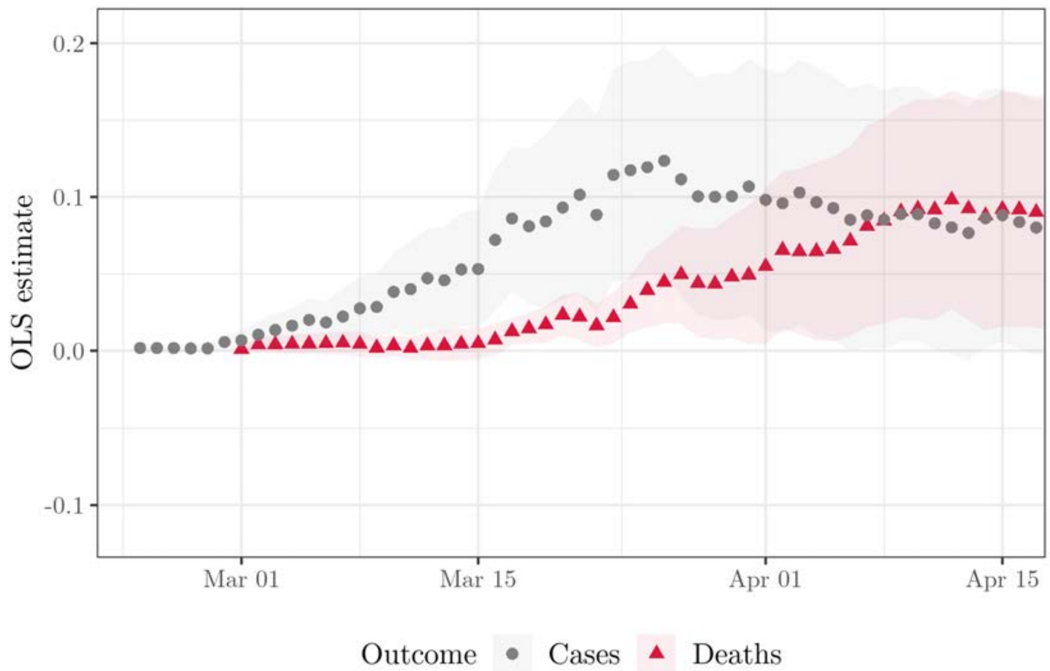
Notes: Figure 4 plots DMAs by the average share of TVs turned on during *Tucker Carlson Tonight*'s timeslot and the average share of TVs turned on during *Hannity*'s timeslot.

Figure 5: Residualized Hannity-Carlson viewership difference



Notes: Figure 5 plots the residual of the standardized difference in the viewership of *Hannity* and *Tucker Carlson Tonight* for each of the 207 DMAs in the continental United States, where the difference in viewership has been standardized to mean zero and a standard deviation of one and the residual is taken with respect to 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 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 sixty-five, 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.

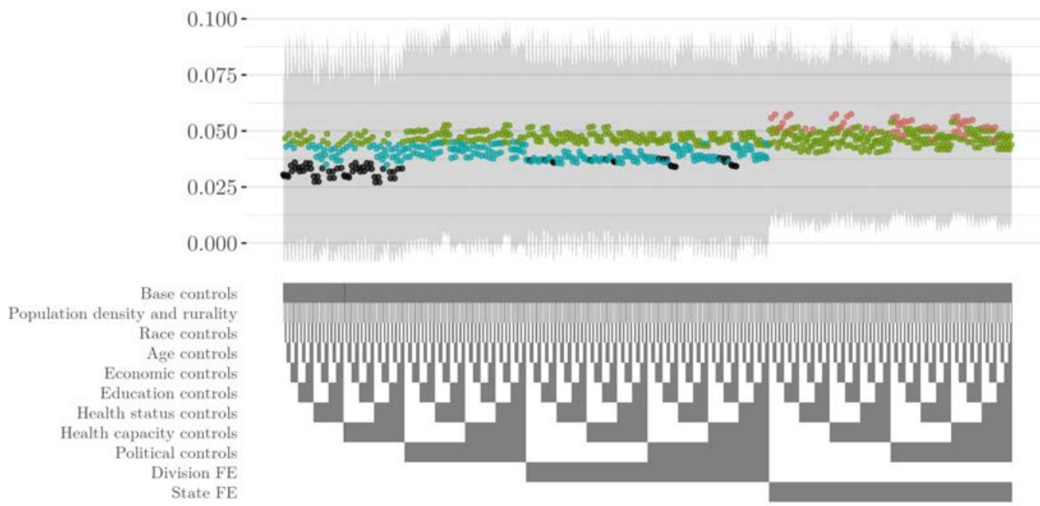
Figure 6: OLS estimates of effect of differential viewership on cases and deaths



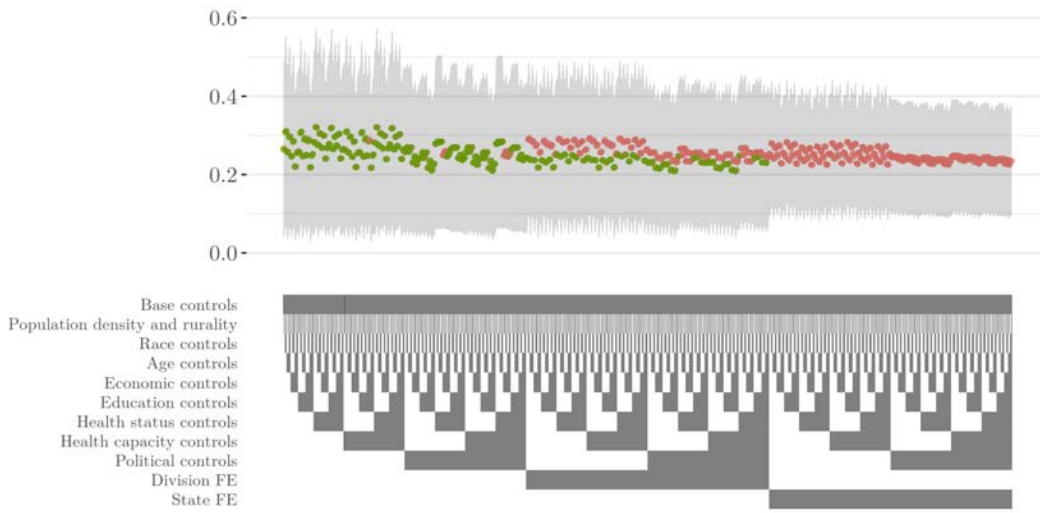
Notes: Figure 6 displays effects of differential viewership of *Hannity* and *Tucker Carlson Tonight* on log one plus cases and log one plus deaths. We report day-by-day results for the correlation between log deaths and log cases with the standardized viewership difference between *Hannity* and *Tucker 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 sixty-five, 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 percent confidence intervals.

Figure 7: Estimates on deaths on March 28: robustness to combinations of controls

Panel A: OLS estimates on deaths

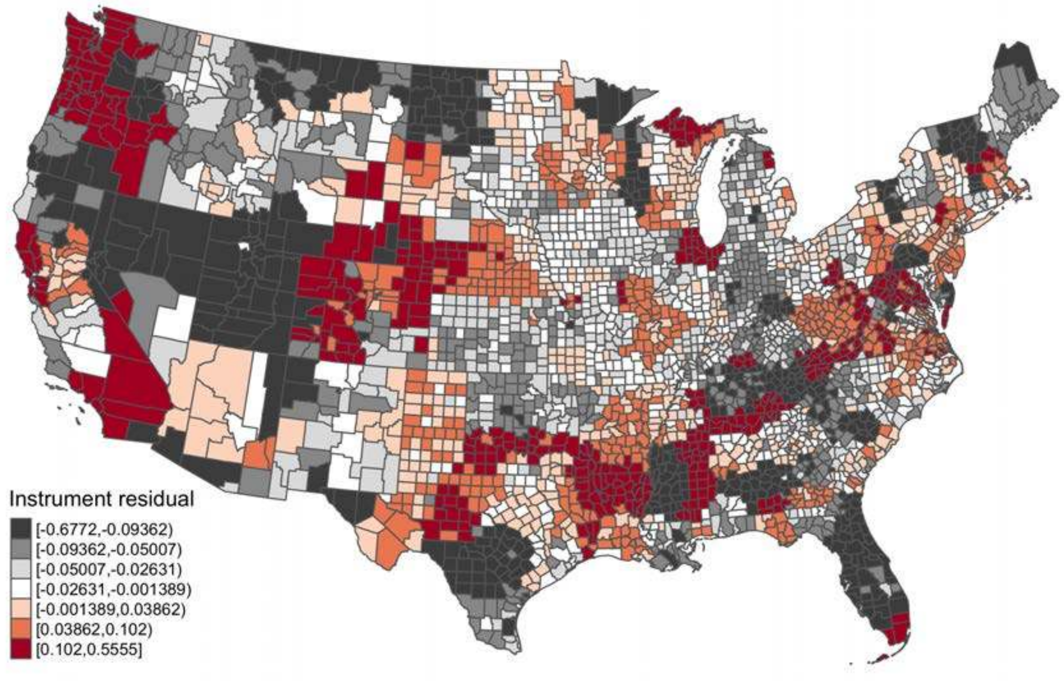


Panel B: IV estimates on deaths



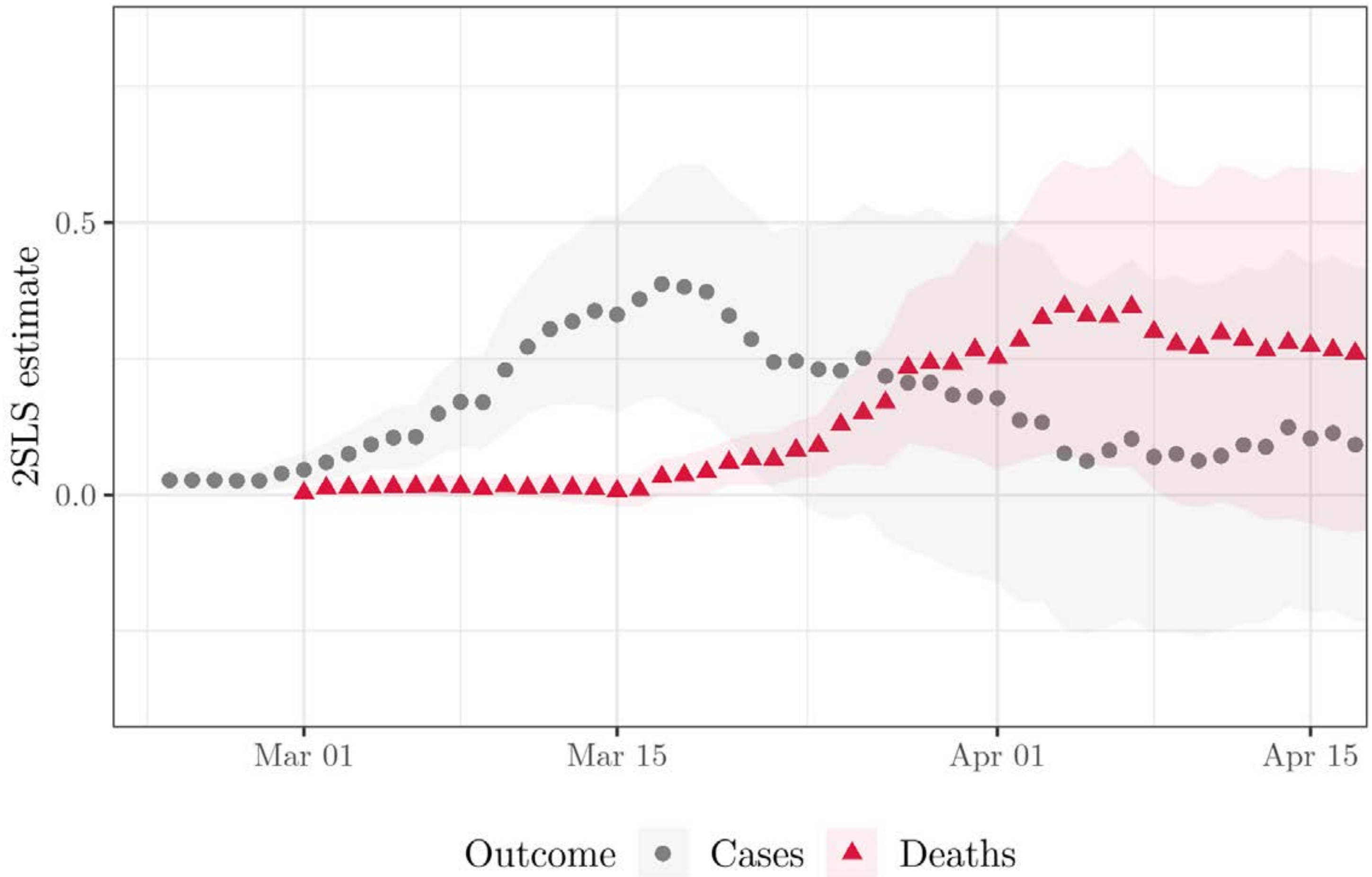
Notes: Figure 7 shows robustness of our OLS and IV estimates for the specifications for log one plus deaths on March 28 under every possible combination of our eight sets of county-level controls (population density and rurality, race, age, economic, education, health status, health capacity, politics) and our three levels of fixed effects (no fixed effects, Census division fixed effects, and state fixed effects). We cluster standard errors at the DMA level and report 95 percent confidence intervals. Black points are not significant at the ten percent level; blue points are significant at the ten percent level; green points are significant at the five percent level, and red points are significant at the one percent level.

Figure 8: Residualized Hannity-Carlson instrument values



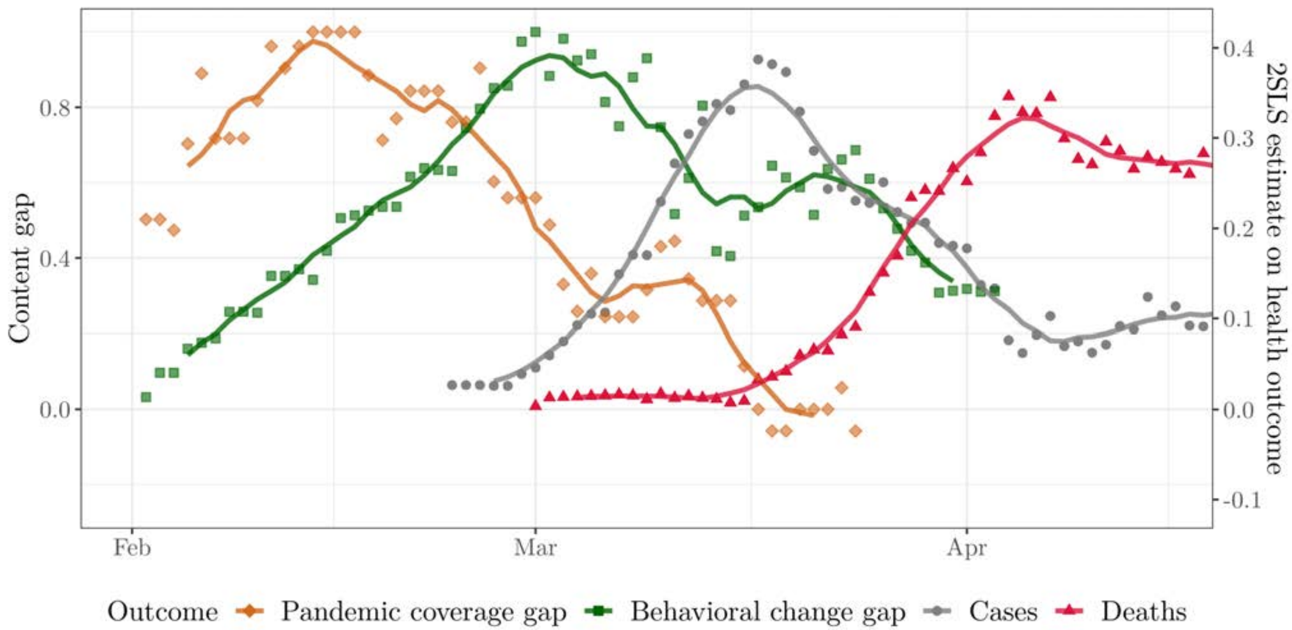
Notes: Figure 8 plots the values of our instrument, $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$, residualized by our full set of controls: the November 2018 and January 2020 market share of Fox News, the November 2018 market share of MSNBC, log total population, population density, the predicted share 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 sixty-five, 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.

Figure 9: 2SLS estimates of effect of differential viewership on cases and deaths



Notes: Figure 9 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 sixty-five, 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 percent confidence intervals.

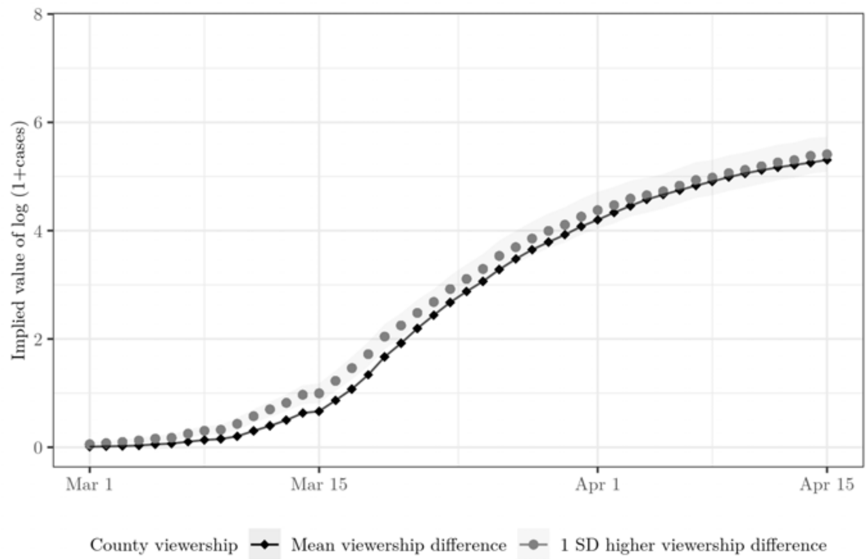
Figure 10: Carlson-Hannity content gaps and effects on cases and deaths



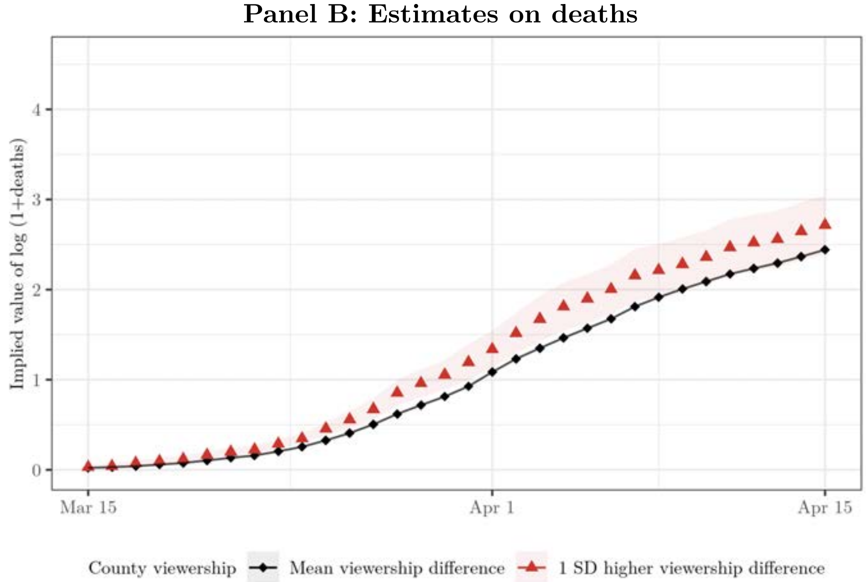
Notes: Figure 10 shows four time series. First, in tan diamonds corresponding to the left y-axis, we plot the "pandemic coverage gap": the difference in portrayed seriousness of the coronavirus threat on *Tucker Carlson Tonight* vs. *Hannity*, as rated by Amazon Mechanical Turk coders (as previously reported in Panel B of Figure 1). Second, in green squares also corresponding to the left y-axis, we plot the "behavioral 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 behavior to act more cautiously in response to the coronavirus by the date in question on indicators for viewership of difference Fox News shows (as previously reported in Figure 2). To facilitate plotting on the same figure, we rescale both the pandemic coverage and behavioral change gaps by dividing each series' coefficients by the maximum coefficient value over the series. Finally, in gray circles and red triangles, both corresponding to the right y-axis, we plot the 2SLS estimates of the Hannity-Carlson viewership gap (instrumented by $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$) on log one plus cases and log one plus deaths, respectively (as previously reported in Panel B of Figure 9). These latter two 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 sixty-five, 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.

Figure 11: Implied COVID-19 curves

Panel A: Estimates on cases

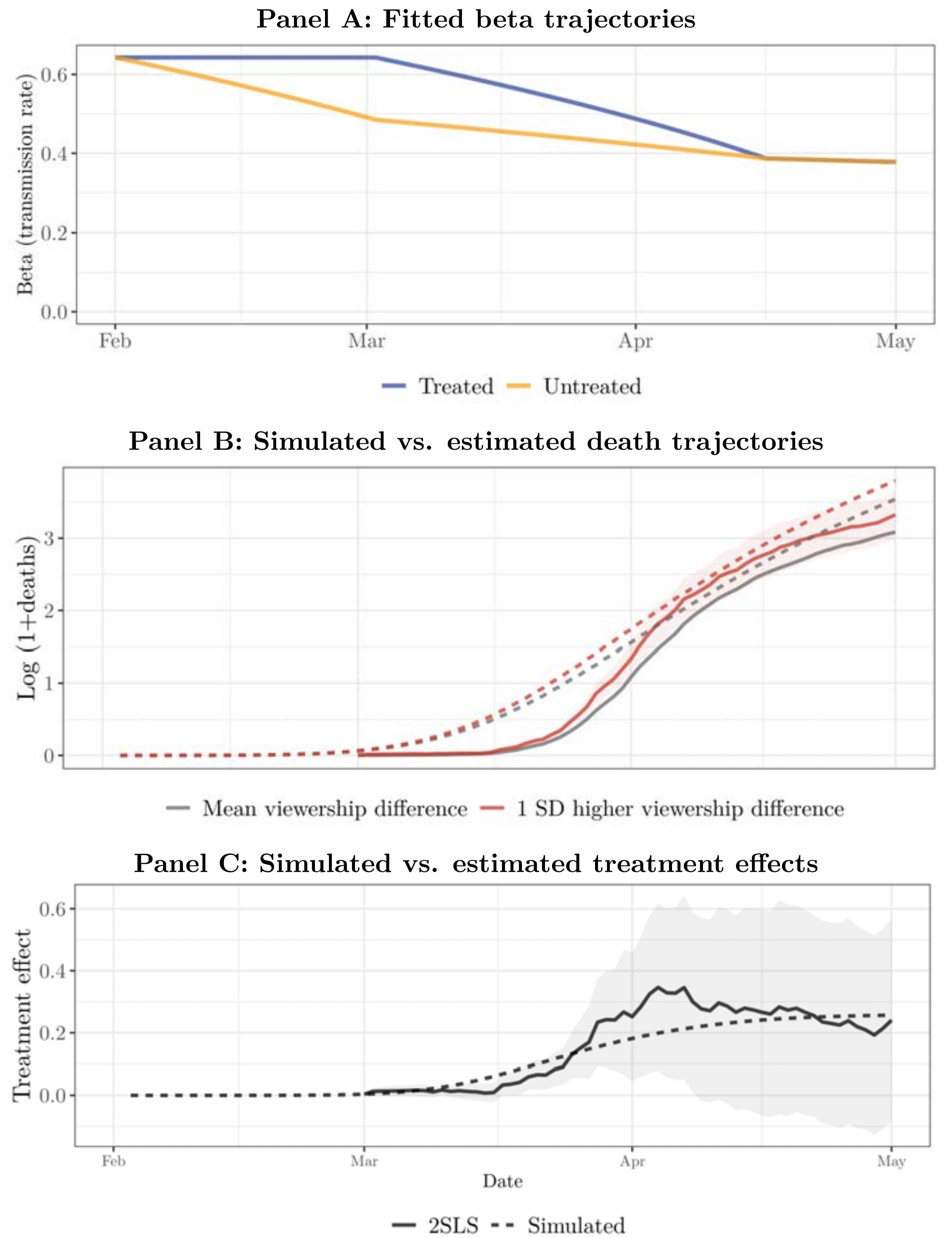


Panel B: Estimates on deaths



Notes: Panel A of Figure 11 plots, in black, the logarithm of (one plus the) mean number of cases in each day across all counties. In gray, the figure plots the the implied counterfactual values (based on our 2SLS estimates) for a county with a one standard deviation higher viewership difference between *Hannity* and *Tucker Carlson Tonight*. Panel B replicates Panel A, taking log one plus deaths as the outcome rather than log one plus cases. We report 95 percent confidence intervals on the counterfactual estimates. Standard errors are clustered at the DMA level.

Figure 12: MG-SIR simulations



Notes: Panel A of Figure 12 plots, in orange, the β trajectory implied by our simulation for non-compliers (which comprise the entire county with a mean viewership difference and almost the entire county with a one standard deviation higher viewership difference) and, in blue, the corresponding trajectory for compliers (which comprise the remaining population of the county with a one standard deviation higher viewership difference). Panel B plots the simulated trajectories of deaths (dashed line) and the trajectories of deaths implied by our 2SLS estimates (solid line) for a representative county with a mean *Hannity-Tucker Carlson Tonight* viewership difference (gray) and for a representative county with a one standard deviation higher viewership difference (red). Panel C plots the simulated treatment effect, i.e. the difference between the two dashed lines, and the 2SLS treatment effects, i.e. the difference between the solid lines.

Tables

Table 1: Demographics of Tucker Carlson Tonight vs. Hannity viewers

Demographic	***Tucker Carlson Tonight***	***Hannity***
Age	65.41	64.9
Male	0.52	0.56
Retired	0.57	0.49
Works full time	0.2	0.27
Household income ($)	75982.14	71816.41
White	0.89	0.96
Years of education	14.71	14.44
Watches CNN	0.16	0.24
Watches MSNBC	0.07	0.15

Notes: Table presents mean values of each demographic characteristic among exclusive viewers of *Hannity* and *Tucker Carlson Tonight*, based on our survey of 1,045 Republican over the age of 65 who watch Fox News.

Table 2: Correlation between show viewership and timing of behavior 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 February 1, 2020 on which the respondent reported having significantly changed any of their behaviors in response to the coronavirus. For respondents who report not changing behavior by the date of the survey, we recode the dependent variable to the date of the survey (April 3). The dependent variables in Columns 2-4 are indicators for whether the respondent reported having significantly changed their behaviors 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, and 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.

Table 3: OLS estimates of effect of differential viewership

	Dependent variable:						
	COVID-19 outcomes						
	Feb 29	Mar 07	Mar 14	Mar 21	Mar 28	Apr 04	Apr 11
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Estimates on cases							
Hannity-Carlson viewership difference	0.006**	0.022**	0.053***	0.101***	0.100**	0.097**	0.083**
	(0.002)	(0.009)	(0.019)	(0.033)	(0.039)	(0.045)	(0.042)
Panel B: Estimates on deaths							
Hannity-Carlson viewership difference	0.001	0.005	0.004	0.022***	0.044**	0.065**	0.092**
	(0.001)	(0.004)	(0.005)	(0.008)	(0.018)	(0.030)	(0.037)
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 deaths in the county as of the date referenced in the column. Panel A reports OLS estimates of the log of one plus cases upon the standardized difference in Hannity-Carlson viewership; Panel B replicates for the log of one plus deaths. All specifications include controls for the 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, the population density of the county, the log of the county's total population, MSNBC's share of cable in January 2018, population-weighted latitude and longitude, the percent of the population living in a rural area, the population over the age of 65, the percent male with no high school degree, the percent female with no high school degree, the percent male with no college degree, the percent female with no college degree, an age-adjusted measure of the average physical health in the county, the percent uninsured, the percent below the federal poverty line, the log of the median household income, the unemployment rate, the Republican vote share in 2016, and the log of the total number of votes in the county in 2016. Standard errors are clustered at the DMA level.

Table 4: First-stage regressions

	Dependent variable:					
	Difference in Hannity-Carlson viewership					
Non-Fox TVs on × Fox share	1.063***	1.039***	1.133***	1.075***	1.138***	1.124***
	(0.330)	(0.316)	(0.277)	(0.270)	(0.273)	(0.269)
Controls	Base	Full	Base	Full	Base	Full
Fixed effects	None	None	Division	Division	State	State
Observations	3,103	3,100	3,103	3,100	3,103	3,100
R^2	0.720	0.739	0.790	0.796	0.823	0.827
F-statistic	10.40	10.84	16.70	15.88	17.38	17.44

Notes: Table reports regressions of the standardized difference between viewership of *Hannity* and *Tucker Carlson Tonight* on our instrument, $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$ — 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*.. Fox share and predicted viewership include the predicted share of TVs tuned to non-Fox channels during *Hannity* and during the show immediately before and immediately afterward, as well as Fox News' share of cable, leaving out *Hannity* and *Tucker Carlson Tonight*. "Base controls" include 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 population density and log population, and population-weighted latitude and longitude. "Full controls" additionally include the percent of the population living in a rural area, the population over the age of 65, the percent male with no high school degree, the percent female with no high school degree, the percent male with no college degree, the percent female with no college degree, an age-adjusted measure of the average physical health in the county, the percent uninsured, the percent below the federal poverty line, the log of the median household income, the unemployment rate, the Republican vote share in 2016, and the log of the total number of votes in the county in 2016. Standard errors are clustered at the DMA level.

Table 5: Effect of differential viewership on COVID-19 outcomes

	Dependent variable:						
	COVID-19 outcomes						
	Feb 29	Mar 07	Mar 14	Mar 21	Mar 28	Apr 04	Apr 11
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Estimates on cases							
Subpanel A.1: Reduced form							
Non-Fox TVs on × Fox share	0.044***	0.168***	0.380***	0.321**	0.231	0.086	0.080
	(0.011)	(0.040)	(0.088)	(0.139)	(0.171)	(0.184)	(0.183)
Subpanel A.2: Two-stage least squares							
H-C viewership difference (predicted)	0.039***	0.149***	0.338***	0.286**	0.206	0.077	0.072
	(0.013)	(0.039)	(0.089)	(0.123)	(0.157)	(0.165)	(0.164)
Panel B: Estimates on deaths							
Subpanel B.1: Reduced form							
Non-Fox TVs on × Fox share	0.004*	0.019	0.013	0.074**	0.263***	0.389***	0.333**
	(0.002)	(0.012)	(0.017)	(0.030)	(0.064)	(0.127)	(0.160)
Subpanel B.2: Two-stage least squares							
H-C viewership difference (predicted)	0.003**	0.016*	0.011	0.066***	0.234***	0.346**	0.296*
	(0.002)	(0.010)	(0.014)	(0.024)	(0.072)	(0.137)	(0.158)
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 reduced-form estimates of the log of one plus cases upon the instrument, $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$ — 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 A.2 replicates for deaths. Panel B.1 reports two-stage least squares estimates of the log of one plus cases upon the standardized difference in Hannity-Carlson viewership, instrumented by $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$; 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, the population density of the county, the log of the county's total population, MSNBC's share of cable in January 2018, population-weighted latitude and longitude, the percent of the population living in a rural area, the population over the age of 65, the percent male with no high school degree, the percent female with no high school degree, the percent male with no college degree, the percent female with no college degree, an age-adjusted measure of the average physical health in the county, the percent uninsured, the percent below the federal poverty line, the log of the median household income, the unemployment rate, the Republican vote share in 2016, and the log of the total number of votes in the county in 2016. Standard errors are clustered at the DMA level.

Table 6: Exogenous model parameters

Parameter	**Description**	**Value**	**Source**
P_o	Share of simulated population above the age of 65	0.3216	American Comunity Survey (ACS)
$\bar{N}_{yt}$	Share of treated among young in representative county with mean viewership	0	
$\bar{N}_{ot}$	Share of treated among old in representative county with mean viewership	0	
N^{+}_{yt}	Share of treated among young in representative county with 1 SD higher viewership	0.0097	Nielsen
N^{+}_{ot}	Share of treated among old in representative county with 1 SD higher viewership	0.0112	Nielsen
$i(0)$	Initial fraction of infected individuals	3.030×10^{-8}	Estimated 10 infections in US on Feb 1
$I_j(0)$	Initial share of infected individuals in group j	$i(0) \times N_j$	
$S_j(0)$	Initial share of susceptible individuals in group j	$N_j - I_j$	
$R_j(0)$	Initial share of recovered individuals in group j	0	
$D_j(0)$	Initial share of dead individuals in group j	0	
γ	Estimated recovery arrival rate	0.125	Allcott et al. (2020) (derived)
δ_y	Estimated fatality arrival rate among young individuals	6.354×10^{-4}	Ferguson et al. (2020) (derived)
δ_o	Estimated fatality arrival rate among older individuals	0.0101	Ferguson et al. (2020) (derived)
α	"Returns to scale" in matching of individuals	2.000	Acemoglu et al. (2020)
ρ	Matrix of group interaction rates (first row/column for young, second for old)	$\begin{bmatrix} 1.51 & 0.57 \\ 0.53 & 0.47 \end{bmatrix}$	Akbarpour et al. (2020)

Table 7: Differential coverage and COVID-19 outcomes across all Fox News evening shows

	Dependent variable:					
	Inverse pandemic coverage index				Cases Mar 14	Deaths Mar 28
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *OLS: inverse pandemic coverage index on relative viewership*						
H-C viewership difference	0.548^{***}	0.545^{***}				
	(0.053)	(0.052)				
Panel B: *RF: inverse pandemic coverage index on instrument*						
Non-Fox TVs on $\times$ Fox share			0.502^{**}	0.490^{**}		
			(0.230)	(0.227)		
Panel C: *2SLS: cases and deaths on inverse predicted pandemic coverage index*						
$-1\times$ coverage index (predicted)					0.776^{**}	0.538^{*}
					(0.364)	(0.281)
Controls	Base	Full	Base	Full	Full	Full
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,102	3,102	3,102	3,102	3,102	3,102

Notes: Panel A reports OLS estimates of the (inverse of the) pandemic coverage index on the standardized difference between viewership of *Hannity* and *Tucker Carlson Tonight*. Panel B reports reduced-form estimates of the inverse pandemic coverage index on our instrument, $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$ — 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.*. Columns (5) and (6) in Panel C report 2SLS estimates of the log of one plus the number of cases on March 14 and the log of one plus the number of deaths on March 28, respectively, on the standardized difference between viewership of *Hannity* and *Tucker Carlson Tonight*, instrumented by $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$. Base OLS controls include the 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, the population density of the county, and the log of the county's total population. Base controls for the reduced form and the two-stage least squares are identical, except the share of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle* are replaced with the predicted share of TVs tuned to non-Fox channels during these timeslots. 'Full controls" additionally include all controls described in Section 5.2. Standard errors are clustered at the DMA level.

Supplementary Appendix

Our supplementary material is organized as follows. In Appendix A, we report appendix figures and tables referenced in the main body of the text. In Appendix B, we report versions of the figures and tables included in the main text, but using the alternative instrument described in Section 7.3.1. In Appendix C, we report versions of the figures and tables included in the main text, but using the alternative instrument described in Section 7.3.2. In Appendix D, we report versions of the figures and tables included in the main text, but with cases and deaths transformed by the inverse hyperbolic sine rather than the natural logarithm. In Appendix E, we include a copy of the survey instrument described in Section 3.

A Appendix Tables and Figures

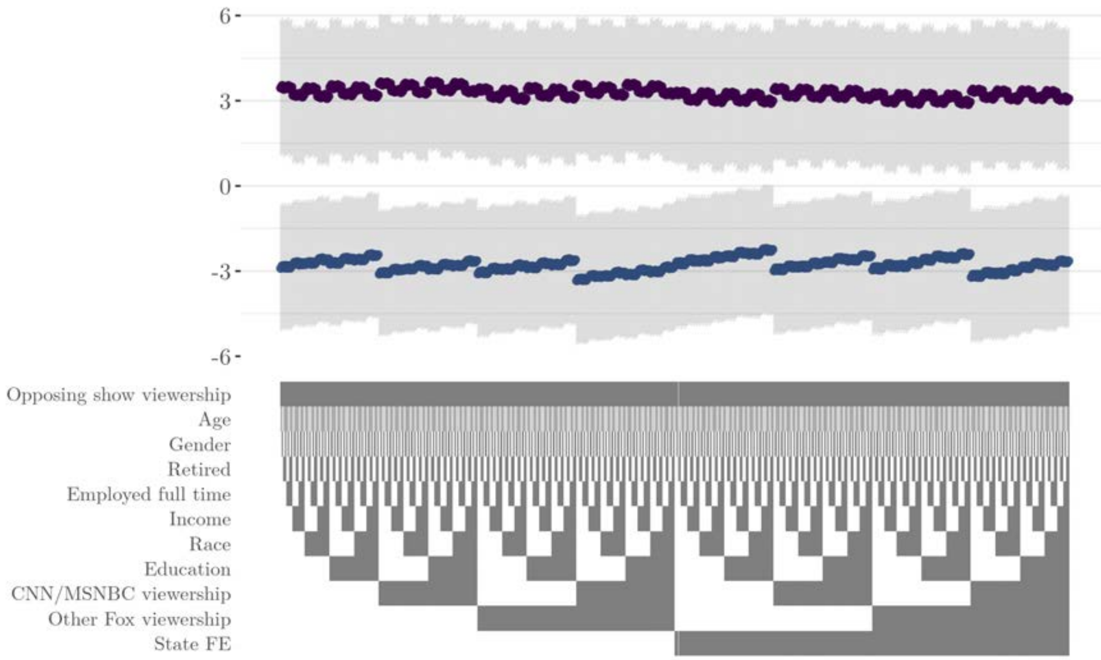
A.1 Survey

Table A1: Sample representativeness

Variables:	Survey	Gallup
Male	0.61	0.50
Age	65.34	67.31
Race: White	0.95	0.93
At least high school degree	0.99	0.93
Bachelor degree or above	0.38	0.30
Employed full-time	0.26	0.29
Annual household income (USD)	71758.37	60115.93
Observations	1045	12932

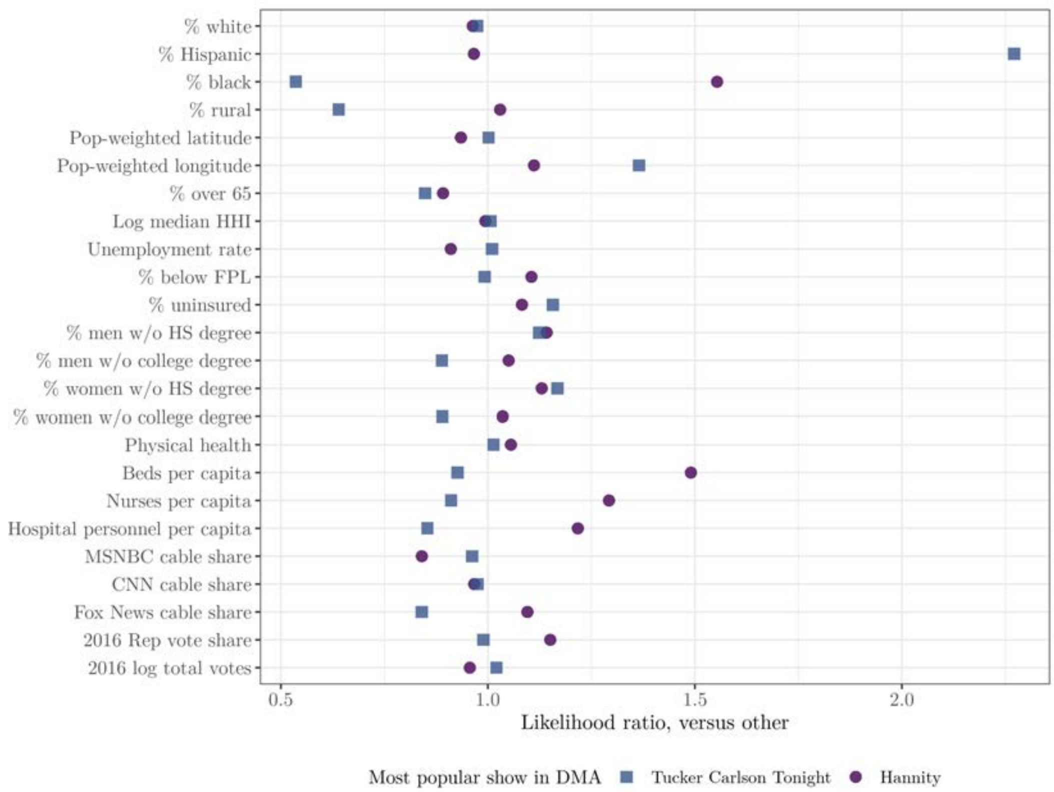
A.2 Data and OLS

Figure A1: Timing of behavioral change: robustness to inclusion of controls



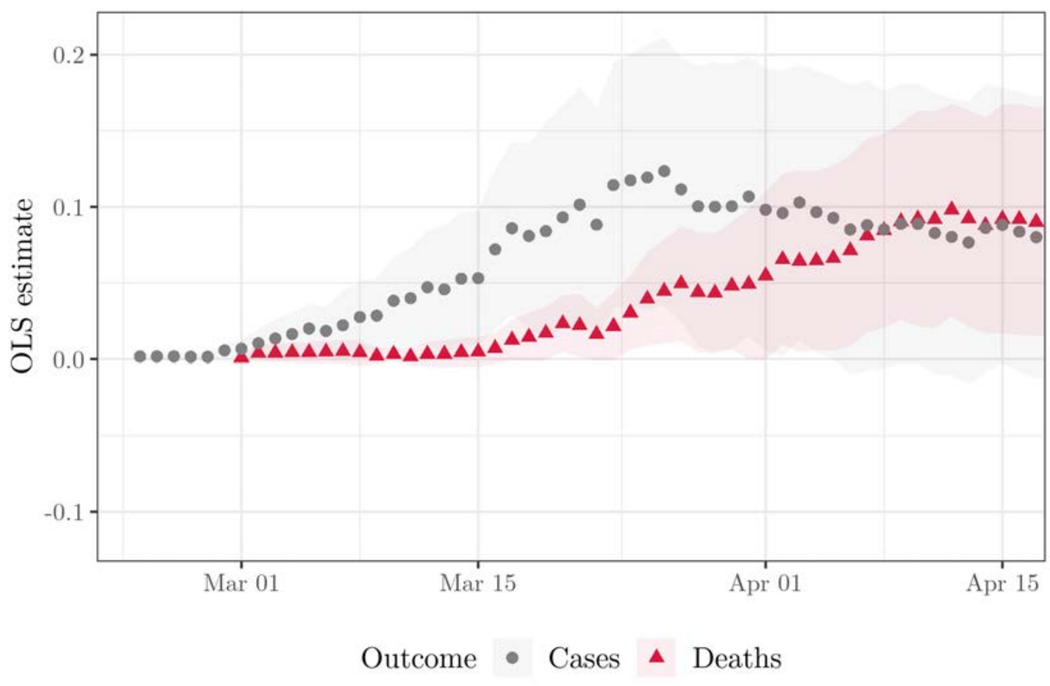
Notes: Figure A1 displays OLS estimates of the relationship between rerespondents' reported day of behavior change in response to the coronavirus (from our survey of 1045 Republican Fox News viewers over the age of 55) and viewership of *Hannity* (top) and *Tucker Carlson Tonight* (bottom). Respondents were asked to indicate the date on which they changed any of their behaviors (e.g. cancelling travel plans, practicing social distancing, or washing hands more often) in response to the coronavirus. In every specification, we control for viewership of the "opposing show" (i.e. all specifications include two indicator variables taking value 1 if the respondent watches *Hannity* and *Tucker Carlson Tonight*, respectively). We report coefficient estimates under every possible combination of the remaining covariates: age, gender, employment status, income, race, education, viewership of CNN and MSNBC, viewership of other Fox News shows, and state fixed effects. We report 95% confidence intervals.

Figure A2: Selection into watching Hannity versus Carlson



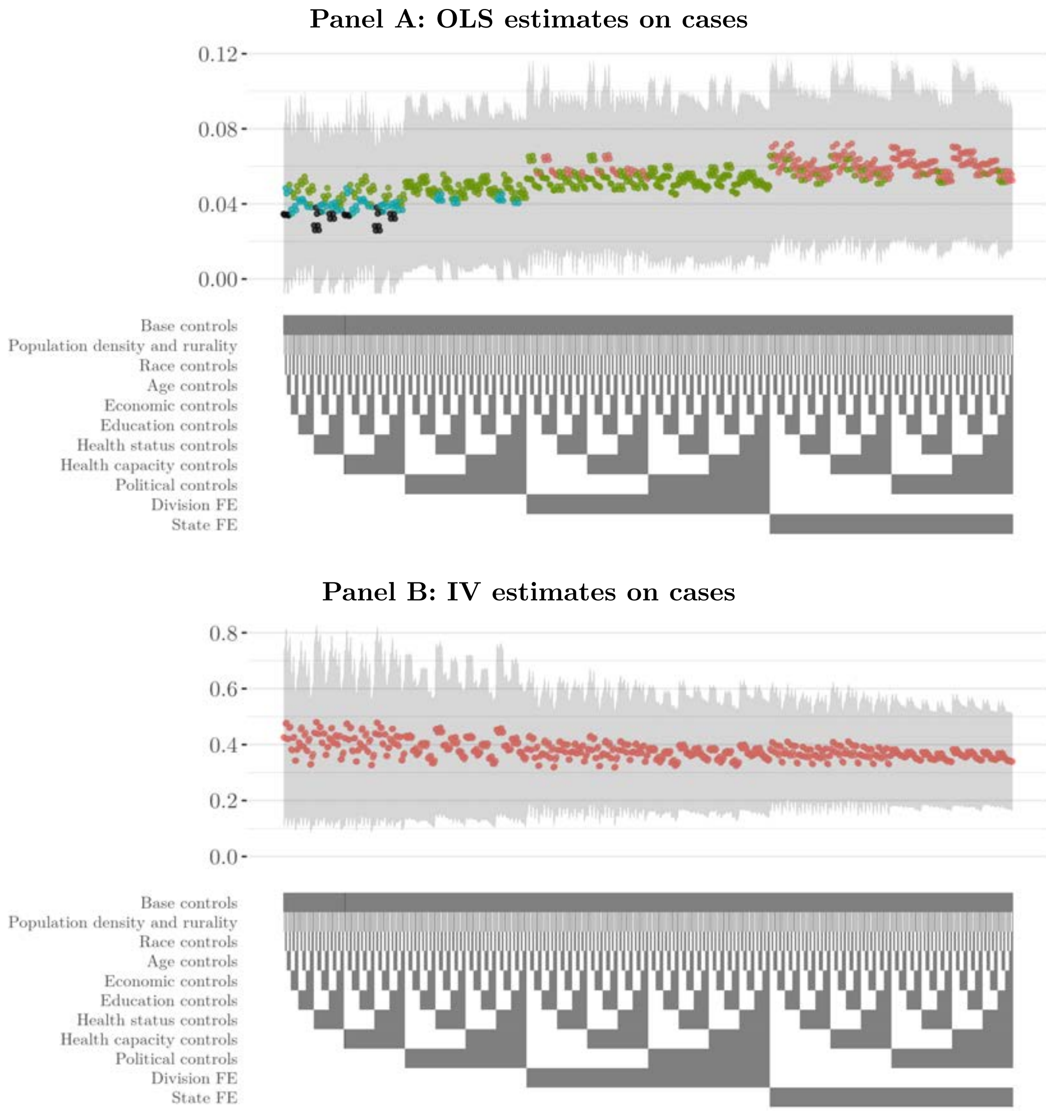
Notes: For each demographic characteristic, Figure A2 shows, in blue, ratios of the average value among counties in which *Hannity* is the most popular show relative to the average value among counties in which neither *Hannity* nor *Tucker Carlson Tonight* is the most popular show. Similarly, Figure A2 shows, in red, ratios of the average value among counties in which *Tucker Carlson Tonight* is the most popular show relative to the average value among counties in which neither *Hannity* nor *Tucker Carlson Tonight* is the most popular show.

Figure A3: OLS estimates of effect of differential viewership on cases and deaths (state clustering)



Notes: Figure A3 displays OLS estimates of the effect 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 sixty-five, 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 state level and report 95 percent confidence intervals.

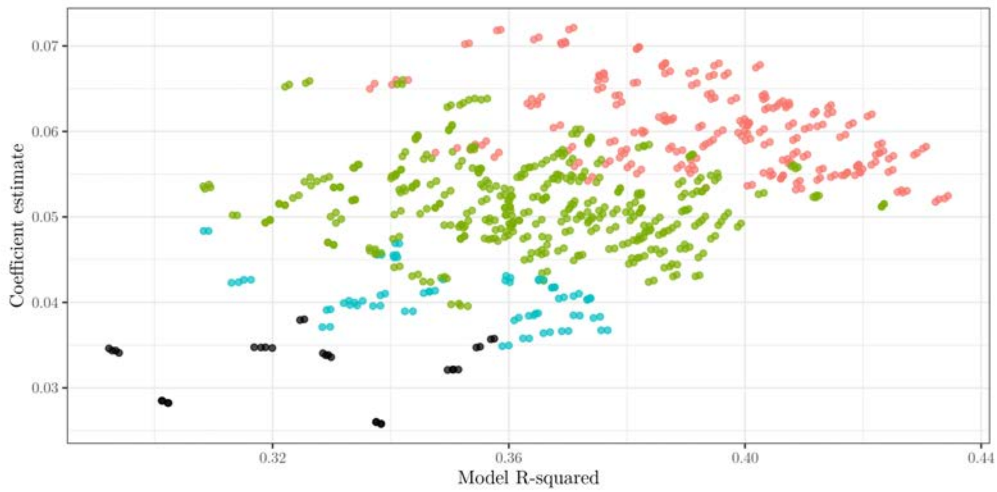
Figure A4: Estimates on cases on March 14: robustness to combinations of controls



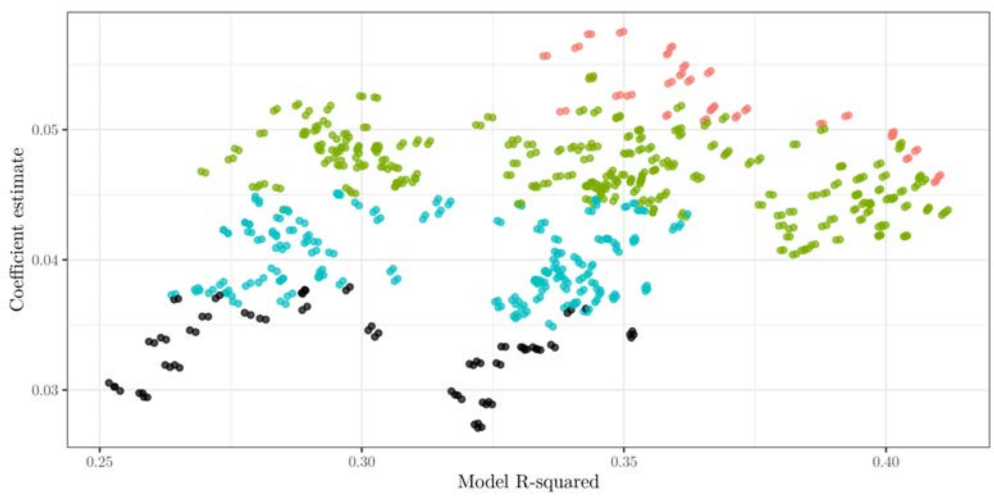
Notes: Figure A4 shows robustness of our OLS and IV estimates for the specifications for log one plus cases on March 14 under every possible combination of our eight sets of county-level controls (population density and rurality, race, age, economic, education, health status, health capacity, and politics) and our three levels of fixed effects (no fixed effects, Census division fixed effects, and state fixed effects). All specifications control for a base set of controls: Fox News' share of television in January 2020, the log of the county's total population, the share of TVs turned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle*, the population-weighted latitude and longitude, and Fox News' and MSNBC's share of cable in January 2018. We cluster standard errors at the DMA level and report 95 percent confidence intervals. Black points are not significant at the ten percent level; blue points are significant at the ten percent level; green points are significant at the five percent level, and red points are significant at the one percent level.

Figure A5: OLS: R^2 vs. coefficient estimates under combinations of controls

Panel A: Estimates on log cases (March 14, 2020)



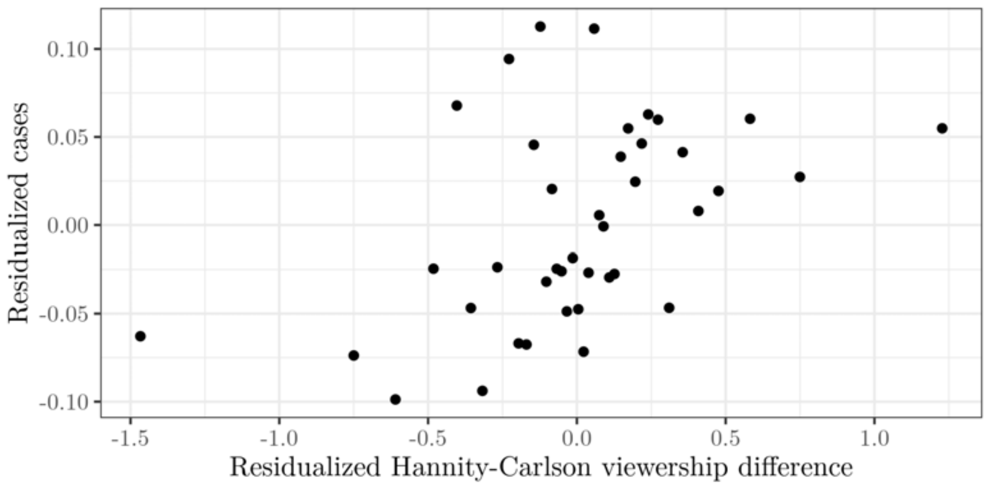
Panel B: Estimates on log deaths (March 28, 2020)



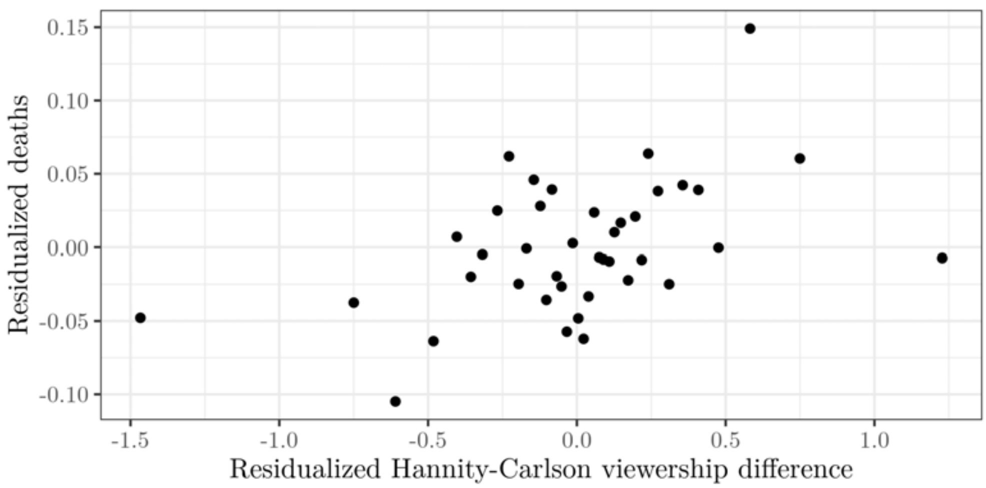
Notes: Figure A5 shows the relationship between the OLS coefficient estimates (y-axis) and the model R^2 (x-axis) for log cases on March 14 (Panel A) and for log deaths on March 28 (Panel B) from specifications with every possible combination of our eight sets of county-level controls (population density and rurality, race, age, economic, education, health status, health capacity, politics) and our three levels of fixed effects (no fixed effects, Census division fixed effects, and state fixed effects). We cluster standard errors at the DMA level. Black points are not significant at the $p < 0.1$ level; blue points are significant at the $p < 0.1$ level; green points are significant at the $p < 0.05$ level, and red points are significant at the $p < 0.01$ level.

Figure A6: OLS: residual-residual plot

Panel A: Estimates on log cases (March 14, 2020)

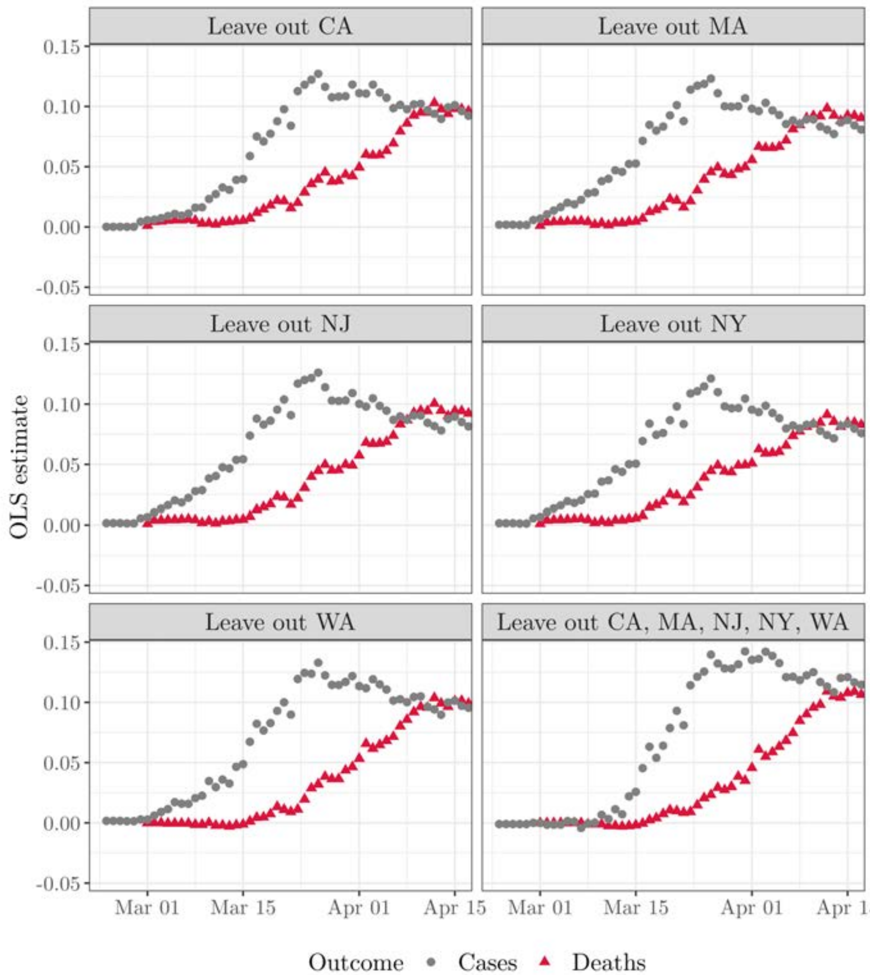


Panel B: Estimates on log deaths (March 28, 2020)



Notes: Figure A6 displays a binscatter of the residuals of log one plus cases (Panel A) and log one plus deaths (Panel B) on the residuals of the standardized difference in viewership, where both outcome variables and the standardized difference in viewership are residualized by state fixed effects and our full 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 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 sixty-five, 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.

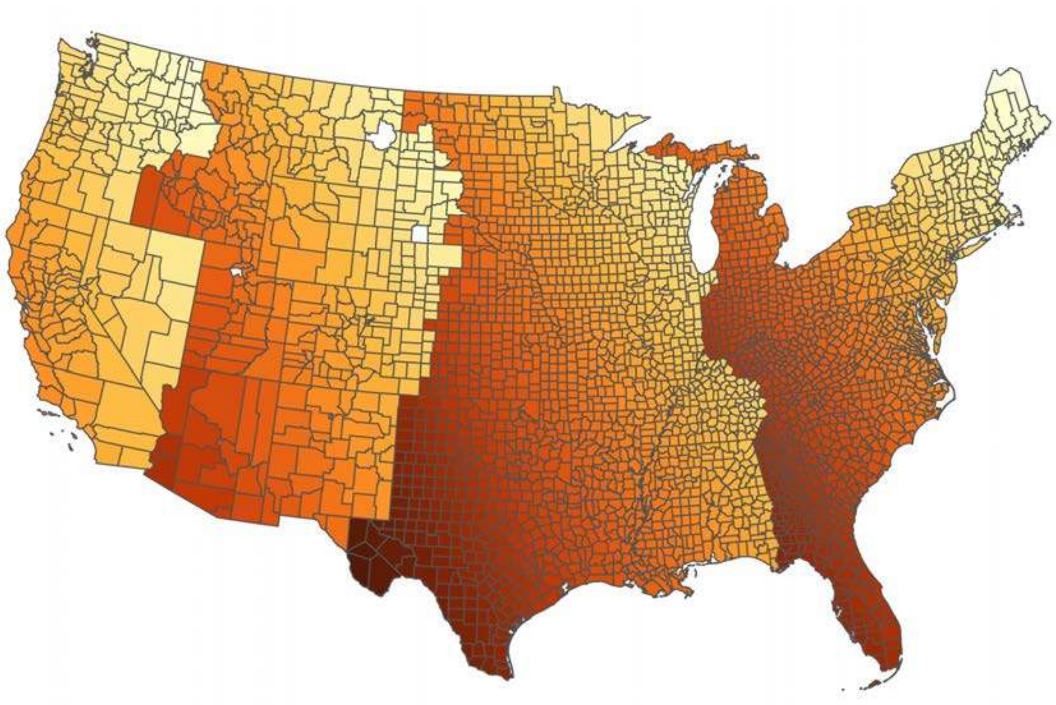
Figure A7: Leave-out OLS estimates of effect of differential viewership on cases and deaths



Notes: Figure A7 displays effects of differential viewership of *Hannity* and *Tucker Carlson Tonight* on log one plus cases and log one plus deaths, leaving out states containing known COVID-19 hotspots. 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 sixty-five, 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 percent confidence intervals.

A.3 Construction of Instrument

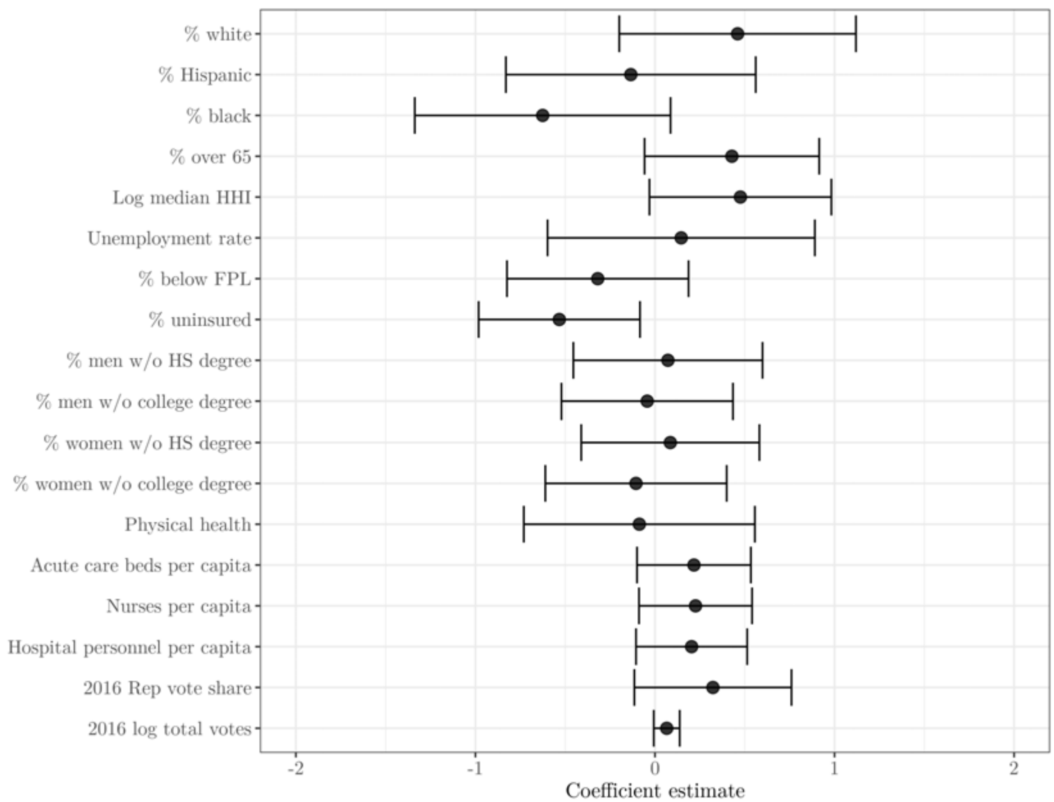
Figure A8: Sunset time on February 1, 2020 by county



Notes: Map plots the time of sunset on February 1, 2020 for each county in the continental United States. Data from `www.timeanddate.com`.

A.4 Instrument Exclusion and First Stage

Figure A9: Instrument correlation with county-level demographics



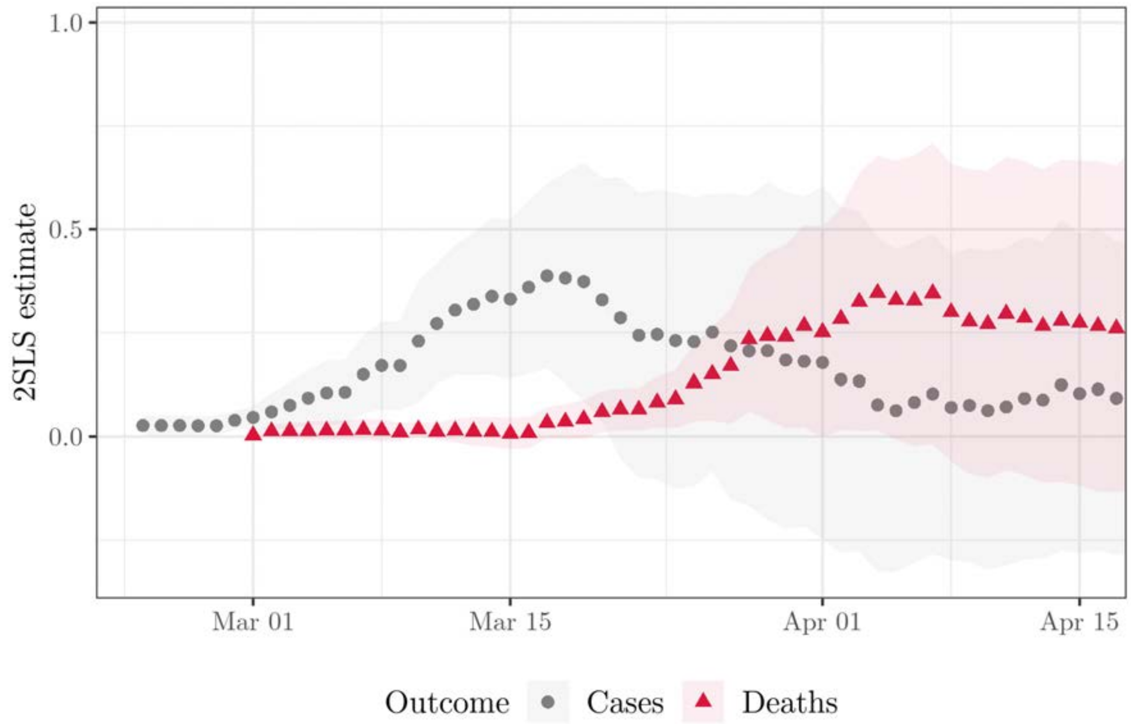
Notes: Figure A9 shows the coefficients from a series of regressions of each demographic characteristic on our instrument, $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$, conditional on the two interactants and a small set of other controls accounting for local viewership patterns (the predicted share of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle*, the local viewership share of MSNBC, log population and population density, and population-weighted latitude and longitude). All dependent variables are standardized to mean zero and standard deviation one. We cluster standard errors at the DMA level and report 95 percent confidence intervals.

Table A2: 2SLS estimates: robustness to choice of controls and instrument variations

	Dependent variable:					
	COVID-19 outcomes					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *COVID-19 cases on March 14*						
H-C viewership difference (predicted)	0.338***	0.313***	0.354***	0.338***	0.736**	0.558**
	(0.089)	(0.087)	(0.095)	(0.093)	(0.303)	(0.226)
Panel B: *COVID-19 deaths on March 28*						
H-C viewership difference (predicted)	0.234***	0.228***	0.267***	0.263***	0.517**	0.477**
	(0.072)	(0.073)	(0.079)	(0.080)	(0.230)	(0.212)
F-statistic (Kleibergen-Paap)	17.90	9.49	18.45	9.36	6.27	3.17
Controls	Full	Full	Full	Full	Full	Full
Instruments	H	H&T	H	H&T	H	H&T
Instrument	Leave-out	Leave-out	Sunset	Sunset	Division sunset	Division sunset
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,100	3,100	3,100	3,100	3,100	3,100

Notes: Table reports 2SLS regressions of the log of one plus the number of cases on March 14 (Panel A) and the log of one plus the number of deaths on March 28 (Panel B) on the standardized difference between viewership of *Hannity* and *Tucker Carlson Tonight*. In Column 1, we instrument this difference by $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$; in Column 2, we additionally instrument by $\tilde{s}_{mc,T} \times \tilde{f}_{mc,-HT}$ — that is, an analogous instrument for viewership during the *Tucker Carlson Tonight* timeslot. Columns 3-4 are identical to Columns 1-2, except that we use fitted rather than actual values of $\tilde{s}_{mc,H}$ (fitted based on sunset time, where the viewership curve is estimated at the DMA level): that is, the instruments are $\widehat{\tilde{s}_{mc,H}}_d \times \text{FoxShare}_d$ and $\widehat{\tilde{s}_{mc,T}}_d \times \text{FoxShare}_d$. Columns 5-6 are identical to Columns 1-2, except that we use fitted rather than actual values of $\tilde{s}_{mc,H}$ (fitted based on sunset time, where the viewership curve is estimated at the Census division level): that is, the instruments are $\widehat{\tilde{s}_{mc,H}}_d \times \text{FoxShare}_d$ and $\widehat{\tilde{s}_{mc,T}}_d \times \text{FoxShare}_d$. "Full controls" include 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 population density and log population, population-weighted latitude and longitude, the percent of the population living in a rural area, the population over the age of 65, the percent male with no high school degree, the percent female with no high school degree, the percent male with no college degree, the percent female with no college degree, an age-adjusted measure of the average physical health in the county, the percent uninsured, the percent below the federal poverty line, the log of the median household income, the unemployment rate, the Republican vote share in 2016, and the log of the total number of votes in the county in 2016. As a test for weak instruments, we report first-stage Kleibergen-Paap F-statistics. Standard errors are clustered at the DMA level.

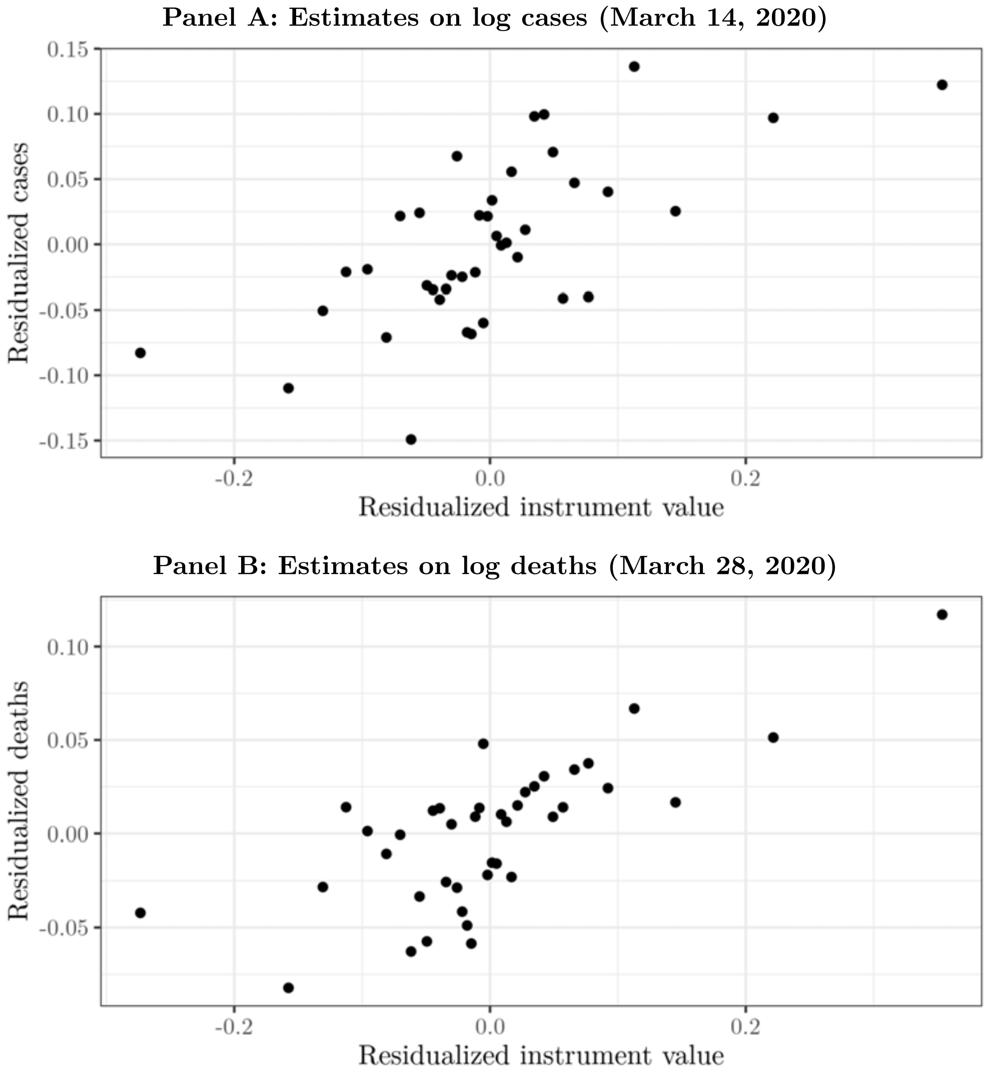
Figure A10: 2SLS estimates of effect of differential viewership on cases and deaths (state clustering)



Notes: Figure A10 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 sixty-five, 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 state level and report 95 percent confidence intervals.

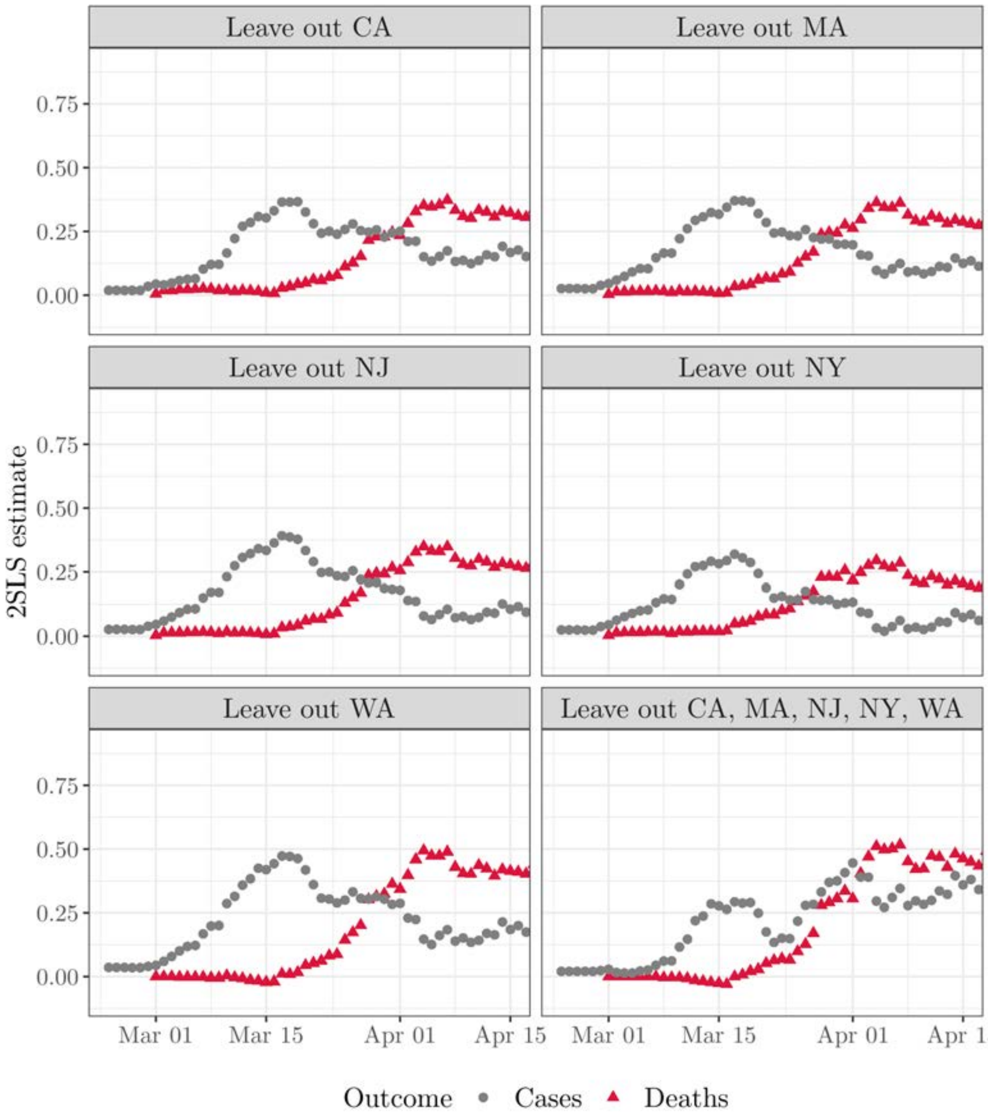
A.5 Robustness

Figure A11: IV: residual-residual plot



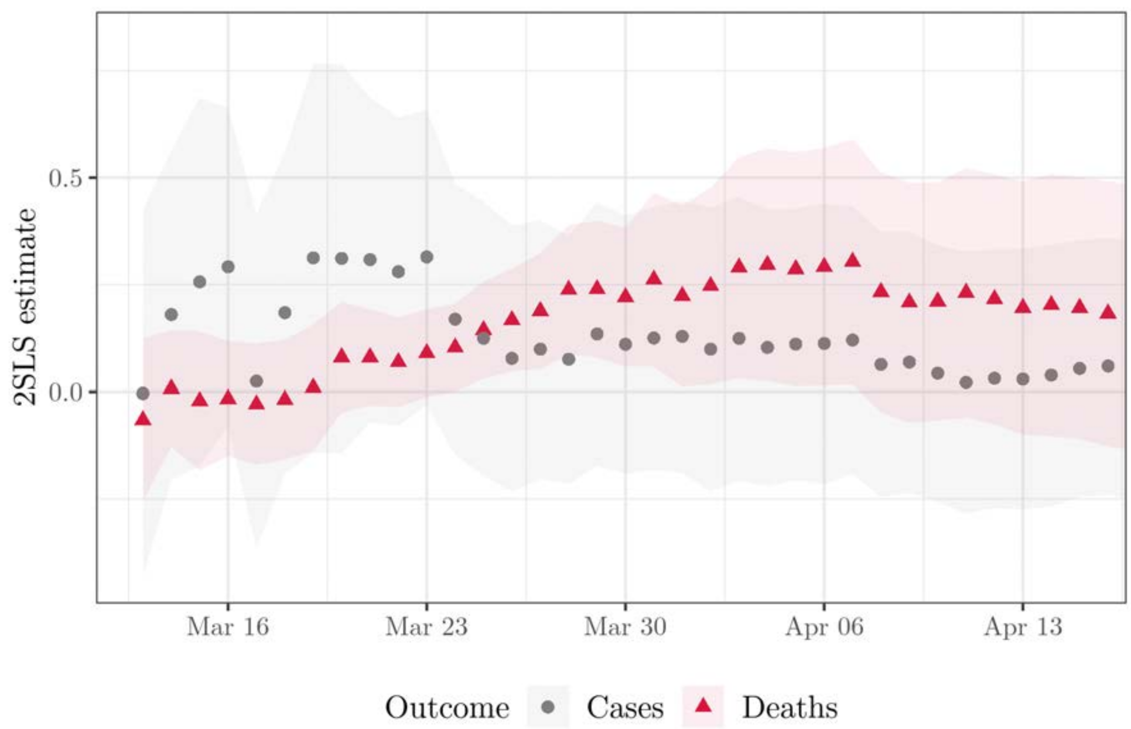
Notes: Figure A11 displays a binscatter of the residuals of log one plus cases (Panel A) and log one plus deaths (Panel B) on the residuals of $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$, where both outcome variables and the instrument are residualized by state fixed effects and our full set of controls: 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 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 sixty-five, 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.

Figure A12: Leave-out IV estimates of effect of differential viewership on cases and deaths



Notes: Figure A12 displays effects of differential viewership of *Hannity* and *Tucker Carlson Tonight* on log one plus cases and log one plus deaths, leaving out states containing known COVID-19 hotspots. 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 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 sixty-five, 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 percent confidence intervals.

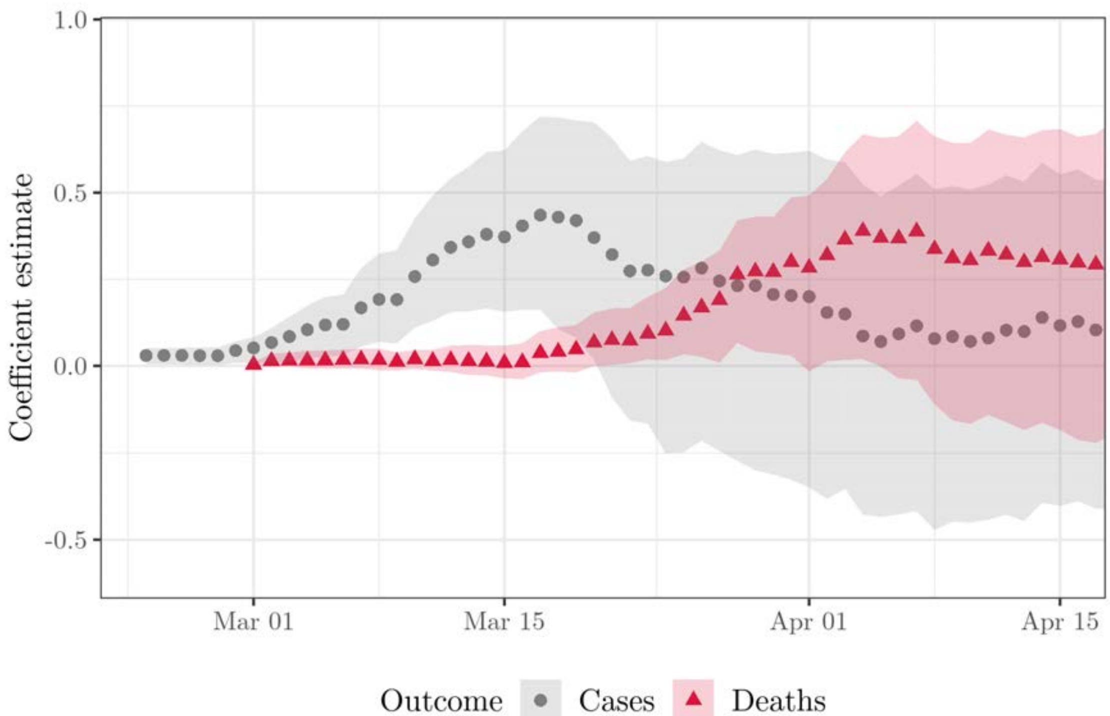
Figure A13: 2SLS estimates of effect of differential viewership on cases and deaths (unbalanced panel)



Notes: Figure A13 shows day-by-day 2SLS estimates on log one plus cases and log one plus deaths, in which a county only appears in the panel once it has a positive number of cases. 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 sixty-five, 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 percent confidence intervals.

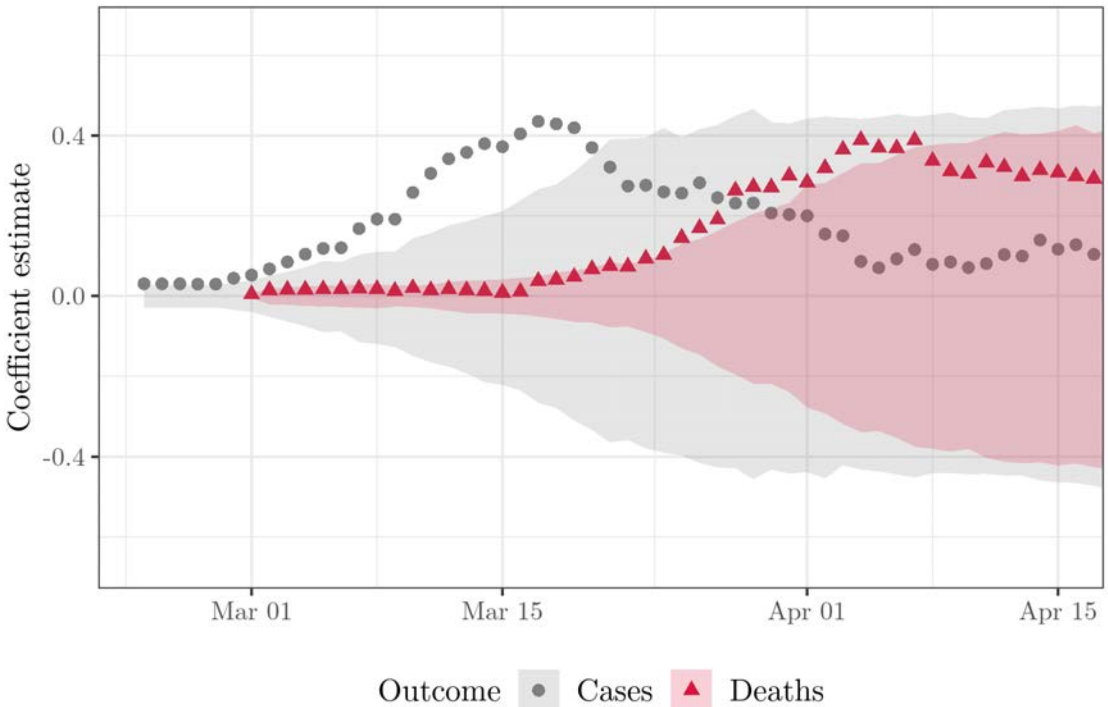
A.6 Resampling Inference

Figure A14: DMA-level block bootstrap



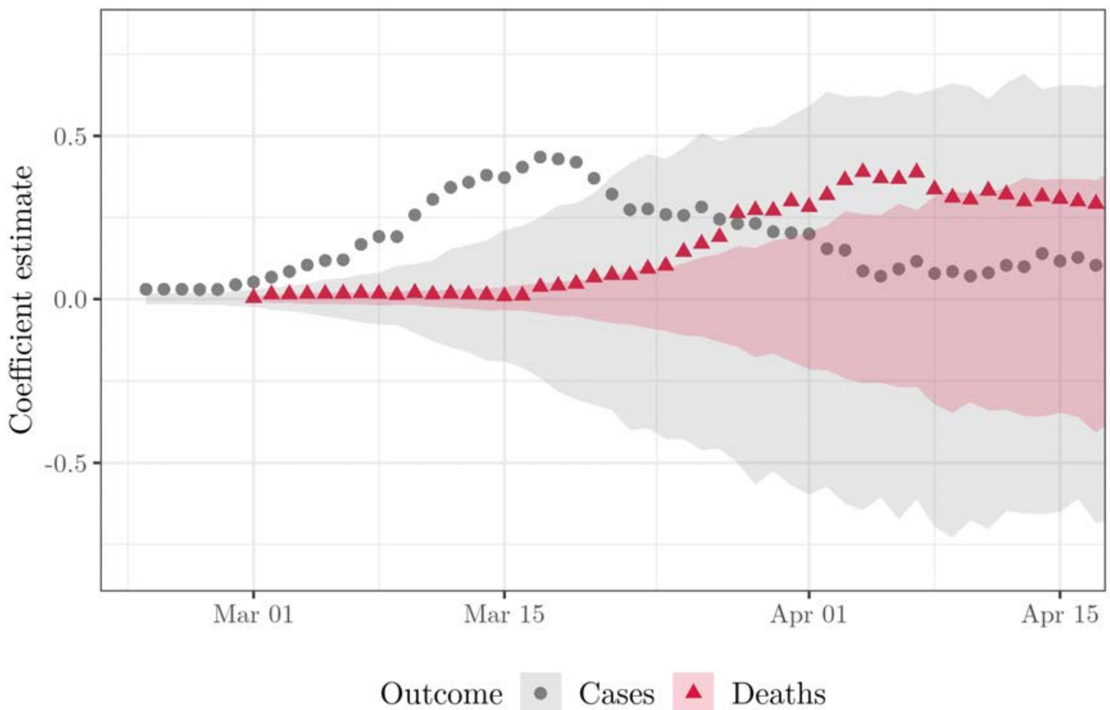
Notes: Figure A14 presents confidence intervals derived from a block bootstrapping procedure. We randomly sample DMAs with replacement and estimate counterfactual treatment effects for each day. We repeat 1000 times to calculate a distribution of counterfactual treatment effects for each day. Confidence intervals are calculated separately for each day: the upper boundary of the confidence interval corresponds to the 0.975-quantile of treatment effects on that day, while the lower boundary corresponds to the 0.025-quantile.

Figure A15: Randomization inference



Notes: Figure A15 presents placebo treatment effects derived from a randomization inference procedure. We permute the plausibly exogenous "shift" ($\tilde{s}_{mc,H}$) across DMAs while leaving the "shares" (FoxShare$_d$), the county-level covariates, and cases and deaths unchanged. For each repetition, we then regenerate our instrument as the interaction of the placebo $\tilde{s}_{mc,H}$ with FoxShare$_d$, then calculate placebo treatment effects. We repeat 1000 times to calculate a distribution of counterfactual treatment effects for each day. The upper boundary of the shaded region corresponds to the 0.975-quantile of treatment effects on that day, while the lower boundary corresponds to the 0.025-quantile.

Figure A16: Permutation test

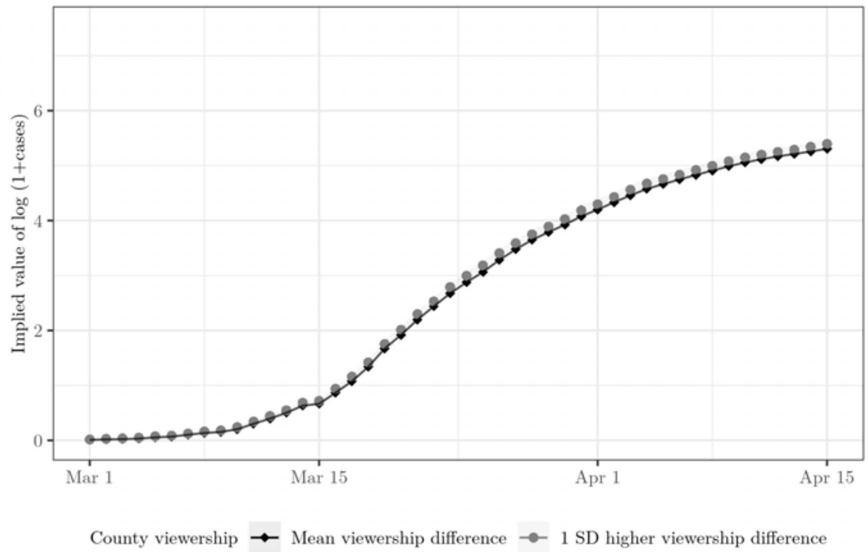


Notes: Figure A16 presents placebo treatment effects derived from a permutation test. We permute the joint tuple of cases and deaths across counties, leaving all other covariates unchanged, then estimate placebo treatment effects. We repeat 1000 times to calculate a distribution of counterfactual treatment effects for each day. The upper boundary of the shaded region corresponds to the 0.975-quantile of treatment effects on that day, while the lower boundary corresponds to the 0.025-quantile.

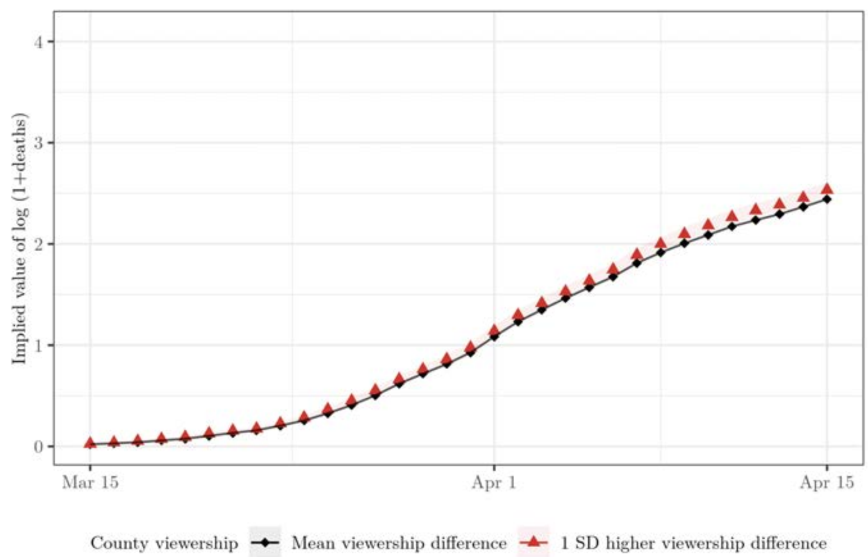
A.7 Effect Sizes

Figure A17: Implied COVID-19 curves (OLS)

Panel A: Estimates on cases

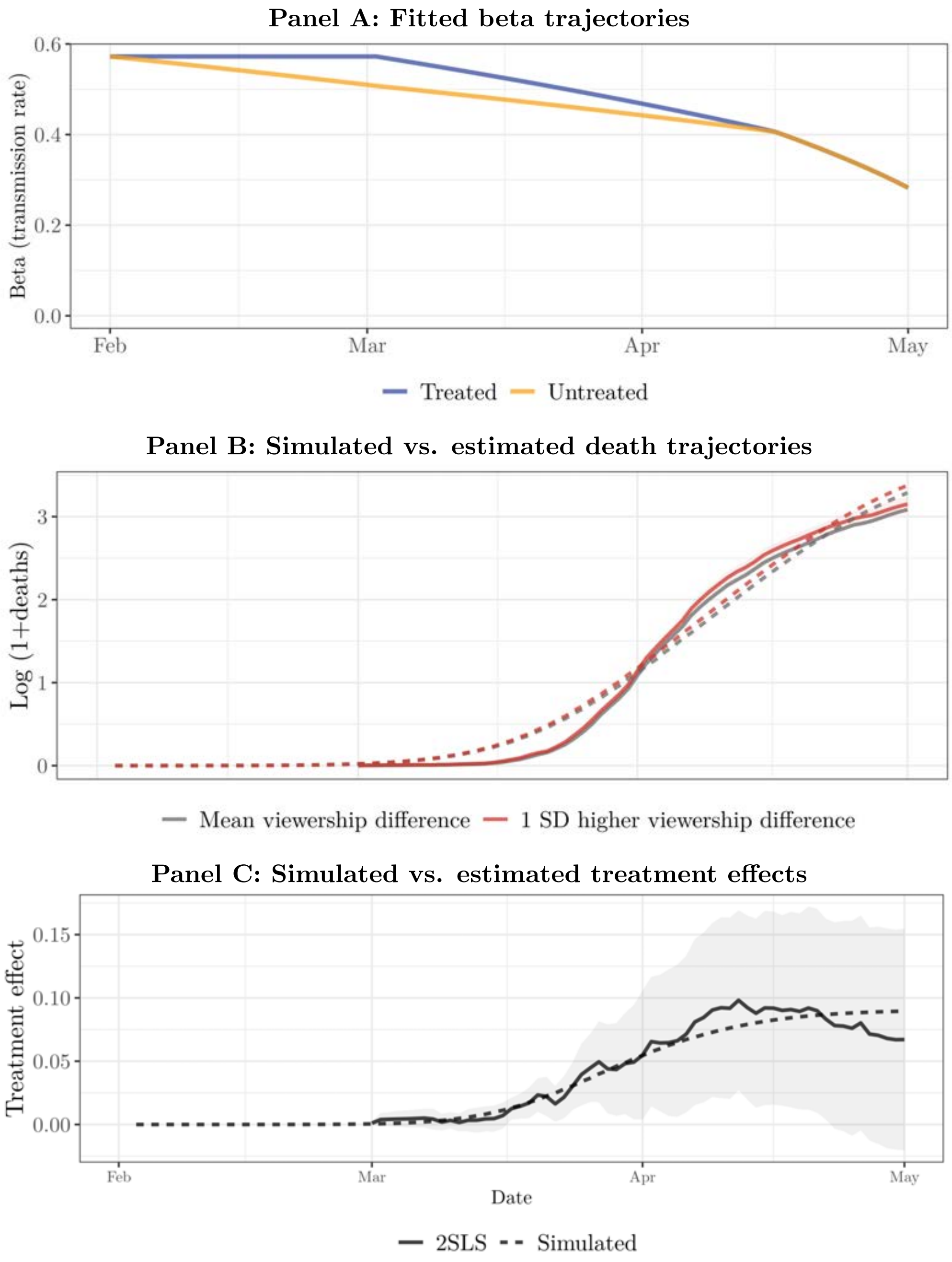


Panel B: Estimates on deaths



Notes: Panel A of Figure A17 plots, in black, the logarithm of (one plus the) mean number of cases in each day across all counties. In gray, the figure plots the the implied counterfactual values (based on our OLS estimates) for a county with a one standard deviation higher viewership difference between *Hannity* and *Tucker Carlson Tonight*. Panel B replicates Panel A, taking log one plus deaths as the outcome rather than log one plus cases. We report 95 percent confidence intervals on the counterfactual estimates. Standard errors are clustered at the DMA level.

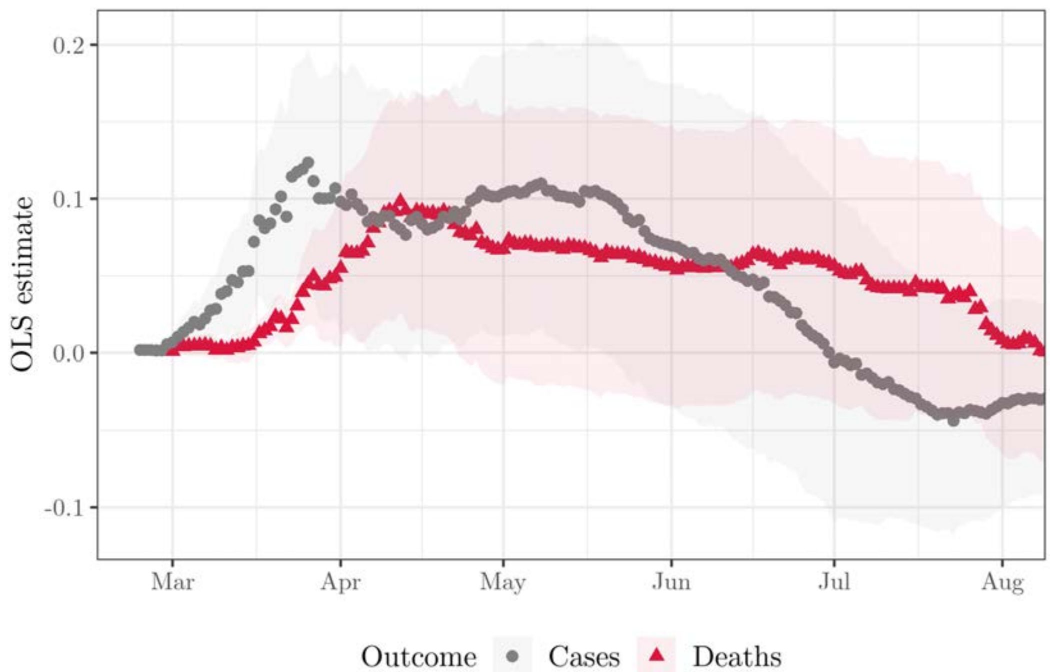
Figure A18: MG-SIR simulations (OLS)



Notes: Panel A of Figure A18 plots, in orange, the β trajectory implied by our simulation for non-compliers (which comprise the entire county with a mean viewership difference and the vast majority of the county with a one standard deviation higher viewership difference) and, in blue, the corresponding trajectory for compliers (which comprise the remaining fraction of the county with a one standard deviation higher viewership difference). Panel B plots the simulated trajectories of deaths (dashed line) and the trajectories of deaths implied by our 2SLS estimates (solid line) for a representative county with a mean *Hannity-Tucker Carlson Tonight* viewership difference (gray) and for a representative county with a one standard deviation higher viewership difference (red). Panel C plots the simulated treatment effect, i.e. the difference between the two dashed lines, and the 2SLS treatment effects, i.e. the difference between the solid lines.

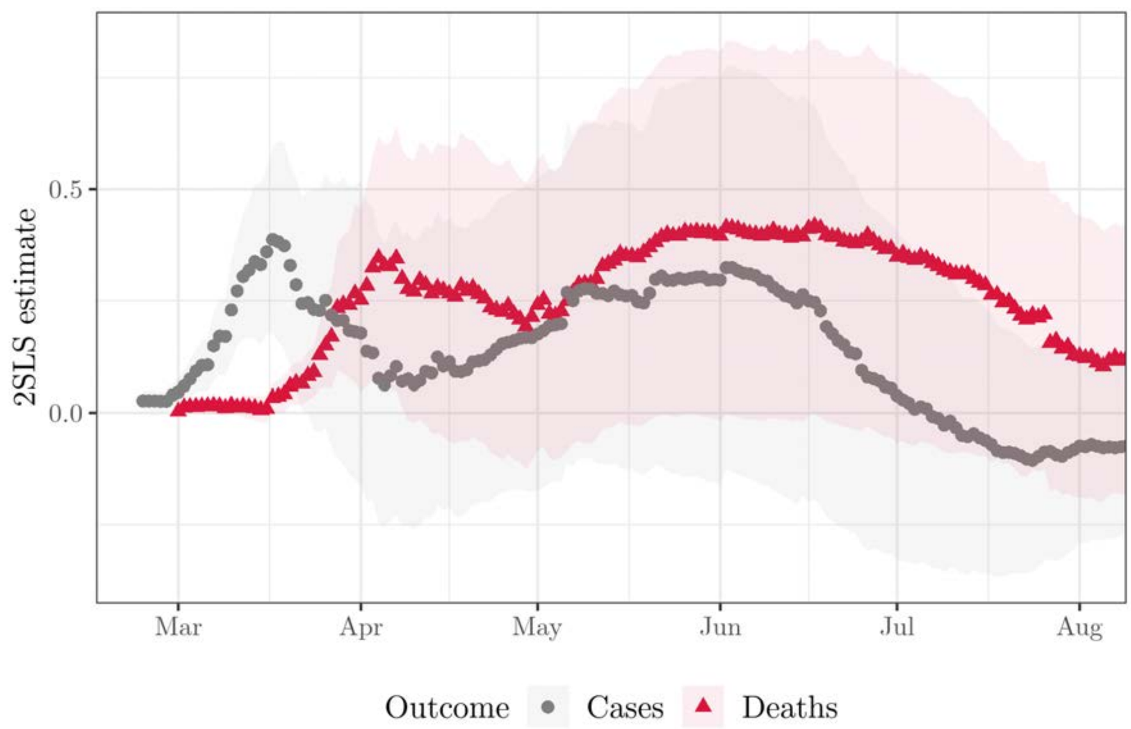
A.8 Extended Results

Figure A19: OLS estimates of effect of differential viewership on cases and deaths (extended)



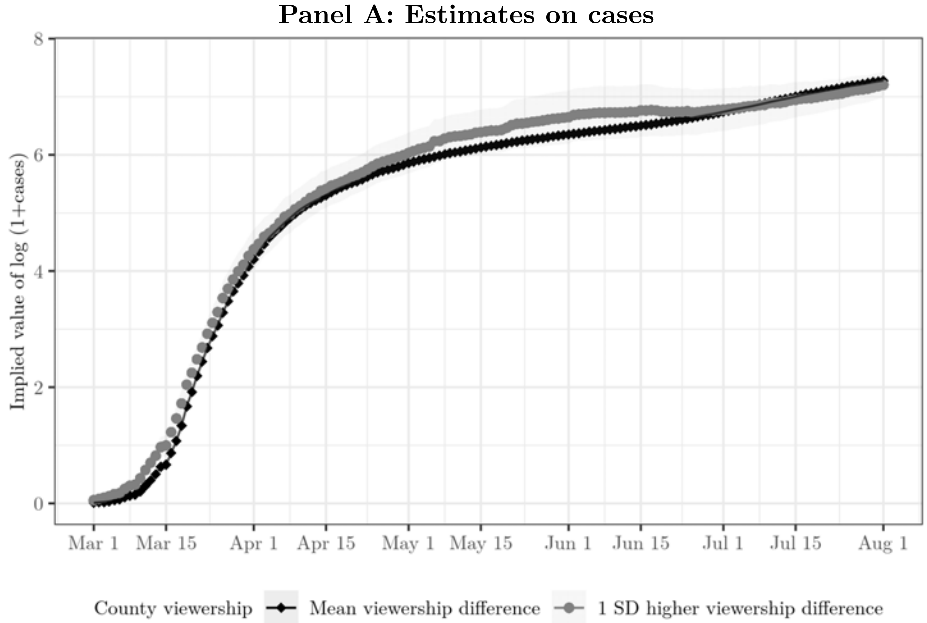
Notes: Figure A19 displays effects of differential viewership of *Hannity* and *Tucker Carlson Tonight* on log one plus cases and log one plus deaths. We report day-by-day results for the correlation between log deaths and log cases with the standardized viewership difference between *Hannity* and *Tucker 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 sixty-five, 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 percent confidence intervals.

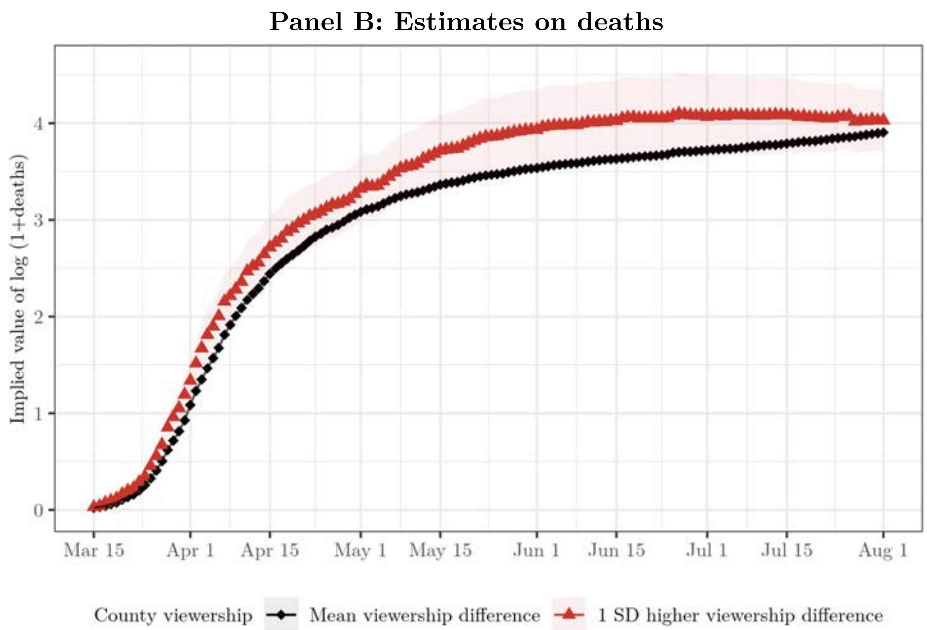
Figure A20: 2SLS estimates of effect of differential viewership on cases and deaths (extended)



Notes: Figure A20 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 sixty-five, 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 percent confidence intervals.

Figure A21: Implied COVID-19 curves

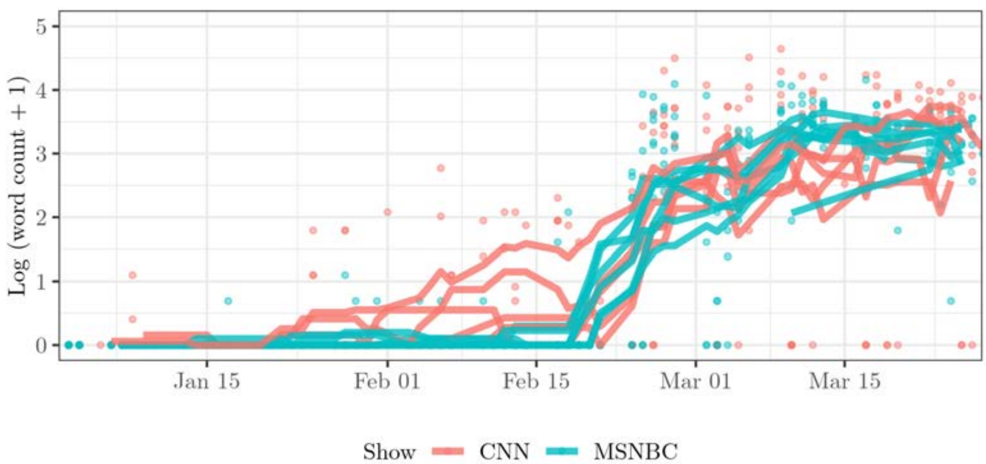




Notes: Panel A of Figure A21 plots, in black, the logarithm of (one plus the) mean number of cases in each day across all counties. In gray, the figure plots the the implied counterfactual values (based on our 2SLS estimates) for a county with a one standard deviation higher viewership difference between *Hannity* and *Tucker Carlson Tonight*. Panel B replicates Panel A, taking log one plus deaths as the outcome rather than log one plus cases. We report 95 percent confidence intervals on the counterfactual estimates. Standard errors are clustered at the DMA level.

A.9 Generalized Misinformation Exposure

Figure A22: Show content: CNN and MSNBC



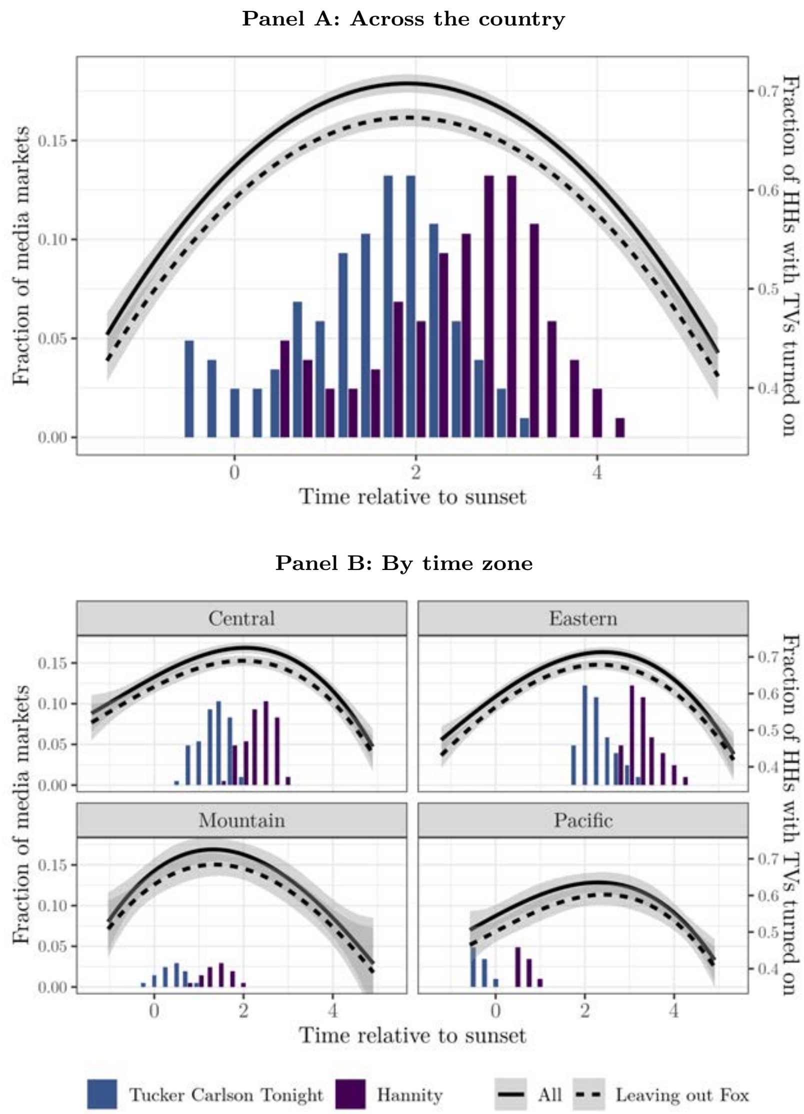
Notes: Figure displays counts of coronavirus-related terms (coronavirus, COVID, virus, influenza, and flu) separately for all shows aired on CNN and MSNBC between 5pm and 11pm local time across all four major time zones in the continental US. We display one-week rolling means.

Figure A23: 2SLS estimates of effect of the pandemic coverage index on cases and deaths

Notes: Figure A23 shows day-by-day 2SLS estimates from regressions of log one plus cases and log one plus deaths on the inverse of the pandemic coverage index described in Section 9, instrumented by $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$. All 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 sixty-five, 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 percent confidence intervals.

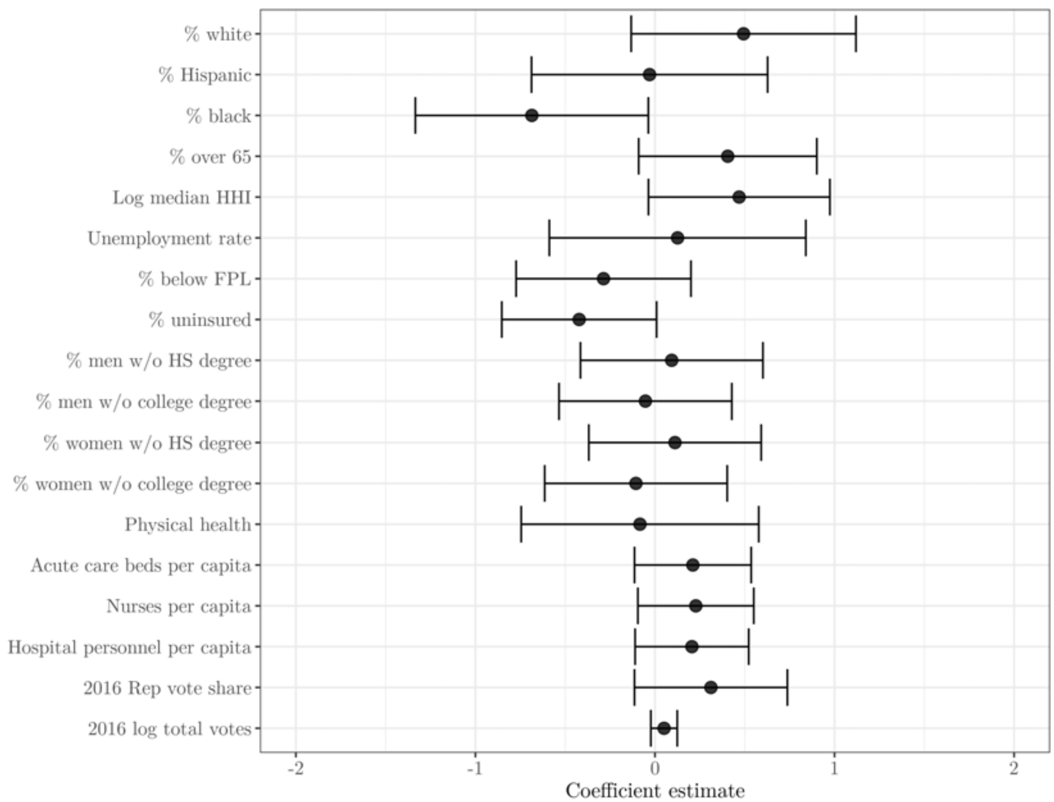
B Robustness: Predicted Viewership

Figure B1: Viewership and program start relative to sunset



Notes: Panel A of Figure B1 plots a third-degree polynomial fitting the relationship between time since sunset in a DMA and the fraction of households in that DMA with TVs turned on (solid line) and the relationship between time since sunset and the fraction of households with TVs turned on and tuned to non-Fox channels (dashed line). 95% confidence intervals are reported. Panel A also shows a histogram depicting, at each fifteen-minute interval relative to sunset, the number of DMAs in which *Tucker Carlson Tonight* begins in that interval (blue) and in which *Hannity* begins in that interval (purple). Episodes of *Tucker Carlson Tonight* and *Hannity* are generally re-run three hours after they first air, and because our data spans 5pm to 11pm, we observe repeats in more western time zones but not in Eastern Time. Panel B is similar, but plots the relationship and histogram separately for each of the four major time zones in the continental United States.

Figure B2: Instrument correlation with county-level demographics



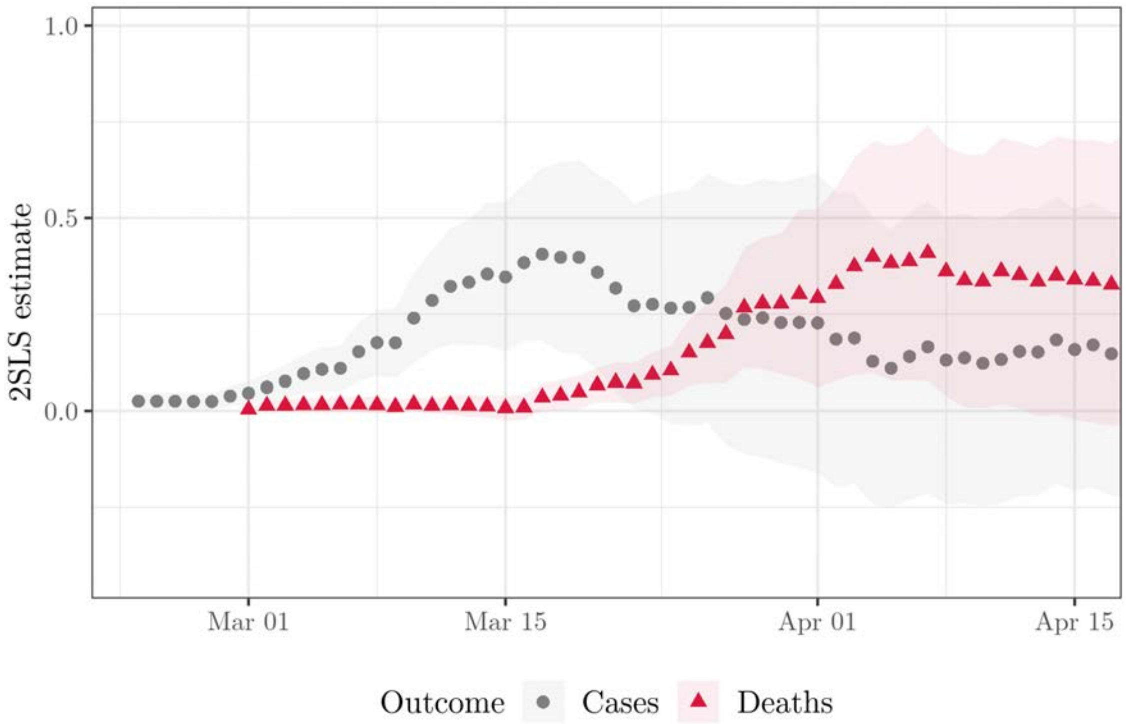
Notes: Figure B2 shows the coefficients from a series of regressions of each demographic characteristic on our instrument, $\widehat{s}_{mc,H} \times \tilde{f}_{mc,-HT}$, conditional on the two interactants, $\widehat{s}_{mc,H}$ and FoxShare$_d$, and a small set of other controls accounting for local viewership patterns (the predicted share of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle*, the local viewership share of MSNBC, log population and population density, and population-weighted latitude and longitude). All dependent variables are scaled to a standard normal distribution. We cluster standard errors at the DMA level and report 95 percent confidence intervals.

Table B1: Effect of differential viewership on COVID-19 outcomes

	Dependent variable:						
	COVID-19 outcomes						
	Feb 29	Mar 07	Mar 14	Mar 21	Mar 28	Apr 04	Apr 11
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Estimates on cases							
Subpanel A.1: Reduced form							
Predicted non-Fox TVs on × Fox share	0.040***	0.156***	0.362***	0.325**	0.242	0.130	0.135
	(0.011)	(0.039)	(0.088)	(0.138)	(0.173)	(0.187)	(0.186)
Subpanel A.2: Two-stage least squares							
H-C viewership difference (predicted)	0.039***	0.153***	0.354***	0.318**	0.236	0.128	0.132
	(0.013)	(0.039)	(0.095)	(0.137)	(0.177)	(0.189)	(0.189)
Panel B: Estimates on deaths							
Subpanel B.1: Reduced form							
Predicted non-Fox TVs on × Fox share	0.004*	0.018	0.012	0.075**	0.273***	0.408***	0.370**
	(0.002)	(0.011)	(0.016)	(0.029)	(0.064)	(0.125)	(0.156)
Subpanel B.2: Two-stage least squares							
H-C viewership difference (predicted)	0.004**	0.018*	0.011	0.074***	0.267***	0.399***	0.362**
	(0.002)	(0.010)	(0.015)	(0.026)	(0.079)	(0.154)	(0.176)
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 reduced-form estimates of the log of one plus cases upon the instrument, $\widehat{\tilde{s}_{mc,H}} \times \tilde{f}_{mc,-HT}$ — that is, the predicted number of TVs on during Hannity's timeslot, excluding TVs watching *Hannity*, multiplied by Fox News' viewership share, excluding *Hannity* and *Tucker Carlson Tonight*.; Panel A.2 replicates for deaths. Panel B.1 reports two-stage least squares estimates of the log of one plus cases upon the standardized difference in Hannity-Carlson viewership, instrumented by $\widehat{\tilde{s}_{mc,H}} \times \tilde{f}_{mc,-HT}$; 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, the population density of the county, the log of the county's total population, MSNBC's share of cable in January 2018, population-weighted latitude and longitude, the percent of the population living in a rural area, the population over the age of 65, the percent male with no high school degree, the percent female with no high school degree, the percent male with no college degree, the percent female with no college degree, an age-adjusted measure of the average physical health in the county, the percent uninsured, the percent below the federal poverty line, the log of the median household income, the unemployment rate, the Republican vote share in 2016, and the log of the total number of votes in the county in 2016. Standard errors are clustered at the DMA level.

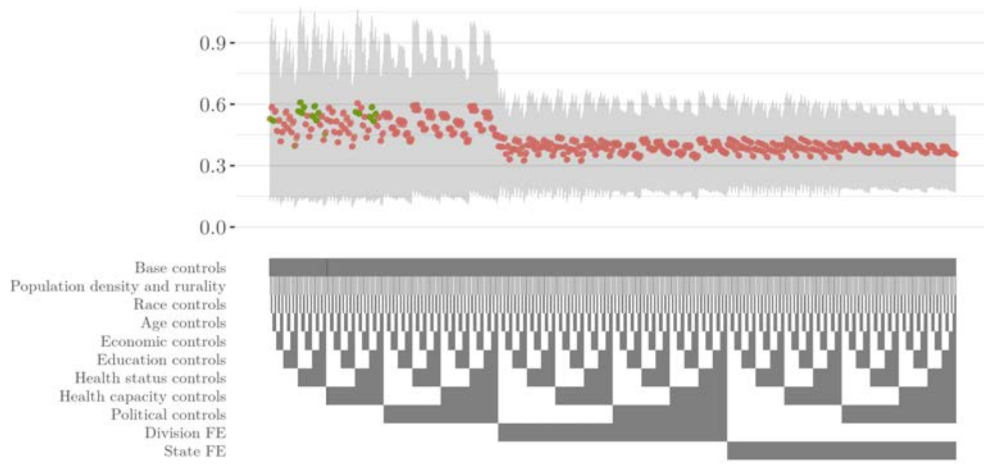
Figure B3: 2SLS estimates of effect of differential viewership on cases and deaths



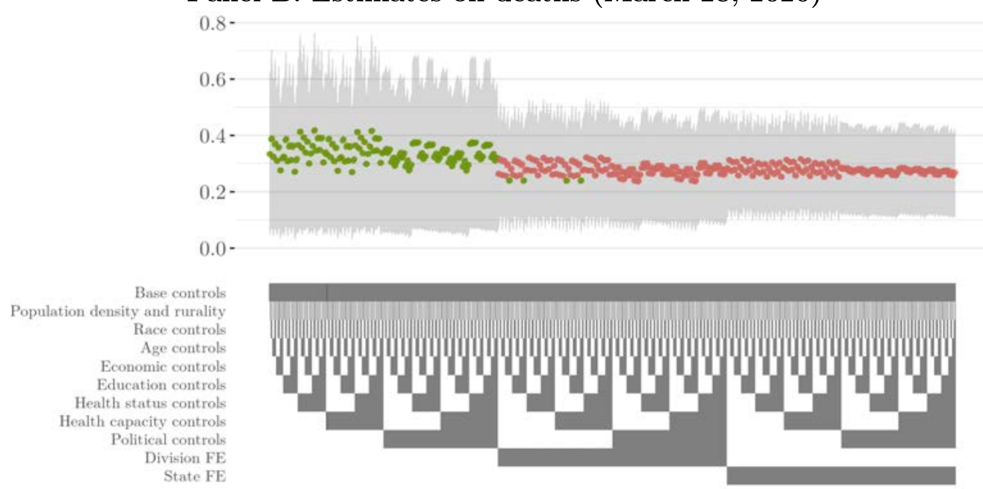
Notes: Figure B3 shows day-by-day 2SLS estimates on log one plus cases and log one plus deaths. shows day-by-day 2SLS estimates on log one plus cases and log one plus deaths. We report day-by-day effects of the standardized difference in viewership of *Hannity* vs. *Tucker Carlson Tonight*, instrumented by $\widehat{s}_{mc,H} \times \tilde{f}_{mc,-HT}$ 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 log of the distance to Seattle, the percent white, Hispanic, and black, the percent over the age of sixty-five, 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 percent confidence intervals.

Figure B4: 2SLS: robustness to combinations of controls

Panel A: Estimates on cases (March 14, 2020)

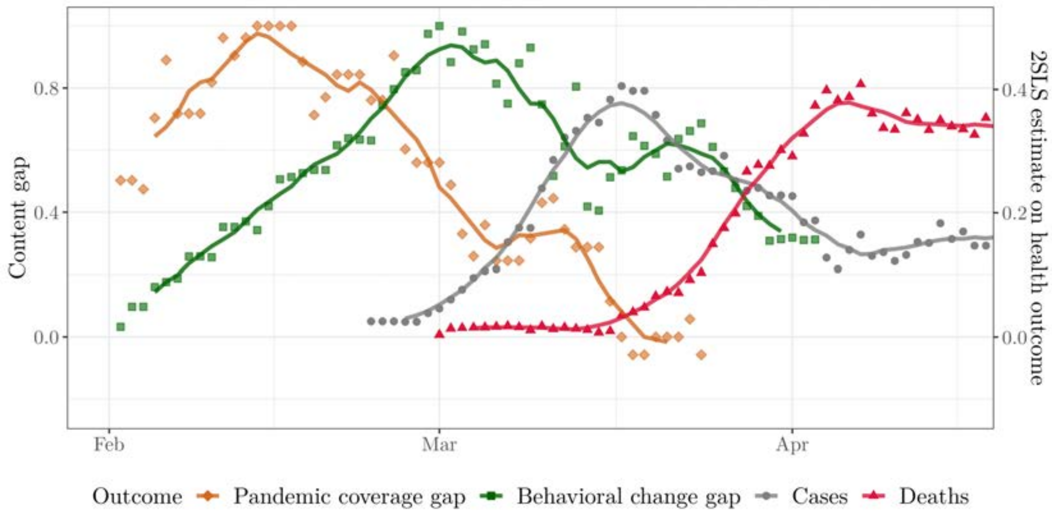


Panel B: Estimates on deaths (March 28, 2020)



Notes: Figure B4 shows robustness of our two-stage least squares estimates for the specifications for log one plus cases on March 14 (Panel A) and log one plus deaths on March 28 (Panel B) under every possible combination of our eight sets of county-level controls (population density and rurality, race, age, economic, education, health status, health capacity, and politics) and our three levels of fixed effects (no fixed effects, census division fixed effects, and state fixed effects). All specifications control for a base set of controls: Fox News' share of television in January 2020, 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, and Fox News' and MSNBC's share of cable in January 2018. We cluster standard errors at the DMA level and report 90 percent and 95 percent confidence intervals for each model. Blue points are significant at the 5 percent level; red points are significant at the 10 percent level; black points are not significant at the 10 percent level.

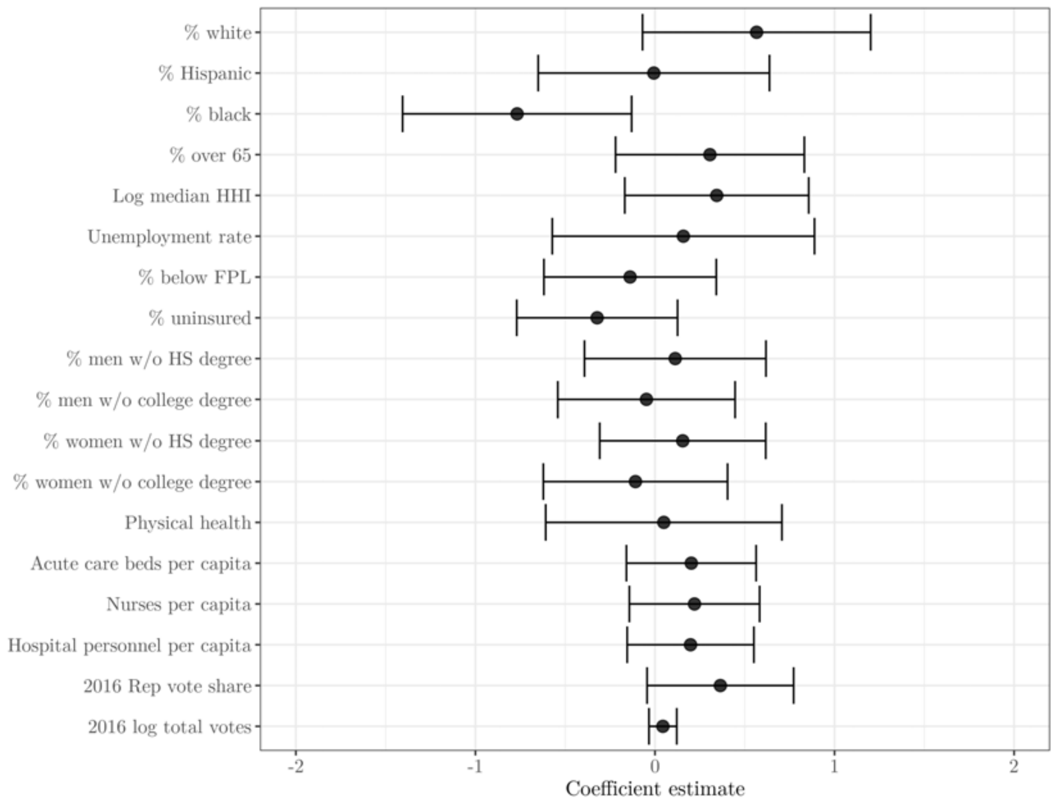
Figure B5: Carlson-Hannity pandemic coverage gap and effects on cases and deaths



Notes: Figure B5 shows, in brown squares corresponding to the left y-axis, the difference in portrayed seriousness of the coronavirus threat on *Tucker Carlson Tonight* vs. *Hannity*, as rated by Amazon Mechanical Turk coders. The difference peaks in mid-February, a period during which there was no discussion of the coronavirus on *Hannity* and during which *Tucker Carlson Tonight* discussed the coronavirus virtually every show. The figure also shows, in gray circles and red triangles corresponding to the right y-axis, 2SLS estimates of the Hannity-Carlson viewership gap (instrumented by $\widehat{s}_{mc,H} \times \tilde{f}_{mc,-HT}$) on log one plus cases and log one plus deaths. All 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 log of the distance to Seattle, the percent white, Hispanic, and black, the percent over the age of sixty-five, 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.

C Robustness: Division-Level Viewership Prediction

Figure C1: Instrument correlation with county-level demographics



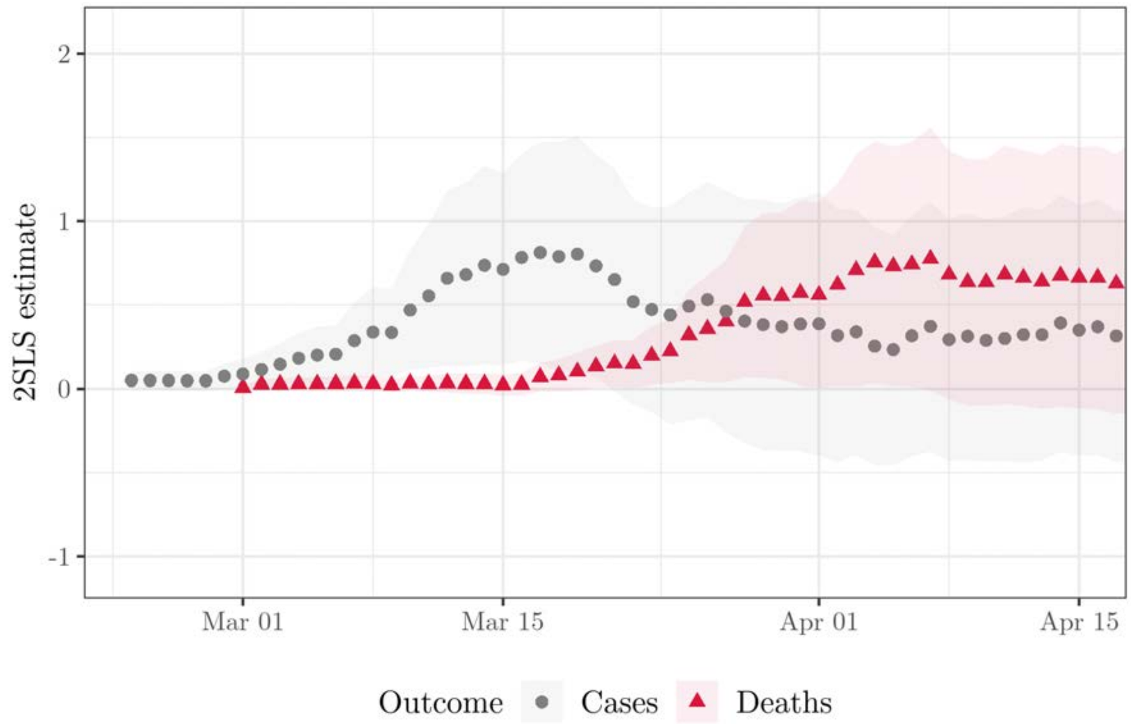
Notes: Figure C1 shows the coefficients from a series of regressions of each demographic characteristic on our instrument, $\widehat{s}_{mc,H} \times \tilde{f}_{mc,-HT}$, conditional on the two interactants and a small set of other controls accounting for local viewership patterns (the predicted share of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle*, the local viewership share of MSNBC, and population size and density). All dependent variables are scaled to a standard normal distribution. We cluster standard errors at the DMA level and report 95 percent confidence intervals.

Table C1: Effect of differential viewership on COVID-19 outcomes

	Dependent variable:						
	COVID-19 outcomes						
	Feb 29	Mar 07	Mar 14	Mar 21	Mar 28	Apr 04	Apr 11
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Estimates on cases							
Subpanel A.1: Reduced form							
Predicted non-Fox TVs on × Fox share	0.039***	0.151***	0.389***	0.344**	0.213	0.134	0.158
	(0.010)	(0.039)	(0.096)	(0.152)	(0.185)	(0.183)	(0.183)
Subpanel A.2: Two-stage least squares							
H-C viewership difference (predicted)	0.073*	0.286**	0.736**	0.651*	0.402	0.253	0.298
	(0.038)	(0.117)	(0.303)	(0.338)	(0.370)	(0.362)	(0.373)
Panel B: Estimates on deaths							
Subpanel B.1: Reduced form							
Predicted non-Fox TVs on × Fox share	0.004**	0.017*	0.015	0.079***	0.274***	0.399***	0.360**
	(0.002)	(0.010)	(0.015)	(0.026)	(0.064)	(0.129)	(0.157)
Subpanel B.2: Two-stage least squares							
H-C viewership difference (predicted)	0.007	0.033	0.029	0.149**	0.517**	0.754**	0.680*
	(0.004)	(0.023)	(0.030)	(0.070)	(0.230)	(0.370)	(0.393)
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 reduced-form estimates of the log of one plus cases upon the instrument, $\widehat{\tilde{s}_{mc,H}} \times \tilde{f}_{mc,-HT}$ — that is, the predicted number of TVs on during Hannity's timeslot based on all DMAs in the Census division, excluding TVs watching *Hannity*, multiplied by Fox News' viewership share, excluding *Hannity* and *Tucker Carlson Tonight.*; Panel A.2 replicates for deaths. Panel B.1 reports two-stage least squares estimates of the log of one plus cases upon the standardized difference in Hannity-Carlson viewership, instrumented by $\widehat{\tilde{s}_{mc,H}} \times \tilde{f}_{mc,-HT}$; 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, the population density of the county, the log of the county's total population, MSNBC's share of cable in January 2018, population-weighted latitude and longitude, the percent of the population living in a rural area, the population over the age of 65, the percent male with no high school degree, the percent female with no high school degree, the percent male with no college degree, the percent female with no college degree, an age-adjusted measure of the average physical health in the county, the percent uninsured, the percent below the federal poverty line, the log of the median household income, the unemployment rate, the Republican vote share in 2016, and the log of the total number of votes in the county in 2016. Standard errors are clustered at the DMA level.

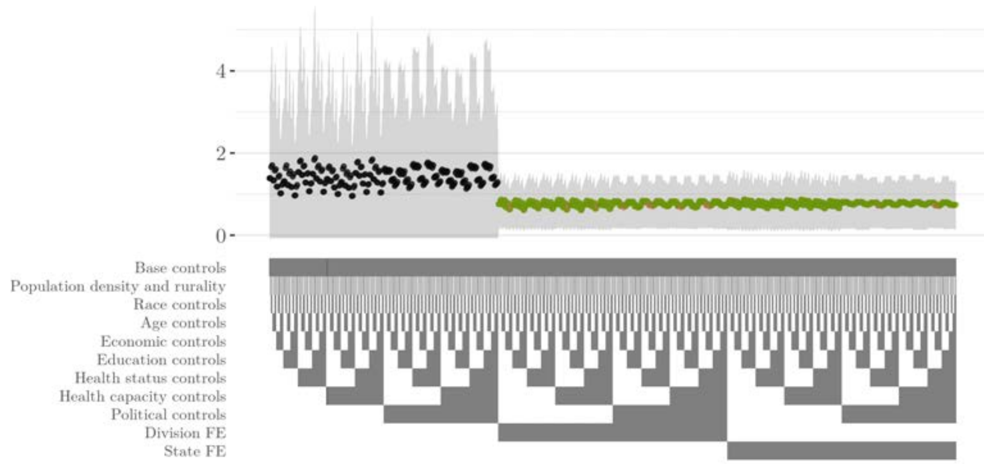
Figure C2: 2SLS estimates of effect of differential viewership on cases and deaths



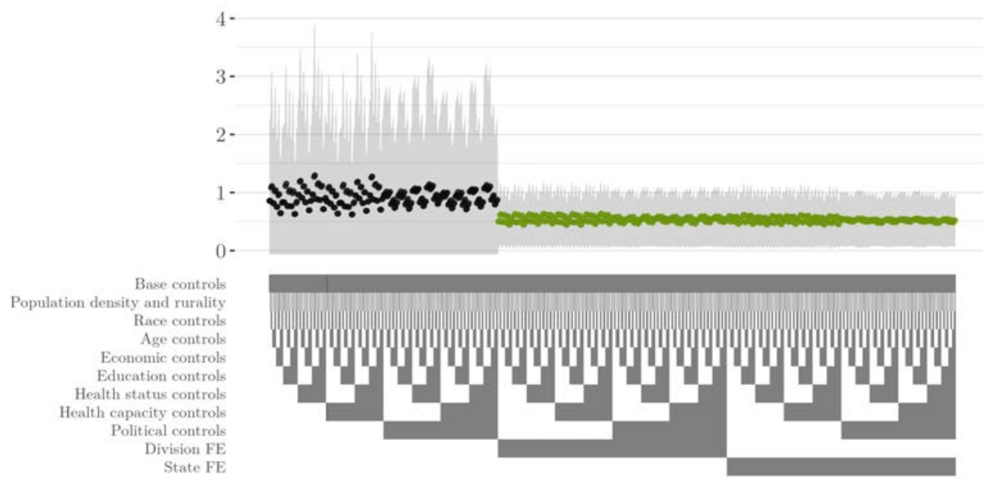
Notes: Figure C2 shows day-by-day 2SLS estimates on log one plus cases and log one plus deaths. We report day-by-day effects of the standardized difference in viewership of *Hannity* vs. *Tucker Carlson Tonight*, instrumented by $\widehat{s}_{mc,H} \times \tilde{f}_{mc,-HT}$ (where $\widehat{s}_{mc,H}$ is fit based on other DMAs in the same Census division) 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 number of predicted 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 sixty-five, 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 percent confidence intervals.

Figure C3: 2SLS: robustness to combinations of controls

Panel A: Estimates on cases (March 14, 2020)

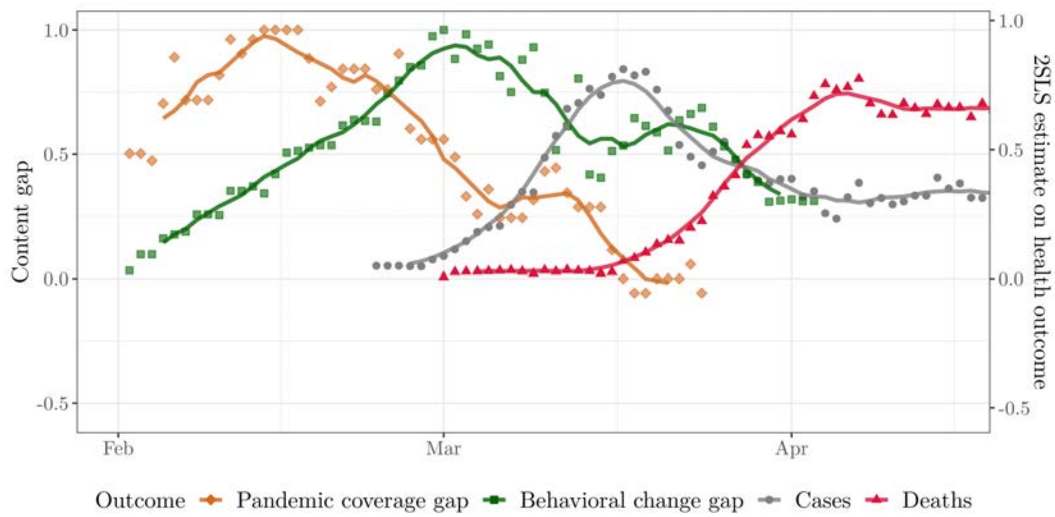


Panel B: Estimates on deaths (March 28, 2020)



Notes: Figure C3 shows robustness of our two-stage least squares estimates for the specifications for log one plus cases on March 14 (Panel A) and log one plus deaths on March 28 (Panel B) under every possible combination of our eight sets of county-level controls (population density and rurality, race, geography, age, economic, education, health status, health capacity, politics) and our three levels of fixed effects (no fixed effects, census division fixed effects, and state fixed effects). All specifications control for a base set of controls: Fox News' share of television in January 2020, the log of the county's total population, the number of predicted TVs turned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle*, the population-weighted latitude and longitude, and Fox News' and MSNBC's share of cable in January 2018. We cluster standard errors at the DMA level and report 90 percent and 95 percent confidence intervals for each model. Black points are not significant at the $p < 0.1$ level; blue points are significant at the $p < 0.1$ level; green points are significant at the $p < 0.05$ level, and red points are significant at the $p < 0.01$ level.

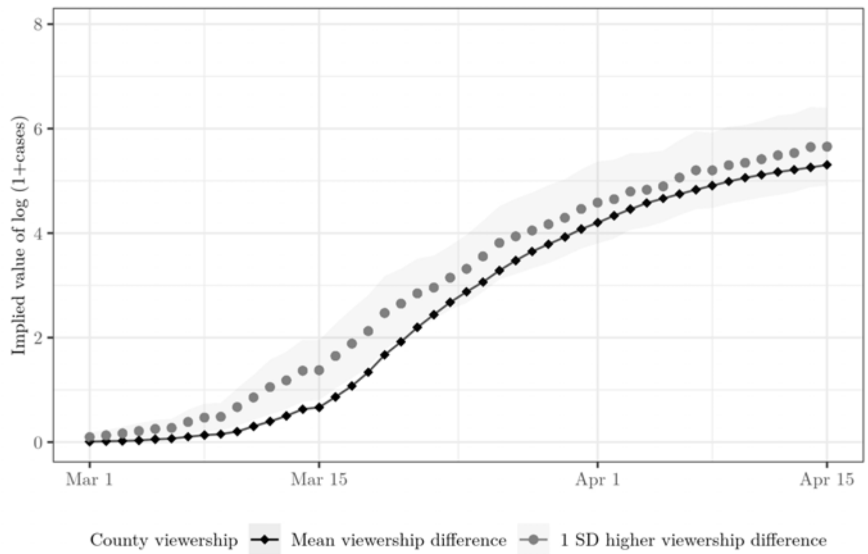
Figure C4: Carlson-Hannity pandemic coverage gap and effects on cases and deaths



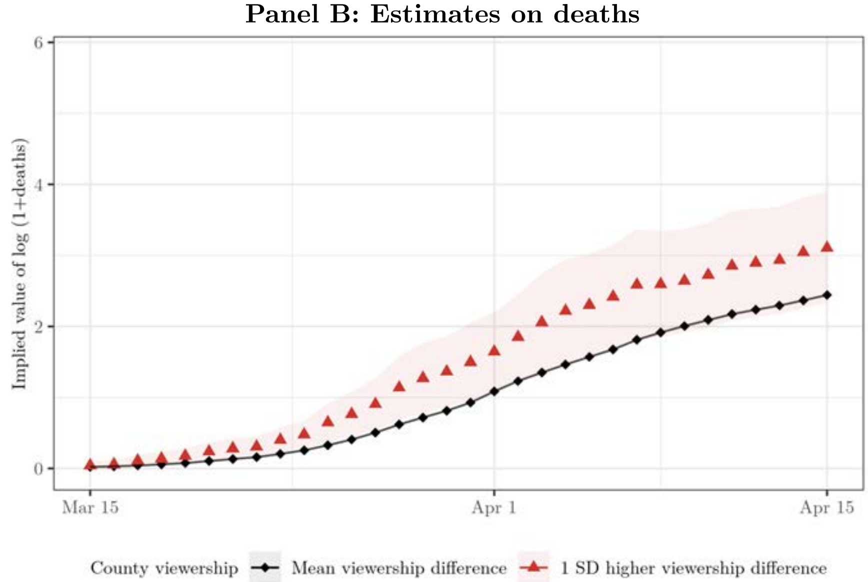
Notes: Figure C4 shows, in brown squares corresponding to the left y-axis, the difference in portrayed seriousness of the coronavirus threat on *Tucker Carlson Tonight* vs. *Hannity*, as rated by Amazon Mechanical Turk coders. The difference peaks in mid-February, a period during which there was no discussion of the coronavirus on *Hannity* and during which *Tucker Carlson Tonight* discussed the coronavirus virtually every show. The figure also shows, in gray circles and red triangles corresponding to the right y-axis, 2SLS estimates of the Hannity-Carlson viewership gap (instrumented by $\widehat{s}_{mc,H} \times \tilde{f}_{mc,-HT}$) on log one plus cases and log one plus deaths. All 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 sixty-five, 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.

Figure C5: Implied COVID-19 curves

Panel A: Estimates on cases



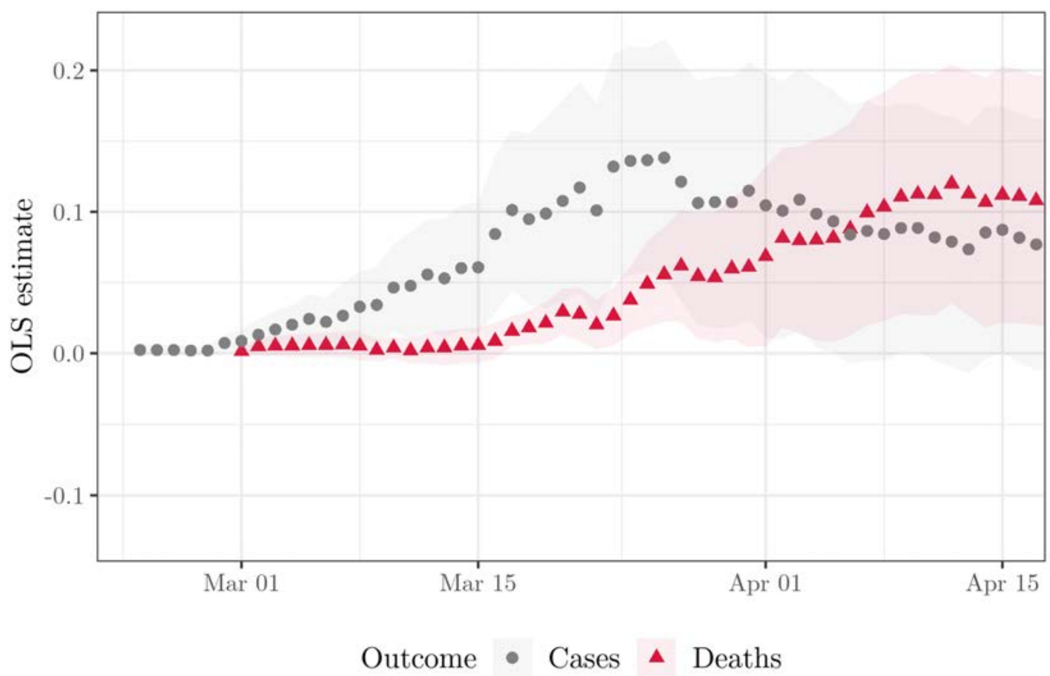
Panel B: Estimates on deaths



Notes: Panel A of Figure C5 plots, in black, the logarithm of (one plus the) mean number of cases in each day across all counties. In gray, the figure plots the the implied counterfactual values (based on our 2SLS estimates) for a county with a one standard deviation higher viewership difference between *Hannity* and *Tucker Carlson Tonight*. Panel B replicates Panel A, taking log one plus deaths as the outcome rather than log one plus cases. We report 95 percent confidence intervals on the counterfactual estimates. Standard errors are clustered at the DMA level.

D Robustness: Inverse Hyperbolic Sine Transformation

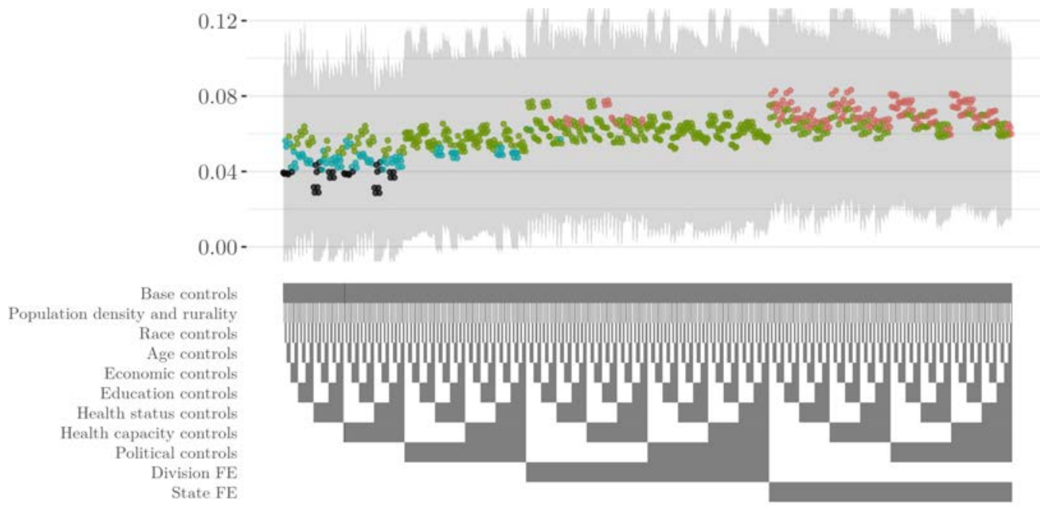
Figure D1: OLS estimates of effect of differential viewership on cases and deaths



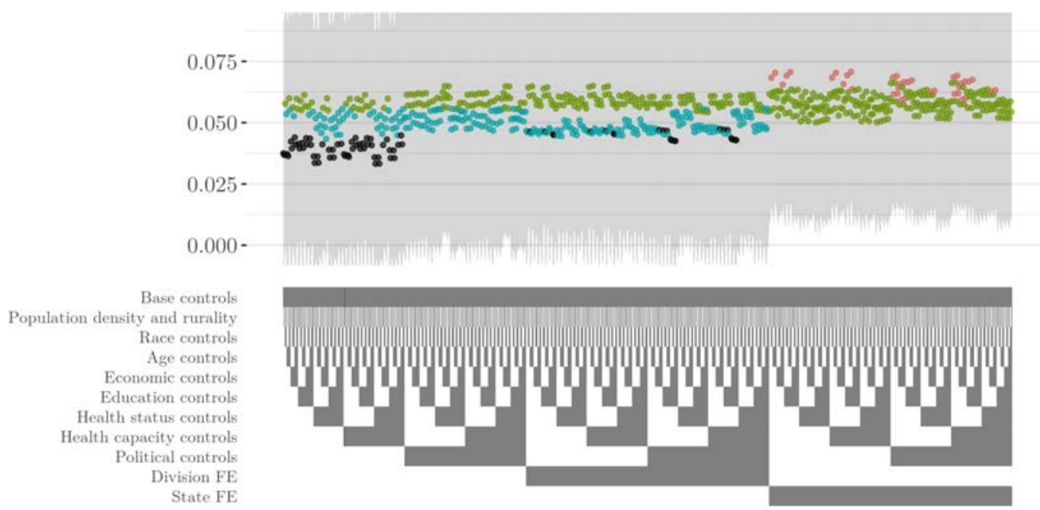
Notes: Figure D1 displays effects of differential viewership of *Hannity* and *Tucker Carlson Tonight* on the inverse hyperbolic sine of cases and deaths. We report day-by-day results for the correlation between log deaths and log cases with the standardized viewership difference between *Hannity* and *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 sixty-five, 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 percent confidence intervals.

Figure D2: OLS: robustness to combinations of controls

Panel A: Estimates on cases (March 14, 2020)



Panel B: Estimates on deaths (March 28, 2020)



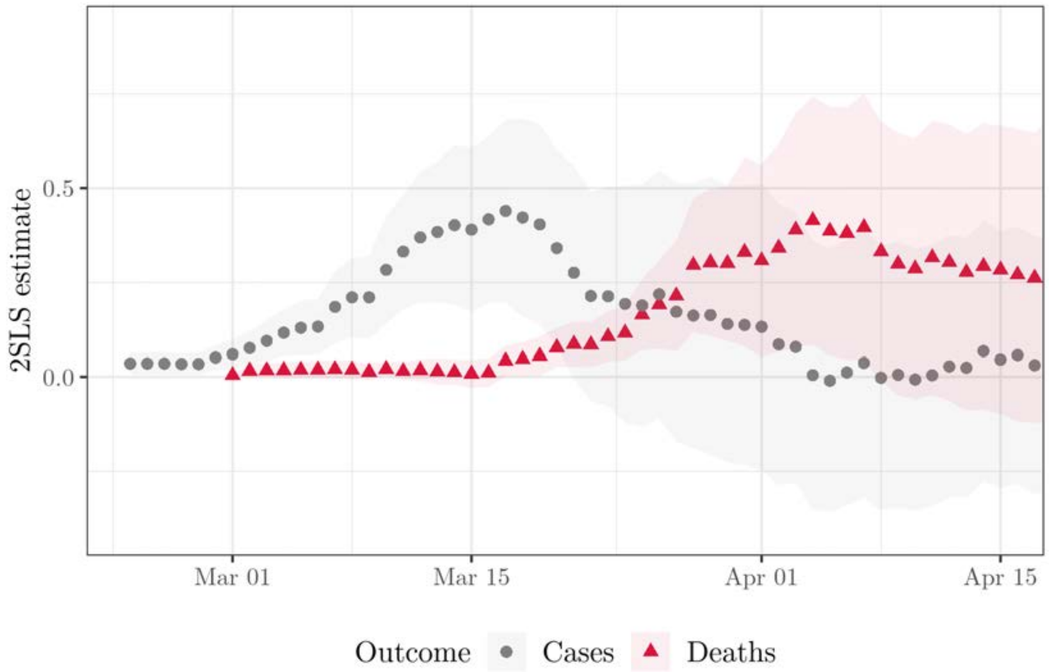
Notes: Figure D2 shows robustness of our OLS estimates for the specifications for log one plus cases on March 14 (Panel A) and log one plus deaths on March 28 (Panel B) under every possible combination of our eight sets of county-level controls (population density and ruraltiy, race, age, economic, education, health status, health capacity, and politics) and our three levels of fixed effects (no fixed effects, census division fixed effects, and state fixed effects). All specifications control for a base set of controls: Fox News' share of television in January 2020, the log of the county's total population, the share of TVs turned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle*, the population-weighted latitude and longitude, and Fox News' and MSNBC's share of cable in January 2018. We cluster standard errors at the DMA level and report 90 percent and 95 percent confidence intervals for each model. Black points are not significant at the $p < 0.1$ level; blue points are significant at the $p < 0.1$ level; green points are significant at the $p < 0.05$ level, and red points are significant at the $p < 0.01$ level.

Table D1: Effect of differential viewership on cases

	Dependent variable:						
	COVID-19 outcomes						
	Feb 29	Mar 07	Mar 14	Mar 21	Mar 28	Apr 04	Apr 11
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Estimates on cases							
Subpanel A.1: Reduced form							
Predicted non-Fox TVs on × Fox share	0.051***	0.193***	0.430***	0.314*	0.193	0.056	0.063
	(0.014)	(0.048)	(0.106)	(0.164)	(0.201)	(0.209)	(0.202)
Subpanel A.2: Two-stage least squares							
H-C viewership difference (predicted)	0.050***	0.188***	0.421***	0.307*	0.189	0.055	0.062
	(0.017)	(0.049)	(0.115)	(0.159)	(0.202)	(0.207)	(0.201)
Panel B: Estimates on deaths							
Subpanel B.1: Reduced form							
Predicted non-Fox TVs on × Fox share	0.005*	0.022	0.013	0.099***	0.345***	0.488***	0.399**
	(0.003)	(0.014)	(0.020)	(0.036)	(0.080)	(0.155)	(0.187)
Subpanel B.2: Two-stage least squares							
H-C viewership difference (predicted)	0.005**	0.022*	0.013	0.096***	0.338***	0.478**	0.391*
	(0.002)	(0.012)	(0.018)	(0.033)	(0.101)	(0.188)	(0.206)
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 reduced-form estimates of the inverse hyperbolic sine of cases upon the instrument, $\widehat{\tilde{s}_{mc,H}} \times \tilde{f}_{mc,-HT}$ — that is, the predicted number of TVs on during Hannity's timeslot, excluding TVs watching *Hannity*, multiplied by Fox News' viewership share, excluding *Hannity* and *Tucker Carlson Tonight*.; Panel A.2 replicates for deaths. Panel B.1 reports two-stage least squares estimates of the inverse hyperbolic sine of cases upon the standardized difference in Hannity-Carlson viewership, instrumented by $\widehat{\tilde{s}_{mc,H}} \times \tilde{f}_{mc,-HT}$; 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, the population density of the county, the log of the county's total population, MSNBC's share of cable in January 2018, population-weighted latitude and longitude, the percent of the population living in a rural area, the population over the age of 65, the percent male with no high school degree, the percent female with no high school degree, the percent male with no college degree, the percent female with no college degree, an age-adjusted measure of the average physical health in the county, the percent uninsured, the percent below the federal poverty line, the log of the median household income, the unemployment rate, the Republican vote share in 2016, and the log of the total number of votes in the county in 2016. Standard errors are clustered at the DMA level.

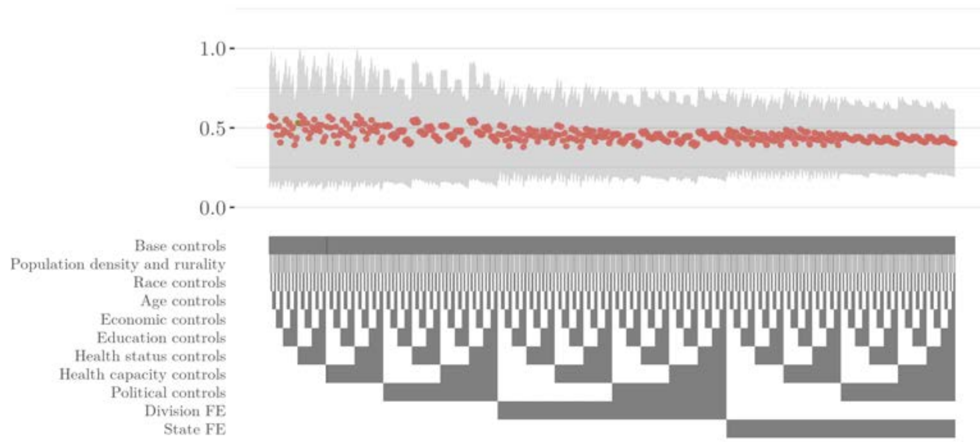
Figure D3: 2SLS estimates of effect of differential viewership on cases and deaths



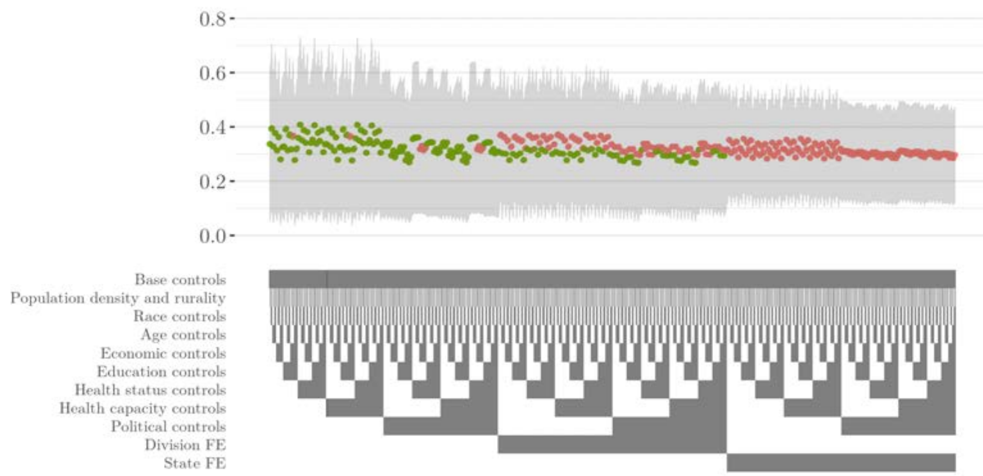
Notes: Figure D3 shows day-by-day 2SLS estimates on the inverse hyperbolic sine of cases and deaths. We report day-by-day effects of the standardized difference in viewership of *Hannity* vs. *Tucker Carlson Tonight*, instrumented by $s_{mc,H} \times \tilde{f}_{mc,-HT}$ and controlling for state fixed 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 number of predicted 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 sixty-five, 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 percent confidence intervals.

Figure D4: 2SLS: robustness to combinations of controls

Panel A: Estimates on cases (March 14, 2020)

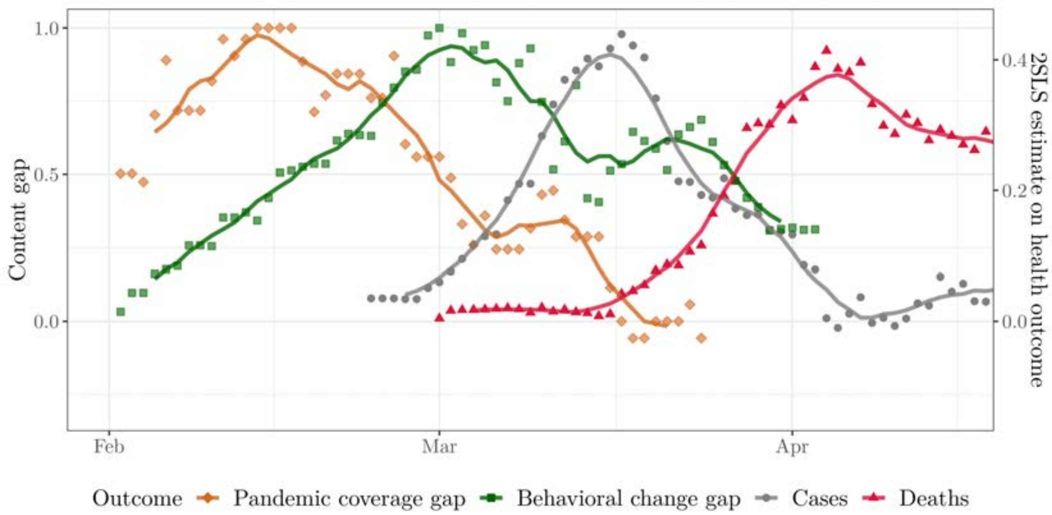


Panel B: Estimates on deaths (March 28, 2020)



Notes: Figure D4 shows robustness of our two-stage least squares estimates for the specifications for log one plus cases on March 14 (Panel A) and log one plus deaths on March 28 (Panel B) under every possible combination of our eight sets of county-level controls (population density and rurality, race, geography, age, economic, education, health status, health capacity, politics) and our three levels of fixed effects (no fixed effects, census division fixed effects, and state fixed effects). All specifications control for a base set of controls: Fox News' share of television in January 2020, 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, and Fox News' and MSNBC's share of cable in January 2018. We cluster standard errors at the DMA level and report 90 percent and 95 percent confidence intervals for each model. Black points are not significant at the $p < 0.1$ level; blue points are significant at the $p < 0.1$ level; green points are significant at the $p < 0.05$ level, and red points are significant at the $p < 0.01$ level.

Figure D5: Carlson-Hannity pandemic coverage gap and effects on cases and deaths



Notes: Figure D5 shows, in brown squares corresponding to the left y-axis, the difference in portrayed seriousness of the coronavirus threat on *Tucker Carlson Tonight* vs. *Hannity*, as rated by Amazon Mechanical Turk coders. The difference peaks in mid-February, a period during which there was no discussion of the coronavirus on *Hannity* and during which *Tucker Carlson Tonight* discussed the coronavirus virtually every show. The figure also shows, in gray circles and red triangles corresponding to the right y-axis, 2SLS estimates of the Hannity-Carlson viewership gap (instrumented by $\mathrm{s}_{mc,H} \times \tilde{f}_{mc,-HT}$) on the inverse hyperbolic sine of cases and deaths. All 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 sixty-five, 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.

Table D2: Differential coverage and COVID-19 outcomes across all Fox News evening shows

	Dependent variable:					
	Inverse pandemic coverage index				Cases Mar 14	Deaths Mar 28
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *OLS: inverse pandemic coverage index on relative viewership*						
H-C viewership difference	0.548***	0.545***				
	(0.053)	(0.052)				
Panel B: *RF: inverse pandemic coverage index on instrument*						
Non-Fox TVs on × Fox share			0.502**	0.490**		
			(0.230)	(0.227)		
Panel C: *2SLS: cases and deaths on inverse predicted pandemic coverage index*						
$-1\times$ coverage index (predicted)					0.922**	0.678*
					(0.438)	(0.355)
Controls	Base	Full	Base	Full	Full	Full
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,102	3,102	3,102	3,102	3,102	3,102

Notes: Panel A reports OLS estimates of the (inverse of the) pandemic coverage index on the standardized difference between viewership of *Hannity* and *Tucker Carlson Tonight*. Panel B reports reduced-form estimates of the inverse pandemic coverage index on our instrument, $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$ — 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.*. Columns (5) and (6) in Panel C report 2SLS estimates of the inverse hyperbolic sine of the number of cases on March 14 and the inverse hyperbolic sine of the number of deaths on March 28, respectively, on the standardized difference between viewership of *Hannity* and *Tucker Carlson Tonight*, instrumented by $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$. Base OLS controls include the 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, the population density of the county, and the log of the county's total population. Base controls for the reduced form and the two-stage least squares are identical, except the share of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle* are replaced with the predicted share of TVs tuned to non-Fox channels during these timeslots. 'Full controls" additionally include all controls described in Section 5.2. Standard errors are clustered at the DMA level.

E Survey Instrument

E.1 Consent and demographics questions

Please review the following consent form before proceeding with this survey.
Consent for Participation in a Research Study

DESCRIPTION: We are researchers at the University of Warwick studying how the news media portrays the coronavirus. Participation should take about 10 minutes.

RISKS and BENEFITS: The risks to your participation in this online study are those associated with basic surveys including boredom, fatigue, mild stress, or breach of confidentiality. The benefit to you is the learning experience from participating in a research study. The benefit to society is the contribution to scientific knowledge. The University of Warwick will only use this data for research purposes.

SUBJECT'S RIGHTS: Your participation is voluntary. You may stop participating at any time by closing the browser window.

For additional questions about this research, you may contact:

- Christopher Roth at Christopher.Roth@warwick.ac.uk

Please indicate, in the box below, that you are at least 18 years old, have read and understand this consent form, and you agree to participate in this online research study.

- ○ I agree to participate in the research
- ○ I do not agree to participate in the research

→

What is your exact age?

What is your gender?

- Male
- Female

With which political party do you identify?

- Democratic Party
- Republican Party
- Independent

Do you have a job outside of taking surveys?

- ◯ Yes: full-time (35+ hours a week)
- ◯ Yes: part-time (less than 35 hours a week)
- ◯ No: homemaker
- ◯ No: currently seeking employment
- ◯ No: student
- ◯ No: retired
- ◯ No: other

What was your family's gross household income in 2019 in US dollars?

- ◯ Less than $15,000
- ◯ $15,000 to $24,999
- ◯ $25,000 to $49,999
- ◯ $50,000 to $74,999
- ◯ $75,000 to $99,999
- ◯ $100,000 to $149,999
- ◯ $150,000 to $200,000
- ◯ More than $200,000

Which of the following best describes your race or ethnicity?

- ○ African American/Black
- ○ Asian/Asian American
- ○ Caucasian/White
- ○ Native American, Inuit or Aleut
- ○ Native Hawaiian/Pacific Islander
- ○ Other

Are you of Hispanic, Latino, or Spanish origin?

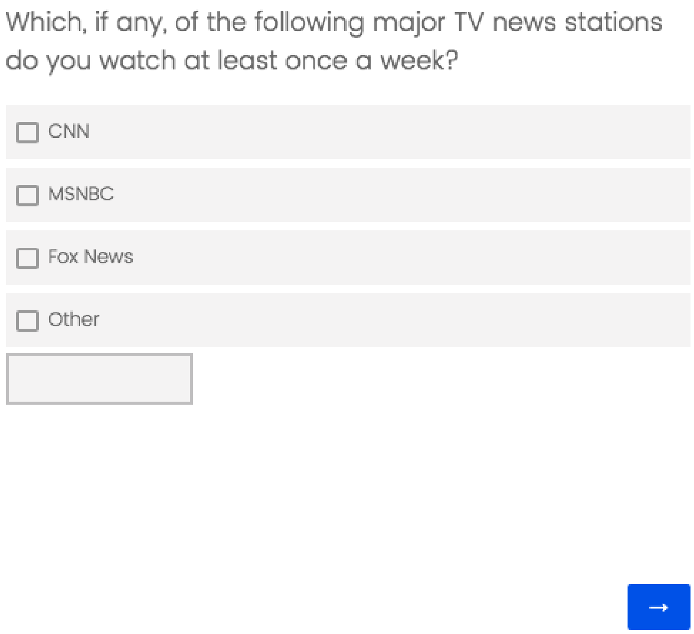
- ○ Yes
- ○ No

What is the highest level of education you have completed or the highest degree you have received?

- ○ Less than high school degree
- ○ High school graduate (high school diploma or equivalent including GED)
- ○ Some college but no degree
- ○ Associate degree in college (2-year)
- ○ Bachelor's degree in college (4-year)
- ○ Master's degree
- ○ Doctoral degree
- ○ Professional degree (JD, MD)

→

E.2 Media consumption questions


Which, if any, of the following major TV news stations do you watch at least once a week?

- [ ] CNN
- [ ] MSNBC
- [ ] Fox News
- [ ] Other

→

E.2.1 Fox News

You indicated that you watch Fox News at least once a week. How often do you watch each of the following shows on Fox News?

	Never	Occasionally	Every day or most days
Sean Hannity	○	○	○
The Ingraham Angle	○	○	○
Other Fox show	○	○	○
The Five	○	○	○
The Story with Martha MacCallum	○	○	○
Tucker Carlson	○	○	○

→

E.2.2 CNN News

You indicated that you watch CNN at least once a week. How often do you watch each of the following shows on CNN?

	Never	Occasionally	Every day or most days
Anderson Cooper 360	○	○	○
Erin Burnett OutFront	○	○	○
CNN Tonight	○	○	○
Cuomo Prime Time	○	○	○
Other CNN show	○	○	○
The Situation Room	○	○	○

→

E.2.3 MSNBC News

You indicated that you watch MSNBC at least once a week. How often do you watch each of the following shows on MSNBC?

	Never	Occasionally	Every day or most days
The Beat with Ari Melber			
Other MSNB show			
All In with Chris Hayes			
The Last Word with Lawrence O'Donnell			
The 11th Hour with Brian Williams			
The Rachel Maddow Show			

→

E.3 Behavior change questions

Did you change any of your behaviors (for example: cancelling travel plans, washing hands or disinfecting significantly more than often, staying six feet away from others, asking to work from home, etc.) in response to the coronavirus over the last few weeks?

- ○ Yes
- ○ No

When did you first significantly change any of your behaviors (For example, cancelling travel plans, washing hands or disinfecting significantly more than often, staying six feet away from others, asking to work from home, etc.) in response to the coronavirus? How did you change your behavior? Why did you change your behavior?

On which date, did you first significantly change any of your behaviors in response to the coronavirus? (For example, cancelling travel plans, washing hands or disinfecting significantly more than often, staying six feet away from others, asking to work from home, etc.).

	Month	Day
Date of change in behavior		

→

E.4 Post-outcome questions

What is your zipcode of residence?

→

Thank you very much participating in this survey. If you have any comments, please let us know below.

→