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

September 4, 2021

Abstract

To what extent do mass media outlets influence viewers' trust in scientific evidence and compliance with behavior recommended by scientific experts? Exploiting the US lock-down period of the COVID-19 pandemic in early 2020, we analyze a large longitudinal database that combines daily stay-at-home behavior from approximately 8 million mobile phones and local viewership of cable news networks. Early in the pandemic, several of Fox News' hosts downplayed the severity of the pandemic and the risks associated with the transmission of the virus. A combination of regression analysis and a natural experiment finds that a 10% increase in viewership of Fox News in a zip code causes a 0.76 percentage point reduction in compliance with stay-at-home behavior. The results imply a media persuasion rate that is larger than typical advertising persuasion rates on consumer behavior. Similar analyses using viewership of MSNBC and CNN, which supported lock-down measures, were inconclusive but suggested a smaller, positive effect on compliance with social distancing regulations.

1 Introduction

By early 2020, global health experts mostly agreed about the severity of the COVID-19 pandemic and the need for social distancing to mitigate transmission. The WHO declared a public health emergency on January 30, 2020 (Nedelman, 2020), the White House declared a national emergency in the U.S. on March 13, (85 FR 15337) and Johns Hopkins and the CDC recommended social distancing on March 13 and 14, respectively (Kopecki, 2020; Pearce, 2020). Nevertheless, the U.S. response to the COVID-19 pandemic was deeply divided, with suggestive evidence of a role of differential coverage by left- and right-leaning news sources, in particular the largest U.S. cable news channel: Fox News (Aleem, 2020; PewResearch, 2020).[1] To the extent that a leading news media channel persuaded viewers to disregard the leading health experts' and health organizations' recommendations to practice social distancing, viewers may have exposed themselves to higher personal health risks (CDC, 2020b; Kissler et al., 2020) and generated negative health externalities 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 U.S. The COVID-19 outbreak is not the first instance where a U.S. media outlet like Fox News finds itself accused of broadcasting misinformation.[2] However, the pandemic offers a unique opportunity to test whether media outlets like Fox News can persuade consumers to defy the recommended behaviors from the world's leading health experts and expose themselves to higher risks, even in a high-stakes decision.

We assemble several novel datasets to measure the effect of news viewership on compliance with social distancing. We start with a database tracking viewership and the numeric channel positions across approximately $2,500$ U.S. cable systems covering 30 thousand zip codes for the major cable news channels. We match the television data with a large, daily U.S. mobile phone panel that tracks individual propensities to stay at home across 27 thousand zip codes. We use

[1] Several Fox anchors downplayed the risks of disease transmission and questioned the recommendations of the scientific community. Laura Ingraham, for instance, branded the Democrat party as "pandemic party," accusing them of "weaponizing fear" (The Ingraham Angle, 2020c) and claims that "[the] Coronavirus crisis is teaching us a lot about so-called experts" and their "lame panic-inducing models" (The Ingraham Angle, 2020a). As late as April 30, Ingraham broadcast that "Experts don't like to admit their wrong, do they?" (The Ingraham Angle, 2020b). As a result, a Class Action, Claim #604 171 241, was filed on April 2, 2020 by the Washington League For Increased Transparency and Ethics alleging that Fox and other defendants "willfully and maliciously disseminate false information denying and minimizing the danger posed by the spread of the novel Coronavirus..." (Ecarma, 2020).

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

the mobile data to measure geographic differences in compliance with social-distancing behavior (hereafter "SD") based on the share of mobile phone users staying home or going to work. The combined dataset allows us to compare the SD behavior in regions with high and low viewership of the major cable news channels: Fox News, MSNBC, and CNN.

Panel regression analysis with flexible controls for persistent differences in SD across markets and market-specific trends fails to detect any significant associations of viewership and SD prior to the emergency declarations in early March. However, we find a rapid increase in the association between Fox News viewership and SD non-compliance in early March, stabilizing around the timing of the national state-of-emergency declaration in mid-March 2020. These relationships persist if we extend the model to add controls for a large number of zip-code-level demographic controls – local income, education, labor force participation, racial composition, age, population density, and persistent political preferences – strongly suggesting the causal effect of Fox News on SD compliance. In contrast, areas with higher viewership of MSNBC and CNN has the opposite effect to Fox News, with higher SD compliance from early March.

To interpret the panel regression estimates as a causal effect of Fox News viewership on social distancing compliance, we address the potentially self-selected manner in which consumers choose which news to watch and whether or not to comply with social distancing. We also address the potential measurement error in the viewership data. Following Martin and Yurukoglu (2017), we exploit the quasi-random assignment of the numeric channel positions of Fox News across cable markets as an instrument for viewership. In the first stage, we show that Fox News channel positions are strong predictors of its viewership. The instrumental variables (IV) analog of our panel regressions should correct for both the potential endogeneity and attenuation bias in the channel viewership data.

Our IV estimates confirm the results of the panel regression analysis. The effect of Fox News viewership on SD compliance takes off in early March 2020 and a stabilization in mid March, almost immediately after the White House's declaration of a national emergency. Immediately after the emergency declaration, a 10% increase in Fox News cable viewership leads to a 0.76 percentage point reduction in a zipcode's SD. The estimates imply an average persuasion rate of Fox News on SD during the crisis of about 12.8%, comparable to other persuasion rates typically found in the media persuasion literature (DellaVigna and Gentzkow, 2010). A novel aspect of this study is that the media persuasion affects a behavior broadly viewed by experts to promote public safety during a crisis, with public health and macroeconomic implications. The analogous IV regression analysis for MSNBC – another channel for which cable line-ups should be quasi-random per Martin and Yurukoglu (2017) – generates viewership effects that are mostly inconclusive; although the point

estimates are consistent with MSNBC viewership increasing SD compliance.

Our findings might also reflect, in part, an indirect effect moderated by political polarization, with Republicans less likely to comply with SD (Allcott et al., 2020; Barrios and Hochberg, 2020; Gauchat, 2012; Martin and Yurukoglu, 2017). As suggestive evidence of a direct effect, we find that the Fox effect on SD is strongest in Democrat-leaning markets where we would expect polarization to work in the opposite direction. Consistent with this direct effect, cultural worldviews have been found to be stronger predictors of trust in scientific experts than political opinions (Leiserowitz et al., 2013; Weaver et al., 2017).

Our work contributes to a broad marketing literature on the measurement of the persuasive effects of televised media. Most of the extant literature has focused on the measurement of the causal effect of advertising on consumer behavior(e.g., Gordon and Hartmann, 2016; Hartmann and Klapper, 2016; Shapiro et al., 2021; Sinkinson and Starc, 2019; Stephens-Davidowitz et al., 2017). A related product positioning literature has analyzed televised news media outlets' incentives to slant the broadcasted content (e.g. Mullainathan and Shleifer, 2005; Xiang and Sarvary, 2007; Xiang and Soberman, 2014; Zhu and Dukes, 2015). However, the empirical literature has focused on understanding media consumption choices (e.g. Deng and Mela, 2018; Goettler and Shachar, 2001; Lehmann, 1971; Wilbur, 2008) and not the impact of the content on viewer behavior.[3] Our findings add to this literature by documenting a large persuasive effect of news viewership on the high-stakes decision to comply with social distancing measures recommended by the world's leading health experts. The news media persuasion rate is found to be larger than typical advertising persuasion rates on consumer behavior. In a related, contemporaneous work, Bursztyn et al. (2020) study the effects of viewership for *Hannity* and *Tucker Carlson Tonight* on SD.[4]

Our findings add to an extant literature studying the persuasive effect of slanted news on viewers' acceptance of well-established scientific expert advice on policies for global warming (Hmielowski et al., 2014) and vaccinations (Lewandowsky et al., 2017).[5] Similarly, our field evidence builds on extant lab studies on advice-taking and the tendency for decision-makers to overweight their opinions relative to those of an advisor, even when the advisor is recognized as

[3]One exception is Martin and Yurukoglu (2017) who measure a persuasive effect of news viewership on voting behavior.

[4]We measure the causal effect of overall Fox New viewership, as opposed to two specific shows. We also use observed, as opposed to self-reported social distancing behavior. Finally, we use a granular television viewership panel spanning thousands of cable systems, as opposed to 210 aggregate DMA markets.

[5]Following DellaVigna and Gentzkow (2010), we use the term "persuasion" herein to refer broadly to informative and noninformative dimensions of communication. Since our data do not track awareness of the degree of scientific expert consensus for SD, we cannot rule out whether viewers rejected scientific expert advice or were merely persuaded not to comply with SD.

a highly-trained expert (e.g., Bonaccio and Dalal, 2006; Harvey and Fischer, 1997)[6]. Our work is broadly related to studies of news media persuasion on such topics as political opinion (Gerber et al., 2009), political participation (Cagé, 2019; Gentzkow, 2006), voting (Chiang and Knight, 2011; DellaVigna and Kaplan, 2007; Enikolopov et al., 2011; Martin and Yurukoglu, 2017; Snyder Jr and Strömberg, 2010), criminal sentencing decisions (Ash and Poyker, 2019; Lim et al., 2015), hurricane evacuations (Long et al., 2019), global warming (Hmielowski et al., 2014), and genocide (Yanagizawa-Drott, 2014).[7]

2 Data and Descriptive Analysis

2.1 Cable News Viewership

Through a partnership with Nielsen and the NBER, we obtained Nielsen's monthly NLTV data for 2006 to 2015 which includes viewership at the three leading U.S. cable news channels: Fox News, CNN and MSNBC. We also purchased the 2020 NLTV data directly from Nielsen. Nielsen tracks cable television audience sizes with a rotating panel of households equipped with meters and diaries to record their television viewing behavior. The NLTV data measure each channel's viewership by market and month as the average percentage of panelists who tuned in to the channel for at least five successive minutes across quarter-hour time intervals and days. These data represent approximately 43% of the population.[8]

Due to a recent change in Nielsen's survey methodology, the 2020 NLTV data only track 44 of the 210 DMAs and the panelist counts are low.[9] To see the potential for classical measurement error in our analyses below, consider that, during an average week, we observe zero panelists viewing Fox News in 59.9% of these zipcodes even though Fox is the most highly-watched cable news channel.

We therefore use the 2015 data, the most recent period for which we have access to broad geographic coverage spanning all 210 U.S. DMAs. Our data are measured at the cable system level,

[6] An exception is Simonsohn (2011) who finds that consumers pay attention to objective expert advice on product quality.

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

[8] 71% of U.S. households had access to television in 2019 (see `https://nscreenmedia.com/us-pay-tv/`) and 61% of these households subscribed to cable service.

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

or "headend,"[10] covering 2,536 unique headends representing 30,517 zip codes.[11] Below we show that channel positions change very infrequently, generating a stable within-market relationship between viewership and position that persists more than a decade. Zipcode-level channel viewership is strongly correlated across years, both in the period from 2006-2015 and comparing the 2015 and 2020 viewership.[12] Therefore, the 2015 viewership data provide a reliable proxy for 2020.

Table 1(i) reports descriptive statistics for each channel's viewership ratings in November 2015. On average, 1.32% of a headend's viewers tune into Fox News during a given time slot in a given month, higher than the combined rating of both CNN and MSNBC (0.51% and 0.34% respectively).[13] Although not reported, 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 U.S. viewers rely on Fox News as their primary source for news.

[Table 1 about here.]

2.2 Cable Systems' Assignments of Channel Positions

We purchased Nielsen's 2006 to 2015 FOCUS data to determine the channel lineups across headends. To correct for occasional gaps in the lineups, we use the channel's ordinal position ("position") instead of the exact numeric position to which a cable channel is assigned, as in Martin and Yurukoglu (2017).[14] Positions are quite stable over time: headends account for between 81% and 85% of the position variation, whereas years account for less than 2.5%. Only 4% of the headend-channel positions change from year to year.[15] In sum, 2015 head-end positions should provide a good proxy for 2020.

Table 1(ii) presents summary statistics of the channel positions across headends for each channel. On average, CNN has the most favorable position due to its earlier entry, 34.8, relative to Fox

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

[11] See Apppendix A.1 for how we pre-process the data.

[12] Figures A1-A3 in Online Appendix A.2 present the zipcode-level correlations of channel viewership in 2006-2015. The average correlation in local channel viewership across time periods of our data is 15.7%, 13.2%, and 9.9% for Fox News, MSNBC, and CNN, respectively, and stronger in neighboring time periods. Similarly, the 2015 Fox News viewership strongly correlates with the 2020 Fox News viewership: an OLS regression (weighted by the number of panelists) of 2020 viewership on 2015 viewership generates a point estimate of 0.461 (s.e. of 0.081) and F-statistic of 32.15.

[13] Using Martin and Yurukoglu (2017)'s conversion rate of 1.68 hours per week of Fox viewership per rating point, this corresponds to households watching an average 1.32 * 1.68 = 2.2 hours of Fox News per week. For CNN and MSNBC, these averages are 0.86 and 0.57 hours per week, respectively.

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

[15] The percents of changes from year to year for each channel are reported in A1 in Online Appendix A.3.

News' and MSNBC's respective average positions of 43.2 and 49.6. However, each channel's position varies across headends, with standard deviations ranging from 17.7 to 23.4 and coefficients of variation ranging from 0.41-0.53. 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. To demonstrate the variation in positions, we present the distribution of cable news channel positions across headends in Figure A10 in Appendix A.8.

2.3 Stay-at-Home Rates

We use Safegraph's cellphone GPS location data between January 1, 2020 and June 1, 2020 to measure SD. We observe a daily average of 7.75 million devices nationally or 265.17 per zipcode.[16] We construct a panel tracking two of Safegraph's daily measures of staying at home propensity by zipcode: (1) the share of devices that stayed at home, and (2) the share of devices that traveled to work for either a part-time or a full-time day.[17]

Table 1(iii) presents summary statistics of within-zipcode means for each of our Safegraph propensity variables during January 2020. We will use these January means as our baseline stay-at-home level in each market prior to the COVID-19 outbreak in the U.S..[18] On average, 24% of mobile devices remain at home in January. Our SD measures account for cross-market heterogeneity by taking the difference in stay-at-home propensity relative to January.

Figure 1 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 relative to the base period before March 13th, the date President Trump declared a national emergency. Several states had already issued 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 had increased by over 60% relative to January. We see similar SD timing using the work trips measure.

Table 1(iv) presents summary statistics of the daily SD measures across zipcodes between February 1 and June 1st, 2020. By April, all zipcodes have experienced at least some changes

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

[17] Safegraph infers part-time and full-time work locations based on dwelling in an away-from-home location for 3 to 6 hours and at least 6 hours, respectively.

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

in SD. On April 1, 2020, the average SD is 16 and -9 percentage points based on the share of homebound devices and share of devices at work, respectively. We observe a positive SD based on homebound devices in more than 98% of zipcodes.

[Figure 1 about here.]

3 Model and Regression Specification

Individual h in market z on day t derives the following incremental indirect utility from leaving home versus staying:

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

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 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.[19] Component $\beta_{ct}\text{rating}_{cz}$ can be interpreted as the causal effect of viewership of channel c on expected future health risks.

The expected utility-maximizing probability of staying at home in market z on day t is:

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

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

We define the pre-COVID-19 base period in 2020 as $\{\tau | \tau < \underline{t}\}$, where $\underline{t}$ denotes the first date during which compliance with social distancing became relevant. During the base period, the expected stay-at-home behavior is $\mathbb{E}(y_{z\tau})$ and cable news has no impact: $\beta_{c\tau} = 0, \ \forall \tau < \underline{t}$. Since market fixed-effects, α_z, capture persistent viewership effects on behavior, β_{ct} captures deviations over time in channel c's impact on behavior.

We define social-distancing compliance, SD_{zt}, as the change in stay-at-home behavior relative

[19] 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.

to the base period:

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

Our model of SD_{zt} combines (2) and (3):

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

where $\Delta\lambda_z(t)$ captures the cross-market differential evolution in SD (relative to the base period) in response to such factors 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}. For instance, we expect a market B, with one additional viewership rating point of channel c than a market A, to exhibit β_{ct} percentage points less SD_{zt} on day t than market A.

Regression Specification. We use panel data regressions to estimate the causal effect of news viewership on SD while controlling for persistent geographic differences and cross-geography differential trends. SD is defined by equation (3) with January 2020 as the base period, $\mathbb{E}(y_{z\tau}|\tau < \underline{t}) = \bar{y}_{z,Jan}$. Our statistical analysis of the viewership effect on SD is based on the following empirical specification:

$$SD_{zt} = \beta_{ct}\text{rating}_{cz} + \delta_z + \sum_{s \in States} \phi_{st}\mathbb{I}_{\{z \in s\}} + \sum_{c' \in \mathscr{C}_{-c}} \zeta_{c't}\text{position}'_c + \omega_t X_z + \xi_{zt}. \tag{5}$$

The inclusion of state-specific time effects, ϕ_{st}, and time-specific competitor position effects, $\zeta_{c't}$ where $c' \in \mathscr{C}_{-c}$, controls for cross-market differences in timing of emergency measures and news messaging. We also include a large set of zip code demographic variables and state fixed effects, each of which is interacted with daily fixed effects. Consequently, we include extremely flexible controls not only for geographic differences, but for cross-geography differential trends. Due to the large number of fixed effects in our panel regressions, we estimate the models using a separate regression each date between February 1, 2020 and June 1, 2020.[20] In the empirical analysis below, we report both OLS and IV versions of our panel regressions. The IV regressions address the potential self-selection and measurement error of viewership levels across markets.

[20] We obtain similar results using a single, pooled panel regression as reported in Appendix A.7.

4 Results

4.1 Panel OLS

We start with our OLS panel regression estimates of the cable news viewership effect on SD. In our main specification (indicated in brown in the figures below), we include daily, state fixed effects as well as daily coefficients on the two basic socio-econommic factors that have the highest predictive power for our SD measures: local income and population density. We include daily coefficients on the channel positions of a news channel's competitors (e.g., MSNBC and CNN when estimating the Fox News effect) to allow for cross-geography differences in the evolution of a news channel's persuasive effect to vary according to the relative proximity of competitors broadcasting a different message regarding the pandemic. To explore the robustness of our findings, we also report a saturated version of our OLS and IV panel regressions (indicated in green in the figures below) that includes an extensive set of additional demographic variables with daily effects to control even more flexibly for differential geographic trends: local income, level of poverty, education, labor force participation, racial composition, age, population density, and persistent political preferences.

Figure 2 plots the panel OLS estimates of the daily effects of viewership on SD for each of the three leading cable news channels: Fox, CNN and MSNBC. Shading indicates the daily 95% confidence intervals. Standard errors are clustered at the headend level.[21]

[Figure 2 about here.]

We begin with the analysis of SD measured using homebound devices (Panel a). Focusing on our main specification (brown), we can see that controlling for zip code level differential trends reduces the magnitude of our viewership effects. Our saturated specification (green) generates qualitatively similar viewership effects,[22] even though it is slightly less precise as expected due to the large number of controls. Even after including these controls, we observe several interesting patterns in our viewership effects. As late as February 28, before any state declared an emergency, we estimate small and statistically insignificant effects of viewership on SD for all three news networks. On February 28, we can reject magnitudes of the effect of a 1-rating point increase in viewership on SD larger than 0.3, 0.4 and 0.3 percentage points for Fox, CNN and MSNBC, respectively, at the 5% significance level. In early March, the viewership effects start to increase in magnitude. However, while Fox News viewership decreases SD, MSNBC and CNN viewership

[21] Our results are robust to clustering on the state level.

[22] On each day, we fail to reject equal viewership effects for the main and saturated specifications at the 5% significance level.

both increase SD. On March 16th, the Monday after the national state-of-emergency declaration, our estimates imply that a 1 rating point increase (nearly double) in Fox News viewership decreases SD by 0.6 percentage points; although we cannot reject that the decrease would be as small as 0.3 percentage points at the 5% significance level. The effect continues to increase in magnitude throughout mid March until it stabilizes. On March 23, we can reject decreases in SD associated with a 1 rating point increase in Fox viewership that are smaller in magnitude than 0.6 percentage points at the 5% significance level.

The effects of MSNBC and CNN viewership are smaller in magnitude and, once extended controls are included in the saturated specification, mostly statistically insignificant. Nevertheless, in contrast with Fox, the daily point estimates are all positive and, in spite of low precision, we fail to reject that on March 16th the effect of a 1 rating point increase in MSNBC and CNN viewership, respectively, causes corresponding increases in SD as high as 1.3 and 1 percentage points. In sum, the results suggest that Fox News viewership increases non-compliance with SD measures after the declaration of the national emergency. Qualitatively, CNN and MSNBC have the reverse effect and appear to rally compliance with SD.

We observe analogous viewership effects when we instead measure SD based on work behavior (Panel b). We find qualitatively similar timing patterns as with the homebound-device measure, with the point estimates stabilizing by mid-March.

4.2 Panel IV

We now turn to the IV versions of our panel regressions to ensure that our viewership effects above are robust to potential self-selection and measurement errors concerns in viewership levels across markets. Appendix A.4 reports a simulation exercise to show how the attenuation bias from measurement error in our viewership data could overwhelm the endogeneity bias, requiring the OLS estimates to be multiplied by 1/0.0753 or more to correct for this attenuation bias. The pandemic-related spike in news viewership in early 2020 raises an additional potential endogeneity concern if its effect was experienced differentially across cable news channels (e.g. Homan, 2021). We use a news channel's position in the local cable market as an IV for its viewership, exploiting the quasi-random assignment of channel positions across cable systems in the U.S. for Fox News and MSNBC (Martin and Yurukoglu, 2017).[23]

It is typically not possible to prove the validity of an IV in practice. However, the fact that

[23] As explained in Martin and Yurukoglu (2017), we cannot apply the channel position instrument to CNN since it is an older channel that entered before the rapid expansion and upgrade of cable systems, thereby violating the exclusion restriction. In particular, CNN has systematically lower positions, as we show in Figure A10 in Appendix A.8

channel position is uncorrelated with any of our demographic variables that predict SD behavior serves as placebo evidence that channel positions are not systematically most favorable in markets where we would have predicted low SD, as shown in Table A3 in Appendix A.9.

A bigger potential concern is whether channel position has predictive power for viewership now that consumers have programmable remote controls. To assess the power of the IV, panel (a) of Table 2 presents the first-stage results for the regression of viewership on channel position along with the other exogenous variables in our panel SD regressions. The point estimates imply that a 1 position improvement for Fox news (towards 0) increases viewership by $0.0077 - 00089$ rating points or $0.6 - 0.7\%$. Therefore, channel position has a non-trivial and statistically significant impact on viewership. We also find a first-stage incremental F-statistics of 14.22 in the baseline specification, 11.39 in our main specification, and 11.49 in our saturated specification with extensive demographic controls.[24] Although not reported herein, we also re-ran a pooled version of our first-stage analysis combining Fox and MSNBC for each year between 2006 and 2015. We find no evidence of a trend, with a stable position effect between 0.005 and 0.01, confirming that our 2015 results were not due to chance. Therefore, our findings are not an artifact of weak instruments (e.g., Staiger and Stock, 1997).

[Table 2 about here.]

Figure 3 plots the results from two sets of panel regressions: our IV regression (Panel a) and the corresponding reduced form regression that replaces viewership with the channel position (Panel b). The reduced form regression tests whether we find a significant relationship between SD and channel position and serves as additional confirmation of the reliability of our key IV results. The figure plots the daily viewership effects from the IV regressions and daily channel position coefficients from the reduced form regression. The reduced form regressions (Panel b) confirm that a higher Fox channel position is associated with less SD after March 1. Taken at face value, a 20-position improvement in Fox News position is associated with an almost 1-percentage-point decline in SD (point estimate is approximately 0.0004). The IV regressions (Panel a) summarize the causal effect of viewership on SD for Fox News (top) and MSNBC (bottom).

[Figure 3 about here.]

Focusing again on our main specification (brown), we observe a qualitatively similar timing pattern in viewership effects as we found in our OLS panel regressions above: the effect of Fox

[24] In Table A2 in Appendix A.9, we report analogous first-stage results for MSNBC.

News viewership on SD starts to increase in early March and stabilizes around mid-March. The saturated specification generates almost identical results. In sum, our IV results indicate that our qualitative findings about the impact of viewership on social distancing compliance are robust to endogeneity concerns with viewership. In fact, consistent with the measurement error concerns, our IV estimates of the Fox New viewership effect on SD are larger in magnitude than our earlier OLS estimates.

To quantify the magnitudes of the Fox News viewership effects, Table 2 present the IV regression estimates for several dates in our sample before and after the declaration of the national emergency. In February, our point estimates are extremely small and statistically insignificant. On February 3, for instance, we can reject Fox News viewership effects larger in absolute value than 1.31 percentage points, at the 5% significance level. When we instead consider the March dates after the timing of the declaration of a national emergency, we find large and statistically significant effects in our main specification. On March 16, we find that a 1 rating point increase in Fox News viewership will decrease SD by 5.78 percentage points, and reject effect sizes less than 1.63 percentage points at the 5% significance level. In relative terms, a 10% increase in Fox News viewership (0.132 rating points) leads to a 0.76 percentage points decrease in SD. Similarly, one week later, on March 23, we find that a 1 rating point increase in Fox News viewership will decrease SD by 4.4 percentage points, and we reject effect sizes less than 3.2 percentage points at the 5% significance level. Our IV estimates are consistent with our concerns about attenuation bias from measurement error: the IV estimates are larger in magnitude than the OLS estimates in 2.

For completeness of the analysis, we now turn to MSNBC, another channel for which cable line-ups should be quasi-random per the analysis in Martin and Yurukoglu (2017). The lower portion of Figure 3 presents the IV and reduced form estimates for MSNBC. As reported in Table A2 in Appendix A.9, channel position is a weak instrument for MSNBC if we only use the 2015 viewership cross section, a possible explanation for the imprecise IV estimates (Panel a). To ensure the instrument power more generally, the second part of Appendix Table A2 shows that MSBC's channel position is a very strong instrument when we pool all the viewership cross-sections for all available time periods (2006-2015): the incremental F-statistic ranges from 22.13 to 24.72 and a 1 position improvement (towards 0) increases MSNBC viewership by 0.0027 rating points, or 0.7%. In fact, the magnitude of the position effect for MSNBC closely tracks the first-stage effect size for Fox News ($0.6-0.7\%$). To examine the effect of MSNBC viewership on SD, the lower part of Figure 3b presents the reduced-form results, which confirm the direction of the OLS estimates for MSNBC. Only after the national emergency declaration do we estimate a large, positive effect of channel position on SD compliance, and the effects are significant for 56 out of

78 days in our main (brown) specification. Using the channel position effect coefficient from the pooled MSNBC viewership regression, the reduced-form estimates imply that on March 23 a 10% increase in MSNBC viewership causes a 0.18 percentage point increase in SD.

Several factors suggest that the impact of Fox viewership on SD reflects a direct effect, in addition to any indirect effect mediated by political polarization (Allcott et al., 2020; Barrios and Hochberg, 2020). 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). Similarly, partisan media has been shown to reduce long-term trust in media (Guess et al., 2021). As additional suggestive evidence, we classify the zip codes into terciles based on the Democrat vote share from the 2016 presidential election: liberal, neutral and conservative. Re-running our IV analysis by terciles allows us to test for Fox News position effects on SD using only position variation within those zip codes that are already the most polarized in favor of the Republican party and Democratic party, respectively. We find small and insignificant effects in Republican markets, which is consistent with the polarization findings in Allcott et al. (2020). Residents of these markets are already persuaded regardless of Fox News. We also find large and significant Fox News channel position effects in the most Democratic-party-leaning markets, consistent with Fox viewership having a direct persuasive effect. See Figure A7 in Appendix A.5 for plots of the results.

4.3 The Persuasion Rate of Cable News

To compare our results with past work on media persuasion, we use our IV estimates to compute a persuasion rate (DellaVigna and Kaplan, 2007), which corresponds to the effect of a two-standard-deviation change in Fox News' channel position, or a shift from the 10th to 90th percentile position.[25] Following DellaVigna and Gentzkow (2010), we measure the persuasion rate as follows:

$$P_{FOX,t} = 100 \times \frac{1}{S^{Fox}} \frac{E^{Fox}}{S_P^{Fox}} \tag{6}$$

where E^{Fox} measures the treatment effect, S^{Fox} measures the treated share of the population, and S_P^{Fox} measures the expected persuadable share of the population (i.e., SD compliers and would-be SD compliers). See Appendix A.6 for details.

The average persuasion rate between March 15 and June 1 is 12.8%; although on a median day we cannot rule out a persuasion rate as high as 20.1% and as low as 1.6% at the 5% significance

[25] Following Martin and Yurukoglu (2017), we let 1 rating point correspond to 1.68 hours per week of Fox News

level. Our persuasion rates are comparable to the average rate of 9.5% for other communication media reported in DellaVigna and Gentzkow (2010), while higher than the 0.7-6.9% persuasion rates reported for persuasion of consumer through advertising. The persuasion rates herein are novel because they involve a behavior that defies highly-publicized social-distancing recommendations by leading health experts. Therefore our findings provide real-world evidence for the media to moderate the "advice discounting" phenomenon typically measured in laboratory studies (Bonaccio and Dalal, 2006). Similarly, our findings provide suggestive real-world evidence of a role for the media (Dunlap and McCright, 2010; Hmielowski et al., 2014) in explaining the growing distrust in scientific experts, especially among conservatives (Gauchat, 2012). While we cannot rule out that the persuasion rates herein reflect political polarization (Allcott et al., 2020), previous research has found that trust in scientific experts is moderated more by an individual's cultural worldviews than by her political orientation (Leiserowitz et al., 2013; Weaver et al., 2017).

5 Conclusions

In spite of a large extant literature measuring the persuasive effect of television advertising on consumer behavior, there are few studies measuring the persuasive effect of broadcast content on behavior. We find strong evidence of a persuasive effect of Fox New viewership on SD, measured as the incremental propensity to stay at home during the early stages of the COVID-19 crisis in the United States. Unlike previous research on media persuasion, these effects cause behaviors that not only defy expert recommendations from leaders of the global health community, but also are believed to influence rates of disease transmission and death. The news media persuasion rate is larger in magnitude than typical short and medium term advertising persuasion rates on consumer behavior.

We defer to health experts to determine whether the magnitude of the Fox persuasion rate would have a material effect on transmission and death rates. An important direction for future research consists of testing the extent to which Fox News persuasion affects economic outcomes like consumer demand and business performance, both of which are associated with SD in an emerging macroeconomic literature on COVID-19.

The stability of our effects may be suggestive of a long-term effect of exposure to Fox News and growing distrust in institutions more broadly. The timing of our Fox New effects suggests a direct effect on viewers, in addition to any potential indirect effects from political polarization towards Republican sentiment against SD. 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; albeit not conclusive. Testing these alternative mechanisms for the Fox News effect would be interesting directions for future research.

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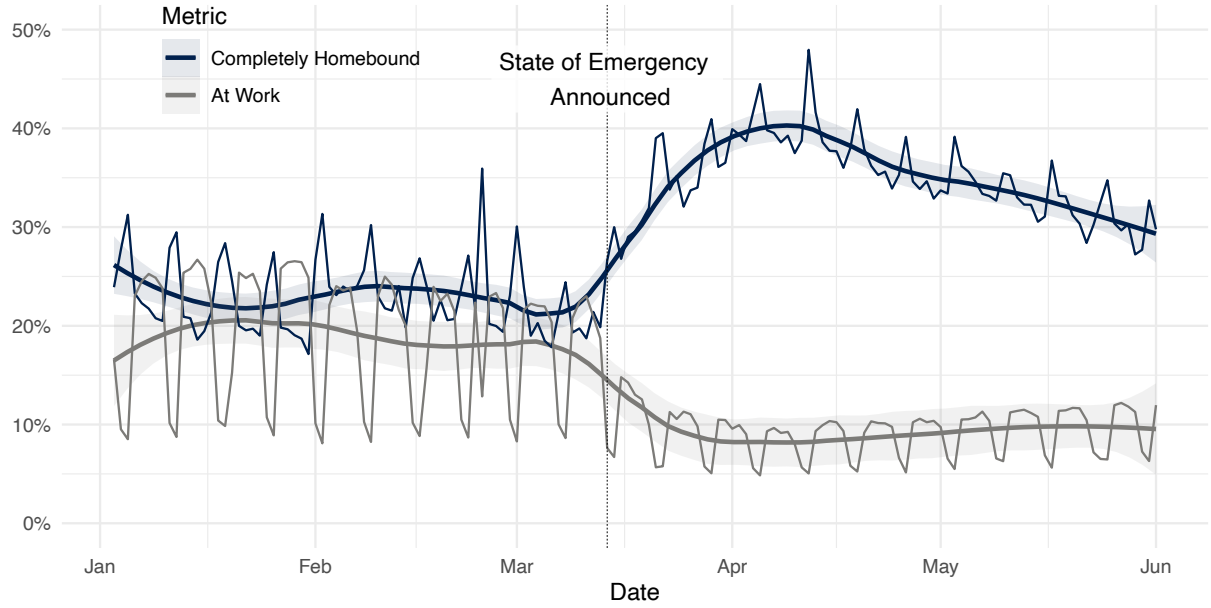
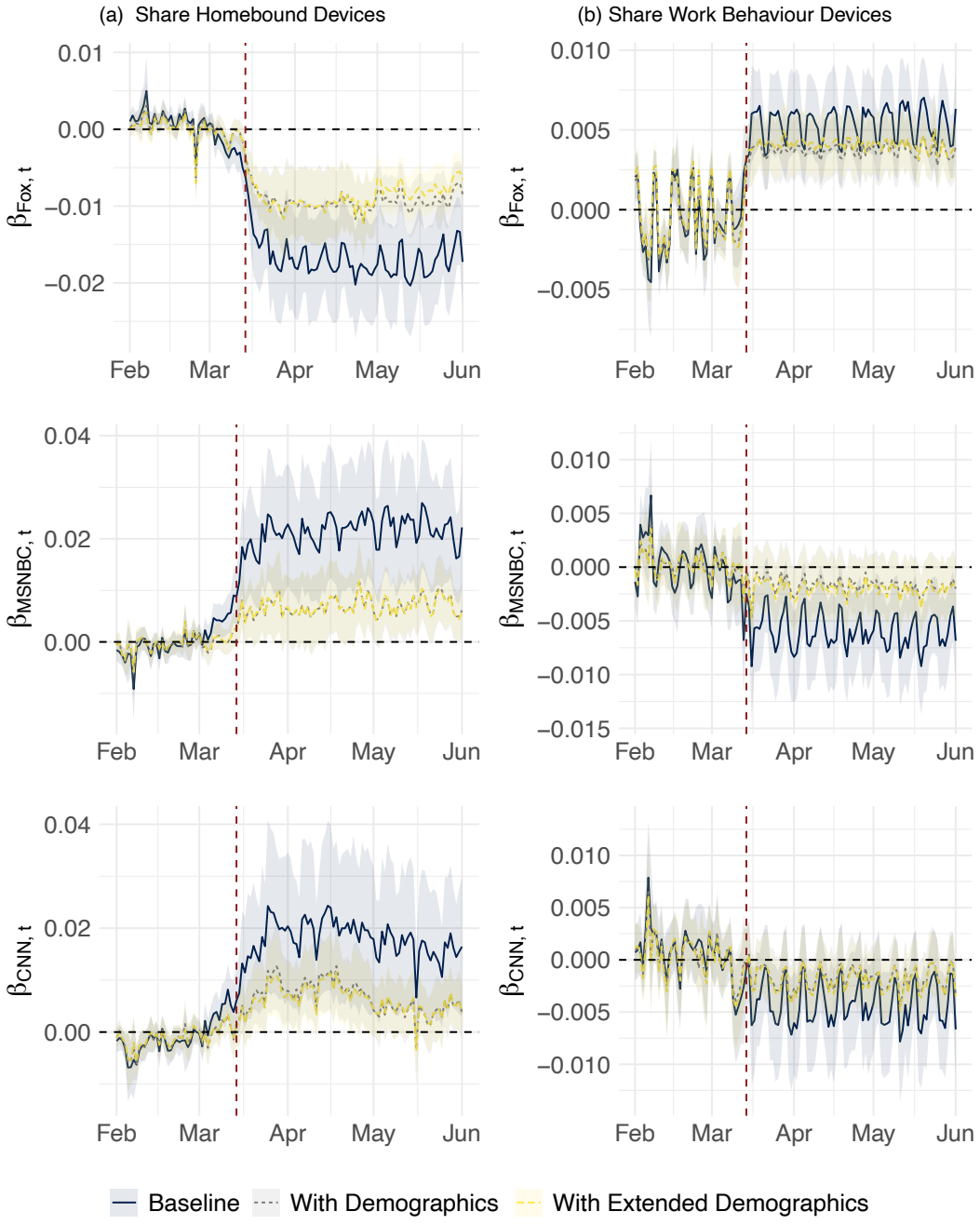
Figure 1: Stay-at-home propensity over time.



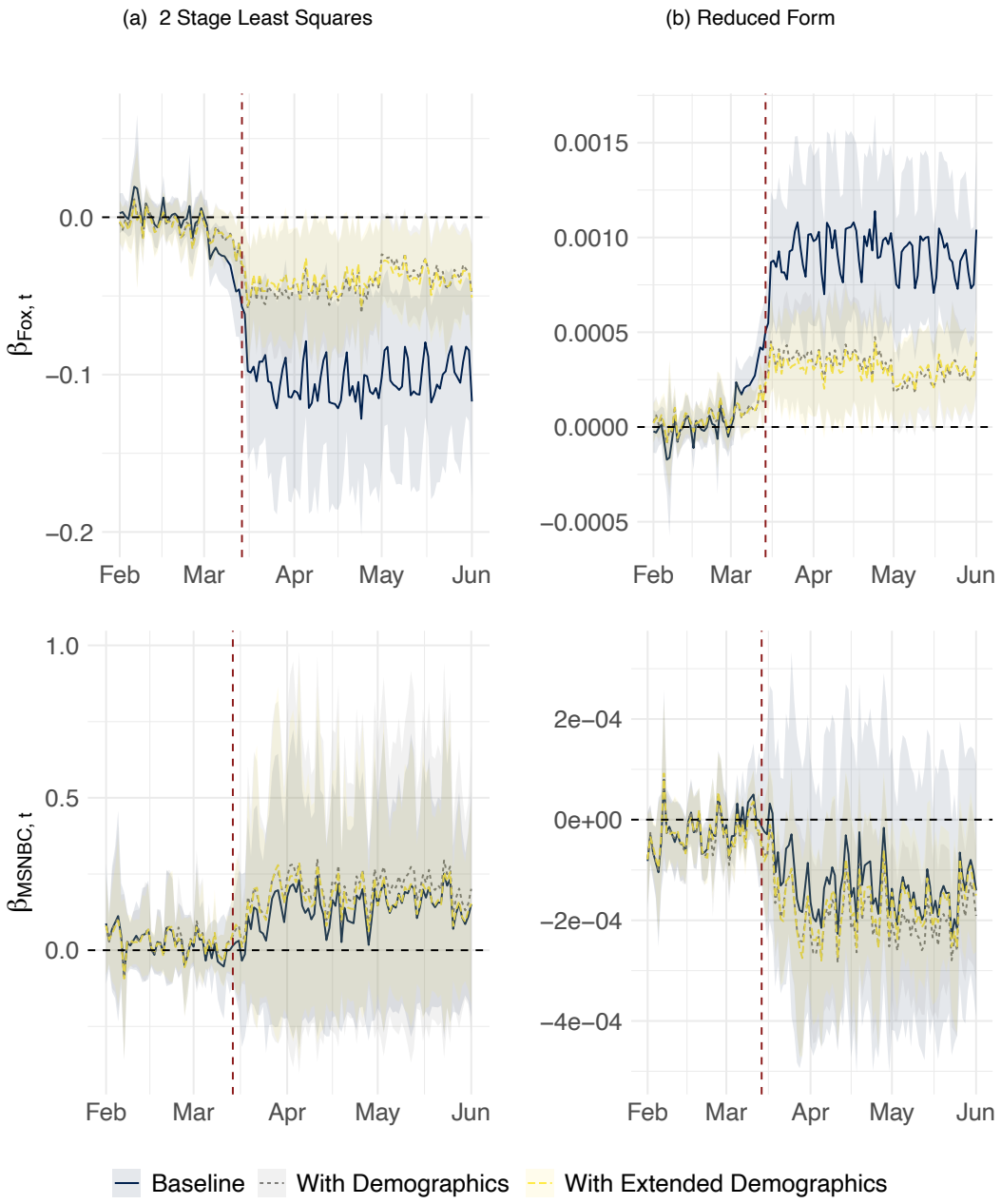
The solid lines and the shared regions correspond to the predicted values and confidence regions of the local polynomial regression, estimated with LOESS method.

Figure 2: Day-by-day Repeated Cross-Section OLS Results



These Figures use the 2020 Safegraph data at the zipcode-day level between February 1, 2020 and June 1, 2020. Share of Homebound Devices computes the daily cross-zipcode average of the share of tracked mobile phones that did not leave home. Share of Work Behaviour computes the daily cross-zipcode average of the share of tracked mobile phones that did leave home to travel to a work location. The OLS regressions use the 2015 NLTV data for each zipcode's viewership of each of the three news channels: Fox, CNN and MSNBC. The baseline OLS specification includes state fixed effects, number of channels in the cable system, and positions of competing channels as controls. The "With Demographics" specification adds demographic controls for each zipcode's log median zip code income and population density in 2020. The "With Extended Demographics" specification also adds controls for each zipcode's share of population with a Bachelor's degree, labor force participation rate, share of population that is white, share of population below the poverty line, median age, and county-level Republican vote share in 1996 elections. Daily point estimates are indicated by solid lines and 95% confidence intervals are indicated by shaded regions. All standard errors are clustered at the headend level.

Figure 3: Day-by-day Repeated Cross-Section 2SLS and Reduced Form Results



These Figures use the 2020 Safegraph data at the zipcode-day level between February 1, 2020 and June 1, 2020. Share of Homebound Devices computes the daily cross-zipcode average of the share of tracked mobile phones that did not leave home. Share of Work Behaviour computes the daily cross-zipcode average of the share of tracked mobile phones that did leave home to travel to a work location. The 2SLS regressions use the 2015 NLTV data for each zipcode's viewership of each of the three news channels: Fox, CNN and MSNBC. The instrumental variable for viewership consists of the channel's local numeric channel position, which we obtain from the 2015 FOCUS data. The baseline 2SLS specification includes state fixed effects, number of channels in the cable system, and positions of competing channels as controls. The "With Demographics" specification adds demographic controls for each zipcode's log median zip code income and population density in 2020. The "With Extended Demographics" specification also adds controls for each zipcode's share of population with a Bachelor's degree, labor force participation rate, share of population that is white, share of population below the poverty line, median age, and county-level Republican vote share in 1996 elections. Daily point estimates are indicated by solid lines and 95% confidence intervals are indicated by shaded regions. All standard errors are clustered at the headend level.

Table 1: Summary statistics of the stay-at-home propensity variables

Measure	Mean	Median	SD	Min	Max	# Headends	# Zips	# Days
(i) NLTV data: Ratings								
Ratings: CNN	0.51	0.17	1.5	0	40.03	2502		
Ratings: Fox News	1.32	0.49	2.6	0	32.59	2499		
Ratings: MSNBC	0.34	0.03	1.11	0	17.16	2335		
(ii) Focus data: Channel Positions								
Position: CNN	34.85	32	18.31	1	163	2502		
Position: Fox News	43.2	41	17.77	1	177	2499		
Position: MSNBC	49.64	46	23.43	3	182	2335		
(iii) 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	0.19	0.19	0.04	0.04	0.34		27,173	
(iv) Social Distancing Compliance based on Safegraph Data (Feb 1st - June 1st)								
SD (Share Homebound Devices)	0.07	0.06	0.09	-0.41	0.69		27,173	122
SD (Share Devices at Work)	-0.07	-0.07	0.07	-0.32	0.57		27,173	122

Viewership ratings are average cable viewership for each channel within a market across days and quarter-hour time slots. Positions correspond to ordinal positions of channels in local cable system lineups. Homebound devices are defined as devices that did not leave Geohash-7 of their home. The unit of analysis is zipcode-day.

Table 2: First Stage and Cross-Sectional IV Results

	(a) First-stage results Dep Var: Fox Viewership Ratings			
		(i)	(ii)	(iii)
	Fox Channel Position	-0.0089***	-0.0078***	-0.0077***
		(0.0024)	(0.0023)	(0.0023)
	Fit statistics			
	R^2	0.26467	0.27453	0.28305
	Incremental F-Stat	14.22	11.39	11.49
	(b) IV Estimates of Fox viewership Effect on SD for select dates			
		(i)	(ii)	(iii)
Pre-pandemic	Feb3	0.0005	-0.0012	-0.0034
		(0.0055)	(0.0060)	(0.0058)
	Feb 10	0.0088*	0.0093	0.0074
		(0.0052)	(0.0060)	(0.0058)
During pandemic	March 16	-0.0978***	-0.0578***	-0.0562***
		(0.0290)	(0.0214)	(0.0208)
	March 23	-0.1043***	-0.0440**	-0.0396**
		(0.0055)	(0.0060)	(0.0058)
	Controls			
	State FEs	x	x	x
	Cable System Controls	x	x	x
	Basic Demographics		x	x
	Extended Demographics			x

Stars: *p<0.1; **p<0.05; ***p<0.01. Table uses the 2020 Safegraph data at the zip code-day level between February 1, 2020 and June 1, 2020. Share of Homebound Devices computes the daily cross-zip code average of the share of tracked mobile phones that did not leave home. Share of Work Behaviour computes the daily cross-zip code average of the share of tracked mobile phones that did leave home to travel to a work location. The 2SLS regressions use the 2015 NLTV data for each zip code's viewership of each of the three news channels: Fox, CNN and MSNBC. The instrumental variable for viewership consists of the channel's local numeric channel position, which we obtain from the 2015 FOCUS data. Specification (i) corresponds to "baseline" 2SLS and includes as controls state fixed effects ("state FEs"), number of channels in the cable system and positions of competing channels ("cable system controls"). Specification (ii) corresponds to "With Demographics" 2SLS and adds demographic controls for each zip code's log median zip code income and population density in 2020 ("Basic Demographics"). Specification (iii) corresponds to "With Extended Demographics" 2SLS and also adds controls for each zip code's share of population with a Bachelor's degree, labor force participation rate, share of population that is white, share of population below the poverty line, median age, and county-level Republican vote share in 1996 elections ("Extended Demographics"). All standard errors are clustered at the headend level.

[FOR ONLINE PUBLICATION]

A Appendix

A.1 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 U.S. 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.2 Correlations in Channel Viewership over Time

In spite of potential concerns about measurement error in the local viewership data from NLTV due to the limited number of panelists used by Nielsen, we nevertheless observe a lot of persistence in local channel viewership. This local viewership persistence allows us to use past viewership of the channels as a proxy for the current viewership. Figures A1-A3 present the correlations in the zip code level viewership of Fox News, MSNBC, and CNN for 20 time periods in our data. The average correlation in local channel viewership across time periods of our data is 15.7%, 13.2%, and 9.9% for Fox News, MSNBC, and CNN, respectively. The correlation is stronger for the neighboring time periods – for instance, ranging from 27% to 83% for two adjacent time periods for Fox News – and gets weaker as the time periods get further apart.

[Figure A1 about here.]

[Figure A2 about here.]

[Figure A3 about here.]

A.3 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 A1 reports these results. We see that for the large majority for headends, (numeric) positions of the three news channels remain constant.

[Table A1 about here.]

Table 2 in the main text report the first-stage regression results (9) for Fox News. The 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, controls for basic demographics (household income and urban density), and weights observations by the number of panelists (Column 2), a one-position increase in the lineup is associated with 0.0078 lower rating for Fox News. A one standard-deviation improvement in channel position increases Fox News viewership by over 0.139 rating points, with the mean and standard deviation of Fox viewership of 1.32 and 2.6 rating points. The magnitude of Fox's own-position effect is robust across specifications and is slightly lower in our preferred specification (column 2) that includes controls and weights, generating an incremental F-statistic of 11.32. The channel-position effect is robust to excluding (Column 1) and expanding (Column 3) the demographic controls.

Table A2 presents the first stage results specification for MSNBC. In the first three columns, we report the first stage results for MSNBC using our main viewership data period using in the IV estimation, November 2015. In this period, the relationship between MSNBC's position and viewership is weak, with the point estimates implying that a 1 position improvement (towards 0) increases viewership by approximately 0.0009-0.001 rating points, or 0.3%. While the estimate is imprecise, the point estimate of the effect lines up well with the effect we have found for Fox News, where a 1 position improvement increased viewership by 0.6-0.7% – our results for MSNBC cannot reject this magnitude.

To examine whether this weak relationship is idiosyncratic or more systematic, in columns (iv)-(vi) of Table A2 we present the first stage results pooling data across all 20 viewership time periods (2006-2015) that we observe. For each specification, we interact the corresponding controls – for instance, state fixed effects and cable system controls in column (iv) – with period fixed effects. As before, we cluster the standard errors at the headend level. The estimates reveal a strong and stable effect of MSNBC's position on viewership, with a 1 position improvement for MSNBC (towards 0) increasing its viewership by approximately 0.00249 rating points (s.e. 0.00049), or 0.7% – closely

tracking the magnitudes that we find for Fox News. The position effect is highly significant, with the implied F-statistics of the instrument of 22.13-24.72. We conclude that the imprecision of the first stage for MSNBC using our main viewership data period is idiosyncratic, with otherwise the relationship between MSNBC's position and viewership is strong.

[Table A2 about here.]

[Table A3 about here.]

A.4 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. 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 $\beta_{FOX,t}$ 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 A4-A5 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 A6 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 A4 about here.]

[Figure A5 about here.]

[Figure A6 about here.]

A.5 Heterogeneous Effects By Terciles of Zip Codes Ideology

[Figure A7 about here.]

A.6 The Persuasion Rate of Cable News

Following DellaVigna and Gentzkow (2010), we measure the persuasion rate as follows:

$$P_{FOX,t} = 100 \times \frac{1}{S^{Fox}} \frac{E^{Fox}}{S_P^{Fox}} \tag{7}$$

where E^{Fox} measures the treatment effect, S^{Fox} measures the treated share of the population, and S_P^{Fox} measures the expected persuadable share of the population (i.e., SD compliers and would-be SD compliers).

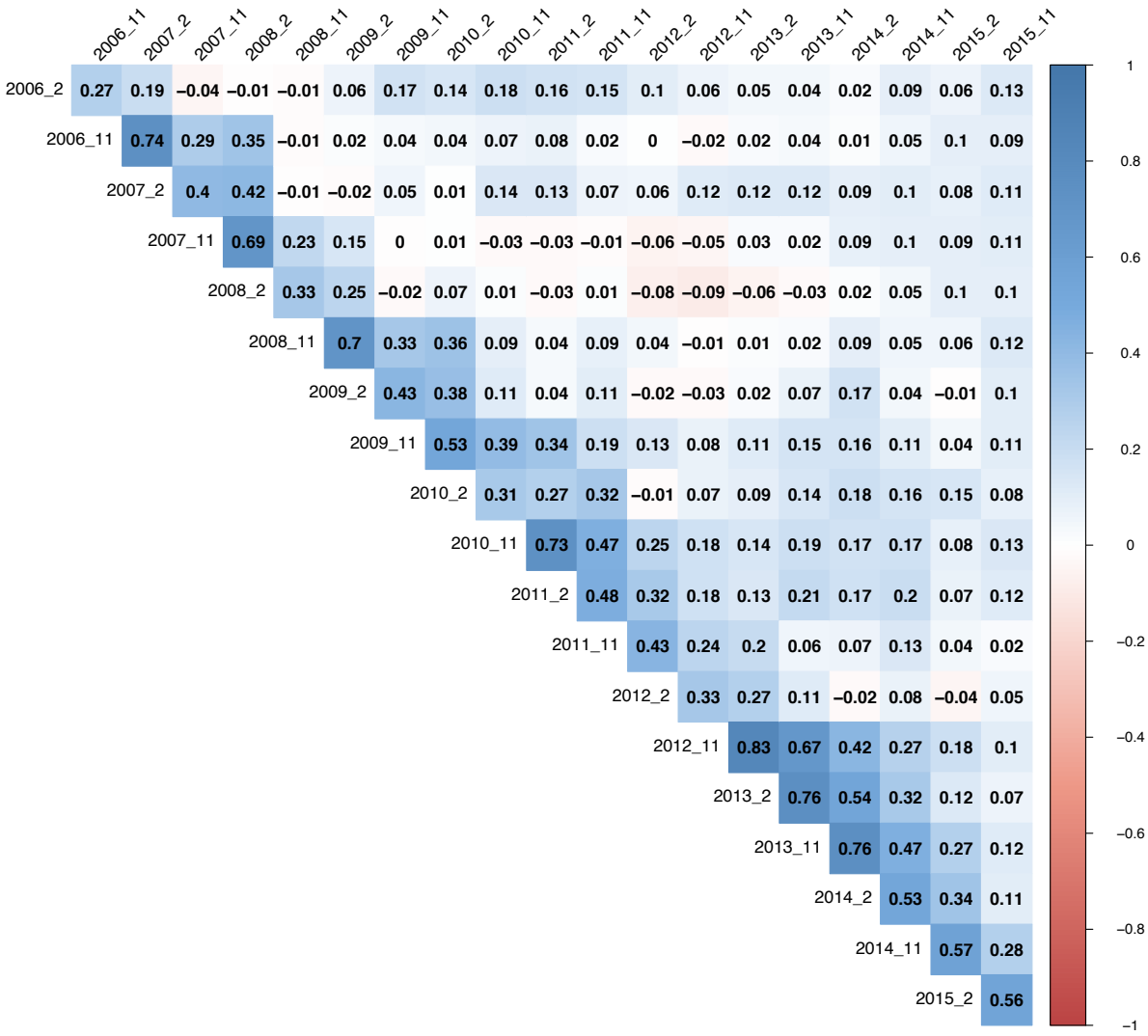
We set $E_t^{Fox} = -\frac{0.298}{0.6}\beta_{Fox,t}$ since the APE of Fox News was estimated for cable subscribers, accounting for approximately 60% of total television viewership according to the 2020 NLTV data. We set $S^{Fox} = 100\%$ which assumes everyone in the U.S. is exposed to Fox News through such sources as paid television, the internet, or other news sources. A more conservative value, such as 33% Kennedy and Prat (2019), or 71%, corresponding to 2019 television service subscribers (`https://nscreenmedia.com/us-pay-tv/`), would mechanically increase the persuasion rate. We also set $S_P^{Fox} = \bar{SD}_t - \frac{0.298}{0.6}\beta_{FOX,t}$ where $\bar{SD}_t$ is the cross-market average SD in period t. We implicitly assume that 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.

A.7 Results Based on the Panel Specification

[Figure A8 about here.]

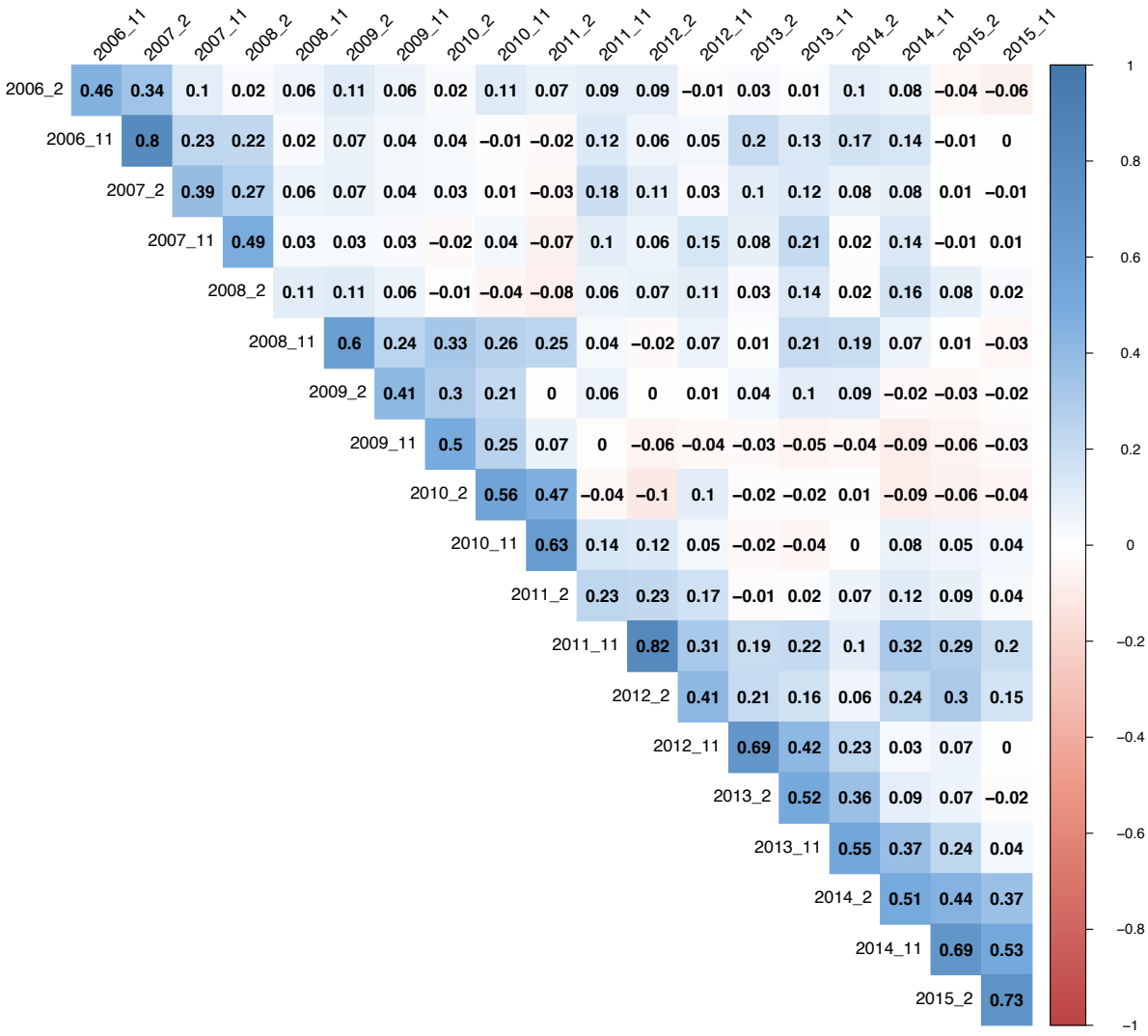
[Figure A9 about here.]

Figure A1: Correlations in Rating Measures Over Time: Fox News



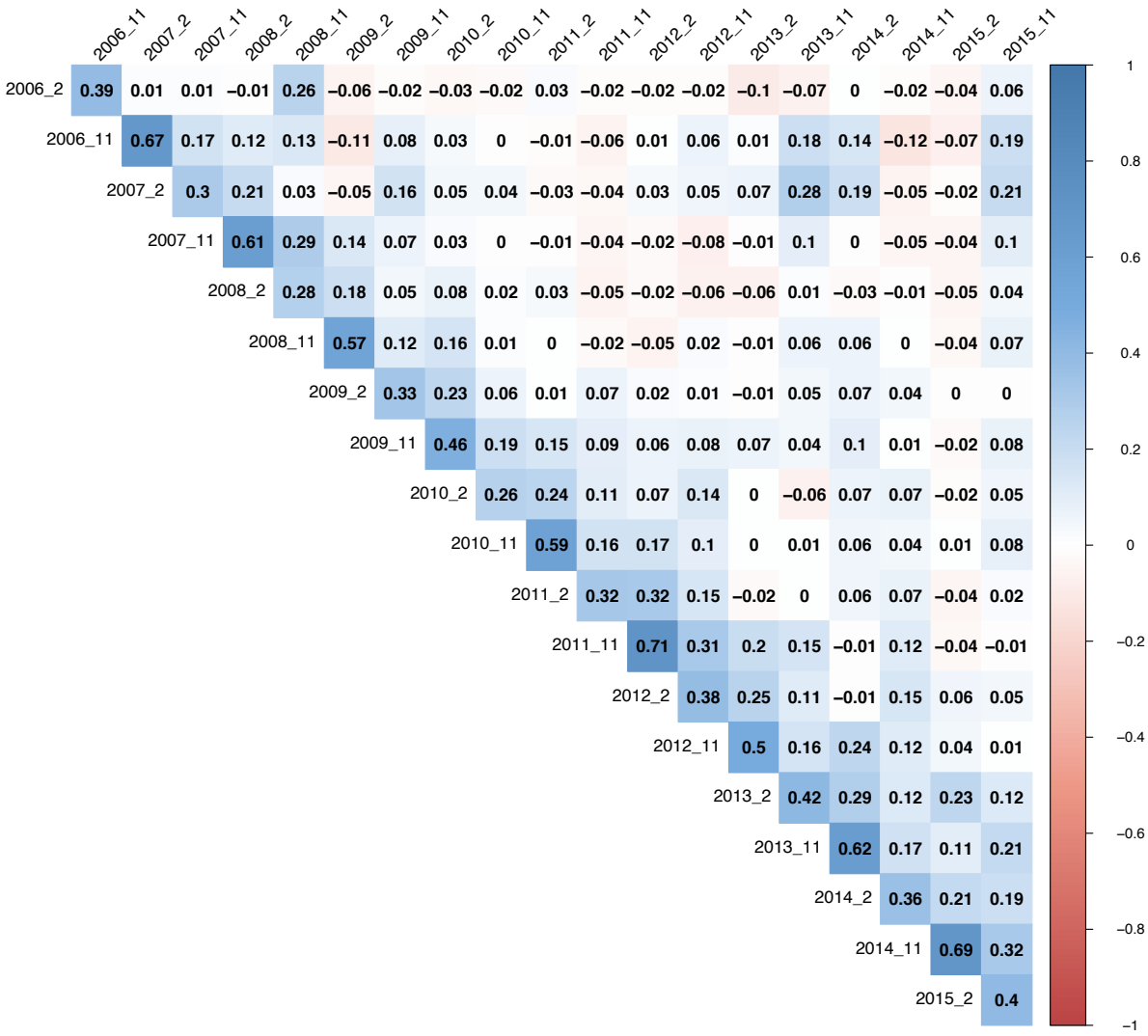
The coefficients represent the correlation in the channel rating points across the months of February and November, 2006-2015, based on 32,698 zip codes in our sample. The corresponding year and month are indicated in the rows and columns of the correlation matrix.

Figure A2: Correlations in Rating Measures Over Time: MSNBC



The coefficients represent the correlation in the channel rating points across the months of February and November, 2006-2015, based on 32,698 zip codes in our sample. The corresponding year and month are indicated in the rows and columns of the correlation matrix.

Figure A3: Correlations in Rating Measures Over Time: CNN



The coefficients represent the correlation in the channel rating points across the months of February and November, 2006-2015, based on 32,698 zip codes in our sample. The corresponding year and month are indicated in the rows and columns of the correlation matrix.

Figure A4: The distribution of the scale of the attenuation bias based on "2010" simulated data (OLS estimates with 2010 data / OLS estimates with 2015 data): No endogeneity ($\alpha = 0$) and endogeneity ($\alpha = \frac{\beta sd(r^{2015}_{FOX,z})}{sd(\varepsilon_{z2})}$)

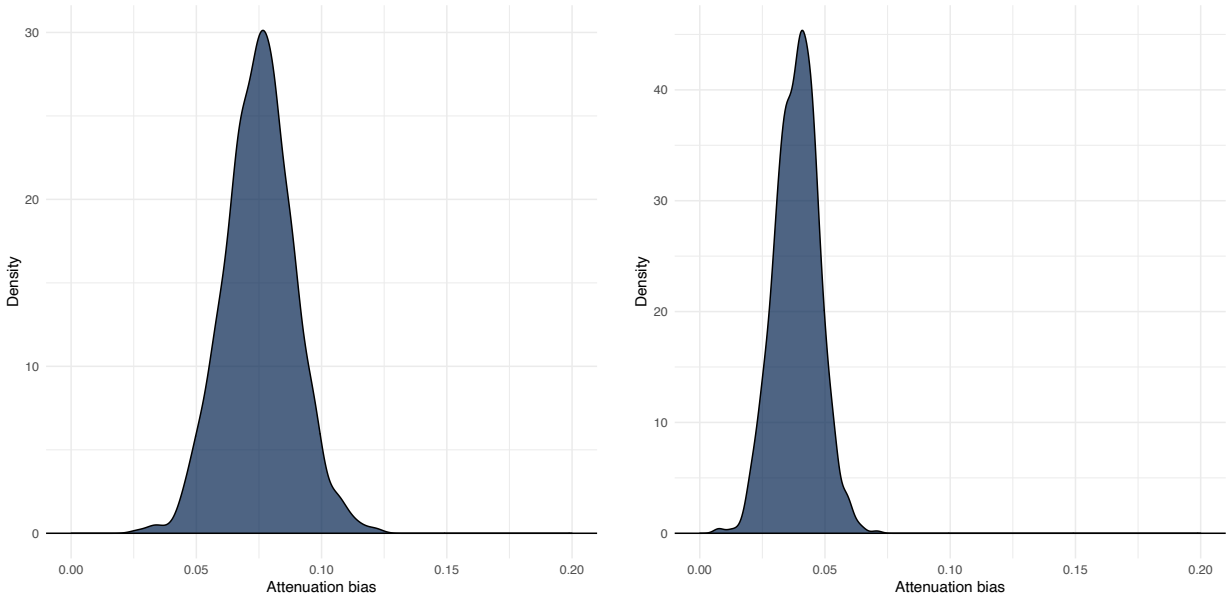


Figure A5: The distribution of the OLS estimates of β using "2010" and "2015" simulated data: No endogeneity ($\alpha = 0$) and endogeneity ($\alpha = \frac{\beta sd(r^{2015}_{FOX,z})}{sd(\varepsilon_{z2})}$)

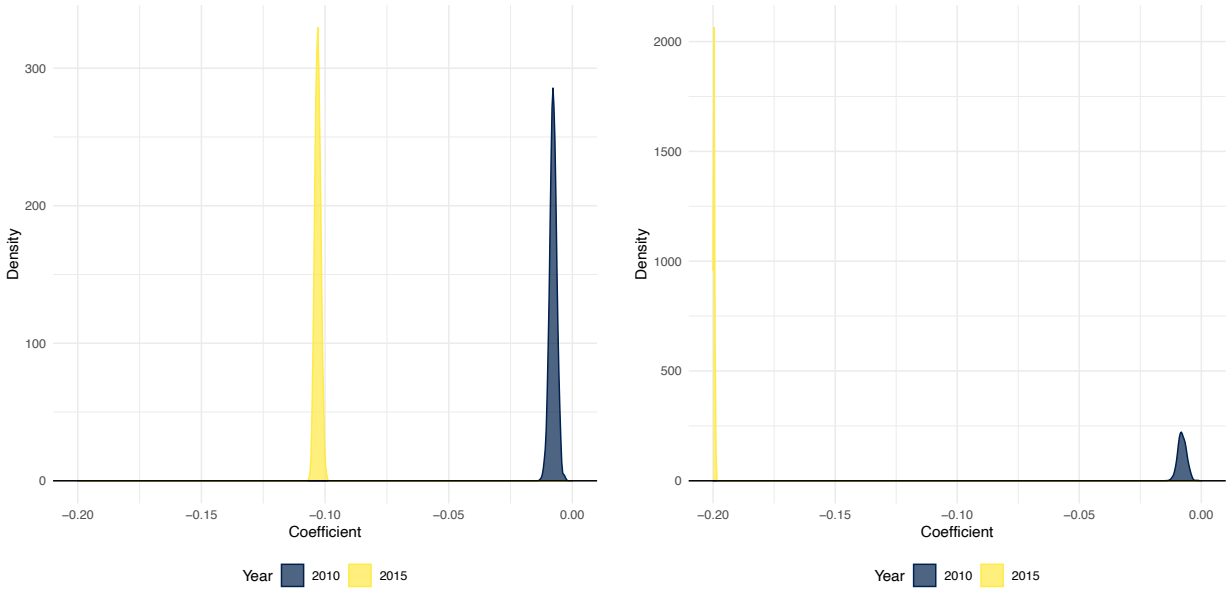


Figure A6: The distribution of the IV estimates of β using "2010" and "2015" simulated data: No endogeneity ($\alpha = 0$) and endogeneity ($\alpha = \frac{\beta sd(r^{2015}_{FOX,z})}{sd(\varepsilon_{z2})}$)

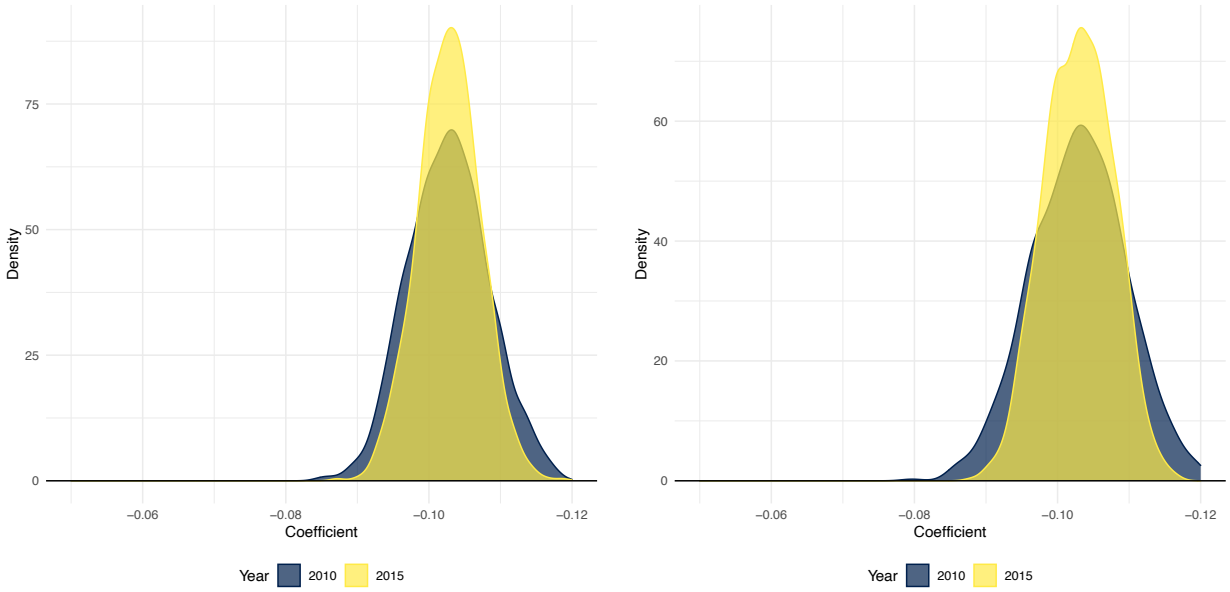
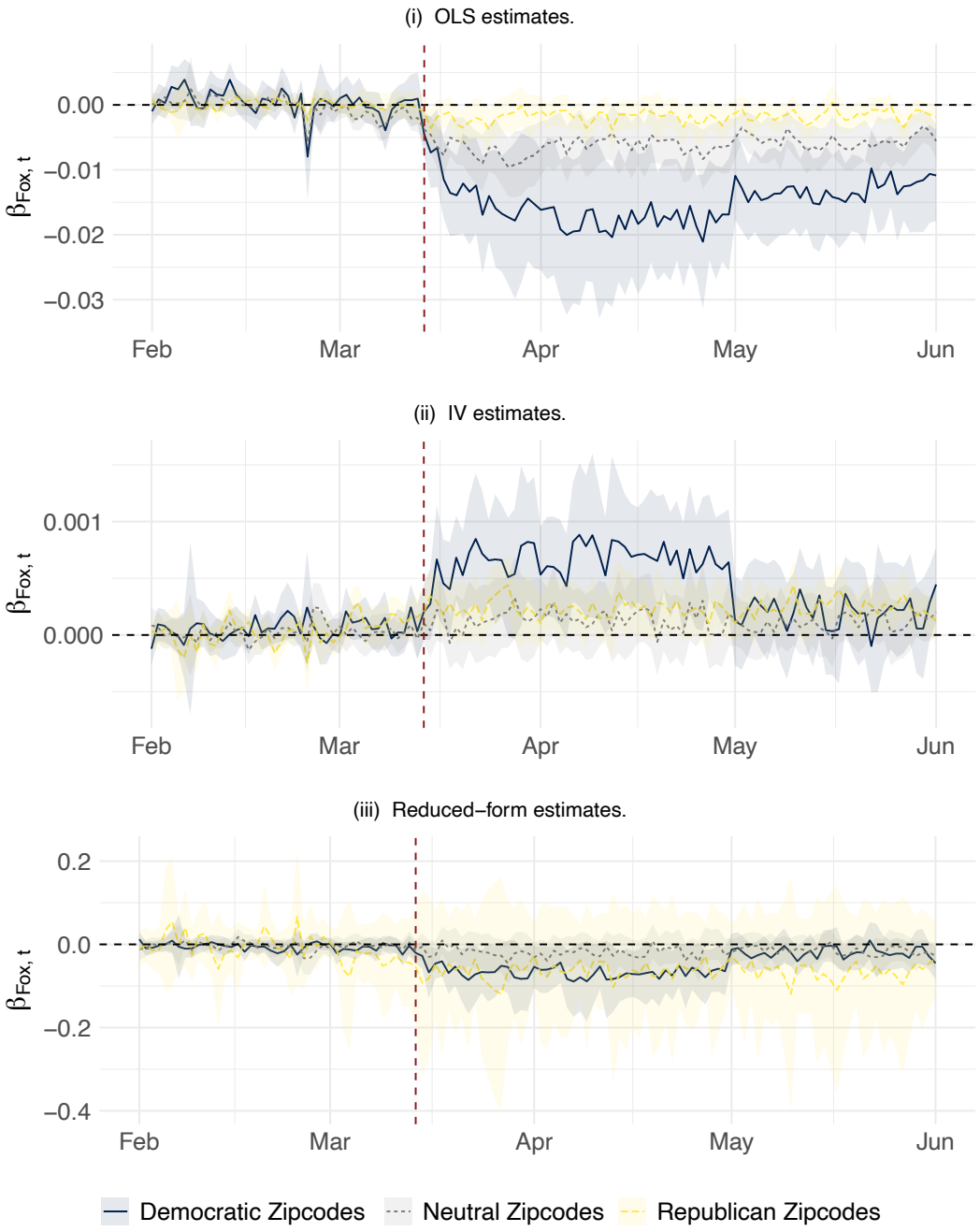
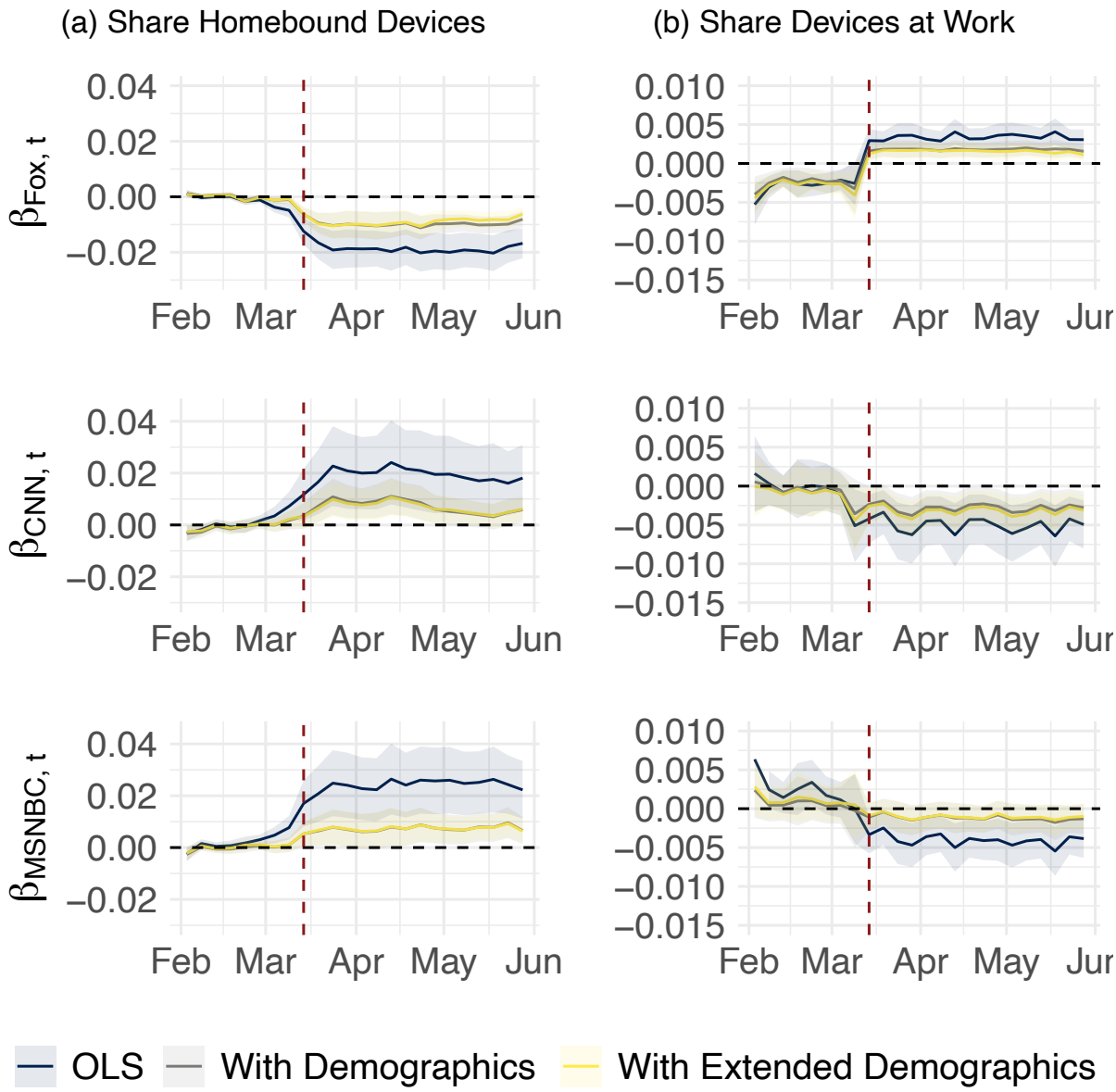


Figure A7: Regression estimates by terciles of zip code ideology.



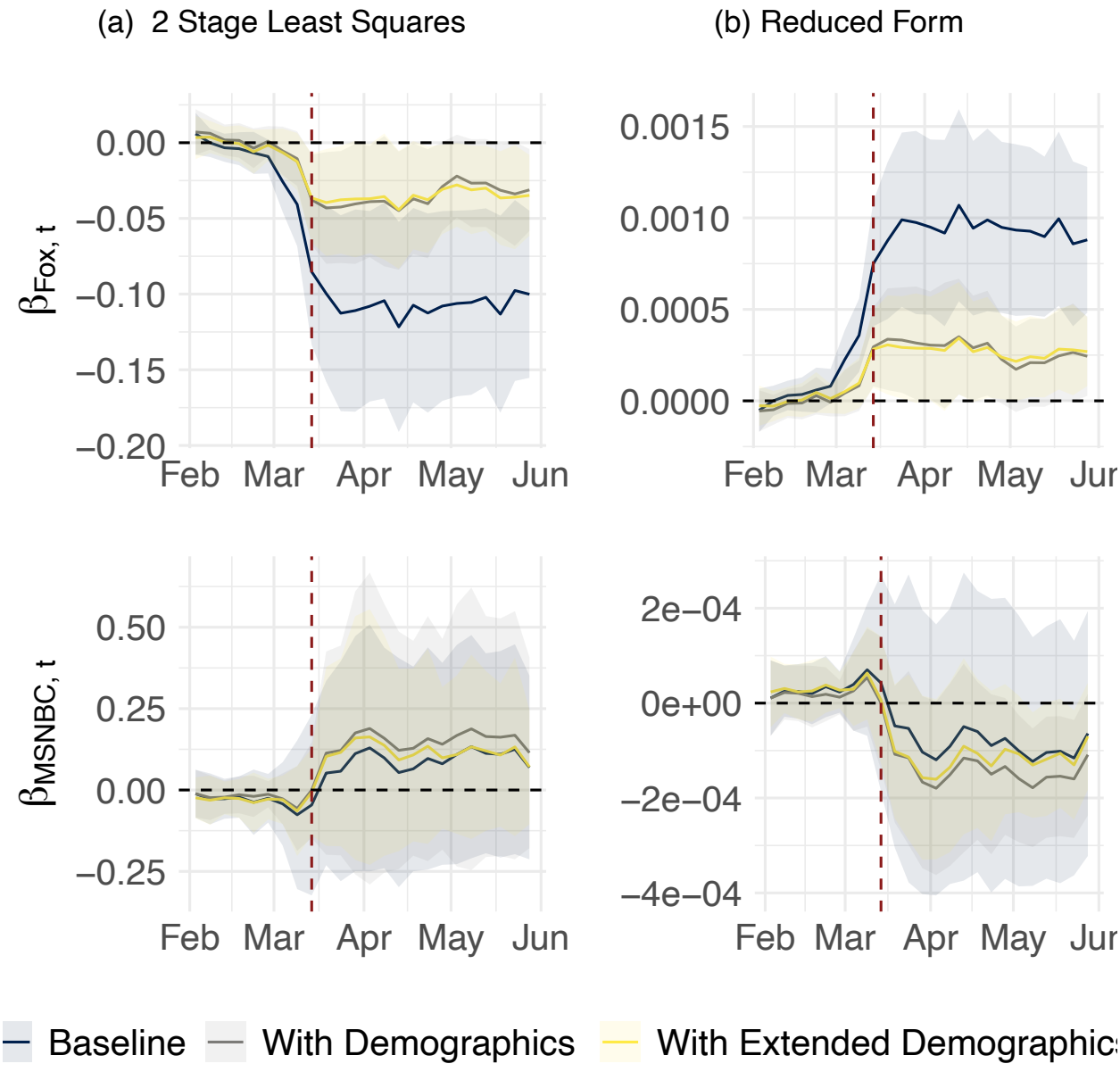
The Figure presents the OLS, IV, and reduced-form regression estimates from the main model for each of the three terciles of zip codes based on the Democrat vote share from the 2016 presidential election. The main specification includes state fixed effects, the number of channels in the cable system, positions of competing channels, log median zip code income, and population density as controls. The line and shaded region correspond to the coefficient estimate and its 95% confidence interval, respectively. Standard errors are clustered at the headend level.

Figure A8: Panel Model OLS Results



Figures present the panel OLS regression estimates of the 4-day zip code level social distancing (SD) on the zip code channel viewership for three main cable news channels: Fox News, MSNBC, and CNN. All models include state fixed effects, number of channels in the cable system, and positions of competing channels as controls. The specification "With Demographics" includes demographic controls for log median zip code income and population density. The specification "With Extended Demographics" additionally includes controls for share of population with bachelor degree, labor force participation, share of population that is white, share of population below poverty line, median age, and county-level Republican vote share in 1996 elections. All controls are interacted with time fixed effects. The line and shaded region correspond to the coefficient estimate and its 95% confidence interval, respectively. Standard errors are clustered at the headend level.

Figure A9: Panel 2SLS and Reduced Form Results



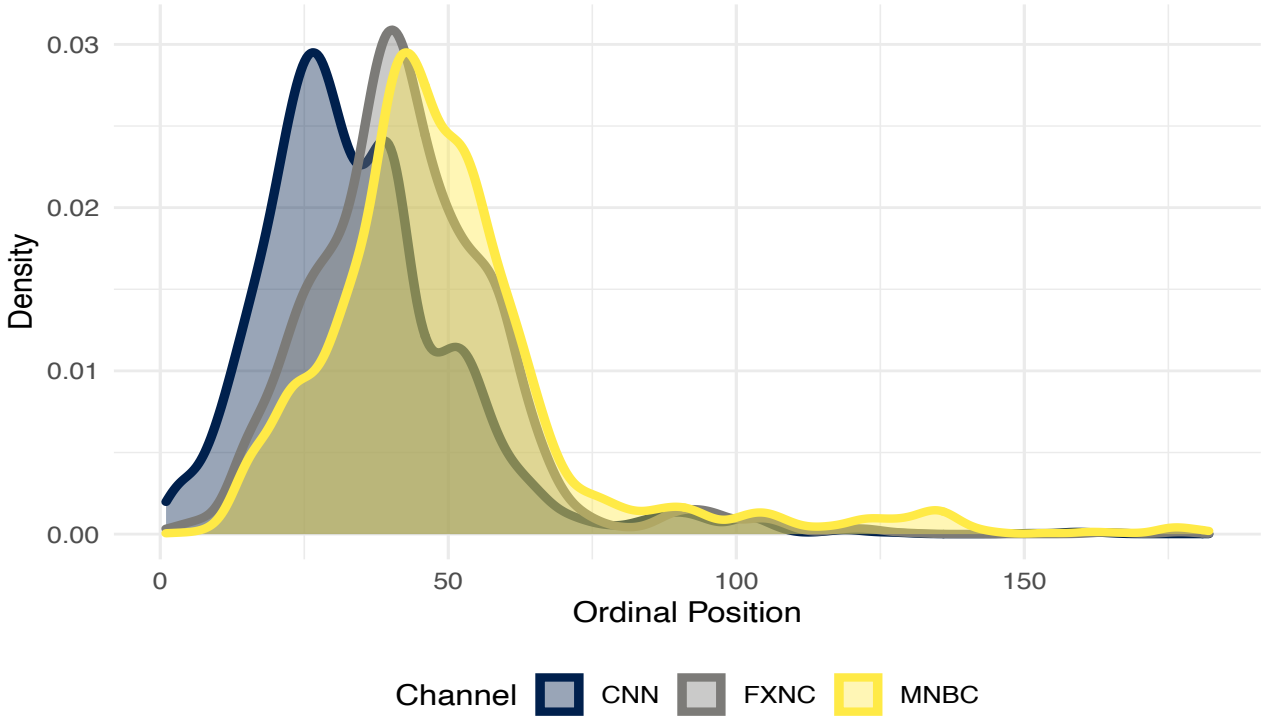
Figures present the panel IV (panel a) and reduced-form (panel b) regression estimates of the 4-day zip code level social distancing (SD) on the zip code channel viewership, with the channel position as an instrumental variable for channel viewership. All models include state fixed effects, number of channels in the cable system, and positions of competing channels as controls. The specification "With Demographics" includes demographic controls for log median zip code income and population density. The specification "With Extended Demographics" additionally includes controls for share of population with bachelor degree, labor force participation, share of population that is white, share of population below poverty line, median age, and county-level Republican vote share in 1996 elections. All controls are interacted with time fixed effects. The line and shaded region correspond to the coefficient estimate and its 95% confidence interval, respectively. Standard errors are clustered at the headend level.

Table A1: 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

A.8 Distribution of Channel Positions

Figure A10: Distribution of channel positions across headends for each of the three news channels



The histogram is based on the ordinal channel positions of Fox News, MSNBC, and CNN across the observed headends (cable systems).

A.9 First Stage: Channel Positions and Viewership

A concern with our OLS estimator, even after including flexible controls for persistent market differences and heterogeneous regional trends, is the potential endogeneity bias in the viewership effect on SD. One such source of bias arises if cable news viewership behavior is self-selected on aspects of viewers' preferences that also influence their SD compliance. Another such source of bias is measurement error in the viewership variable. Referring to our economic model in Appendix 3, our formal econometric concern is that: $E(\xi_{zt} \cdot \text{rating}_{cz}|X_z) \neq 0$.

To obtain consistent estimates of the viewership effect, 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:

$$E(\xi_{zt} \cdot \text{position}_{cz}|X_z) = 0 \tag{8}$$

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.

Although we cannot formally test the moment 8, we can provide supporting evidence for the validity of the instrument and its power. We refer the interested reader to Martin and Yurukoglu (2017) for a thorough discussion of the validity of the moment condition. As additional supporting evidence, conditional on number of channels available, Fox New's and MSNBC's respective positions 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 (see Appendix Tables A3 and A4).

To assess the power of the instrument, we run the first-stage regression of ratings_{cz} on the exogenous variables in the model:

$$\text{rating}_{cz} = \gamma_c \text{position}_{cz} + \rho_c X_z + \eta_{cz} \quad \forall c \in C \tag{9}$$

where X_z contains market characteristics including the total number of channels in zipcode z, state fixed effects, and demographic controls. We cluster standard errors at the headend level and we weight our observations by the number of panelists in the headend to correct for sampling error in our viewership variable.

Table A2: The effect of channel position on ratings - MSNBC

	First-stage results Dep Var: MNBC Viewership Ratings					
	Main period: November 2015			All periods: 2006-2015		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
MSNBC Channel Position	-0.0009	-0.0009	-0.0010	-0.0027***	-0.0027***	-0.0027***
	(0.0012)	(0.0012)	(0.0011)	(0.0006)	(0.0006)	(0.0005)
Fit statistics						
Incremental F-Stat	0.6400	0.6800	0.7400	22.13	23.38	24.72
R^2	0.1754	0.1867	0.1881	0.2774	0.287	0.2937
# of observations	26,412	25,499	25,453	445,841	431,831	430,986
			Controls			
State FEs	x	x	x	x	x	x
Cable System Controls	x	x	x	x	x	x
Basic Demog		x	x		x	x
Extended Demog			x			x

[a] Stars: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered on cable system level. Basic demographic controls include log median zip code income and log population density. Extended demographic controls include: share of population with bachelor degree, labor force participation, share of population that is white, share of population below poverty line, median age, 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. In Columns (iv)-(vi), all controls are interacted with period fixed effects.

Table A3: 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	−0.0383	0.0001	−0.0022	−0.0001
	(0.0005)	(0.0003)	(0.0001)	(0.0049)	(0.0423)	(0.0001)	(0.0100)	(0.0007)
State FEs	x	x	x	x	x	x	x	x
# Channels	x	x	x	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	0.1017	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 A4: Correlations between demographic characteristics and position of MSNBC

	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 MNBC	0.0003	−0.0001	0.0001	−0.0019	−0.0191	0.00004	0.0112	−0.0009*
	(0.0003)	(0.0002)	(0.0001)	(0.0025)	(0.0349)	(0.0001)	(0.0074)	(0.0004)
State FEs	x	x	x	x	x	x	x	x
# Channels	x	x	x	x	x	x	x	x
Observations	25,628	26,446	26,456	26,539	26,544	6,663	6,675	6,675
Adjusted R^2	0.1882	0.1425	0.1256	0.2506	0.1006	0.3279	0.3143	0.2521

[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.