WORKING PAPER · NO. 2020-67

The Persuasive Effect of Fox News: Non-Compliance with Social Distancing During the COVID-19 Pandemic

Andrey Simonov, Szymon Sacher, Jean-Pierre Dubé, and Shirsho Biswas

JULY 2020

Becker Friedman Institute
FOR ECONOMICS AT UCHICAGO

5757 S. University Ave.
Chicago, IL 60637
Main: 773.702.5599
bfi.uchicago.edu

The Persuasive Effect of Fox News: Non-Compliance with Social Distancing During the Covid-19 Pandemic

Andrey Simonov, Columbia Business School*
Szymon Sacher, Columbia University
Jean-Pierre Dubé, Chicago Booth and NBER
Shirsho Biswas, Chicago Booth

July 28, 2020

Abstract

We test for and measure the effects of cable news in the US on regional differences in compliance with recommendations by health experts to practice social distancing during the early stages of the COVID-19 pandemic. We use a quasi-experimental design to estimate the causal effect of Fox News viewership on stay-at-home behavior by using only the incremental local viewership due to the quasi-random assignment of channel positions in a local cable line-up. We find that a 10% increase in Fox News cable viewership (approximately 0.13 higher viewer rating points) leads to a 1.3 percentage point reduction in the propensity to stay at home. We find a persuasion rate of Fox News on non-compliance with stay-at-home behavior during the crisis of about $5.7\% - 28.4\%$ across our various social distancing metrics.

*Authors contributed equally and names are listed in reverse alphabetical order. E-mail: as5443@gsb.columbia.edu, szymon.sacher@columbia.edu, jdube@chicagobooth.edu, sbiswas@chicagobooth.edu. We thank Nielsen, SafeGraph, HomeBase and Facteus for providing access to the data. We also thank the NBER for helping with the purchase of some of the Nielsen data. The opinions expressed in this paper do not reflect those of the data providers. We are extremely grateful to Matt Gentzkow for extensive comments and suggestions. We also thank Tomomichi Amano, Charles Angelucci, Oded Netzer, Maria Petrova, Andrea Prat, Anita Rao, Olivier Toubia, Raluca Ursu, Ali Yurukoglu, participants of the NYC Media Seminar, 2020 Marketing Science conference, and the Columbia COVID-19 Symposium for comments and suggestions. Supported by the Chazen Institute for Global Business at Columbia Business School. Dubé acknowledges research support from the Kilts Center for Marketing and the Charles E. Merrill faculty research fund.

1 Introduction

The COVID-19 crisis has renewed concerns about the dangers of misinformation and its persuasive effects on behavior. The US response to the pandemic is deeply divided along partisan lines, with Republicans more skeptical about the risks of the pandemic and less engaged in social distancing than Democrats (Barrios and Hochberg, 2020; Allcott et al., 2020). Correlations between these differences in reactions and beliefs and exposure to the left- and right-leaning news sources (PewResearch, 2020) are suggestive, albeit inconclusive, of an effect of differential messaging by politicians (Beauchamp, 2020) and the major media outlets that support them (Aleem, 2020). The largest US cable news channel, Fox News, finds itself at the heart of this controversy, with a class action[1] alleging that Fox News and other defendants "willfully and maliciously disseminate false information denying and minimizing the danger posed by the spread of the novel Coronavirus, or COVID-19, which is now recognized as an international pandemic" (Ecarma, 2020). The persuasive effect of a leading news media channel could have harmful consequences for the public if viewers disregard the social-distancing practices recommended by leading health experts and health organizations (CDC, 2020b; Kissler et al., 2020a). In addition to personal health risks, non-compliance could also create a negative health externality through the transmission of disease to others in the community (Ferguson et al., 2020).

We test for and measure the potential persuasive effect of Fox News viewership on social distancing compliance during the early stages of the COVID-19 pandemic in the US.[2] The COVID-19 outbreak is not the first instance where a US media outlet like Fox News finds itself accused of broadcasting misinformation.[3] However, a persuasive effect during the COVID-19 crisis allows us to test whether Fox can affect behavior in a way that defies the recommendations of health experts. An extant literature has found how slanted news coverage can cause viewers to doubt or reject well-established scientific expert advice on policies for global warming (Hmielowski et al., 2014) and vaccinations (Lewandowsky et al., 2017). The literature on advice-taking has found in lab studies that decision-makers tend to overweight their opinions relative to those of an advisor leading to inferior outcomes, even when the advisor is recognized as a highly-trained expert (e.g, Harvey and Fischer (1997) and survey by Bonaccio and Dalal (2006)). Our case study therefore

[1] Claim #604 171 241, filed on April 2, 2020 by the Washington League For Increased Transparency and Ethics. See https://www.sos.wa.gov/corps/business.aspx?ubi=604171241.

[2] See also the contemporaneous study by Bursztyn et al. (2020).

[3] A recent literature has analyzed what appears to be an increase in the supply of fake news, especially online (Flynn et al., 2017; Lazer et al., 2018; Allcott et al., 2019). Some studies have demonstrated that fake news is seen and recalled by consumers and, in some cases, changes their beliefs. During the 2016 elections, Allcott and Gentzkow (2017) estimate that the average US voter saw and remembered at least one fake news story. Media misinformation can also have a persuasive impact on beliefs (Allcott and Gentzkow, 2017; Guess et al., 2018).

offers a novel opportunity both to test for a persuasive effect of news media and its potential to impact behavior in a manner that defies expert advice during a crisis.

Our key data consist of Nielsen's NLTV panel, measuring differences across US cable systems in the viewership of the three leading cable news channels: FOX News, CNN and MSNBC; although in the main analysis we focus on the first two due to their higher viewership levels. Nielsen's FOCUS data tracking the line-up of channels across US cable markets will also play a key role in our empirical strategy. We match viewership with a specific form of social distancing behavior: the propensity to stay at home. Stay-at-home behavior is not only easier to measure, it also matches more closely with state and municipal measures to manage compliance with social-distancing behavior (hereafter "SD"). Since most social distancing policies allow for some forms of essential trips away from home, we use SafeGraph data that track multiple forms of stay-at-home behavior derived from cellphone location data. We then measure SD as the within-market evolution in daily stay-at-home propensity relative to the baseline level in January 2020, before the US outbreak of COVID-19. To measure the impact of social distancing on economic outcomes, we use transaction data from Facteus and firm closure data and employee counts from Homebase.

Our key empirical challenge arises from the likely self-selection of consumers' cable news viewing choices. Consumers base their television viewership choices on preferences that are likely to be correlated with the factors influencing their SD choices. Following Martin and Yurukoglu (2017), we exploit the quasi-random assignment of each news channel's relative position across cable markets. We find that channel position is a strong instrument and that a 1 standard deviation decrease in position (towards 0) increases viewership by 0.158 rating points for Fox, and 0.091 rating points for CNN. News channel position across markets is also independent of the socio-demographic factors that predict differences in SD behavior, consistent with our assumption of random position assignment. Our IV approach will only use the incremental viewership across markets induced by differences in channel position to measure the persuasive effect of viewership on SD.

OLS analysis of our SD measures generate a positive and statistically significant effect of Fox News viewership from early March onwards. However, our IV estimates are considerably larger and indicate a take-off in the Fox News effect in early March and a stabilization in mid March, almost immediately after the declaration of a national emergency. We find that a 10% increase in Fox News cable viewership (approximately 0.13 viewer rating points), which is approximately the viewership change induced by a one standard deviation change in the Fox News channel position, leads to a 1.3 percentage point reduction in the propensity to stay at home. The corresponding average partial effect of Fox news viewership implies that 1 rating point increase (near doubling) in cable viewership of Fox News reduces the propensity to stay at home by 9.9 percentage points compared to the pre-pandemic average. Since the supply-side measures, such as business closures, start to happen only two weeks later after the take-off of Fox News effects, the magnitudes of the viewership effects reflect the persuasive effect of Fox News on viewers and not a feedback effect from the equilibrium response of firms, at least early on. Our findings for CNN are inconclusive, with imprecise point estimates centered near zero. Our findings imply a persuasion rate of Fox News on non-compliance with stay-at-home behavior during the crisis of about $5.7\% - 28.4\%$ across our various social distancing metrics. These magnitudes are comparable with the persuasion rate of Fox News on voting behavior in the 2004 and 2008 presidential elections (Martin and Yurukoglu, 2017). An exploratory analysis of transaction data from debit cards produces inconclusive findings regarding an effect of Fox News viewership on consumer shopping behavior.

Our data do not enable us to test the underlying mechanism through which Fox News viewership generates a persuasive effect on social distancing compliance. DellaVigna and Gentzkow (2010) discuss two potential mechanisms. First, Fox News may change viewers' beliefs in ways that diverge from those expressed by leading health experts, causing a divergence from the recommended behavior or "egocentric advice discounting" (e.g. Yaniv and Kleinberger (2000) and Yaniv (2004)). For instance, the coverage of COVID-19 may persuade viewers that social distancing is less effective than experts claim.[4] Independently of the content of current broadcasts, long-term exposure to Fox News may simply cause broad distrust in scientific experts (Hmielowski et al., 2014) or in institutions (Sapienza and Zingales, 2012), including government agencies like the CDC, perhaps destroying local social capital (Guiso et al., 2004) and, in turn, reducing the propensity to internalize the externality from leaving home during the pandemic. Second, Fox News viewership may reduce a viewer's utility from SD compliance.[5]

We also cannot directly test the extent to which our Fox News viewership effects reflect direct persuasive effects as opposed to indirect effects mediated by political polarization (Martin and Yurukoglu, 2017; Allcott et al., 2020). A growing association between distrust in scientific research and conservative political views has emerged in the US since the 1970s (Gauchat, 2012); although cultural worldviews have been found to be stronger predictors of trust in scientific experts than political opinions (Weaver et al., 2017; Leiserowitz et al., 2013). We provide suggestive evidence supporting the direct persuasive effect of Fox News on SD. Our findings are strongest in markets

[4] Several studies have studied the impact of fake news on beliefs (Allcott and Gentzkow, 2017; Barrera et al., 2020) and its potential persuasive effect on voting behavior (Guess et al., 2018).

[5] For instance, Tuchman et al. (2018) find a complementary effect of brand advertising on consumer propensity to buy the advertised brand, and Kamenica et al. (2013) find a physiological effect of advertising on the efficacy of a drug. Viewership of Fox News might value the defiant aspects of non-compliance in social distancing behavior.

with the highest Democratic party vote shares during the 2016 election, suggesting that viewers in strong Democrat markets are the most likely to be persuaded. In addition, our Fox News effects are largest in late March and April when the White House actively endorsed the CDC's recommendations for SD and lockdown but several Fox News hosts maintained their active stance against these measures.

We do not attempt to attribute the Fox News effects to health outcomes, namely cases and deaths, for several reasons. First, to the best of our knowledge, COVID-19-related cases and deaths are tracked at the more aggregate county level and not at the zipcode level. Second, at the time of writing, experts still disagreed about the accuracy and reliability of current data which would limit the interpretabilty of any association we might find with our behavioral outcomes (e.g., Nishiura et al. (2020) and Akhmetzhanov et al. (2020)); although Hortacsu et al. (2020) have developed a promising approach to infer the number of unreported infections. Multiple studies have pointed towards the importance of social distancing for containing the disease (Matrajt and Leung, 2020; Kissler et al., 2020b). Therefore, we believe our findings of FOX News effect on compliance should inform epidemiological models on the extent to which, if any, these viewership effects are large enough to impact transmission rates of the disease.

Our findings add to a rapidly-emerging body of literature studying differential rates of compliance in social distancing across the US in response to the Covid-19 pandemic. Several studies have looked at differences associated with political partisanship, such as the correlation between perceptions of risk, Trump support and social distancing (Barrios and Hochberg, 2020; Allcott et al., 2020), beliefs associated with support for the Republican versus Democratic party (Painter and Qiu, 2020), income (Wright et al., 2020), ethnic diversity (Egorov et al., 2020), or internet access (Chiou and Tucker, 2020). Our work complements these findings by establishing a causal effect of Fox News viewership on SD, which may account for some of these other correlates to the extent that Fox viewership is correlated with political beliefs and other factors.[6]

Closest to our work is the contemporaneous study by Bursztyn et al. (2020) to compare the effects of viewership for *Hannity* and *Tucker Carlson Tonight*, two shows with different coverage of COVID-19 coverage, on social distancing behavior. Our work differs in three important ways. First, we measure the effect of TV viewers' exposure to Fox News overall, rather than to a specific show. Second, we measure SD compliance using actual cellphone movement data, allowing us to attribute the effect of Fox News viewership on realized forms of social distancing. In contrast, Bursztyn et al. (2020) use self-reported behavior from a survey of approximately 1,000 people.

[6]Gitmez et al. (2020) discuss this causal effect in the context of a theoretical model with endogenous acquisition of information by news consumers in the economy.

Similarly, our data and identification strategy uses a granular cross-section of thousands of cable-system level markets, as opposed to the coarser 210 DMA markets used in Bursztyn et al. (2020).

More broadly, our work contributes to research on the persuasive effects of the news media on on political opinion (Gerber et al., 2009) and various behaviors including political participation (Gentzkow, 2006; Cagé, 2019), voting (Chiang and Knight, 2011; Snyder Jr and Strömberg, 2010; Enikolopov et al., 2011), criminal sentencing decisions (Lim et al., 2015), hurricane evacuations (Long et al., 2019), global warming (Hmielowski et al., 2014), and genocide (Yanagizawa-Drott, 2014).[7] A subset of this work has found a persuasive effect of Fox News on voting behavior (DellaVigna and Kaplan, 2007; Martin and Yurukoglu, 2017) and criminal sentencing (Ash and Poyker, 2019). A related literature has looked at the supply of fake news (e.g., Allcott et al., 2019) and the persuasive effect of fake news on beliefs (Allcott and Gentzkow, 2017; Guess et al., 2018); although persuasive effects have mainly been measured for small news outlets and online social media platforms. Our use of the Martin and Yurukoglu (2017) instrument reflects a broader literature devising empirical strategies to measure the causal effect of communication media on sales.[8]

Sections 2, 3, 4, 5 and 6, respectively, present a discussion of misinformation during the US COVID-19 outbreak, our empirical model, our data, our results and our conclusions.

2 Fox, Misinformation and Social Distancing During the COVID-19 Outbreak in the US

Forty-nine percent of the US population uses television news programs as their primary source of news (Shearer, 2018). It is therefore unsurprising that groups like the WLFITE have concentrated their concerns about the potential harmful effects of alleged misinformation during the COVID-19 outbreak at Fox News, the largest US cable news channel for the past decade (Wulfsohn, 2020). Of interest is whether exposure to cable news can persuade viewers to disregard warnings by the global health community and engage in behaviors deemed risky by most health experts. As explained above, it is unclear whether viewership effects reflect the impact of specific broadcasts per se or reflect the effects of long-term exposure on trust in institutions or polarized attitudes

[7] Shapiro (2016) provides a model of media coverage of scientific information and applies it to the coverage of climate change.

[8] These methods include geographic regression discontinuities (e.g., Shapiro, 2018; Shapiro et al., 2019; Spenkuch and Toniatti, 2016), timing discontinuities (e.g., Sinkinson and Starc, 2019), instrumental variables (e.g., Gordon and Hartmann, 2016) and the difference in timing between advertising scheduling and viewership, especially for Superbowl ads (e.g., Hartmann and Klapper, 2016; Stephens-Davidowitz et al., 2017).

towards a specific political party. Regardless of the mechanism, Fox News' coverage of COVID-19 has renewed concerns about potential risks from exposure (short or long-term) to misinformation.

On January 30, 2020 the WHO declared COVID-19 as an international public health emergency (Nedelman, 2020). Meanwhile, FOX News broadcast a series of stories downplaying the potential risks from Covid-19 in the US throughout March 2020 as the virus began to threaten the US and as Americans were forming beliefs about the severity of the threat. On February 27, host Laura Ingraham accused the Democratic party of "weaponizing fear," referring to them as the "pandemic party" (The Ingraham Angle, 2020c). On March 10, popular Fox News host, Sean Hannity, downplayed the risks of the outbreak:

> "So far in the United States, there's 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...Put it in perspective: 26 people were shot in Chicago alone over the weekend. I doubt you heard about it. You notice there's no widespread hysteria about violence in Chicago." (MediaMatters, 2020)

On the same day, Ingraham echoed this sentiment of the low risks from COVID-19:

> "We need to take care of our seniors. If you're an elderly person or have a serious underlying condition, avoid tight, closed places, a lot of people, don't take a cruise maybe. Everyone else wash your hands, use good judgment about your daily activities." (Farhi and Ellison, 2020)

Some of the Fox News opinions echoed statements from the White House. On February 2, 2020, President Trump explained to Fox New host, Sean Hannity: "We pretty much shut it [COVID-19] down coming in from China." (Puhak, 2020). On March 9, the day before the Hannity broadcast above, President Trump tweeted: "The Fake News Media and their partner, the Democrat Party, is doing everything within its semi-considerable power (it used to be greater!) to inflame the CoronaVirus situation, far beyond what the facts would warrant. Surgeon General, "The risk is low to the average American." It was not until President Trump's declaration of a National Emergency on March 13 (85 FR 15337) that Hannity suddenly referred to the virus as a "crisis."

In spite of these parallels, Fox News coverage frequently diverged from the opinions of the White House. On March 13, Johns Hopkins recommended social distancing in the US (Pearce, 2020) and, the following day, the CDC recommended cancelling events with more than 50 people (Kopecki, 2020). Later that week, President Trump explained in a news conference: "Therefore, my administration is recommending that all Americans, including the young and healthy, work to engage in schooling from home when possible, avoid gathering in groups of more than 10 people, avoid discretionary travel and avoid eating and drinking at bars, restaurants and public food courts." (Ari Shapiro and Richard Harris, 2020). Nevertheless, several Fox News hosts continued to question the efficacy of social distancing and the reliability of health experts' recommendations. Ingraham broadcast "Coronavirus crisis is teaching us a lot about so-called experts," referring to scientific predictions of the disease spread as "lame panic-inducing models" (The Ingraham Angle, 2020a). Even as late as April 30, Ingraham continued to dispute the effectiveness of social distancing, arguing "Experts don't like to admit their wrong, do they?" (The Ingraham Angle, 2020b).

The second-largest US cable news channel, CNN, adopted a more dire tone consistent with the views and recommendations of health experts. For instance, On February 13, CNN broadcast an interview with CDC Director Dr. Robert Redfield, who predicted a widespread community transmission. On February 26, CNN highlighted the following warning from a senior CDC official: "It's not a question of if coronavirus will spread, but when." (Darcy, 2020) On March 2, they published a story criticizing the Trump administration's response as being out of step with the CDC (McLaughlin and Almasy, 2020). CNN also warned about potentially misleading information on Fox News (Cohen and Merrill, 2020). The third-largest channel, MSNBC, broadcast coverage that was materially similar to CNN, including early warnings about the severity of COVID-19 (The Rachel Maddow Show, 2020; Deadline: White House, 2020).

A persuasive effect of cable news viewership during the pandemic could potentially generate important health and economic implications. According to the Imperial College COVID-19 Team (Ferguson et al. (2020), page 1), an optimal mitigation policy "...might reduce peak healthcare demand by 2/3 and deaths by half." (Ferguson et al. (2020), page 14). Similarly, Lewnard and Lo (2020) describe social distancing as "the only strategy against COVID-19" while pharmaceutical intervention are not available (p. 1).

A persuasive effect of cable news viewership could also have economic implications:

> "In the near term, public health objectives necessitate people staying home from shopping and work, especially if they are sick or at risk. So production and spending must inevitably decline for a time." (Bernanke and Yellen, 2020)

Exposure to the virus impacts the economy both through its effect on consumer spending, on the demand side, and through labor supply, on the supply side. Eichenbaum et al. (2020) demonstrate how "these [containment] policies exacerbate the recession but raise welfare by reducing the death toll caused by the epidemic" (p.1). We therefore anticipate that a persuasive effect of cable news viewership on SD compliance could, in turn, generate both supply and demand-side economic impacts.

3 Model

The CDC defines social distancing as "keeping space between yourself and other people outside of your home. To practice social or physical distancing: stay at least 6 feet (2 meters) from other people, do not gather in groups, stay out of crowded places and avoid mass gatherings" (CDC, 2020b). To enforce social distancing, many state and local governments adopted stay-at-home and shelter-in-place orders to increase the local propensity to stay at home.[9] We focus the remainder of our analysis on compliance with increased stay-at-home behavior.

For an individual h in a given market z on day t, the difference in indirect utility from leaving home versus staying is given by:

$$U_{zt}^{h} = \alpha_z + \sum_{c\in\mathscr{C}} \beta_{ct}\text{rating}_{cz} + \lambda_z(t) + \xi_{zt} + \varepsilon_{zt}^{h} \tag{1}$$

where α_z captures local differences in amenities like stores and labor opportunities, $\lambda_z(t)$ allows for potentially differential trends across markets such as seasonality and weather as well as changes in local economic amenities, ξ_{zt} is a (unobserved to the researcher) mean-zero, common shock to the market, and ε_{zt}^{h} is a uniformly-distributed idiosyncratic random utility shock. Finally, rating_{cz} measures the time-invariant (long term) viewership measure for news channel $c \in \mathscr{C}$ in market z. This model is consistent with a dynamic discrete choice version of the framework in Allcott et al. (2020) where staying at home reflects the inter-temporal trade-offs between leaving home today (e.g., for consumption and/or labor purposes captured by α_z, $\lambda_z(t)$ and ξ_{zt}) and the expected, future health risks to the individual. In that framework, $\beta_{ct}\text{rating}_{cz}$ captures the impact of viewership of channel c on an individual's expected future health risks.

If individuals make decisions to stay at home to maximize utility, then the probability of staying at home, y_{zt}, in market z on day t is:

$$y_{zt} = \alpha_z + \sum_{c\in\mathscr{C}} \beta_{ct}\text{rating}_{cz} + \lambda_z(t) + \xi_{zt}, \tag{2}$$

[9]For instance, Sonoma County imposed the following measures: "Stay home and only go out for 'essential activities,' to work for an 'essential business,' or for 'essential travel' as those terms are defined in the Order" (socoemergency.org, 2020).

the linear probability model (Heckman and Snyder, 1997).

During the base period, before social distancing was relevant in the US, expected stay-at-home behavior is $\mathbb{E}(y_{z\tau})$. We define this base period as $\{\tau|\tau < \underline{t}\}$ where $\underline{t}$ denotes the first date during which compliance with social distancing became relevant. We assume that cable news has no impact on a household's propensity to stay at home prior to the COVID-19 outbreak in the US in 2020: $\beta_{c\tau} = 0, \ \forall\tau \ < \underline{t}$. The market fixed-effect α_z already accounts for persistent effects of viewership on behavior and, thus, β_{ct} captures deviations over time in channel c's impact on behavior. In our analysis below, we will analyze the timing of the start of social distancing as well as the potential impact of news on this behavior.

We then define compliance with social distancing as the change in staying-at-home behavior after the emergence of COVID-19 in the US relative to a base pre-COVID period $\tau < \underline{t}$. Formally, we define compliance, SD_{zt} as follows

$$SD_{zt} \equiv y_{zt} - \mathbb{E}(y_{z\tau}|\tau < \underline{t}). \tag{3}$$

Combining (2) and (3), we obtain our model of SD_{zt} and its determinants:

$$SD_{zt} = \beta_{ct}\text{rating}_{cz} + \Delta\lambda_z(t) + \xi_{zt} \tag{4}$$

where $\Delta\lambda_z(t)$ is a difference relative to the base period $\tau < \underline{(t)}$ allowing for SD to evolve in response to differential changes across markets such as the timing and stringency of local stay-at-home and shelter-in-place orders.

Our key parameter, β_{ct}, measures the daily effect of cable news channel c viewership on SD_{zt}. Suppose we compare two markets, A and B, where market B has 1 rating point higher viewership of channel c, r_{cz}. We would expect to observe $|\beta_{ct}|$ percentage points less SD_{zt} on any given day t in market B than in market A, measured as the change in stay-at-home behavior relative to the base, pre-COVID period.

4 Data and Descriptive Analysis

4.1 Cable News Viewership

We use Nielsen's monthly NLTV data to measure viewership of the three leading US cable news channels – Fox News, CNN and MSNBC. We obtained the 2015 data through a partnership between Nielsen and the NBER. Since 2015 is the most recent year available through the NBER, we also purchased the 2020 data directly from Nielsen. Nielsen tracks cable television audience sizes using a rotating panel of households with meters and diaries recording their television viewing behavior. We do not have access to the individual-level viewership behavior. The NLTV data we obtained measure each channel's viewership as the percentage of panelists who tune in to the channel for at least five successive minutes during a given quarter-hour time interval of the day. Each channel's monthly viewership rating consists of the average cable viewership for each channel within a market across days and quarter-hour time slots.

Ideally, we would use viewership from 2020. However, recent changes to Nielsen's survey methodology limit the scope of geographic regions for which cable system level or zipcode level data are available. In 2020, only 44 of the 210 DMAs have zipcode-level data and the panelist counts are low,[10] exacerbating potential classical measurement error in our analyses below. For instance, we observe zero panelists viewing Fox News in 71.3% of these zipcodes even though Fox is the most highly-watched cable news channel.

Instead, we use cable system level, or "headend"[11], data from November 2015, the most recent period for which we have access to broad geographic coverage spanning 2,536 unique headends, representing 30,517 zip codes from the 210 DMAs across the US.[12] As we demonstrate below, channel positions change very infrequently within a cable market. So, as long as the relationship between viewership and position is persistent over time, our use of 2015 viewership data should provide a reasonable proxy for 2020. We look at the persistent in this relationship in section 5.1 below. Furthermore, since our channel position instrument only affects cable subscribers in a market, we use viewership data for cable subscribers in the headend. Analogous cable-subscriber data were also used in previous work measuring viewership effects (Martin and Yurukoglu, 2017). In 2019, 71% of US households had access to television[13] and, according to 2020 NLTV data, 61% of these households subscribed to cable service. Therefore, our viewership data represent approximately 43% of the population.

We report descriptive statistics for each channel's viewership ratings in November 2015 in Table 1. Fox News stands out in its viewership, with an average monthly rating of 1.32%, higher than the combined rating of both CNN and MSNBC (0.51% and 0.34% respectively). In other words, on average, 1.32% of a headend's viewers tune into Fox News during a given time slot in a given month. Although not reported in the table, the population-adjusted probability of being the highest-watched news channel in a headend is 65% for Fox News, 25% for CNN and 10%

[10] Only 7,294 zipcodes have at least one panelist and 94% of these zipcodes have less than 10 panelists.

[11] A cable television headend is a master facility for receiving television signals for processing and distribution over a cable television system.

[12] Apppendix A.3 describes how we pre-process the data.

[13] `https://nscreenmedia.com/us-pay-tv/`

for MSNBC. Therefore, the overwhelming majority of US viewers rely on Fox News as their primary source for news. For the remainder of our analysis, we will focus on the effect of Fox News viewership, while controlling for CNN and MSNBC as relevant competitors. In each of our analyses, we will also look at the effect of the second-ranked channel, CNN, as a basis of comparison.

[Table 1 about here.]

4.2 Cable Systems' Assignments of Channel Positions

We purchased Nielsen's 2015 FOCUS data to determine the channel lineups across headends. As in Martin and Yurukoglu (2017), we use the channel's ordinal position (hereafter referred to as "position") instead of the exact numeric position to which a cable channel is assigned.[14] Ordinal positions correct for the occasional gaps in the lineups in some headends. We observe very little change in a channel's position over time within a market. Pooling each year between 2006 and 2015, we find that headend fixed-effects explain between 81% and 85% of the variation in positions across headends and years for the three channels, whereas time fixed effects explain less than 2.5%. In Table A6 in the Appendix A.11, we show that only 4% of the headend-channel positions change from year to year. In sum, 2015 head-end positions should provide a good proxy for 2020.

Table 2 presents summary statistics of the channel positions across headends for each channel. On average, CNN has the most favorable position, 34.8, relative to Fox News and MSNBC, with respective average positions of 43.2 and 49.6. However, we also observe variation in each channel's position across headends, with standard deviations ranging from 17.7 to 23.4 and coefficients of variation ranging from 0.41-0.53. To demonstrate the variation in positions, we present the distribution of cable news channel positions across headends in Figure 1. On average, the population-adjusted probability that each channel has the most favorable position in a given market is 74% for CNN, versus 14% for MSNBC and 12% for Fox News. As we show in section 5.1 below, this variation in position is uncorrelated with market characteristics that predict viewership levels.

[Table 2 about here.]

[Figure 1 about here.]

[14] Our substantive findings do not change if we instead use the numeric positions.

4.3 Stay-at-Home Rates

We base our SD measures on household propensities to stay at home. Besides being more consistent with state and local orders to enforce social distancing, staying at home is also easier to measure than social distancing which would require monitoring the geographic proximity of individuals and the density of gatherings of individuals.[15]

We use Safegraph data that track the GPS locations from millions of US cellphones to construct a daily panel of census-block-level aggregate movements measures from January 1 to April 24, 2020.[16] Safegraph makes these data available to academic researchers through their SafeGraph COVID-19 Data Consortium. During this period, we observe an average daily number of 7.75 million devices overall and 265.17 in a given zipcode. We use these device data to construct three daily measures of staying at home propensity by zipcode: (1) the share of devices that stayed at home, (2) the share of devices that traveled to work for a part-time day, and (3) the share of devices that traveled to work for a full-time day. The measures of full-time and part-time work travel are inferred by Safegraph as follows. Part-time work is the share of devices in a market-day that dwell in the same away-from-home location between 3 and 6 hours between 8am and 6pm local time. Full-time work is measured the same way using a minimum of 6 hours of away-from-home dwell time in the same location.

Table 3 panel (a) presents summary statistics of within-zipcode means for each of our Safegraph propensity variables during January 2020. Recall that we will use these means as our baseline stay-at-home level in each market prior to the COVID-19 outbreak in the US.[17] On average, we see that 23% of mobile devices remain at home in January; although we observe a lot of cross-market heterogeneity. Accordingly, our SD measures account for these heterogeneous baseline behaviors by looking at the difference in stay-at-home propensity relative to January.

[Table 3 about here.]

To summarize the evolution of stay-at-home behavior, Figure 2(a) reports the cross-zipcode daily mean for each of our three Safegraph propensity variables. Surprisingly, we see no evidence of a change in the overall mean daily stay-at-home propensity before March 13th, the date President Trump declared a national emergency. On March 13th, the level of stay-at-home propensity lies within the range observed as far back as January 1, 2020. In fact, several states had already issued

[15] Bursztyn et al. (2020) circumvent this problem using self-reported rates of social distancing with a survey.

[16] For a detailed description of the data, please visit: `https://docs.safegraph.com/docs/social-distancing-metrics`.

[17] The CDC reports the first US case of COVID-19 on January 22, 2020 (CDC, 2020a). But as we show below, we find no discernible change in SD behavior until March 2020.

their own emergency declarations much earlier: Washington (February 29), California (March 4), New York (March 7) and Lousiana (March 11) (Lasry et al., 2020). We do not detect a national increase in SD (i.e., growth in stay-at-home relative to January) until March 14 for each of our three measures. By April 1, 2020, the share of devices staying home almost doubles relative to January, an increase of almost 20 percentage points. We see comparable timing in the pattern of declines in SD measured through work trips; although the magnitudes are smaller at approximately 5 percentage points.

For the remainder of our analysis, we use equation (3) to define SD for each of our three Safegraph measures where January 2020 is our base, per-COVID-19 period:

$$SD_{zt} = y_{zt} - \bar{y}_{z,Jan} \tag{5}$$

where $\bar{y}_{z,Jan}$ is the within-market-z mean SD across each of the days in January, 2020. Table 3 presents summary statistics of the daily SD measures across zipcodes between February 1 and July 10, 2020. This period pools days before and after the start of the COVID-19 crisis in the US. On April 1, 2020, we find that the average SD is 16.5, -7.3 and -4.4 percentage points based on the share of homebound devices, share of devices at work full time and share of devices at work part time, respectively. That same day, we observe a positive SD based on homebound devices in more than 98% of zipcodes. Therefore, by April all zipcodes have experienced at least some compliance in the sense of higher stay-at-home rates than in January 2020.

[Figure 2 about here.]

4.4 Business Closures and the Supply Side

By reducing consumption, social distancing compliance also generates a demand shock to local businesses, as well as a potential labor supply shock. We use local US business data from Homebase,[18] a scheduling and timesheet company that tracks the hours worked by the employees of small businesses. The data track the daily hours worked for 695,782 employees and managers from 68,307 firms and 78,850 business locations, across 9 industries. The data span 15,783 zipcodes for the period from January 1, 2020 to July 4th, 2020. The largest industries represented are food and beverages, retail, and health care and fitness. For each zipcode and day, we compute the total number of firms reported "still open" (at least one worker checked in) and the total number of workers that sign into work. We report descriptive statistics in the part (c) of Table 3. The average zipcode-day has 2.43 open firms and 10.72 signed-in workers.

[18] `https://joinhomebase.com/data/`

To analyze the potential impact of COVID-19, we plot the time-series of the cross-zipcode average daily number firms open and number of workers signed-in in Figure 2, panel (b). As expected, our two supply-side variables track our three SD variables closely, with a large negative shock on March 13, the timing of the declaration of a national emergency. We observe a gradual decline that stabilizes in late March. Prior to March 13, both number of businesses open and number of workers that sign into work are stable from January until mid March, except for the systematic day-of-week effects. This coincidence of changes in supply-side and demand-side variables with the emergency declaration raises a potential concern about the exact interpretation of a persuasive effect of Fox News Viewership on SD. To the extent that a Fox News effect on SD contributes to incremental local business closures, our estimates of a Fox News effect on SD might be over-stated if they also capture an indirect feedback effect through business closures on the supply-side of the market. We discuss this issue in our analysis of the results in section 5.4 below.

4.5 Consumer Spending

The recent macroeconomic literature analyzing the economic and health trade-offs from COVID-19 and containment policies recognizes the direct impact of social distancing on consumer demand and consumption behavior. We use Facteus, a provider of financial data for business analytics, to obtain measures of consumer spending activity by zipcode. The Facteus debit card transaction panel contains approximately 10 million debit cards issued by "Challenger Banks,"[19] payroll cards,[20] and government cards.[21] Therefore, the cardholder panelists tend to come from middle and lower income brackets, a segment of the population that is likely more affected by COVID-19 financially. The transactions are aggregated each day for each of 321 Merchant Category Codes (MCCs) and 1,484 brand names. Table 3, panel (d), presents descriptive statistics of the number of observed transactions, debit cards used, and total expenditure.

5 Empirical Results

We analyze the determinants of SD, social distance compliance, and the role of cable news viewership. A concern with OLS estimates of equation (4) is the potential endogeneity bias in β_{ct}, which arises if cable news viewership behavior, rating_{cz}, is self-selected on aspects of viewers' preferences that also influence their SD compliance: $\mathbb{E}(\xi_{zt} \cdot \text{rating}_{cz} | X_z) \neq 0$.

[19]Challenger banks tend to be newer banks that serve underbanked consumers.
[20]Payroll cards are employer-issued debit cards for direct debit of wages to employees.
[21]Government cards are primarily issued to alimony recipients to access funds from garnished wages.

To obtain consistent estimates of β_{ct}, we instrument for viewership using the channel line-ups in local cable systems (Martin and Yurukoglu, 2017). Our key identifying moment condition is

$$\mathbb{E}(\xi_{zt} \cdot \text{position}_{cz} | X_z) = 0 \quad \forall c \in C. \tag{6}$$

We discuss our instrument and the first stage analysis in the next subsection. We then discuss our IV and OLS results for the determinants of SD.

5.1 First Stage: Channel Positions and Viewership

We now discuss our position instruments and the first-stage regression results for our IV estimator. We refer the interested reader to Martin and Yurukoglu (2017) for a thorough discussion of the validity of the moment condition (6). Our first and second stages control for the total number of channels available in a cable system since markets with more channels are more likely to assign cable news channels to higher-numbered positions. As supporting evidence of the validity of our instrument, Appendix Tables A2 and A3 show that, conditional on number of channels available, the ordinal positions of Fox News and CNN channels are uncorrelated with (i) the socio-demographic factors that predict SD, (ii) pre-COVID-19 stay-at-home behavior (January 2020), and (iii) timing of the first COVID-19 case in the county.

We run the following first-stage regression of ratings_{cz} on the exogenous variables in the model:

$$\text{rating}_{cz} = \gamma_c \text{position}_{cz} + \rho_c X_z + \eta_{cz} \quad \forall c \in C \tag{7}$$

where X_z contains market characteristics including the total number of channels in zipcode z and state fixed effects. Standard errors are clustered at the headend level. In several specifications, we weight our observations by the number of panelists in the headend to correct for sampling error in our viewership variable.

Tables 4 and A1 (latter in the Appendix) report the results from our first-stage regressions (7) for Fox and CNN, respectively. Consistent with prior literature, higher-numbered channel positions are associated with lower viewership, a finding that is robust across specifications. In the preferred specification that accounts for state fixed effects and weights observations by the number of panelists (Column 1), we find that increasing a channel's position by one position in the lineup is associated with 0.0089 and 0.005 lower rating for Fox and CNN, respectively. Therefore, a one standard-deviation improvement in channel position would increase viewership by over 0.158 rating points for Fox and over 0.092 rating points for CNN, all else equal.[22]

[22] The mean and standard deviation of Fox viewership are 1.32% and 2.6 respectively, and 0.51 and 1.5 for CNN.

Our instrument seems to work well. The magnitude of Fox's own-position effect is robust across specifications and is slightly larger in our preferred specification (column 1) that includes controls and weights and generates an incremental F-statistic of 14.22. The effect of Fox News channel position on viewership is robust to including demographic controls (Column 2), with the magnitude of the effect and precision almost unchanged. We find a similar result for the role of own-position on CNN viewership with a robust, statistically significant magnitude across specification and an incremental F-statistic that varies from 7.4 to 13.2 across specifications.

We also verify whether 2015 viewership and position data provide a reasonable proxy for 2020. As we established in section 4.2 above, channel positions change very infrequently over time. Since we use these stable channel positions as our instrument, then 2015 data will work well as long as the relationship between viewership and channel position is also stable over time. In a separate Appendix,[23] we use the November 2010 and November 2015 data on viewership to test for persistence in the first-stage relationship between positions and viewership. We fail to reject the hypotheses of equal means (i.e., equal expected viewership) and equal slope coefficients for 2010 and 2015. At the 5% significance level, we can rule out that the difference in means is larger in absolute value than 25% of one standard deviation in the observed 2015 viewership levels. We can also rule out that the difference in the predicted effect of a 1 standard deviation change in position on viewership in 2010 differs from that of 2015 by more than 14% of one standard deviation in the observed 2015 viewership levels. Using the 2020 viewership data for the first stage generates inconclusive position effects; although we fail to reject that these effects equal those using 2015 data. Finally, as we show below, the IV point estimates of the Fox News effect are qualitatively similar when we use 2020 and 2015 viewership data, but are too imprecise to be conclusive when we use 2020. Collectively, these findings confirm that the position-viewership relationship is stable over time and that 2015 viewership data provide a reasonable proxy for 2020.

[Table 4 about here.]

5.2 Second Stage: The Persuasive Effects of Cable News Viewership on SD

We now report our results for the determinants of SD and the effects of cable news viewership. Since the exact timing of emergency declarations varies over time and across states and messaging from the various news channels also varies over time, we let $\Delta\lambda_z(t)$ from equation (4) include state-specific time fixed-effects as well as competitor-channel-position time effects. We use the

[23] Available upon request.

following empirical specification of our SD model:

$$SD_{zt} = \beta_{ct}\text{rating}_{cz} + \delta_z + \sum_{s \in States} \phi_{st}\mathbb{I}_{\{z \in s\}} + \sum_{c' \in \mathscr{C}_{-c}} \zeta_{c't}\text{position}'_c + \omega_t N_z + \xi_{zt} \tag{8}$$

where the dependent variable SD_{zt} is measured as described in equation (3) above. N_z denotes the number of channels in the cable system, and $\mathscr{C}_{-c}$ denotes the set of other news channels (i.e., *CNN* and *MSNBC* when $c = Fox$) since we include time-specific effects of competitor news channel positions to control for substitution between news channels.

We report both OLS and IV estimates of equation (8).[24] To facilitate the large number of fixed effects, we collapse our daily time series into four-day periods so that t indexes the 41 four-day intervals between February 1, 2020 and July 10th, 2020.[25] For identification purposes, we restrict $\beta_{c,Feb1} = 0$ for the first time period in the sample (February 1, 2020). In placebo regressions, using only the cross-section of markets on a given date in early February, we systematically find null effects for β_{ct}, typically rejecting values larger than 0.01 (i.e., less than 1 percentage point of SD propensity). Therefore, we interpret non-zero values of β_{ct} later in our sample as actual changes in compliance in social distancing, and not relative to a base period.

[Table 5 about here.]

Table 5 summarizes our analysis of variation in the SD measure, based on the share of home-bound devices, using the panel regression (8).[26] Column (1) shows that market characteristics including demographics, X_z, explain only 7% of the variation in SD. However, several of these characteristics turn out to have large effects on SD, in particular population density and median income. These findings could be due to the fact that the outbreak started earlier in urban areas than in rural areas (Dingel and Neiman, 2020) thereby increasing the incentive to comply with SD in urban areas, and the fact that income may correlate with professions that are more conducive to working from home. Column (2) replaces these demographics with the zipcode fixed-effects, which increase the explained variation to 32%, suggesting substantial additional unexplained persistent heterogeneity across markets. Column (3) adds time-specific state fixed effects to control for differential timing and stringency of stay-at-home orders, increasing the share of explained

[24] Our IV estimator includes the interaction effects between our position instruments and two-day time fixed effects. The first-stage results are the same for each interaction since we use cross-sectional data on Fox News viewership and channel positions.

[25] Using a daily frequency would quarduple the number of viewership$\times$time interaction coefficients and time effects for each channel, in addition to the $27,173$ zip code and $2,009$ state by time fixed effects already in the model. The IV regression would require a very high-dimensional set of instruments, substantially increasing computational costs.

[26] See Appendix A.4 for analogous tables for SD measured using Full-Time and Part-Time Work Travel.

variation in SD to 82%. Columns (4) through (6) report OLS results that include the viewership effects. Column (4) adds time-varying viewership effects, increasing the explained variation to 85%. Column (5) also includes time-specific position effects for competitor news channels, CNN and MSNBC, respectively.[27] Finally, column (6) controls for zipcode-level differential trends in SD by including time-specific effects of median income and population density, two factors that we find (in column 1) to be important drivers of SD. For the remainder of this section, unless we state otherwise, assume results are based on the specification in column (5).

Defining SD as the overall share of homebound devices, Figure 3 displays the time-specific estimates of the effect of viewership on SD, β_{ct}, for Fox News and CNN, respectively. We report both the IV and the OLS estimates along with their respective 95% confidence intervals. Standard errors are clustered at the headend level.[28] The systematically smaller magnitude of the OLS estimates most likely reflects attenuation bias from measurement error in the use of 2015 viewership levels as noisy proxies for 2020. In Appendix A.12, we use a simulation exercise to show how we expect the measurement error in our empirical setting to create a larger attenuation bias than the endogeneity bias. The OLS estimates should be multiplied by a factor of 1/0.0753 or more to correct for this attenuation bias.

Even with this attenuation bias, our OLS estimates indicate a significant pattern of Fox News viewership effects on SD compliance. The IV and OLS point estimates of β_{ct} first become negative and statistically significant on the 4-day window starting February 28, 2020, the day before the Governor of the State of Washington issued the first emergency declaration in the US.[29] These Fox News viewership results are robust to a "saturated" OLS specification that includes time-specific effects for a large number of demographic variables that predict SD; although the magnitudes fall by about 50% (see Figure A4 in Appendix A.7.).

[Figure 3 about here.]

Before discussing our IV estimates, we first run reduced-form regressions of model (8) using the channel position instrument in the place of viewership for the specifications corresponding to column (5) of Table 5. The estimates and confidence intervals for the effect of Fox's, CNN's and MSNBC's respective positions on share of homebound devices are plotted in Figure A3 in the Appendix A.6. For Fox News, we find significant position effects that closely track the cross-time patterns of our IV estimates discussed below. In contrast, our point estimates for CNN and

[27] Although not reported herein, we find similar results if we use own viewership of CNN or MSNBC instead, and position of competitors.

[28] Figure A5 in Appendix A.8 shows that our main results are robust to clustering the standard errors at the state level.

[29] See Proclamation 20-25 (2020).

MSNBC positions, respectively, are not significant. For MSNBC, the magnitudes are also quite small.

The interpretation of the IV estimates requires some care. The IV estimate of $\beta_{FOX,t}$ measures a local average treatment effect (hereafter "LATE"), which we interpret as the average partial effect (hereafter "APE") of Fox News viewership by cable subscribers on overall SD for date t across markets.[30] As we discussed above in section 4, we use viewership for the subset of the population with cable subscriptions since this is the sub-population affected by our position instrument.

Turning to our IV estimates of $\beta_{FOX,t}$, we observe some interesting dynamics in the viewership APE on SD compliance that seem too systematic to be driven by chance alone. As anticipated, we find extremely small and statistically insignificant viewership effects throughout February, prior to the first emergency declaration. Only after March 1st, the day after the first emergency declaration in the US as explained above, do the IV estimates become systematically negative and statistically significant. The magnitudes increase between March 1st and March 13th, after which the point estimates appear to stabilize. As explained earlier, President Trump declared a national emergency on March 13th. At least two mechanisms might lead to the evolution in $\beta_{FOX,t}$ during those two first two weeks of March. First, the Fox News effect may have become more persuasive over time early on during the crisis, possibly due to evolving messaging. Alternatively, if the causal effect of Fox News viewership on SD only activates when local residents perceive a risk, the evolution in $\beta_{FOX,t}$ may reflect geographic differences in the timing of a perceived need for SD and/or of a statewide emergency declaration. We explore the role of emergency declarations and timing in more detail in section 5.4 below. For most of the analysis below, we will focus on the post-March 13th period when the Fox News effect appears to have stabilized.

We observe a small point estimate as late as the 4-day window between February 24 and 28: -3.38×10^{-4}. At the 5% significance level, we can rule out that, on average across markets, a 1 rating point increase in Fox News viewership among cable subscribers would not decrease SD by more than 1.5 percentage points. However, on February 28, 2020, the average across-market decrease in SD due to a 1 rating point increase in Fox Viewership among cable subscribers jumps to 2.1 percentage points, and we cannot rule out a decrease as large as -3.8 percentage points at the 5% significance level. By March 15th (includes first business day after national emergency declaration), when the Fox viewership effects have stabilized, our point estimate implies that a 1 rating point increase in Fox News viewership among cable subscribers would decreases SD by

[30] If we assume a homogeneous effect of position on viewership in our first stage, then IV is a consistent estimate of the average partial effect (e.g., Wooldridge (2008)). This assumption rules out, for instance, that markets with a high taste for Fox News, including non-cable-subscribers such as satellite, do not have a larger incremental viewership due to position.

-9.9 percentage points and we can rule out decreases smaller than 4.3 percentage points at the 5% significance level. The shift in the estimates towards the origin at the start of June coincide with the Black Lives Matter protests in response to the death of George Floyd.

As a robustness check, Figure A7 in Appendix A.10 compares the panel IV regression (8) estimates of $\beta_{Fox,t}$ corresponding to columns (5) and (6) of Table 5. The latter specification controls for zipcode-level differential trends through time-specific effects of population density and median income, in addition to our time-specific state fixed effects. These demographic interactions add 82 more parameters to the regression model. As expected, our viewership effects become more precise; although the point estimates become smaller in magnitude. Our qualitative results are robust to these controls: for each time period prior to April 24, we fail to reject the equality of each of our Fox News point estimates under models (5) and (6). In Section 5.5, we report the implied persuasion rates based on both models.

As a final robustness check, Figure A6 in Appendix A.9 plots the time-series of IV point estimates using our 2020 viewership data, which span a more limited set of zipcodes. As expected, the point estimates are extremely imprecise. However, they follow the same qualitative pattern as our results using the 2015 viewership data. Besides demonstrating robustness, the persistence in the point estimates using 2015 and 2020 data may point towards a longer-term mechanism driving our Fox News effects. While the extant literature has considered persuasive effects through beliefs and preferences (e.g., DellaVigna and Gentzkow, 2010), the robustness from using either 2015 or 2020 viewership levels may also indicate a longer-term effect of viewership that is not driven by specific messaging on a given day. For instance, long-term exposure to Fox News may generate broad distrust in institutions and a taste for defiance.

In contrast, our results for CNN are mixed at best. Our OLS estimates become positive and significant shortly after March 1, 2020. These findings could be suggestive of a positive causal effect of CNN viewership on SD, that reinforces the recommendations of health experts. However, OLS could be incidentally correlated with SD purely due to self-selected viewership choices. Our IV estimates are extremely imprecise and inconclusive. While we fail to reject that IV is the same as OLS, we also fail to reject that IV is zero or even negative.

In Appendix A.5, we report the analogous results for SD measured as share of people working full time and share of people working part time, in Figures A1 and A2, respectively. Although more imprecise, our qualitative findings are consistent with the stay-at-home rates above, with the point estimates stabilizing around March 15. Our OLS estimates are significant and positive: Fox News viewership decreases compliance by increasing the propensity to go to work relative to the (unreported) negative estimated time effects. OLS is again much smaller than IV. On March

15, our APE interpretation of our IV estimates imply that a 1 rating point increase in Fox News viewership among cable subscribers would increase the share of devices leaving home for work by 0.4 percentage points for full-time work and 1.7 percentage points for part-time work; although we fail to reject increases as small as 0 percentage points and 0.7 percentage points for full- and part-time work respectively at the 5% significance level. These deviations are smaller in magnitude than the overall stay-at-home effects above, but nevertheless confirm the negative impact of Fox News viewership on compliance with social distancing.

The corresponding results for CNN are once again mixed. While our OLS estimates suggest a positive effect of CNN on social distancing compliance, we fail to reject that our IV estimates have a zero or even negative effect due to lack of precision.

Although not reported herein, we also applied the same approach to test for and measure a Fox News viewership effect on the local number of debit card transactions across 45 categories of businesses using the Facteus data. Our findings were inconclusive, with statistically insignificant and imprecise Fox News viewership effects.[31]

5.3 Media Persuasion vs Political Polarization

We believe our findings above reflect a direct, persuasive effect of Fox News on viewers' SD behavior. However, the strong association between SD and political polarization during the pandemic (Allcott et al., 2020; Barrios and Hochberg, 2020) combined with the causal effect of Fox News viewership on republican vote shares during several past presidential elections (Martin and Yurukoglu, 2017) suggest an alternative explanation. Our estimated Fox News effects might reflect, at least in part, an indirect effect mediated by political polarization.

We have several reasons to doubt that our findings merely reflect political polarization. Contemporaneous survey research finds a positive association between conservative media use and beliefs that the CDC was exaggerating the seriousness of the virus, even after controlling for political preferences (Hall Jamieson and Albarracín, 2020). While suggestive, our estimated Fox News effects in Figure 3 stabilize shortly after the national emergency declaration, by which point the White House endorsed the CDC's recommendation for SD and partial shut-down.[32] President Trump continued to endorse SD throughout March and April, stating, "Social distancing: That's the way you win."[33] Meanwhile, Fox News maintained its stance against the lockdown and SD

[31] Results available upon request.

[32] https://www.whitehouse.gov/articles/15-days-slow-spread/

[33] https://www.whitehouse.gov/briefings-statements/remarks-president-trump-vice-president-pence-members-coronavirus-task-force-press-briefing-14/

and, in April, a "slew of Fox News opinion hosts and anchors [were] pushing back on public health experts and urging President Donald Trump to abandon its social distancing policies and reopen the economy" (Relman, 2020). Therefore, our Fox News effects arise and persist throughout a period when Fox News repeatedly broadcast anti-SD content that was contrary to the recommendations of the White House.

In fact, we see no change in the Fox News effect at the start of May, when the White House switched its stance in favor of the re-opening of social and economic activity as the CDC recommendations expired (Freking and Colvin, 2020). If we instead use our saturated model with demographic controls (Figure A7), we observe a reduction in the Fox News effect (towards zero) which again corroborates the direct persuasion interpretation of the estimates. As expected, the polarizing effect of having the Republican party actively recommended against SD crowds out some of the Fox News effect.

We conduct an additional suggestive check. We split the zip codes into three groups based on the terciles of the vote share from the 2016 presidential election outcomes: liberal, neutral and conservative. We re-run our reduced-form regression (8) separately in each of these groups. Therefore, we test for Fox News channel position effects on SD using only position variation within zip codes that are already the most polarized in favor of the Republican party and Democratic party, respectively. We plot the channel position effects for each group in Figure 4. We find small and insignificant effects in republican markets, which is consistent with the polarization findings in (Allcott et al., 2020; Barrios and Hochberg, 2020): residents of these markets are already persuaded regardless of Fox News. More surprising are the large and significant Fox News channel position effects in the most Democratic-party-leaning markets, consistent with Fox viewership having a direct persuasive effect. Therefore, we find a persuasive effect of Fox News even when we do not pool across our entire cross-section of politically polarized areas.

[Figure 4 about here.]

5.4 Supply vs Demand and the Timing of Response to COVID-19

As explained in section 4.4, we observe an almost simultaneous take-off in cross-market, daily average SD and supply-side variables (e.g., business closures and worker sign-in rates) on March 13th. This co-movement raises some concerns about the exact interpretation of $\beta_{FOX,t}$ and a mis-attribution of the supply side to the persuasive effect of the news. While we cannot fully disentangle the supply and demand side drivers of SD compliance, we provide some suggestive evidence below supporting a direct effect of Fox viewership on SD.

We split the zipcodes into two groups: (1) early-case markets that reported at least one case according to the Johns Hopkins University Center for Systems Science and Engineering (CSSE) before March 13, 2020; and (2) late-case markets that had not yet reported at least one case by March 13, 2020. Using overall share of homebound devices, we then compute the daily difference in the cross-market national average SD between early-case markets and late-case markets. Using the Homebase data on number of businesses open, we also compute the daily difference in the cross-market national average number of businesses open between early-case and later-case markets. Figure 5 displays the time-series for each of these two differences. The difference in SD between these markets is flat throughout January and February and close to zero. However, only after February 29th, the date that Washington became the first state to declare an emergency, do we observe a deviation in the share of people staying at home between the early-case and late-case markets. The difference grows steadily until just after March 13th, the date of the declaration of a national emergency, and then stabilizes. In contrast, the difference in number of businesses open is flat all the way until March 13, after which we see more business closures in early-case than late-case markets.

[Figure 5 about here.]

Figure 5 also plots the time-series in our IV estimates of $\beta_{Fox,t}$. The daily estimates of the Fox viewership APE closely track the evolution in the difference in SD between early-case and late-case markets. We see a similar take-off on February 29th, followed by a steady increase until March 13th, at which point there is a jump and stabilization shortly thereafter. In sum, $\beta_{FOX,t}$ appears to have stabilized by the time business closures are beginning. Once again, the evidence is suggestive of a direct effect of Fox News on SD compliance since business closures on the supply side of the market do not appear to be driving our estimated Fox News viewership APEs during the early days of the pandemic.

5.5 The Persuasion Rate of Cable News

The findings in the previous section contribute to a growing literature documenting the persuasive effects of media communications. Following DellaVigna and Gentzkow (2010), we compute the corresponding persuasion rate for Fox News during the early stages of the COVID-19 outbreak. To determine the persuasion rate, we use our overall propensity to stay-at-home measures of SD. Recall that SD is measured relative to the baseline rate of staying at home in January, before the US outbreak had begun.

For consistency with past research measuring the Fox News persuasion rate, we consider the binary "treatment" of an additional 30 minutes exposure to Fox News per week (DellaVigna and Kaplan, 2007).[34] Increasing the average household's viewership by thirty minutes per week (0.298 rating points) corresponds to the change in viewership induced by a two-standard-deviation change in Fox News' channel position, or a shift from the 10th to 90th percentile position.[35]

Following DellaVigna and Gentzkow (2010), we measure the persuasion rate of Fox News on non-compliance with SD as follows:

$$P_{FOX,t} = 100 \times \frac{1}{S^{Fox}} \frac{E^{Fox}}{S_P^{Fox}} \tag{9}$$

where E^{Fox} measures the effect of 30 minutes of Fox News viewership on SD, S^{Fox} measures the share of the population that watches Fox News, and S_P^{Fox} measures the expected share of the population potentially persuadable to cease SD (i.e., SD compliers and would-be SD compliers but for the treatment of 30 minutes of Fox News viewership).

Our estimated APE for Fox News corresponds to the sub-population of Fox News viewers with cable subscriptions, approximately 60% of total television viewership according to the 2020 NLTV data. Therefore, the Fox News viewership effect on SD for cable viewers is $\frac{\beta_{Fox,t}}{0.6}$. If we also assume that all viewers of Fox News, regardless of the source of their service, have the same average viewership effect, and consider our treatment of additional 0.298 rating points, then $E_t^{Fox} = -\frac{0.298}{0.6}\beta_{Fox,t}$.

We do not observe the share of the population exposed to Fox News.[36] Therefore, we start with the assumption that everyone in the US is exposed to Fox News in some way through such sources as paid television, the internet, or other news sources: $S^{Fox} = 100\%$. This assumption is plausible for at least two reasons. First, Fox News is the most highly-watched news channel in the US and 49% of US households cite cable news channels as their primary news source (Shearer, 2018). Given that the average Fox News viewership rating is around 1.32% and following Martin and Yurukoglu (2017)'s conversion rate of viewership points to hours of television, the average household sees 2.22 hours of Fox News per week. Second, this assumption is conservative in the sense that the persuasion rate mechanically increases in magnitude if we define the exposed

[34] Martin and Yurukoglu (2017) report using a "continuous version" of this treatment.

[35] To convert rating points to minutes watched per week, we follow Martin and Yurukoglu (2017) and let 1 rating point correspond to 1.68 hours per week of Fox News viewership for the average household. A two-standard-deviation change in Fox News' channel position, $17.77 * 2 = 35.54$, induces a viewership change of $0.0089 * 35.54 = 0.316$ rating points, or $0.316 * 100.80 = 31.9$ minutes per week.

[36] Based on a 2017 survey, Kennedy and Prat (2019) report that 33% of people report getting news from Fox News Channel in the last 7 days, providing a lower bound on the number of people exposed to Fox news.

population more narrowly. For instance, we could use the alternative, narrower definition based on the 71% of US households that subscribe to a television service in 2019 and, therefore, had access to Fox News since it is available in 99% of headends: $S^{Fox} = 71\%$.[37]

Finally, we need to determine the share of persuadable viewers who would comply with social-distancing but-for the Fox News effect. We assume the random utility from staying at home, ε_t^h in equation (2), is independent of television viewing behavior so that Fox viewers have the same expected probability of staying home as the rest of the market. We can measure the expected persuadable share of the population on date t as follows: $S_P^{Fox} = \bar{SD}_t - \frac{0.298}{0.6}\beta_{FOX,t}$ where $\bar{SD}_t$ is the cross-market average SD in period t.

The resulting persuasion rate is:

$$P_{FOX,t} = 100 \times \frac{\frac{-0.298}{0.6}\beta_{Fox,t}}{\bar{SD}_t - \frac{0.298}{0.6}\beta_{Fox,t}}. \tag{10}$$

We report the time-series of the persuasion rates (10) from March 15, 2020 onwards in Figure 6(a). On March 15, the day President Trump declared a national emergency, our point estimate of the persuasion rate is 41.9%; although we cannot rule a rate as high as 55.9% and as low as 28% at the 5% significance level. The persuasion rates fall slightly between mid March and early April (although most of these differences are statistically insignificant), and remains stable afterwards. For instance, our lowest point estimate is 20.1% on April 4; although we cannot rule out rates between 10.8% and 31.1% at the 5% significance level. The decline reflects the increase in $\bar{SD}_t$ between mid March and early April (Figure 2) along with the relative stability of $\beta_{FOX,t}$ (Figure 3).

Our average persuasion rate is 28.4% when we use share of homebound devices to measure SD. If we narrow the viewership population to the 71% of television service subscribers, the average persuasion rate increases to 40%. Defining SD with homebound devices is quite stringent given that most social distancing policies allow essential trips, such as grocery shopping. In Figure 6(b), we also report the persuasion rates using full-time and part-time work travel. As expected, the average persuasion rate is much lower at 5.7% and 14.5% for part-time and full-time, respectively.

As a robustness check, we also compute the average persuasion rate using our Fox viewership effects that control for zipcode level trends, as in column (6) of Table 5 and Figure A7. The corresponding average persuasion rate between March 15 and July 10 is 9.5%.

These persuasion rates are larger than the average rate of 9.5% for other communication media reported in DellaVigna and Gentzkow (2010). Recall that our APE does not account for the poten-

[37] `https://nscreenmedia.com/us-pay-tv/`

tial heterogeneity in Fox viewership effects across markets. Nevertheless, our persuasion rate for Fox News on social distancing compliance is comparable to the 58%, 27% and 28% persuasion rates reported in Martin and Yurukoglu (2017)'s analysis of the ability of Fox News viewership to convert voters from one party to another in the 2000, 2004 and 2008 federal elections. Some of this work has measured larger persuasion rates, particularly for negative messages: Enikolopov et al. (2011) find a voter persuasion rate of 66% from an independent television channel broadcasting against voting for United Russia in the 1999 Russian parliamentary elections; and Adena et al. (2015) measure a voter persuasion rate of 36.8% from the radio message "do not vote for the extremist parties" during Germany's 1930 elections.[38]

An important and novel distinction herein is that our persuasion rate arises in spite of the highly-publicized social-distancing recommendations by leading health experts in the US and globally. Therefore our findings also contribute to the advice-taking literature which has mostly documented the "advice discounting" phenomenon in laboratory studies (Bonaccio and Dalal, 2006). Our field evidence demonstrates how the media can contribute to such advice discounting in a real-world setting. Our findings also contribute to the growing literature documenting a growing distrust in scientific experts, especially among conservatives (Gauchat, 2012), and the mediating role of media in creating this distrust (Hmielowski et al., 2014; Dunlap and McCright, 2010). We cannot rule out that our Fox News viewership effects reflect political polarization around SD compliance (Allcott et al., 2020), with long-term viewership primarily polarizing viewers towards Republican sentiment. That said, the extant literature has found that trust in scientific experts is moderated more by an individual's cultural worldviews than by her political orientation (Weaver et al., 2017; Leiserowitz et al., 2013).

[Figure 6 about here.]

6 Conclusions

We find strong evidence of a Fox New viewership effect on several measures of the incremental propensity to stay at home during the early stages of the COVID-19 crisis in the US, relative to January 2020 immediately before the outbreak. While comparable in magnitude to the voting context, the persuasive effect of Fox Viewership on social distancing compliance is quite large, especially given that it defies the expert recommendations from leaders of the US and global health com-

[38] Our findings also align with a literature on negative political advertising (Ansolabehere et al., 1999; Wattenberg and Brians, 1999).

munities. Interestingly, we fail to find conclusive effects of CNN viewership on social distancing compliance.

We do not analyze the implications for the spread of COVID-19 cases or deaths. However, we believe our findings would be relevant to policies to flatten-the-curve. In particular, news media appears to be sufficiently persuasive to dissuade many individuals from complying with containment policies. However, we leave it to health experts to determine whether the magnitude of these changes in compliance are sufficient to affect health outcomes in a material way.

We also believe our findings are relevant to the on-going macroeconomic research to study the economic trade-offs associated with social distancing. However, our exploratory analysis of consumer transactions data were inconclusive. We believe an important direction for future research would use more detailed expenditure data to determine whether and how social distancing compliance affects demand and consumption behavior.

Our data do not permit us to test the exact mechanism through which Fox News viewership persuades individuals against complying with social distancing. It is likely the effect stems from the contrarian and allegedly misleading broadcasts starting in early March regarding the risks of COVID-19 and the effectiveness of distancing. However, we cannot rule out that persistent, long-term differences in exposure to Fox News across region have generated long-term differences in trust in governments and institutions. Similarly, we cannot rule out that exposure to Fox News is changing tastes for defiance of institutions. The qualitative similarities between our point estimates using 2015 viewership data and 2020 viewership data may be suggestive of such a long-term effect. Testing between these mechanisms would represent an interesting and important direction for future research.

Similarly, we cannot rule out that Fox News viewership effects during the COVID-19 outbreak reflect public statements by the Republican administration, as opposed to statements by Fox News anchors. During the 2014 US midterm elections, Campante et al. (2020) show that Republican candidates' associations between Ebola virus risks and immigration shifted voter attitudes against immigration, in spite of the fact that health experts described Ebola risks in the US as very low. The fact that our findings coincide with a period when the White House endorsed distancing and lockdown while Fox News' anchors and hosts maintained their contrarian stance is suggestive of persuasion, but not conclusive. Similarly, the finding that our Fox News effects appear to be strongest in the most Democrat-leaning markets is also suggestive of a persuasive effect that is distinct from polarization. Nevertheless, we see an interesting future research direction that studies whether news media broadcasts directly influence viewer beliefs or merely serve as a platform to promote the beliefs of political candidates.

References

Adena, M., Enikolopov, R., Petrova, M., Santarosa, V., and Zhuravskaya, E. (2015). Radio and the Rise of the Nazis in Prewar Germany. *The Quarterly Journal of Economics*, 130(4):1885–1939. 5.5

Akhmetzhanov, A. R., Mizumoto, K., Jung, S.-M., Linton, N. M., Omori, R., and Nishiura, H. (2020). Estimation of the actual incidence of coronavirus disease (COVID-19) in emergent hotspots: The example of Hokkaido, Japan during February-March 2020. *2020, Vol. , Page: 1*, page 1. 1

Aleem, Z. (2020). A new poll shows a startling partisan divide on the dangers of the coronavirus. *Vox*. 1

Allcott, H., Boxell, L., Conway, J., Gentzkow, M., Thaler, M., and Yang, D. Y. (2020). Polarization and Public Health: Partisan Differences in Social Distancing during COVID-19. *Available at SSRN 3570274*. 1, 3, 5.3, 5.5

Allcott, H. and Gentzkow, M. (2017). Social Media and Fake News in the 2016 Election. *Journal of Economic Perspectives*, 31(2):211–236. 3, 4, 1

Allcott, H., Gentzkow, M., and Yu, C. (2019). Trends in the diffusion of misinformation on social media. *Research & Politics*, 6(2). 3, 1

Ansolabehere, S. D., Iyengar, S., and Simon, A. (1999). Replicating experiments using aggregate and survey data: The case of negative advertising and turnout. *American political science Review*, 93(4):901–909. 38

Ari Shapiro and Richard Harris (2020). White House Announces New Social Distancing Guidelines Around Coronavirus. https://www.npr.org/2020/03/16/816658125/white-house-announces-new-social-distancing-guidelines-around-coronavirus. 2

Ash, E. and Poyker, M. (2019). Conservative News Media and Criminal Justice: Evidence from Exposure to Fox News Channel. *Columbia Business School Research Paper*. 1

Barrera, O., Guriev, S., Henry, E., and Zhuravskaya, E. (2020). Facts, alternative facts, and fact checking in times of post-truth politics. *Journal of Public Economics*, 182:104123. 4

Barrios, J. M. and Hochberg, Y. V. (2020). Risk perception through the lens of politics in the time of the COVID-19 pandemic. *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2020-32). 1, 5.3

Beauchamp, Z. (2020). The stunning contrast between Biden and Trump on coronavirus. *Vox*. 1

Bernanke, Y. and Yellen, J. (2020). The Federal Reserve must reduce long-term damage from coronavirus. https://www.ft.com/content/01f267a2-686c-11ea-a3c9-1fe6fedcca75. 2

Bonaccio, S. and Dalal, R. S. (2006). Advice taking and decision-making: An integrative literature review, and implications for the organizational sciences. *Organizational Behavior and Human Decision Processes*, 101(2):127–151. 1, 5.5

Bursztyn, L., Rao, A., Roth, C., and Yanagizawa-Drott, D. (2020). Misinformation During a Pandemic. Becker Friedman Institute for Economics Working Paper Series 2020-44, Becker Friedman Institute, Chicago, Il. 2, 1, 15

Cagé, J. (2019). Media competition, information provision and political participation: Evidence from French local newspapers and elections, 1944–2014. *Journal of Public Economics*, page 104077. 1

Campante, F., Depetris-Chauvin, E., and Durante, R. (2020). The Virus of Fear: The Political Impact of Ebola in the U.S. Technical Report w26897, National Bureau of Economic Research, Cambridge, MA. 6

CDC (2020a). Cases of Coronavirus Disease (COVID-19) in the U.S. https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/cases-in-us.html. 17

CDC (2020b). Social Distancing, Quarantine, and Isolation. https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/social-distancing.html. 1, 3

Chiang, C.-F. and Knight, B. (2011). Media bias and influence: Evidence from newspaper endorsements. *The Review of Economic Studies*, 78(3):795–820. 1

Chiou, L. and Tucker, C. (2020). Social distancing, internet access and inequality. Technical Report 0898-2937, National Bureau of Economic Research. 1

Cohen, M. and Merrill, C. (2020). Timeline: How Trump was out of step with the CDC during coronavirus response. https://www.cnn.com/interactive/2020/03/politics/coronavirus-trump-cdc-timeline. 2

Darcy, O. (2020). How Fox News misled viewers about the coronavirus. https://www.cnn.com/2020/03/12/media/fox-news-coronavirus/index.html. 2

Deadline: White House (2020). Officials warn of coronavirus spread in the United States. https://www.msnbc.com/deadline-white-house/watch/officials-warn-of-coronavirus-spread-in-the-united-states-79426117558. 2

DellaVigna, S. and Gentzkow, M. (2010). Persuasion: Empirical evidence. *Annual Review of Economics, Vol 3*, 2(1):643–669. 1, 5.2, 5.5, 5.5

DellaVigna, S. and Kaplan, E. (2007). The Fox News effect: Media bias and voting. *The Quarterly Journal of Economics*, 122(3):1187–1234. 1, 5.5

Dingel, J. I. and Neiman, B. (2020). How Many Jobs Can be Done at Home? Working Paper 26948, National Bureau of Economic Research. 5.2

Dunlap, R. E. and McCright, A. M. (2010). 14 Climate change denial: Sources, actors and strategies. *Routledge handbook of climate change and society*, page 240. 5.5

Ecarma, C. (2020). Fox News Is Preparing to Be Sued Over Coronavirus Misinformation. *Vanity Fair*. 1

Egorov, G., Enikolopov, R., Makarin, A., and Petrova, M. (2020). Divided we stay home: Social distancing and ethnic diversity. Technical Report 0898-2937, National Bureau of Economic Research. 1

Eichenbaum, M. S., Rebelo, S., and Trabandt, M. (2020). The Macroeconomics of Epidemics. Working Paper 26882, National Bureau of Economic Research. 2

Enikolopov, R., Petrova, M., and Zhuravskaya, E. (2011). Media and political persuasion: Evidence from Russia. *The American Economic Review*, 101(7):3253–3285. 1, 5.5

Farhi, P. and Ellison, S. (2020). On Fox News, suddenly a very different tune about the coronavirus - The Washington Post. *The Washington Post*. 2

Ferguson, N., Laydon, D., Nedjati-Gilani, G., Imai, N., Ainslie, K., Baguelin, M., Bhatia, S., Boonyasiri, A., Cucunubá, Z., and Cuomo-Dannenburg, G. (2020). Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. Imperial College COVID-19 Response Team. *Preprint at Spiral https://doi. org/10.25561/77482*. 1, 2

Flynn, D., Nyhan, B., and Reifler, J. (2017). The nature and origins of misperceptions: Understanding false and unsupported beliefs about politics. *Political Psychology*, 38:127–150. 3

Freking, K. and Colvin, J. (2020). Trump says he won't extend social distancing guidelines. *Associated Press News*. 5.3

Gauchat, G. (2012). Politicization of science in the public sphere: A study of public trust in the United States, 1974 to 2010. *American sociological review*, 77(2):167–187. 1, 5.5

Gentzkow, M. (2006). Television and voter turnout. *The Quarterly Journal of Economics*, 121(3):931–972. 1

Gerber, A. S., Karlan, D., and Bergan, D. (2009). Does the media matter? A field experiment measuring the effect of newspapers on voting behavior and political opinions. *American Economic Journal: Applied Economics*, 1(2):35–52. 1

Gitmez, A., Sonin, K., and Wright, A. L. (2020). Political Economy of Shelter-in-Place Compliance. page 43. 6

Gordon, B. R. and Hartmann, W. R. (2016). Advertising competition in presidential elections. *Quantitative Marketing and Economics*, 14(1):1–40. 8

Guess, A., Nyhan, B., and Reifler, J. (2018). Selective exposure to misinformation: Evidence from the consumption of fake news during the 2016 US presidential campaign. *European Research Council*, 9. 3, 4, 1

Guiso, L., Sapienza, P., and Zingales, L. (2004). The role of social capital in financial development. *American economic review*, 94(3):526–556. 1

Hall Jamieson, K. and Albarracín, D. (2020). The Relation between Media Consumption and Misinformation at the Outset of the SARS-CoV-2 Pandemic in the US. *Harvard Kennedy School Misinformation Review*. 5.3

Hartmann, W. and Klapper, D. (2016). Super Bowl Ads. Stanford University Graduate School of Business Research Paper No. 15-16, Stanford University. 8

Harvey, N. and Fischer, I. (1997). Taking advice: Accepting help, improving judgment, and sharing responsibility. *Organizational behavior and human decision processes*, 70(2):117–133. 1

Heckman, J. J. and Snyder, J. M. (1997). Linear Probability Models of the Demand for Attributes with an Empirical Application to Estimating the Preferences of Legislators. *The RAND Journal of Economics*, 28:S142–S189. 3

Hmielowski, J. D., Feldman, L., Myers, T. A., Leiserowitz, A., and Maibach, E. (2014). An attack on science? Media use, trust in scientists, and perceptions of global warming. *Public Understanding of Science*, 23(7):866–883. 1, 5.5

Hortacsu, A., Liu, J., and Schwieg, T. (2020). Estimating the Fraction of Unreported Infections in Epidemics with a Known Epicenter: An Application to. Technical Report WP No. 2020-37, Becker Friedman Institute, Chicago. 1

Kamenica, E., Naclerio, R., and Malani, A. (2013). Advertisements impact the physiological efficacy of a branded drug. *Proceedings of the National Academy of Sciences of the United States of America*, 110(32):12931–12935. 5

Kennedy, P. J. and Prat, A. (2019). Where do people get their news? *Economic Policy*, 34(97):5–47. 36

Kissler, S. M., Tedijanto, C., Goldstein, E., Grad, Y. H., and Lipsitch, M. (2020a). Projecting the transmission dynamics of SARS-CoV-2 through the postpandemic period. *Science*. 1

Kissler, S. M., Tedijanto, C., Lipsitch, M., and Grad, Y. (2020b). Social distancing strategies for curbing the COVID-19 epidemic. *medRxiv*. 1

Kopecki, D. (2020). CDC recommends canceling events with 50 or more people for the next eight weeks throughout US. https://www.cnbc.com/2020/03/16/cdc-recommends-the-cancellation-of-events-with-50-or-more-people-for-the-next-eight-weeks-throughout-us.html. 2

Lasry, A., Kidder, D., Hast, M., Poovey, J., Sunshine, G., Winglee, K., Zviedrite, N., Ahmed, F., and Kidder, D. (2020). Timing of Community Mitigation and Changes in Reported COVID-19 and Community Mobility — Four U.S. Metropolitan Areas, February 26–April 1, 2020. *MMWR. Morbidity and Mortality Weekly Report*, 69(15):451–457. 4.3

Lazer, D. M., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., Metzger, M. J., Nyhan, B., Pennycook, G., Rothschild, D., et al. (2018). The science of fake news. *Science*, 359(6380):1094–1096. 3

Leiserowitz, A. A., Maibach, E. W., Roser-Renouf, C., Smith, N., and Dawson, E. (2013). Climategate, public opinion, and the loss of trust. *American behavioral scientist*, 57(6):818–837. 1, 5.5

Lewandowsky, S., Ecker, U. K., and Cook, J. (2017). Beyond misinformation: Understanding and coping with the "post-truth" era. *Journal of applied research in memory and cognition*, 6(4):353–369. 1

Lewnard, J. A. and Lo, N. C. (2020). Scientific and ethical basis for social-distancing interventions against COVID-19. *The Lancet. Infectious diseases*. 2

Lim, C. S., Snyder Jr, J. M., and Strömberg, D. (2015). The judge, the politician, and the press: Newspaper coverage and criminal sentencing across electoral systems. *American Economic Journal: Applied Economics*, 7(4):103–35. 1

Long, E., Chen, M. K., and Rohla, R. (2019). Political Storms: Emergent Partisan Skepticism of Hurricane Risks. SSRN Scholarly Paper ID 3339723, Social Science Research Network, Rochester, NY. 1

Martin, G. J. and Yurukoglu, A. (2017). Bias in Cable News: Persuasion and Polarization. *American Economic Review*, 107(9):2565–2599. 1, 4.1, 4.2, 5, 5.1, 5.3, 5.5, 34, 35, 5.5, A.3

Matrajt, L. and Leung, T. (2020). Evaluating the Effectiveness of Social Distancing Interventions to Delay or Flatten the Epidemic Curve of Coronavirus Disease. *Emerging Infectious Diseases*, 26(8). 1

McLaughlin, E. and Almasy, S. (2020). CDC official warns Americans it's not a question of if coronavirus will spread, but when. https://www.cnn.com/2020/02/25/health/coronavirus-us-american-cases/index.html. 2

MediaMatters (2020). Sean Hannity attempts to minimize the coronavirus concerns by comparing it to violence in Chicago. https://www.mediamatters.org/coronavirus-covid-19/sean-hannity-attempts-minimize-coronavirus-concerns-comparing-it-violence. 2

Nedelman, M. (2020). World Health Organization declares coronavirus a public health emergency of international concern - CNN. https://www.cnn.com/2020/01/30/health/coronavirus-who-public-health-emergency-international-concern-declaration/index.html. 2

Nishiura, H., Kobayashi, T., Miyama, T., Suzuki, A., Jung, S.-M., Hayashi, K., Kinoshita, R., Yang, Y., Yuan, B., Akhmetzhanov, A. R., and Linton, N. M. (2020). Estimation of the asymptomatic ratio of novel coronavirus infections (COVID-19). *International journal of infectious diseases: IJID: official publication of the International Society for Infectious Diseases*, 94:154–155. 1

Painter, M. and Qiu, T. (2020). Political Beliefs affect Compliance with COVID-19 Social Distancing Orders. SSRN Scholarly Paper ID 3569098, Social Science Research Network, Rochester, NY. 1

Pearce, K. (2020). What is Social Distancing and How Can it Slow the Spread of Covid-19. https://hub.jhu.edu/2020/03/13/what-is-social-distancing/. 2

PewResearch (2020). Cable TV and Coronavirus: How Americans perceive the outbreak and view media coverage differ by main news source. *Pew Research Center's Journalism Project*. 1

Proclamation 20-25 (2020). 29

Puhak, J. (2020). Coronavirus: President Trump said US authorities 'shut it down.' Here's what that means. https://www.foxnews.com/travel/airlines-us-coronavirus-outbreak-travelers-china. 2

Relman, E. (2020). Coronavirus: Fox News hosts pressure Trump to end lockdowns, reopen economy - Business Insider. https://www.businessinsider.com/coronavirus-fox-news-hosts-pressure-trump-end-lockdowns-reopen-economy-2020-4. 5.3

Sapienza, P. and Zingales, L. (2012). A Trust Crisis. *International Review of Finance*, 12(2):123–131. 1

Shapiro, B., Hitsch, G. J., and Tuchman, A. (2019). Generalizable and Robust TV Advertising Effects. SSRN Scholarly Paper ID 3273476, Social Science Research Network, Rochester, NY. 8

Shapiro, B. T. (2018). Positive Spillovers and Free Riding in Advertising of Prescription Pharmaceuticals: The Case of Antidepressants. *Journal of Political Economy*, 126(1):381–437. 8

Shapiro, J. M. (2016). Special interests and the media: Theory and an application to climate change. *Journal of public economics*, 144:91–108. 7

Shearer, E. (2018). Social media outpaces print newspapers in the U.S. as a news source. https://www.pewresearch.org/fact-tank/2018/12/10/social-media-outpaces-print-newspapers-in-the-u-s-as-a-news-source. 2, 5.5

Sinkinson, M. and Starc, A. (2019). Ask your doctor? Direct-to-consumer advertising of pharmaceuticals. *The Review of Economic Studies*, 86(2):836–881. 8

Snyder Jr, J. M. and Strömberg, D. (2010). Press coverage and political accountability. *Journal of political Economy*, 118(2):355–408. 1

socoemergency.org (2020). No. C19-03 Order of the Health Officer of the County of Sonoma: Shelter in Place. https://socoemergency.org/order-of-the-health-officer-shelter-in-place/. 9

Spenkuch, J. and Toniatti, D. (2016). Political Advertising and Election Outcomes. CESifo Working Paper Series 5780, CESifo. 8

Stephens-Davidowitz, S., Varian, H., and Smith, M. D. (2017). Super returns to Super Bowl ads? *Quantitative Marketing and Economics*, 15(1):1–28. 8

The Ingraham Angle (2020a). The coronavirus crisis is teaching us a lot about the so-called experts. http://video.foxnews.com/v/6149181785001/. 2

The Ingraham Angle (2020b). Experts don't like to admit they're wrong. http://video.foxnews.com/v/6153322981001/. 2

The Ingraham Angle (2020c). The pandemic party. Left weaponizing coronavirus fears. http://video.foxnews.com/v/6136344806001/. 2

The Rachel Maddow Show (2020). Rachel Maddow Coronavirus Special. http://www.msnbc.com/transcripts/nav-rachel-maddow-show/2020-02-25. 2

Trump, D. (2020). Declaring a National Emergency Concerning the Novel Coronavirus Disease (COVID-19) Outbreak. *Federal Register*, pages 15337–15338.

Tuchman, A. E., Nair, H. S., and Gardete, P. M. (2018). Television ad-skipping, consumption complementarities and the consumer demand for advertising. *Quantitative Marketing and Economics*, 16(2):111–174. 5

Wattenberg, M. P. and Brians, C. L. (1999). Negative campaign advertising: Demobilizer or mobilizer? *American political science review*, 93(4):891–899. 38

Weaver, S. R., Jazwa, A., Popova, L., Slovic, P., Rothenberg, R. B., and Eriksen, M. P. (2017). Worldviews and trust of sources for health information on electronic nicotine delivery systems: Effects on risk perceptions and use. *SSM-population health*, 3:787–794. 1, 5.5

Wooldridge, J. M. (2008). Instrumental variables estimation of the average treatment effect in the correlated random coefficient model. *Advances in econometrics*, 21:93–117. 30

Wright, A. L., Sonin, K., Driscoll, J., and Wilson, J. (2020). Poverty and economic dislocation reduce compliance with covid-19 shelter-in-place protocols. *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2020-40). 1

Wulfsohn, J. A. (2020). Fox News reaches highest viewership in network's history, topping MSNBC, CNN in 2020. https://www.foxnews.com/media/highest-viewership-network-history-msnbc-cnn-2020. 2

Yanagizawa-Drott, D. (2014). Propaganda and conflict: Evidence from the Rwandan genocide. *The Quarterly Journal of Economics*, 129(4):1947–1994. 1

Yaniv, I. (2004). The Benefit of Additional Opinions. *Current Directions in Psychological Science*, 13(2):75–78. 1

Yaniv, I. and Kleinberger, E. (2000). Advice Taking in Decision Making: Egocentric Discounting and Reputation Formation. *Organizational Behavior and Human Decision Processes*, 83(2):260–281. 1

Figure 1: Distribution of channel positions across headends for each of the three news channels

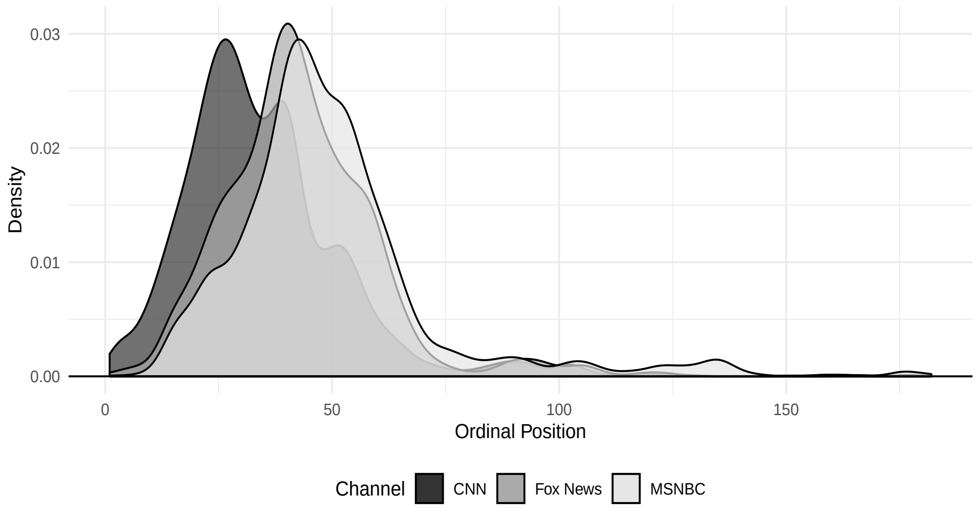
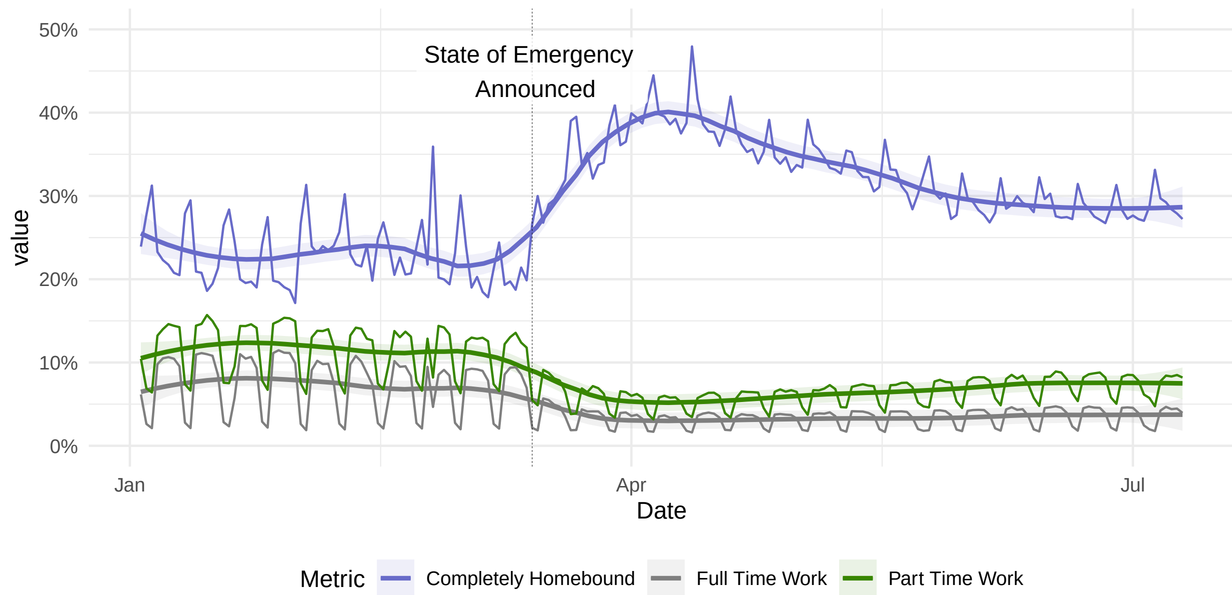
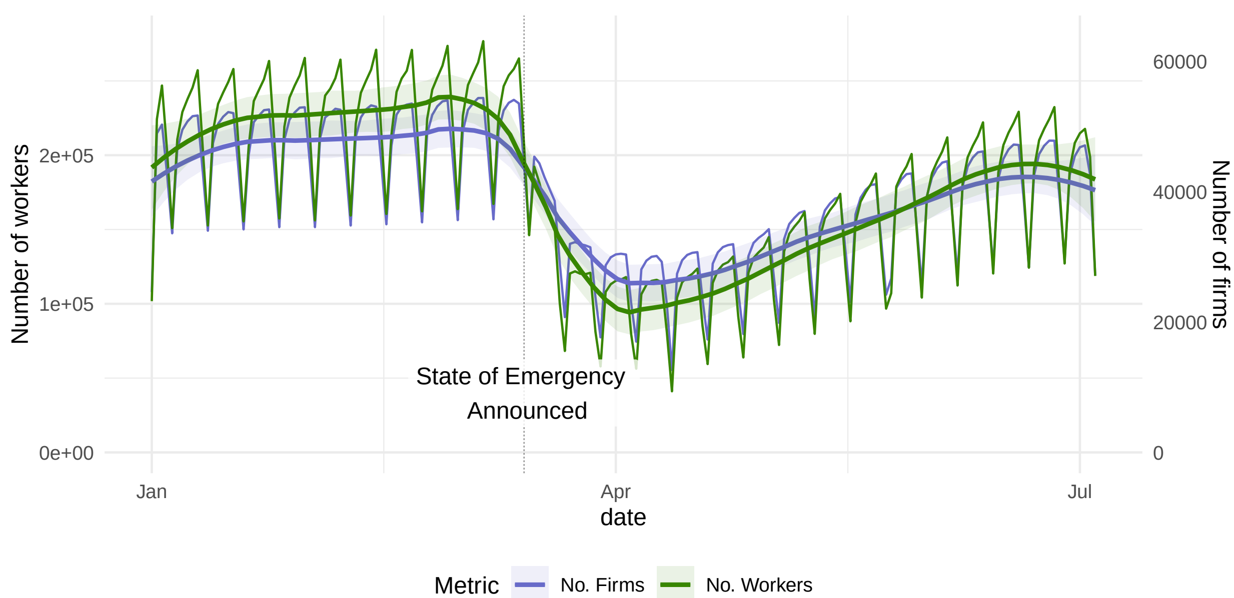


Figure 2: Stay-at-home propensity over time



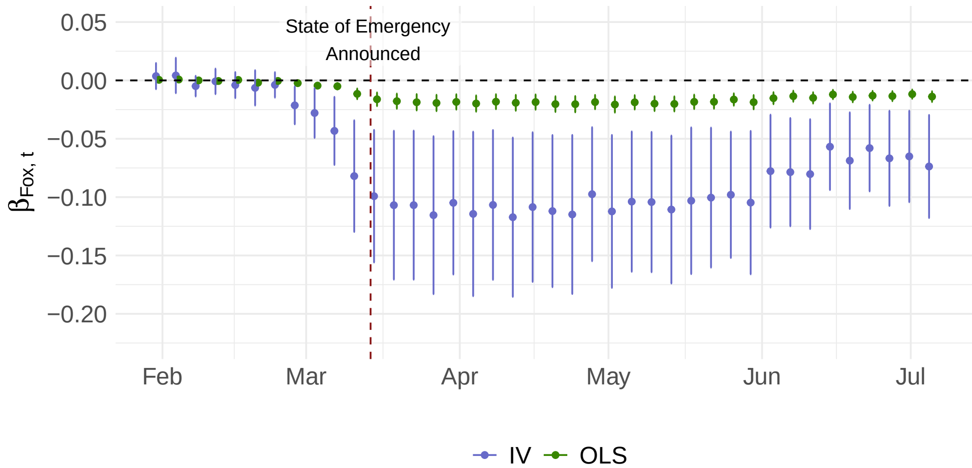
(a) Safegraph Data



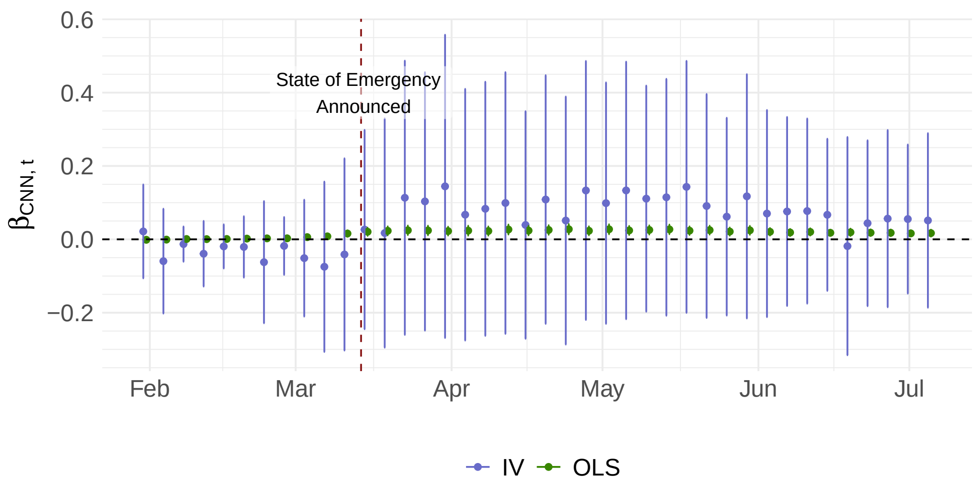
(b) Homebase Data

The solid lines and the shared regions correspond to the predicted values and confidence regions of the local polynomial regression, estimated with LOESS method.

Figure 3: Effect of channel viewership on share of people at home



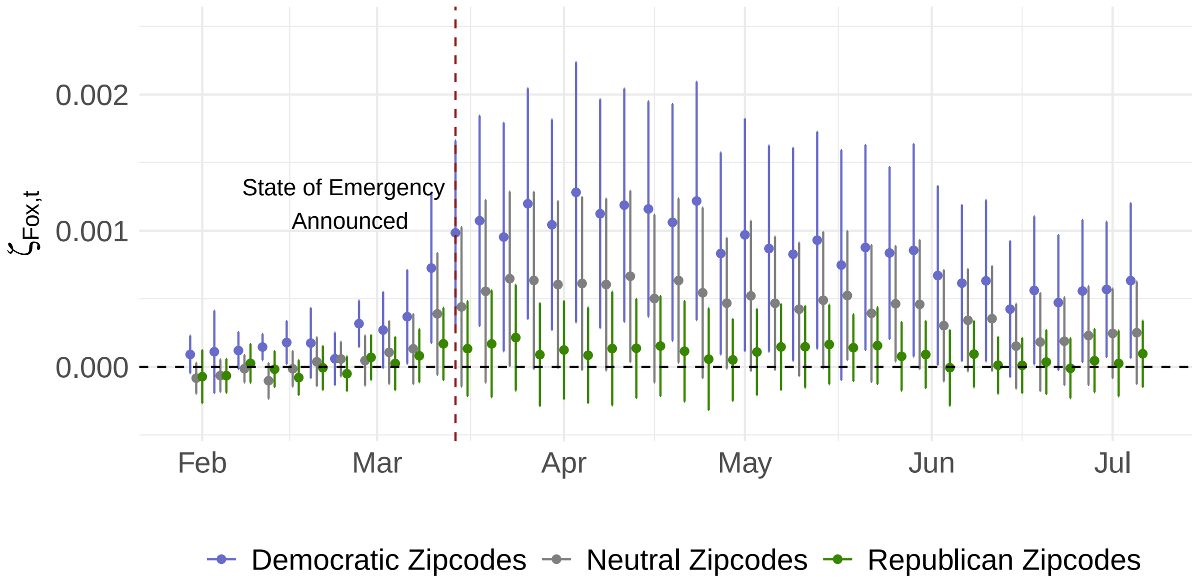
(a) Fox News effect – β_{ct}^{Fox}



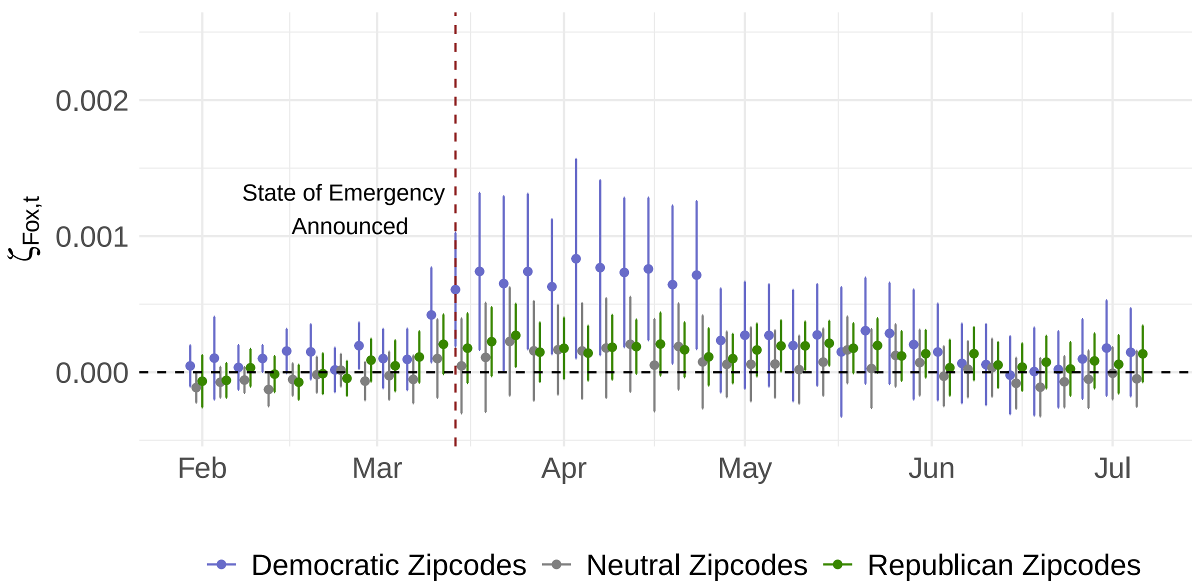
(b) CNN effect – β_{ct}^{CNN}

We allow for flexible state-level trends by including a state by time fixed effects interactions, as well as for flexible effects of other news channels' viewership by including an interaction of time fixed effects with number of channels in cable system and other news channels' positions.

Figure 4: Reduced Form Fox News effect by Terciles of Republican 2016 Vote Share



(a) Baseline Model



(b) With Demograpics

Figure 5: Fox News viewership effects, social distancing compliance and business closures

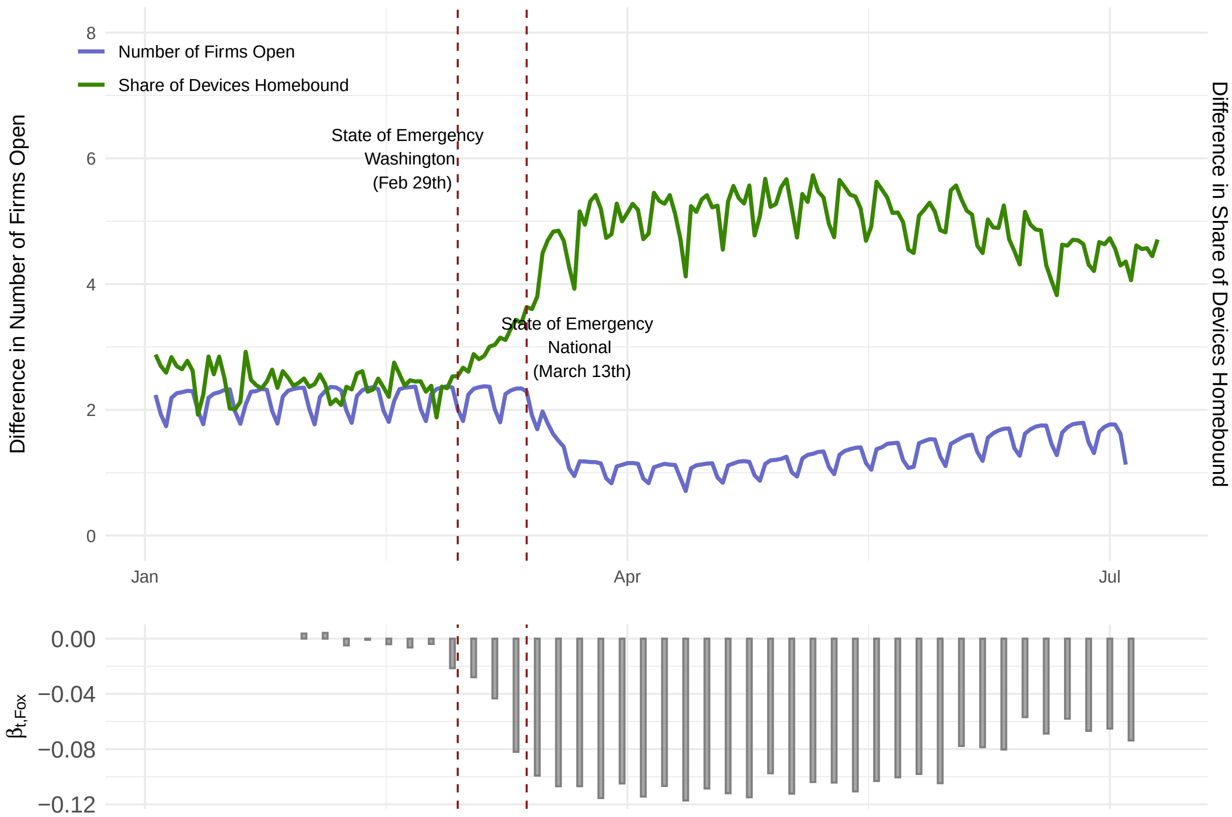
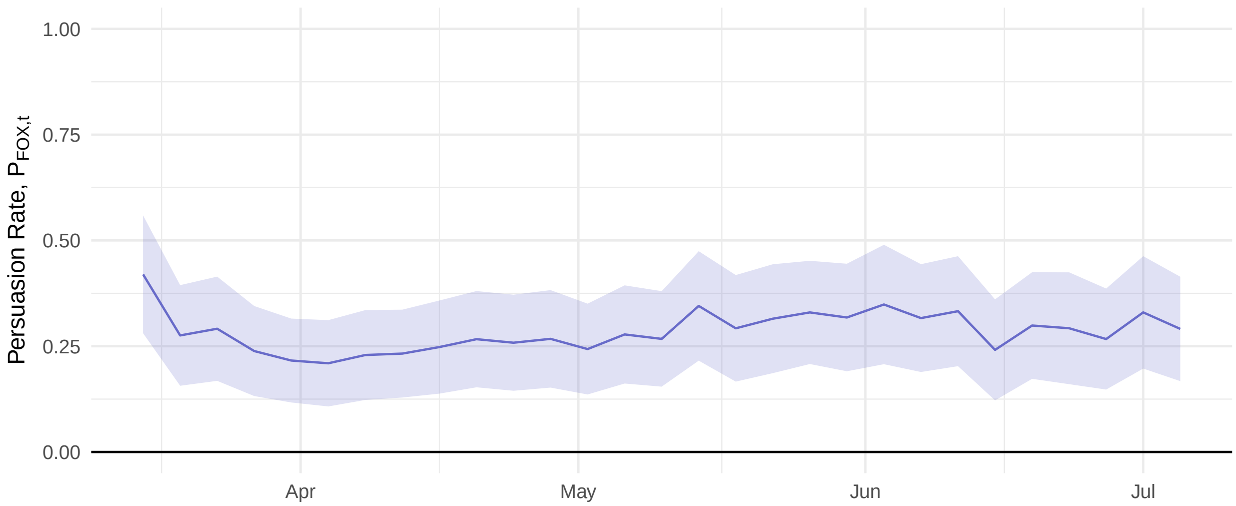
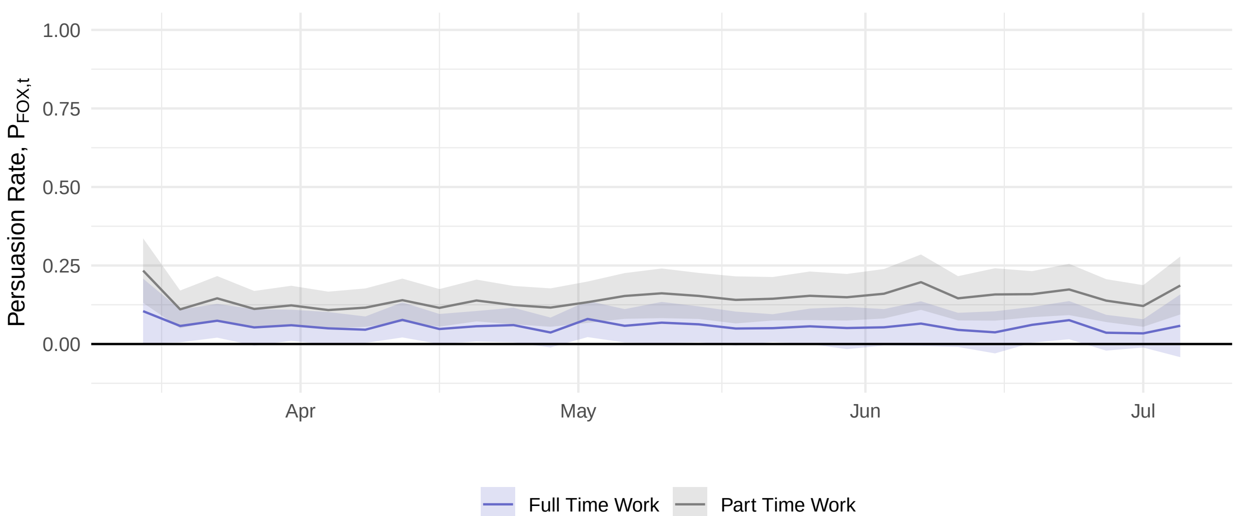


Figure 6: Persuasion rates, $P_{FOX,t}$



(a) Share of Homebound Devices



(b) Part-Time and Full-Time Work Travel

Table 1: Summary statistics for NLTV data

	Mean	Median	SD	Min	Max	Num Headends
	Ratings					
CNN	0.51	0.17	1.5	0	40.03	2502
Fox News	1.32	0.49	2.6	0	32.59	2499
MSNBC	0.34	0.03	1.11	0	17.16	2335

Viewership ratings are average cable viewership for each channel within a market across days and quarter-hour time slots.

Table 2: Summary statistics for FOCUS data

	Mean	Median	SD	Min	Max	Num Headends
	Positions					
CNN	34.85	32	18.31	1	163	2502
Fox News	43.2	41	17.77	1	177	2499
MSNBC	49.64	46	23.43	3	182	2335

Positions correspond to ordinal positions of channels in local cable system lineups.

Table 3: Summary statistics of the stay-at-home propensity variables

Measure	Mean	Median	SD	Min	Max	Obs	# Zips	# Days
(a) Baseline (January Average) Stay-at-Home Propensity in Safegraph Data								
Share Homebound Devices	0.24	0.24	0.04	0.05	0.5		27,173	
Share Devices at Work Full Time	0.07	0.07	0.02	0.01	0.18		27,173	
Share Devices at Work Part Time	0.11	0.11	0.02	0.03	0.21		27,173	
(b) Social Distancing Compliance based on Safegraph Data (Feb 1st - July 10th)								
SD (Share Homebound Devices)	0.07	0.06	0.09	-0.41	0.69	4,374,628	27,173	161
SD (Share Devices at Work Full Time)	-0.03	-0.03	0.03	-0.17	0.35	4,374,628	27,173	161
SD (Share Devices at Work Part Time)	-0.04	-0.04	0.04	-0.2	0.37	4,374,628	27,173	161
(c) Homebase Data								
Number of Workers	10.72	4	18.63	0	523	2,446,365	15,783	155
Number of Firms	2.43	1	3.58	0	61	2,446,365	15,783	155
(d) Facteus Data								
Number of Cards	822.94	259	1633.27	0	164547	197,379	21,931	9
Number of Transactions	1010.63	317	2012.35	0	201769	197,379	21,931	9
Total Spent ($1000)	30.37	9.11	64.82	0	6773.57	197,379	21,931	9

Homebound devices are defined as devices that did not leave Geohash-7 of their home. Devices displaying full-time (respectively, part-time) work behavior are those that spent more than 6 (respectively, 3-6) hours at Geohash-7 location other than their home. The unit of analysis is zipcode-day.

Table 4: The effect of channel position on ratings - FOX

	Effect of channel position's on ratings of Fox News			
	(1)	(2)	(3)	(4)
Ordinal Position of Fox News	-0.0089^{***}	-0.0083^{***}	-0.0067^{***}	-0.0057^{**}
	(0.0024)	(0.0023)	(0.0026)	(0.0025)
Demographic Controls		x		x
Intab weights	x	x		
Cable System Controls	x	x	x	x
State FEs	x	x	x	x
F (pos variables)	14.22	13.34	6.86	5.28
Observations	26,411	22,854	21,234	18,155
Adjusted R^2	0.3040	0.3256	0.2016	0.2172

[a] Stars: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered on cable system level. Demographic controls include: median zipcode income, share of population with bachelor degree, labor force participation, share of population that is white, share of population below poverty line, median age, log population density and county-level republican vote share in 1996 elections. Cable system controls include number of channels in cable system and positions of competing news channels.

Table 5: Summary statistics for panel regressions - FOX

	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0.07	0.32	0.82	0.85	0.86	0.89
N	1043570	1043570	1043570	1043570	1043570	1043570
# Clusters	2253	2253	2253	2253	2253	2253
Demographic controls	x					
Zip FE		x	x	x	x	x
State X Time			x	x	x	x
FXNC Viewership X Time				x	x	x
Cable System Controls X Time					x	x
Basic Demographics X Time						x

Standard errors are clustered on cable system level. Observations are weighted by the number of panelists in the NLTV data. Demographic controls include: median income, share of population with bachelor degree, labor force participation, share of population that is white, share of population below poverty line, median age, log population density and county-level republican vote share in 1996 elections. Cable System Controls include the positions of competing news channels and number of channels in a system. Basic Demographics include median income and log population density.

A Appendix

A.1 First Stage Regressions for CNN

[Table A1 about here.]

A.2 Instrumental Validity

[Table A2 about here.]

[Table A3 about here.]

A.3 Cleaning and Merging NLTV and FOCUS Data

The data were pre-processed for a universe of channels that are available on local cable systems in the US and recorded in the NLTV and FOCUS datasets. We merge the November 2015 NLTV viewership data with the annual 2015 FOCUS data on channel positions by headend number and station name. Following Martin and Yurukoglu (2017), we convert the numeric positions of channels to their ordinal positions based on the sequential order of each channel in the lineup. Similar data are available for each February and November between 2006 and 2015.

We follow the procedure outlined by Martin and Yurukoglu (2017) to map headends to zip codes. 52.7% of the zip codes have a single headend in the NLTV/FOCUS data. For zip codes with 2 or more headends, we use the headend with the largest number of cable subscribers. This assignment rule is unlikely to influence our results since the largest headend accounts for at least half of total subscribers in 97.2% of the zip codes (subscribers are counted as subscribers of headends present in each zip code).

For our analysis, we retain the viewership and position information for the three largest cable news channels: Fox News, CNN, and MSNBC. The data from November 2015 span 2,536 headends, representing 30,517 zip codes from 210 DMAs.

A.4 Additional Tables

[Table A4 about here.]

[Table A5 about here.]

A.5 Other SD Outcomes

[Figure A1 about here.]

[Figure A2 about here.]

A.6 Reduced Form Estimates

[Figure A3 about here.]

A.7 "Saturated" OLS Estimates Controlling for Demographics

[Figure A4 about here.]

A.8 OLS and IV Estimates with State-Level Clustering

[Figure A5 about here.]

A.9 IV Estimates with 2020 Viewership

[Figure A6 about here.]

A.10 IV Estimates with Flexible Demographic Controls

[Figure A7 about here.]

A.11 Channel Position Changes

Using the historical FOCUS data going back to 2006, we count, for each of the three news channels, the number of headends where (numeric) channel position stays exactly the same from one year to the next (for those headends which are present in both years). Table A6 reports these results. We see that for the large majority for headends, (numeric) positions of the three news channels remain constant.

[Table A6 about here.]

A.12 Simulation of the Attenuation Bias

We present a simulation exercise to demonstrate how attenuation bias in the OLS estimates due to measurement error in Fox New viewership can overwhelm the endogeneity bias, as in Figure 3. To mimic our setting where we use the 2015 data to proxy for 2020 viewership, we use the empirically observed correlation in 2010 and 2015 Fox News viewership from the NLTV data. We assume the 2010 and 2015 viewership are drawn from the same data-generating process.

Let $r^t_{FOX,z}$ denote the true Fox News viewership in market z in year t. We assume that social distancing compliance, SD_z, is determined by viewership:

$$SD_z = \beta r^{2015}_{FOX,z} + \varepsilon_z + \mu_z$$

where ε_z and μ_z are random disturbances, such that $E(r^{2015}_{FOX,z}\mu_z) = 0$; but $E(r^{2015}_{FOX,z}\varepsilon_z) \neq 0$ as viewership is endogenous.

In the data, we observe a noisy measure of viewership, $\tilde{r}^t_{FOX,z} = r^t_{FOX,z} + \xi_z$, where ξ_z is the sampling error from the NLTV household sample. Using $\tilde{r}^t_{FOX,z}$ as a proxy for viewership introduces classical measurement error, an additional form of endogeneity bias, into our key SD_z regression:

$$SD_z = \beta \tilde{r}^{2015}_{FOX,z} + \varepsilon_z + \mu_z - \beta\xi_z.$$

Of interest is whether we expect that the magnitude of endogeneity bias from measurement error in our setting, $\beta\xi_z$, will attenuate the OLS coefficients to an extent that it will offset the endogeneity bias from ε_z, leading to OLS estimates that are smaller in magnitude than the IV estimates.

We run the simulation in five steps:

1. Compute the correlation between the observed Fox News viewership in 2010 and 2015: $\text{corr}(\text{rating}^{2010}_{FOX,z}, \text{rating}^{2015}_{FOX,z}) = 0.07535$;

2. Regress the observed 2015 Fox New viewership on channel positions to determine the data-generating process:

$$\text{rating}^{2015}_{FOX,z} = 1.3322 - 0.0056 * \text{position}^{2015}_{FOX,z}.$$

3. Use the data-generating process from (2) to simulate two sets of Fox News viewership ratings for 2010 and 2015, respectively:

$$r^{2010}_{FOX,z} = 1.33222 - 0.0056 * \text{position}^{2015}_{FOX,z} + \varepsilon_{z1},$$

$$r^{2015}_{FOX,z} = 1.33222 - 0.0056 * \text{position}^{2015}_{FOX,z} + \varepsilon_{z2},$$

where $\varepsilon_{zi} \sim i.i.d.N(0, \hat{\sigma}^2)$, $i \in \{1,2\}$, and $\hat{\sigma}^2 = \frac{S}{S - corr}$ with $S = \text{var}(-0.0056 * \text{position}^{2015}_{FOX,z})$ to maintain the empirical correlation of $\text{corr}(\text{rating}^{2010}_{FOX,z}, \text{rating}^{2015}_{FOX,z}) = 0.07535$.

Similar to our empirical application, we treat $\tilde{r}^{2015}_{FOX,z} \equiv r^{2010}_{FOX,z} = r^{2015}_{FOX,z} + \xi_z$, where ξ_z is the measurement error, $\xi_z = \varepsilon_{z1} - \varepsilon_{z2}$.

4. Use $r^{2015}_{FOX,z}$ and the IV estimate of $\beta_{FOX,t}$ from column (5) of Table 5 for t = March 16 ($\beta = -0.089$) to simulate 2015 social distancing data:

$$SD_z = -0.089 * r^{2015}_{FOX,z} + \alpha\varepsilon_{z2} + \mu_z$$

where

- $\alpha\varepsilon_{z2}$ is the endogenous component with α moderating the degree of enodgeneity in Fox News viewership. We run the simulation separately with $\alpha = 0$ (no endogeneity) and $\alpha = \frac{\beta sd(r^{2015}_{FOX,z})}{sd(\varepsilon_{z2})}$ (variance in SD arising due to the exposure to Fox News is the same as the variance arising due to the endogenous component); and
- $\mu \sim N(0, \Sigma)$, where $\Sigma = 0.00405$ is the empirical variance of SD on March 16.

5. Run two different OLS regressions of simulated SD on $r^{2015}_{FOX,z}$ and $r^{2010}_{FOX,z}$. The OLS estimates using the "true" $r^{2015}_{FOX,z}$ viewership should exhibit an upward bias due to the endogeneity of viewership, $\alpha\varepsilon_{2z}$, in the absence of measurement error. In contrast, the OLS estimates using the "observed" $r^{2010}_{FOX,z}$ viewership could exhibit either an upward or downward bias due to the combination of the endogeneity of viewership, $\alpha\varepsilon_{2z}$, and the measurement error, ξ_z.

6. Run two different IV regressions of simulated SD on $r^{2015}_{FOX,z}$ and $r^{2010}_{FOX,z}$, both using 2015 channel positions as an IV. We expect both IV estimators to produce consistent estimates of β.

We run 1,000 independent replications, computing the OLS and IV estimates based on the "2015" (correct) and "2010" (with the measurement error) data. Figures A8 and A9 present histograms of the resulting OLS estimates. The attenuation bias is characterized by the difference between the two distributions. Subfigure (a) compares the OLS estimates when there is no endogeneity, $\alpha = 0$. As expected, the average scale of the attenuation bias across simulations is 0.0753 (biased OLS / true OLS estimates), which matches $\text{corr}(\text{rating}^{2010}_{FOX,z}, \text{rating}^{2015}_{FOX,z})$. Subfigure (b) presents results with endogeneity, $\alpha = \frac{\beta sd(r^{2015}_{FOX,z})}{sd(\varepsilon_{z2})}$. The average scale of the attenuation bias across simulations is larger, making the ratio of biased and true OLS estimates even smaller, 0.0386.

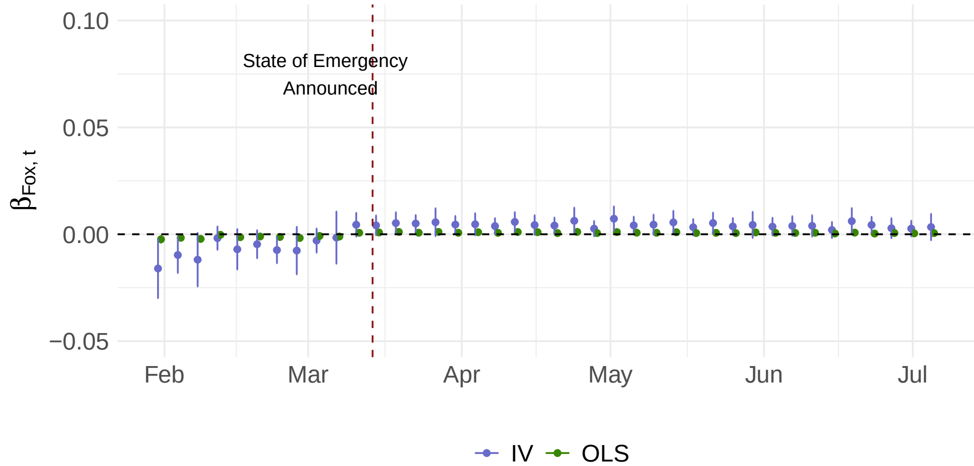
Figure A10 plots the estimates of β from the IV regressions. As expected, the regressions based on the "2010" and "2015" data both generate consistent estimates of β. Now, the measurement error in the viewership data only affects the variance, as can be seen by the higher variance in the "2010"results.

[Figure A8 about here.]

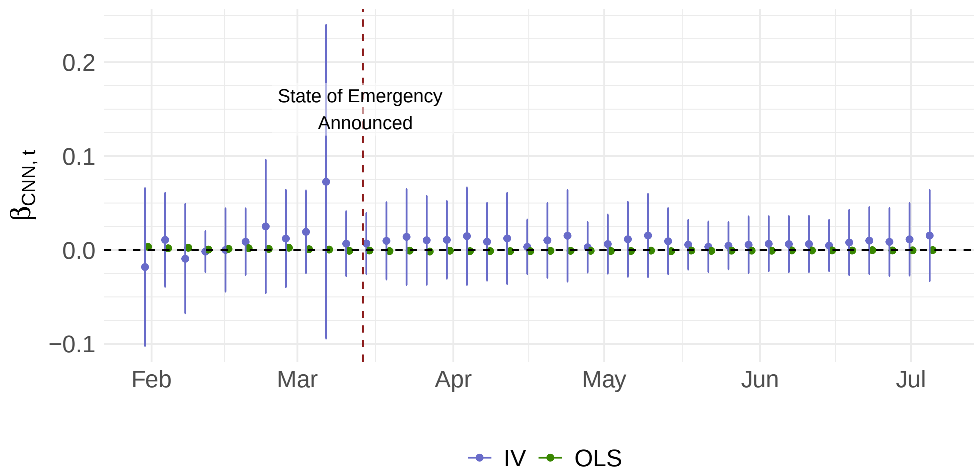
[Figure A9 about here.]

[Figure A10 about here.]

Figure A1: Effect of channel viewership on share of people working full time

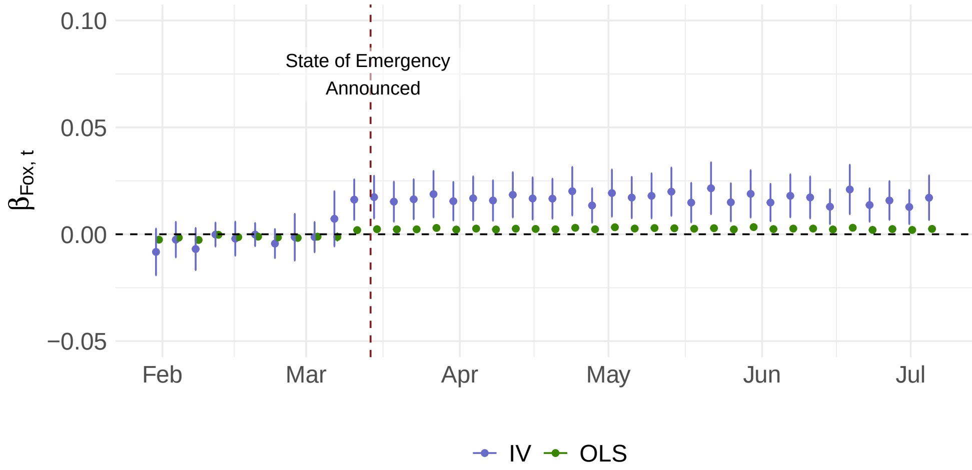


(a) Fox News effect – β_{ct}^{Fox}

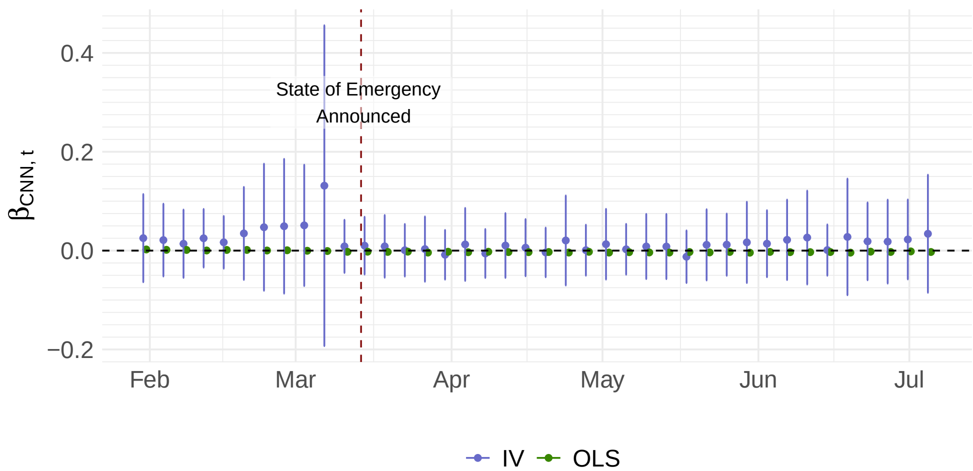


(b) CNN effect – β_{ct}^{CNN} for share of people at home

Figure A2: Effect of channel viewership on share of people working part time

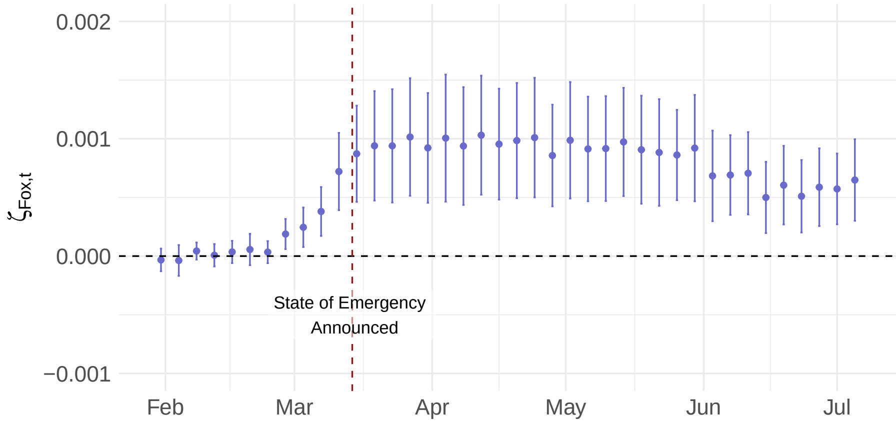


(a) Fox News effect – β_{ct}^{Fox}

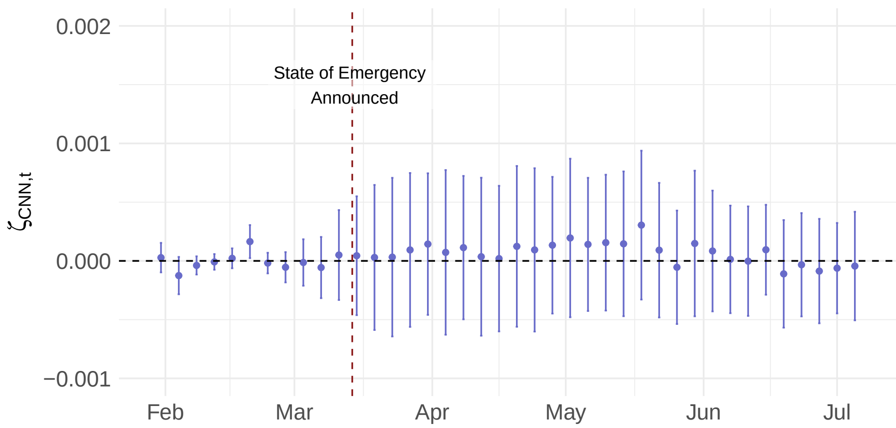


(b) CNN effect – β_{ct}^{CNN} for share of people at home

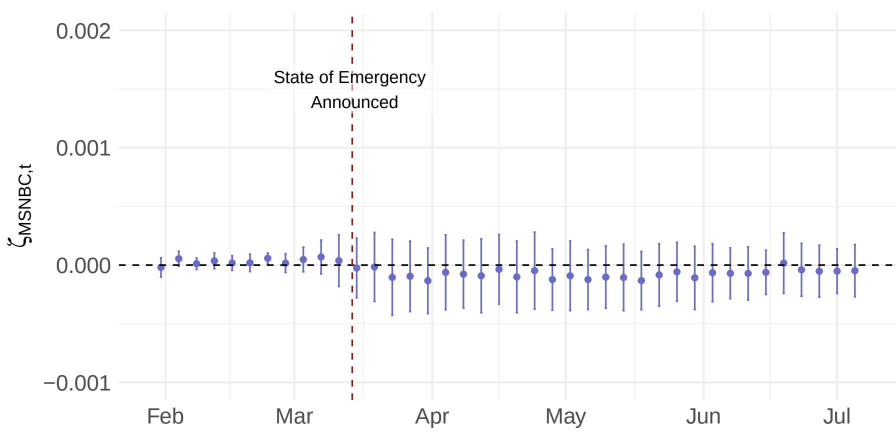
Figure A3: The effect of channel positions of share of homebound devices



(a) Fox News



(b) CNN



(c) MSNBC

Figure A4: OLS estimates controlling for extended demographics

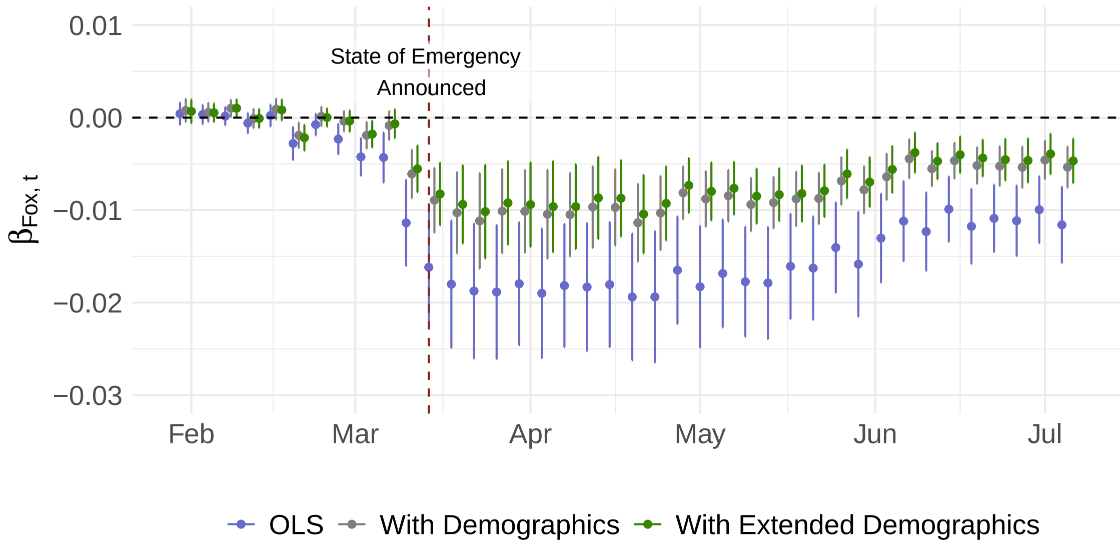


Figure A5: OLS and IV estimates with state-level clustering

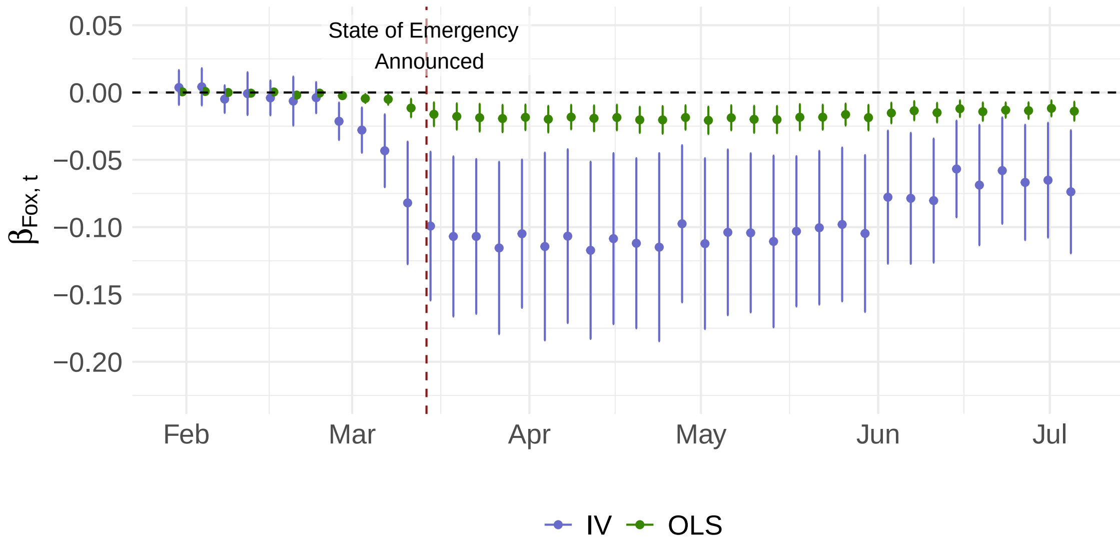


Figure A6: IV estimates using 2015 and 2020 viewership data

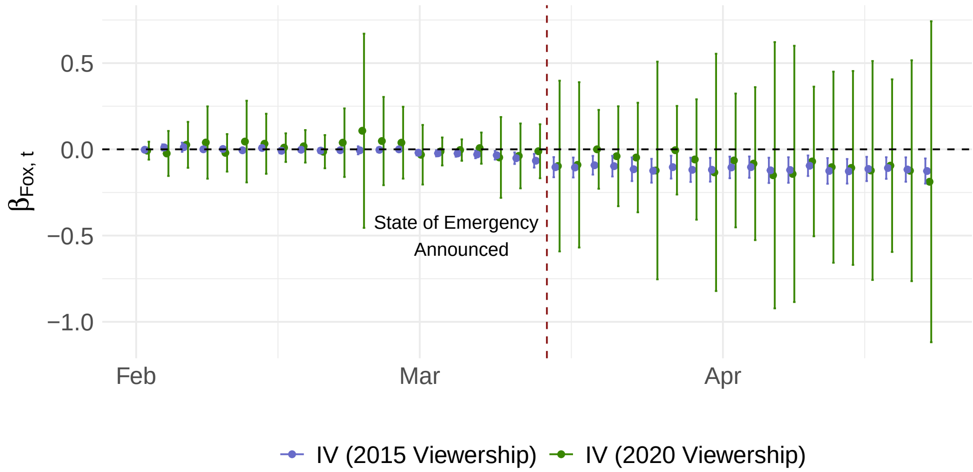
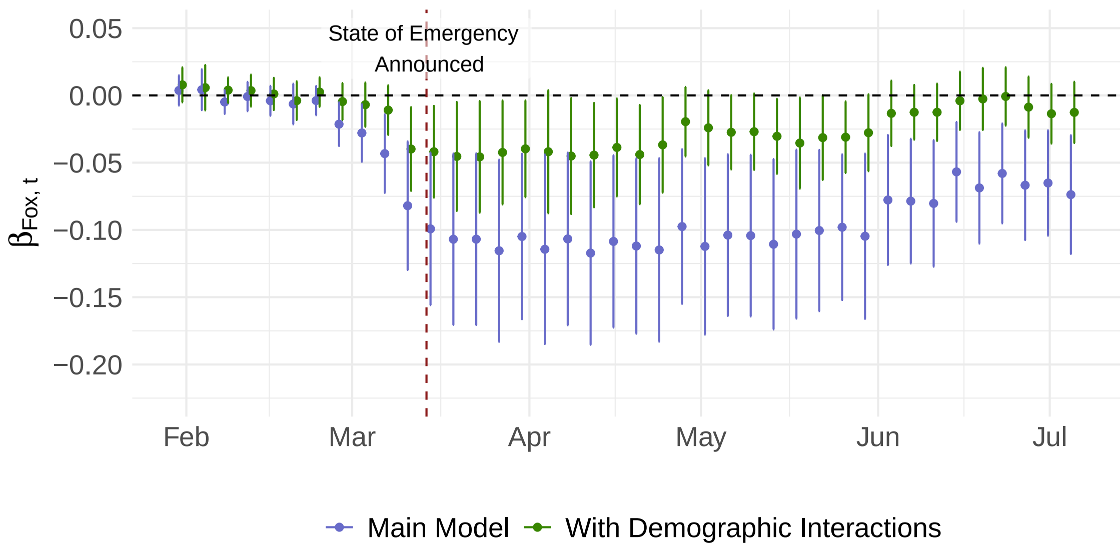
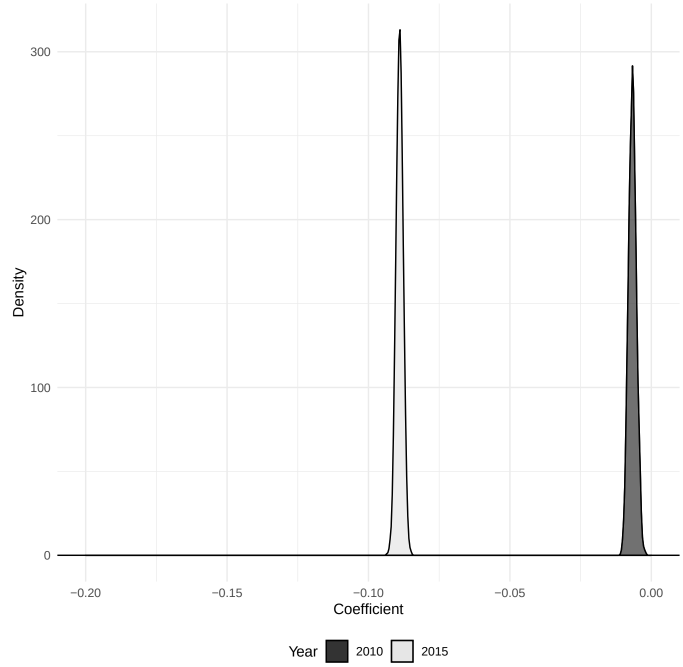


Figure A7: IV with time-varying demographic controls

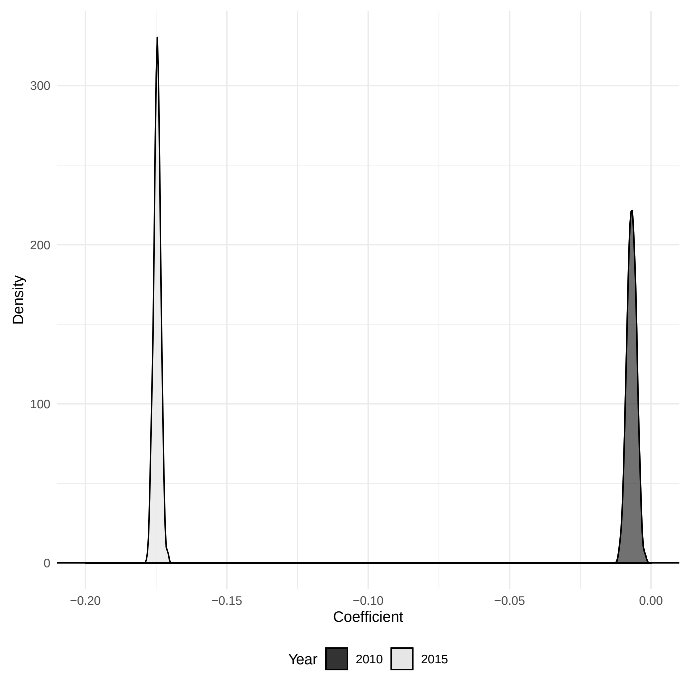


Blue points (Main Model) correspond to the results from Figure 3. Green points correspond to the analogous model with additional controls for time-specific demographic effects from log population density and median income.

Figure A8: The distribution of the OLS estimates of β using “2010” and “2015” simulated data

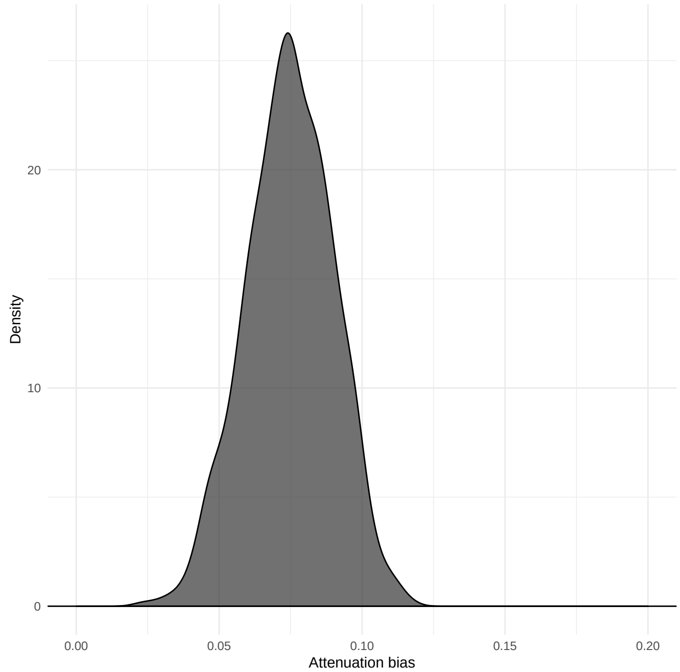


(a) No endogeneity ($\alpha = 0$)

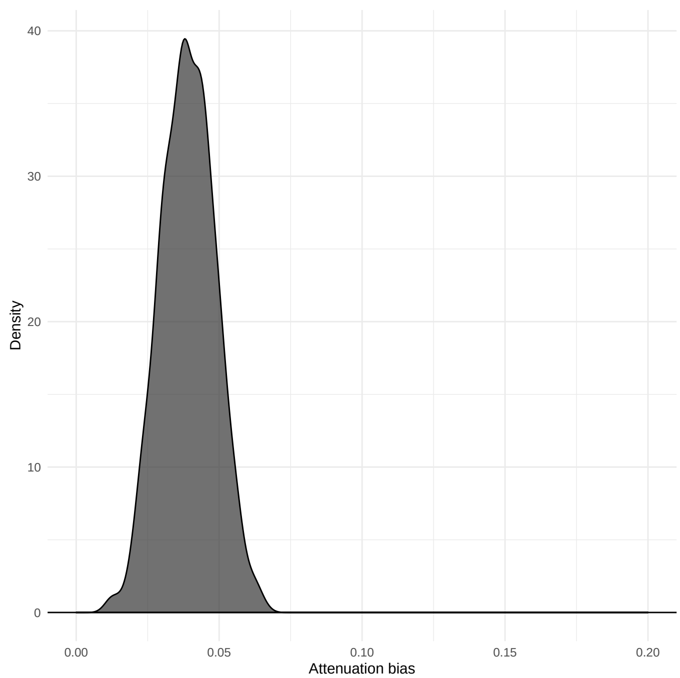


(b) Endogeneity ($\alpha = \frac{\beta sd(r_{FOX,z}^{2015})}{sd(\varepsilon_{z2})}$)

Figure A9: The distribution of the scale of the attenuation bias based on "2010" simulated data (OLS estimates with 2010 data / OLS estimates with 2015 data)

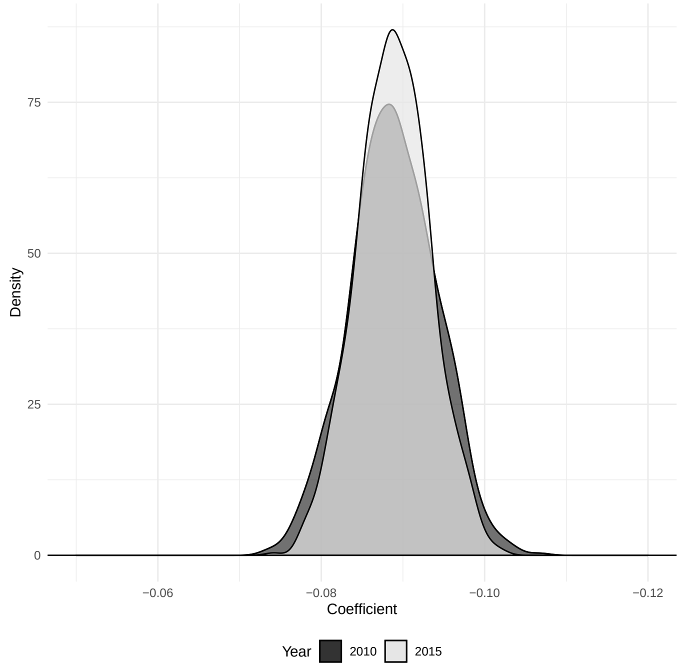


(a) No endogeneity ($\alpha = 0$)

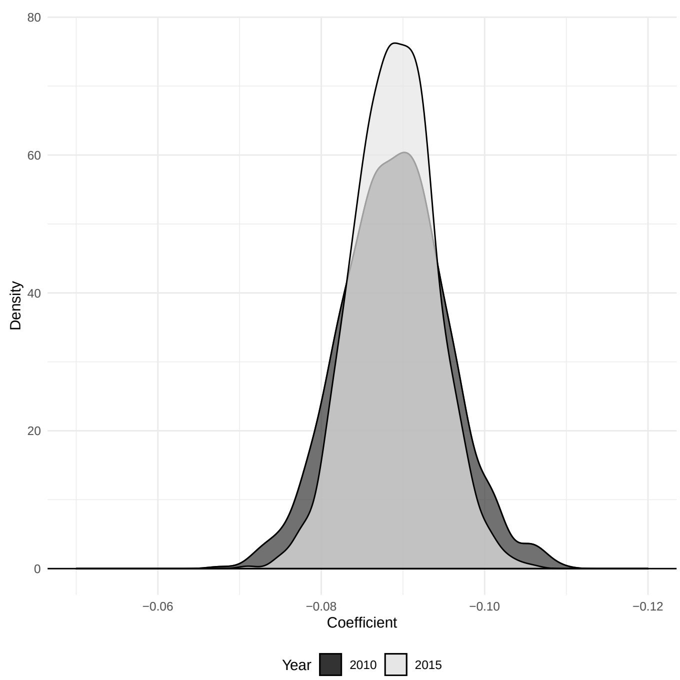


(b) Endogeneity ($\alpha = \frac{\beta sd(r^{2015}_{FOX,z})}{sd(\varepsilon_{z2})}$)

Figure A10: The distribution of the IV estimates of β using "2010" and "2015" simulated data



(a) No endogeneity ($\alpha = 0$)



(b) Endogeneity ($\alpha = \frac{\beta sd(r^{2015}_{FOX,z})}{sd(\varepsilon_{z2})}$)

Table A1: The effect of channel position on ratings - CNN

	Effect of channel position's on ratings of CNN			
	(1)	(2)	(3)	(4)
Ordinal Position of CNN	-0.0050^{***}	-0.0047^{***}	-0.0053^{***}	-0.0052^{***}
	(0.0018)	(0.0016)	(0.0015)	(0.0014)
Demographic Controls		x		x
Intab weights	x	x		
Cable System Controls	x	x	x	x
State FEs	x	x	x	x
F (pos variables)	7.38	8.89	12.73	13.2
Observations	26,411	22,854	21,234	18,155
Adjusted R^2	0.2137	0.2292	0.1712	0.1851

[a] Stars: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered on cable system level. Demographic controls include: median zipcode income, share of population with bachelor degree, labor force participation, share of population that is white, share of population below poverty line, median age, log population density and county-level republican vote share in 1996 elections. Cable system controls include number of channels in cable system, and positions of competing news channels.

Table A2: Correlations between demographic characteristics and position of FOX

	Characteristic							
	Log Median Income	% Bachelor Degree	% in Labor Force	Log Density	Jan Avg SAH	1996 Rep Vote Share	Date of First Case	Log Cases (March 15th)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ordinal Position of FXNC	0.0011*	0.0004	0.0001	0.0054	−0.0350	0.0001	−0.0022	−0.0001
	(0.0005)	(0.0003)	(0.0001)	(0.0049)	(0.0389)	(0.0001)	(0.0100)	(0.0007)
State FEs	x	x	x	x	x			
# Channels	x	x	x	x	x			
Observations	26,148	26,999	27,005	27,093	27,098	6,947	6,959	6,959
Adjusted R^2	0.1961	0.1491	0.1328	0.2620	0.1001	0.3240	0.3161	0.2522

[a] Stars: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered on cable system level. Columns 6-8 run the regression using unique headend-county pairs.

Table A3: Correlations between demographic characteristics and position of CNN

	Characteristic							
	Log Median Income	% Bachelor Degree	% in Labor Force	Log Density	Jan Avg SAH	1996 Rep Vote Share	Date of First Case	Log Cases (March 15th)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ordinal Position of CNN	0.0007	0.00005	−0.00002	−0.0035	−0.0728*	0.0001	0.0162*	0.0004
	(0.0005)	(0.0003)	(0.0001)	(0.0051)	(0.0393)	(0.0001)	(0.0098)	(0.0007)
State FEs	x	x	x	x	x			
# Channels	x	x	x	x	x			
Observations	26,111	26,962	26,968	27,056	27,061	6,942	6,954	6,954
Adjusted R^2	0.1948	0.1480	0.1337	0.2599	0.1015	0.3251	0.3159	0.2482

[a] Stars: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Standard errors clustered on cable system level. Columns 6-8 run the regression using unique headend-county pairs.

Table A4: Summary statistics for panel regressions - SD based on share of full time work devices

	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0	0.37	0.86	0.88	0.88	0.89
N	1043570	1043570	1043570	1043570	1043570	1043570
# Clusters	2253	2253	2253	2253	2253	2253
Demographic controls	x					
Zip FE		x	x	x	x	x
State X Time			x	x	x	x
FXNC Viewership X Time				x	x	x
Cable System Controls X Time					x	x
Basic Demographics X Time						x

Standard errors are clustered on cable system level. Observations are weighted by the number of panelists in the NLTV data. Demographic controls include: median income, share of population with bachelor degree, labor force participation, share of population that is white, share of population below poverty line, median age, log population density and county-level republican vote share in 1996 elections. Cable System Controls include the positions of competing news channels and number of channels in a system. Basic Demographics include median income and log population density.

Table A5: Summary statistics for panel regressions - SD based on share of part time work devices

	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0.01	0.28	0.85	0.87	0.87	0.89
N	1043570	1043570	1043570	1043570	1043570	1043570
# Clusters	2253	2253	2253	2253	2253	2253
Demographic controls	x					
Zip FE		x	x	x	x	x
State X Time			x	x	x	x
FXNC Viewership X Time				x	x	x
Cable System Controls X Time					x	x
Basic Demographics X Time						x

Standard errors are clustered on cable system level. Observations are weighted by the number of panelists in the NLTV data. Demographic controls include: median income, share of population with bachelor degree, labor force participation, share of population that is white, share of population below poverty line, median age, log population density and county-level republican vote share in 2016 elections. Cable System Controls include the positions of competing news channels and number of channels in a system. Basic Demographics include median income and log population density.

Table A6: Persistence of channel positions

Years	% of headends where (numeric) position is retained		
	CNN	Fox News	MSNBC
2006-2007	95.3	94.8	94.1
2007-2008	96.0	95.5	93.4
2008-2009	95.0	95.9	94.8
2009-2010	95.1	93.2	93.4
2010-2011	98.0	97.0	96.1
2011-2012	96.6	96.5	96.6
2012-2013	98.0	97.7	97.4
2013-2014	97.1	97.0	96.6
2014-2015	96.9	96.9	95.9