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NON-COMPLIANCE WITH SOCIAL DISTANCING DURING THE COVID-19 PANDEMIC

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

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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. The average partial effect of Fox News viewership in a zipcode implies that 1 percentage point increase in cable viewership reduces the propensity to stay at home by 8.9 percentage points compared to the pre-pandemic average. We find a persuasion rate of Fox News on non-compliance with stay-at-home behavior during the crisis of about 33.5%-50% across our various social distancing metrics.

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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 action¹ 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 Bonnacio and Dalal 2006). Our case study therefore offers

¹Claim #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>.

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

³A 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).

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 0.137 percentage points for Fox, and 0.088 percentage 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. 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 33.5% – 50% across our various social distancing metrics. This magnitude aligns with the persuasion rate of Fox News on voting behavior in the 2000 presidential election (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.

While our data do not enable us to test why Fox News viewership has a persuasive effect on social distancing compliance behavior, 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 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. Alternatively, long-term exposure to Fox News may have polarized viewers towards the Republican party (Martin and Yurukoglu, 2017), such that the Fox News effects during the COVID-19 crisis reflect Republican attitudes (Allcott et al., 2020) rather than messaging by Fox News anchors. Second, Fox News viewership may reduce a viewer's utility from SD compliance.⁵

In addition, 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, experts still disagree about the accuracy and reliability of current data which limits the interpretability 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.

⁴Several 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).

⁵For 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.

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), 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.

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. 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), and genocide (Yanagizawa-Drott, 2014). 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.⁶

Sections 2, 3, 4, 5 and 6, respectively, present a discussion of misinformation during the US

⁶These methods include geographic regression discontinuities (e.g., Shapiro (2016) and Shapiro et al. (2019)), 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) and Stephens-Davidowitz et al. (2017)).

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 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 News 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: “we’re asking everyone to work at home, if possible, postpone unnecessary travel, and limit social gatherings to no more than 10 people.” (White House, 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 Almasry, 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.⁷ 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:

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

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}

⁷For 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).

measures the time-invariant (long term) viewership measure for news channel $c \in \mathcal{C}$ 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:

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

the linear probability model (Heckman and Snyder, 1996).

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

$$SD_{zt} \equiv y_{zt} - \mathbb{E}(y_{z\tau}). \quad (3)$$

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

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

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 percentage 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, and 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,⁸ 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”⁹, 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.¹⁰ 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).

⁸Only 7,294 zipcodes have at least one panelist and 94% of these zipcodes have less than 10 panelists.

⁹A cable television headend is a master facility for receiving television signals for processing and distribution over a cable television system.

¹⁰Appendix A.3 describes how we pre-process the data.

In 2019, 71% of US households had access to television¹¹ 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% 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.¹² 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.9, 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

¹¹<https://nscreenmedia.com/us-pay-tv/>

¹²Our substantive findings do not change if we instead use the numeric positions.

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.]

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.¹³

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, 2020.¹⁴ 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.¹⁵ On average, we see that

¹³Bursztyrn et al. (2020) circumvent this problem using self-reported rates of social distancing with a survey.

¹⁴For a detailed description of the data, please visit: <https://docs.safegraph.com/docs/social-distancing-metrics>.

¹⁵The 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.

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 their own emergency declarations much earlier: Washington (February 29), California (March 4), New York (March 7) and Louisiana (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:

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

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 April 24, 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,¹⁶ 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 14,981 zipcodes for the period from January 1, 2020 to April 25th, 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” 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 2.6 open firms and 11.53 signed-in workers.

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 5.3 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,”¹⁷ payroll

¹⁶<https://joinhomebase.com/data/>

¹⁷Challenger banks tend to be newer banks that serve underbanked consumers

cards,¹⁸ and government cards.¹⁹ 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_c , which arises if cable news viewership behavior, rating_{cz} , is self-selected on aspects of viewers' preferences that also influence their SD compliance: $\mathbb{E}(\varepsilon_z \cdot \text{rating}_{cz} | X_z) \neq 0$.

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

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

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 the socio-demographic factors that predict SD.

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

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

¹⁸Payroll cards are employer-issued debit cards for direct debit of wages to employees

¹⁹Government cards are primarily issued to alimony recipients to access funds from garnished wages

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, demographics and weights observations by the number of panelists (Column 2), we find that increasing a channel's position by one position in the lineup is associated with 0.0077 and 0.0048 lower percentage rating for Fox and CNN, respectively. Therefore, a one standard-deviation improvement in channel position would increase viewership by over 0.137 percentage points for Fox and over 0.088 percentage points for CNN, all else equal.²⁰

Our instrument seems to work well. The magnitude of Fox's own-position effect is robust across specifications and is slightly larger and more precise in our preferred specification (column 2) that includes controls and weights and generates an incremental F-statistic of 11.97. 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 7.3 to 12.7 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,²¹ 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

²⁰The mean and standard deviation of Fox viewership are 1.32% and 2.6 respectively, and 0.51 and 1.5 for CNN.

²¹Available upon request.

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 following empirical specification of our SD model:

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

where the dependent variable SD_{zt} is measured as described in equation (3) above. \mathcal{C}_{-c} denotes the set of other news channels (i.e., *CNN* and *MSNBC* when $c = \text{Fox}$) 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).²² To facilitate the large number of fixed effects, we collapse our daily time series into two-day periods so that t indexes the 41 two-day intervals between February 1, 2020 and April 24, 2020.²³ For identification purposes, we restrict $\beta_{c, \text{Feb1}} = 0$ 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.]

We now explore the sources of variation in our SD measure, based on share of homebound devices, using the panel regression (8), as summarized in Table 5.²⁴ Column (1) shows that market

²²Our IV estimator includes the interaction effects between our position instruments and two-day 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.

²³Using a daily frequency would double the number of viewership \times time interaction coefficients and time effects for each channel, in addition to the 27,173 zip code and 2,091 state by time fixed effects already in the model. For IV regression, this leads to a very high-dimensional set of instruments.

²⁴See Appendix A.4 for analogous tables for SD measured using Full-Time and Part-Time Work Travel.

characteristics including demographics, X_z , explain only 8% 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 lowering the urban cost of SD for a household, 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 17%, 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 variation in SD to 84%. Columns (4) through (6) report OLS results that include the viewership effects. Column (4) adds time-varying viewership effects, increasing the explained variation to 87%. Column (5) also includes time-specific position effects for competitor news channels, CNN and MSNBC, respectively.²⁵ 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. We use column (5) as our main specification in the discussion below.

We now turn to our estimates of the effect of viewership on SD compliance corresponding to column (5) from Table 5. Starting with our key measure of SD based on the overall share of Homebound Devices, Figure 3 displays the time-specific estimates of effect of viewership on SD, $\beta_{Fox,t}$ for Fox News and CNN respectively. Analogous Figures for our SD measures based on Full-Time and Part-Time Work travel are reported in Figures A1 and A2 in Appendix A.5. We report both the IV and the OLS estimates along with their respective 95% confidence intervals. Standard errors are clustered at the headend level.²⁶ Both our IV and OLS estimates of $\beta_{Fox,t}$ are negative and statistically significant starting on March 1, 2020, the day after the State of Washington declared a national emergency.²⁷ The OLS estimates are systematically smaller in magnitude than the IV estimates. The smaller magnitudes could reflect the fact that, in addition to endogeneity bias, OLS estimates also exhibit an attenuation bias since 2015 viewership levels are noisy proxies for 2020.

[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

²⁵Although not reported herein, we find similar results if we use own viewership of CNN or MSNBC instead, and position of competitors.

²⁶Results are robust to clustering standard errors at the state level.

²⁷See Proclamation 20-25 (2020).

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 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 the 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.²⁸ 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 initial dynamics in the viewership APE on SD compliance. As anticipated, we find extremely small and statistically insignificant viewership effects throughout February, prior to the first emergency declaration. Interestingly, the Fox News effect is negative and significant for every date after March 1st, the day after the State of Washington declared an emergency, as explained above. After March 1st, we find a negative causal effect of Fox News on viewership, in stark contrast with the recommended behavior from health experts. We observe a gradual increase in the magnitude 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. It is possible the Fox News effect became more persuasive over time early on during the crisis, possibly due to evolving messaging. Alternatively, if Fox News only has a persuasive effect once local residents in a market perceive a risk and begin SD and the timing of the perception of risk varies geographically, then our $\beta_{FOX,t}$ may simply be changing as the Fox News effect on SD activates in successively more markets, in particular markets in states that declared an emergency prior to the national declaration. We explore the role of emergency declarations and timing in more detail in section 5.3 below. For the remainder of our analysis, we will focus on the post-March 13th period when the Fox News effect appears to have stabilized.

As late as February 28, the day before Washington became the first state to declare an emer-

²⁸If 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.

gency, our point estimate is still very small, -4.83×10^{-5} , and we can conclude that, on average across markets, a 1 percentage point increase in Fox News viewership among cable subscribers would not decrease SD by more than 0.83 percentage points at the 5% significance level. However, on March 1, 2020, the average across markets decrease in SD due to a 1 percentage point increase in Fox Viewership among cable subscribers jumps to 1.7 percentage points, and we cannot rule out a decrease as large as -3.0 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 percentage point increase in Fox News viewership among cable subscribers would decrease SD by -8.9 percentage points and we can rule out decreases smaller than 4.3 percentage points at the 5% significance level.

As a robustness check, Figure A5 in Appendix A.8 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. For each date, we fail to reject the equality of our point estimates with versus without the demographic-time interactions. We compare the implied persuasion rates from these two specifications below.

As a final robustness check, Figure A4 in Appendix A.7 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 2015 viewership. Besides robustness, these findings 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 exposures 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 percentage point increase in Fox News viewership among cable subscribers would increase the share of devices leaving home for work by 2.5 percentage points for full-time work and 1.9 percentage points for part-time work; although we fail to reject increases as small as 0.8 percentage points and 0.9 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 Factus data. Our findings were inconclusive, with statistically insignificant and very imprecise Fox News viewership effects.²⁹

5.3 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.

To confirm that $\beta_{FOX,t}$ reflects the direct effect of 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

²⁹Results available upon request.

average number of businesses open between early-case and later-case markets. Figure 4 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 4 about here.]

Figure 4 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. Therefore, while business closures on the supply side of the market may indeed be drivers of SD, they do not appear to be driving our estimated Fox News viewership APEs, at least during the early days of the pandemic. In addition, the period of growth in our Fox News APEs in early March appears to be driven, in part, by the gradual activation of SD behavior in successively more markets. Therefore, in the remainder of our analysis, we focus on the post-March-13 period to discuss the Fox News effect on SD.

5.4 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.

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

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

where E^{Fox} measures the effect 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 Fox News effect who watch Fox News).

We estimated the APE for Fox News using only the viewership variation from the sub-population 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 viewership effect then $E_t^{Fox} = -\frac{\beta_{Fox,t}}{0.6}$.

We do not observe the share of the population exposed to Fox News. Therefore, we start with the assumption that that everyone in the US is exposed to Fox News in some way, such as through paid television, the internet, other news sources: $S^{Fox} = 100\%$. This assumption is plausible for at least two reasons. First, Fox News is the 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% and following Martin and Yurukoglu (2017)'s conversion rate of viewership points to hours of television, the average household sees 1.68 hours of Fox News per month. Second, this assumption is conservative in the sense that the persuasion rate mechanically increases in magnitude if we define the exposed 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: $S^{Fox} = 71\%$.³⁰

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: $S_P^{Fox} = \bar{SD}_t - \frac{\beta_{FOX,t}}{0.6}$ where \bar{SD}_t is the cross-market average SD in period t .

The resulting persuasion rate is:

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

We report the time-series of the persuasion rates (10) from March 13, 2020 onwards in Figure 5(a). On March 13, the day President Trump declared a national emergency, our point estimate

³⁰<https://nscreenmedia.com/us-pay-tv/>

of the persuasion rate is 57.2%; although we cannot rule a rate as high as 70.2% and as low as 44% at the 5% significance level. The persuasion rates fall slightly between mid March and early April, although most of these differences are statistically insignificant. For instance, our lowest point estimate is 36.4% on April 10; although we cannot rule out rates between 22.5% and 50.2% 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 49.3% 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 70%. Defining SD with homebound devices is quite stringent given that most social distancing policies allow essential trips, such as grocery shopping. In Figure 5(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 33.5% and 40% 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 A5. The corresponding average persuasion rate is 27.7%, ranging from 16.4% to 49% throughout the second part of March and the month of April.

These persuasion rates are considerably 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 potential heterogeneity in Fox viewership effects across markets. Nevertheless, our persuasion rate for Fox News on social distancing compliance is comparable to the 58% 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 federal elections. Some of this work has measured large 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.³¹ 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.

³¹Our findings also align with a literature on negative political advertising (Ansolabehere et al., 1999; Wattenberg and Brians, 1999).

[Figure 5 about here.]

6 Conclusions

We find strong evidence of a Fox News 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 News viewership on social distancing compliance is quite large, especially given that it defies the expert recommendations from leaders of the US and global health communities. 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 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. In future research, it could be interesting to study whether news media broadcasts directly influence viewer beliefs or merely serve as a platform to promote the beliefs of political candidates.

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Figure 1: Distribution of Channel Positions across headends for each of the three news channels

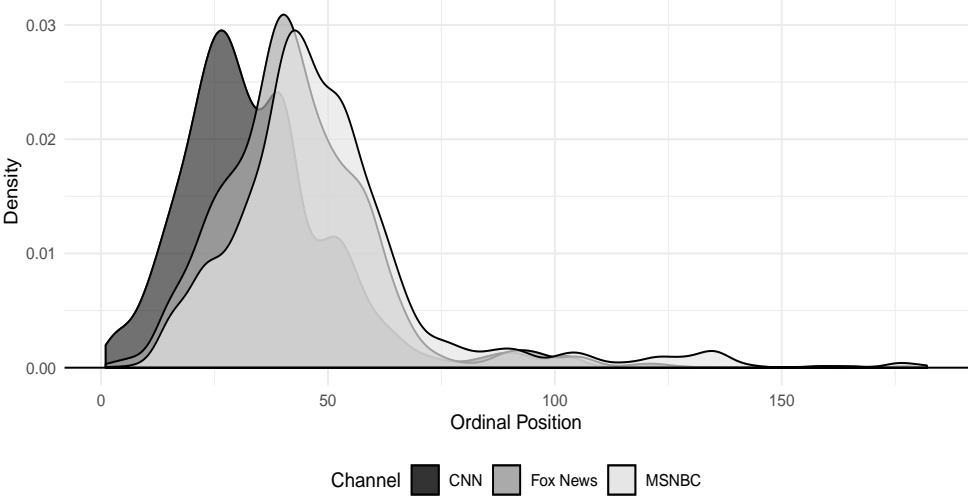
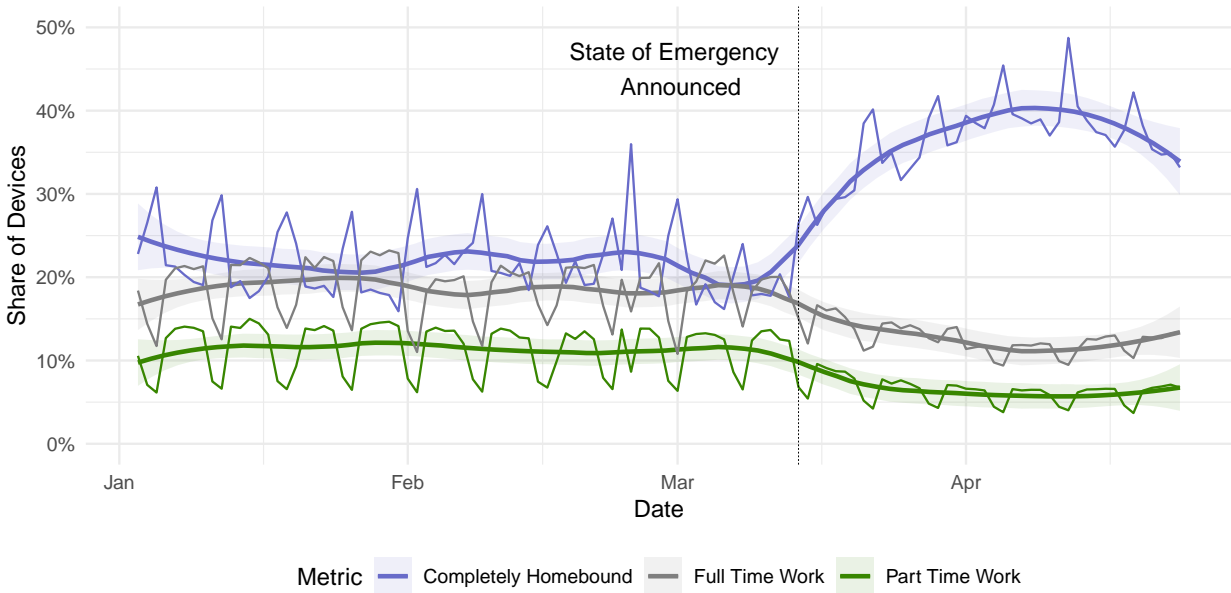


Figure 2: Stay-at-home propensity over time



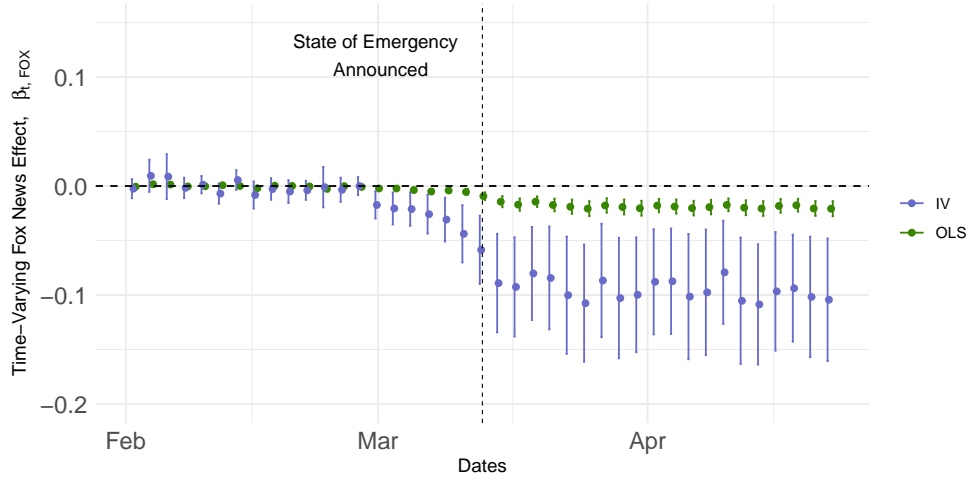
(a) Safegraph Data



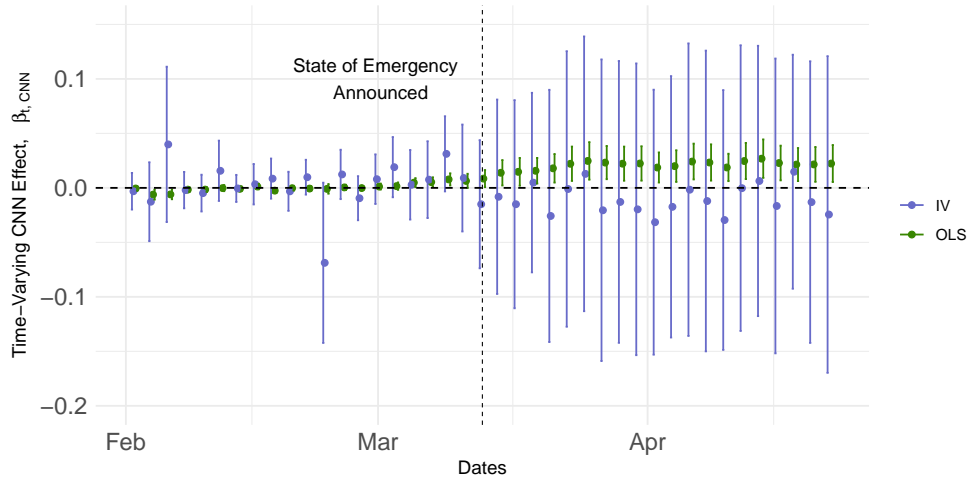
(b) Homebase Data

The solid lines and the shaded 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 $-\beta_{ct}^{Fox}$



(b) CNN effect $-\beta_{ct}^{CNN}$ for share of people at home

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 other news channels' positions.

Figure 4: Fox News Viewership Effects, Social Distancing Compliance and Business Closures.

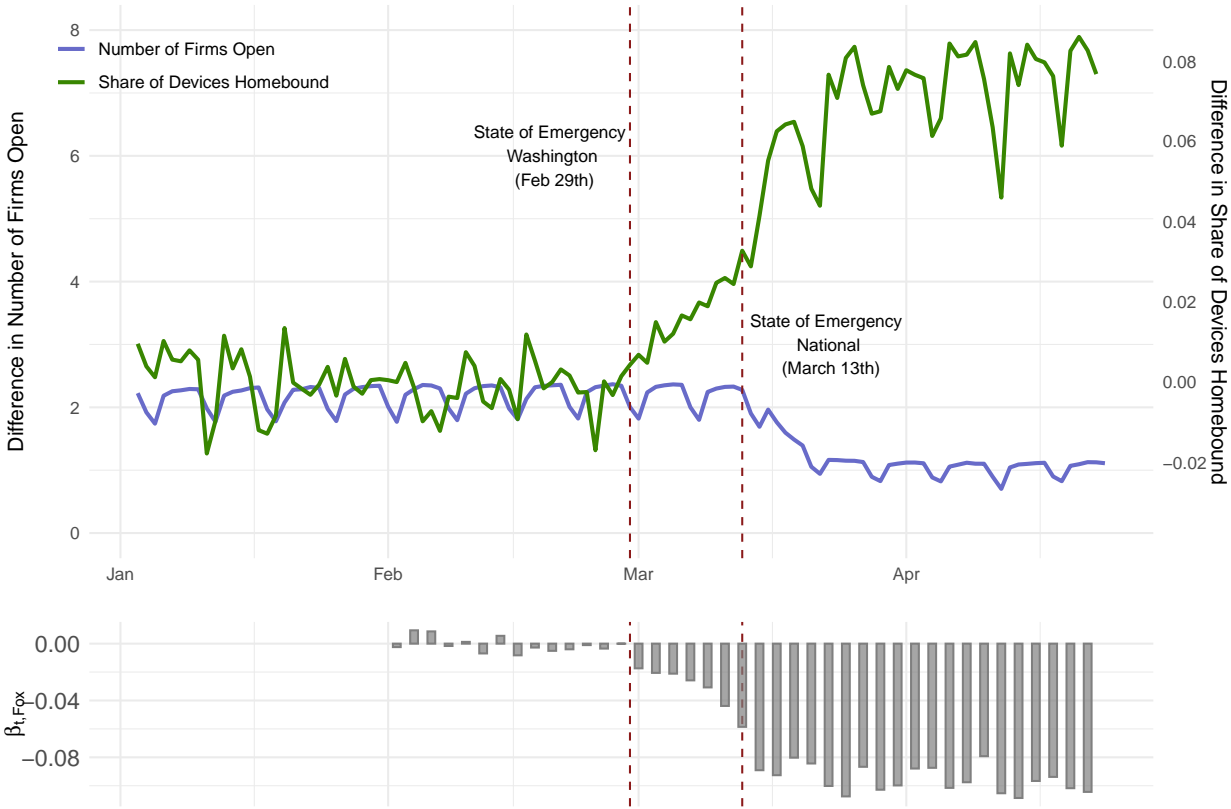
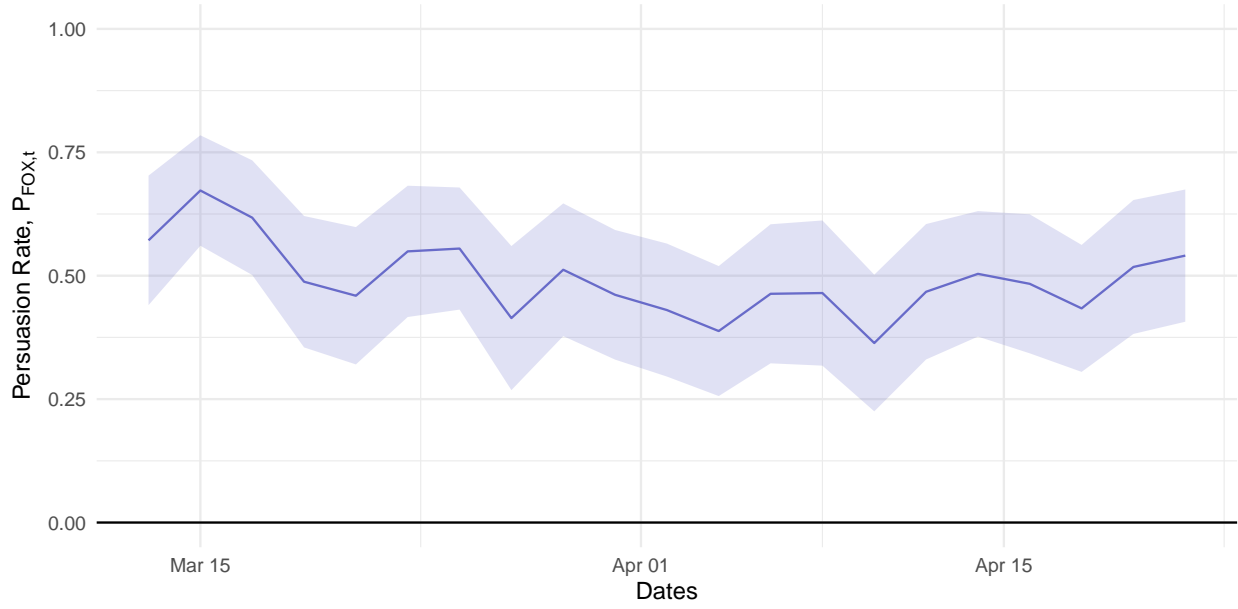
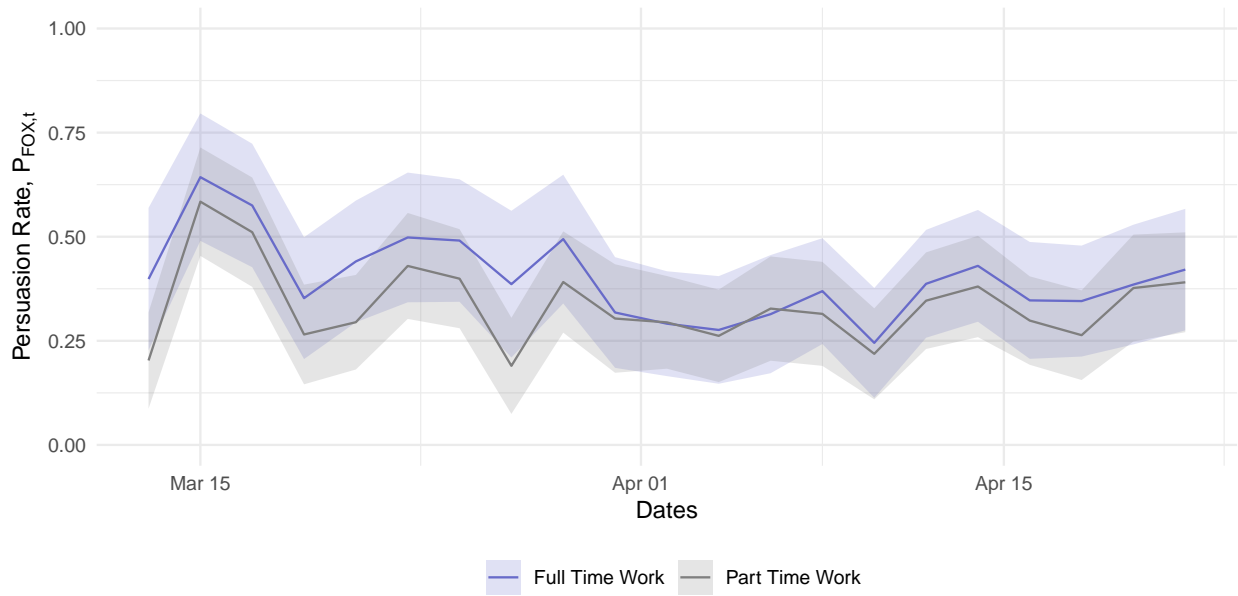


Figure 5: Persuasion Rate, $P_{FOX,t}$



(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

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

Table 3: Summary Statistics of the Stay-at-Home Propensity Variables

Measure	Mean	Median	SD	Min	Max	N	# Zips	# Days
(a) Baseline (January Average) Stay-at-Home Propensity in Safegraph Data								
Share Homebound Devices	0.23	0.23	0.04	0.05	0.49		27,173	
Share Devices at Work Full Time	0.19	0.18	0.03	0.08	0.51		27,173	
Share Devices at Work Part Time	0.11	0.11	0.02	0.03	0.2		27,173	
(b) Social Distancing Compliance based on Safegraph Data (Feb 1st - April 24th)								
SD (Share Homebound Devices)	0.06	0.04	0.11	-0.43	0.64	2,282,440	27,173	84
SD (Share Devices at Work Full Time)	-0.03	-0.03	0.05	-0.41	0.69	2,282,440	27,173	84
SD (Share Devices at Work Part Time)	-0.02	-0.03	0.04	-0.19	0.37	2,282,440	27,173	84
(c) Homebase Data								
Number of Workers	11.53	4	20.26	0	523	1,258,404	14,981	84
Number of Firms	2.6	1	3.8	0	61	1,258,404	14,981	84
(d) Facticeus Data								
Number of Cards	118.27	38	238.65	1	43,934	1,439,343	21,947	67
Number of Transactions	145.06	47	293.88	1	48,434	1,439,343	21,947	67
Total Spent (\$1000)	4.37	1.36	10.01	0	2,522.47	1,439,343	21,947	67

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			
	(1)	(2)	(3)	(4)
Ordinal Position of Fox	-0.0084*** (0.0023)	-0.0077*** (0.0022)	-0.0066*** (0.0026)	-0.0054** (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)	13.18	11.97	6.69	4.91
Observations	26,411	25,477	21,234	20,504
Adjusted R ²	0.2727	0.2902	0.2069	0.2258

^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 2016 elections. Cable system controls include number of channels in cable system, its square, and positions of competing news channels.

Table 5: Summary Statistics for Panel Regressions - FOX

	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0.08	0.17	0.84	0.87	0.87	0.91
N	1070032	1070032	1070032	1070032	1070032	1070032
# Clusters	2254	2254	2254	2254	2254	2254
Demographic controls	x					
Zip FE		x	x	x	x	x
State X Time FE			x	x	x	x
FXNC Viewership X Time				x	x	x
Other Channels X Time					x	x
Basic Demographics X Time						x

Standard errors clustered on cable system level. 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. Other News Channels include the positions of competing news channels. 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 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 IV Estimates with 2020 Viewership

[Figure A4 about here.]

A.8 IV Estimates with flexible demographic controls

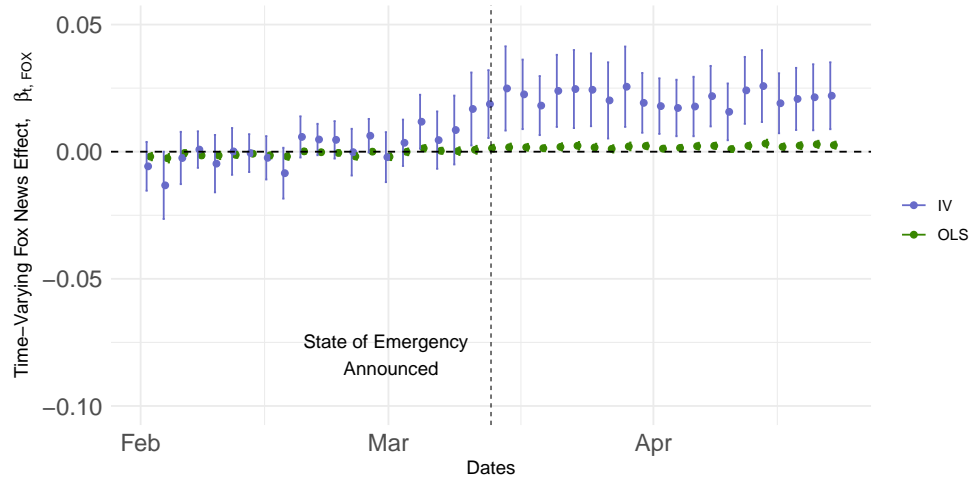
[Figure A5 about here.]

A.9 Channel Position Changes

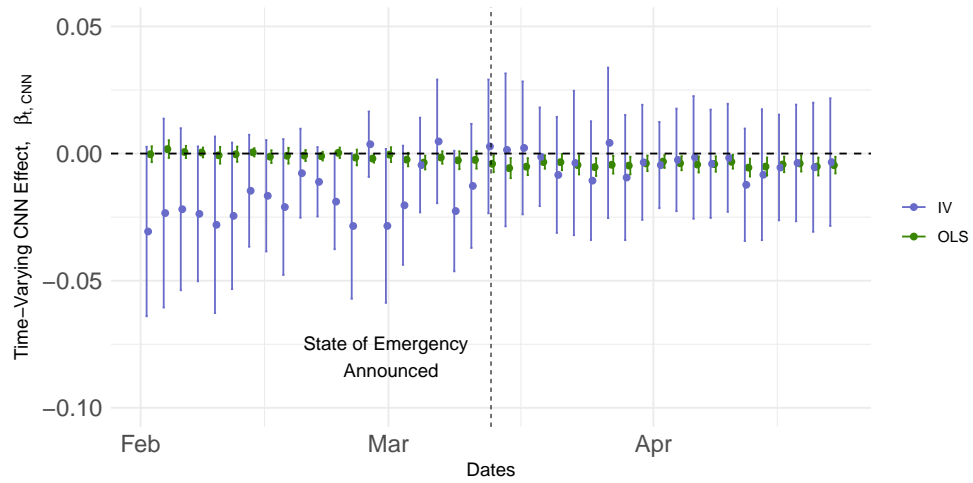
Using historical FOCUS data going back to 2006, we count, for each of the three news channels, the number of headends where (numeric) channel position stays exactly the same from one year to the next (for those headends which are present in both years). Table A6 reports these results. We see that for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

[Table A6 about here.]

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

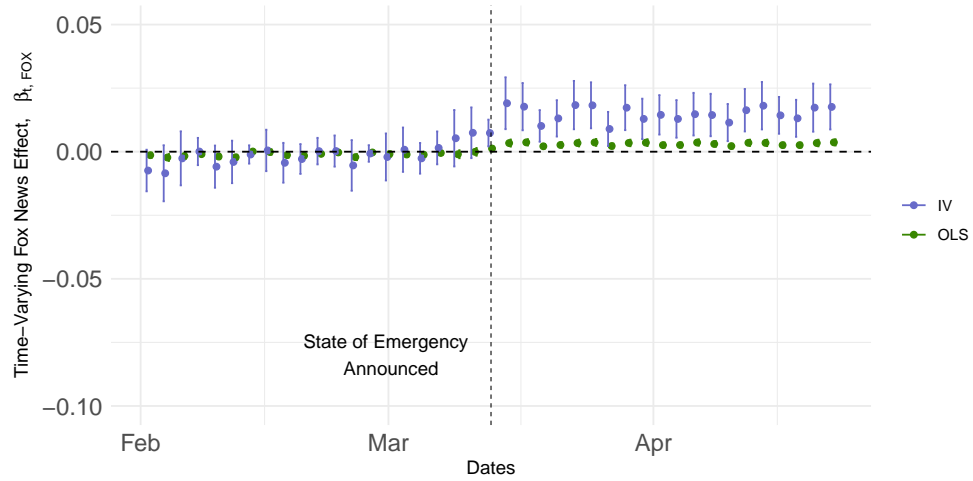


(a) Fox News effect $-\beta_{ct}^{Fox}$

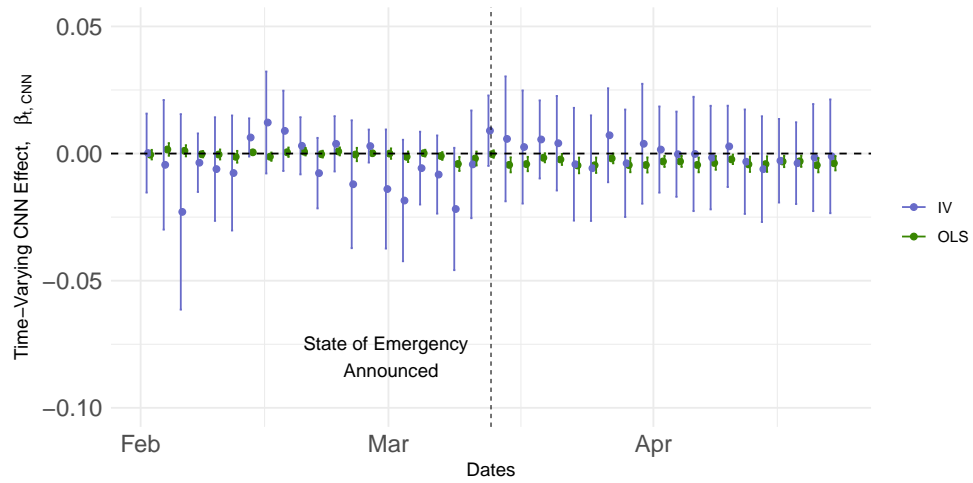


(b) CNN effect $-\beta_{ct}^{CNN}$ for share of people at home

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



(a) Fox News effect $-\beta_{ct}^{Fox}$



(b) CNN effect $-\beta_{ct}^{CNN}$ for share of people at home

Figure A3: The effect of channel positions of Share of Homebound Devices.

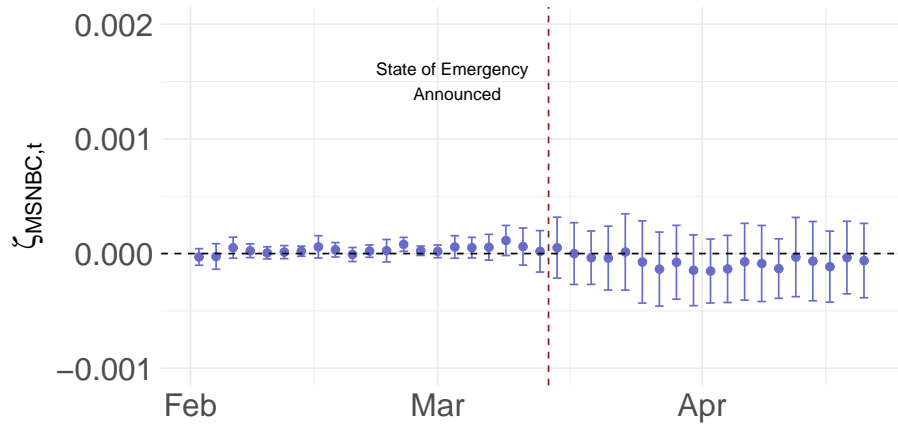
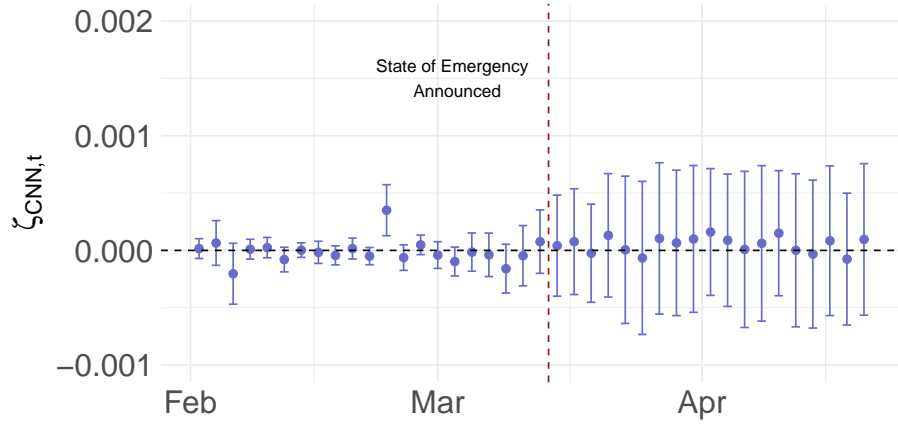
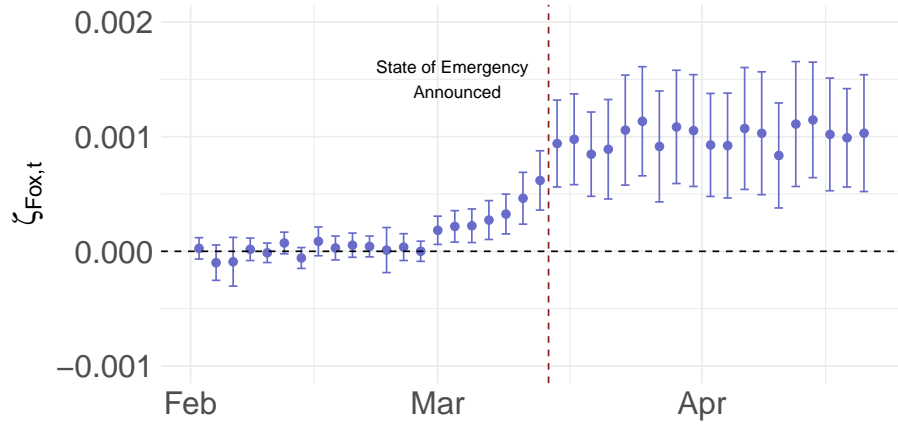


Figure A4: IV Estimates using 2015 and 2020 Viewership Data.

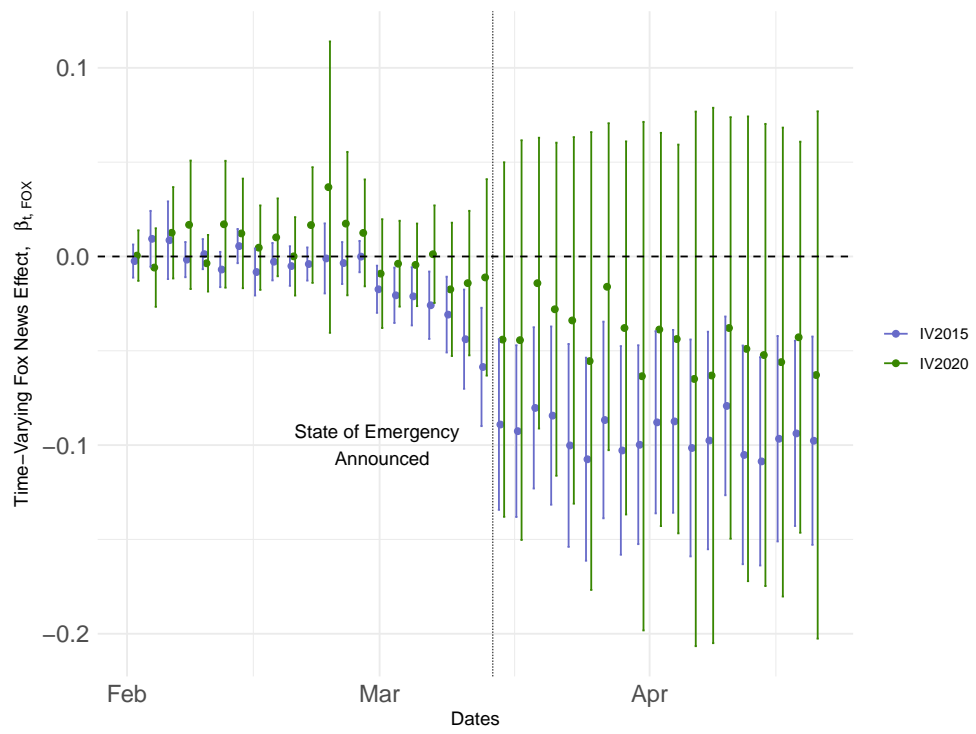
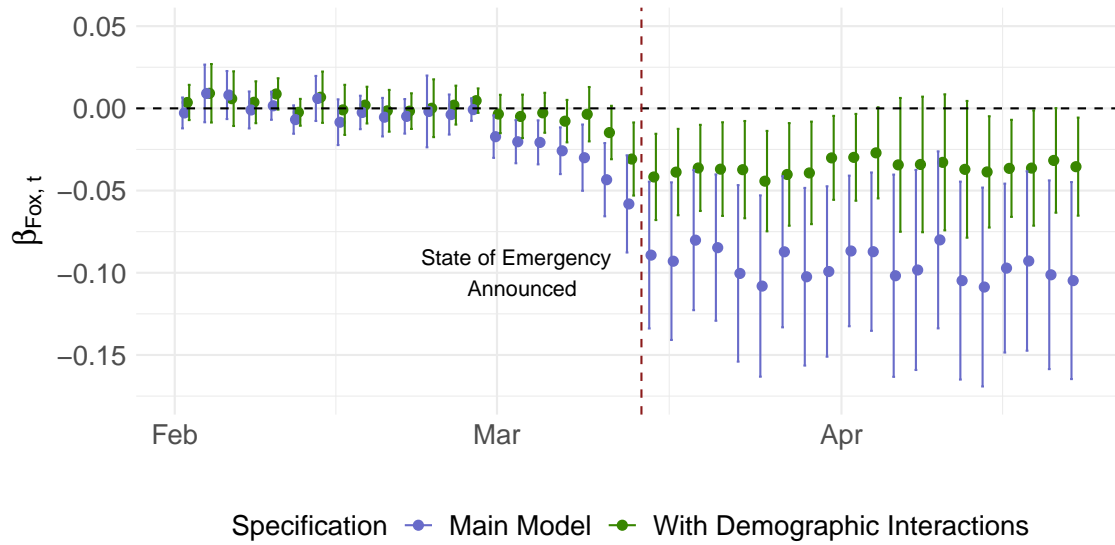


Figure A5: IV with time-varying demographic controls



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.

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 CNN	-0.0049*** (0.0018)	-0.0048*** (0.0017)	-0.0053*** (0.0015)	-0.0050*** (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)	7.32	7.87	12.72	12.22
Observations	26,411	25,477	21,234	20,504
Adjusted R ²	0.2193	0.2328	0.1748	0.1865

^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 2016 elections. Cable system controls include number of channels in cable system, its square, 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	Rep Vote Share	Median Age	Log Population Density
	(1)	(2)	(3)	(4)	(5)	(6)
Ordinal Position of FXNC	0.0011* (0.0006)	0.0004 (0.0003)	0.0001 (0.0001)	-0.0005 (0.0003)	0.0025 (0.0088)	0.0054 (0.0050)
State FEs	x	x	x	x	x	x
# Channels	x	x	x	x	x	x
Observations	25,499	26,313	26,323	26,388	26,259	26,406
Adjusted R ²	0.1893	0.1428	0.1245	0.3604	0.0766	0.2491

^a Stars: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered on cable system level.

Table A3: Correlations between demographic characteristics and position of CNN

	Characteristic					
	Log Median Income	% Bachelor Degree	% in Labor Force	Rep Vote Share	Median Age	Log Population Density
	(1)	(2)	(3)	(4)	(5)	(6)
Ordinal Position of CNN	0.0008 (0.0006)	0.0001 (0.0003)	-0.00002 (0.0001)	-0.0001 (0.0003)	0.0229*** (0.0085)	-0.0032 (0.0052)
State FEs	x	x	x	x	x	x
# Channels	x	x	x	x	x	x
Observations	25,499	26,313	26,323	26,388	26,259	26,406
Adjusted R ²	0.1885	0.1418	0.1244	0.3588	0.0784	0.2482

^a Stars: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered on cable system level.

Table A4: Summary Statistics for Panel Regressions - SD based on Share of Part Time Work Devices

	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0.03	0.11	0.79	0.82	0.82	0.85
N	1070032	1070032	1070032	1070032	1070032	1070032
# Clusters	2254	2254	2254	2254	2254	2254
Demographic controls	x					
Zip FE		x	x	x	x	x
State X Time FE			x	x	x	x
FXNC Viewership X Time				x	x	x
Other Channels X Time					x	x
Basic Demographics X Time						x

Standard errors clustered on cable system level. 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. Other News Channels include the positions of competing news channels. Basic Demographics include median income and log population density.

Table A5: Summary Statistics for Panel Regressions - SD based on Share of Full Time Work Devices

	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0.03	0.19	0.74	0.75	0.76	0.77
N	1070032	1070032	1070032	1070032	1070032	1070032
# Clusters	2254	2254	2254	2254	2254	2254
Demographic controls	x					
Zip FE		x	x	x	x	x
State X Time FE			x	x	x	x
FXNC Viewership X Time				x	x	x
Other Channels X Time					x	x
Basic Demographics X Time						x

Standard errors clustered on cable system level. 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. Other News Channels include the positions of competing news channels. 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