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MISINFORMATION DURING A PANDEMIC

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ABSTRACT

We study the effects of COVID-19 coverage early in the pandemic by the two most widely-viewed cable news shows in the United States – Hannity and Tucker Carlson Tonight, both on Fox News – on downstream health outcomes. We first document large differences in content between the shows and in cautious behavior among viewers. Through both a selection-on-observables strategy and a novel instrumental variable approach, we find that areas with greater exposure to the show downplaying the threat of COVID-19 experienced a greater number of cases and deaths. We assess magnitudes through a simple epidemiological model highlighting the role of externalities and provide evidence that misinformation is a key underlying mechanism.

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We're not just fighting an epidemic; we're fighting an infodemic.

Dr. Tedros Ghebreyesus, WHO Director-General, February 15, 2020

1 Introduction

Efforts to contain a pandemic depend crucially on citizens understanding the associated risks. Yet the spread of the novel coronavirus (SARS-CoV-2) in 2020 was accompanied by the spread of news downplaying the extent of the threat and dismissing the importance of measures designed to contain the epidemic. In particular, Fox News, the most-watched cable network in the United States, has faced widespread criticism for spreading misinformation about the pandemic.[1] If true, this could be of particular concern, not only due to Fox's large viewer base but also because its viewers are disproportionately elderly — a population among whom COVID-19 may be up to ten times more fatal than among the general population (Wu et al., 2020). Moreover, given the large externalities inherent in a pandemic, misinformation may have harmful effects far beyond those on viewers themselves by affecting disease transmission trajectories in the broader population.

Media outlets from both sides of the political spectrum substantially differed in their coverage of COVID-19 during the early stages of the pandemic.[2] In particular, Fox News evening shows strongly differed in the extent to which they portrayed the coronavirus as a serious threat to US citizens. This was especially true for the network's two most popular shows (which are also the two most widely-viewed cable news shows in the United States) — *Hannity* and *Tucker Carlson Tonight*. 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 diverged sharply as the coronavirus began to spread beyond China. 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.

In this paper, we study how differential exposure to these two shows affected behavior and downstream health outcomes. Examining the differential effects of two shows *within the same network* allows us to compare two *ex ante* similar viewer populations. To examine the relationship between viewership of *Hannity* and *Tucker Carlson Tonight* and changes in behavior in response to the coronavirus — e.g. washing hands more often, practicing social distancing, cancelling travel plans, etc. — we fielded a survey to 1,045 Fox News viewers aged 55 or older in early April 2020. 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 viewers; while viewership of *Tucker Carlson Tonight* is associated with changing behavior three days earlier

[1] 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. Relatedly, a group of over seventy journalism professors wrote an open letter highlighting the danger of misinformation spread by Fox News: "Rupert Murdoch, Fox News' Covid-19 misinformation is a danger to public health," *The Guardian*, April 9, 2020. Fox News is currently being sued by the Washington League for Transparency and Ethics, which alleges that the network intentionally misled people about the threat posed by the coronavirus and thus facilitated its spread.

[2] See for example, the discussion on "What went wrong with the media's coronavirus coverage?", *Vox, April 13, 2020.*

(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), this one-week difference in the timing of changes in 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 between March 15 and May 3 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 — from late February to April 15 — though in additional analyses we report our main outcomes until the time of writing. 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. Indeed, the estimated effects of exposure become stronger as we control for more covariates.

Even so, 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 predicted fraction of TVs on during the start time of *Hannity* (leaving out Fox News) and ii) the local market share of Fox News from 2018, leaving out *Hannity* and *Tucker Carlson Tonight*. To generate cleaner variation in the first term of the interaction, we exploit cross-county variation in local sunset times, which predicts the likelihood that people turn their TV on at different points in the evening. The idea is simple: if people like to turn on their TVs to watch *something* when *Hannity* happens to be on instead of *Tucker Carlson Tonight*, the likelihood that viewers are shifted to watch Hannity is disproportionately large in areas where Fox News is popular in general. We show that, conditional on a minimal set of controls, 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 indicate that a one standard deviation increase in relative viewership of *Hannity* relative to *Tucker Carlson Tonight* is associated with approximately 32 percent more COVID-19 cases on March 14 and approximately 23 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 somewhat decline from mid-March onwards.[3]

[3]It is important to note that we cannot account for county to county externalities: riskier behavior by individuals in one

Our results survive a large number of robustness checks and two alternative identification strategies. We also use a multi-group epidemiological model from Acemoglu et al. (2020) and show that the delay in 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 the number of cases and deaths.

Our work contributes to a literature on the effects of media and propaganda on political behavior and health outcomes (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). Previous work has shown that media exposure can increase hate crimes (Muller and Schwarz, 2018; Bursztyn et al., 2019) and 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 Kaplan, 2007; Martin and Yurukoglu, 2017) and judicial outcomes (Ash and Poyker, 2019).[4] Relating to the literature on the effects of biased media, we show that even holding fixed the network, and even focusing on short-term variation in content, show content can affect high-stakes outcomes. Our approach therefore 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. We are thus able to identify a mechanism of contemporaneous information as the driver of

area may expose other people in different areas to the virus.

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

the treatment effects by exploiting variation in informational content. We also provide evidence highlighting that misinformation can have significant negative externalities on the broader population.

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. Simonov et al. (2020) use the instrument developed by Martin and Yurukoglu (2017) alongside 2015 viewership data to establish that long-term exposure to Fox News causes counties to engage in less social distancing (an effect potentially consistent with Fox News contemporaneously influencing viewers' information sets, or having previously shaped viewers' ideology, partisanship, and/or trust in science or experts). 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.[5] Analyzing Brazil's case, Ajzenman 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. Our work contributes to this recent literature by establishing effects on downstream health outcomes (COVID-19 cases and deaths), presenting a novel instrumental variables approach to identify the effects of exposure to specific TV shows, and establishing the role of a specific *mechanism* of exposure to (mis)information during the period under consideration.

We also contribute to a literature on the determinants and economic consequences of pandemics more broadly. Christensen et al. (2020) study health care delivery during the ebola crisis. Adda (2016) studies how economic activity affects the spread of viral diseases and assesses the effectiveness of social distancing measures. More generally, we relate to the broad literature on perceptions of health risks (Fortson, 2011; Oster et al., 2013; Kerwin, 2018; Fetzer et al., 2020; Dupas et al., 2018; Martinez-Bravo and Stegmann, 2017). Kerwin (2018) studies how information about HIV prevalence affects health behaviors. Oster et al. (2013) studies the role of expectations in shaping medical testing in the context of Huntington disease. Martinez-Bravo and Stegmann (2017) study how anti-vaccine propaganda affects demand for health services in Pakistan.

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 assess effect sizes through the lens of an epidemiological model. In Section 8, we conduct a number of exercises to examine the robustness of our estimates. 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.

[5] 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).

2 Setting

2.1 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.[6] 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). As of April 7, 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."[7]

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).[8] Moreover, the median age of primetime Fox News viewers is 68, substantially higher than that of CNN and MSNBC viewers.[9] Both due to its reach and the fact that over 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. 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.

[6] "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.

[7] "Coronavirus: These US states refuse to issue stay-at-home orders. *Al Jazeera*, April 15, 2020.

[8] "Fox News Channel ratings for first quarter of 2020 are the highest in network history." *Fox News*, March 31, 2020.

[9] Half of Fox News' Viewers Are 68 and Older

Qualitative evidence: Carlson vs. Hannity Many observers have criticized Fox News' coverage of the novel coronavirus, claiming that the network, and in particular Sean Hannity, misled viewers about the dangers the virus posed.[10] Tucker Carlson, however, stood out as an outlier on Fox News for his insistence as early as beginning of February that the coronavirus posed a serious threat to the United States.[11] Qualitative evidence suggests that *Tucker Carlson Tonight* and *Hannity* differed dramatically in their coverage of the coronavirus, standing out from other Fox shows and particularly from one another. 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:

> 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:

[10] 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. Moreover, a group of over 70 journalism professors have signed an open letter highlighting the danger of misinformation spread by Fox News: "Rupert Murdoch, Fox News' Covid-19 misinformation is a danger to public health." *The Guardian*, April 9, 2020.

[11] 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.

> 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.[12] 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.

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

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

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.[13]

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 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. On April 3, 2020, we fielded a survey targeting 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.[14] 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.

Relative to existing survey datasets on individual-level responses to COVID-19, our survey has two key advantages. First, we can observe individual-level viewership of Fox News shows alongside individuals' reported behavior, allowing us to examine the correlation between show viewership and the timing of behavioral change. Second, our survey captures behavioral change along multiple dimensions, including more subtle forms of behavioral change such as hand washing or disinfecting more often. This is particularly important given that the differences in show content peak during a period when large-scale behavioral changes such as staying at home or wearing face masks were less prevalent.

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").

[13] 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).

[14] The median age among Fox News viewers is 68 (see Half of Fox News' Viewers Are 68 and Older).

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.

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.[15] 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 1. 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 ($p < 0.01$). 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.[16] 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 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

[15]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.

[16]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.

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.

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. We focus on the continental United States, excluding the two DMAs in Alaska (Anchorage and Fairbanks) and the single DMA in Hawaii (Honolulu).[17] Our dataset contains viewership data between 5pm and 11pm (local time) at the DMA-by-timeslot-by-day level. In addition to the number of TVs watching Fox News, we observe the total number 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

[17] 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.

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 that our identification strategy relies on differences in sunset times across DMAs).

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. However, in Appendix A.7, we report our main outcomes up until the time of writing.[18]

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

[18]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 (see e.g. Alsan et al. 2020), motivating our choice to focus on results until April 15.

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, 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.

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 solving the identification problem.

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 2020 when both shows are aired. We scale this variable a standard normal distribution for ease of interpretation. In our primary analysis, we estimate the following specification separately for each day between February 24 and April 15 and between March 1 and April 15 (for deaths):

$$Y_{ct} = \alpha_t + \beta_t D_c + \Pi_t X_c + \varepsilon_{ct}$$

where Y_{ct} is an outcome (log one plus cases or log one plus deaths) in county c on day t, D_c is the standardized difference between viewership of *Hannity* and *Tucker Carlson Tonight*, and X_c is a vector of county-level controls. Since we are interested in examining differential viewership across the two major shows on Fox News, while holding constant the popularity of the network, we 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). To account for the overall popularity of Fox News over any other network, or the county-level tendency to watch TV around the time of *Hannity* and *Tucker Carlson Tonight*, we also include the number of households watching Fox News as a share across all networks and the average number of TVs turned on to non-Fox channels between 8pm and 11pm Eastern Time (three variables, each capturing one hour). We always include log total population and population density, since at a minimum, we would expect these to be key determinants of COVID-19 outcomes. To account for 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. 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, resulting in a total of 204 clusters. 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. Figure 4 displays the values of D_c across the U.S., residualized by the controls described above.

Our most extensive OLS specification, which is the preferred one for the reasons outlined above, will include state fixed effects and an extensive set of county-level controls for *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); *political* factors (Republican vote share and the log total number of votes cast in the 2016 Presidential election); and *geographical* factors (latitude, longitude, and the share of the county living in rural areas).

Results We report day-by-day results for cases and deaths in Figure 5, 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 coefficients on deaths are continuing to rise. The lag between the coefficient estimates on cases and the coefficient estimates on deaths is consistent with the approximately two-to-three week lag between infection and death (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. Panel A of Tables 2 and 3 replicate these results in regression table form, reporting OLS results at one-week intervals. 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 ($p < 0.1$), 5 percent more cases on March 14 ($p < 0.01$), and 10 percent more cases on March 21 ($p < 0.01$). The effect size then begins to decline.

Deaths follow a similar trajectory on a two-week lag: our estimates imply that 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.[19]

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 (race, geography, 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). Figure 6 reports coefficient estimates and 90 percent and 95 percent confidence intervals for each of these 768 models. The majority of coefficient estimates on cases and deaths are statistically significant at the 5 percent level. All coefficient estimates from specifications including state fixed effects, our most demanding and most precisely estimated specifications, are significant at the 5 percent level. Moreover, our coefficient estimates are relatively stable. Appendix Figure A3 shows a generally positive correlation between the R^2 of each model and the coefficient estimate, providing suggestive evidence that, if anything, omitted variable bias seems to be downward biasing our coefficient of interest (Oster, 2019). 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 A4; 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 A5, 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 a novel instrumental variables strategy to isolate plausibly exogenous variation in relative viewership.

[19] In Appendix Figure A17, 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.

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 a novel approach to generate plausibly exogenous variation in relative viewership of these two shows exploiting cross-DMA variation in when the sun sets. 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 Identification strategy

6.1.1 Construction of the instrument

We begin by showing important systematic patterns that drive TV viewership over the course of the evening. 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 7 plots a non-parametric local polynomial fitting the relationship between time since sunset and the total number 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 (green) and in which *Hannity* begins in that interval (red). 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 7 highlights, even holding constant what (clock) time shows air, there remains substantial variation in start time relative to sunset. For example, on February 1, 2020, the sun set at 6:05pm in Louisville, KY — one of the westernmost cities on Eastern Time — whereas it set at 5:15pm in New York, NY, nearly an hour earlier.[20] 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.[21]

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 H_{ds} denote viewership of *Hannity* in DMA d and during timeslot s. Let $\widehat{\text{NonFoxHannity}}_{d,s}$ denote the predicted total number of TVs turned on in DMA d at time s, *leaving*

[20] Appendix Figure A6 highlights this phenomenon across the continental United States, plotting sunset times in each county on February 1, 2020.

[21] 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 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.

out TVs watching Fox News (i.e. leaving out TVs watching *Hannity*).[22] We predict $\text{NonFoxHannity}_{d,s}$ parametrically for each DMA using a third-order polynomial. Denoting by n_{dt} the sunset time in DMA d on day t, we have:

$$\text{NonFoxHannity}_{dst} = \alpha_d + \delta_{d1}(s - n_{dt}) + \delta_{d2}(s - n_{dt})^2 + \delta_{d3}(s - n_{dt})^3 + \epsilon_{dst} \tag{1}$$

We map the fitted values $\widehat{\text{NonFoxHannity}}_{dst}$ in Appendix Figure A7 for February 1, 2020.

In constructing our instrument, we also exploit substantial variation in the market share of Fox News, which we map in Appendix Figure A8. The intuition is simple: the difference in viewership between the two shows will be larger when the fraction of TVs turned on during Hannity's time slot is larger, and when the total share of viewers watching Fox News is large. Thus, our identifying variation is based on *interaction* of the predicted fraction of (non-Fox) TV viewership during Hannity's timeslot with the local Fox News share (again computed leaving out *Hannity* and *Tucker Carlson Tonight* to avoid capturing DMA-specific preferences for either anchor). Letting FoxShare_d denote the viewership share of Fox News in DMA d, leaving out *Hannity* and *Tucker Carlson Tonight*, our instrument is given by $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$.

6.1.2 Specifications

Our first-stage and reduced-form specifications, respectively, are:

$$D_{cd} = \beta_0 + \beta_1 \widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d + \beta_2 \widehat{\text{NonFoxHannity}}_d + \beta_3 \text{FoxShare}_d + \Pi_t X_c + \epsilon_{cd},$$

$$Y_{cdt} = \beta_0 + \beta_1 \widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d + \beta_2 \widehat{\text{NonFoxHannity}}_d + \beta_3 \text{FoxShare}_d + \Pi_t X_c + \epsilon_{cd},$$

where, in the first-stage, D_{cd} is the standardized difference between the number of viewers of *Hannity* and *Tucker Carlson Tonight* in county c of DMA d, $\widehat{\text{NonFoxHannity}}_d$ is the predicted fraction of TVs turned to non-Fox channels during Hannity's timeslot in DMA d (containing county c) and FoxShare_d is the Fox market share in DMA d (leaving out *Tucker Carlson Tonight* and *Hannity*). As in the OLS, in the reduced form, we run cross-sectional regressions for some outcome Y_{cdt} (cases, deaths) in county c of DMA d on day t. We also always include the same parsimonious set of baseline county-level controls from our OLS specification, X_c, except that to avoid a bad controls problem due to the variation our instrument is meant to capture, we control for the *predicted* share of households with TVs turned on between 8pm and 11pm ET rather than the actual values. We will also show results using the full set of controls and fixed effects, which also are the same as in the OLS specifications.

The instrument is relevant if $\beta_1 > 0$. The underlying logic is simple: if people like to turn on their TVs to watch *something* when *Hannity* happens to be on instead of when another Fox show happens to be on, the likelihood that viewers are shifted into watching Hannity is disproportionately large in areas where Fox News is popular in general.

[22] 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).

6.1.3 Instrument validity

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. No coefficient is significantly different from zero at the 5 percent level, and coefficient magnitudes are generally small. 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 is designed to shift differential 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 $\beta_1 > 0$, it is important to consider potential violations of a more narrowly defined exclusion restriction and how such violations influence how we should interpret 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 exclusion restriction that the reduced form mainly captures effects from exposure to initially diverging (followed by converging) coverage of the coronavirus by *Hannity* and *Tucker Carlson Tonight*, it is important to keep in mind the aforementioned limitations of the approach. We will provide 2SLS estimates, but we urge caution in interpreting coefficients. We view 2SLS as a convenient way to scale the reduced form in order to assess the magnitudes involved under the narrow exclusion restriction. 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 graphically in Figure 9, and in regression table form in Appendix Table A2, our instrument strongly predicts viewership of *Hannity* relative to *Tucker Carlson Tonight*. The first-stage F-statistic is never lower than 7, but is substantially higher when fixed effects are included.

Coefficient estimates are relatively stable: 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 reduced form and 2SLS results across all these specifications, as well as permutations across all of the additional combinations.

6.2 Results on COVID-19 cases and deaths

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

6.2.1 Reduced-form effects

Our reduced form specification follows our specification for the first stage, but studies the impact of our instrument on deaths and cases, conditional on the same set of controls as in the first-stage equation.

Panel A of Figure 10, which for consistency and ease of comparison mirrors the OLS specification of Figure 5 (that is, the specification with the most extensive set of controls and fixed effects), shows the day-by-day reduced form effects of our instrument on cases and deaths. Effects on cases start to rise in early March and peak in mid-March before gradually declining, consistent with Hannity's changing position on the coronavirus. Consistent with medical evidence, effects on deaths start emerging approximately three weeks after cases. The effects on deaths gradually rise from mid-March until the end of the month and then level off. The initial divergence, subsequent convergence, 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.[23]

Two-stage least squares To quantify effect sizes, we scale the reduced-form estimates by the first stage coefficient using a simple two-stage least squares procedure. 2SLS allows us to compute confidence intervals on the effects if we are willing to impose the exclusion restriction that all effects operate through relative exposure to *Hannity* relative to *Tucker Carlson Tonight*. However, as mentioned above, it is important to keep in mind the implicit assumptions that we need to make about consumer preferences and cross-show spillovers.

With this caveat in mind, Panel B of Figure 10 shows the day-by-day 2SLS estimates on cases and deaths. The qualitative pattern follows the pattern from the reduced-form estimates discussed above. A one standard deviation higher viewership of *Hannity* relative to *Tucker Carlson Tonight* is associated with approximately 15 percent more cases on March 7 ($p < 0.001$), 33 percent more cases on March 14 ($p < 0.001$), and 28 percent more cases on March 21 ($p < 0.01$); the effect then declines to a statistically-insignificant 8 percent more cases on April 4. A one standard deviation greater viewership of *Hannity* relative to *Tucker Carlson*

[23] In Panel A of Appendix Figure A18, we report day-by-day results for cases and deaths extending until the time of writing. Like the OLS results, reduced-form point estimates remain positive; effects on both cases and deaths increase, though these coefficients are imprecisely estimated, and we cannot rule out null effects.

Tonight is associated with 23 percent more deaths on March 28 ($p < 0.001$), 34 percent more deaths on April 4 ($p < 0.01$), and 29 percent more deaths on April 11 ($p < 0.10$).[24]

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 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 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 11 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 11 also plots the 2SLS estimates of the Hannity-Carlson viewership gap (instrumented by $\text{Non}\widehat{\text{FoxHannity}}_d \times \text{FoxShare}_d$) on log one plus cases and log one plus deaths in gray circles and red triangles, respectively (as previously reported in Panel B of Figure 10).

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 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 coverage 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

[24]In Panel B of Appendix Figure A18, we report day-by-day results for cases and deaths extending until the time of writing, as discussed in Footnote 22.

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.7). As we show in Section 7.2, 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 mid June).

7 Assessing Effect Sizes

7.1 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 it, 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 10. 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 13 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 13 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 10 also shows clearly. The relative effect remains relatively stable with a slight decline. As the pandemic spreads, however, the slightly declining relative magnitude becomes more economically meaningful as the base grows.[25]

[25] In Appendix Figure A15, we present results from an equivalent exercise using the OLS estimates. The magnitudes of the estimated effects are in general smaller, but remain significant for a longer period. In Appendix Figure A19, we extend the figure with treatment effects estimated until the time of writing, as discussed in Footnote 22.

7.2 Assessing treatment effects through an epidemiological model

We now assess the effect sizes documented in Section 7.1 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.[26]

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 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 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.[27] Following Acemoglu et al. (2020), we normalize the total population size $N = \sum_j N_j$ to 1.

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 $\iota = 1$ (such that there is no distinction between infected patients in the ICU vs. infected patients outside the ICU; standard SIR models also make this simplification). We then set δ_j^d, originally defined as the death rate of members of group j in the ICU, to δ_j, the estimated fatality rate among group j, and we set δ_j^r, originally defined as the recovery rate of those in the ICU, to γ_j, the estimated recovery rate among group j.[28] We assume that these rates are invariant to time and the number of patients. To capture differential interaction patterns — the

[26] 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 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.

[27] 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).

[28] Note that the fatality rate for group j is equal to $\frac{\delta_j}{\delta_j + \gamma_j}$, such that the fatality rate and γ pin down δ.

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).[29] 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 disinfecting — and thus, the effect of differential viewership of *Hannity* and *Tucker Carlson Tonight* — by assuming that they directly affect the transmission rate β_j.[30]

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 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 4.

We take the timing of behavioral responses 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, almost returning to zero by the date of the survey on April 3. We thus fix $\bar{\beta}(t) = \beta^+_n(t) = \beta^+_c(t)$ for $t =$ Feb 1 and $t \geq$ Apr 3. 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 3. Informed by recent epidemiological estimates (e.g., Unwin

[29]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).

[30]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. However, our results are qualitatively similar if we instead assume $c(\beta_a, \beta_b) = \beta_a \beta_b$.

et al. 2020), we allow the transmission rate to decline linearly from April 3 to May 1. This leaves us with five parameters to estimate: $\bar{\beta}(\text{Feb }1) = \beta_u^+(\text{Feb }1) = \beta_t^+(\text{Feb }1)$, $\bar{\beta}(\text{Mar }1) = \beta_u^+(\text{Mar }1)$, $\beta_t^+(\text{Mar }1)$, $\bar{\beta}(\text{Apr }3) = \beta_u^+(\text{Apr }3) = \beta_t^+(\text{Apr }3)$, and $\bar{\beta}(\text{May }1) = \beta_u^+(\text{May }1) = \beta_t^+(\text{May }1)$.

COVID-19 cases are vastly underreported (as discussed in Section 4) 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.[31] As a result, we focus on fitting the trajectories of *deaths* estimated in Section 7.1. 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.[32]

Panel A of Figure 14 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).[33] The peak difference in $\bar{\beta}$ and β_t^+ on March 1 is 0.094, representing an approximately 23.4% difference.[34] Put differently, the transmission rate among the treated reaches the March 1 transmission rate among the untreated by March 18. 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 $R_0 \approx \frac{\beta^2}{\gamma} = 4.39$; R_t falls to approximately 1.74 by April 3 and approximately 0.64 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 14 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 14 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.[35]

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 10.6% of the additional deaths occur in the treated group, with the remaining 89.4% of additional deaths occurring in the untreated group.[36] Since there is substantial uncertainty about the true values of the exogenously taken input parameters of the model, we should be cautious when interpreting the output. Nonetheless, our model highlights the relevance of externalities in generating our estimated treatment effects. 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

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

[32] We begin our simulations on February 6, 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.)

[33] We repeat this exercise for our OLS estimates; the results are reported in Appendix Figure A16.

[34] This difference is approximately equal to the March 1 persuasion rate we identify in the survey (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 2.25%.

[35] 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.

[36] The comparable estimate for our OLS estimates is 10.4% of additional deaths.

differences in transmissibility among the broader population, which ultimately translate into effect sizes of roughly the same magnitude as those we estimate.

8 Robustness

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

8.1 Robustness to choice of specification and to 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 (race, geography, 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. Figure 12 reports coefficient estimates and 90 percent and 95 percent confidence intervals for each of these 768 models. All coefficient estimates on cases and deaths are statistically significant at the 5 percent level.

Robustness to outliers and COVID-19 hotspots One potential concern is that COVID-19 hotspots with large numbers of cases or deaths may skew our results. We probe robustness to outliers by residualizing our outcome variables and the instrument by our controls and fixed effects, then plotting the residuals of our outcome variables against the residuals of the instrument in Appendix Figure A10. 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 A11, 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.

8.2 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 A12, 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 early April. However, our findings remain qualitatively unchanged.

Randomization inference To address error arising from treatment variation, in Appendix Figure A13, we employ a randomization inference approach (Athey and Imbens, 2017), permuting the plausibly exogenous "shift" ($\widehat{\text{NonFoxHannity}}_d$) 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 $\widehat{\text{NonFoxHannity}}_d$ with FoxShare_d, 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 of the log(1+x) transformation, in Appendix Figure A14 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.

8.3 Robustness to alternative constructions of instrument

8.3.1 Division-level viewership curve

One possible concern with our main instrument is that it 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 number 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 lower order terms. 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 particular, we estimate the following first-stage regression separately for each of the nine Census divisions in the United States:

$$\log(\text{NonFoxHannity}_{ds}) = \alpha_d + \delta_1(s - n_d) + \delta_2(s - n_d)^2 + \delta_3(s - n_d)^3 + \epsilon_{ds},$$

where the DMA-specific fixed effect α_d allows the level of the curve to vary between DMAs and the log transformation of NonFoxHannity allows the scale of the curve to vary between DMAs. We re-define $\widehat{\text{NonFoxHannity}}_{ds} = \exp(\log \widehat{\text{NonFoxHannity}}_{ds})$ and, as before, construct our instrument based on the interaction of $\widehat{\text{NonFoxHannity}}_{ds}$ with the viewership share of Fox News in DMA d, leaving out *Hannity* and *Tucker Carlson Tonight*. Our first-stage and reduced-form specifications are otherwise identical to those in Section 6.1.2.

Results Like our main instrument, conditional upon the small set of controls accounting for local viewership patterns, this alternative instrument is not significantly correlated with any among our extensive set of county-level demographic characteristics (Appendix Figure B1), and it has a strong first stage on viewership (Appendix Figure B2). In Appendix B, 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.

8.3.2 Empirical viewership curve

As an additional robustness check, we present estimates from an alternative instrumental variables approach that follows the same logic as the one based on local sunset times, but that is substantially simpler in its execution and does not rely on functional form assumptions. Rather than *predicting* the fraction of TVs tuned to non-Fox channels during Hannity's timeslot based on sunset times, which in principle raises questions about the appropriate functional form and the uncertainty surrounding its estimation, we simply take the *actual* mean of TVs tuned to non-Fox channels during Hannity's timeslot during the month of January and February 2020, NonFoxHannity_d. As before, we interact this value with Fox News' viewership share in the DMA (calculated leaving out *Hannity* and *Tucker Carlson Tonight*), FoxShare_d to construct our instrument. This approach therefore closely resembles a standard shift-share instrument (Bartik, 1991), in which the (endogenous) "share" is the Fox viewership share in the DMA and the (exogenous) "shift" is generated by cross-DMA differences in preferences for watching TV during the timeslot when *Hannity* is aired.

Results As before, conditional upon the small set of controls accounting for local viewership patterns, this instrument is not significantly correlated with any among our demographic characteristics (Appendix Figure C1) and has a strong first stage on viewership (Appendix Figure C2). In Appendix C, we replicate our analysis with this alternative instrument and find qualitatively identical and quantitatively similar results.

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 6.1.3, 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).[37] Despite the fact that the

[37] 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; capturing such spillovers is beyond the scope of this paper. Such spillovers are likely minor given that viewers tend to favor shows within the same

other evening shows are neither as widely watched as *Hannity* and *Tucker Carlson Tonight* nor as extreme 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 5 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, $\text{Non}\widehat{\text{FoxHannity}}_d \times \text{FoxShare}_d$, is associated with the pandemic coverage index. Columns 3 and 4 of Table 5 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 5, 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

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.

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 Figure 15, 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 and may, at the time of writing, be beginning to decline (though, given the wide confidence intervals, these results must be interpreted with caution).

10 Conclusion

Examining the effects of misinformation 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. The two most widely-viewed cable news shows in the United States — *Hannity* and *Tucker Carlson Tonight*, both on Fox News – originally took very different stances on the risks associated with the novel coronavirus. While *Hannity* downplayed the threat during the initial period of the virus' spread in the United States, *Tucker Carlson Tonight* warned its viewers that the virus posed a serious threat from early February. In this paper, we show that differential exposure to these two shows affected behavior and downstream health outcomes.

We begin by validating differences in content with independent coding of shows' transcripts. Consistent with the differences in content, we present new survey evidence that Hannity's viewers changed behavior in response to the virus later than other Fox News viewers, while Carlson's viewers changed behavior earlier. Using both OLS regressions with a rich set of controls and different instrumental variable strategies exploiting variation in the timing of TV consumption, 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. We also show that a standard epidemiological model can, with reasonable parameter levels, match the approximate magnitude of our measured treatment effects. Finally, we also provide additional evidence that misinformation is an important mechanism driving the effects in the data. Our results indicate that the provision of misinformation on mass media can have significant societal consequences.

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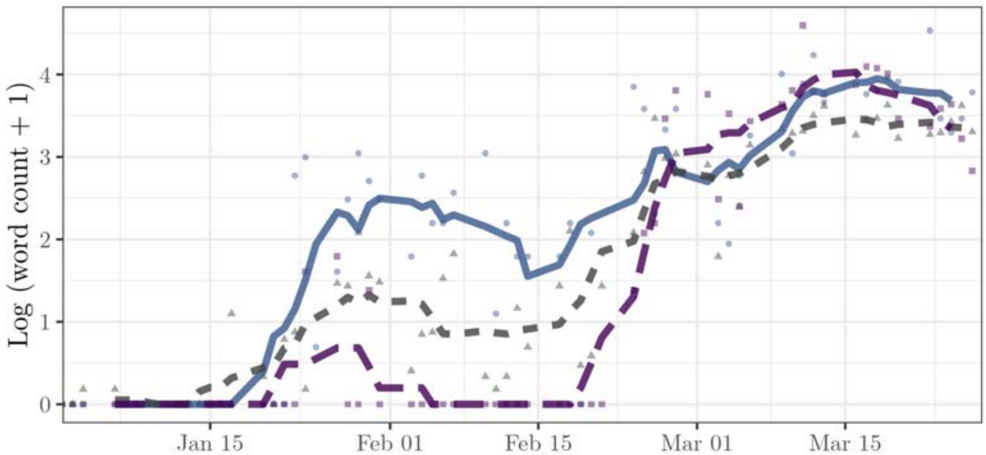
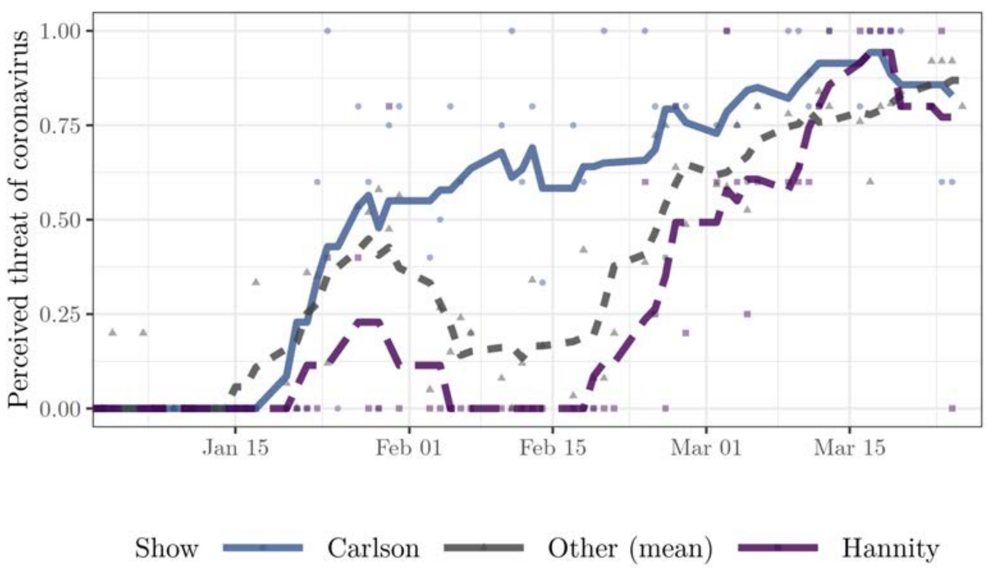
Figures

Figure 1: Show content validation

Panel A: Counts of coronavirus-related terms by episode (one-week rolling means)

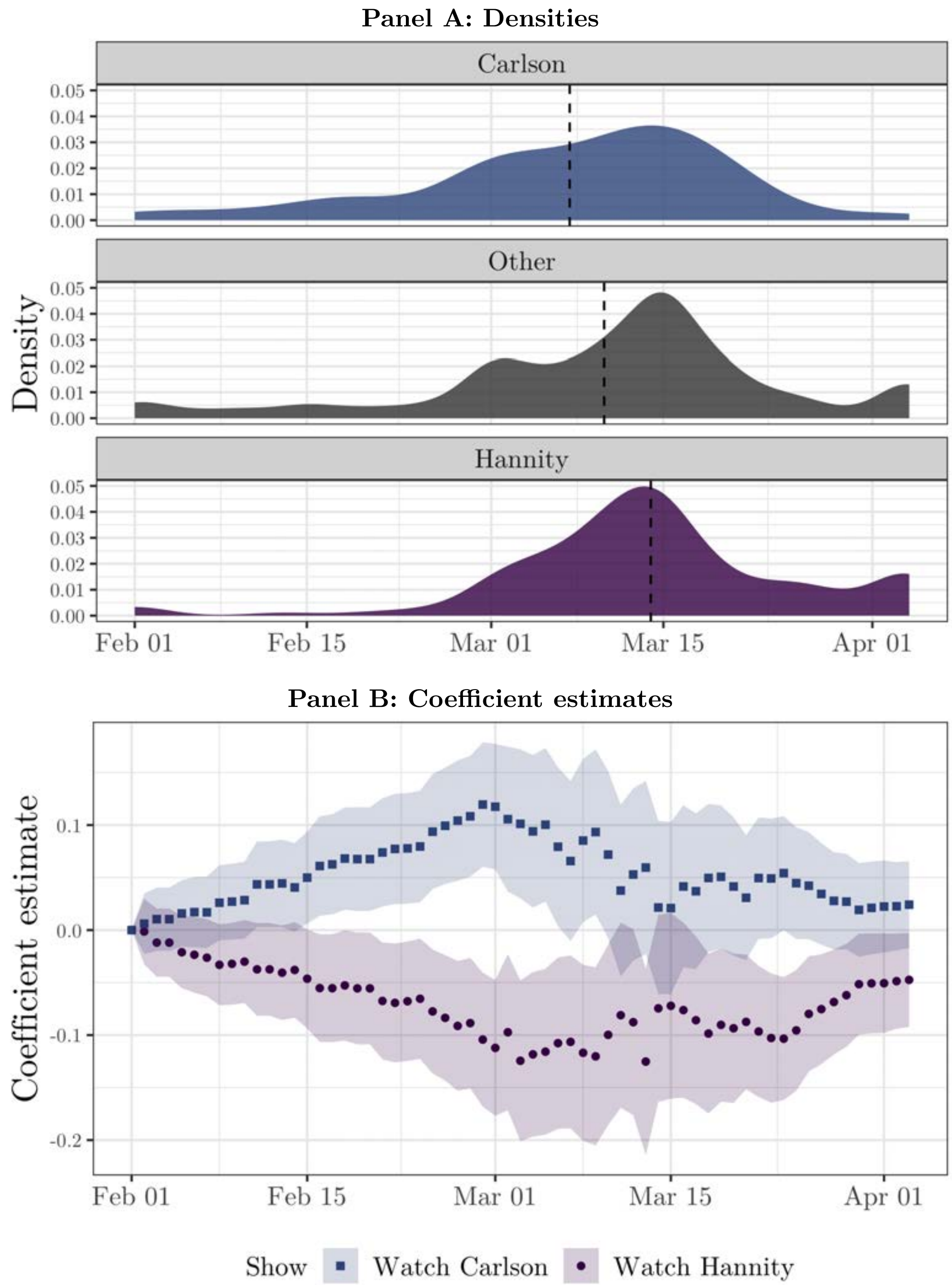


Panel B: MTurk seriousness rating by episode (one-week rolling means)



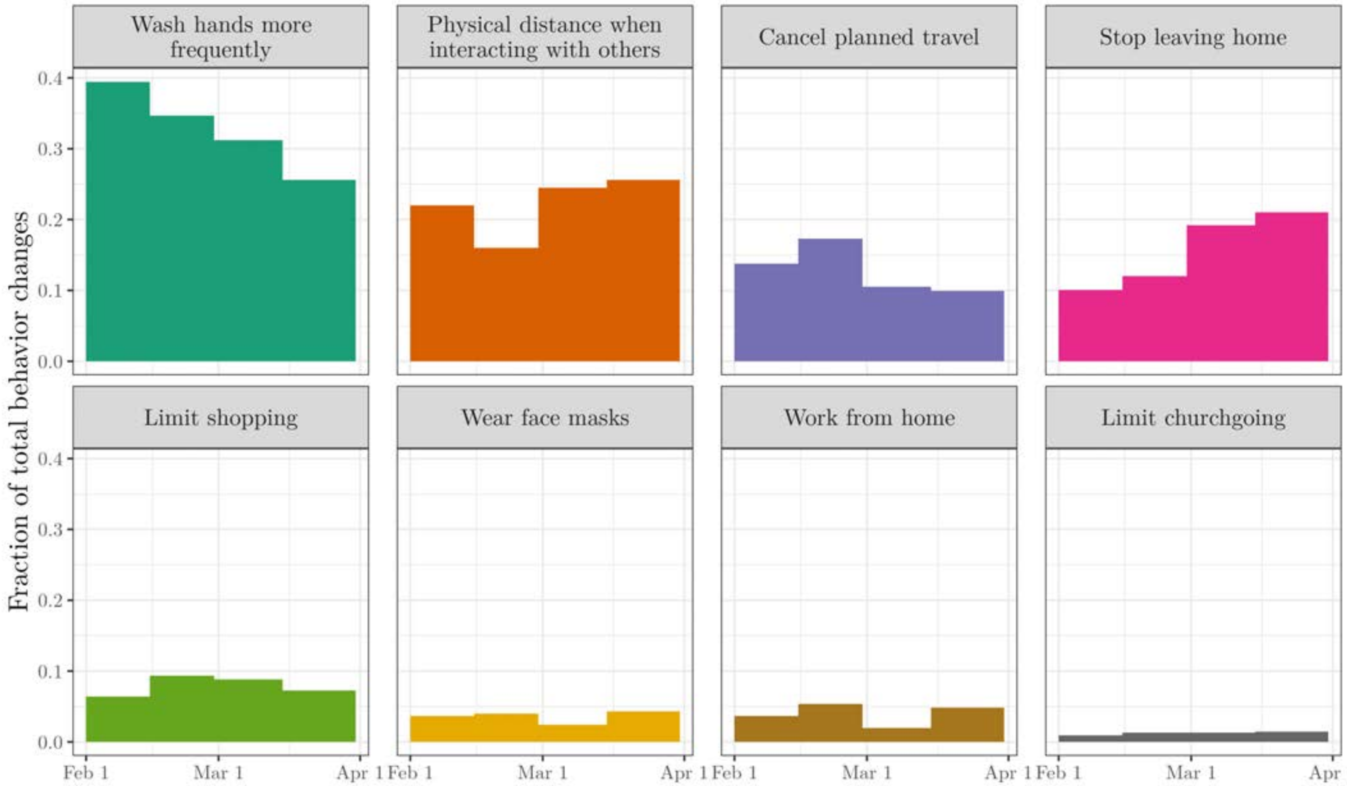
Notes: Panel A shows counts of coronavirus-related terms (coronavirus, COVID, virus, influenza, and flu) separately for *Hannity*, *Tucker Carlson Tonight*, and the other Fox News shows aired on Fox News between 5pm and 11pm local time across all four major time zones in the continental US (*The Five*,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



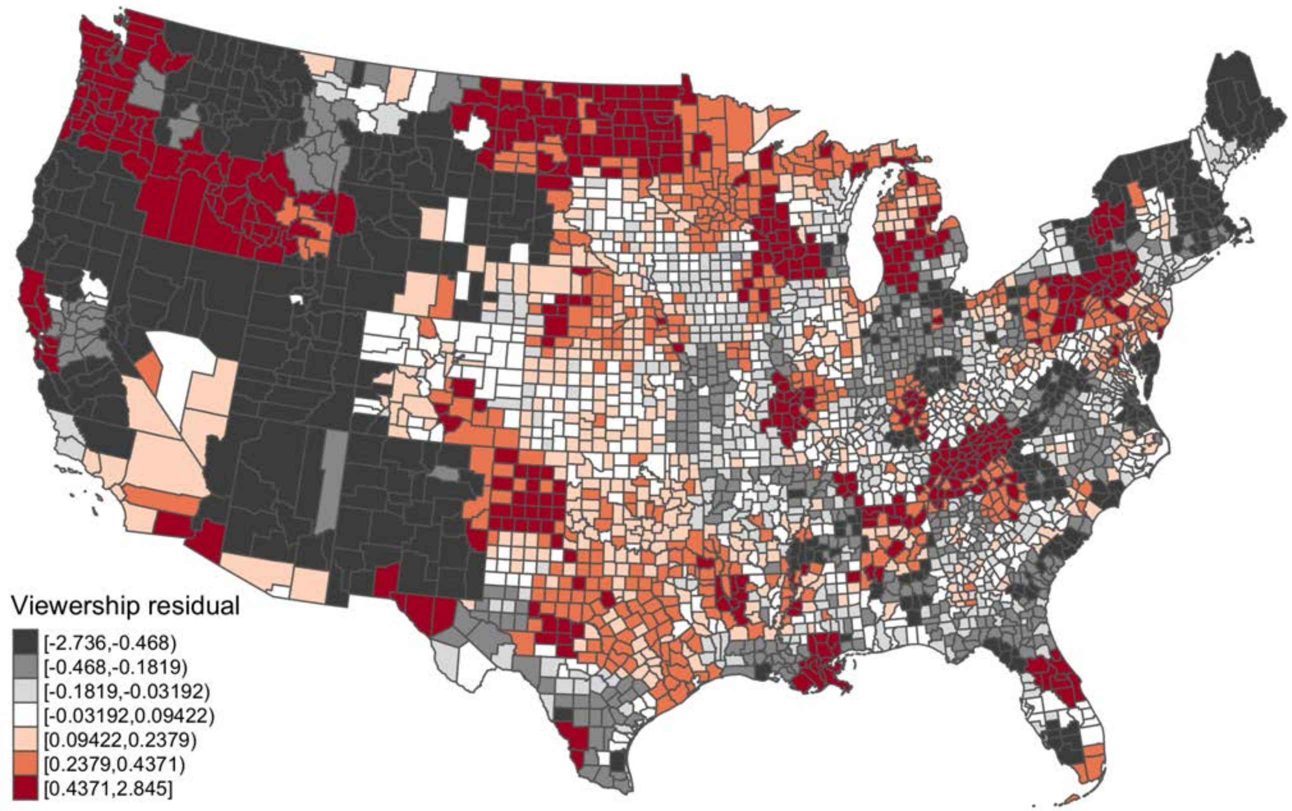
Notes: Panel A of Figure 2 displays the density function of viewers' reported day of behavior change in response to the coronavirus. For respondents who report that they have not changed any of their behaviors by the date of the survey, we impute the date of the survey (April 3). The dashed line indicates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



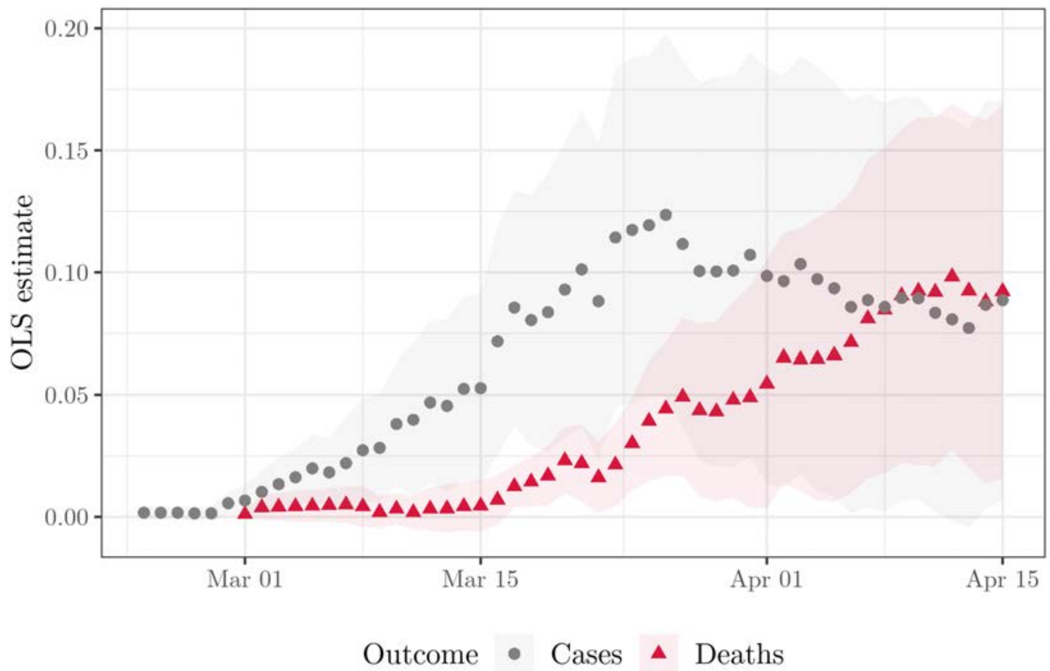
Notes: For each two-week interval between February 1 and April 1, Figure 3 shows the fraction of reported behavioral changes falling under each category. Behaviors were coded based upon responses to the following open-ended question from our survey: "When did you first significantly change any of your 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: Residualized Hannity-Carlson viewership difference



Notes: Figure 4 plots the difference in the viewership of *Hannity* and *Tucker Carlson Tonight* for each of the 207 DMAs in the continental United States, residualized by our base 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 number of TVs turned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle*.

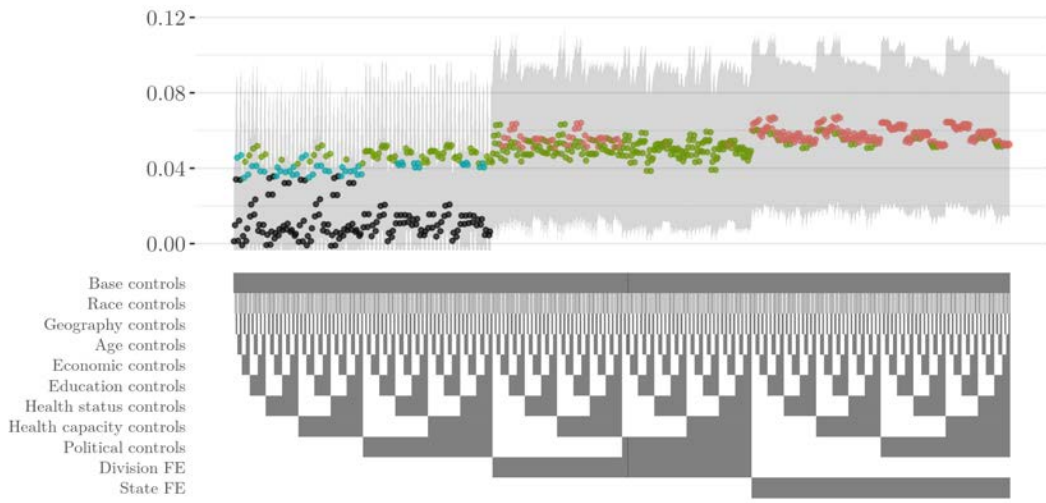
Figure 5: OLS estimates of effect of differential viewership on cases and deaths



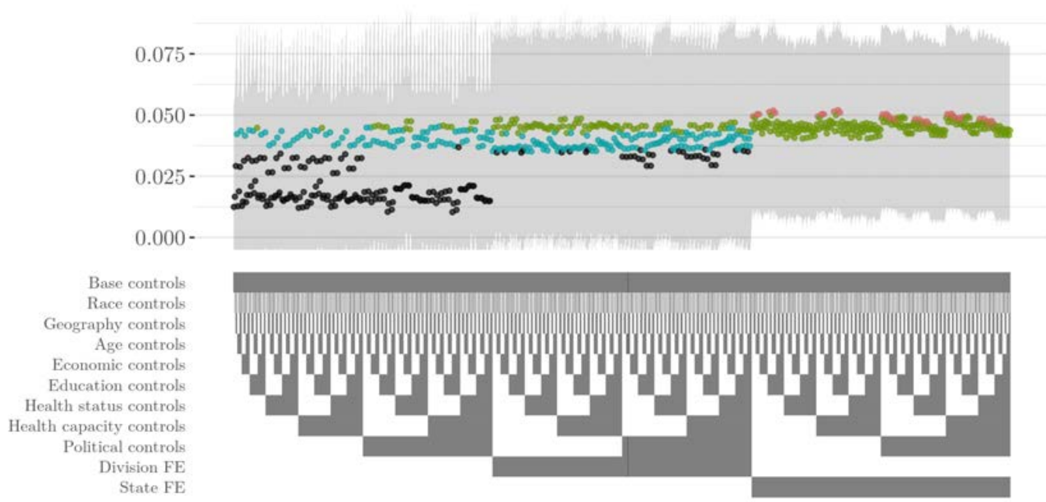
Notes: Figure 5 displays effects of differential viewership of *Hannity* and *Tucker Carlson Tonight* on log one plus cases and log one plus deaths. We report day-by-day results for the correlation between log deaths and log cases with the standardized viewership difference between *Hannity* and *Tucker 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 number 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 6: OLS: robustness to combinations of controls

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



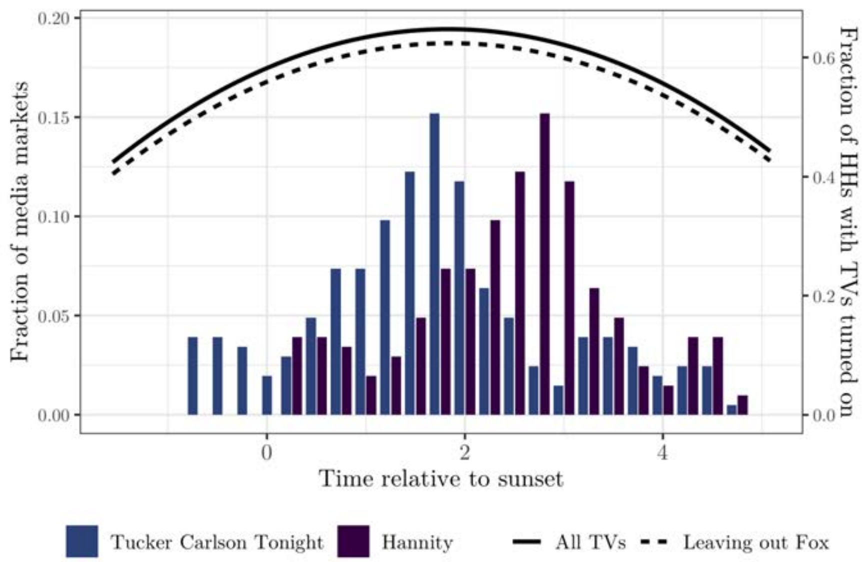
Panel B: Estimates on deaths (March 28, 2020)



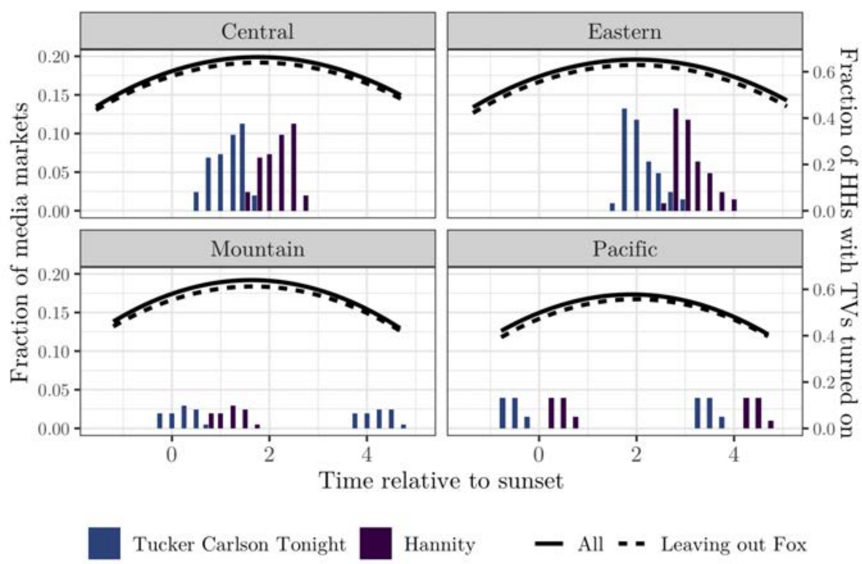
Notes: Figure 6 shows robustness of our OLS estimates for the specifications for log one plus cases on March 14 (Panel A) and log one plus deaths on March 28 (Panel B) under every possible combination of our seven sets of county-level controls (race, geography, age, economic, education, health, politics) 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 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 7: Viewership and program start relative to sunset

Panel A: Across the country

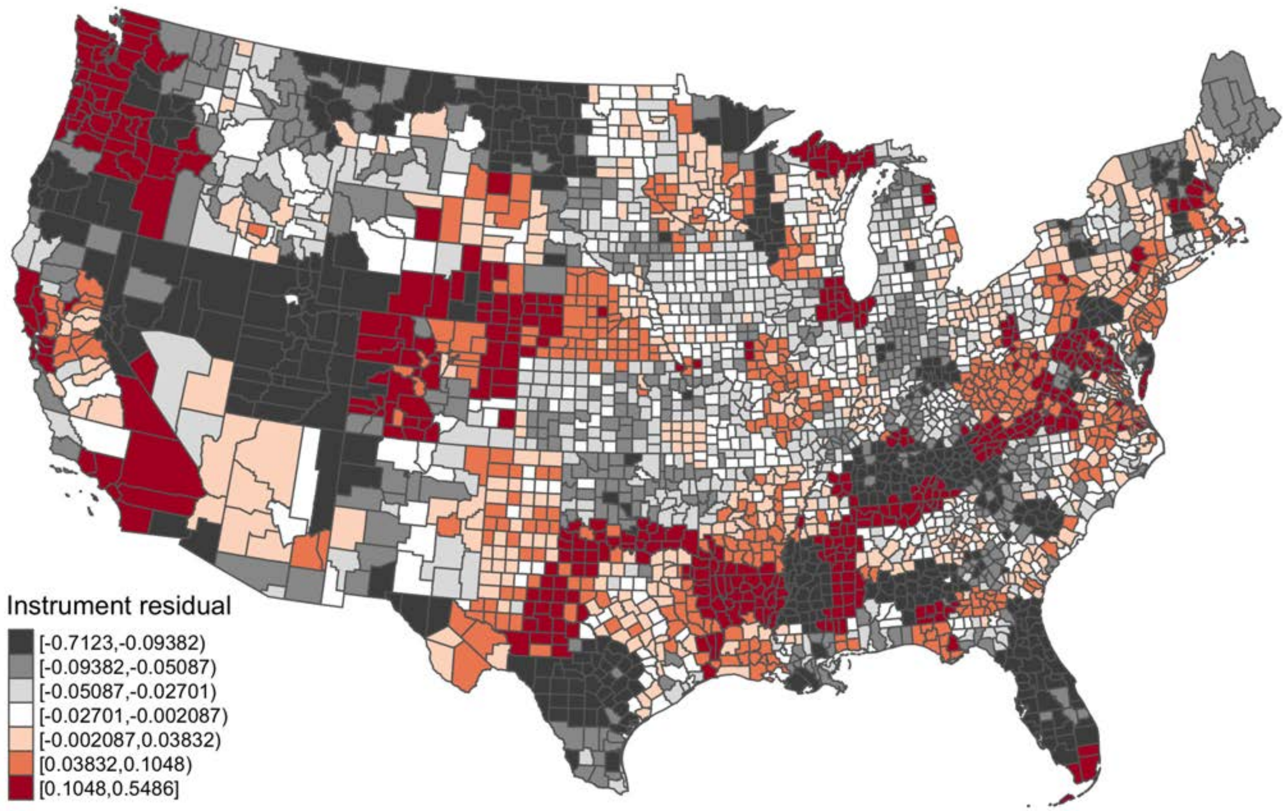


Panel B: By time zone



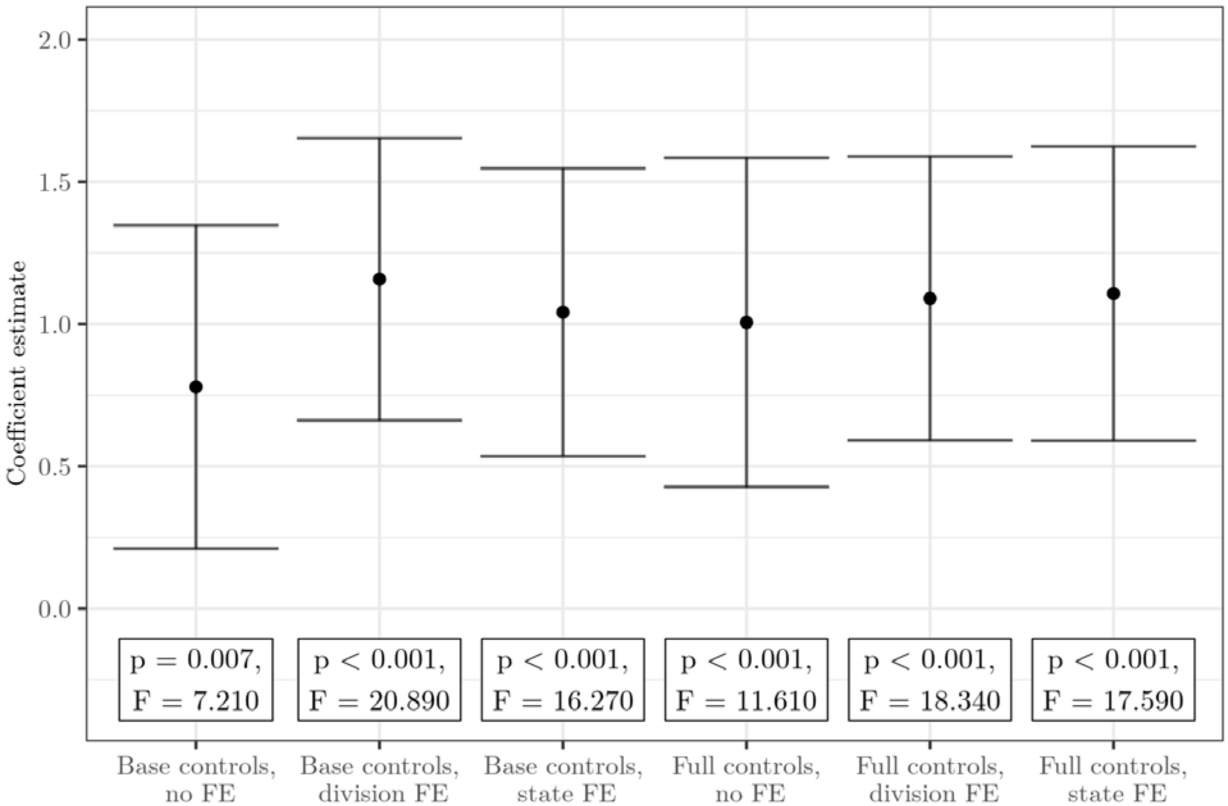
Notes: Panel A of Figure 7 plots a plots a non-parametric local polynomial fitting the relationship between time since sunset in a DMA and the fraction of households in that DMA with TVs turned on (solid line) and the relationship between time since sunset and the fraction of households with TVs turned on and tuned to non-Fox channels (dashed line). 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 (green) and in which *Hannity* begins in that interval (red). 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 8: Residualized Hannity-Carlson instrument values



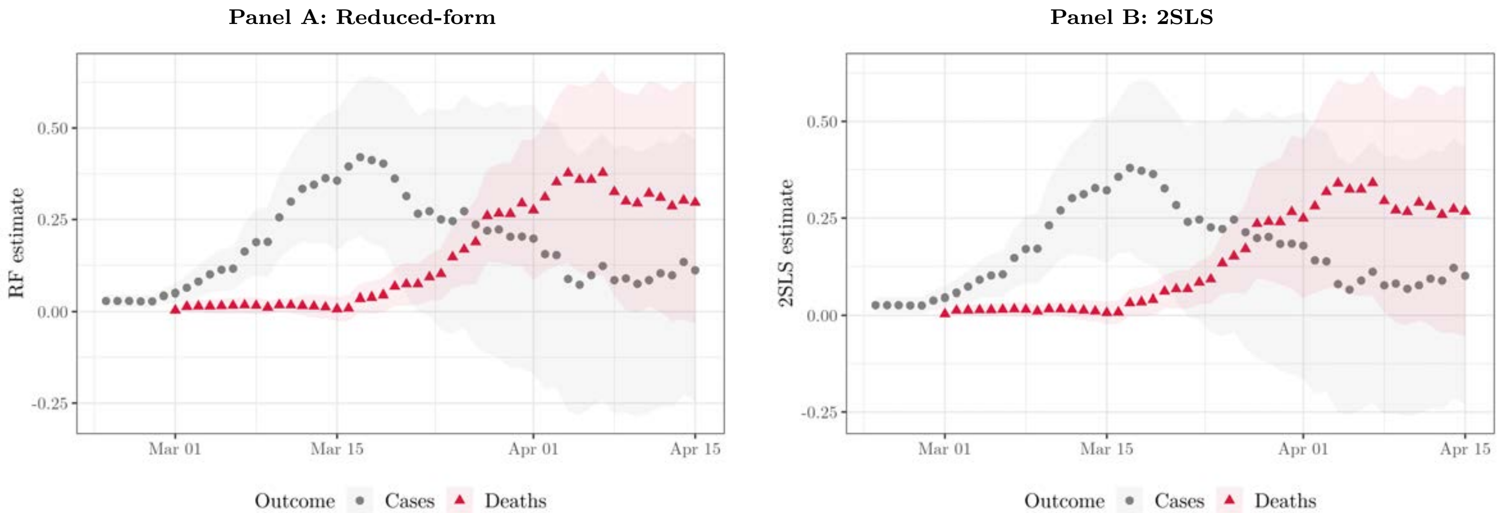
Notes: Figure 8 plots the values of our instrument, $\text{Non}\widehat{\text{FoxHannity}}_d \times \text{FoxShare}_d$, residualized by our minimum set of controls: Fox News' and MSNBC's share of cable in January 2018, Fox News' share of television in January 2020, the population density of the county, 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*.

Figure 9: Instrument first stage on relative viewership



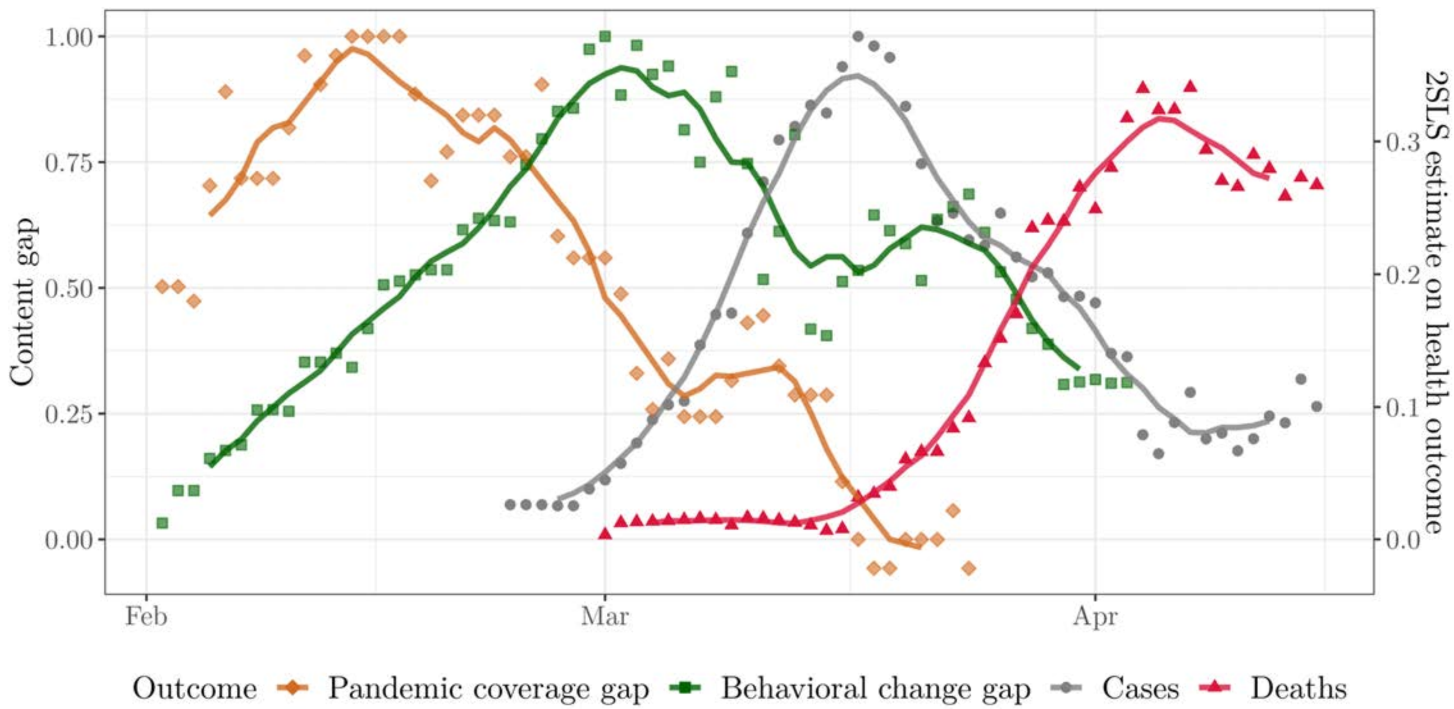
Notes: Figure 9 plots the coefficients from regressions of the standardized viewership difference between *Hannity* and *Tucker Carlson Tonight*, D_c, on our instrument, $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$ — that is, the predicted number of TVs on during Hannity's timeslot, excluding TVs watching *Hannity*, multiplied by Fox News' viewership share, excluding *Hannity* and *Tucker Carlson Tonight*.. "Base controls" include the predicted number 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 2018, Fox News' share of television in January 2020, the population density of the county, and the log of the county's total population. "Full controls" additionally include 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 from 2018, 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. Robust standard errors are clustered at the DMA level. 95 percent confidence intervals are reported.

Figure 10: Reduced-form and 2SLS estimates of effect of differential viewership on cases and deaths



Notes: Figure 10 shows day-by-day reduced form (Panel A) and 2SLS (Panel B) estimates on log one plus cases and log one plus deaths. In Panel A, we report day-by-day effects of our instrument, $\text{NonFo}\widehat{\text{xHa}}\text{nnity}_d \times \text{FoxShare}_d$, on log deaths and log cases, conditional on 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. In Panel B, we report day-by-day effects of the standardized difference in viewership of *Hannity* vs. *Tucker Carlson Tonight*, instrumented by $\text{NonFo}\widehat{\text{xHa}}\text{nnity}_d \times \text{FoxShare}_d$ and controlling for state fixed effects and the same set of covariates as in Panel A. We cluster standard errors at the DMA level and report 95 percent confidence intervals.

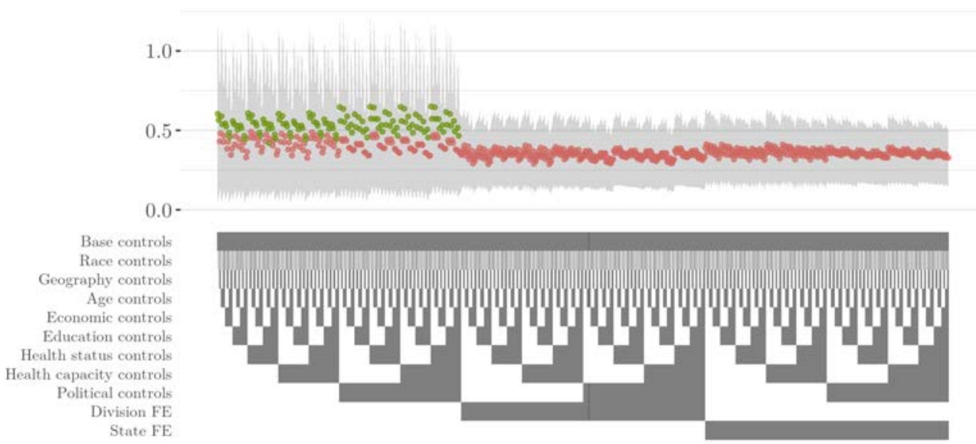
Figure 11: Carlson-Hannity content gaps and effects on cases and deaths



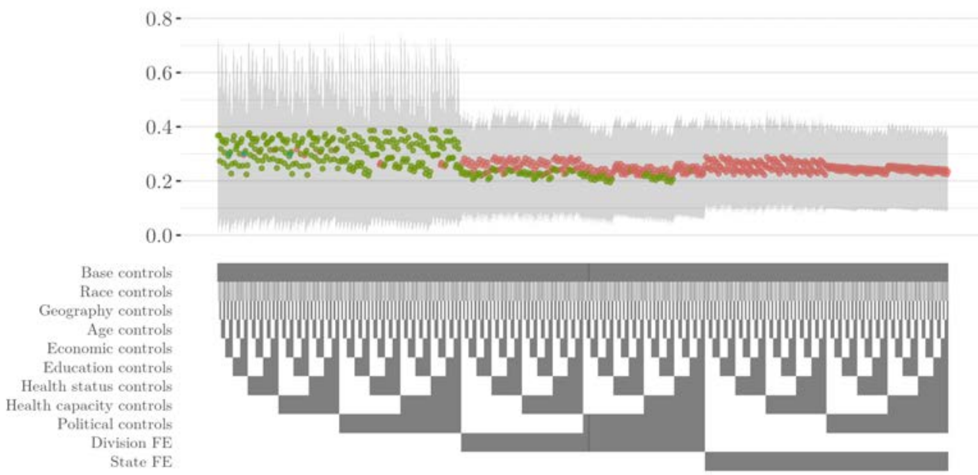
Notes: Figure 11 shows four time series. First, in tan diamonds corresponding to the left y-axis, we plot the "pandemic coverage gap": the difference in portrayed seriousness of the coronavirus threat on *Tucker Carlson Tonight* vs. *Hannity*, as rated by Amazon Mechanical Turk coders (as previously 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 $\text{Non}\widehat{\text{FoxHannity}}_d \times \text{FoxShare}_d$) on log one plus cases and log one plus deaths, respectively (as previously reported in Panel B of Figure 10). 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 number 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 12: 2SLS: robustness to combinations of controls

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



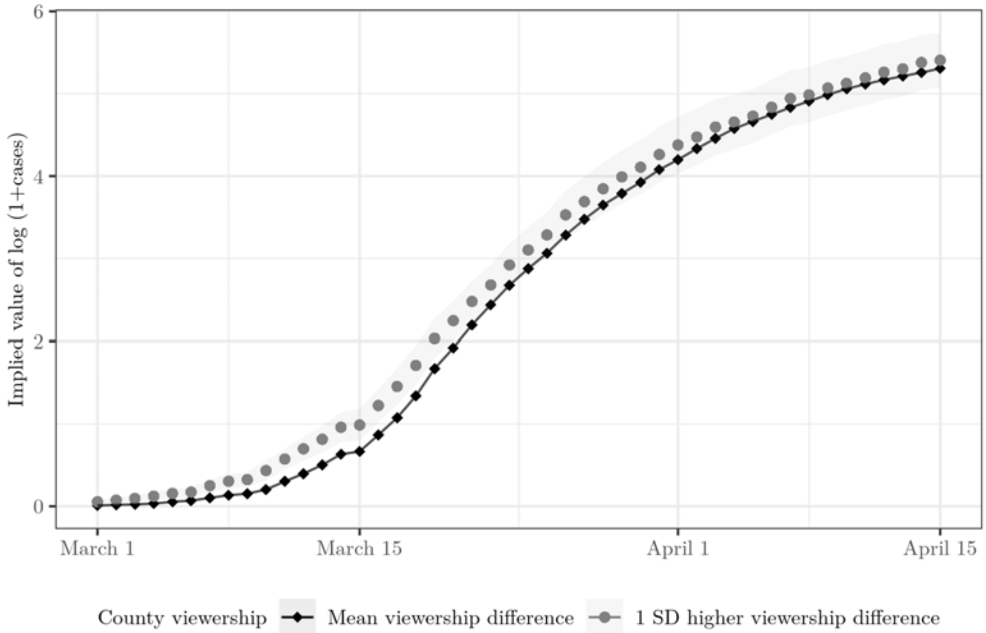
Panel B: Estimates on deaths (March 28, 2020)



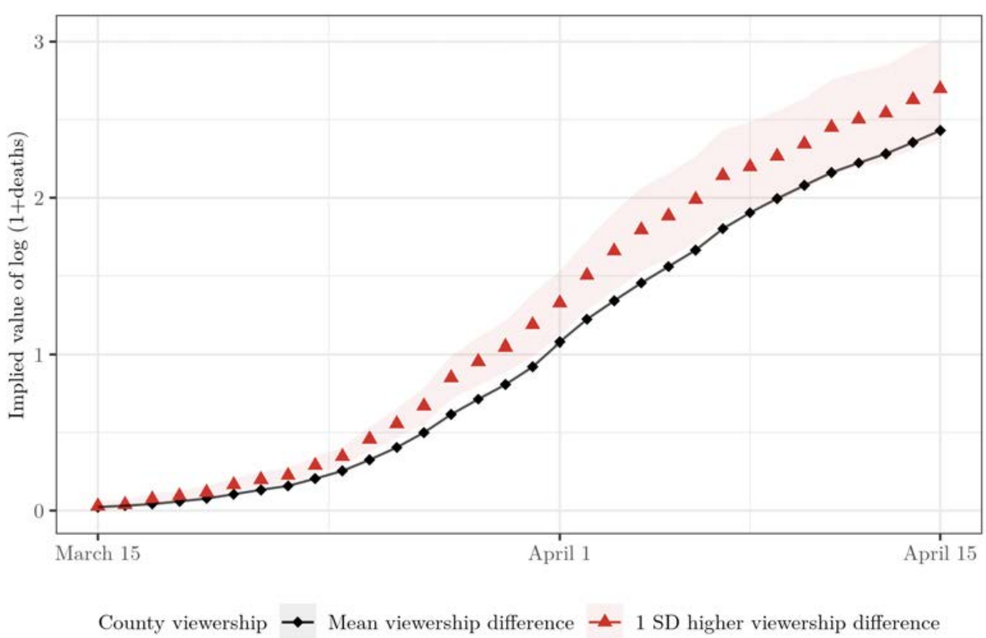
Notes: Figure 12 shows robustness of our two-stage least squares estimates for the specifications for log one plus cases on March 14 (Panel A) and log one plus deaths on March 28 (Panel B) under every possible combination of our seven sets of county-level controls (race, geography, age, economic, education, health, 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 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 13: Implied COVID-19 curves

Panel A: Estimates on cases

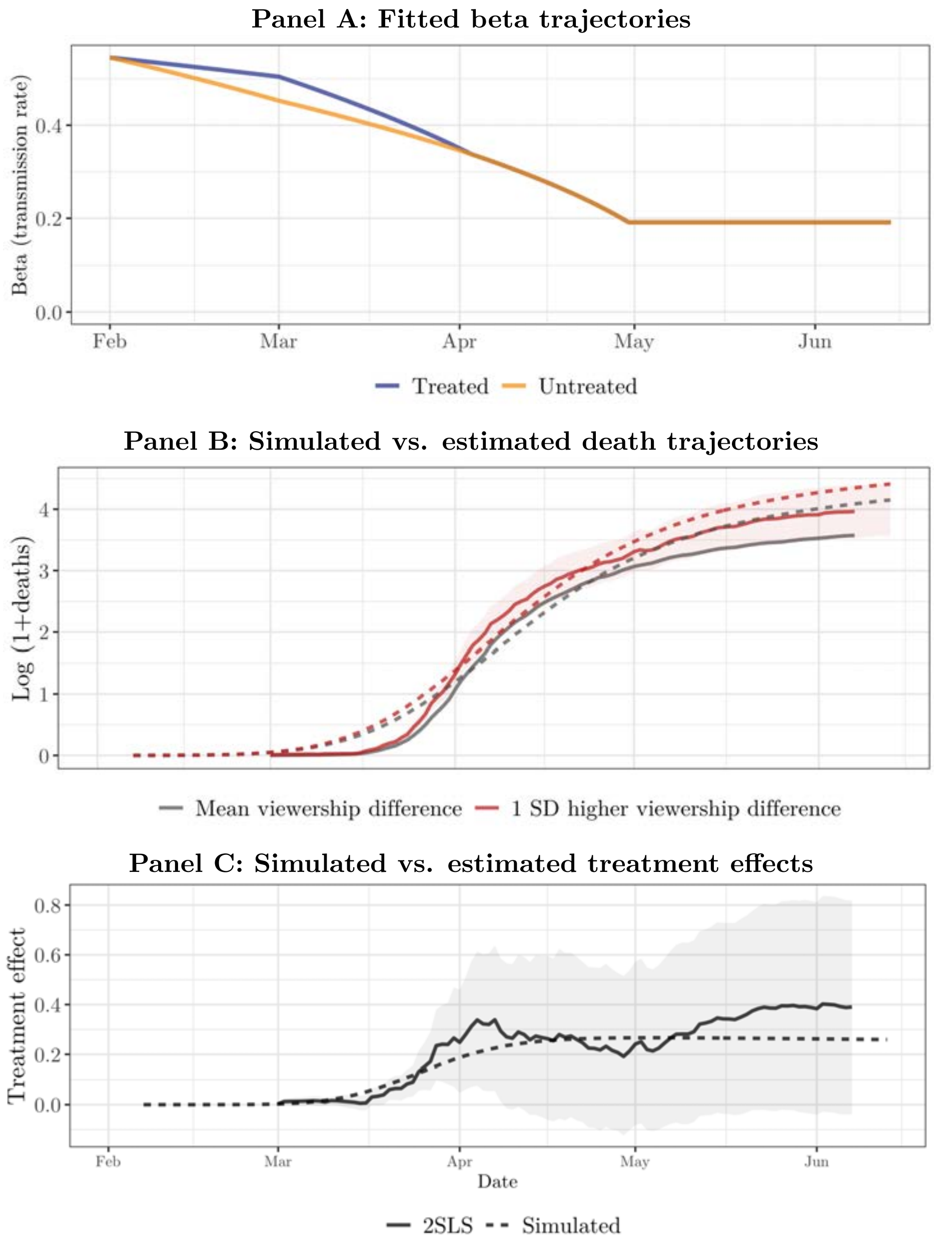


Panel B: Estimates on deaths



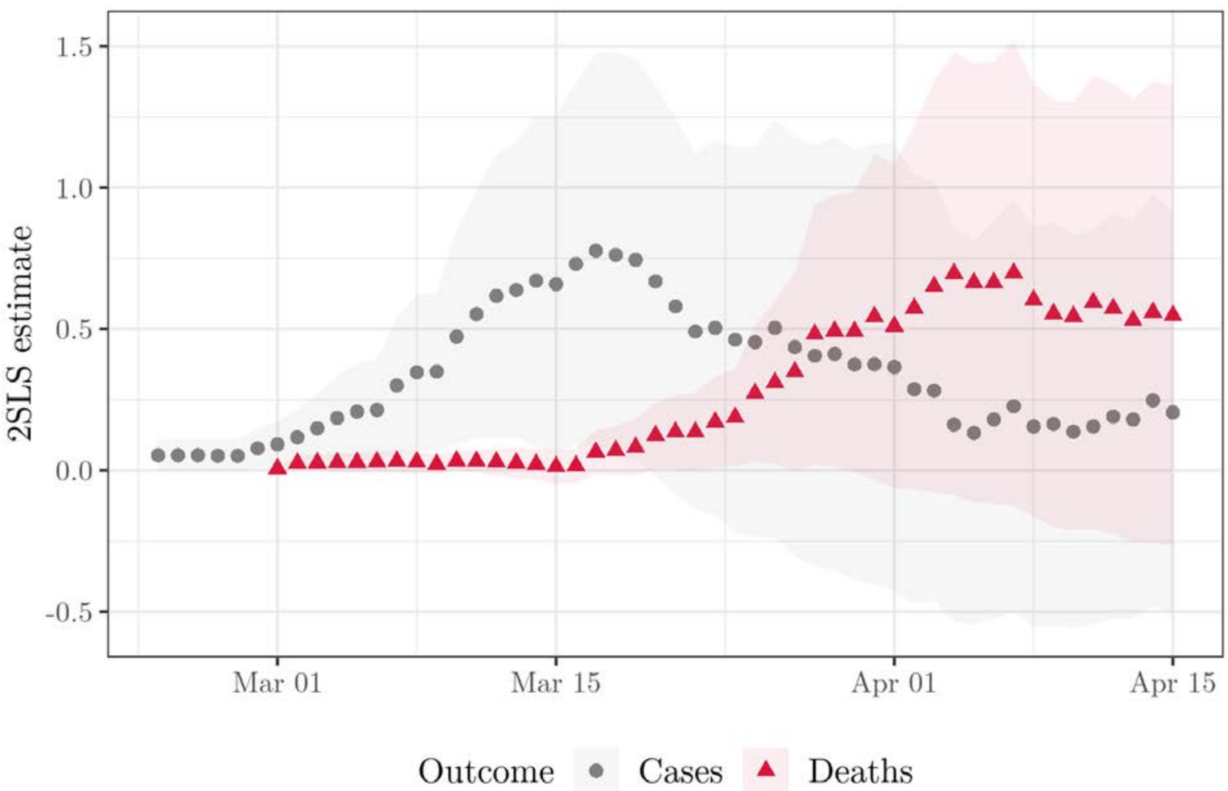
Notes: Panel A of Figure 13 plots, in black, the logarithm of (one plus the) mean number of cases in each day across all counties. In gray, the figure plots the the implied counterfactual values (based on our 2SLS estimates) for a county with a one standard deviation higher viewership difference between *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 14: MG-SIR simulations



Notes: Panel A of Figure 14 plots, in orange, the β trajectory implied by our simulation for non-compliers (which comprise the entire county with a mean viewership difference and 96% of the county with a one standard deviation higher viewership difference) and, in blue, the corresponding trajectory for compliers (which comprise the remaining 4% of the county with a one standard deviation higher viewership difference). Weighting by these fractions, 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 2.25%. 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.

Figure 15: 2SLS estimates of effect of the pandemic coverage index on cases and deaths



Notes: Figure 15 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 $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$. 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 number 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.

Tables

Table 1: 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 2: Effect of differential viewership on cases

	Dependent variable:						
	COVID-19 cases						
	Feb 29	Mar 07	Mar 14	Mar 21	Mar 28	Apr 04	Apr 11
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: *Ordinary least squares*							
Hannity-Carlson viewership difference	0.006**	0.022**	0.052***	0.101***	0.100**	0.097**	0.083**
	(0.002)	(0.010)	(0.019)	(0.033)	(0.039)	(0.044)	(0.042)
Panel B: *Reduced form*							
Non-Fox TVs on × Fox share	0.042***	0.163***	0.363***	0.314**	0.220	0.087	0.084
	(0.011)	(0.040)	(0.090)	(0.138)	(0.171)	(0.184)	(0.184)
Panel C: *Two-stage least squares*							
H-C viewership difference (predicted)	0.038***	0.147***	0.328***	0.283**	0.198	0.079	0.076
	(0.012)	(0.039)	(0.092)	(0.125)	(0.158)	(0.169)	(0.168)
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 reports OLS estimates of the log of one plus cases upon the standardized difference in Hannity-Carlson viewership. Panel B reports reduced-form estimates of the log of one plus cases upon the instrument, $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$— that is, the 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 C reports two-stage least squares estimates of the log of one plus cases upon the standardized difference in Hannity-Carlson viewership, instrumented by $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$. OLS controls include the number 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, log distance to Seattle, 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. IV controls are identical to OLS controls, except the number of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle* are replaced with the predicted number of TVs tuned to non-Fox channels during these timeslots. Standard errors are clustered at the DMA level. Robust standard errors are reported.

Table 3: Effect of differential viewership on deaths

	Dependent variable:					
	COVID-19 deaths					
	Mar 07	Mar 14	Mar 21	Mar 28	Apr 04	Apr 11
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *Ordinary least squares*						
Hannity-Carlson viewership difference	0.005	0.004	0.022***	0.044**	0.065**	0.092**
	(0.004)	(0.005)	(0.008)	(0.018)	(0.030)	(0.036)
Panel B: *Reduced form*						
Non-Fox TVs on × Fox share	0.018	0.012	0.073**	0.260***	0.377***	0.321**
	(0.011)	(0.016)	(0.030)	(0.065)	(0.125)	(0.157)
Panel C: *Two-stage least squares*						
H-C viewership difference (predicted)	0.016*	0.011	0.066***	0.235***	0.340**	0.290*
	(0.009)	(0.014)	(0.025)	(0.072)	(0.137)	(0.155)
Full controls	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	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 deaths upon the standardized difference in Hannity-Carlson viewership. Panel B reports reduced-form estimates of the log of one plus deaths upon the instrument, $\text{Non}\widehat{\text{FoxHannity}}_d \times \text{FoxShare}_d$— that is, the 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 C reports two-stage least squares estimates of the log of one plus deaths upon the standardized difference in Hannity-Carlson viewership, instrumented by $\text{Non}\widehat{\text{FoxHannity}}_d \times \text{FoxShare}_d$. OLS controls include the number 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, log distance to Seattle, 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. IV controls are identical to OLS controls, except the number of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle* are replaced with the predicted number of TVs tuned to non-Fox channels during these timeslots. Standard errors are clustered at the DMA level. Robust standard errors are reported.

Table 4: Exogenous model parameters

Parameter	**Description**	**Value**	**Source**
$\bar{N}_{yu}$	Population share of young non-compliers in representative county with mean viewership	0.6784	ACS, Nielsen
$\bar{N}_{yt}$	Population share of young compliers in representative county with mean viewership	0	
$\bar{N}_{ou}$	Population share of old non-compliers in representative county with mean viewership	0.3216	$1 - \bar{N}_{yu}$
$\bar{N}_{ot}$	Population share of old compliers in representative county with mean viewership	0	
N^+_{yu}	Population share of young non-compliers in representative county with 1 SD higher viewership	0.6593	ACS, Nielsen
N^+_{yt}	Population share of young compliers in representative county with 1 SD higher viewership	0.0191	$N^+_{yu} + N^+_{yt} = \bar{N}_{yu}$
N^+_{ou}	Population share of old non-compliers in representative county with 1 SD higher viewership	0.3003	ACS, Nielsen
N^+_{ot}	Population share of old compliers in representative county with 1 SD higher viewership	0.0212	$N^+_{ou} + N^+_{ot} = \bar{N}_{ou}$
$i(0)$	Initial fraction of infected individuals	9.14×10^{-7}	Estimated 600 infections in US on Feb 6
$I_j(0)$	Initial population share of infected individuals in group j	$i(0) \times N_j$	
$S_j(0)$	Initial population share of susceptible individuals in group j	$N_j - I_j$	
$R_j(0)$	Initial population share of recovered individuals in group j	0	
$D_j(0)$	Initial population share of dead individuals in group j	0	
γ	Estimated recovery arrival rate	1/8	Allcott et al. (2020)
δ_y	Estimated fatality arrival rate among young individuals	6.35×10^{-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	Acemoglu et al. (2020)
ρ	Matrix of group interaction rates (rows and columns ordered as yu, yt, ou, ot)	$\begin{bmatrix} 1.41 & 0.614 \\ 1.43 & 0.566 \end{bmatrix}$	Akbarpour et al. (2020)

Table 5: 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	0.551***	0.545***				
	(0.053)	(0.052)				
Panel B: *RF: inverse pandemic coverage index on instrument*						
$\text{Non}\widehat{\text{FoxHa}}\text{nnity}_d \times \text{FoxShare}_d$			0.510**	0.541**		
			(0.218)	(0.226)		
Panel C: *2SLS: cases and deaths on inverse predicted pandemic coverage index*						
$-1\times$ coverage index (predicted)					0.671**	0.481**
					(0.299)	(0.234)
Base controls	Yes	Yes	Yes	Yes	Yes	Yes
Main controls	No	Yes	No	Yes	Yes	Yes
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, $\text{Non}\widehat{\text{FoxHa}}\text{nnity}_d \times \text{FoxShare}_d$— that is, the number of TVs on during Hannity's timeslot, 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 $\text{Non}\widehat{\text{FoxHa}}\text{nnity}_d \times \text{FoxShare}_d$. Base OLS controls include the number 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 number of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle* are replaced with the predicted number of TVs tuned to non-Fox channels during these timeslots. Main controls for both OLS and IV include population-weighted latitude and longitude, log distance to Seattle, 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. Robust standard errors are reported.

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 8.3.1. In Appendix C, we report versions of the figures and tables included in the main text, but using the alternative instrument described in Section 8.3.2. 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

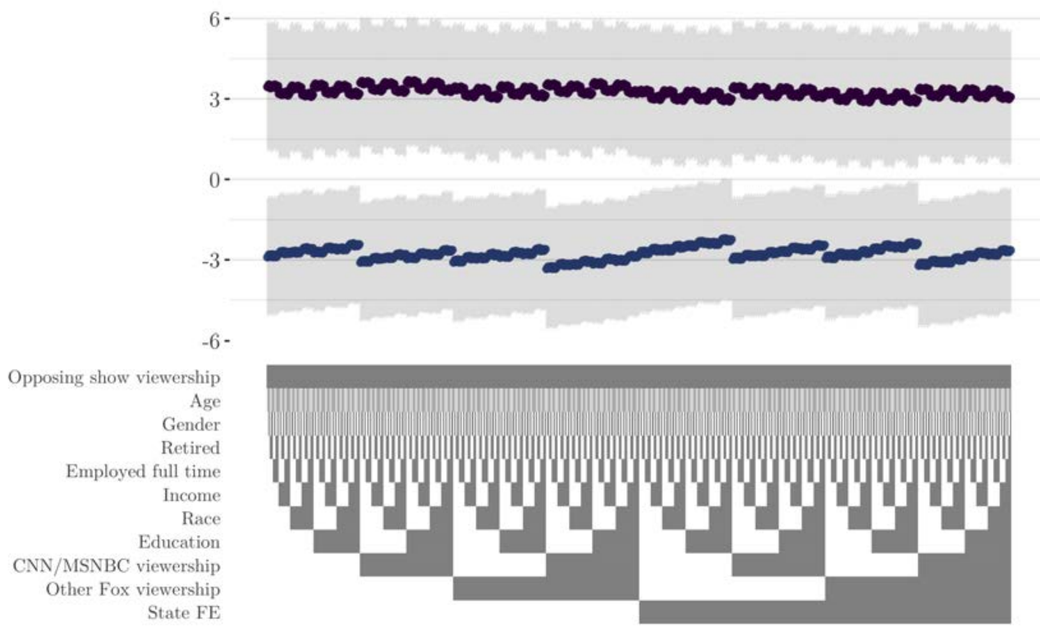
A.1 Survey

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

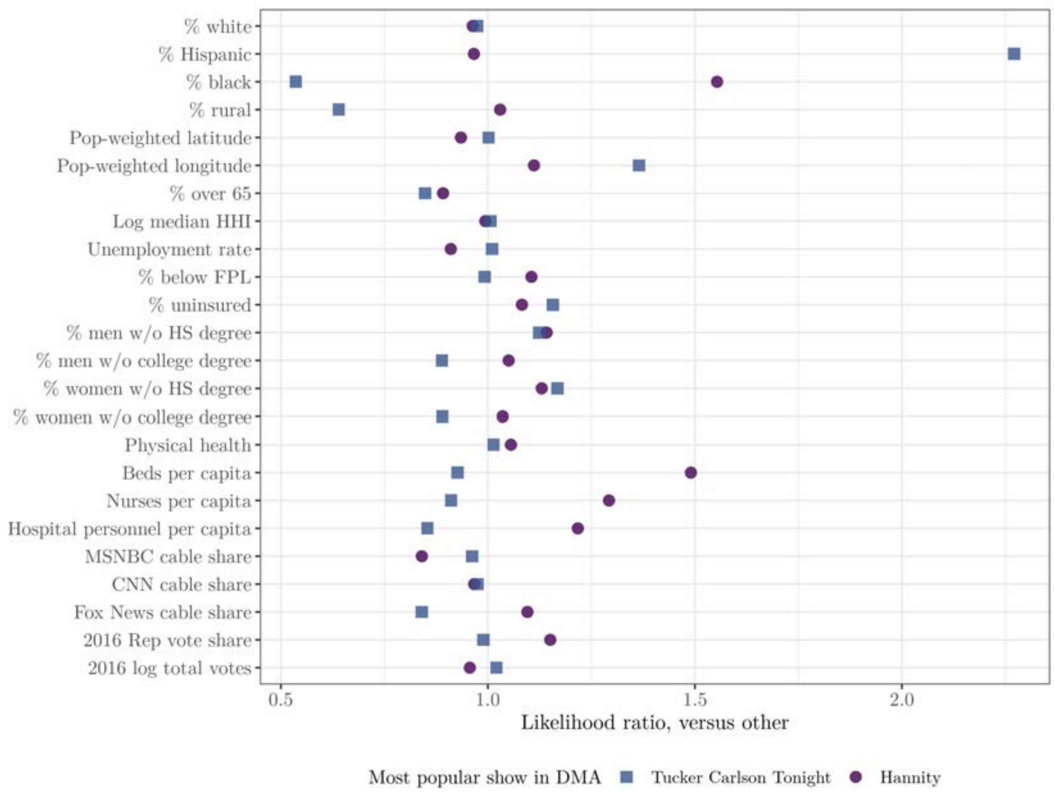
A.2 Data and OLS

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.

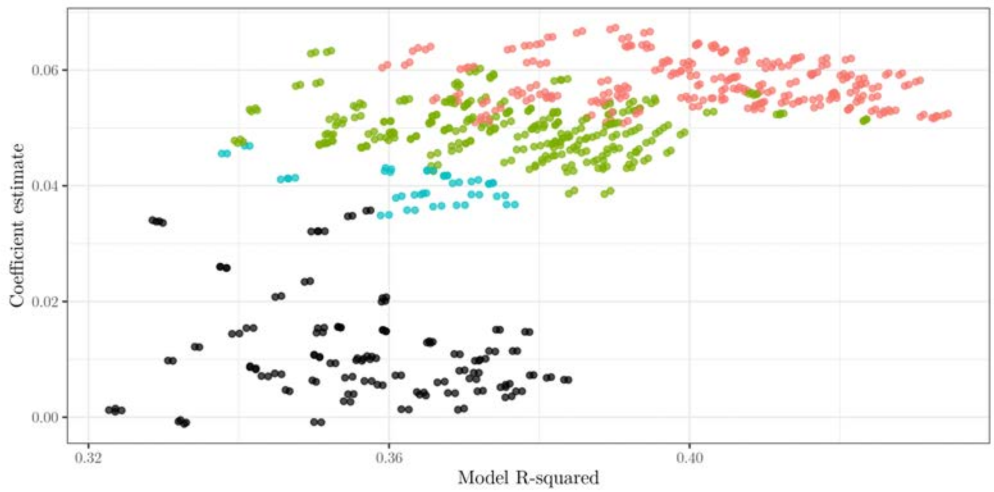
Figure A2: Selection into watching Hannity versus Carlson



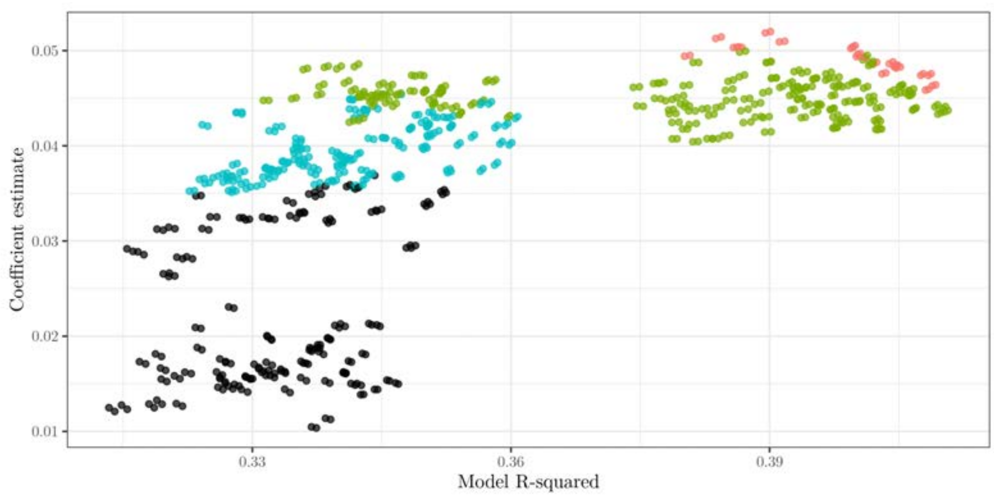
Notes: For each demographic characteristic, Figure A2 shows, in blue, ratios of the average value among counties in which *Hannity* is the most popular show relative to the average value among counties in which neither *Hannity* nor *Tucker Carlson Tonight* is the most popular show. Similarly, Figure 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: R^2 vs. coefficient estimates under combinations of controls

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

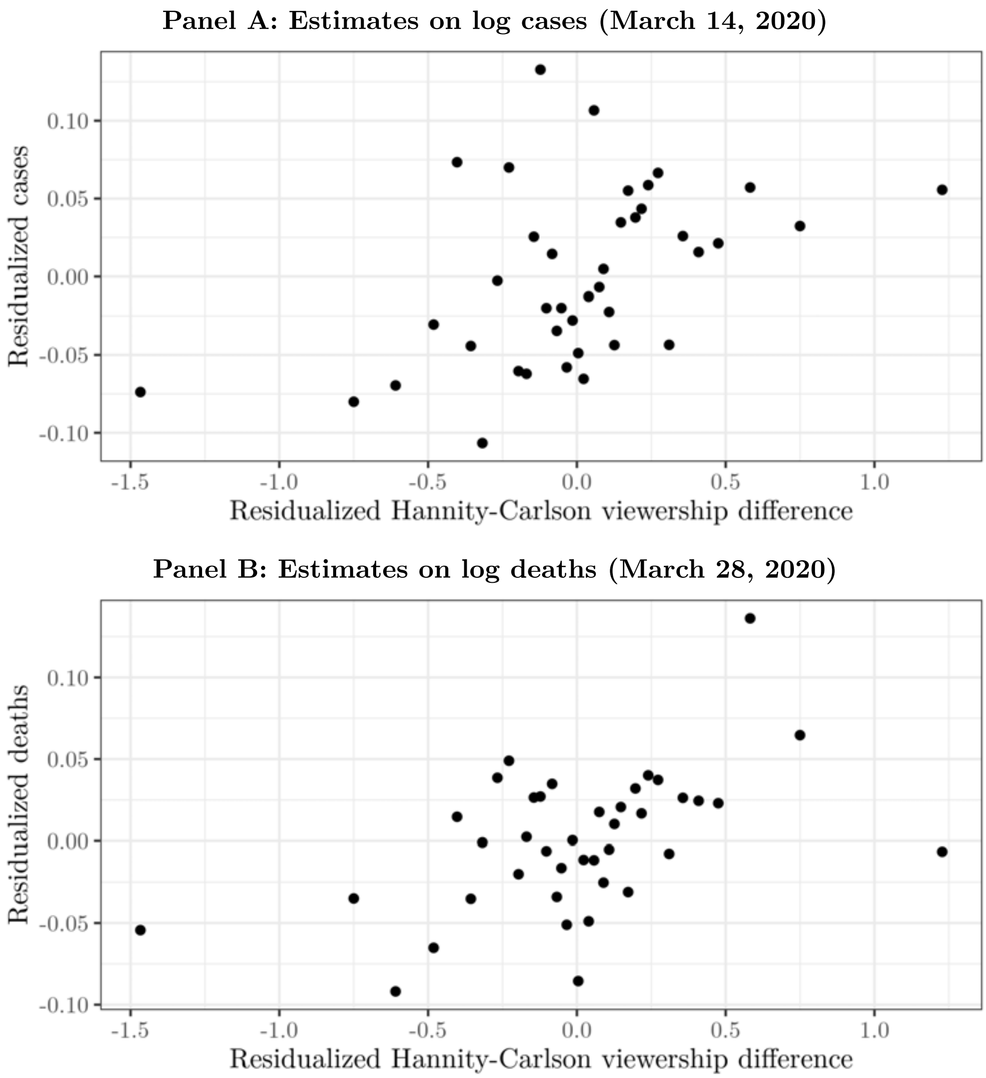


Panel B: Estimates on log deaths (March 28, 2020)



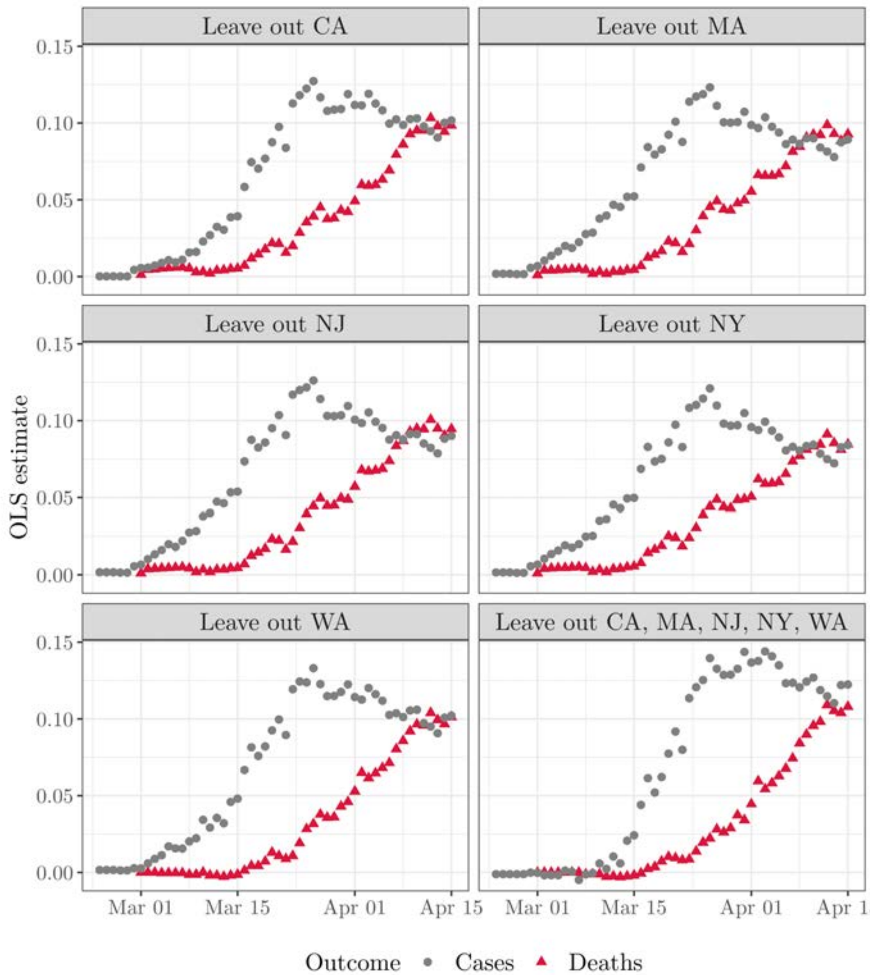
Notes: Figure A3 shows the relationship between the OLS coefficient estimates (y-axis) and the model R^2 (x-axis) for log cases on March 14 (Panel A) and for log deaths on March 28 (Panel B) from specifications with every possible combination of our seven sets of county-level controls (race, geography, age, economic, education, health, 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.

Figure A4: OLS: residual-residual plot



Notes: Figure A4 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 number 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.

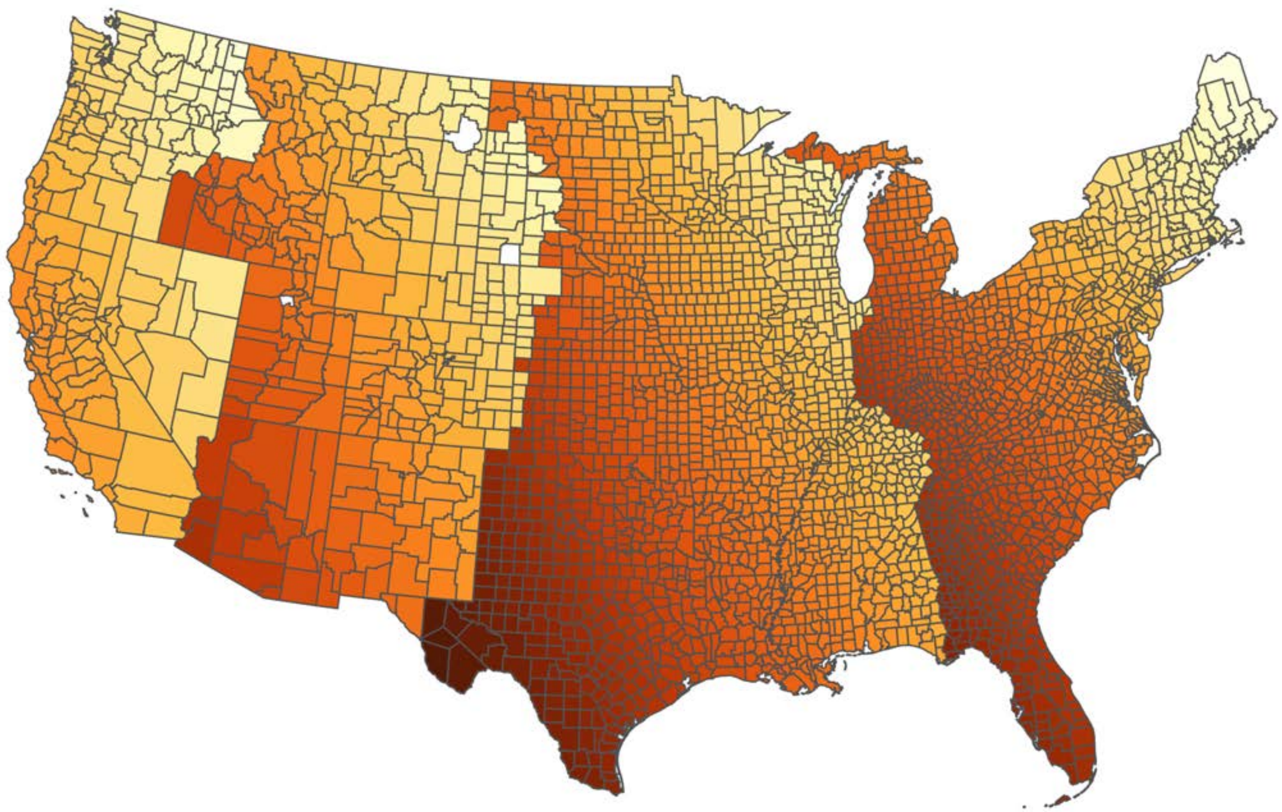
Figure A5: Leave-out OLS estimates of effect of differential viewership on cases and deaths



Notes: Figure A5 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 number 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.

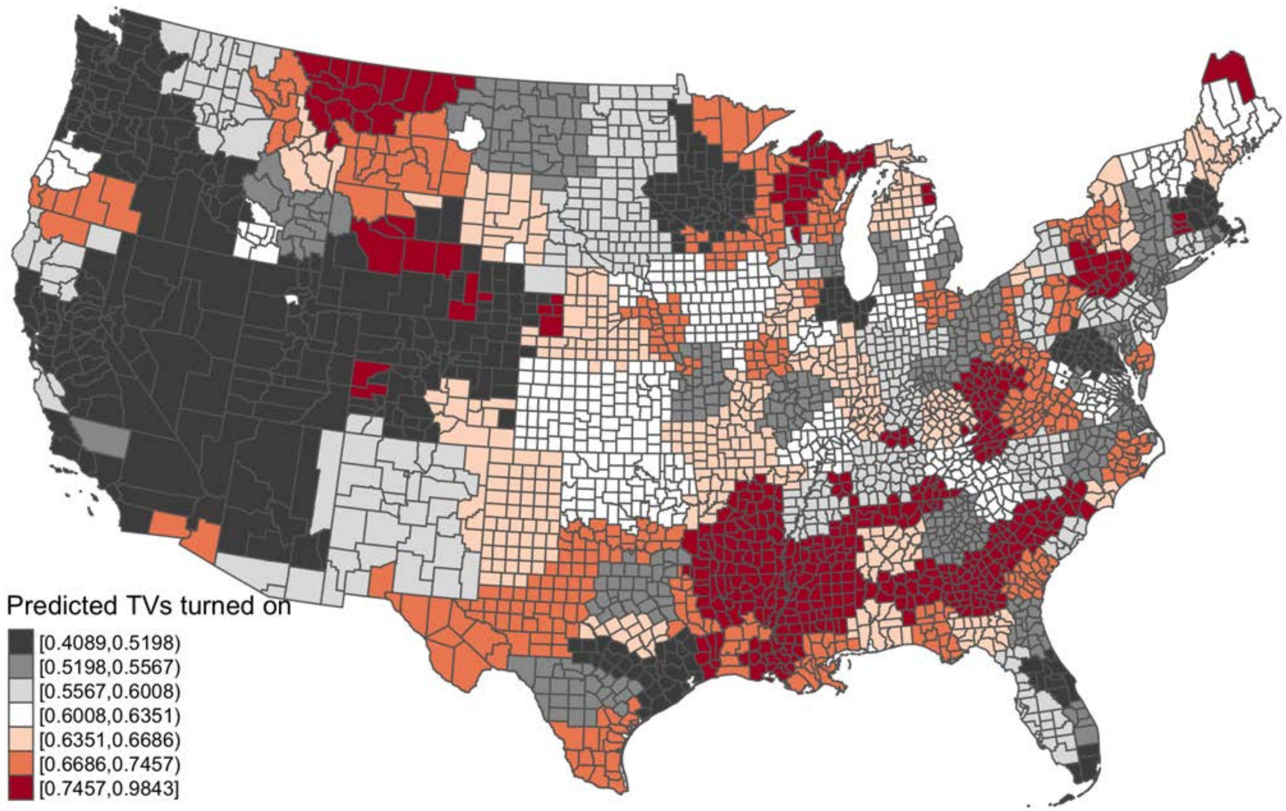
A.3 Construction of Instrument

Figure A6: Sunset time on February 1, 2020 by county



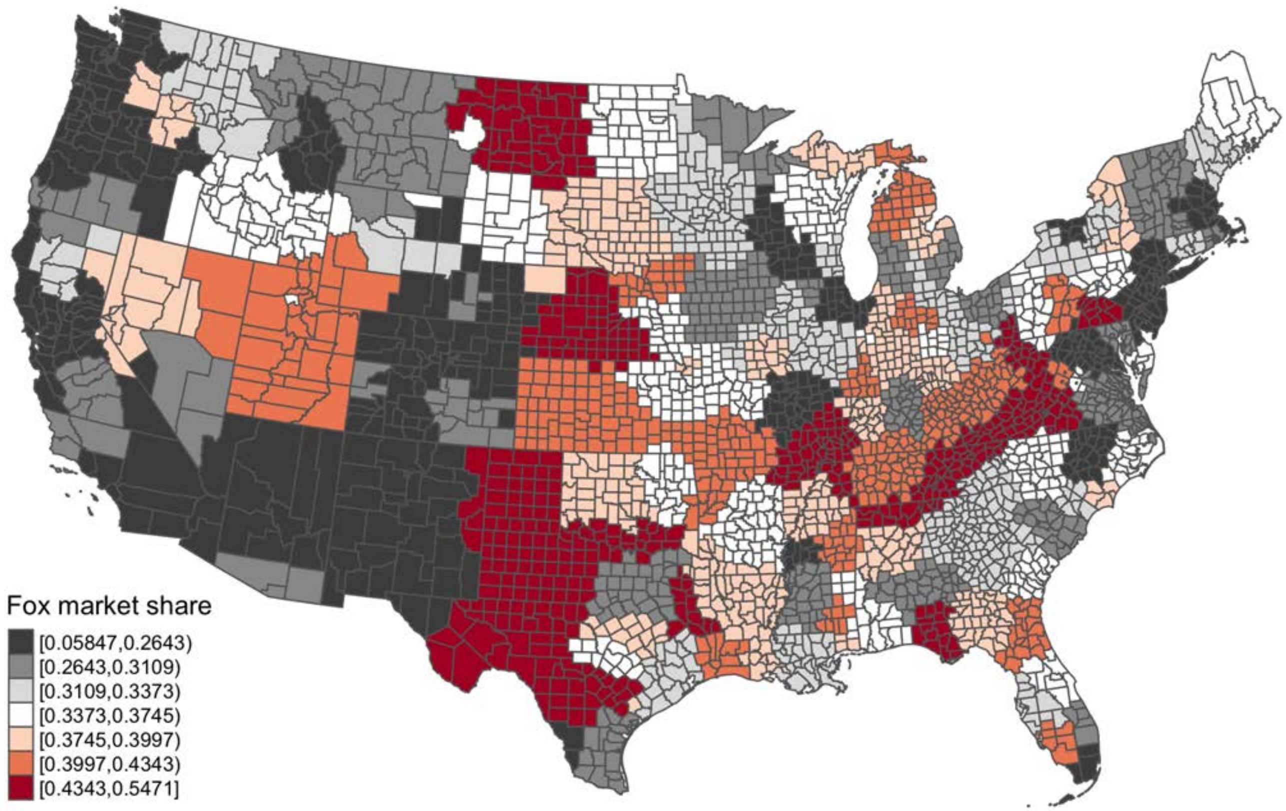
Notes: Map plots the time of sunset on February 1, 2020 for each county in the continental United States. Data from `www.timeanddate.com`.

Figure A7: Predicted number of TVs turned on during *Hannity*, leaving out TVs watching *Hannity*



Notes: For each of the 207 DMAs in the continental United States, Figure A7 plots the predicted number of TVs turned on and tuned to non-Fox channels (i.e. TVs that are turned on and not watching Hannity) during the timeslot when *Hannity* airs, 9PM Eastern Time.

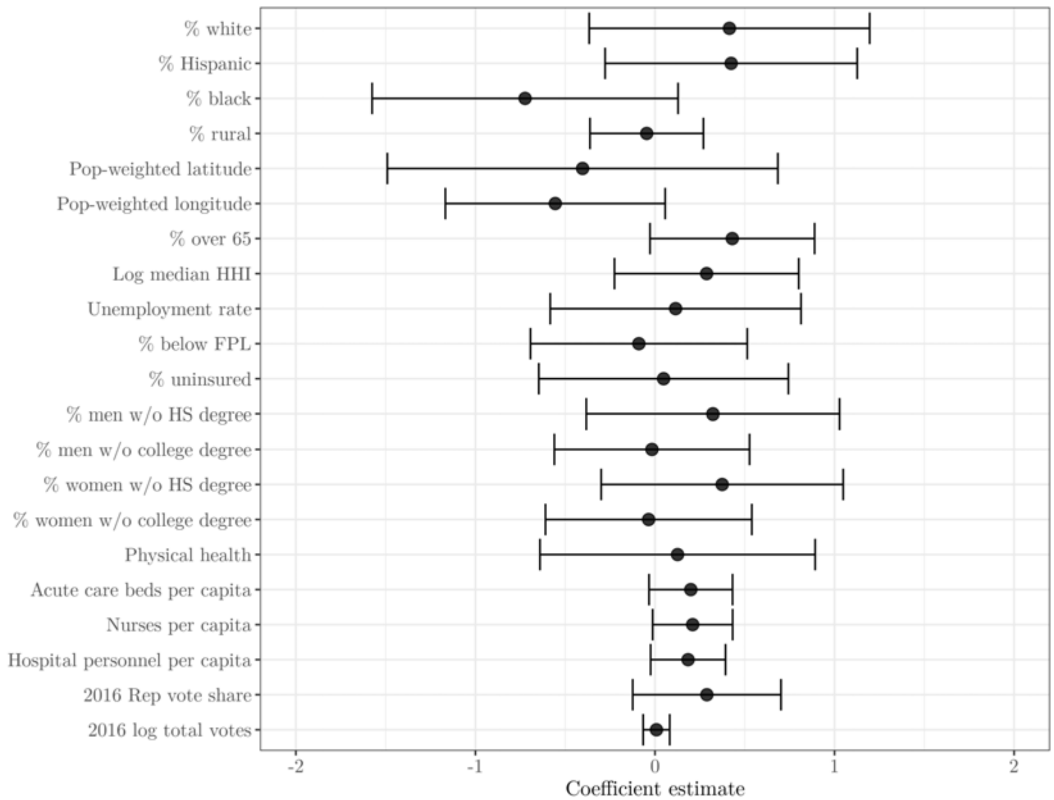
Figure A8: Fox News viewership share, leaving out *Hannity* and *Tucker Carlson Tonight*



Notes: For each of the 207 DMAs in the continental United States, Figure A8 plots the market share of Fox News in January 2020, leaving out viewership of *Hannity* and *Tucker Carlson Tonight*.

A.4 Instrument Exclusion, First Stage, and Robustness

Figure A9: Instrument correlation with county-level demographics



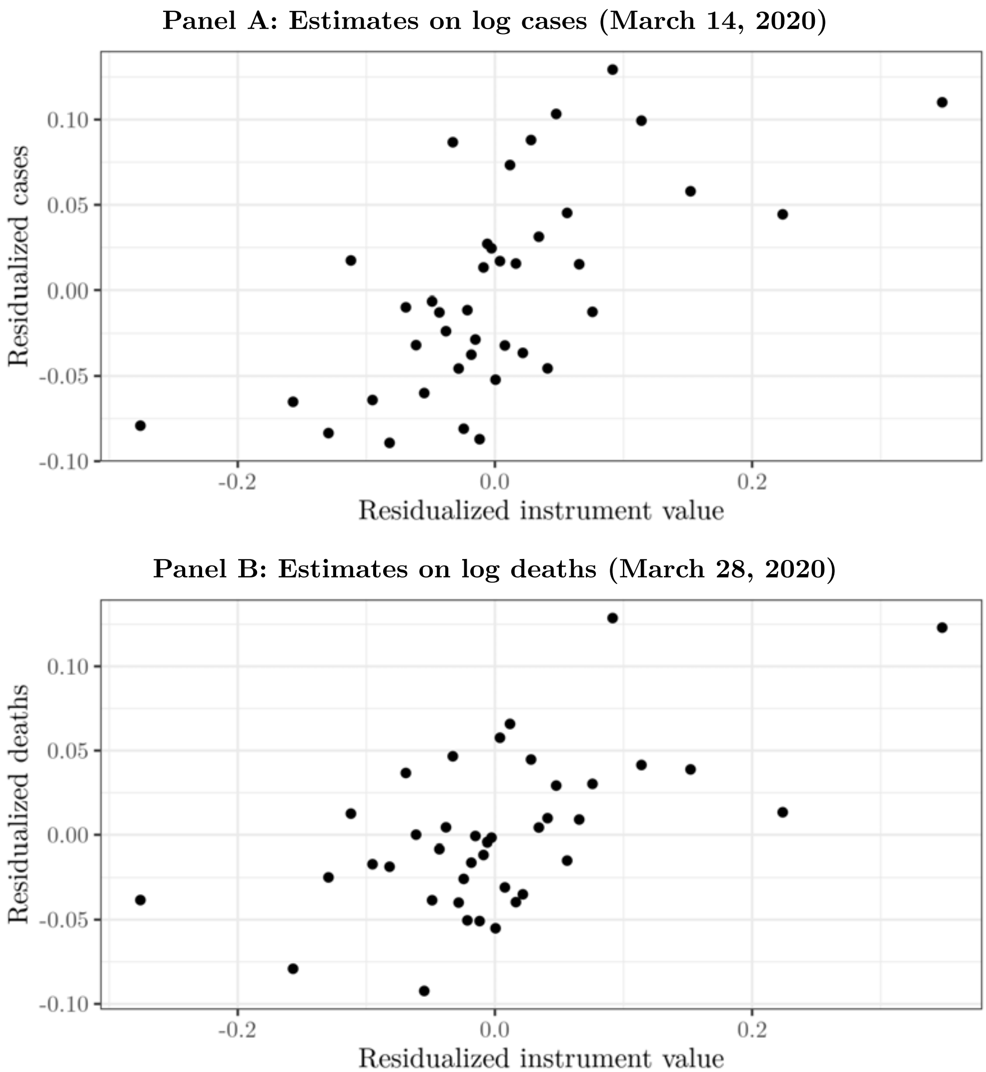
Notes: Figure A9 shows the coefficients from a series of regressions of each demographic characteristic on our instrument, $\mathrm{NonFox}\widehat{\mathrm{Hannity}}_d \times \mathrm{FoxShare}_d$, conditional on the two interactants, $\mathrm{NonFox}\widehat{\mathrm{Hannity}}_d$ and $\mathrm{FoxShare}_d$, and a small set of other controls accounting for local viewership patterns (the predicted number 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 A2: First-stage regressions

	Dependent variable:					
	Difference in Hannity-Carlson viewership					
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Fox TVs on × Fox share	0.779***	1.158***	1.041***	1.006***	1.090***	1.107***
	(0.290)	(0.253)	(0.258)	(0.295)	(0.255)	(0.264)
F-statistic	7.210	20.890	16.270	11.610	18.340	17.590
Controls	Base	Base	Base	All	All	All
Fixed effects	None	Division	State	None	Division	State
Observations	3,103	3,103	3,103	3,100	3,100	3,100
R^2	0.656	0.777	0.811	0.727	0.787	0.820

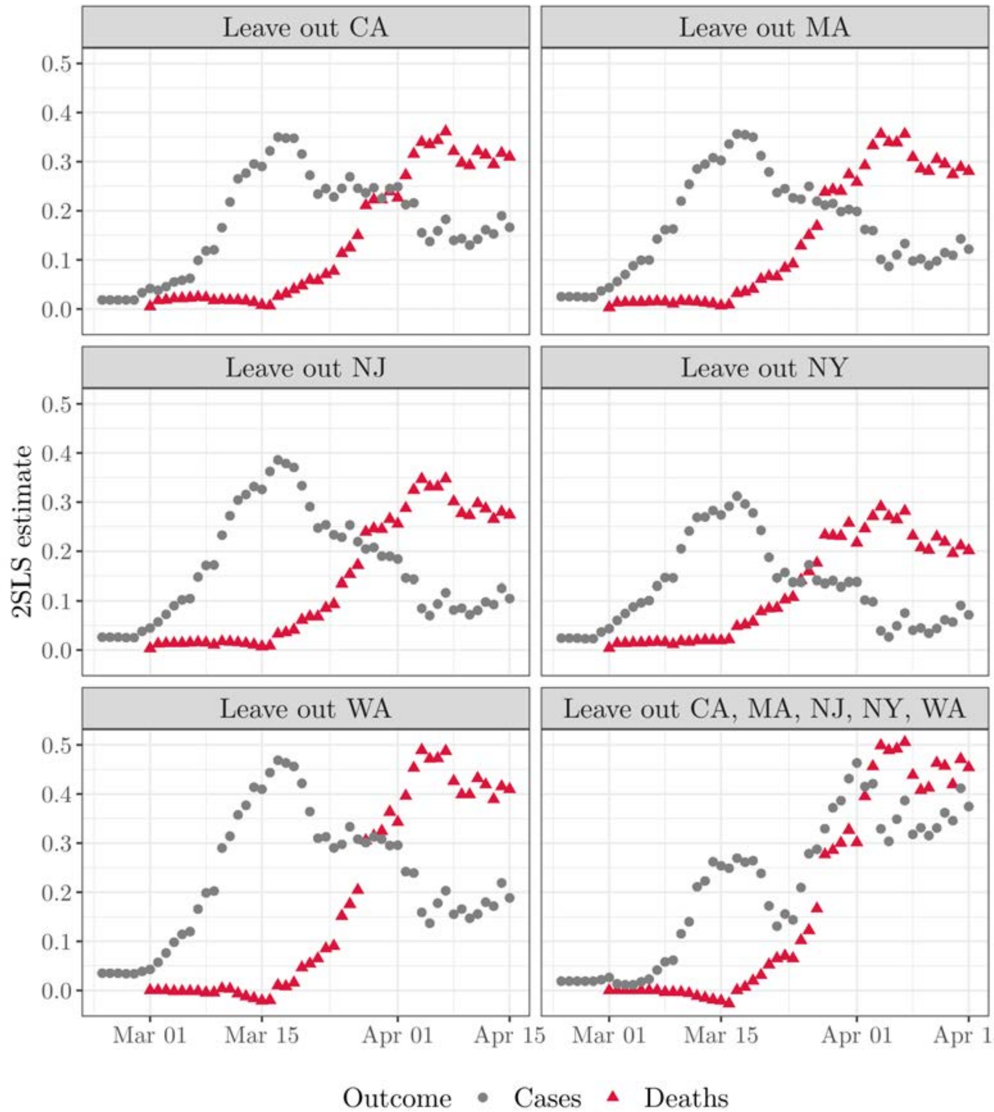
Notes: Table reports regressions of the standardized difference between viewership of *Hannity* and *Tucker Carlson Tonight* on our instrument, $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$— that is, the number of TVs on during Hannity's timeslot, excluding TVs watching *Hannity*, multiplied by Fox News' viewership share, excluding *Hannity* and *Tucker Carlson Tonight*.. "Base controls" include the predicted number 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. "All controls" additionally include population-weighted latitude and longitude, log distance to Seattle, 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. Robust standard errors are reported.

Figure A10: IV: residual-residual plot



Notes: Figure A10 displays a binscatter of the residuals of log one plus cases (Panel A) and log one plus deaths (Panel B) on the residuals of $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$, 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 number 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.

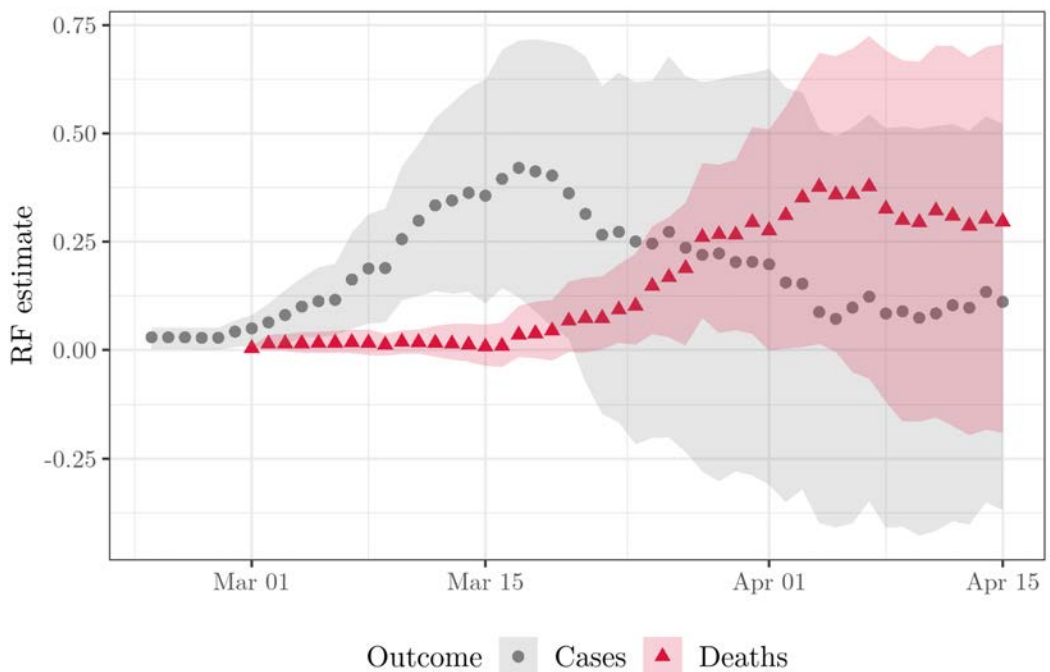
Figure A11: Leave-out IV estimates of effect of differential viewership on cases and deaths



Notes: Figure A11 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 number 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.

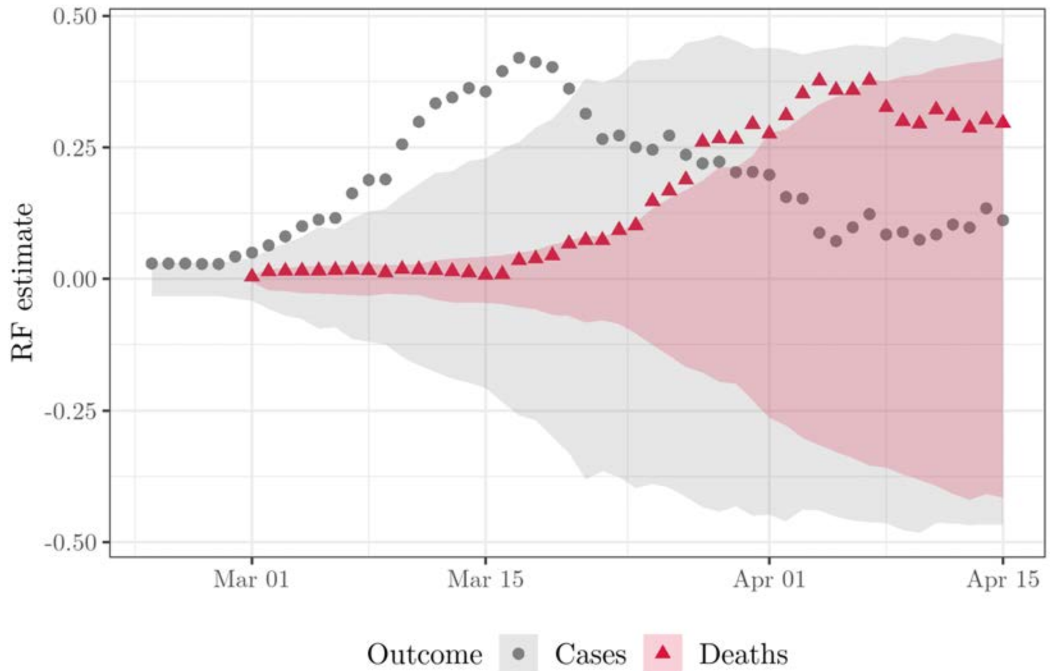
A.5 Resampling Inference

Figure A12: DMA-level block bootstrap



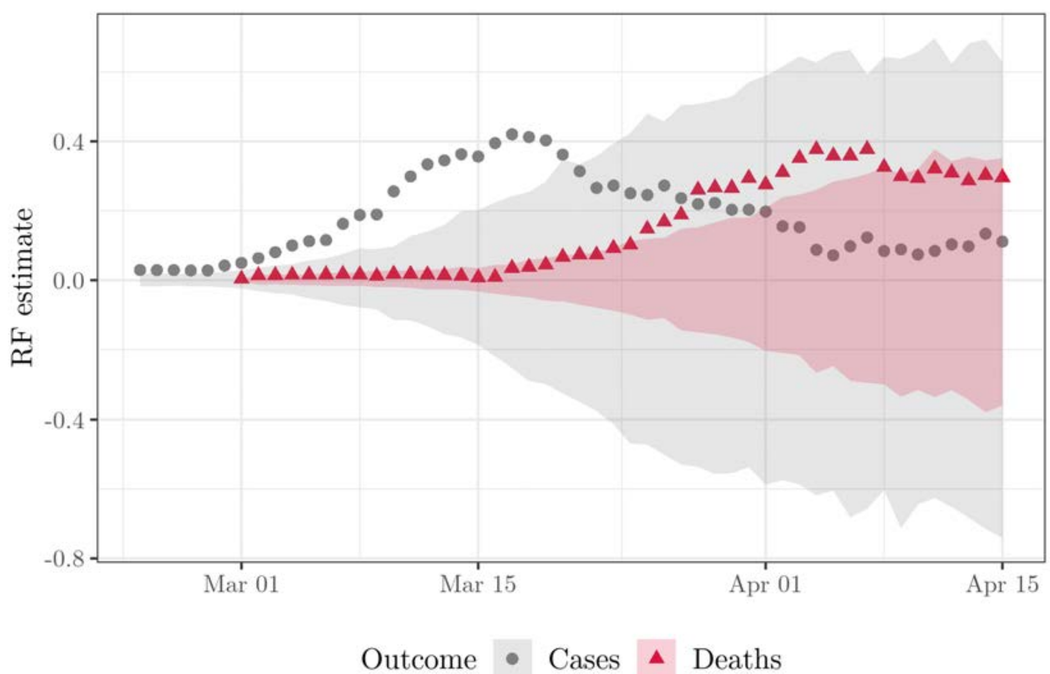
Notes: Figure A12 presents confidence intervals derived from a block bootstrapping procedure. We randomly sample DMAs with replacement and estimate counterfactual treatment effects for each day. We repeat 1000 times to calculate a distribution of counterfactual treatment effects for each day. Confidence 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 A13: Randomization inference



Notes: Figure A13 presents placebo treatment effects derived from a randomization inference procedure. We permute the plausibly exogenous "shift" ($\text{Non}\widehat{\text{FoxHannity}}_d$) 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 $\text{Non}\widehat{\text{FoxHannity}}_d$ 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.

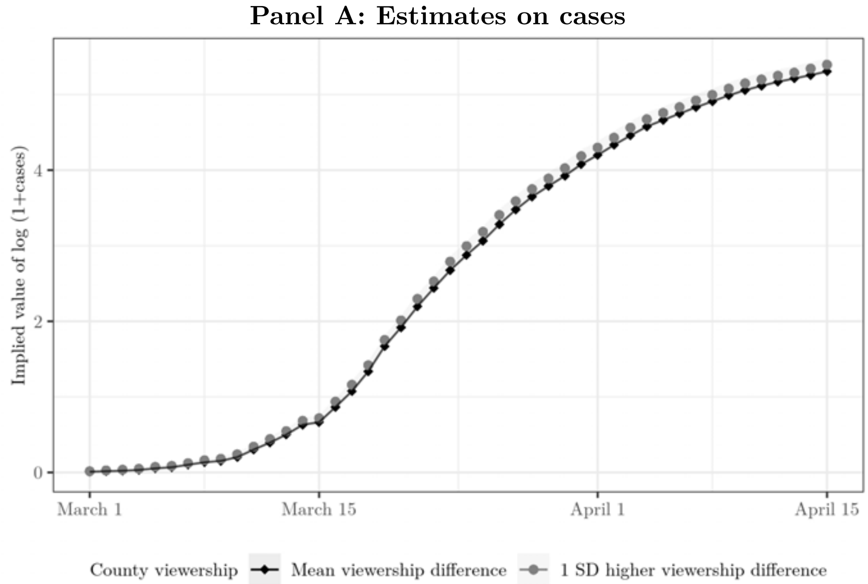
Figure A14: Permutation test

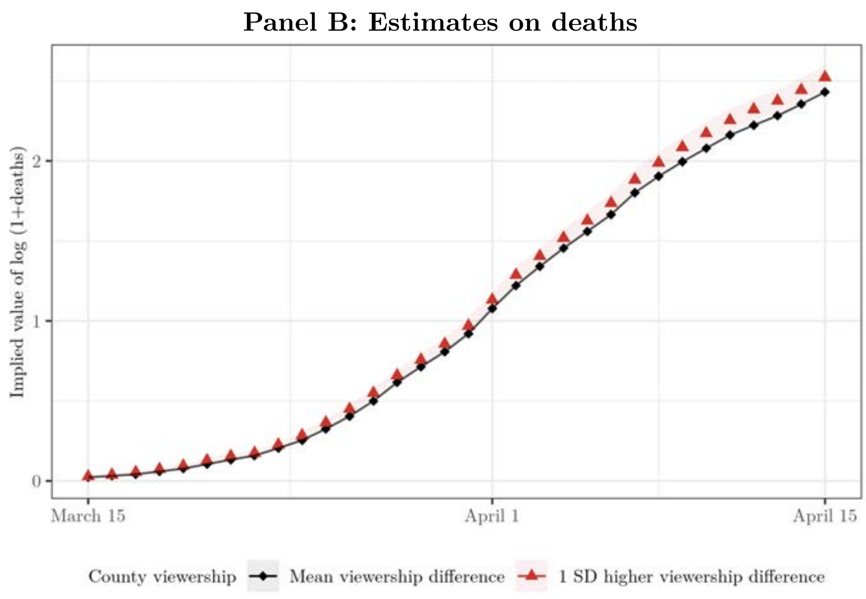


Notes: Figure A14 presents placebo treatment effects derived from a permutation test. We permute the joint tuple of cases and deaths across counties, leaving all other covariates unchanged, then estimate placebo treatment effects. We repeat 1000 times to calculate a distribution of counterfactual treatment 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.6 Effect Sizes

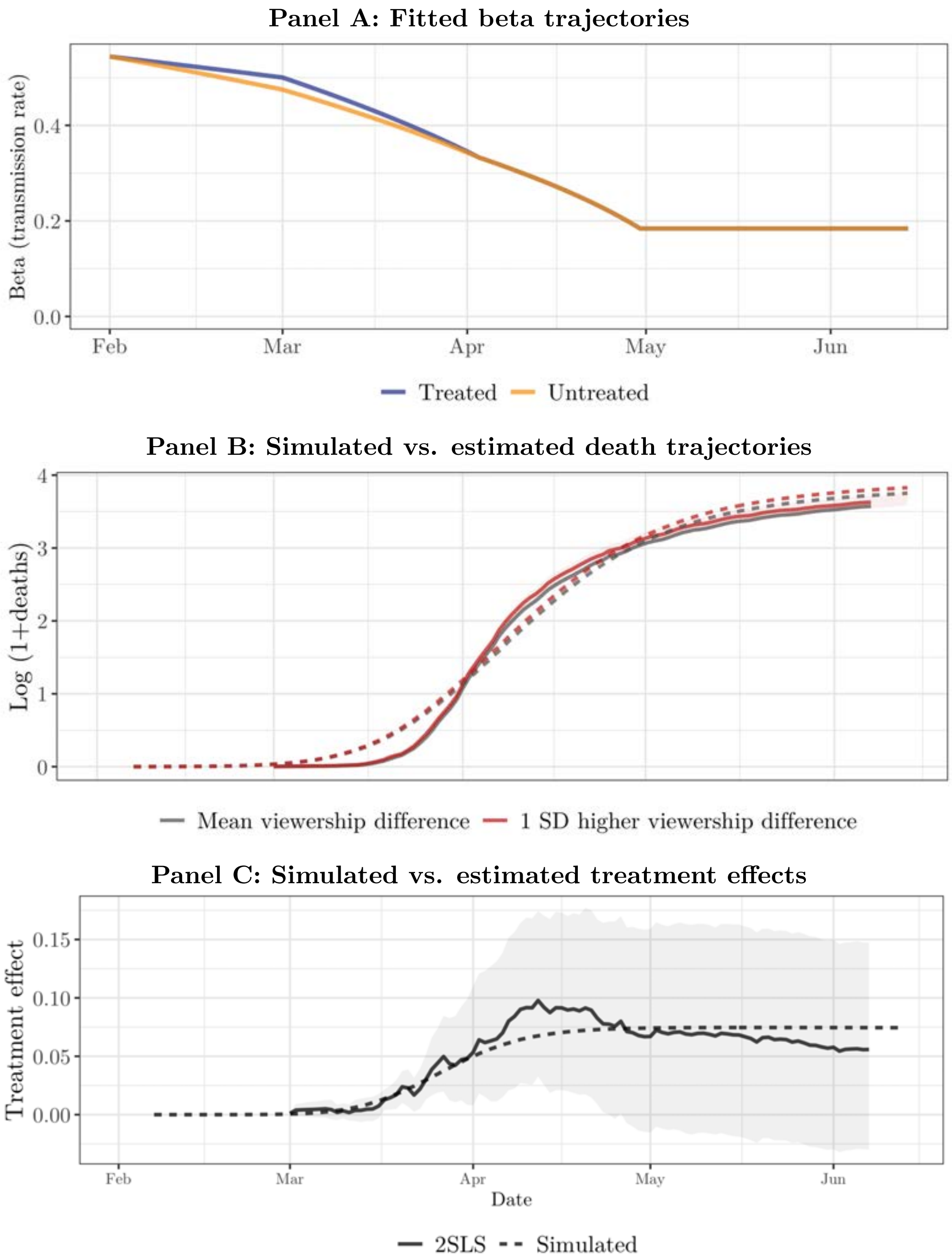
Figure A15: Implied COVID-19 curves (OLS)





Notes: Panel A of Figure A15 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.

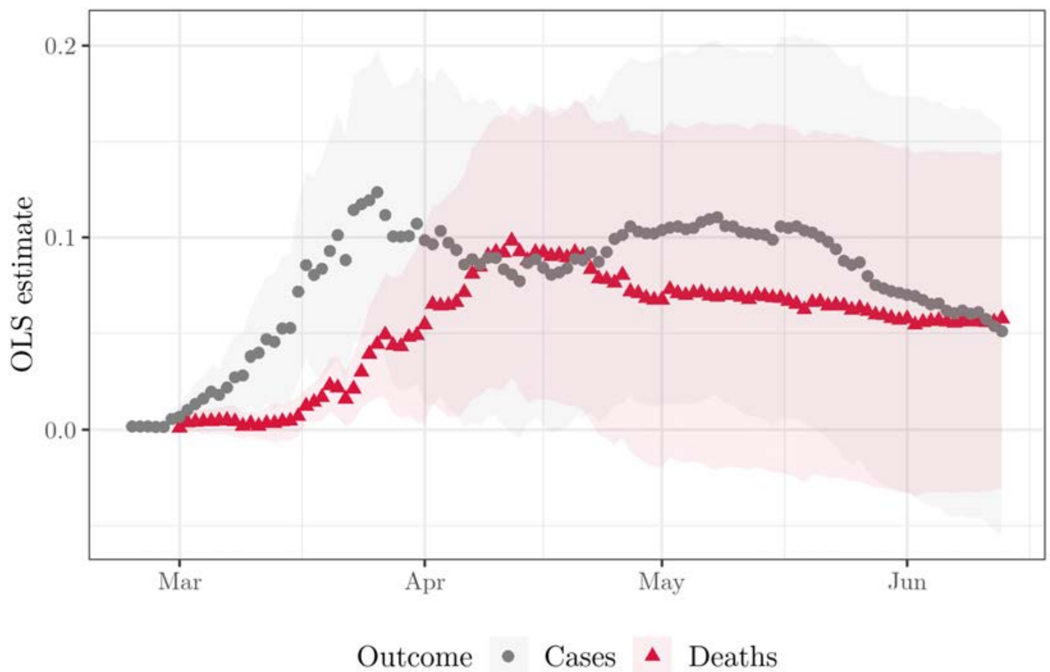
Figure A16: MG-SIR simulations (OLS)



Notes: Panel A of Figure A16 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 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.

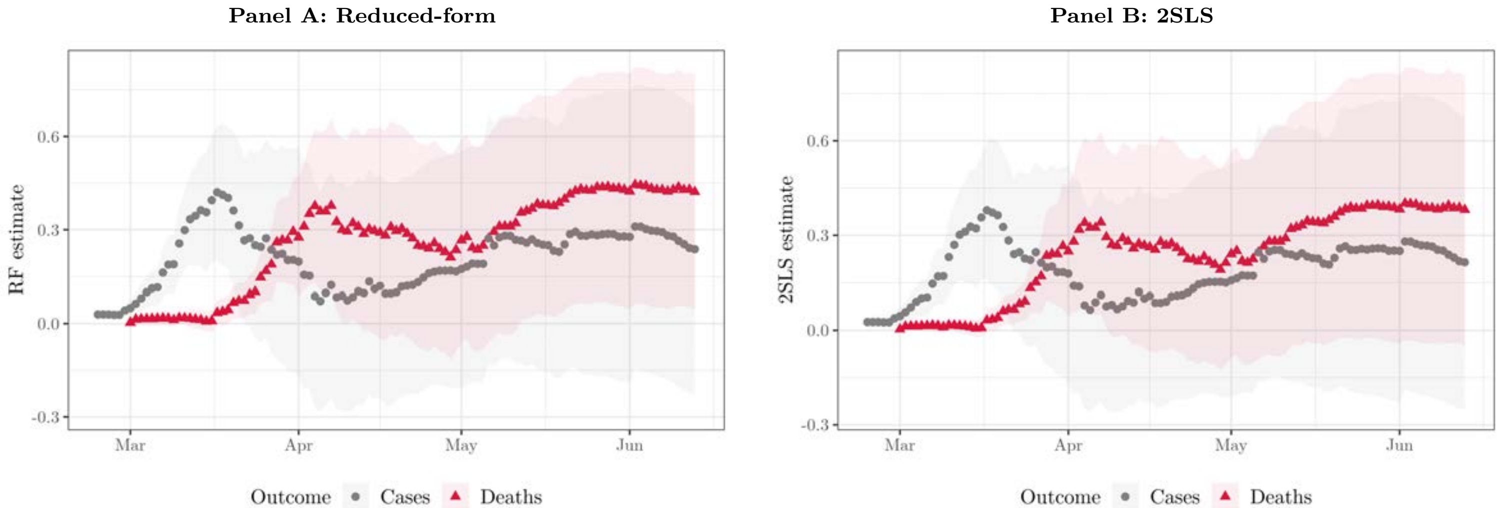
A.7 Extended Results

Figure A17: OLS estimates of effect of differential viewership on cases and deaths (extended)



Notes: Figure A17 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 number 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.

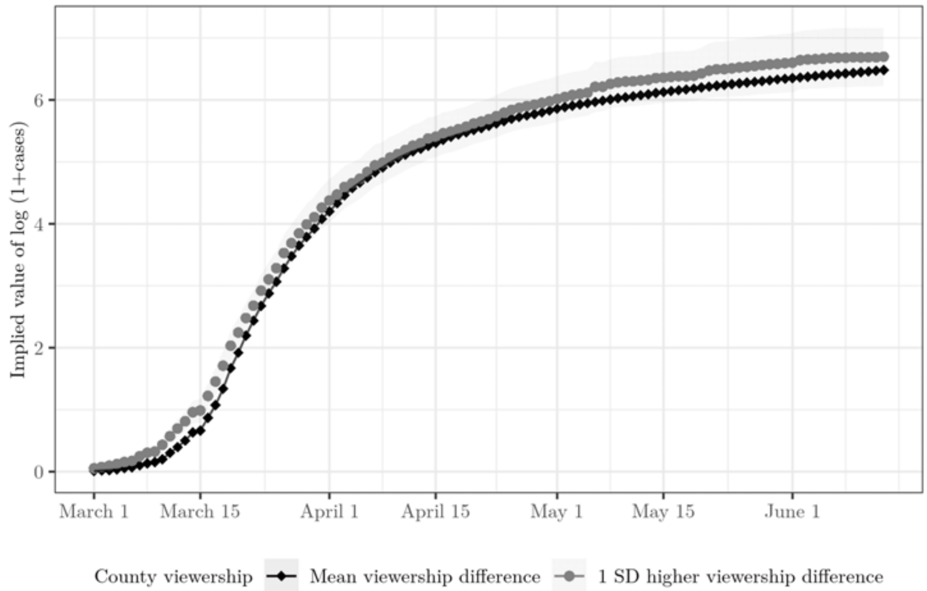
Figure A18: Reduced-form and 2SLS estimates of effect of differential viewership on cases and deaths (extended)



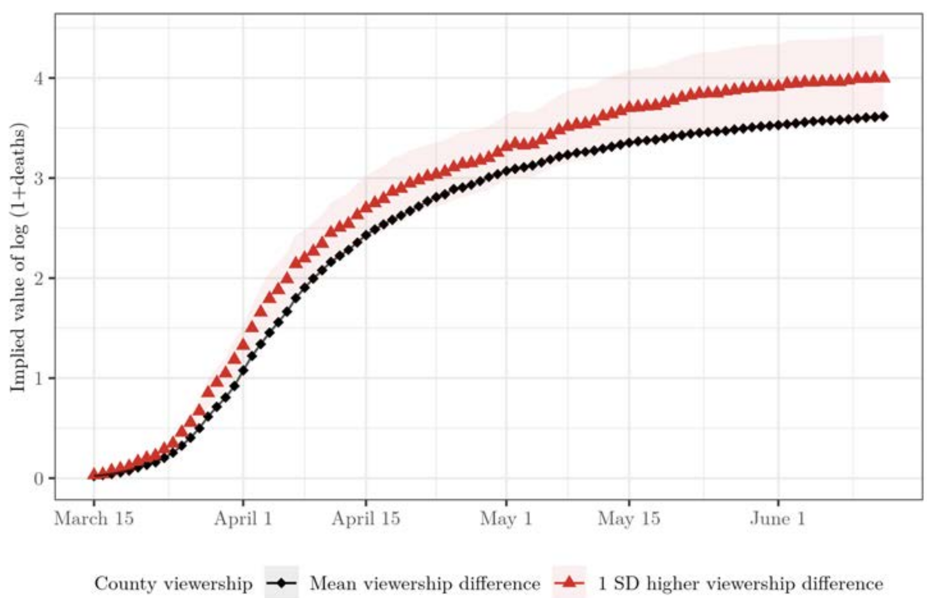
Notes: Figure A18 shows day-by-day reduced form (Panel A) and 2SLS (Panel B) estimates on log one plus cases and log one plus deaths. In Panel A, we report day-by-day effects of our instrument, $\text{NonF}\widehat{\text{oxHa}}\text{nnity}_d \times \text{FoxShare}_d$, on log deaths and log cases, conditional on 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. In Panel B, we report day-by-day effects of the standardized difference in viewership of *Hannity* vs. *Tucker Carlson Tonight*, instrumented by $\text{NonF}\widehat{\text{oxHa}}\text{nnity}_d \times \text{FoxShare}_d$ and controlling for state fixed effects and the same set of covariates as in Panel A. We cluster standard errors at the DMA level and report 95 percent confidence intervals.

Figure A19: Implied COVID-19 curves

Panel A: Estimates on cases

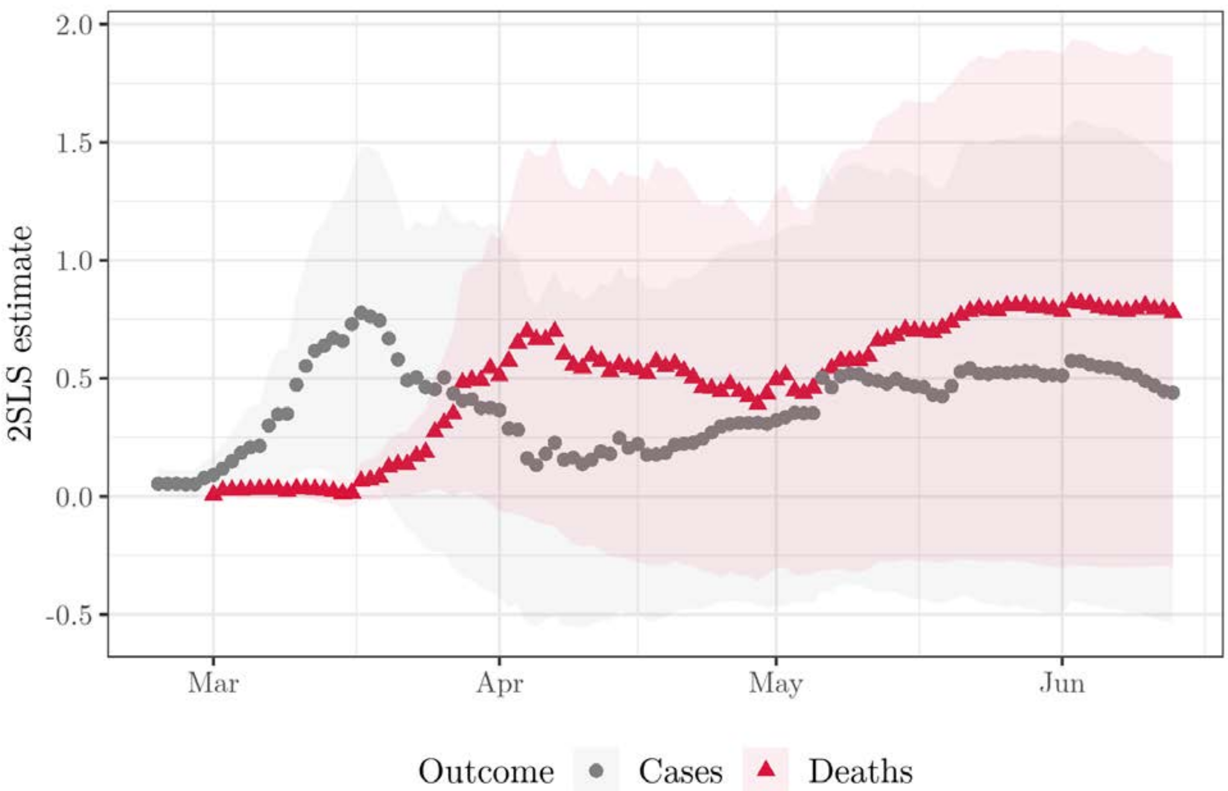


Panel B: Estimates on deaths



Notes: Panel A of Figure A19 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.

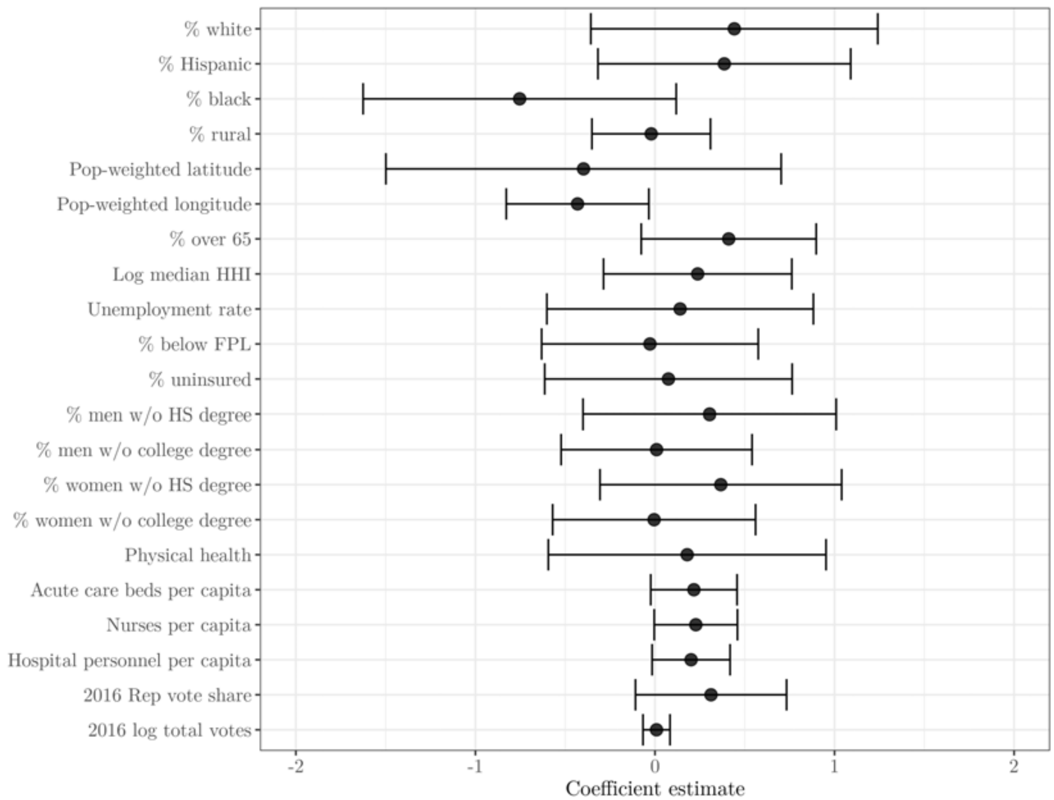
Figure A20: 2SLS estimates of effect of the pandemic coverage index on cases and deaths



Notes: Figure A20 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 $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$. 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 number 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.

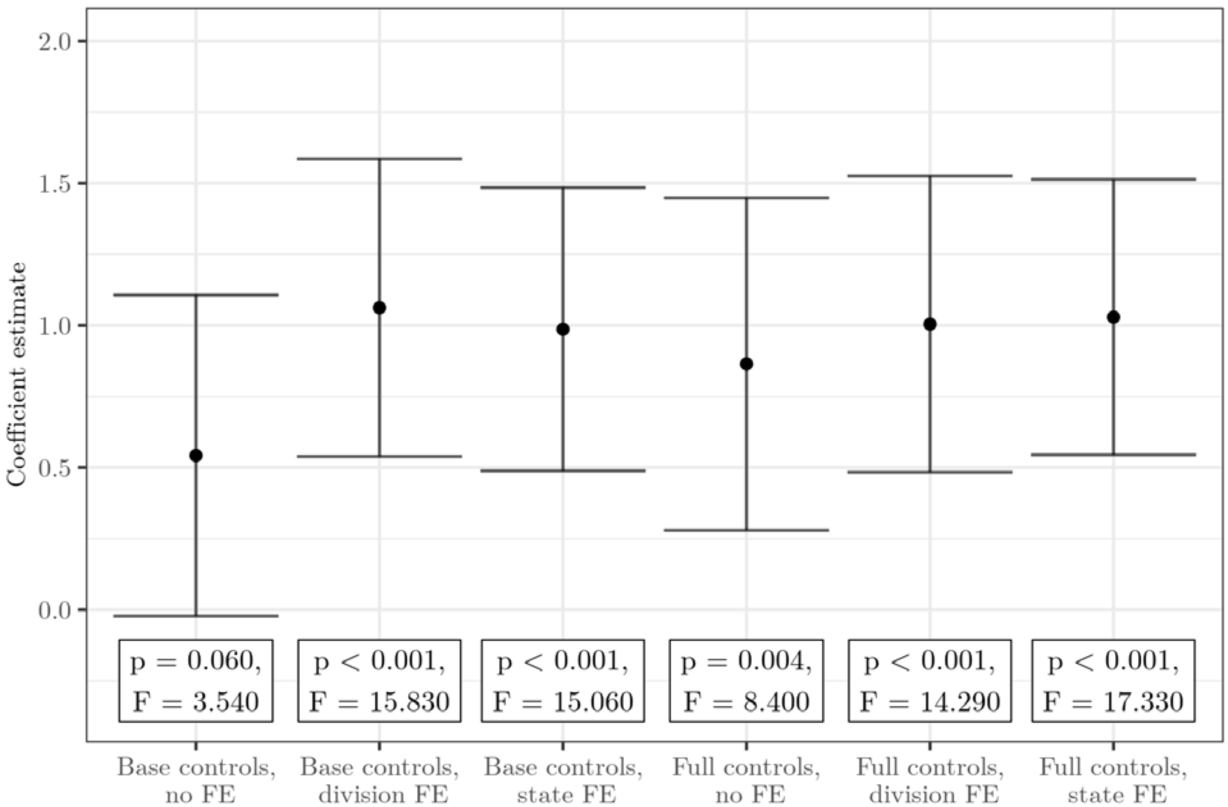
B Robustness: Division-Level Viewership Prediction

Figure B1: Instrument correlation with county-level demographics



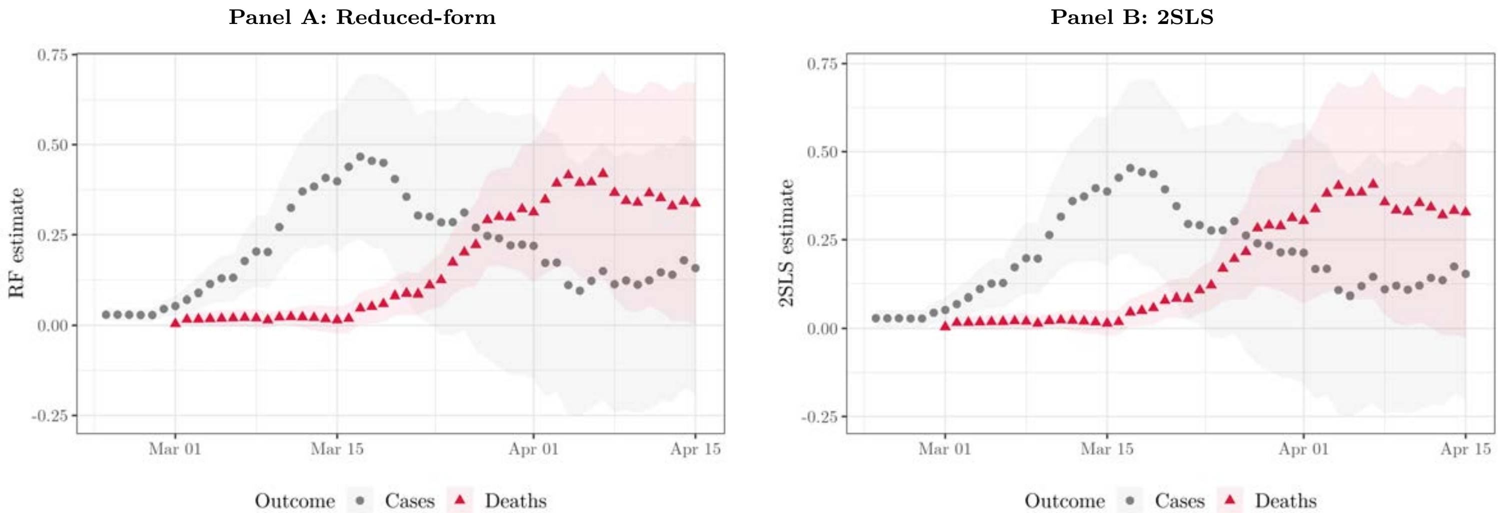
Notes: Figure B1 shows the coefficients from a series of regressions of each demographic characteristic on our instrument, $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$, conditional on the two interactants, $\widehat{\text{NonFoxHannity}}_d$ and FoxShare_d, and a small set of other controls accounting for local viewership patterns (the predicted number 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.

Figure B2: Instrument first stage on relative viewership



Notes: Figure B2 plots the coefficients from regressions of the standardized viewership difference between *Hannity* and *Tucker Carlson Tonight*, D_c, on our instrument, $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$ — 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.*. "Base controls" include the predicted number 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 2018, Fox News' share of television in January 2020, the population density of the county, and the log of the county's total population. "Full controls" additionally include population-weighted latitude and longitude, log distance to Seattle, 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 from 2018, 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. Robust standard errors are clustered at the DMA level. 95 percent confidence intervals are reported.

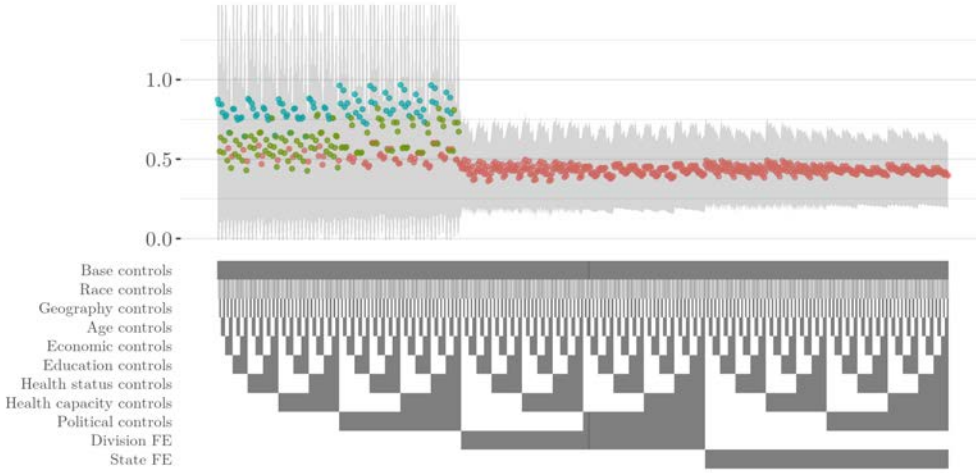
Figure B3: Reduced-form and 2SLS estimates of effect of differential viewership on cases and deaths



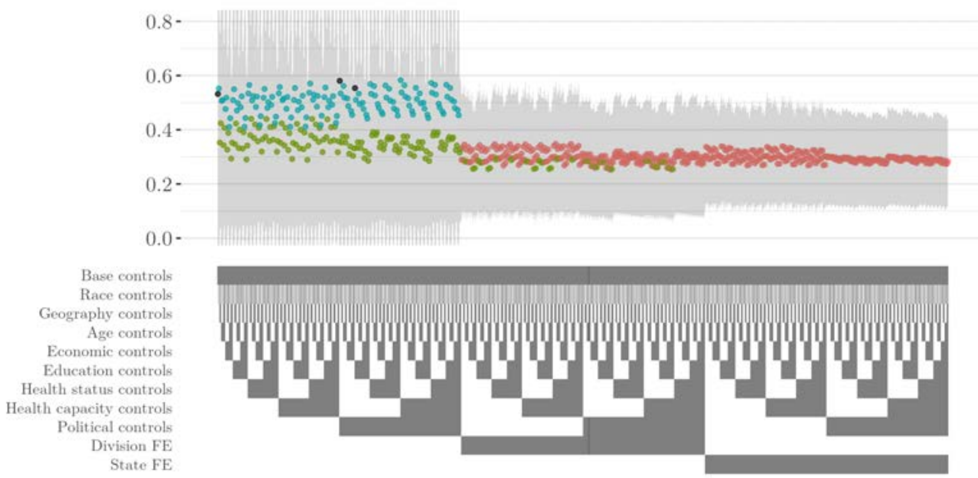
Notes: Figure B3 shows day-by-day reduced form (Panel A) and 2SLS (Panel B) estimates on log one plus cases and log one plus deaths. In Panel A, we report day-by-day effects of our instrument, $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$, on log deaths and log cases, conditional on state 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. In Panel B, we report day-by-day effects of the standardized difference in viewership of *Hannity* vs. *Tucker Carlson Tonight*, instrumented by $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$ and controlling for state fixed effects and the same set of covariates as in Panel A. 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)

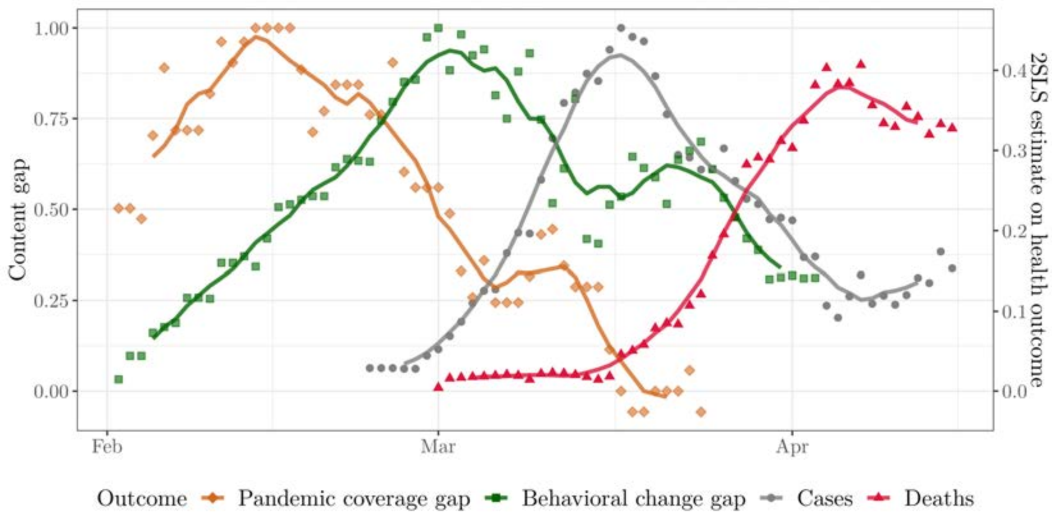


Panel B: Estimates on deaths (March 28, 2020)



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 seven sets of county-level controls (race, geography, age, economic, education, health, 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 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.

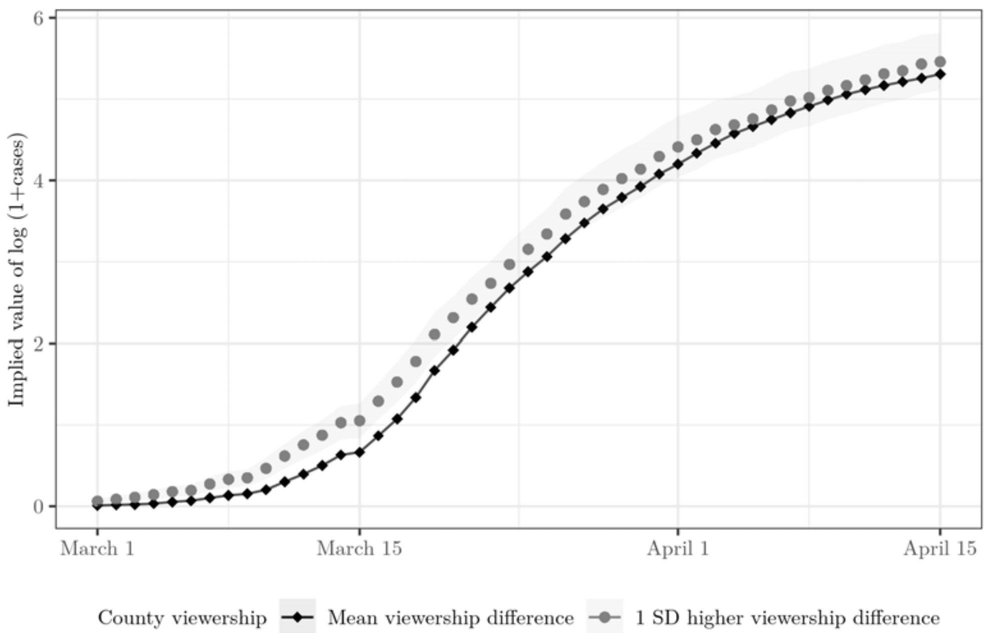
Figure B5: Carlson-Hannity pandemic coverage gap and effects on cases and deaths



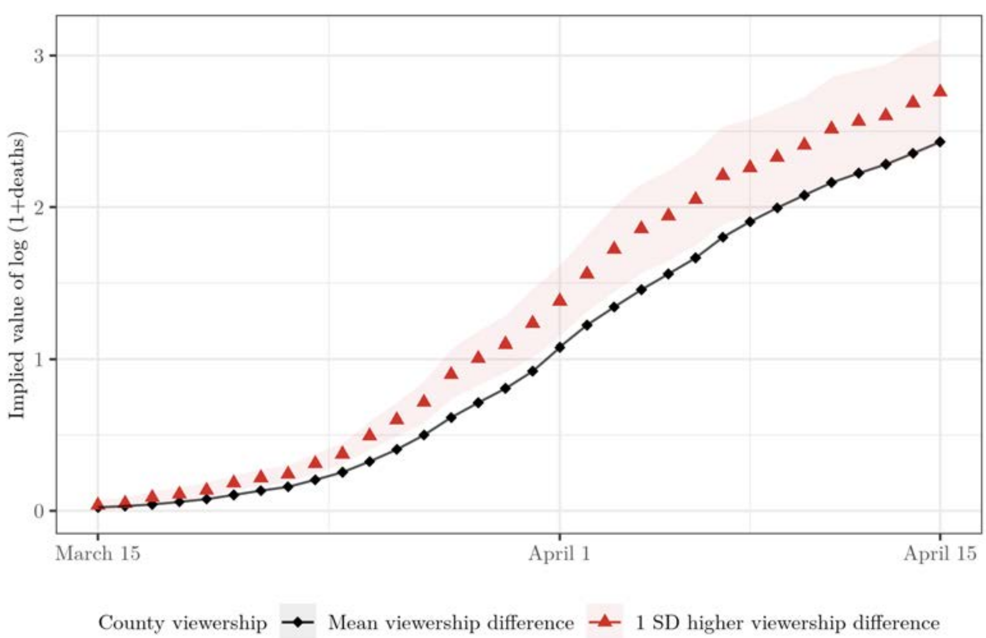
Notes: Figure B5 shows, in brown squares corresponding to the left y-axis, the difference in portrayed seriousness of the coronavirus threat on *Tucker Carlson Tonight* vs. *Hannity*, as rated by Amazon Mechanical Turk coders. The difference peaks in mid-February, a period during which there was no discussion 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 $\mathrm{Non}\widehat{\mathrm{FoxHannity}}_d \times \mathrm{FoxShare}_d$) 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 number 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 B6: Implied COVID-19 curves

Panel A: Estimates on cases

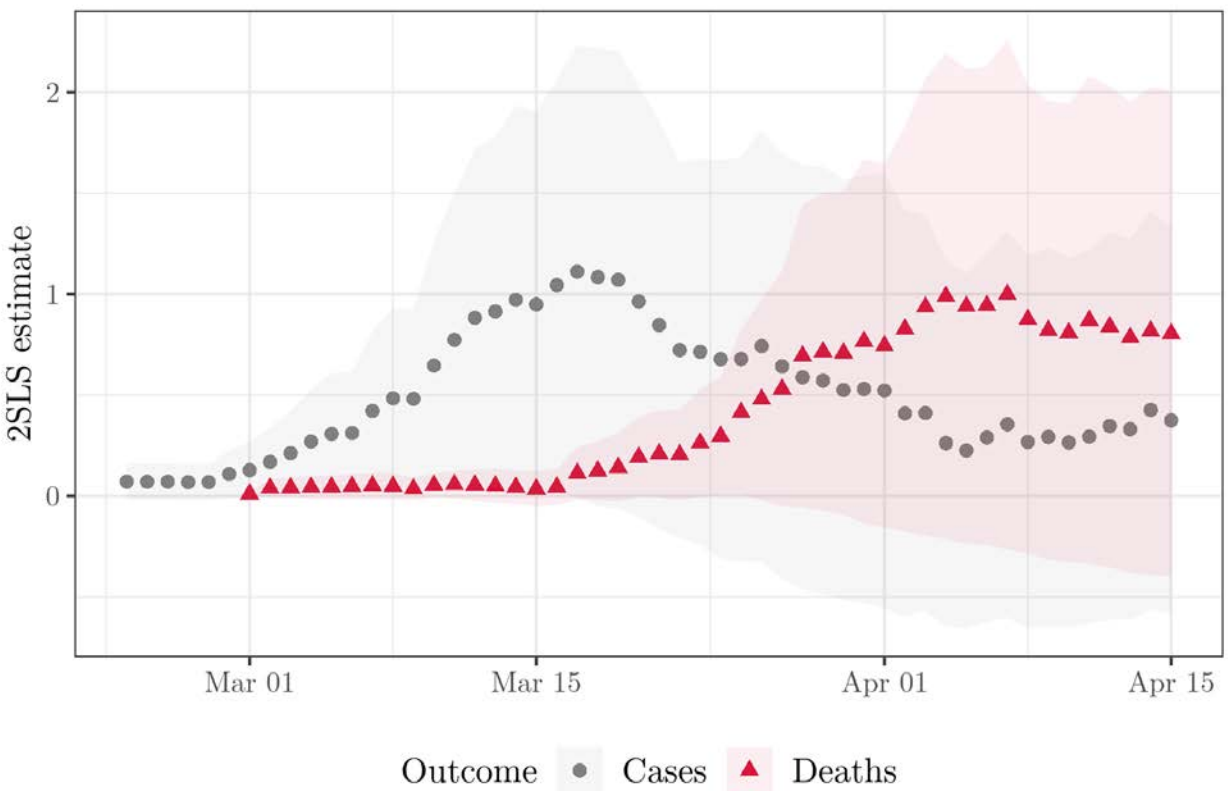


Panel B: Estimates on deaths



Notes: Panel A of Figure B6 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 B7: 2SLS estimates of effect of the pandemic coverage index on cases and deaths



Notes: Figure B7 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 $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$. 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 number 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.

Table B1: Effect of differential viewership on cases

	Dependent variable:						
	COVID-19 cases						
	Feb 29	Mar 07	Mar 14	Mar 21	Mar 28	Apr 04	Apr 11
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: *Ordinary least squares*							
Hannity-Carlson viewership difference	0.006**	0.022**	0.052***	0.101***	0.100**	0.097**	0.083**
	(0.002)	(0.010)	(0.019)	(0.033)	(0.039)	(0.044)	(0.042)
Panel B: *Reduced form*							
Non-Fox TVs on × Fox share	0.046***	0.177***	0.408***	0.355**	0.247	0.110	0.123
	(0.011)	(0.043)	(0.094)	(0.144)	(0.174)	(0.181)	(0.181)
Panel C: *Two-stage least squares*							
H-C viewership difference (predicted)	0.044***	0.172***	0.396***	0.345**	0.240	0.107	0.120
	(0.016)	(0.045)	(0.105)	(0.139)	(0.173)	(0.179)	(0.180)
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 reports OLS estimates of the log of one plus cases upon the standardized difference in Hannity-Carlson viewership. Panel B reports reduced-form estimates of the log of one plus cases upon the instrument, $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$ — that is, the predicted number of TVs on during Hannity's timeslot based on the five closest DMAs, excluding TVs watching *Hannity*, multiplied by Fox News' viewership share, excluding *Hannity* and *Tucker Carlson Tonight*. Panel C reports two-stage least squares estimates of the log of one plus cases upon the standardized difference in Hannity-Carlson viewership, instrumented by $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$. OLS controls include the number 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, log distance to Seattle, 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. IV controls are identical to OLS controls, except the number of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle* are replaced with the predicted number of TVs tuned to non-Fox channels during these timeslots. Standard errors are clustered at the DMA level. Robust standard errors are reported.

Table B2: Effect of differential viewership on deaths

	Dependent variable:					
	COVID-19 deaths					
	Mar 07	Mar 14	Mar 21	Mar 28	Apr 04	Apr 11
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *Ordinary least squares*						
Hannity-Carlson viewership difference	0.005	0.004	0.022***	0.044**	0.065**	0.092**
	(0.004)	(0.005)	(0.008)	(0.018)	(0.030)	(0.036)
Panel B: *Reduced form*						
Non-Fox TVs on × Fox share	0.021*	0.018	0.088***	0.291***	0.415***	0.365**
	(0.012)	(0.018)	(0.030)	(0.065)	(0.128)	(0.159)
Panel C: *Two-stage least squares*						
H-C viewership difference (predicted)	0.021*	0.018	0.085***	0.283***	0.403***	0.355**
	(0.012)	(0.017)	(0.028)	(0.083)	(0.151)	(0.172)
Full controls	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	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 deaths upon the standardized difference in Hannity-Carlson viewership. Panel B reports reduced-form estimates of the log of one plus deaths upon the instrument, $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$ — that is, the predicted number of TVs on during Hannity's timeslot based on the five closest DMAs, excluding TVs watching *Hannity*, multiplied by Fox News' viewership share, excluding *Hannity* and *Tucker Carlson Tonight*. Panel C reports two-stage least squares estimates of the log of one plus deaths upon the standardized difference in Hannity-Carlson viewership, instrumented by $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$. OLS controls include the number 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, log distance to Seattle, 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. IV controls are identical to OLS controls, except the number of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle* are replaced with the predicted number of TVs tuned to non-Fox channels during these timeslots. Standard errors are clustered at the DMA level. Robust standard errors are reported.

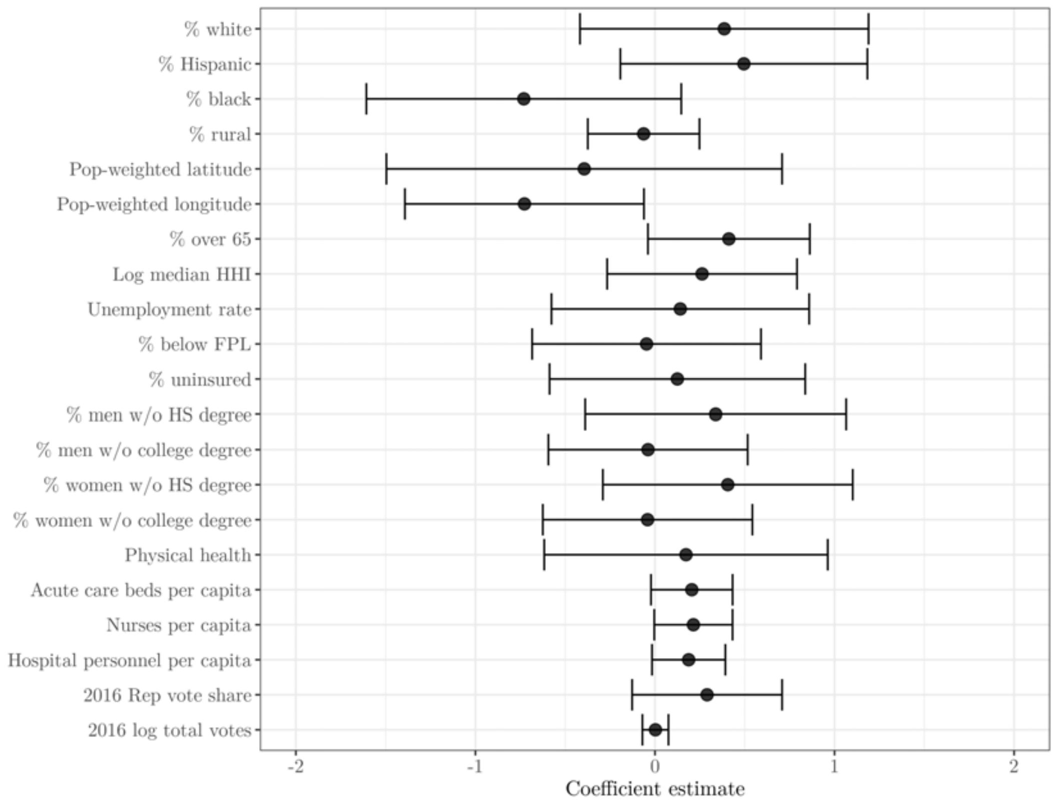
Table B3: Differential coverage and COVID-19 outcomes across all Fox News evening shows

	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	0.551***	0.545***				
	(0.053)	(0.052)				
Panel B: *RF: inverse pandemic coverage index on instrument*						
$\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$			0.396*	0.420**		
			(0.204)	(0.209)		
Panel C: *2SLS: cases and deaths on inverse predicted pandemic coverage index*						
$-1\times$ coverage index (predicted)					0.971**	0.693*
					(0.490)	(0.382)
Base controls	Yes	Yes	Yes	Yes	Yes	Yes
Main controls	No	Yes	No	Yes	Yes	Yes
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, $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$ — that is, the predicted number of TVs on during Hannity's timeslot based on the five closest DMAs, 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 $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$. Base OLS controls include the number 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 number of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle* are replaced with the predicted number of TVs tuned to non-Fox channels during these timeslots. Main controls for both OLS and IV include population-weighted latitude and longitude, log distance to Seattle, 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. Robust standard errors are reported.

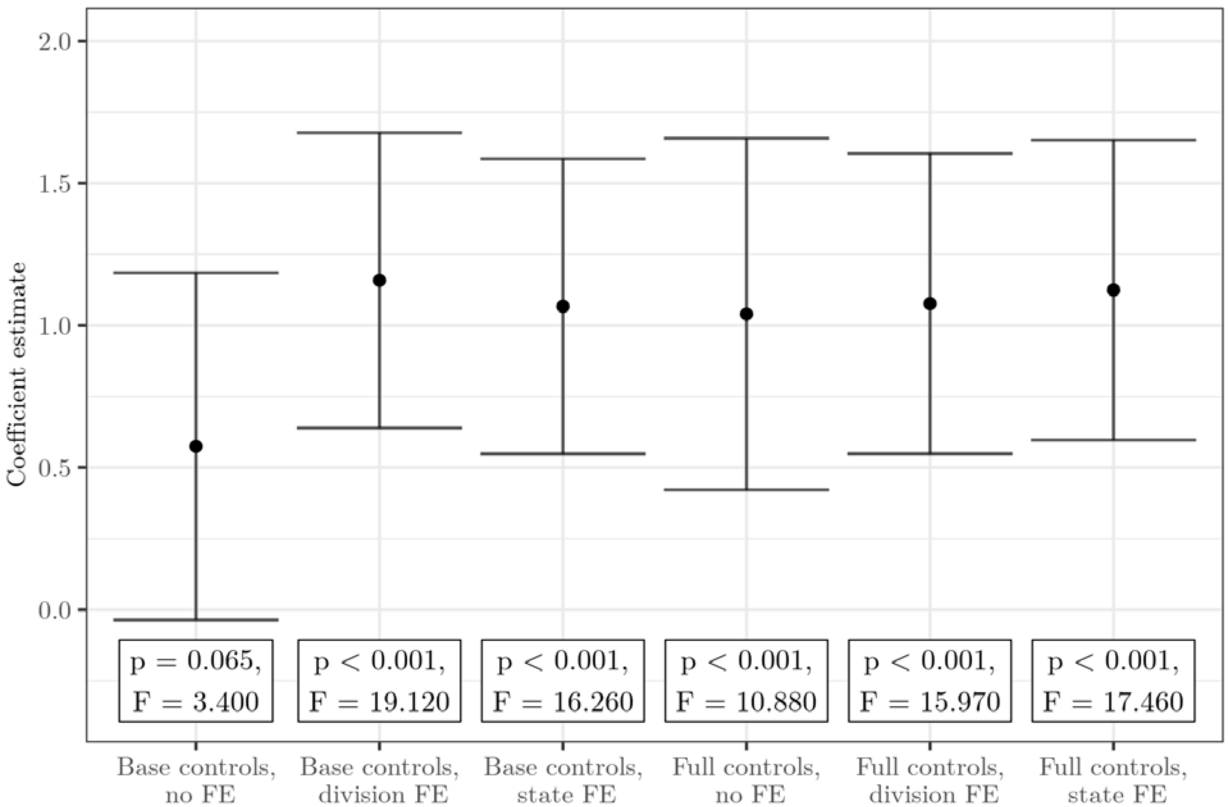
C Robustness: Non-Predicted Viewership

Figure C1: Instrument correlation with county-level demographics



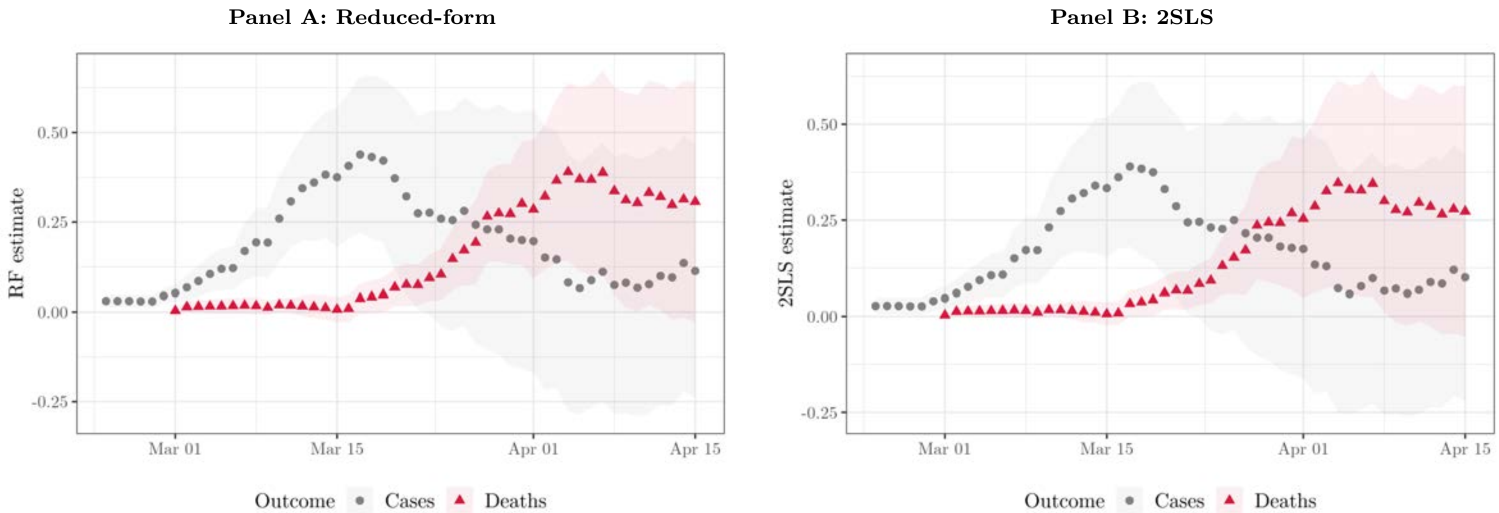
Notes: Figure C1 shows the coefficients from a series of regressions of each demographic characteristic on our instrument, $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$, conditional on the two interactants, $\widehat{\text{NonFoxHannity}}_d$ and FoxShare_d, and a small set of other controls accounting for local viewership patterns (the predicted number 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.

Figure C2: Instrument first stage on relative viewership



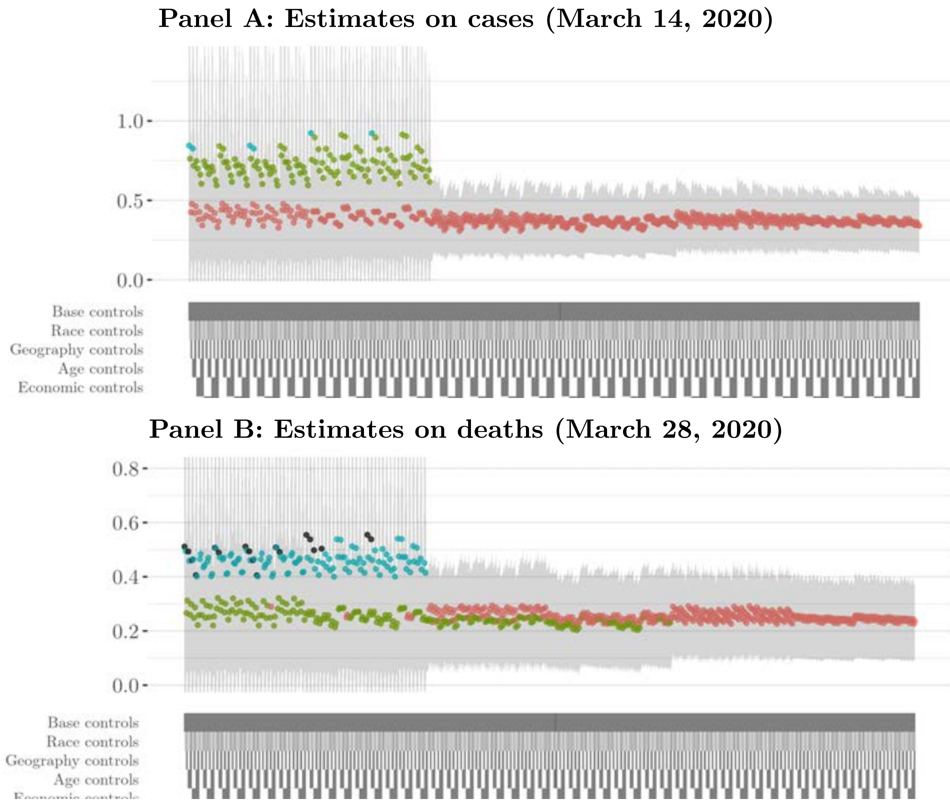
Notes: Figure C2 plots the coefficients from regressions of the standardized viewership difference between *Hannity* and *Tucker Carlson Tonight*, D_c, on our instrument, $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$ — that is, the predicted number of TVs on during Hannity's timeslot, excluding TVs watching *Hannity*, multiplied by Fox News' viewership share, excluding *Hannity* and *Tucker Carlson Tonight.*. "Base controls" include the predicted number 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 2018, Fox News' share of television in January 2020, the population density of the county, and the log of the county's total population. "Full controls" additionally include population-weighted latitude and longitude, log distance to Seattle, 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 from 2018, 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. Robust standard errors are clustered at the DMA level. 95 percent confidence intervals are reported.

Figure C3: Reduced-form and 2SLS estimates of effect of differential viewership on cases and deaths



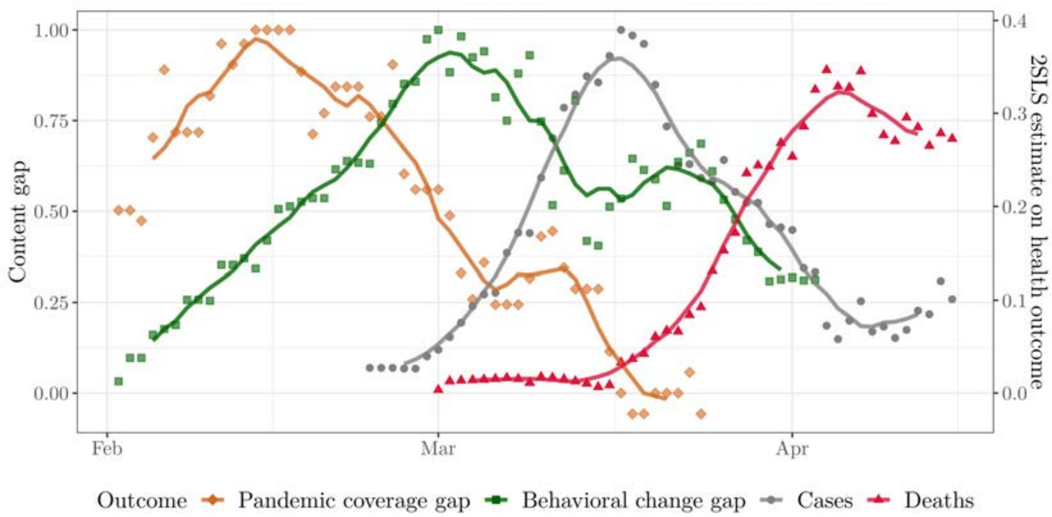
Notes: Figure C3 shows day-by-day reduced form (Panel A) and 2SLS (Panel B) estimates on log one plus cases and log one plus deaths. In Panel A, we report day-by-day effects of our instrument, $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$, on log deaths and log cases, conditional on state 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 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. In Panel B, we report day-by-day effects of the standardized difference in viewership of *Hannity* vs. *Tucker Carlson Tonight*, instrumented by $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$ and controlling for state fixed effects and the same set of covariates as in Panel A. We cluster standard errors at the DMA level and report 95 percent confidence intervals.

Figure C4: 2SLS: robustness to combinations of controls



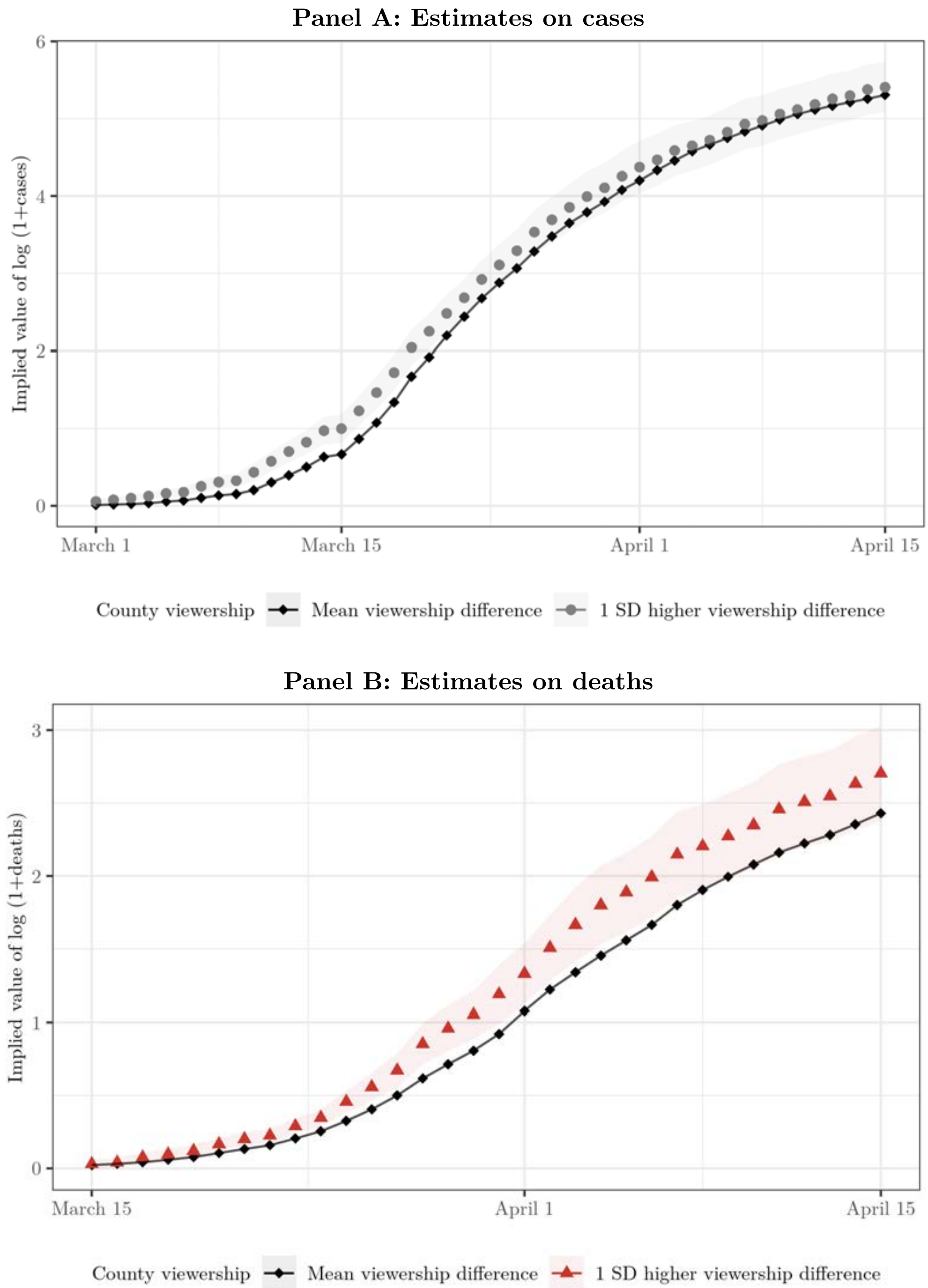
Notes: Figure C4 shows robustness of our two-stage least squares estimates for the specifications for log one plus cases on March 14 (Panel A) and log one plus deaths on March 28 (Panel B) under every possible combination of our seven sets of county-level controls (race, geography, age, economic, education, health, 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 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 C5: Carlson-Hannity pandemic coverage gap and effects on cases and deaths



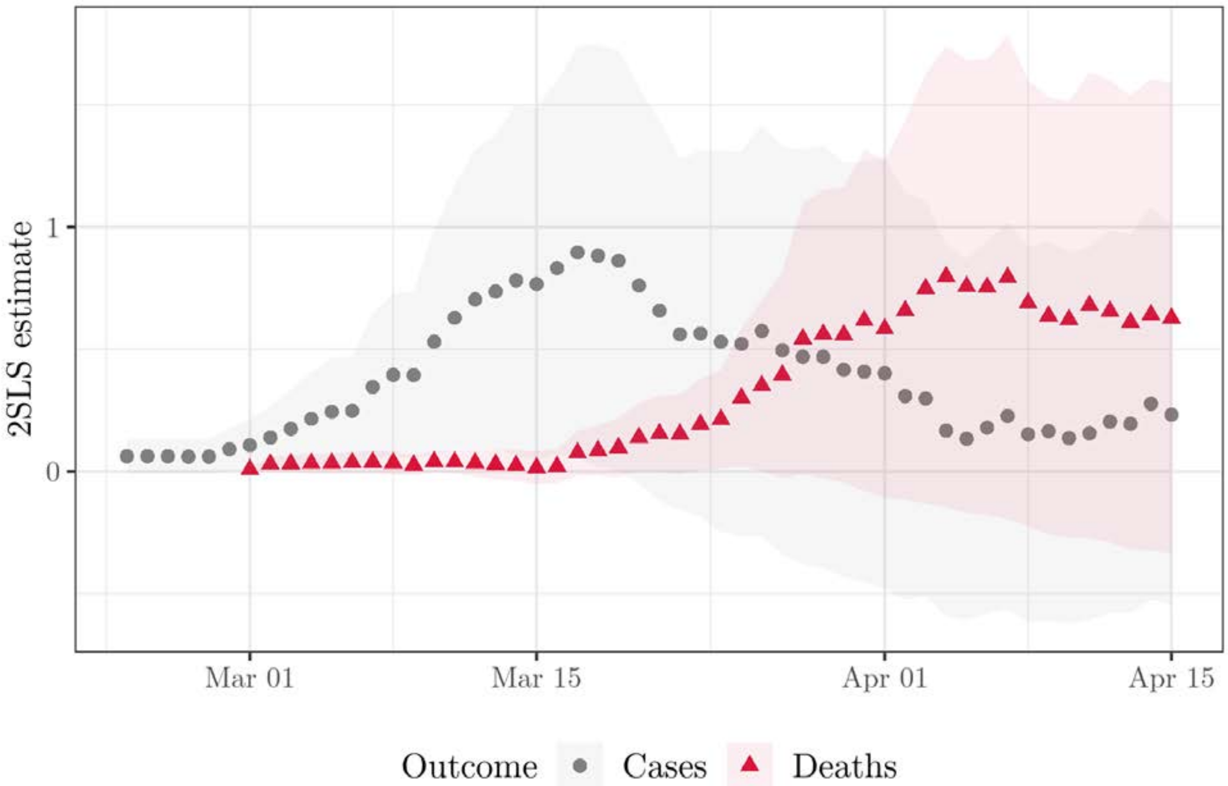
Notes: Figure C5 shows, in brown squares corresponding to the left y-axis, the difference in portrayed seriousness of the coronavirus threat on *Tucker Carlson Tonight* vs. *Hannity*, as rated by Amazon Mechanical Turk coders. The difference peaks in mid-February, a period during which there was no discussion 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 $\text{Non}\widehat{\text{FoxHannity}}_d \times \text{FoxShare}_d$) 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 number 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.

Figure C6: Implied COVID-19 curves



Notes: Panel A of Figure C6 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 C7: 2SLS estimates of effect of the pandemic coverage index on cases and deaths



Notes: Figure C7 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 $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$. 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 number 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. We cluster standard errors at the DMA level and report 95 percent confidence intervals.

Table C1: Effect of differential viewership on cases

	Dependent variable:						
	COVID-19 cases						
	Feb 29	Mar 07	Mar 14	Mar 21	Mar 28	Apr 04	Apr 11
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: *Ordinary least squares*							
Hannity-Carlson viewership difference	0.006**	0.022**	0.052***	0.101***	0.100**	0.097**	0.083**
	(0.002)	(0.010)	(0.019)	(0.033)	(0.039)	(0.044)	(0.042)
Panel B: *Reduced form*							
Non-Fox TVs on × Fox share	0.045***	0.169***	0.382***	0.322**	0.229	0.082	0.077
	(0.011)	(0.041)	(0.090)	(0.139)	(0.170)	(0.182)	(0.183)
Panel C: *Two-stage least squares*							
H-C viewership difference (predicted)	0.040***	0.150***	0.340***	0.286**	0.204	0.072	0.068
	(0.013)	(0.039)	(0.090)	(0.123)	(0.156)	(0.164)	(0.164)
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 reports OLS estimates of the log of one plus cases upon the standardized difference in Hannity-Carlson viewership. Panel B reports reduced-form estimates of the log of one plus cases upon the instrument, $\text{NonFoxHannity}_d \times \text{FoxShare}_d$— that is, the predicted 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 C reports two-stage least squares estimates of the log of one plus cases upon the standardized difference in Hannity-Carlson viewership, instrumented by $\text{NonFoxHannity}_d \times \text{FoxShare}_d$. OLS controls include the number 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, log distance to Seattle, 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. IV controls are identical to OLS controls, except the number of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle* are replaced with the predicted number of TVs tuned to non-Fox channels during these timeslots. Standard errors are clustered at the DMA level. Robust standard errors are reported.

Table C2: Effect of differential viewership on deaths

	Dependent variable:					
	COVID-19 deaths					
	Mar 07	Mar 14	Mar 21	Mar 28	Apr 04	Apr 11
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *Ordinary least squares*						
Hannity-Carlson viewership difference	0.005	0.004	0.022***	0.044**	0.065**	0.092**
	(0.004)	(0.005)	(0.008)	(0.018)	(0.030)	(0.036)
Panel B: *Reduced form*						
Non-Fox TVs on × Fox share	0.019	0.012	0.076**	0.265***	0.390***	0.332**
	(0.012)	(0.017)	(0.030)	(0.065)	(0.127)	(0.160)
Panel C: *Two-stage least squares*						
H-C viewership difference (predicted)	0.017*	0.010	0.067***	0.236***	0.347**	0.296*
	(0.010)	(0.014)	(0.025)	(0.072)	(0.137)	(0.158)
Full controls	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	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 deaths upon the standardized difference in Hannity-Carlson viewership. Panel B reports reduced-form estimates of the log of one plus deaths upon the instrument, $\text{NonFoxHannity}_d \times \text{FoxShare}_d$— that is, the predicted 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 C reports two-stage least squares estimates of the log of one plus deaths upon the standardized difference in Hannity-Carlson viewership, instrumented by $\text{NonFoxHannity}_d \times \text{FoxShare}_d$. OLS controls include the number 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, log distance to Seattle, 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. IV controls are identical to OLS controls, except the number of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle* are replaced with the predicted number of TVs tuned to non-Fox channels during these timeslots. Standard errors are clustered at the DMA level. Robust standard errors are reported.

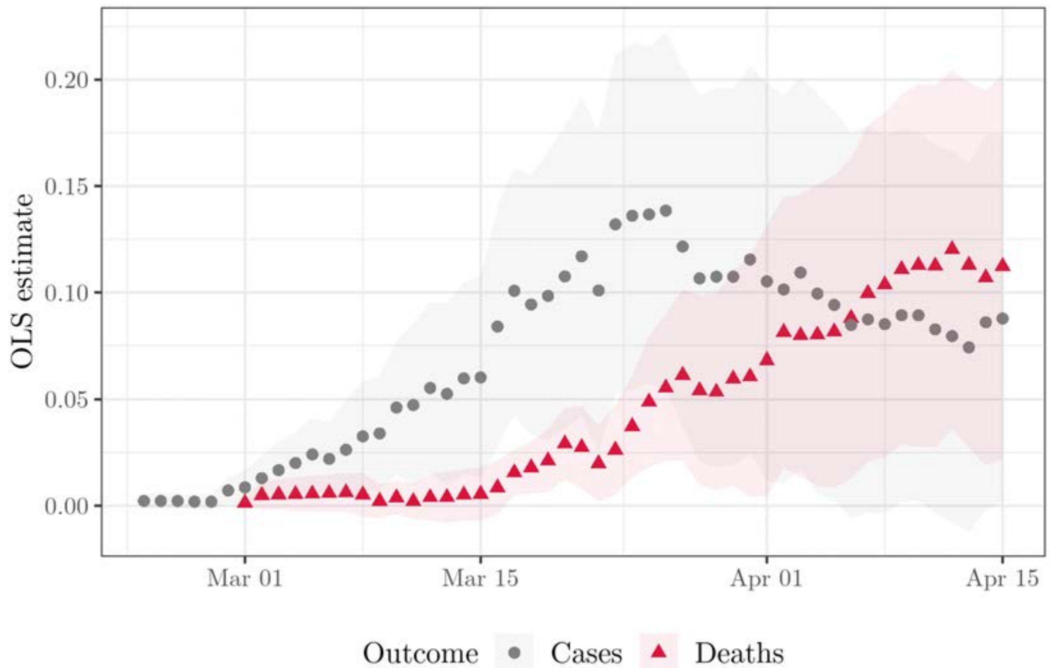
Table C3: Differential coverage and COVID-19 outcomes across all Fox News evening shows

	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	0.551^{***}	0.545^{***}				
	(0.053)	(0.052)				
Panel B: *RF: inverse pandemic coverage index on instrument*						
$\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$			0.463^{**}	0.489^{**}		
			(0.216)	(0.227)		
Panel C: *2SLS: cases and deaths on inverse predicted pandemic coverage index*						
$-1\times$ coverage index (predicted)					0.781^{**}	0.542^{*}
					(0.367)	(0.283)
Base controls	Yes	Yes	Yes	Yes	Yes	Yes
Main controls	No	Yes	No	Yes	Yes	Yes
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, $\text{NonFoxHannity}_d \times \text{FoxShare}_d$— that is, the predicted 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 $\text{NonFoxHannity}_d \times \text{FoxShare}_d$. Base OLS controls include the number 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 number of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle* are replaced with the predicted number of TVs tuned to non-Fox channels during these timeslots. Main controls for both OLS and IV include population-weighted latitude and longitude, log distance to Seattle, 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. Robust standard errors are reported.

D Robustness Check: Inverse Hyperbolic Sine Transformation

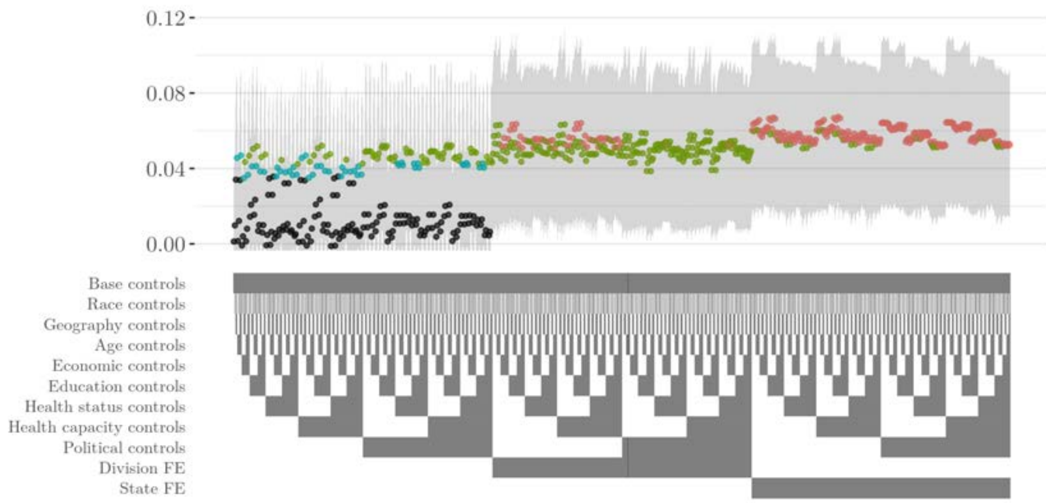
Figure D1: OLS estimates of effect of differential viewership on cases and deaths



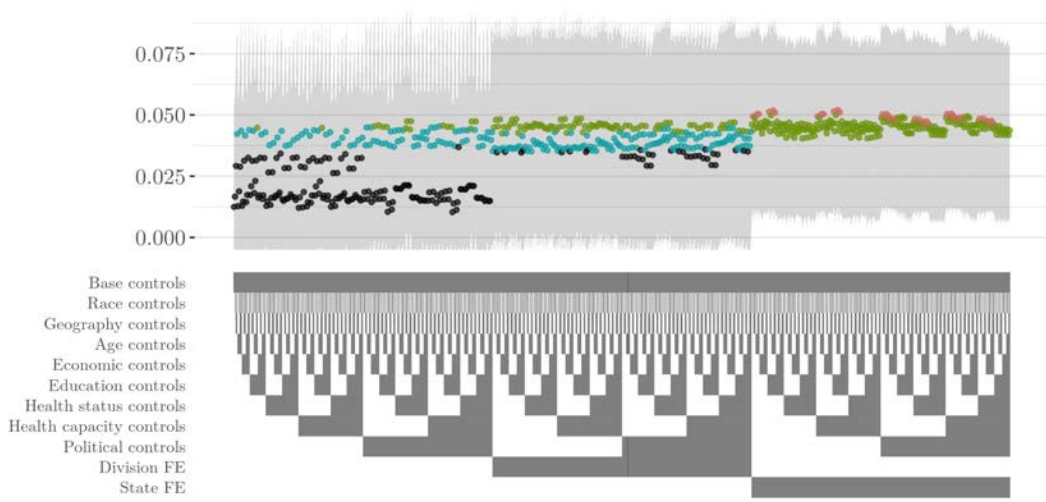
Notes: Figure D1 displays effects of differential viewership of *Hannity* and *Tucker Carlson Tonight* on the inverse hyperbolic sine of cases and deaths. We report day-by-day results for the correlation between log deaths and log cases with the standardized viewership difference between *Hannity* and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

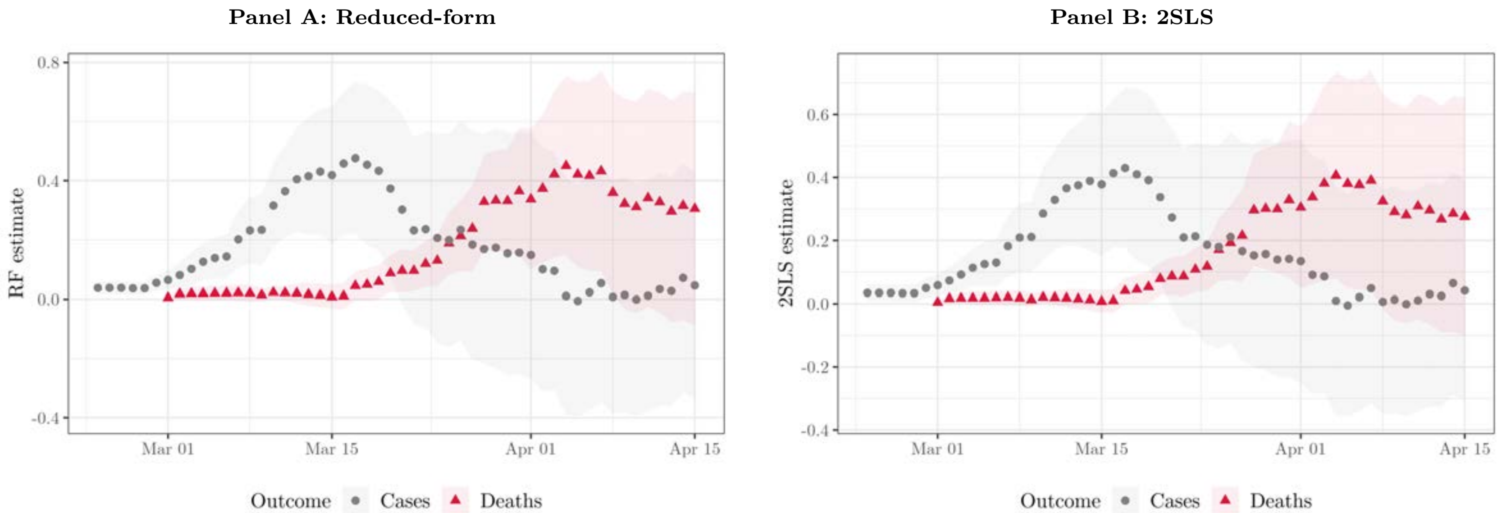


Panel B: Estimates on deaths (March 28, 2020)



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 seven sets of county-level controls (race, geography, age, economic, education, health, 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 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.

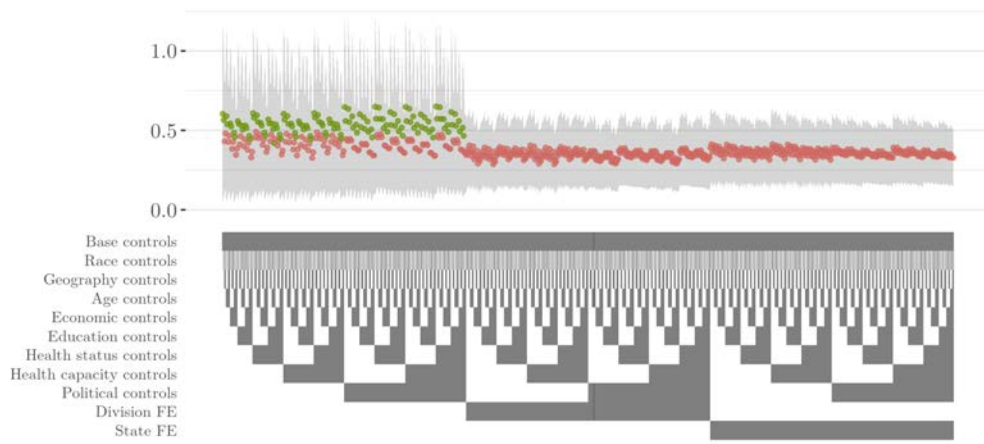
Figure D3: Reduced-form and 2SLS estimates of effect of differential viewership on cases and deaths



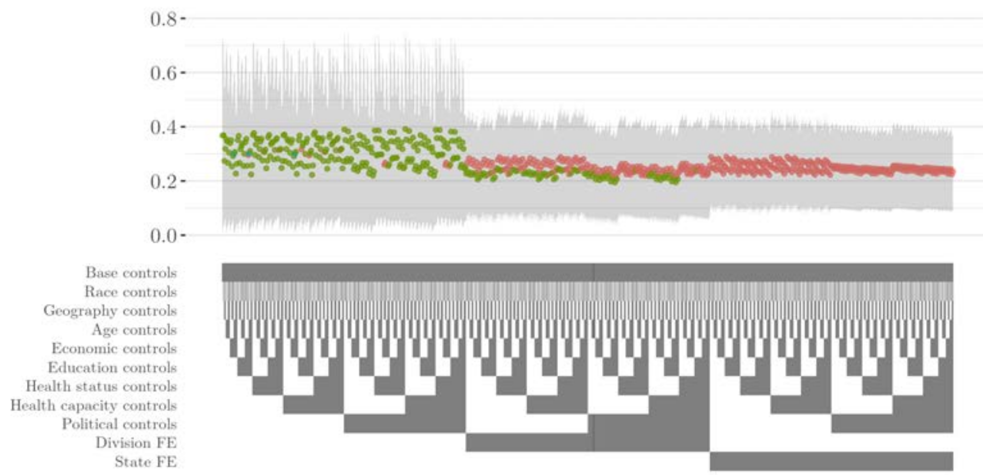
Notes: Figure D3 shows day-by-day reduced form (Panel A) and 2SLS (Panel B) estimates on the inverse hyperbolic sine of cases and deaths. In Panel A, we report day-by-day effects of our instrument, $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$, on log deaths and log cases, conditional on 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. In Panel B, we report day-by-day effects of the standardized difference in viewership of *Hannity* vs. *Tucker Carlson Tonight*, instrumented by $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$ and controlling for state fixed effects and the same set of covariates as in Panel A. 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)

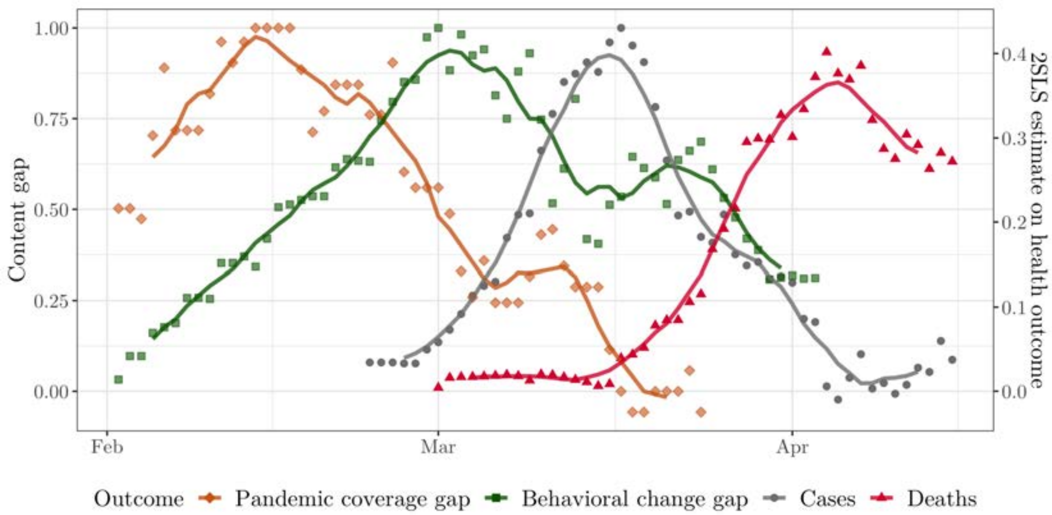


Panel B: Estimates on deaths (March 28, 2020)



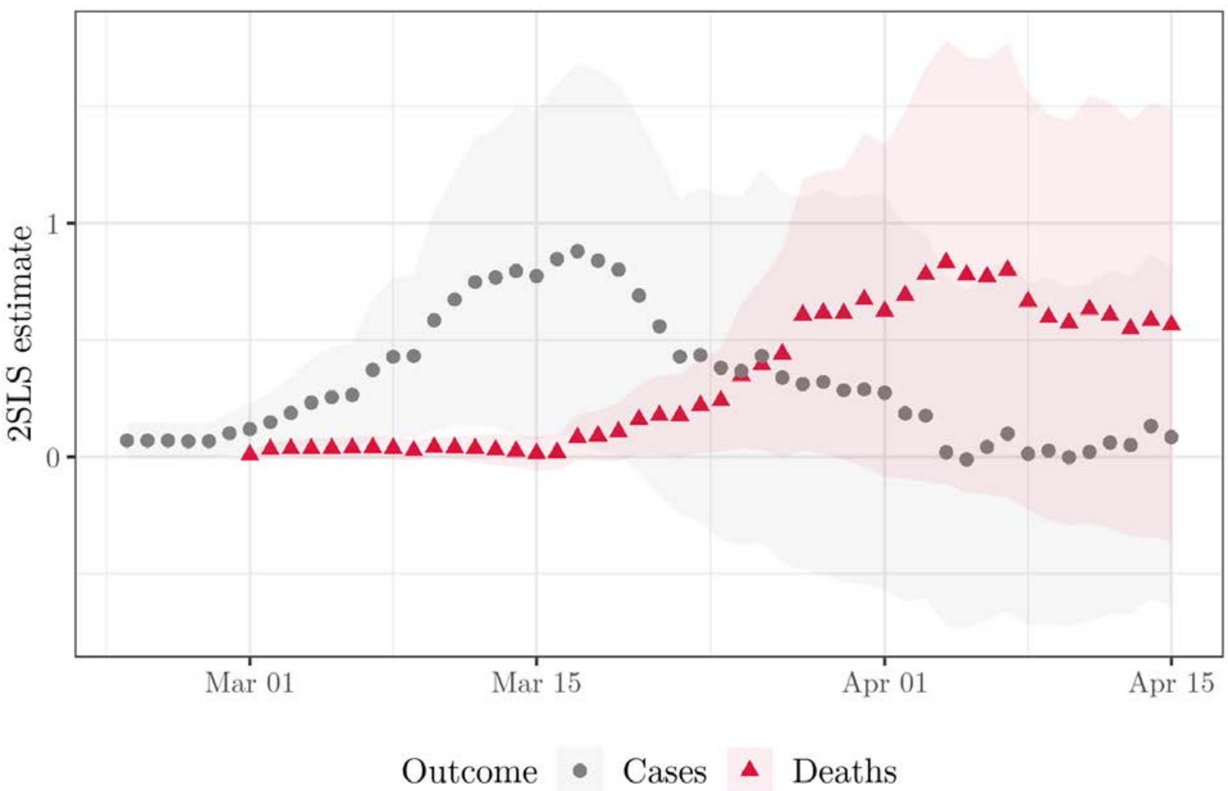
Notes: Figure D4 shows robustness of our two-stage least squares estimates for the specifications for log one plus cases on March 14 (Panel A) and log one plus deaths on March 28 (Panel B) under every possible combination of our seven sets of county-level controls (race, geography, age, economic, education, health, 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 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 $\text{Non}\widehat{\text{FoxHannity}}_d \times \text{FoxShare}_d$) 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 number 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 D6: 2SLS estimates of effect of the pandemic coverage index on cases and deaths



Notes: Figure D6 shows day-by-day 2SLS estimates from regressions of on the inverse hyperbolic sine of cases and deaths on the inverse of the pandemic coverage index described in Section 9, instrumented by $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$. 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 number 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.

Table D1: Effect of differential viewership on cases

	Dependent variable:						
	COVID-19 cases						
	Feb 29	Mar 07	Mar 14	Mar 21	Mar 28	Apr 04	Apr 11
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: *Ordinary least squares*							
Hannity-Carlson viewership difference	0.007**	0.026**	0.060***	0.117***	0.107**	0.099**	0.083*
	(0.003)	(0.012)	(0.023)	(0.038)	(0.044)	(0.048)	(0.044)
Panel B: *Reduced form*							
Non-Fox TVs on × Fox share	0.055***	0.201***	0.431***	0.302*	0.169	0.011	0.012
	(0.014)	(0.049)	(0.108)	(0.163)	(0.198)	(0.205)	(0.199)
Panel C: *Two-stage least squares*							
H-C viewership difference (predicted)	0.049***	0.182***	0.389***	0.273*	0.152	0.010	0.011
	(0.016)	(0.049)	(0.112)	(0.145)	(0.180)	(0.185)	(0.180)
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 reports OLS estimates of the inverse hyperbolic sine of cases upon the standardized difference in Hannity-Carlson viewership. Panel B reports reduced-form estimates of the inverse hyperbolic sine of cases upon the instrument, $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$— that is, the 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 C reports two-stage least squares estimates of the inverse hyperbolic sine of cases upon the standardized difference in Hannity-Carlson viewership, instrumented by $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$. OLS controls include the number 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, log distance to Seattle, 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. IV controls are identical to OLS controls, except the number of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle* are replaced with the predicted number of TVs tuned to non-Fox channels during these timeslots. Standard errors are clustered at the DMA level. Robust standard errors are reported.

Table D2: Effect of differential viewership on deaths

	Dependent variable:					
	COVID-19 deaths					
	Mar 07	Mar 14	Mar 21	Mar 28	Apr 04	Apr 11
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *Ordinary least squares*						
Hannity-Carlson viewership difference	0.006	0.005	0.027***	0.054**	0.080**	0.112***
	(0.005)	(0.006)	(0.010)	(0.023)	(0.036)	(0.043)
Panel B: *Reduced form*						
Non-Fox TVs on × Fox share	0.022	0.013	0.096***	0.328***	0.450***	0.342*
	(0.014)	(0.020)	(0.037)	(0.082)	(0.154)	(0.188)
Panel C: *Two-stage least squares*						
H-C viewership difference (predicted)	0.020*	0.012	0.087***	0.297***	0.407**	0.308*
	(0.011)	(0.017)	(0.031)	(0.091)	(0.168)	(0.182)
Full controls	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	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 inverse hyperbolic sine of deaths upon the standardized difference in Hannity-Carlson viewership. Panel B reports reduced-form estimates of the inverse hyperbolic sine of deaths upon the instrument, $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$— that is, the 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 C reports two-stage least squares estimates of the inverse hyperbolic sine of deaths upon the standardized difference in Hannity-Carlson viewership, instrumented by $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$. OLS controls include the number 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, log distance to Seattle, 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. IV controls are identical to OLS controls, except the number of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle* are replaced with the predicted number of TVs tuned to non-Fox channels during these timeslots. Standard errors are clustered at the DMA level. Robust standard errors are reported.

Table D3: 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	0.551***	0.545***				
	(0.053)	(0.052)				
Panel B: *RF: inverse pandemic coverage index on instrument*						
$\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$			0.510**	0.541**		
			(0.218)	(0.226)		
Panel C: *2SLS: cases and deaths on inverse predicted pandemic coverage index*						
$-1\times$ coverage index (predicted)					0.796**	0.607**
					(0.359)	(0.297)
Base controls	Yes	Yes	Yes	Yes	Yes	Yes
Main controls	No	Yes	No	Yes	Yes	Yes
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, $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$— that is, the number of TVs on during Hannity's timeslot, 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 $\widehat{\text{NonFoxHannity}}_d \times \text{FoxShare}_d$. Base OLS controls include the number 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 number of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle* are replaced with the predicted number of TVs tuned to non-Fox channels during these timeslots. Main controls for both OLS and IV include population-weighted latitude and longitude, log distance to Seattle, 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. Robust standard errors are reported.

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?

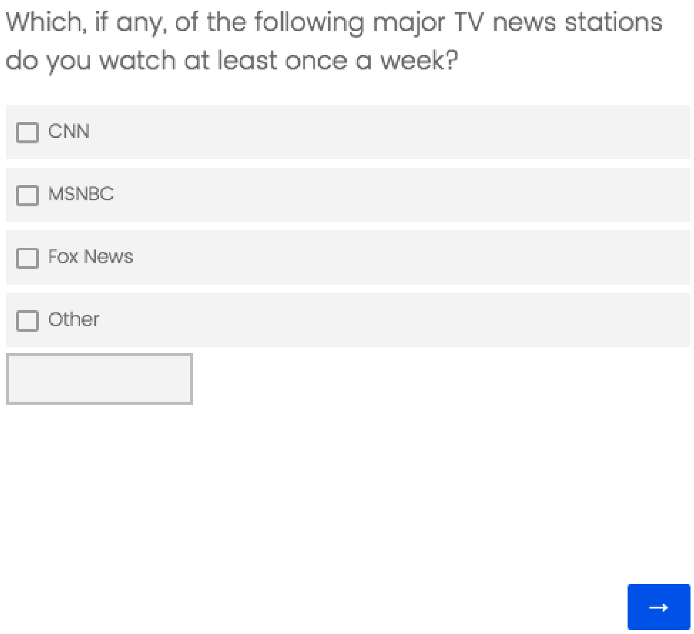
- ◯ Yes
- ◯ No

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.

→