

Competing for Attention – The Effect of Talk Radio on US Politics*

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Abstract

Opinion programs play a critical role in constructing and shaping political narratives. In this paper, we analyze the political effects of the archetype of opinion programs, “The Rush Limbaugh Show”. Treating the radio frequency space in each county as a market where several stations vie for listeners’ attention, we construct a spatial Herfindahl–Hirschman index (HHI) in radio frequencies as a local radio competition measure. Our identification strategy exploits the variation in competition arising from unintentional frequency overlaps in a county. We find that counties with higher exposure to Rush Limbaugh had a systematically higher vote share for Donald Trump in the 2016 and 2020 US presidential elections. We then combine the exposure measure with individual survey data to investigate mechanisms. The talk radio program did not necessarily change individual policy preferences but rather framed preexisting political beliefs within a cohesive conservative narrative. Self-identifying Republicans in counties with higher exposure to the show expressed more conservative political views, while self-identifying Democrats in these same counties expressed more moderate political views. Exploiting data on mass shootings and the timing of Rush Limbaugh’s death, we show that exposure to the program influenced audiences’ views on gun control and Covid-19 vaccinations in a way that aligned with the host’s narrative. Finally, we present evidence that the exposure to the Rush Limbaugh show increased political polarization in particular among Republican voters. Our results highlight the importance of media plurality on political preferences and polarization.

Keywords: Talk radio, elections, political polarization, US.

JEL classification: D72, L82, N42

*We thank Sascha Becker, Jeanet Bentzen, Filipe Campante, Ruben Durante, Gabriele Gratton, Pauline Grosjean, Ethan Kaplan, Federico Masera, Paul Schaudt, Ekaterina Zhuravskaya, and seminar participants at the Workshop on Natural Experiments in History at Deakin University, Australian Political Economy Network Workshop at University of Queensland, Australian Public Choice Conference at the University of Western Australia, Western Economic Association International Conference at the University of Melbourne, ASREC Conference at Chapman University, ASREC Australasia Conference at Monash University, Econometric Society Australasia Meeting at the University of New South Wales, University of Sydney, Australian National University and Melbourne Institute of Applied Economic and Social Research for helpful comments and suggestions. We also thank Shaun Astbury for excellent research assistance Samantha Eyler-Driscoll for manuscript editing and proofreading.

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*How did you start turning away from Rush Limbaugh?
In the late 90s, just playing around the radio dial, [...] I found a very very funny show, it was
“Wait Wait ... Don’t Tell Me!” on NPR.*

*Interview with a former Rush Limbaugh fan.
The Brainwashing of My Dad (2015)*

1 Introduction

Narratives play a crucial role in shaping political perspectives and influencing political polarization (e.g., [Eliaz and Spiegler, 2020](#)), and opinion programs on all media platforms (e.g., “The Rush Limbaugh Show” on radio, Tucker Carlson’s and Sean Hannity’s appearances on Fox News, Alex Jones’s and Ben Shapiro’s commentary on online media, and the editorial pages of newspapers such as the *New York Times* and *Wall Street Journal*) play a pivotal role in constructing, shaping and communicating these narratives (e.g., [Bursztyn et al., 2022](#)).

In an era when the internet and social media are predominant, this paper revisits the enduring influence of traditional media—specifically radio—in shaping contemporary political polarization and decision-making.¹ In particular, we focus on the case of “The Rush Limbaugh Show,” a radio show epitomizing opinion-driven programming that, beyond merely reporting news, crafted a compelling narrative that integrated various conservative ideologies, influencing audience interpretations of political events. It can be considered the prototype of modern, opinion-driven programming with a concept of narrative construction fostering a polarized view of political phenomena and echoing a pattern observed in the burgeoning success of opinion shows on platforms such as Fox News and online outlets ([Jamieson and Cappella, 2008](#)). Most empirical work² on the media’s role

¹For example, [Boxell et al. \(2017\)](#) document that the recent increase in polarization has occurred mainly among those older than 65 years, the demographic group least likely to use the internet and social media (Pew Research Center, *Internet/Broadband Fact Sheet 2021*, <https://www.pewresearch.org/internet/fact-sheet/internet-broadband/>).

²Studies analysing the impact of TV programs and the internet on political outcomes in the US include, for example, [Gentzkow \(2006\)](#), [DellaVigna and Kaplan \(2007\)](#), [Gentzkow and Shapiro \(2011\)](#), [Campante and Hojman \(2013\)](#), [Martin and Yurukoglu \(2017\)](#), and [Melnikov \(2021\)](#). Regarding the effects of television, internet and social media on populist sentiment in other countries, see, for example, [Durante and Knight \(2012\)](#), [Campante et al. \(2017\)](#), [Peisakhin and Rozenas \(2018\)](#) and [Durante et al. \(2019\)](#).

in political polarization and electoral outcomes predominantly centers on television, the internet, and social media.³ However, radio, with its unique audio-only format, serves as a complementary medium to TV and online platforms. It facilitates the consumption of entertainment and news during daily activities where visual engagement is impractical. Radio talk shows and opinion programs offer a more personal, individualized experience than TV and newspapers and are often consumed during solitary activities such as driving and working. Combined with the call-in segments on some of the shows, the talk radio format is very conducive to building and strengthening political narratives, which in turn can mobilize voters and also contribute to political polarization.

Our paper takes this intuition to the data and complements the literature by first showing that “The Rush Limbaugh Show” impacted *electoral outcomes* in the United States. We then unravel some of the mechanisms through which opinion programs on traditional media continue to exert political influence. Talk radio exposure does not systematically change listeners’ *policy preferences* but rather frames their preexisting political beliefs within a cohesive conservative narrative. This intensifies existing conservative beliefs, influences audiences’ *views on political events* in a way that aligns with the narrative, and increases *political polarization*.

To implement our analysis, we first construct a county-level measure of exposure to “The Rush Limbaugh Show” based on georeferenced data on the radio frequency contours of all US radio stations that aired the show. We then combine this measure with county-level election results from US presidential elections from 1980 to 2020 to estimate the effect of show exposure on *electoral outcomes*. Next, we switch to individual-level analyses and combine our county-level measure of show exposure with a series of individual survey data. We begin with survey data from the Cooperative Election Study (CES, formerly the Cooperative Congressional Election Study or CCES) to examine whether exposure to the show had a systematic effect on *policy preferences* and *political attitudes*. To investigate the show’s effect on *views on political events*, we combine our exposure measure with data

³A notable exception is the recent work by Wang (2021), who finds that the populist radio show of Father Coughlin systematically shifted voters’ preferences and political attitudes in the US South in the 1930s. Our study confirms these results and shows that populist radio shows also impact electoral outcomes and political preferences in a more contemporary setting with more diverse media environment.

related to two types of events that are highly politicized in the US: First, using data on the occurrence of mass shootings in the US from [Yousaf \(2021\)](#), we analyse how exposure to the show affected subsequent attitudes toward gun control. Second, we use daily, county-level panel data on Covid-19 vaccination uptake and analyse how vaccination rates changed after Rush Limbaugh’s death on February 17, 2021. In the final step, we merge our data with the restricted version of the American National Election Studies (ANES) data and the American Ideology Project to examine the show’s impact on individual-level *political polarization*.

The major empirical challenge in all these applications is that the show was largely broadcast via AM radio frequencies, making it available almost everywhere in the continental US. Therefore, we cannot apply standard identification strategies that rely on either exogenous spatial variation in radio signal availability (e.g., [Olken, 2009](#)) or the staggered rollout of a particular media program (e.g., [DellaVigna and Kaplan, 2007](#)). We therefore propose a novel identification strategy based on the idea that there is competition for radio listeners’ attention.

We argue that the degree to which listeners within a particular county were exposed to the show depends not only on the (endogenous) number of contours broadcasting the show but also on the number of alternative radio programs available in the county. Accordingly, we view the radio space in each county as a market where multiple stations compete for listeners’ attention. We consider FM stations, which primarily deliver entertainment and musical programs, as the key competitor of the AM stations delivering the show. A larger number of other radio options increases the level of competition in the radio space, in turn lowering the county’s show exposure. Our measure of competition is a spatial Herfindahl–Hirschman index (HHI) in radio frequencies. Since competition for a radio market in itself could be endogenous to a county’s political preferences, we build a measure of radio frequency competition based on accidental frequency overlaps in a county. The identifying assumption is that, conditional on the overall level of radio frequency competition in a county, the variation in radio frequency competition from accidental contour overlaps is not systematically correlated with variation in unobservables that affect election outcomes.

In a first step, we analyse the show’s effect on electoral outcomes, combining the radio frequency competition measure of show exposure with county-level election outcomes. We observe that more-exposed counties had a systematically higher share of votes for Donald Trump in the 2016 and 2020 US presidential elections. We also find that the effect of the show is statistically and economically significant only from the 2000 US presidential election. This result mirrors two relevant facts around the show and conservative politics in the US. First, while the show began airing in 1988, it did not attract much attention until the mid-1990s (Jamieson and Cappella, 2008).⁴ Second, the late 1990s and early 2000s marked the rise of more populist groups within the Republican Party (e.g., the Tea Party movement⁵), which were not only a result of the show but also amplified its relevance and impact on the conservative electorate (Jamieson and Cappella, 2008).

Moving to the series of individual-level results, we first reveal that, conditional on a large set of geographic and socioeconomic controls, individuals located in counties with higher exposure to the Limbaugh show do not systematically differ in their *policy preferences* on abortion, gay marriage, immigration, gun control or environmental regulation. However, we find strongly differential effects of the show on *political ideology* between Republicans and Democrats. Again, conditional on the inclusion of a large set of geographic and socioeconomic controls, Republicans in high-exposure counties are more likely to consider themselves strongly conservative and less likely to be moderate.

With respect to the show’s effect on *views on political events*, in our first application, we find that after mass shootings, Republicans in high-exposure counties expressed even stronger opposition to stricter gun control than did Republicans in low-exposure counties. In our second application, we show that after Rush Limbaugh’s death and the subsequent end of the show’s live talk format, Covid-19 vaccination uptake rates increased more in counties with a higher prior exposure to the show. This effect is particularly pronounced for vaccination uptake among individuals 65 years and older. Finally, we find that show

⁴In March 1994, Rush Limbaugh started to raise red flags in the mainstream media and among Democrats with his announcement on air that Clinton White House confidant Vince Foster “was murdered.” A subsequent inquiry concluded that Foster had killed himself.

⁵References to the Boston Tea Party had been made during Tax Day protests since the early 1990s. An official website declaring the Tea Party a nationwide movement was launched in 2002.

exposure systematically increased almost all measures of *political polarization* among Republicans residing in high-exposure counties.

This paper contributes to multiple strands of the literature. First, we add to the broad economics literature on the effects of media on political outcomes in the US.⁶ Studies within this literature have focused mainly on newspapers (e.g., [Gerber et al., 2009](#); [Snyder and Strömberg, 2010](#); [Gentzkow et al., 2011](#); [Djourelouva, 2023](#)), television (e.g., [Gentzkow, 2006](#); [DellaVigna and Kaplan, 2007](#); [Galletta and Ash, 2021](#); [Ash et al., 2021](#)), and the internet and social media (e.g., [Gentzkow and Shapiro, 2011](#); [Campante and Hojman, 2013](#); [Melnikov, 2021](#); [Allcott et al., 2024](#)). However, the effect of radio on contemporary US politics has been largely understudied, with most empirical work focusing on the historical perspective. [Strömberg \(2004\)](#) shows how the expansion of radio in the 1920s led to voters being more informed, which in turn affected the allocation of relief spending under the New Deal. With respect to radio, [Wang \(2021\)](#) and [Engist et al. \(2024\)](#) study exposure to populist radio from a historical perspective. We are turn focus on the effects of *contemporary* talk radio on political outcomes. To our knowledge, [Barker \(1999\)](#) and [Lee and Cappella \(2001\)](#) are the only other papers to empirically study the relationship between exposure to “The Rush Limbaugh Show” and voting outcomes, however in a non-causal manner. Using ANES panel data from 1994 to 1996, [Barker \(1999\)](#) finds that respondents who listened to the show were more likely to vote for Republican candidates. However, the author explicitly acknowledges the challenges to causal inference in his setting. Our study not only aims to address this identification problem highlighted by [Barker \(1999\)](#) but also analyses the effect of show exposure on political attitudes and polarization. Our measure of radio frequency competition also contributes to the wider literature analysing the importance of media plurality for political outcomes (e.g., [Besley and Prat, 2006](#); [Prat, 2015](#); [Cagé, 2020](#)).

⁶In this respect, our work also relates to the more extensive literature in economics on the media–politics nexus in other contexts such as the relation between newspapers and government responsiveness in India ([Besley and Burgess, 2002](#)), the effect of free digital TV on election outcomes in Italy ([Barone et al., 2015](#)), the effect of mobile internet on political mobilization in Africa ([Manacorda and Tesei, 2020](#)), social media and protests in Russia ([Enikolopov et al., 2020](#)) and China ([Qin et al., 2021](#)), internet availability and election outcomes in Germany ([Falck et al., 2014](#)), and 3G internet access and trust in governments around the world ([Guriev et al., 2020](#)).

Further, our work adds to the research on the determinants of political polarization (e.g., [Boxell *et al.*, 2017](#); [Draca and Schwarz, 2021](#)). In particular, we follow [Boxell *et al.* \(2017\)](#) to construct measures of political polarization from ANES responses. Using these, we complement our analysis of the effect of show exposure on county-level election outcomes by further investigating the show’s impact on political polarization at the individual level, thereby contributing to the literature on partisan media exposure and political polarization (e.g., [Sunstein, 2009](#); [Levendusky, 2013](#)).

While exposure to radio has been studied in other contexts, most of the work relies on exogenous spatial variation in radio signal availability, as proposed by [Olken \(2009\)](#) and applied in recent work such as [Enikolopov *et al.* \(2011\)](#), [Adena *et al.* \(2015\)](#), [Yanagizawa-Drott \(2014\)](#) and [Blouin and Mukand \(2019\)](#). Other branches of this literature exploit the variation in the staggered rollout of programs (e.g., [DellaVigna and Kaplan, 2007](#)) or the position of a channel within the overall channel lineup (e.g., [Martin and Yurukoglu, 2017](#); [Ananyev *et al.*, 2021](#)).⁷ We make a methodological contribution to this literature by developing an alternative measure of exposure. The spatial HHI in radio frequencies developed in this paper, inspired by [Herfindahl \(1950\)](#) and [Hirschman \(1945\)](#), can be more generally applied to facilitate empirical investigations in contexts where the above methods cannot be applied. Conceptually, our identification strategy is of a similar spirit to that of [Barone *et al.* \(2015\)](#), who use a natural experiment in which the number of free-to-view TV channels in Italy increased, decreasing voters’ exposure to the dominant, slanted Berlusconi media.

Our paper also complements the work by [Bursztyn *et al.* \(2022\)](#) documenting the rise of opinion programs and their increasing importance as a source of news and information on TV. Talk radio shows such as “The Rush Limbaugh Show” can be considered a predecessor of other opinion programs, having potentially set the scene for the success of these formats on TV news outlets. We complement the work of [Bursztyn *et al.* \(2022\)](#) by estimating the effect of long-run exposure to opinion programs on political ideology, belief polarization, attitudes towards political events and even behaviour during the Covid-19 pandemic.

⁷Other studies exploit the sudden ban of politically charged terms in the media and its effect on voters’ opinion on associated political issues (e.g., [Djourelouva, 2023](#)).

Finally, our paper relates to recent empirical work that shows that political leaders’ speeches and rhetoric can lead to immediate changes people’s behaviour (e.g., [Grosjean et al., 2022](#); [Ajzenman et al., 2023](#)). Our results show that the political narratives developed by media personalities influence people’s political ideology and views on political events and can also change their behaviour around politically contested issues.

The rest of this paper is organized as follows. In Section [2](#), we provide a brief introduction on talk radio in the US and “The Rush Limbaugh Show.” In Section [3](#), we discuss the data. Section [4](#) discusses the empirical strategy and estimation results related to election outcomes, along with robustness tests. Section [5](#) demonstrates individual-level effects. Section [6](#) concludes.

2 Talk radio in the US and “The Rush Limbaugh Show”

Talk radio shows in the US have their origins in the amplitude modulation (AM) radio space. AM broadcasting was the first method developed for making audio radio transmissions, and radio was the dominant method of broadcasting in the early 1970s, when AM drew approximately 75% of the US radio audience ([Keith and Keith, 1993](#)). This changed with the introduction of frequency modulation (FM) radio. Technological innovations in the 1970s and 1980s led to higher audio quality of FM radio and made it more suitable for the broadcasting of music and entertainment programs. With their lower audio fidelity, this resulted in a natural migration of AM radio stations away from music, and they became more prominently known for the specialized program format known as talk radio.

Talk radio shows, a type of radio program in which social issues considered topical at the given point of time are discussed and debated, are typically hosted by a prominent host, and the talk show itself is closely reflective of the host’s own personality and perspectives. An early example of this format is the highly influential political talk radio show of Catholic priest Father Charles Coughlin in the 1920s ([Wang, 2021](#)). While the AM listenership declined with rising competition from FM stations in the mid-20th century,

one policy that changed the AM radio horizon was the repeal of the Federal Communication Commission’s (FCC’s) fairness doctrine in 1987. Prior to its repeal, the doctrine had required that talk radio shows present balanced information on topical issues, with the objective of exposing the audience to multiple viewpoints. It is estimated that, by 2011, there were close to 3,500 all-talk or all-news stations in the US, with the number of talk radio stations doubling between 2007 and 2011 alone ([Berry and Sobieraj, 2011](#)).

One of the leading shows that from early on capitalized upon the repeal of the fairness doctrine was “The Rush Limbaugh Show.” The show, hosted by Limbaugh himself, commenced in 1988 and delivered conservative discussions and debates nationwide. It first started as a local talk radio show in Sacramento in 1984 but expanded as a nationally syndicated talk radio show in 1988. The show did not attract much attention until March 1994, when Limbaugh started spreading a rumor that a legal confidant of the Clinton White House, Vince Foster, had been murdered. Although a subsequent inquiry concluded that Foster had killed himself, revealing Limbaugh’s claims to be false, the event helped boost his show’s nationwide popularity ([Jamieson and Cappella, 2008](#)).

Until Limbaugh’s death in 2021, his show was delivered across approximately 585 radio stations and was aired for 3 hours during the daytime on weekdays. A weekend edition, featuring highlights of the weekday edition, commenced in 2008. From its inception, the show was widely acknowledged as promoting populist propaganda and controversial opinions.⁸

Limbaugh’s style was to draw his audience in with lengthy discussions of the virtues of conservatism and the dangers inherent to liberalism and the “liberal” media. In this way, his show executed functions formerly identified with party leaders. Like other conservative media (e.g., Fox News), the show reinforced a coherent set of rhetorical frames that empowered its host to act as a conservative opinion leader, mobilizing partisans into action to hold the Republican Party and its leaders accountable. In a world where the party identification of some individuals fluctuates with the political tides, Limbaugh’s show may

⁸We provide some examples in Section A. Additionally, see, for example, *BBC*, “Rush Limbaugh: How he used shock to reshape America,” February 17, 2021. See also *The New York Times*, “Talk radio is turning millions of Americans into conservatives,” October 9, 2020.

have reinforced Republican allegiances, generating a support base more strongly aligned with conservative values and more reliably supportive of the Republican Party even when the Democrats presented appealing moderates or when independent candidates claimed to be the “real” conservatives in an election (Jamieson and Cappella, 2008).

Rush Limbaugh’s persuasive communication was able to mobilize conservative voters and thereby impact the outcome of elections. For example, in November 1995, the Republican Party won control of the House of Representatives for the first time in 40 years. Republican leaders dubbed Limbaugh a “majority creator” and inducted him into the 104th Congress’s rookie class as an honorary member. Tony Blankley, press secretary to then Republican leader Newt Gingrich, stated: “After Newt, Rush was the single most important person in securing a Republican majority in the House of Representatives” (Jamieson and Cappella, 2008). The show also had substantial reach across the US population. Various reports⁹ estimate Rush Limbaugh’s weekly listenership at 13.5–15 million between 2003 and 2010.

In short, “The Rush Limbaugh Show” was one of the most popular conservative talk radio shows in the US from the mid-1990s until 2021. Limbaugh’s audience was more politically involved than average, and he applied a rhetoric painting liberals as a “cultural elite” and Democrats as “enemies” and a “threat” (Jamieson and Cappella, 2008). This rhetoric portraying conservatives’ political opponents as “enemies of America” was a strong unifying narrative to mobilize his listeners during elections. In addition, it moved his already predominately conservative listeners to even more conservative positions, thereby increasing overall political polarization in the United States.

⁹“The State of the News Media,” 2010, Pew Project for Excellence in Journalism (<https://www.pewresearch.org/internet/2010/03/15/state-of-the-news-media-2010/>); “The Top Talk Radio Audiences,” *Talkers Magazine*, March 2011, p. 22; Berry and Sobieraj (2011).

3 Data

3.1 Data on exposure to “The Rush Limbaugh Show”

To identify each county’s exposure to “The Rush Limbaugh Show,” we first obtain from the show’s official website¹⁰ the list of radio stations that delivered the show across the US. We identify 585 US-based stations delivering the show, 347 of which are on AM frequency.¹¹ We focus on the *AM stations* delivering the show since historically these have specialized in talk show broadcasts. As we discussed above, compared to FM stations, AM stations are highly susceptible to interference and have lower audio fidelity, making them less suitable for entertainment and musical programs and more suited for talk radio broadcasts.

Next, we obtain data on AM contours in the US from the Federal Communications Commission (FCC). Panel (a) in Figure 1 shows the spatial distribution of these AM contours across the US. We observe that AM contours are broad in their coverage and are spatially distributed in a manner that covers the entire US. It is also important to distinguish *AM stations* from *AM contours*—each AM station possesses multiple contours at different levels of electric field strength intensity, as measured by millivolts per meter (mV/m). AM contours also receive varying levels of protection against interruptions from adjacent and co-channels depending on whether they are daytime or nighttime contours.

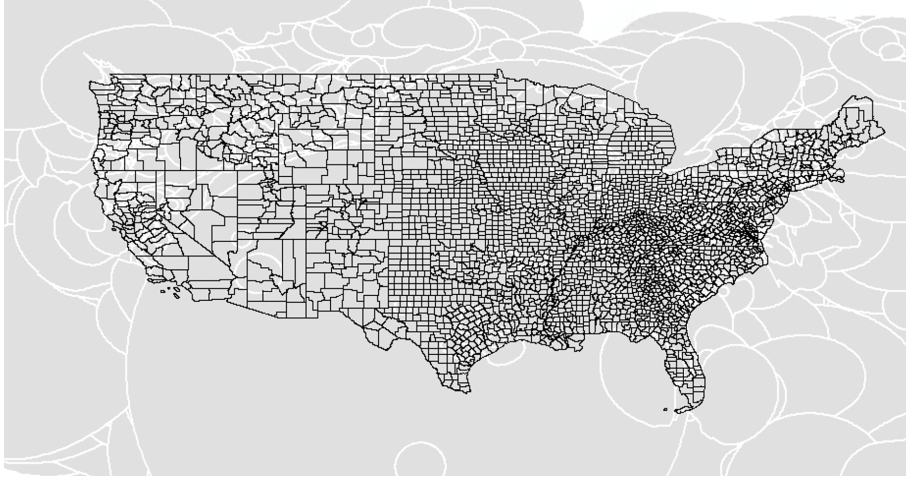
For the purpose of our analysis, we first locate within the FCC data the set of AM contours belonging to the AM stations listed on “The Rush Limbaugh Show” website. We identify 1,388 contours spread across the country that belong to the AM stations airing the show. By overlapping these AM contours with county boundaries, we identify the number of AM contours broadcasting the show in each county.¹² Panel (b) in Figure 1 shows the dispersion of AM contours airing the show across the US. We observe a high concentration of contours broadcasting the show along the East and West Coasts and in

¹⁰<https://www.rushlimbaugh.com/>

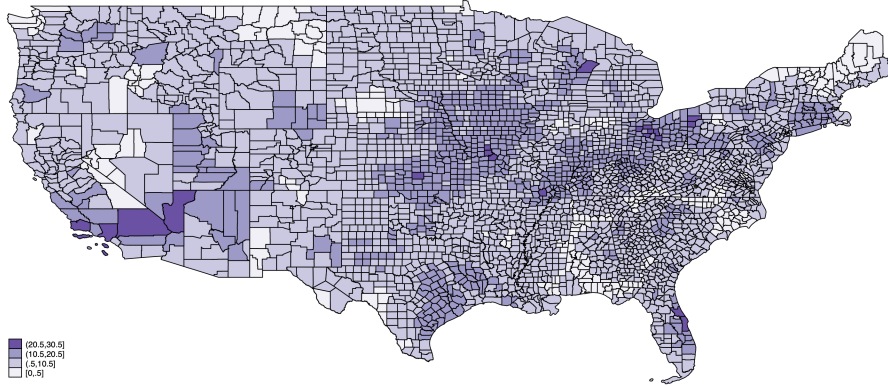
¹¹Of the remaining stations, 112 stations are on FM frequency, while 120 are livestream channels.

¹²Since “The Rush Limbaugh Show” was typically aired during the daytime, we retain only the daytime groundwave contours belonging to each AM station.

Figure 1: AM contours



(a) Spatial distribution of AM contours



(b) County-wide dispersion of AM contours broadcasting “The Rush Limbaugh Show”

Notes: Panel (a) overlays polygons (in light grey) of all AM radio station contours with US county boundaries. Panel (b) presents the dispersion of the number of AM contours broadcasting “The Rush Limbaugh Show” at the county level. Darker colours indicate a higher number of AM contours broadcasting the show.

the Midwest.

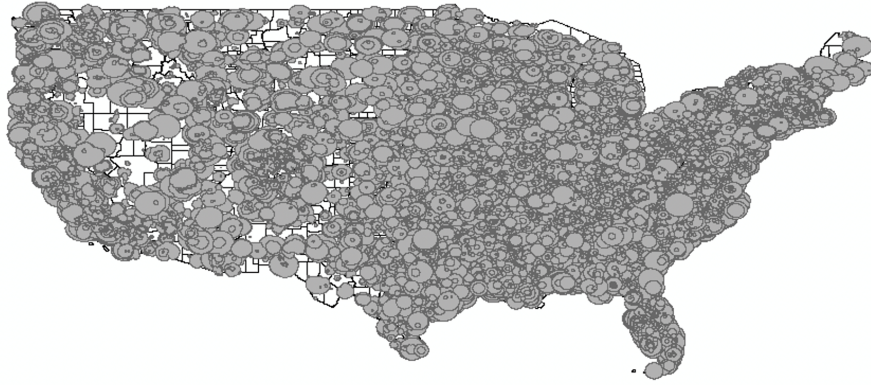
3.2 Data on FM contours

Our empirical strategy exploits the competition faced by Limbaugh’s show from FM contours. To generate the indicator of competition, we first obtain data on the spatial distribution of FM contours from the FCC. Panel (a) in Figure 2 shows the dispersion of FM contours across the US. We observe that FM contours are narrower and more specific in their coverage than AM contours. As with AM contours, we overlap the FM contours with county boundaries to identify the FM exposure in each county. In its simplest form, this overlap can identify the number of FM contours received by each county, as indicated in Panel (b) of Figure 2.

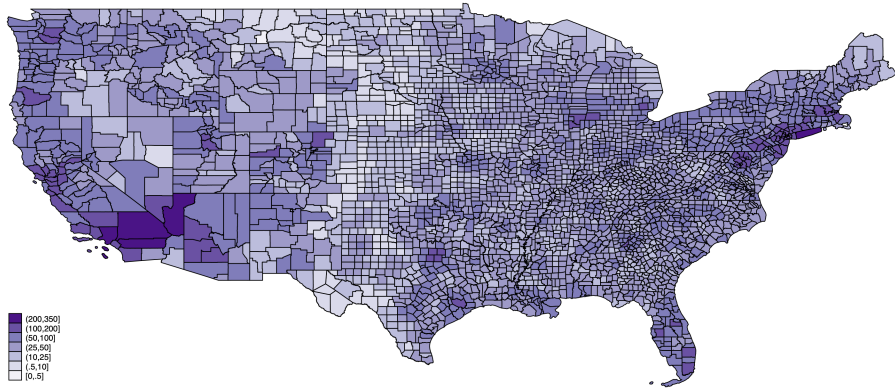
To support our identification strategy, we go a step beyond this “naive” indicator of FM coverage and distinguish between “intentional” and “accidental” FM coverage in each county. To understand the intuition behind this distinction, consider the setting in Panel (a) of Figure 3. Here, the rectangular blue polygon represents Baca County, Colorado. The circular shapes are FM contours. The contour depicted in black is entirely encapsulated within the county borders, and therefore it seems reasonable to assume that this FM contour was intentionally placed for its coverage to have reception in this county. We dub such FM coverage intentional. The grey contours that do not overlap with county borders do not contribute towards the FM exposure of Baca County. The purple polygons represent overlaps between the county boundaries and peripheral FM contours that, while not fully covering the county, do provide a marginal level of FM exposure. Considering their peripheral location and marginal coverage of the county area, it seems reasonable to assume that these contours were not specifically placed to target Baca County, although the county does “accidentally” receive FM coverage from these contours. We refer to such FM coverage as accidental coverage for this county.

Accordingly, within our empirical exercise, we consider all contours either (a) covering the entire county or (b) located completely within the county, as providing intentional FM coverage to the said county. Of the remaining contours, those with a coverage area

Figure 2: FM contours



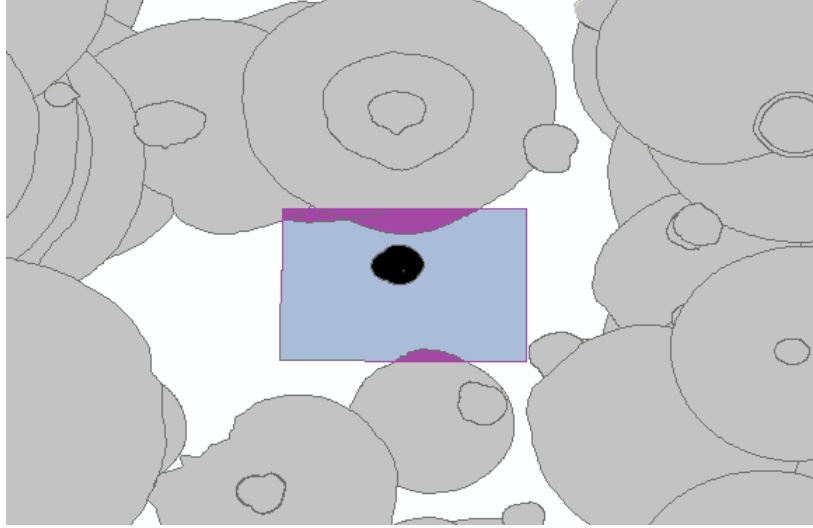
(a) Spatial distribution of FM contours



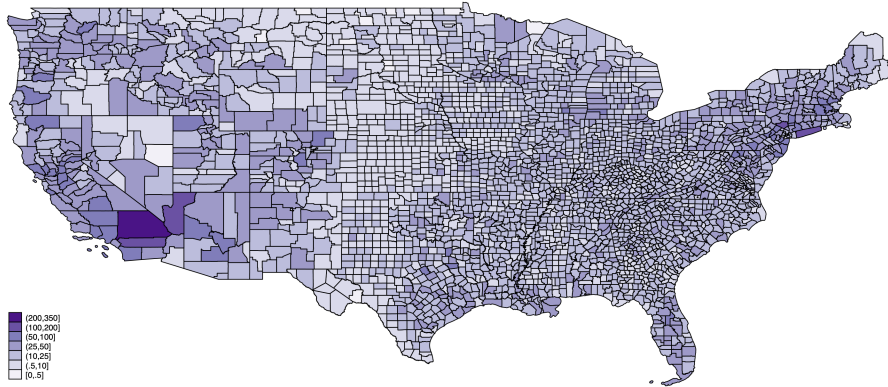
(b) County-wide dispersion of all FM contours

Notes: Panel (a) overlays polygons (in light grey) of all FM radio station contours with US county boundaries. Panel (b) presents the dispersion of the number FM contours at the county level. Darker colours indicate a higher number of FM contours in a county.

Figure 3: Accidental coverage from FM contours



(a) Identifying accidental coverage from FM contours



(b) County-wide dispersion of contours providing accidental FM coverage

Notes: Panel (a) illustrates our construction of FM contours delivering accidental coverage. The rectangular area in the center indicates the boundaries of Baca County, Colorado. The black polygon in the center is an FM contour entirely located in the county. The grey polygons surrounding Baca County are from stations with their centroids in other, neighbouring counties. Some of these contours have small overlaps (in purple) with Baca County's boundaries. These small purple overlaps are used to calculate the number of FM contours providing accidental coverage in Baca County. Panel (b) shows the distribution of the number of these FM contours providing accidental coverage by county across the US.

more than the median size of the overlapping polygons are also identified as providing intentional FM coverage. All contours where the size of the overlapping polygon is less than the median value of all overlapping polygons are identified as providing accidental FM coverage for the given county.¹³ Panel (b) of Figure 3 provides the distribution of FM contours providing accidental coverage across the US. It is important to note that these represent a subset of the total number of FM contours depicted in Panel (b) of Figure 2.

3.3 Deriving indicators of county-level competition

The degree to which listeners within a particular county were exposed to Limbaugh’s show depends not only on the number of contours broadcasting the show but also on the number of alternative contours (i.e., ones that do not broadcast the show) with reception in the county. For example, exposure to the show would be higher in counties where the only radio station received was one that broadcast the show than in another county with many alternative channels. Accordingly, we focus on the radio space in each county as a market where multiple stations compete with each other for listeners’ attention. We consider FM stations, which primarily deliver entertainment and musical programs, as the key competitor of AM stations delivering Limbaugh’s show. Our hypothesis is that a higher number of “alternative” channels increases competition in the radio space, in turn lowering the county’s exposure to the show.

Our measure of competition in the radio market is inspired by the Herfindahl–Hirschman index (Herfindahl, 1950; Hirschman, 1945) of market competition. To calculate the HHI , we first overlap AM contours (for stations delivering “The Rush Limbaugh Show”) and FM contours with county boundaries. Based on this overlap, we identify approximately 1.2 million unique intersecting polygons p and the number of AM and FM contours belonging to each such unique polygon. We then calculate the relative share occupied by AM and FM stations within each unique polygon and calculate the HHI as per the standard HHI equation in Equation 1 below.

¹³Note that the definition of intentional and accidental FM coverage is county specific. An FM contour providing accidental coverage for county A may or may not provide accidental coverage for county B, depending on the size of the overlapping polygon.

$$HHI_{all,c,s} = \sum_{p=1}^N RLS_{share}_{p,c,s}^2 + \sum_{p=1}^N FM_{share}_{p,c,s}^2 \quad (1)$$

where $RLShare_{p,c,s}^2$ is the squared market (geographic) share of all AM stations delivering “The Rush Limbaugh Show” for the unique intersecting polygon p in county c of state s . Likewise, $FMShare_{p,c,s}^2$ is the squared market share of all FM stations received by the unique intersecting polygon p in county c of state s . The HHI is typically valued between 0 and 1, with higher values signaling less competition (more monopoly power).

One concern related to this HHI , however, is that FM stations and their contours are likely strategically placed to maximize coverage: A more populous county is likely covered by more FM contours than a less populous county. Therefore, an identification strategy that simply considers the “naive” AM–FM competition level within each county, as demonstrated in Equation 1 above, will likely suffer from endogeneity bias.

We observe, however, that in the planning of the intentional coverage area of an FM station, some surrounding counties might receive FM coverage “accidentally.” Exploiting such accidental FM coverage allows us to filter out the quasi-random variation in the HHI , which in turn enables us to interpret our estimates as causal. As already discussed in Section 3.2, we define an FM station’s coverage as accidental from the perspective of a county if the overlapping area between the FM contour and the county is less than the median value of all such overlapping areas for the whole sample.¹⁴ It is important to note that an FM station whose coverage we identify as accidental from the perspective of one county may or may not provide accidental coverage to another county, depending on the area covered by each FM contour within each county. We then recalculate the HHI considering the competition posed only by the accidental coverage from FM contours, using Equation 2.

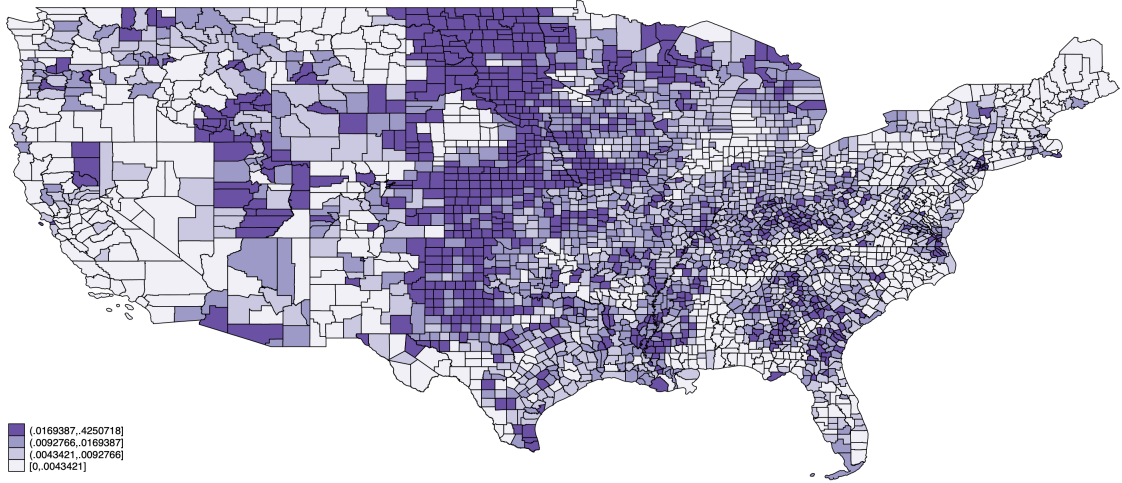
$$HHI_{acc,c,s} = \sum_{p=1}^N RLS_{share}_{p,c,s}^2 + \sum_{p=1}^N AccFM_{share}_{p,c,s}^2 \quad (2)$$

Here, $AccFMShare_{p,c,s}^2$ is the squared market share of FM stations with accidental

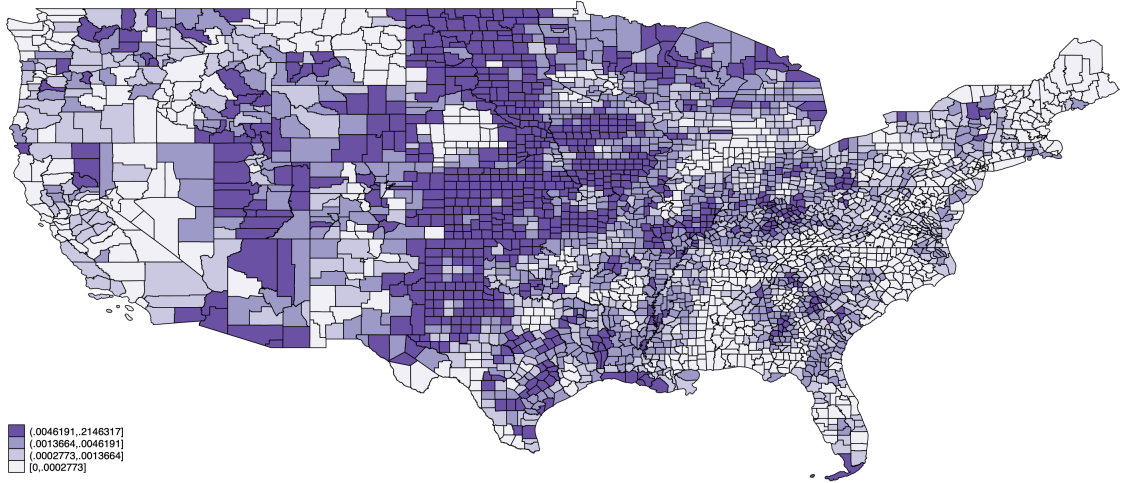
¹⁴Our baseline estimates are robust to our using alternate cutoffs to define coverage from FM contours as accidental, as presented in Table B.6.

coverage received by the unique intersecting polygon p in county c of state s . Again, this HHI_{acc} is typically valued between 0 and 1 but is lower than HHI_{all} as it exploits only a subset of the competition incorporated in the latter. Panels (a) and (b) in Figure 4 display the percentile distribution of HHI_{all} and HHI_{acc} , respectively.

Figure 4: HHI



(a) HHI based on all FM contours



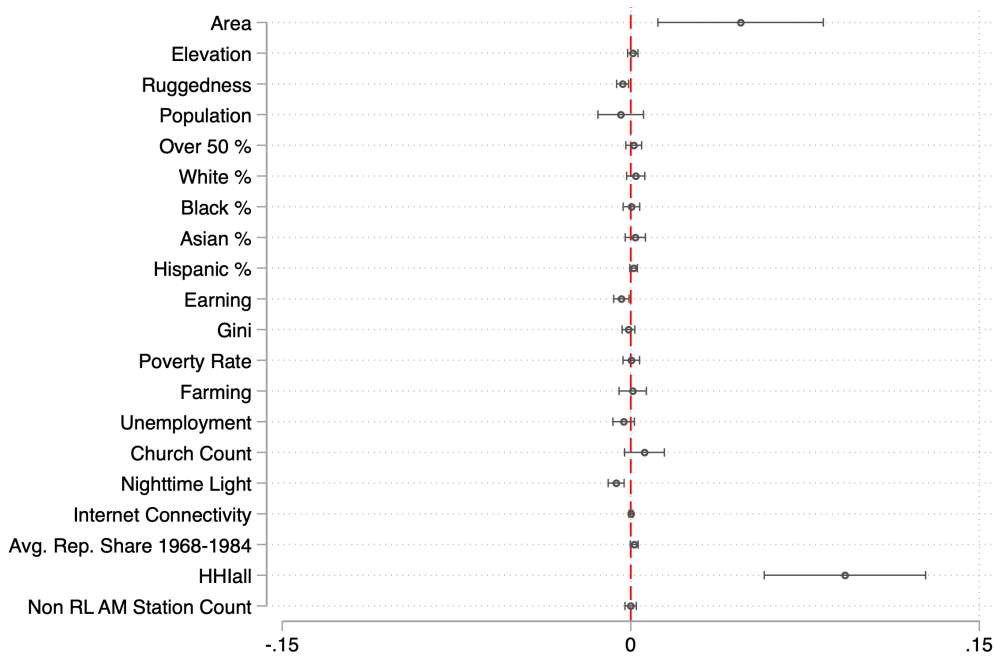
(b) HHI based on FM contours providing accidental coverage

Notes: Panels (a) and (b) show the distribution of the HHI based on all FM contours and on FM contours providing accidental coverage, calculated from Equations 1 and 2, respectively. An FM contour is identified as providing accidental coverage to a given county if the overlapping area between the FM contour and the county is less than the median value of all such overlapping areas for the whole sample.

One key consideration in our using this HHI within the identification strategy is whether radio competition is predetermined by any county-level observables. To alleviate this concern, in Figure 5, we examine the predictability of $HHI_{acc,c,s}$ using a number

of county-specific observable characteristics. We note that the estimated coefficients on almost all variables are statistically insignificant and close to zero. The differences in the extent of HHI_{acc} between counties are statistically significant for county area and HHI_{all} , which is a result of how HHI_{acc} is constructed. In addition, we find small differences in means in nighttime light intensity that are statistically significant at the 10% level, which might hint at differences by level of urbanization. In our specifications, we control for all these observables, and we also conduct a series of robustness checks that show that our identification strategy and results are not sensitive to a county's degree of urbanization.¹⁵

Figure 5: Correlation between HHI_{acc} and county-level characteristics



Notes: Dependent variable is HHI_{acc_i} . Figure shows the correlation between HHI_{acc} and a range of geographic and demographic variables in each county. All predictors are standardized between 0 and 1. Dots show the point estimates, while the vertical lines depict the 95% confidence intervals, based on standard errors clustered at the state level.

Before we proceed to the empirical strategy, some caveats are in order. First, while our focus is only on AM broadcasts of the show, in the last few years of the show's life, some FM stations also started to air it. This means that our HHI underestimates the

¹⁵We present the equivalent prediction exercise for $HHI_{all_{c,s}}$ in Figure B.1.

show’s market presence, and to the extent that this is the case, our estimates are likely to be biased downwards. However, given the absence of a precise matching identifier in the FM contours dataset and the dataset on the FM contours broadcasting the show, we are precluded from quantifying this bias. Moreover, we consider only the show’s competition over listenership from accidental FM contours. It would be interesting to construct a similar HHI measure of accidental coverage based on other, non-Limbaugh-airing, AM contours. However, the large size of AM contours precludes us from constructing a measure of accidental AM HHI coverage with any meaningful variation across counties. To capture the impact of competition in the AM space, all of our specifications control for the number of other, non-Limbaugh-airing AM contours in the county. Further, to prevent our results being driven by outliers from thinly populated, rural counties, our baseline analysis at the county and individual level is restricted to counties with a population size above 15,000.¹⁶

3.4 Data on election outcomes

We obtain county-level data on election outcomes in the US from the Atlas of U.S. Presidential Elections. We calculate the Republican vote share for each presidential election for each county, going back to 1988. We also calculate the average Republican vote share for all counties for the period 1968–1984, i.e., prior to the commencement of “The Rush Limbaugh Show,” which we use in a falsification test.

3.5 Individual-level data on policy preferences, political ideology, views on events, and polarization

We use individual-level survey data for 2006–2020 from the CES to identify individual attitudes on key social issues. Over the sample period, this survey consists of approximately 530,000 respondents from across the US. The survey provides each respondent’s geolocation (i.e., county), which allows us to match the county-level indicators of exposure

¹⁶In Tables B.2 and B.3, we present the results including all counties and for counties with a population size below 15,000 only, respectively. Our results are overall consistent but are less precisely estimated for thinly populated counties with a population below 15,000.

to Limbaugh’s show to each individual.

We first use the CES to first quantify individual *political ideology*. For each respondent, we generate binary indicators on whether her political ideology is “strongly conservative,” “conservative/strongly conservative,” or “moderate.” We also identify the party affiliation based on actual voting in the presidential election. Second, we focus on four questions in this survey that capture the respondent’s *policy preferences* towards abortion, immigrants, gun control and gay marriage. The answers to these question can be either binary (“support”/“do not support”) or hedonic (“strongly support”/“somewhat support”/“neither support nor oppose”/“somewhat oppose/strongly oppose”) responses. We convert these responses to binary format by generating indicators that assume a value of 1 if the respondent supports/strongly supports a statement and zero otherwise.

We complement the CES data with individual-level data on *political polarization* derived from the ANES survey. This survey is run every election year and consists of approximately 22,000 respondents over our sample period from 1988 to 2020. Following [Boxell et al. \(2017\)](#), we use these data and generate 9 indicators of political polarization (partisan affect polarization, ideological affect polarization, partisan sorting polarization, partisan-ideology polarization, perceived partisan-ideology polarization, issue consistency, issue divergence, straight-ticket voting and a combined polarization index) at the individual level.

Finally we examine individual views on events using two additional datasets. To analyse how exposure to the show can influence the political views around mass-shootings, we use data collected by [Yousaf \(2021\)](#) on the timing and location of mass shootings in the US combined with survey data on individual attitudes towards gun regulation. For our analysis on the effect of Rush Limbaugh’s death on Covid-19 vaccination, we accessed data on the daily vaccination uptake at the county level from the US Centers for Disease Control and Prevention (CDC)¹⁷ and combined it with daily, county level Covid-19 cases and fatalities data from the New York Times.¹⁸

¹⁷<https://www.cdc.gov/coronavirus/2019-ncov/vaccines/distributing/about-vaccine-data.html>

¹⁸The New York Times. (2021). *Coronavirus (Covid-19) Data in the United States*. Retrieved [August 2023], from <https://github.com/nytimes/Covid-19-data>.

Table 1: Descriptive statistics for key variables

	No. of Observations	Mean	Standard Deviation	Minimum	Maximum
County-level variables					
<i>HHIacc</i>	2,090	0.0022	0.0041	0	0.0509
<i>HHIall</i>	2,090	0.0100	0.0127	0	0.2646
<i>Rep Vote Share</i> 2016	2,084	0.5995	0.1529	0.0409	0.8948
<i>Rep Vote Share</i> 2020	1,989	0.6286	0.1816	0	1
Individual-level variables – CES					
<i>Strong Cons</i>	297,027	0.1349	0.3416	0	1
<i>Cons/ Strong Cons</i>	297,027	0.3784	0.4850	0	1
<i>Mod</i>	297,027	0.3079	0.4616	0	1
<i>Abortion Always</i>	305,644	0.5479	0.4977	0	1
<i>Deport Illegal Immigrants</i>	127,385	0.4920	0.4999	0	1
<i>Stricter Gun Laws</i>	240,385	0.6338	0.4818	0	1
<i>Support Gay Marriage</i>	188,069	0.5235	0.4994	0	1
Individual-level variables – ANES					
<i>Partisan Affect Polarization</i>	18,808	0.7010	0.1616	0	1
<i>Ideological Affect Polarization</i>	10,277	0.6691	0.1661	0	1
<i>Partisan Sorting Polarization</i>	16,202	0.3076	0.2656	0	1
<i>Partisan – Ideology Polarization</i>	10,447	0.5311	0.2775	0	1
<i>Perceived Partisan – Ideology Polarization</i>	19,499	0.7086	0.2204	0	1
<i>Issue Consistency</i>	18,881	0.4300	0.3004	0	1
<i>Issue Divergence</i>	16,769	0.4763	0.1482	0	1
<i>Straight Ticket Voting</i>	11,630	0.8491	0.3580	0	1
<i>Combined Polarization Index</i>	4,680	0.5905	0.1740	0	1

Notes: This table provides descriptive statistics for variables at the county and individual levels.

4 Effects on electoral outcomes

To estimate the effect of exposure to the show on electoral outcomes, we estimate the following county-level specification.

$$RepVoteShare_{c,s} = \beta_1 HHIacc_{c,s} + \beta_2 HHIall_{c,s} + \beta_3 X_{c,s} + \mathbf{FE}_s + \epsilon_{c,s} \quad (3)$$

where $RepVoteShare_{c,s}$ is the Republican vote share in county c of state s . $HHIacc_{c,s}$ is the competition faced by AM contours broadcasting the show only from FM contours delivering accidental reception, in county c of state s , calculated as per Equation 2. $HHIall_{c,s}$ is the HHI of competition faced by AM contours broadcasting the show from all FM contours (i.e., those delivering intentional and accidental reception), in county c of state s , calculated as per Equation 1. \mathbf{X} is a vector of geographic and demographic controls at the county level. FE_s is a vector of state fixed effects that accounts for any state-level unobservables. The coefficient of interest, β_1 , identifies the effect of competition for listenership faced by the show from accidental FM coverage on the Republican vote share, conditional on the effect of total competition captured by β_2 . Considering the dominant pro-Republican agenda promoted by Limbaugh’s show, we expect β_1 to be positive. We note here that this approach estimates an intention-to-treat (ITT) effect and that the estimated effects are likely to be lower than the true effect.

To begin with, we focus on the two most recent US presidential elections, 2016 and 2020. Panels A and C in Table 2 show the estimates for the 2016 and 2020 elections with no controls for $HHIall_{c,s}$, while Panels B and D present the comparable estimates for these elections when we control for $HHIall_{c,s}$. For all panels, Column (1) presents the unconditional estimates with no controls.

In Column (1) of Panel A, we observe that the coefficient of $HHIacc_{c,s}$ is positive and highly statistically significant, meaning that a high HHI in a given county (equivalent to lower competition for listeners faced by the show) increases the Republican vote share in the same county. In terms of economic significance, a one-standard-deviation increase in $HHIacc$ increases the Republican vote share by approximately 2.5 and 3 percentage

points in Panels A and B, respectively. This effect remains robust when we incorporate state fixed effects in Column (2) and when we control for a rich set of geographic and demographic characteristics and historical voting patterns in Columns (4), (5) and (6), respectively.

In Panel B, we present the estimates derived when we include HHI_{all} as a control variable. Here, the coefficient on HHI_{acc} reflects the effect on the Republican vote share of the purely accidental competition faced by the show, conditional on our accounting for the competition derived from all FM stations. We observe that the coefficients remain qualitatively and quantitatively similar to those recorded in Panel A.

Finally, in Panels C and D, we conduct the same exercise using the 2020 Republican vote share as the outcome variable. Here, too, the pattern remains the same, confirming that a high county-level HHI increases the Republican vote share. We note that the coefficients are slightly higher for 2020 than for 2016.

To further quantify the effect of the show, we follow [DellaVigna and Kaplan \(2007\)](#) and calculate the persuasion rate, which shows us what fraction of the increase in Republican vote share in 2020 was due to exposure to the show. Using the estimated coefficients from Table 2, Panel C, column (5) and Table B.13, column (2) as well as the Democratic vote share in the national popular vote in the 2020 presidential elections (51.3%) suggests a persuasion rate of around 10.8%.¹⁹

Next, we complement these estimates with an examination of the effect on the Republican vote share of the show since its inception in 1988. In Figure B.2, observe that the effects are more precisely observed from the early 2000s and increase in magnitude up to 2020. As mentioned before, prior to the mid-1990s, the show did not attract much nationwide attention. Limbaugh’s audience started to grow around the events of the Vince Foster story in March 1994 and following the Republican sweep of the House elections

¹⁹To calculate the persuasion rate, we use the approach developed by [DellaVigna and Kaplan \(2007\)](#) and the formula by [Mello and Buccione \(2021\)](#): $f = \frac{y_T - y_C}{e_T - e_C} \cdot \frac{1}{1 - y_0}$. In the first part of the expression, $y_T - y_C$ is the change in Republican vote share in the 2020 presidential elections as a result of exposure to the show which is the estimated coefficient in Table 2, Panel C, column (5). The denominator, $e_T - e_C$ is the effect of HHI_{acc} on the show’s listenership taken from Table B.13, column (2). The second term of the expression presents the Democratic vote share in the national popular vote in the 2020 presidential elections, which was 51.3 %.

Table 2: Effect of exposure to “The Rush Limbaugh Show” on Republican vote share

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: 2016 Republican Vote Share _{c,s}				
Panel A					
HHI _{acc_{c,s}}	6.2026*** (1.3589)	5.3675*** (1.1369)	5.1106*** (1.1083)	2.5699*** (0.8303)	2.4987*** (0.7141)
Observations	2,084	2,084	2,063	1,961	1,961
Panel B					
HHI _{acc_{c,s}}	8.0930*** (1.6914)	7.5769*** (1.2684)	7.5376*** (1.3137)	2.4858*** (0.8385)	2.3017*** (0.7439)
HHI _{all_{c,s}}	-1.1795* (0.6283)	-1.5239*** (0.4641)	-1.6734** (0.6278)	0.0623 (0.2348)	0.1458 (0.2641)
Observations	2,084	2,084	2,063	1,961	1,961
Dependent Variable: 2020 Republican Vote Share _{c,s}					
Panel C					
HHI _{acc_{c,s}}	7.4132*** (1.5053)	5.9327*** (1.2855)	5.5599*** (1.2558)	2.7917*** (0.7961)	2.6986*** (0.6935)
Observations	1,989	1,989	1,969	1,871	1,871
Panel D					
HHI _{acc_{c,s}}	9.1169*** (1.7690)	8.5028*** (1.4874)	8.4862*** (1.5249)	3.0263*** (0.8832)	2.8321*** (0.7752)
HHI _{all_{c,s}}	-1.0579 (0.7263)	-1.7703*** (0.5440)	-2.0149*** (0.7208)	-0.1741 (0.3627)	-0.0989 (0.3413)
Observations	1,989	1,989	1,969	1,871	1,871
State FE	NO	YES	YES	YES	YES
Geographic Controls	NO	NO	YES	YES	YES
Demographic Controls	NO	NO	NO	YES	YES
Avg. Rep. Share 1968–1984	NO	NO	NO	NO	YES

Notes: The dependent variable in Panels A and B is the Republican vote share in the 2016 and 2020 presidential elections, respectively. Geographic controls include county area, elevation and ruggedness. Demographic controls include population, population shares for the white, Black, Asian, Hispanic and age 50+ categories, median earnings, Gini coefficient, poverty rate, farming area, unemployment, number of churches, nighttime light, internet connectivity and non-Limbaugh-aring AM station count. Standard errors clustered at the state level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

in November 1994. The show’s popularity saw a further boost with the advent of the Obama administration in 2009. In addition, the Tea Party movement, giving voice to a more fiscally conservative faction within the Republican Party, was launched around this period. Members of this movement were even more receptive to Rush Limbaugh’s rhetoric and amplified his messaging to the broader conservative electorate. Further, this delayed effect could indicate that it took Rush Limbaugh some time to build a more unifying narrative that mobilised additional, conservatives who were undecided to cast their vote. As we will show in Section 5.1.1, the effect of the show seems to be driven by pushing more Republican voters to an even stronger conservative political ideology, which could lead to stronger mobilisation effects of the show that occurred with some temporal lag.

4.1 Robustness checks

We now examine the robustness of these baseline estimates across alternative specifications.

The baseline estimates in Table 2 are based on the set of counties with over 15,000 inhabitants. We restrict the sample to these counties based on the idea that, for the show to have meaningful political influence, there must be a sufficient mass of listeners. It is very unlikely that the polygons of accidental coverage will overlap with inhabited areas in very thinly populated counties. In Table B.2, we provide estimates for the full set of counties. We observe that the baseline effect shrinks in quantitative terms. In Table B.3, we present estimates for only counties with fewer than 15,000 inhabitants, and we find very limited evidence of an effect of the show on voting in 2016 and no evidence of an effect in 2020. These estimates reconfirm our prior that a sufficient mass needed to be exposed to the show’s content for it to impact voting outcomes.

Considering the nature of the key treatment variable, one concern is whether the effect is driven by counties where no FM contours are present. To address this concern, in Table B.4, we present estimates for the set of counties with at least one FM contour. The estimates remain robust both quantitatively and qualitatively.

Importantly, in Table B.5, we show that the measure of show exposure is not sta-

tistically significantly related to the election outcomes in the period prior to the show’s inception. This falsification test confirms the validity of our baseline finding that the increase in the Republican vote share is attributable to listeners’ being exposed to the show.

Next, recall that, in the baseline estimates, we define coverage from an FM contour as accidental if the size of the overlap between the contour and county area is less than the median value of all such overlapping areas. We now consider cutoffs other than the median for this definition. Accordingly, in Column (1) of Table B.6, an FM contour is considered to deliver accidental reception if the size of the overlap area is less than the 10th percentile of all such overlapping areas, while in Column (2), this cutoff is based on the 25th percentile of overlapping areas. In Column (3), an FM contour is considered as delivering accidental reception if the overlap is less than the average value of overlapping areas. Across the three alternative cutoffs, we observe that the baseline findings remain qualitatively and quantitatively similar irrespective of the cutoff for accidental competition.

Considering the broad dispersion of AM contours across the US, another concern is to what extent the level of urbanization affects our estimates. The concern here is twofold. First, the public response to Limbaugh’s content could have differed by whether people live in more or less developed areas. Second, the geographic features of rural vs. urban areas may have affected the show’s delivery, which may affect the treatment variable. While, in our baseline specification, we control for elevation, ruggedness, farming intensity, nighttime light and internet connectivity, which already account for urban vs. rural differences, in Table B.7, we employ an additional robustness check that specifically addresses this concern.

We note that the key empirical barrier here is the absence of spatially granular urbanization data for each of the overlapping polygons. To overcome this problem, we utilize data on nighttime light (NTL). By overlapping geocoded NTL data with the FM contours delivering accidental coverage, we are able to calculate the amount of nighttime light under each such contour. We then identify those with very high (over the 90th percentile)

and very low (below the 10th percentile) NTL levels. In Columns (1) and (2), we test the sensitivity of our baseline estimates to our excluding overlapping polygons with very high and very low levels of urbanization by using the HHIs recalculated after we drop high- and low-NTL polygons, respectively. We observe that the baseline results remain robust to this exclusion, confirming that they are not driven by highly urban or highly rural areas.

Given the spatially clustered nature of show exposure, we examine the robustness of the baseline estimates to our adjusting the standard errors for spatial correlation, as per [Conley \(1999\)](#). In [Figure B.3](#), we show that the results are robust to adjustment for spatial correlation for up to 500 km (in 100 km intervals). Moreover, in [Table B.8](#), we show that the estimates are robust across alternative specifications including spatial lags, i.e., spatial autoregressive and spatial Durbin models, based on the contiguity matrix of adjacency.

In [Table B.9](#), we replace the votes-based outcome variable with an alternative outcome variable on political ideology. We draw from [Tausanovitch and Warshaw \(2013\)](#), who develop two distinct measures of political ideology at the county level. Here, “MRP ideology” refers to an estimate of ideological preferences based on a multilevel regression and poststratification model, while “IRT ideology” refers to ideological preferences based on a Bayesian item-response model. These indicators are provided for three distinct time periods: 2004–2011, 2012–2016 and 2017–2021. Positive values reflect a more right-leaning and negative values a more left-leaning political ideology. The estimates presented in [Table B.9](#) show that, overall, exposure to Limbaugh’s show increased the right-leaning nature of a county’s political ideology. This finding, based on an alternative county-level indicator, further confirms our votes-based baseline findings.

The rise of the effect of Rush Limbaugh’s show on Republican vote share starting in 2000 coincided with the rollout of Fox News across some counties in the US. To check whether there is a relationship between his show, the rollout of Fox News and the Republican vote share, we combine our data on accidental competition for listenership with the data collected by [DellaVigna and Kaplan \(2007\)](#) on the early phase of the Fox News

rollout and the Republican vote share in the 2000 presidential elections. In Columns (1) and (2) of Table B.10, we show that the HHIs of accidental and overall listenership competition do not systematically correlate with the early availability of Fox News in 2000. Indeed, when we include our measure of Rush Limbaugh exposure as an additional regressor in the main model of DellaVigna and Kaplan (2007), we find that the Rush Limbaugh effect is still statistically significant.

5 Effects on individual attitudes

5.1 The show and policy preferences/political attitudes

Next, we focus on how exposure to the show affects individual policy preferences and political attitudes. For this purpose, we use annual survey data from the CES, covering approximately 530,000 respondents over 2006–2020. Particularly relevant for our purpose, the CES provides each respondent’s geolocation (i.e., county), which allows us to link survey responses to our exposure measure. For the individual-level analysis, we then define the following specification.

$$Outcome_{i,c,s,y} = \gamma_1 HHIall_{c,s} + \gamma_2 HHIacc_{c,s} + \beta_1 X_{i,c,s} + \beta_2 Z_{c,s} + \mathbf{FE}_s + \mathbf{FE}_y + \epsilon_{i,c,s} \quad (4)$$

where $Outcome_{i,c,s,y}$ is a binary indicator on the policy preferences and political attitudes of respondent i residing in county c of state s , in year y . As before, $HHIall_{c,s}$ and $HHIacc_{c,s}$ represent county-level exposure to “The Rush Limbaugh Show” based on all reception from FM contours and accidental reception from FM contours, respectively. \mathbf{X} is a vector of individual-level controls, while \mathbf{Z} is a vector of county-level (geographic and demographic) controls. FE_s is a vector of state fixed effects that accounts for any state-level unobservables, while FE_y is a vector of year fixed effects that absorbs any time-varying, year-specific unobservables. The coefficient of interest, γ_2 , identifies the effect of county-level (accidental) exposure to the show on political views of individuals belonging

to the same county c . Again, this approach estimates an intention-to-treat effect.

5.1.1 “The Rush Limbaugh Show” and political attitudes

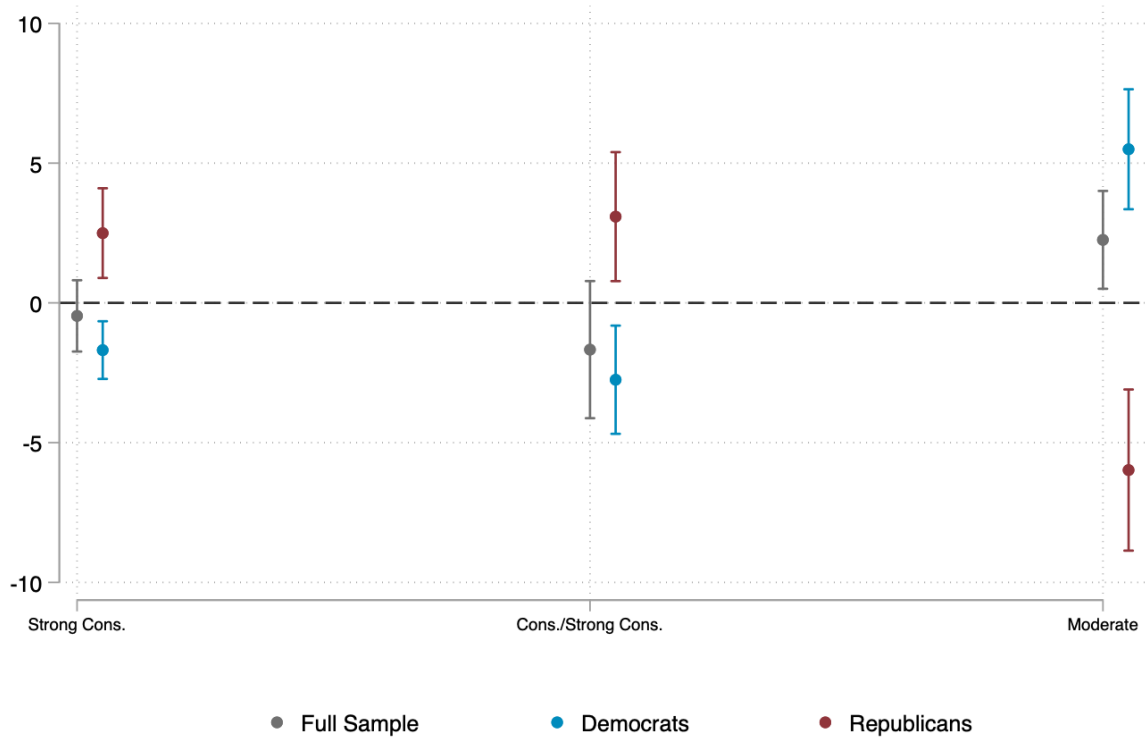
We first examine individual political attitudes. We define binary indicators identifying respondents’ political views based on their answers to the question “How would you define your political views?” This question yields a set of hedonic answers: “very conservative,” “conservative,” “moderate”, “liberal” and “very liberal.” We use this information to define three binary indicators—equalling one if the respondent declared her political views to be (a) “strongly conservative”, (b) “conservative” and (c) “moderate,” respectively, and zero otherwise—and use these as the dependent variables in Equation 4 above.

Rush Limbaugh’s regular audience consisted largely of Republicans. It is therefore very likely that Democrats did not really listen to the stations airing the show and were therefore not exposed (“treated”). Even if they listened to the show, Mutz’s (2001) study on Americans’ exposure to dissimilar political views shows that Democrats are more likely than Republicans to find that the views expressed on talk radio shows are in disagreement with their own. To examine the potential heterogeneity in the effects of show exposure on respondents with different party preferences, we build an interaction term between our HHI measures, $HHI_{all,c,s}$ and $HHI_{acc,c,s}$, and Rep_i , a dummy that switches to one if the respondent voted Republican in previous elections and zero otherwise.

Figure 6 and Table B.11 present the results on the effect of show exposure on individual political attitudes. Ignoring respondent party preference, we find not that exposure to the show leads to more conservative attitudes but that respondents tend to consider themselves more “moderate.” However, once we include the interaction term that indicates whether the respondent voted Republican in the previous elections, we find some interesting patterns. Self-reported Republicans tend to have more strongly conservative political attitudes and are also less moderate. In contrast, Democrats located in counties with high exposure to the show are less likely to agree with more conservative political attitudes but tend to be more moderate. These results reveal two potential mechanisms on how Rush Limbaugh is impacting election outcomes through mobilisation. First, he

not only by mobilises his own, strongly conservative audience to cast a vote to prevent the ideological “enemy” from winning. Second, Democrats living in counties with higher exposure to the show tend to be more moderate and compared to stronger Democrats – moderate Democrats have a lower probability to cast a vote on election day.

Figure 6: Exposure to the show and political attitudes

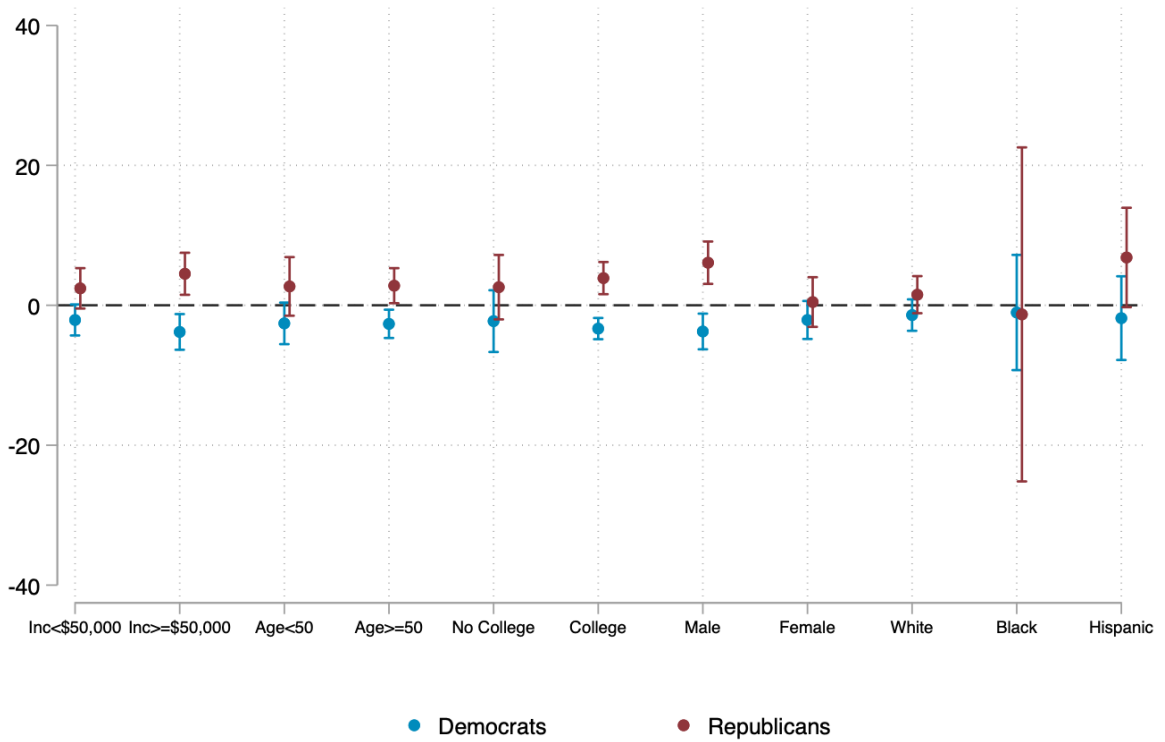


Notes: Dots show the point estimates while the vertical lines depict the 95% confidence intervals, based on standard errors clustered at the county level. Estimates for each political view/attitude category represent a separate regression estimate. All estimates include geographic (county area, elevation and ruggedness) and demographic (total population, population shares for White, Black, Asian, Hispanic and above 50 year categories, median earnings, Gini coefficient, poverty rate, unemployment, farming area, number of churches, average nighttime lights, internet connectivity and non-Rush Limbaugh AM count) controls, as well as individual controls in the form of the respondent’s age, race, gender, educational status, family income and marital status.

In the next step, we analyse the heterogeneity of the effect by demographic groups. The results in Figure 7 and Table B.12 show the estimates for the binary outcome variable indicating if the respondent considers herself “Conservative” or “Very Conservative”. Exposure to the show appears to have a statistically significant effect on respondents with a higher income level ($\geq \$50,000$). Rush Limbaugh’s audience was in general more politi-

cally knowledgeable and interested, which are traits positively correlated with income. In general, the effect of exposure to the show is also more pronounced for older and male respondents as well as people with college education. We do not find systematic differences within ethnic groups.

Figure 7: Exposure to the show and political attitudes - Heterogeneity across demographic groups

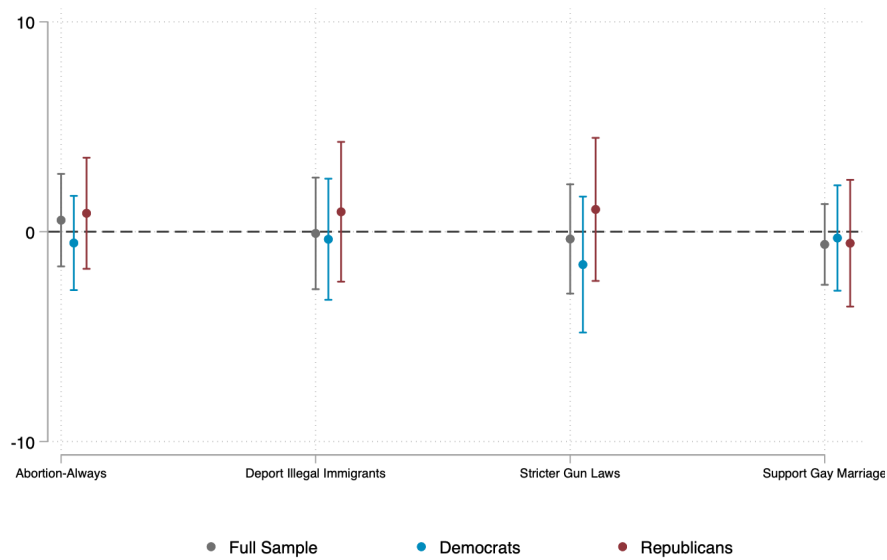


Notes: Dots show the point estimates while the vertical lines depict the 95% confidence intervals, based on standard errors clustered at the county level. Estimates for each demographic category represent a separate regression estimate. All estimates include geographic (county area, elevation and ruggedness) and demographic (population, population shares for white, black, Asian, Hispanic and above 50 year categories, median earnings, Gini coefficient, poverty rate, farming area, unemployment, number of churches, nighttime light, internet connectivity and non-Rush-Limbaugh AM station count) controls, as well as individual controls in the form of the respondent's age, race, gender, educational status, family income and marital status.

5.1.2 “The Rush Limbaugh Show” and policy preferences

In the next step, we analyse the show’s impact on individual preferences for particular policies. Figure 8 presents the coefficients of the point estimates for our exposure measure on five different policy questions for the full sample and for Democrats and Republicans separately. We find only some indication that show exposure led Democrats to adopt a strongly pro-choice stance and had some impact on Republicans’ defense of gun ownership.

Figure 8: Exposure to the show and policy preferences



Notes: Dots show the point estimates, while the vertical lines depict the 95% confidence intervals based on standard errors clustered at the county level. Estimates for each policy preference represent a separate regression estimate. All estimates control for geographic characteristics (county area, elevation and ruggedness), demographic characteristics (total population, population shares for the white, Black, Asian, Hispanic and age 50+ categories, median earnings, Gini coefficient, poverty rate, unemployment, farming area, number of churches, average nighttime lights, internet connectivity and non-Rush Limbaugh AM count) and individual characteristics (respondent age, race, gender, educational status, family income and marital status).

5.2 The show and views on political events

To analyse how exposure to the show can impact people’s views around events of political importance, we combine our cross sectional exposure measures with two types of time series data related to two, highly politicised topics: mass shootings/gun control and Covid-19 vaccinations. For the first analysis we use data compiled by [Yousaf \(2021\)](#) on mass shootings in the US. For the second analyse, we exploit the timing of the death of Rush Limbaugh and the subsequent end of his live show.

5.2.1 Exposure to the show and attitudes towards gun control after mass shooting events

Throughout the show, Rush Limbaugh was a strong advocate against stricter gun control and most forms of gun ownership regulation. In the aftermath of mass shootings, when calls for stricter gun controls increased, his narrative included the use of concealed carry in schools or armed school guards. He also considered the ban on assault rifles, which are often used in mass shootings, as an infringement of the Second Amendment.

To analyse how exposure to the Rush Limbaugh Show can influence the narrative and interpretation of political events, we use data collected by [Yousaf \(2021\)](#) on the timing and location of mass shootings in the US combined with individual attitudes towards gun regulation. In particular, we focus on the part of the study that analyses how Republicans and Democrats update their preferences for gun controls after a shooting occurred. To examine how exposure to the show affects this updating process, we combine our HHI exposure data with the individual level replication data for Table 8 in [Yousaf \(2021\)](#). The results are presented in Table 3. We confirm that after a mass shooting, Republicans are less likely to demand stricter gun controls, and this effect is even stronger for Republicans located in counties with a high exposure to the show. We do not find such an effect on Democrats located in high exposure counties.

Table 3: Exposure to the show and the effect of mass shootings on attitudes towards gun regulation among voters

	(1)	(2)	(3)	(4)	(5)	(6)
	Importance of gun control	Stricter gun control	Background checks for sales	Ban assault rifles	Difficult to obtain concealed- carry	States can publish gun owners' names
Post-MS	0.2087* (0.1154)	-0.0431*** (0.0143)	-0.0428** (0.0195)	-0.0082 (0.0293)	0.0335 (0.0208)	0.0310 (0.0198)
Post-MS \times REP	0.0348 (0.0920)	-0.0413** (0.0167)	-0.0235** (0.0107)	-0.0772*** (0.0137)	-0.0793*** (0.0162)	-0.0694*** (0.0131)
Post-MS \times DEM	0.0409 (0.0887)	0.0429** (0.0172)	0.0331*** (0.0077)	0.0519*** (0.0141)	0.0211 (0.0162)	0.0091 (0.0100)
Post-MS \times <i>HHIacc</i>	1.4560 (25.2919)	17.7870*** (2.8052)	27.6533 (16.5398)	4.7843 (34.8940)	3.7637 (14.4258)	-5.3243 (12.3141)
Post-MS \times <i>HHIacc</i> \times REP	-17.3338 (53.8810)	-13.7685** (6.7234)	-6.0099*** (1.4434)	-2.5821 (2.0697)	-4.0243* (2.0402)	-1.2661 (1.4942)
Post-MS \times <i>HHIacc</i> \times DEM	-1.4608 (19.7170)	-3.7547 (2.7921)	-1.6449 (1.6510)	0.5010 (3.3057)	0.5832 (1.6886)	-1.1082 (2.4262)
Observations	10,011	78820	119,910	119,910	119,910	119,910
R-squared	0.1499	0.2682	0.1512	0.2696	0.2171	0.1091

*Notes:*Notes: The table replicates the estimates from Table 8 from [Yousaf \(2021\)](#) and includes two new variables to the specifications: First, $Post - MS \times HHIacc$ is the interaction of $Post - MS$, a dummy equal to 1 for periods on and after a mass shooting in a county, with *HHIacc* which is the county level exposure to The Rush Limbaugh Show variable using accidental FM contours. Second, $Post - MS \times REP \times HHIacc$, is the previous term further interacted with *REP*, a dummy equal to 1 if the respondent voted for a Republican Presidential candidate in the previous election; The dependent variables are measure of importance All estimates, include area (congressional districts in column (1) and counties in columns (2)–(6)) and year fixed effects along with binary indicators for Republican and Democrat. Additionally, all estimations include individual characteristics: race, education, income, marital status, age, squared-age, and religiosity of the individual (column (1)), and race, education, income, marital status, age, squared-age, gender, employment status, home tenure status, voter registration status, political leaning, and religiosity of the individual (columns (2)–(6)). All estimations are weighted using the survey weights. The standard errors are clustered at the congressional district level in column (1) and state level in columns (2)–(6).Standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.2.2 The death of Rush Limbaugh and Covid-19 vaccination uptake

The Covid-19 pandemic and Covid-19 vaccinations became a highly polarised topic in the US, with political actors from each spectrum trying to push their own narrative about the origins and severity of the disease as well as the effectiveness and side-effects of the vaccine. Rush Limbaugh pushed a narrative that the severity and potential effects of Covid-19 are exaggerated (“[...] a common cold”) and urged his listeners not to get vaccinated.²⁰

Data on daily Covid-19 vaccination uptake at the county level stems from the US Centers for Disease Control and Prevention (CDC). In addition we obtain daily, county level Covid-19 cases and fatalities data from the New York Times.

To estimate the heterogeneous effects on the death of Rush Limbaugh on Covid-19 vaccination uptake across our exposure measure, we estimate the following specification:

$$VACC_{ct} = \alpha_c + \alpha_t + \lambda_1(HHI_c \times RLDeath_t) + \lambda_2(\mathbf{X}_c \times RLDeath_t) + \epsilon_{ct}, \quad (5)$$

where $VACC_{ct}$ is the (natural log of) number of people in county c and week t with at least one dose of Covid-19 vaccination, α_c and α_t are county and week fixed effects, HHI_c are either HHI_{all} or HHI_{acc} of county c , $RLDeath_t$ takes a value of one in and after the week of Rush Limbaugh’s passing; \mathbf{X} is a vector of the standard set of controls used in specification 3.

The results in Table 4 are presented for 4 different outcome variables: Number of all people with at least one dose per county and week (column 1), number of people 12 years and above (2), 18 years and above (3) and 65 years and above (4). Each of the four panels contains results for different specifications. Panels A and B present results using HHI_{all} without and with control interaction terms, respectively. Panels C and D contain results using HHI_{acc} without and with control interaction terms, respectively.

²⁰ “Rush Limbaugh on coronavirus: ‘The common cold’ that’s being ‘weaponized’ against Trump” <https://www.washingtonpost.com/nation/2020/02/25/limbaugh-coronavirus-trump/> and “Four conservative radio talk-show hosts bashed coronavirus vaccines. Then they got sick.” https://www.washingtonpost.com/lifestyle/media/conservative-talk-radio-Covid-deaths/2021/08/31/a912a89c-0a66-11ec-aea1-42a8138f132a_story.html

The results show that in the weeks after Rush Limbaugh’s death, there was a comparatively larger increase in the uptake of Covid-19 vaccinations in counties that have been more exposed to the Rush Limbaugh Show. These results indicate that with the discontinuation of the live program, exposure to anti-vaccination messages in counties with large exposure to the show, has substantially decreased and led to a change in attitudes towards Covid-19 vaccinations. The effect is particularly pronounced for people of the age of 65 and above, which is the demographic group with the largest listener base of the show. These results also complement the findings in a recent study by [Ajzenman *et al.* \(2023\)](#) who show that the dismissal of the risks associated with Covid-19 during speeches by the Brazilian President Bolsonaro, led to a reduction in social-distancing in pro-government regions of Brazil.

Table 4: Exposure to the show, the death of Rush Limbaugh, and Covid-19 vaccination uptake

	(1) No. of People	(2) No. of People 12+	(3) No. of People 18+	(4) No. of People 65+
	with at least one Dose of Covid Vac administered			
Panel A				
<i>HHIall</i> × <i>Post RL Death</i>	2.7280*** (0.7343)	2.0452*** (0.6717)	2.3181*** (0.6780)	2.8232*** (0.9717)
Controls × <i>Post RL Death</i>	NO	NO	NO	NO
Observations	16,767	16,566	16,733	16,733
Panel B				
<i>HHIall</i> × <i>Post RL Death</i>	1.6762** (0.7586)	1.1360* (0.6571)	1.2037* (0.6421)	2.0947** (0.8992)
Controls × <i>Post RL Death</i>	YES	YES	YES	YES
Observations	14,577	14,395	14,548	14,548
Panel C				
<i>HHIacc</i> × <i>Post RL Death</i>	10.2991*** (2.4846)	9.5338*** (2.2786)	9.4697*** (2.2572)	11.9098*** (2.8219)
Controls × <i>Post RL Death</i>	NO	NO	NO	NO
Observations	16,767	16,566	16,733	16,733
Panel D				
<i>HHIacc</i> × <i>Post RL Death</i>	6.0435*** (2.3224)	5.8037*** (2.0624)	5.3596*** (2.0191)	9.3745*** (2.6046)
Controls × <i>Post RL Death</i>	YES	YES	YES	YES
Observations	14,577	14,395	14,548	14,548

Notes: The Table shows estimation results of OLS estimates. The data is at the county and week level for weeks 3 – 12 in 2021. Dependent variables are the natural log of the number of people (total (Column 1), 12 years and above (2), 18 and above (3) and 65 and above (4) in a county and week with at least one dose of a Covid-19 vaccine administered. *Post RL Death* is a binary indicator for weeks post Rush Limbaugh's death (weeks 7–12). All specifications include county and week fixed effects, and the total number of Covid-19 cases and deaths in a week and county. Standard errors, clustered at the county level, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

5.3 The show and political polarization

Finally, we analyse the impact of exposure to the Rush Limbaugh Show on political polarization following the methodology by [Boxell *et al.* \(2017\)](#). We accessed the restricted version of the American National Election Studies (ANES) that allows us to link respondents' place of residence with our county level exposure measures. Based on responses to the survey, we compute eight different measures of political polarization and an aggregate measure of political polarization based on those eight individual measures.

The first two measures, "Partisan affect polarization" and "Ideological affect polarization", capture the respondents' attitudes toward the members of the other political party. "Partisan sorting" and "Partisan-Ideology polarization" measures the difference between an individual's partisan identity and ideology. "Perceived partisan-ideology polarization" captures individual perception in ideological differences between Democrats and Republicans. "Issue consistency" and "issue divergence" capture how the respondent's issue positions line up on a single ideological dimension. Finally, "Straight-ticket voting" measures how often a respondent has split their votes across parties in an election. We then also calculate an "Index" that builds the average across those eight measures.

In [Table 5](#) we show estimates that do not take into account the respondent's party affiliation. Similar to the results using the CCES data we only find some weak evidence that exposure to the show increases political polarization, mainly for Partisan-Ideology Polarisation and the overall Index. However, these results are only statistically significant at the 10% level.

Accounting for the potential differences in exposure between party affiliation, the results in [Table 6](#), show a clearer trend, revealing that exposure to the show has a large impact on Republican voters. Republicans residing in counties with more exposure to the show are more ideologically aligned with their party.

Table 5: Effect of exposure to the show on measures of political polarization (ANES)

	(1) Partisan Affect Polarization	(2) Ideological Affect Polarization	(3) Partisan Sorting Polarization	(4) Partisan -Ideology Polarization	(5) Perceived Partisan-Ideology Polarization	(6) Issue Consistency	(7) Issue Divergence	(8) Straight Ticket Voting	(9) Index
$HHIacc_i$	-0.0744 (0.8846)	1.2855 (1.1784)	-0.5101 (1.5517)	1.4602 (1.5491)	0.9493 (1.2286)	-1.8366 (1.9848)	-1.8359** (0.9304)	4.7437* (2.5800)	2.5178* (1.5002)
$HHIall_i$	0.1200 (0.2053)	0.0654 (0.3346)	0.2389 (0.3830)	0.8768 (0.6643)	0.1941 (0.2897)	1.0527** (0.5139)	-0.1540 (0.2372)	-1.9348** (0.9505)	-0.6495 (0.4390)
Observations	17,095	9,700	14,730	9,487	17,668	17,098	15,182	11,054	4,450
Geographic Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Demographic Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The dependent variable in each column is an indicator for political polarization as per [Boxell et al. \(2017\)](#). All estimates include geographic (county area, elevation and ruggedness) and demographic (total population, population shares for White, Black, Asian, Hispanic and above 50 year categories, median earnings, Gini coefficient, poverty rate, unemployment, farming area, number of churches, average nighttime lights, internet connectivity and non-Rush Limbaugh AM count) controls, as well as individual controls in the form of the respondent's age, race, gender, educational status, family income and marital status. The sample is limited to respondents identifying as Republican/Democratic voters. Standard errors, clustered at the county level, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Effect of exposure to the show on measures of political polarization (ANES) - by party affiliation

	(1) Partisan Affect Polarization	(2) Ideological Affect Polarization	(3) Partisan Sorting Polarization	(4) Partisan -Ideology Polarization	(5) Perceived Partisan-Ideology Polarization	(6) Issue Consistency	(7) Issue Divergence	(8) Straight Ticket Voting	(9) Index
$HHIacc_i$	-1.3175 (1.9108)	-2.5451 (2.6218)	-6.2863*** (2.0186)	6.6912** (2.8028)	-0.9378 (1.8361)	-8.8039*** (2.5823)	-3.8667*** (1.2401)	2.7726 (3.6313)	-6.7329 (4.1914)
$HHIacc_i \times Rep$	2.2735 (2.3849)	5.4870** (2.6864)	9.5208*** (2.7126)	-6.6327** (3.0048)	3.9191** (1.6892)	12.7617*** (2.9929)	3.3929* (1.7650)	4.5339 (3.1435)	10.5588** (4.6905)
$HHIall_i$	0.1205 (0.2056)	0.1729 (0.3508)	0.2301 (0.4075)	0.7132 (0.4710)	0.3221 (0.2947)	1.0436* (0.5447)	-0.0773 (0.2452)	-1.9905** (0.8974)	-0.6508 (0.4410)
Observations	17,095	9,158	13,396	9,487	15,914	15,091	15,091	10,389	4,450
Geographic Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Demographic Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The dependent variable in each column is an indicator for political polarization as per [Boxell et al. \(2017\)](#). All estimates include geographic (county area, elevation and ruggedness) and demographic (total population, population shares for White, Black, Asian, Hispanic and above 50 year categories, median earnings, Gini coefficient, poverty rate, unemployment, farming area, number of churches, average nighttime lights, internet connectivity and non-Rush Limbaugh AM count) controls, as well as individual controls in the form of the respondent's age, race, gender, educational status, family income and marital status. Rep_i is a binary indicator equalling to 1 if the respondent voted for the Republican party at the previous presidential election, and zero otherwise. The sample is limited to respondents identifying as Republican/Democratic voters. Standard errors, clustered at the county level, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

6 Conclusion

Opinion programs run by charismatic hosts enjoy an increasing popularity and play an important role in forming political narratives and attitudes. The Rush Limbaugh Show can be considered as a template for modern opinion programs and played a key role in forming the conservative narrative that has dominated the Republican party for decades (Jamieson and Cappella, 2008). While radio has seen a decline with the rise of the internet, people still consume radio programs during a lot of daily activities where the use of screens is impracticable or prohibited (i.e. driving, manual labour). Combined with a lack of frequency competition in many areas of the US, the Rush Limbaugh Show and other, AM transmitted talk shows, enjoyed a largely uncontested access to a large audience.

In this paper we highlight the effect of a lack of plurality in the radio space on political outcomes. We first show that counties with less contested exposure to the show have a systematically higher Republican vote share. We then unpack the underlying mechanisms on how the show influences electoral outcomes and political polarization. While the show did not systematically influence policy preferences, we find that exposure to the show pushed Republican voters even further to the conservative end of the political spectrum. Along with the theory around the role of narratives in politics, we find that the show has an impact on Republicans' views on political events. More exposure to the show leads to an even stronger opposition to stricter gun laws after mass shootings. The end of the show's broadcast also led to a relatively higher increase in Covid-19 uptake rates in counties that were previously more exposed to the show.

We believe that our paper has two important implications: First, radio is not dead. Across the world, radio is still widely used to distribute political content and narratives. Compared to online media, it also enjoys a stickiness in attention. The recent study by Allcott *et al.* (2024) did not find any systematic effect of social media on effective and issue polarisation. It is possible that the type of political information that is presented on social media might lack a narrator that is able to build a coherent narrative around

events. Once locked into a program, listeners are exposed to the host's content often for hours, making it a very powerful tool to create an echo chamber. Our paper shows that the long-run exposure to radio opinion programs can strongly impact political ideology, belief polarization, attitude towards political events and even individual behaviour in the context of the Covid-19. Second, a lack of radio station and program plurality was potentially a key contributor to the current level of political polarization in the US. The trend towards increased concentration in media markets could further widen political divides along party lines and increase political polarization.

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References

- ADENA, M., ENIKOLOPOV, R., PETROVA, M., SANTAROSA, V. and ZHURAVSKAYA, E. (2015). Radio and the Rise of The Nazis in Prewar Germany. *Quarterly Journal of Economics*, **130** (4), 1885–1939.
- AJZENMAN, N., CAVALCANTI, T. and DA MATA, D. (2023). More than words: Leaders' speech and risky behavior during a pandemic. *American Economic Journal: Economic Policy*, **15** (3), 351–71.
- ALLCOTT, H., GENTZKOW, M., MASON, W., WILKINS, A., BARBERÁ, P., BROWN, T., CISNEROS, J. C., CRESPO-TENORIO, A., DIMMERY, D., FREELON, D., GONZÁLEZ-BAILÓN, S., GUESS, A. M., KIM, Y. M., LAZER, D., MALHOTRA, N., MOEHLER, D., NAIR-DESAI, S., BARJ, H. N. E., NYHAN, B., DE QUEIROZ, A. C. P., PAN, J., SETTLE, J., THORSON, E., TROMBLE, R., RIVERA, C. V., WITTENBRINK, B., WOJCIESZAK, M., ZAHEDIAN, S., FRANCO, A., DE JONGE, C. K., STROUD, N. J. and TUCKER, J. A. (2024). The effects of facebook and instagram on the 2020 election: A deactivation experiment. *Proceedings of the National Academy of Sciences*, **121** (21), e2321584121.
- ANANYEV, M., POYKER, M. and TIAN, Y. (2021). The safest time to fly: pandemic response in the era of Fox News. *Journal of Population Economics*, **34** (3), 775–802.
- ASH, E., GALLETTA, S., PINNA, M. and WARSHAW, C. (2021). *The Effect of Fox News Channel on U.S. Elections: 2000-2020* . <https://ssrn.com/abstract=3837457>.
- BARKER, D. C. (1999). Rushed decisions: Political talk radio and vote choice, 1994-1996. *The Journal of Politics*, **61** (2), 527–539.
- BARONE, G., D'ACUNTO, F. and NARCISO, G. (2015). Telecracy: Testing for channels of persuasion. *American Economic Journal: Economic Policy*, **7** (2), 30–60.
- BERRY, J. M. and SOBIERAJ, S. (2011). Understanding the rise of talk radio. *PS: Political Science & Politics*, **44** (4), 762–767.

- BESLEY, T. and BURGESS, R. (2002). The Political Economy of Government Responsiveness: Theory and Evidence from India. *Quarterly Journal of Economics*, **117** (4), 1415–1451.
- and PRAT, A. (2006). Handcuffs for the grabbing hand? media capture and government accountability. *American Economic Review*, **96** (3), 720–736.
- BLOUIN, A. and MUKAND, S. W. (2019). Erasing ethnicity? propaganda, nation building, and identity in rwanda. *Journal of Political Economy*, **127** (3), 1008–1062.
- BOXELL, L., GENTZKOW, M. and SHAPIRO, J. M. (2017). Greater internet use is not associated with faster growth in political polarization among us demographic groups. *Proceedings of the National Academy of Sciences*, **114** (40), 10612–10617.
- BURSZTYN, L., RAO, A., ROTH, C. and YANAGIZAWA-DROTT, D. (2022). Opinions as Facts. *The Review of Economic Studies*, **90** (4), 1832–1864.
- CAGÉ, J. (2020). Media competition, information provision and political participation: Evidence from french local newspapers and elections, 1944–2014. *Journal of Public Economics*, **185**, 104077.
- CAMPANTE, F., DURANTE, R. and SOBBRIO, F. (2017). Politics 2.0: The Multifaceted Effect of Broadband Internet on Political Participation. *Journal of the European Economic Association*, **16** (4), 1094–1136.
- CAMPANTE, F. R. and HOJMAN, D. A. (2013). Media and polarization: Evidence from the introduction of broadcast tv in the united states. *Journal of Public Economics*, **100**, 79–92.
- CONLEY, T. (1999). Gmm estimation with cross sectional dependence. *Journal of Econometrics*, **92** (1), 1–45.
- DELLAVIGNA, S. and KAPLAN, E. (2007). The Fox News Effect: Media Bias and Voting. *The Quarterly Journal of Economics*, **122** (3), 1187–1234.

- DJOURELOVA, M. (2023). Persuasion through slanted language: Evidence from the media coverage of immigration. *American Economic Review*, **113** (3), 800–835.
- DRACA, M. and SCHWARZ, C. (2021). *How Polarized are Citizens? Measuring Ideology from the Ground-Up* . <https://ssrn.com/abstract=3154431>.
- DURANTE, R. and KNIGHT, B. (2012). Partisan Control, Media Bias, and Viewer Responses: Evidence from Berlusconi’s Italy. *Journal of the European Economic Association*, **10** (3), 451–481.
- , PINOTTI, P. and TESEI, A. (2019). The political legacy of entertainment tv. *American Economic Review*, **109** (7), 2497–2530.
- ELIAZ, K. and SPIEGLER, R. (2020). A model of competing narratives. *American Economic Review*, **110** (12), 3786–3816.
- ENGIST, O., MATZKO, P. and MERKUS, E. (2024). Conservative talk radio and political persuasion in the US, 1950–1970. *Journal of Comparative Economics*.
- ENIKOLOPOV, R., MAKARIN, A. and PETROVA, M. (2020). Social media and protest participation: Evidence from russia. *Econometrica*, **88** (4), 1479–1514.
- , PETROVA, M. and ZHURAVSKAYA, E. (2011). Media and political persuasion: Evidence from russia. *American Economic Review*, **101** (7), 3253–85.
- FALCK, O., GOLD, R. and HEBLICH, S. (2014). E-lections: Voting behavior and the internet. *American Economic Review*, **104** (7), 2238–65.
- GALLETTA, S. and ASH, E. (2021). *How Cable News Reshaped Local Government* . <https://ssrn.com/abstract=3370908>.
- GENTZKOW, M. (2006). Television and Voter Turnout. *Quarterly Journal of Economics*, **121** (3), 931–972.
- and SHAPIRO, J. M. (2011). Ideological Segregation Online and Offline. *Quarterly Journal of Economics*, **126** (4), 1799–1839.

- , — and SINKINSON, M. (2011). The effect of newspaper entry and exit on electoral politics. *American Economic Review*, **101** (7), 2980–3018.
- GERBER, A. S., KARLAN, D. and BERGAN, D. (2009). Does the media matter? a field experiment measuring the effect of newspapers on voting behavior and political opinions. *American Economic Journal: Applied Economics*, **1** (2), 35–52.
- GROSJEAN, P., MASERA, F. and YOUSAF, H. (2022). Inflammatory political campaigns and racial bias in policing. *The Quarterly Journal of Economics*, **138** (1), 413–463.
- GURIEV, S., MELNIKOV, N. and ZHURAVSKAYA, E. (2020). 3G Internet and Confidence in Government. *Quarterly Journal of Economics*, **136** (4), 2533–2613.
- HERFINDAHL, O. (1950). *Concentration in the Steel Industry*. Columbia university.
- HIRSCHMAN, A. O. (1945). *National power and the structure of foreign trade*. Berkeley, California.
- JAMIESON, K. and CAPPELLA, J. (2008). *Echo Chamber: Rush Limbaugh and the Conservative Media Establishment*. Oxford University Press.
- KEITH, M. C. and KEITH, M. C. (1993). Am radio: The status and struggle. *Journal of Radio Studies*, **2** (1), 1–10.
- LEE, G. and CAPPELLA, J. N. (2001). The effects of political talk radio on political attitude formation: Exposure versus knowledge. *Political Communication*, **18** (4), 369–394.
- LEVENDUSKY, M. S. (2013). Why do partisan media polarize viewers? *American Journal of Political Science*, **57** (3), 611–623.
- MANACORDA, M. and TESEI, A. (2020). Liberation technology: Mobile phones and political mobilization in africa. *Econometrica*, **88** (2), 533–567.
- MARTIN, G. J. and YURUKOGLU, A. (2017). Bias in cable news: Persuasion and polarization. *American Economic Review*, **107** (9), 2565–99.

- MELLO, M. and BUCCIONE, G. (2021). *Religious Media, Conversion, and the Socioeconomic Consequences: The Rise of Pentecostals in Brazil*. <https://ssrn.com/abstract=3758231>.
- MELNIKOV, N. (2021). *Mobile Internet and Political Polarization*. <https://ssrn.com/abstract=3937760>.
- MUTZ, D. C. (2001). Facilitating communication across lines of political difference: The role of mass media. *American Political Science Review*, **95** (1), 97–114.
- OLKEN, B. A. (2009). Do television and radio destroy social capital? evidence from indonesian villages. *American Economic Journal: Applied Economics*, **1** (4), 1–33.
- PEISAKHIN, L. and ROZENAS, A. (2018). Electoral effects of biased media: Russian television in ukraine. *American Journal of Political Science*, **62** (3), 535–550.
- PRAT, A. (2015). Media capture and media power. In S. P. Anderson, J. Waldfogel and D. Strömberg (eds.), *Handbook of Media Economics, Handbook of Media Economics*, vol. 1, North-Holland, pp. 669–686.
- QIN, B., STRÖMBERG, D. and WU, Y. (2021). *Social Media and Collective Action in China*. Cepr discussion paper no. dp16731.
- SNYDER, J. M. and STRÖMBERG, D. (2010). Press coverage and political accountability. *Journal of Political Economy*, **118** (2), 355–408.
- STRÖMBERG, D. (2004). Radio’s Impact on Public Spending. *Quarterly Journal of Economics*, **119** (1), 189–221.
- SUNSTEIN, C. R. (2009). *Going to extremes : how like minds unite and divide / Cass R. Sunstein*. Oxford University Press Oxford ; New York.
- TAUSANOVITCH, C. and WARSHAW, C. (2013). Measuring constituent policy preferences in congress, state legislatures, and cities. *Journal of Politics*, **75**, 330–342.

- WANG, T. (2021). Media, pulpit, and populist persuasion: Evidence from father coughlin. *American Economic Review*, **111** (9), 3064–92.
- YANAGIZAWA-DROTT, D. (2014). Propaganda and Conflict: Evidence from the Rwandan Genocide. *Quarterly Journal of Economics*, **129** (4), 1947–1994.
- YOUSAF, H. (2021). Sticking to One’s Guns: Mass Shootings and the Political Economy of Gun Control in the United States. *Journal of the European Economic Association*, **19** (5), 2765–2802.

Online Appendix

Competing for Attention – The Effect of Talk Radio on US Politics

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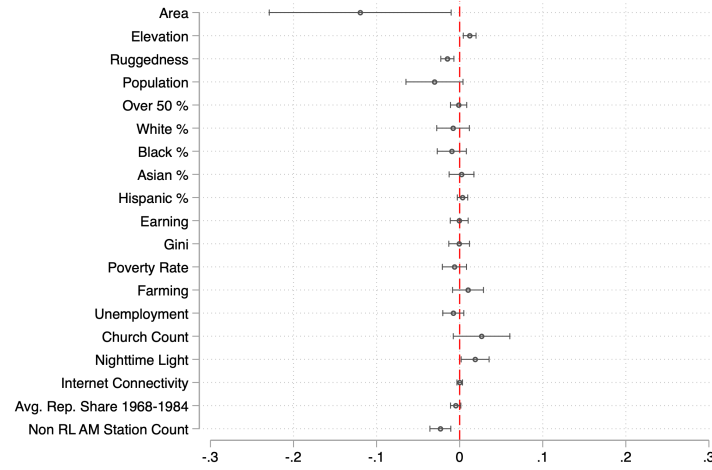
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A Examples of statements made by Rush Limbaugh

- **On slavery:** *“If any race of people should not have guilt about slavery, it’s Caucasians. The white race has probably had fewer slaves and for a briefer period of time than any other in the history of the world ... And yet white guilt is still one of the dominating factors in American politics. It’s exploited, it’s played upon, it is promoted, used, and it’s unnecessary.”*
- **On feminism:** *“Feminism was established so as to allow unattractive women access to the mainstream of society.”*
- **On Hurricane Irma:** *“You can accomplish a lot just by creating fear and panic. You don’t need a hurricane to hit anywhere. All you need is to create the fear and panic accompanied by talk that climate change is causing hurricanes to become more frequent and bigger and more dangerous, and you create the panic, and it’s mission accomplished, agenda advanced.”*
- **On Barack Obama, during the 2008 election:** *“A veritable rookie whose only chance of winning is that he’s black.”*
- **On the NBA:** *“I think it’s time to get rid of this whole National Basketball Association. Call it the TBA, the Thug Basketball Association, and stop calling them teams. Call ’em gangs.”*
- **On Covid-19:** *“This virus is the common cold.”*

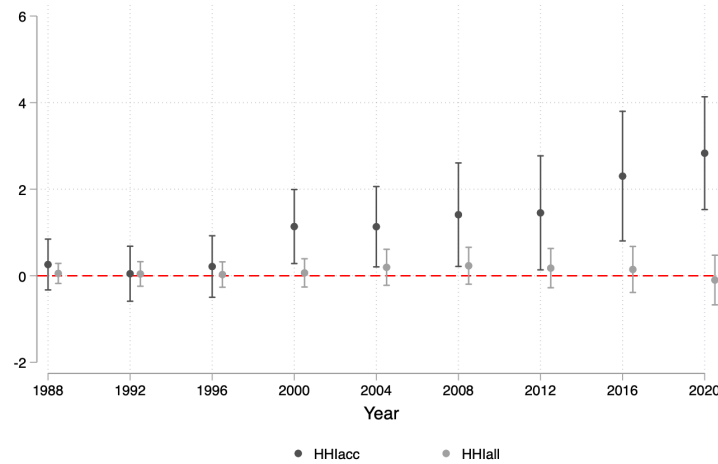
B County-level robustness checks

Figure B.1: Correlation between $HHIall$ and county level characteristics



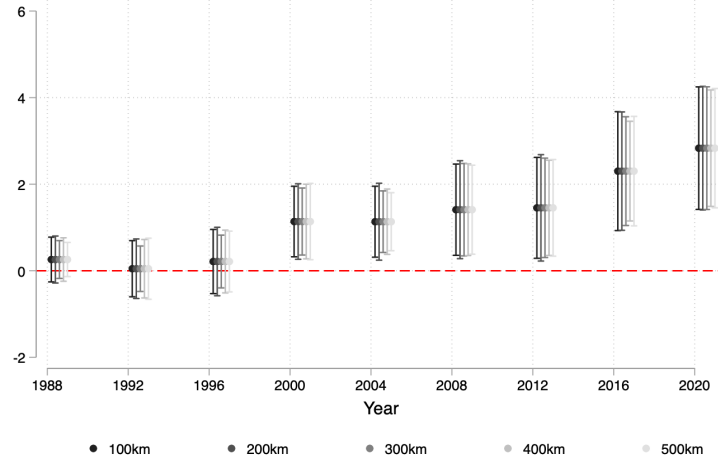
Notes: Dependent variable is $HHIall_i$. Figure shows the correlation between $HHIall$ and a range of geographic and demographic variables in each county. All predictors are standardized between 0-1. Dots show the point estimates while the vertical lines depict the 95% confidence intervals, based on standard errors clustered at the State level.

Figure B.2: Effect of exposure to the show on Republican vote share over time



Notes: Figure shows the effect of $HHIacc_{c,s}$ and $HHIall_{c,s}$ on Republican vote share over time. Dots show the point estimates while the vertical lines depict the 95% confidence intervals, based on standard errors clustered at the State level. Estimates for each election year represent a separate regression estimate. All estimates include geographic (county area, elevation and ruggedness) and demographic (population, population shares for white, black, Asian, Hispanic and above 50 year categories, median earnings, Gini coefficient, poverty rate, farming area, unemployment, number of churches, nighttime light, internet connectivity and non-Rush-Limbaugh AM station count) controls. Estimates also control for the average Republican vote share over 1968-1984.

Figure B.3: Spatial clustering of standard errors



Notes: Figure shows the effect of HHI_{acc} on Republican vote share over time. Dots show the point estimates while the vertical lines depict the 95% confidence intervals, based on standard errors adjusted for spatial autocorrelation at 100, 200, 300, 400 and 500 km, respectively. Estimates for each election year and distance cutoff represent a separate regression estimate. All estimates include geographic (county area, elevation and ruggedness) and demographic (population, population shares for white, black, Asian, Hispanic and above 50 year categories, median earnings, Gini coefficient, poverty rate, farming area, unemployment, number of churches, nighttime light, internet connectivity and non-Rush-Limbaugh AM station count) controls. Estimates also control for the average Republican vote share over 1968-1984.

Table B.1: Raw correlations between radio indicators

	(1)	(2)	(3)	(4)
Republican Vote Share 2016				
<i>AM Count</i>	-0.0008*** (0.0001)			
<i>FM Count</i>		-0.0020*** (0.0001)		
<i>RL AM Count</i>			0.0023*** (0.0007)	
<i>Non – RL AM Count</i>				-0.0008*** (0.0001)
Observations	2,084	2,084	2,084	2,084
Republican Vote Share 2020				
<i>AM Count</i>	-0.0007*** (0.0001)			
<i>FM Count</i>		-0.0021*** (0.0002)		
<i>RL AM Count</i>			0.0024*** (0.0009)	
<i>Non – RL AM Count</i>				-0.0008*** (0.0001)
Observations	1,989	1,989	1,989	1,989

Notes: This table presents the raw correlations between various forms of radio indicators at the county level. Robust standard errors in parentheses.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.2: Effect of exposure to the show on Republican vote share - All counties

	(1)	(2)	(3)	(4)	(5)	(6)
A: Dependent Variable: 2016 Republican Vote Share_{c,s}						
<i>HHIacc_{c,s}</i>	2.3850*** (0.8367)	1.4463** (0.6433)	2.3320*** (0.6496)	2.4888*** (0.7654)	0.6663*** (0.2072)	0.4694** (0.2072)
<i>HHIall_{c,s}</i>			-0.6870*** (0.1487)	-0.9238** (0.4239)	-0.1512 (0.1931)	-0.0282 (0.2061)
Observations	3,104	3,104	3,103	3,073	2,900	2,900
B: Dependent Variable: 2020 Republican Vote Share_{c,s}						
<i>HHIacc_{c,s}</i>	2.8592*** (0.8537)	1.4821** (0.6854)	2.2928*** (0.7419)	2.6760*** (0.9083)	0.6220** (0.2654)	0.4356* (0.2511)
<i>HHIall_{c,s}</i>			-0.6294*** (0.2056)	-1.1062** (0.5241)	-0.1289 (0.2172)	-0.0121 (0.2113)
Observations	2,979	2,979	2,979	2,949	2,781	2,781
State FE	NO	YES	YES	YES	YES	YES
Geographic Controls	NO	NO	YES	YES	YES	YES
Demographic Controls	NO	NO	NO	YES	YES	YES
Avg. Rep. Share 1968-1984	NO	NO	NO	NO	NO	YES

Notes: The dependent variable in Panels A and B is the Republican vote share in the 2016 and 2020 presidential elections, respectively. Geographic controls include county area, elevation and ruggedness. Demographic controls include population, population shares for the white, Black, Asian, Hispanic and age 50+ categories, median earnings, Gini coefficient, poverty rate, farming area, unemployment, number of churches, nighttime light, internet connectivity and non-Limbaugh-airing AM station count. Standard errors clustered at the state level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.3: Effect of exposure to the show on Republican vote share - Counties with population less than 15,000 only

	(1)	(2)	(3)	(4)	(5)	(6)
A: Dependent Variable: 2016 Republican Vote Share_{c,s}						
<i>HHiacc_{c,s}</i>	0.9396 (0.5817)	0.3871 (0.3929)	0.4688 (0.3259)	0.3531 (0.2970)	0.5667** (0.2275)	0.4169** (0.2026)
<i>HHi_{all}_{c,s}</i>			-0.0626 (0.1547)	0.0078 (0.3080)	-0.3142* (0.1724)	-0.2251 (0.1681)
Observations	1,020	1,017	1,017	1,007	936	936
B: Dependent Variable: 2020 Republican Vote Share_{c,s}						
<i>HHiacc_{c,s}</i>	1.3537** (0.6370)	0.4003 (0.3955)	0.1202 (0.3433)	0.2541 (0.2479)	0.2338 (0.2101)	0.0896 (0.2240)
<i>HHi_{all}_{c,s}</i>			0.2148 (0.1875)	0.0604 (0.2678)	-0.0868 (0.1646)	0.0024 (0.1696)
Observations	990	990	987	977	907	907
State FE	NO	YES	YES	YES	YES	YES
Geographic Controls	NO	NO	YES	YES	YES	YES
Demographic Controls	NO	NO	NO	YES	YES	YES
Avg. Rep. Share 1968-1984	NO	NO	NO	NO	NO	YES

Notes: The dependent variable in Panels A and B is the Republican vote share in the 2016 and 2020 presidential elections, respectively. Geographic controls include county area, elevation and ruggedness. Demographic controls include population, population shares for the white, Black, Asian, Hispanic and age 50+ categories, median earnings, Gini coefficient, poverty rate, farming area, unemployment, number of churches, nighttime light, internet connectivity and non-Limbaugh-airing AM station count. Standard errors clustered at the state level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.4: Effect of exposure to the show on Republican vote share - Counties with at least one accidental FM contour only

	(1)	(2)	(3)	(4)	(5)	(6)
A: Dependent Variable: 2016 Republican Vote Share_{c,s}						
<i>HHIacc_{c,s}</i>	6.5314*** (1.3977)	5.7401*** (1.1126)	7.8544*** (1.2277)	7.7868*** (1.2834)	2.6359*** (0.8456)	2.4502*** (0.7406)
<i>HHIall_{c,s}</i>			-1.5548*** (0.4790)	-1.6796** (0.6452)	0.0305 (0.2397)	0.1162 (0.2680)
Observations	3,086	3,086	3,085	3,060	2,889	2,889
B: Dependent Variable: 2020 Republican Vote Share_{c,s}						
<i>HHIacc_{c,s}</i>	7.7807*** (1.5281)	6.3511*** (1.2669)	8.8038*** (1.4475)	8.7467*** (1.4973)	3.1720*** (0.8906)	2.9756*** (0.7729)
<i>HHIall_{c,s}</i>			-1.8029*** (0.5629)	-2.0172*** (0.7411)	-0.2127 (0.3749)	-0.1354 (0.3503)
Observations	2,961	2,961	2,961	2,936	2,770	2,770
State FE	NO	YES	YES	YES	YES	YES
Geographic Controls	NO	NO	YES	YES	YES	YES
Demographic Controls	NO	NO	NO	YES	YES	YES
Avg. Rep. Share 1968-1984	NO	NO	NO	NO	NO	YES

Notes: The dependent variable in Panels A and B is the Republican vote share in the 2016 and 2020 presidential elections, respectively. Geographic controls include county area, elevation and ruggedness. Demographic controls include population, population shares for the white, Black, Asian, Hispanic and age 50+ categories, median earnings, Gini coefficient, poverty rate, farming area, unemployment, number of churches, nighttime light, internet connectivity and non-Limbaugh-airing AM station count. Standard errors clustered at the state level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.5: Falsification test: Effect of exposure to the show on pre-1988 Republican vote share

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: 1968-1984 Republican Vote Share_{c,s}					
<i>HHIacc_{c,s}</i>	2.0765*** (0.6620)	0.5457 (0.4669)	0.8751 (0.5586)	0.9922 (0.5938)	0.5520 (0.5737)
<i>HHIall_{c,s}</i>			-0.2269 (0.2469)	-0.3545 (0.2417)	-0.2504 (0.2899)
Observations	2,079	2,078	2,078	2,063	1,961
State FE	NO	YES	YES	YES	YES
Geographic Controls	NO	NO	NO	YES	YES
Demographic Controls	NO	NO	NO	NO	YES

Notes: The dependent variable is the average Republican vote share in the presidential elections over 1968-1984. Geographic controls include county area, elevation and ruggedness. Demographic controls include population, population shares for the white, Black, Asian, Hispanic and age 50+ categories, median earnings, Gini coefficient, poverty rate, farming area, unemployment, number of churches, nighttime light, internet connectivity and non-Limbaugh-airing AM station count. Standard errors clustered at the state level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.6: Effect of exposure to the show on Republican vote share - Sensitivity to definition of accidental FM

	(1) Accidental = <10th percentile of overlap areas	(2) Accidental = <25th percentile of overlap areas	(3) Accidental = <average of overlap areas
A: Dependent Variable <i>2016 Republican Vote Share_{c,s}</i>			
<i>HHIacc_{c,s}</i>	2.3306*** (0.7599)	2.3295*** (0.7598)	2.2732*** (0.7377)
<i>HHIall_{c,s}</i>	0.1448 (0.2647)	0.1449 (0.2647)	0.1421 (0.2612)
Observations	1,961	1,961	1,961
B: Dependent Variable: <i>2020 Republican Vote Share_{c,s}</i>			
<i>HHIacc_{c,s}</i>	2.8613*** (0.7974)	2.8592*** (0.7972)	2.8633*** (0.7663)
<i>HHIall_{c,s}</i>	-0.0988 (0.3428)	-0.0985 (0.3429)	-0.1168 (0.3384)
Observations	1,871	1,871	1,871
State FE	YES	YES	YES
Geographic Controls	YES	YES	YES
Demographic Controls	YES	YES	YES
Avg. Rep. Share 1968-1980	YES	YES	YES

Notes: The dependent variable in Panels A and B is the Republican vote share in the 2016 and 2020 presidential elections, respectively. In Column (1) an accidental FM contour is defined as one where the overlap area between the FM contour and county is less than the 10th percentile of all such overlapping areas, while in Column (2) an accidental FM contour is defined as one where the overlap area between the FM contour and county is less than the 25th percentile of all such overlapping areas. In Column (3) this cutoff is based on the average value of overlapping areas. Geographic controls include county area, elevation and ruggedness. Demographic controls include population, population shares for the white, Black, Asian, Hispanic and age 50+ categories, median earnings, Gini coefficient, poverty rate, farming area, unemployment, number of churches, nighttime light, internet connectivity and non-Limbaugh-airing AM station count. Standard errors clustered at the state level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.7: Effect of exposure to the show on Republican vote share - The role of nighttime lights

	(1) Exclude Contours with high nighttime light	(2) Exclude Contours with low nighttime light
A: Dependent Variable <i>2016 Republican Vote Share_{c,s}</i>		
<i>HHIacc_{c,s}</i>	2.2983*** (0.6488)	2.3342*** (0.7534)
<i>HHIall_{c,s}</i>	0.1465 (0.2642)	0.1398 (0.2636)
Observations	1,961	1,961
B: Dependent Variable: <i>2020 Republican Vote Share_{c,s}</i>		
<i>HHIacc_{c,s}</i>	2.8283*** (0.7756)	2.8448*** (0.7876)
<i>HHIall_{c,s}</i>	-0.0981 (0.3414)	-0.1009 (0.3424)
Observations	1,871	1,871
State FE	YES	YES
Geographic Controls	YES	YES
Demographic Controls	YES	YES
Avg. Rep. Share 1968-1980	YES	YES

Notes: The dependent variable in Panels A and B is the Republican vote share in the 2016 and 2020 presidential elections, respectively. In Column (1) we exclude accidental FM contours with high (more than the 90th percentile) nighttime light values, while in Column (2) we exclude accidental FM contours with low (less than the 10th percentile) nighttime light values. Geographic controls include county area, elevation and ruggedness. Demographic controls include population, population shares for the white, Black, Asian, Hispanic and age 50+ categories, median earnings, Gini coefficient, poverty rate, farming area, unemployment, number of churches, internet connectivity and non-Limbaugh-airing AM station count. Standard errors clustered at the state level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.8: Effect of exposure to the show on Republican vote share - Spatial autoregressive and Spatial Durbin models

	(1) Spatial Autoregressive Model	(2) Spatial Durbin Model
A: Dependent Variable <i>2016 Republican Vote Share_{c,s}</i>		
<i>HHIacc_{c,s}</i>	2.3034*** (0.7539)	2.3009*** (0.7443)
<i>HHIall_{c,s}</i>	0.1408 (0.2610)	0.1354 (0.2553)
Observations	1,961	1,961
B: Dependent Variable <i>2020 Republican Vote Share_{c,s}</i>		
<i>HHIacc_{c,s}</i>	2.8318*** (0.7748)	2.8206*** (0.7580)
<i>HHIall_{c,s}</i>	-0.0989 (0.3414)	-0.1081 (0.3361)
Observations	1,871	1,871
State FE	YES	YES
Geographic Controls	YES	YES
Demographic Controls	YES	YES
Avg. Rep. Share 1968-1984	YES	YES
Spatial Lag of Dep. Var.	YES	YES
Spatial Lag of Indep. Var.	NO	YES
Spatial Lag of Geographic Controls	NO	YES
Spatial Lag of Demographic Controls	NO	YES

Notes: The dependent variable in Panels A and B is the Republican vote share in the 2016 and 2020 presidential elections, respectively. Column (1) presents the estimates of the spatial autoregressive model, which includes the spatial lag of the dependent variable as a control variable. Column (2) presents the estimates of the spatial Durbin model which includes the spatial lag of the dependent variable as well as spatial lags of all independent variables, including controls. Spatial lags are based on the contiguity network of connectivity. Geographic controls include county area, elevation and ruggedness. Demographic controls include population, population shares for the white, Black, Asian, Hispanic and age 50+ categories, median earnings, Gini coefficient, poverty rate, farming area, unemployment, number of churches, nighttime light, internet connectivity and non-Limbaugh-airing AM station count. Standard errors clustered at the state level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.9: Alternative dependent variable based on political ideology data from the American Ideology Project as per [Tausanovitch and Warshaw \(2013\)](#)

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Period: 2004-2011		Period: 2012-2016		Period: 2017-2021	
	<i>MRP Ideology</i>	<i>IRT Ideology</i>	<i>MRP Ideology</i>	<i>IRT Ideology</i>	<i>MRP Ideology</i>	<i>IRT Ideology</i>
$HHIacc_{c,s}$	1.2987*** (0.4607)	-0.2567 (1.6546)	2.6231*** (0.6443)	5.5333** (2.4692)	2.0833*** (0.7461)	3.5688* (1.9471)
$HHIall_{c,s}$	0.1761 (0.1661)	1.2267 (0.7963)	-0.2391 (0.2128)	0.0091 (1.1903)	-0.0021 (0.3229)	-0.4430 (0.8424)
Observations	1,961	1,961	1,970	1,968	1,968	1,968
State FE	YES	YES	YES	YES	YES	YES
Geographic Controls	YES	YES	YES	YES	YES	YES
Demographic Controls	YES	YES	YES	YES	YES	YES
Avg. Rep. Share 1968-1984	YES	YES	YES	YES	YES	YES

Notes: Dependent variables are county level indicators of political ideology, based on [Tausanovitch and Warshaw \(2013\)](#). *MRP Ideology* refers to an estimate of ideological preferences based on a Multilevel Regression and Post Stratification Model, while *IRT Ideology* refers to ideological preferences based on a Bayesian Item-Response Model. Geographic controls include county area, elevation and ruggedness. Demographic controls include population, population shares for white, black, Asian, Hispanic and above 50 year categories, median earnings, Gini coefficient, poverty rate, farming area, unemployment, number of churches, nighttime light, internet connectivity and non-Rush-Limbaugh AM station count. Standard errors, clustered at the State level, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table B.10: The show, Fox News, and Republican vote share 2000 (based on [DellaVigna and Kaplan \(2007\)](#))

	(1)	(2)	(3)	(4)	(5)
	Availability of Fox News via cable in 2000		Change in Rep. 2-party vote share in Presidential election		
$HHIacc_{c,s}$	-0.8510 (1.8589)	1.5032 (2.8555)	0.4013*** (0.1153)	0.5819*** (0.1425)	
$HHIall_{c,s}$		-1.9694 (1.7482)		-0.1511** (0.0699)	
$HHIacc_{c,s} > 50pct.(0/1)$					0.0024 (0.0016)
<i>Availability of Fox News via cable in 2000</i>			0.0048*** (0.0017)	0.0047*** (0.0017)	0.0041** (0.0016)
US House District FEs	YES	YES	YES	YES	YES
Census Controls	YES	YES	YES	YES	YES
Cable System Controls	YES	YES	YES	YES	YES

Notes: No. of observations: 8,436. Analysis at the town level based on data from [DellaVigna and Kaplan \(2007\)](#). Specifications in columns (1)-(2) corresponds to specification in Table III, column (4) in [DellaVigna and Kaplan \(2007\)](#); specifications in columns (3)-(5) corresponds to specification in Table IV, column (4) in [DellaVigna and Kaplan \(2007\)](#). Dependent variables are: In columns (1)-(2), a binary variable that switches to one if Fox News was part of the town's local cable package in 2000 and zero otherwise. In columns (3)-(5), the two-party Republican vote share for the 2000 presidential election minus the two-party Republican vote share for the 1996 presidential election. All models include the same set of census and cable system controls as in Table III, column (4) and Table IV, column (4) in [DellaVigna and Kaplan \(2007\)](#), respectively. Standard errors, clustered at the county level, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table B.11: Exposure to the show and political ideology

	(1) Strong Cons.	(2) Strong Cons.	(3) Cons./ Strong Cons.	(4) Cons./ Strong Cons.	(5) Moderate	(6) Moderate
$HHIacc_{c,s}$	-0.4648 (0.6505)	-1.6896*** (0.5263)	-1.6722 (1.2510)	-2.7498*** (0.9873)	2.2552** (0.8925)	5.4969*** (1.0944)
$HHIacc_{c,s} \times Rep_i$		2.4963*** (0.8182)		3.0859*** (1.1766)		-5.9819*** (1.4701)
$HHIall_{c,s}$	0.3502 (0.2357)	0.1589 (0.1865)	0.9550** (0.4505)	0.3167 (0.2288)	-0.3493 (0.2304)	-0.1732 (0.2208)
Observations	280,066	280,066	280,066	280,066	280,066	280,066
Geographic Controls	YES	YES	YES	YES	YES	YES
Demographic Controls	YES	YES	YES	YES	YES	YES
Individual Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
Rep_i	NO	YES	NO	YES	NO	YES

Notes: Dependent variables are binary indicators equalling to one if the respondent's political views were strong conservative (Columns (1) - (2)), conservative/strong conservative (Columns (3) - (4)) or moderate (Columns (5) - (6)). All estimates include geographic (county area, elevation and ruggedness) and demographic (total population, population shares for White, Black, Asian, Hispanic and above 50 year categories, median earnings, Gini coefficient, poverty rate, unemployment, farming area, number of churches, average nighttime lights, internet connectivity and non-Rush Limbaugh AM count) controls, as well as individual controls in the form of the respondent's age, race, gender, educational status, family income and marital status. Rep_i is a binary indicator equalling to 1 if the respondent voted for the Republican party at the previous presidential election, and zero otherwise. The sample is limited to respondents identifying as Republican/Democratic voters. Standard errors, clustered at the county level, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table B.12: Effects of the show on political attitudes across demographic groups

	(1) Cons. Strong Cons.	(2) Cons. Strong Cons.	(3) Cons. Strong Cons.	(4) Cons. Strong Cons.	(5) Cons. Strong Cons.	(6) Cons. Strong Cons.	(7) Cons. Strong Cons.	(8) Cons. Strong Cons.	(9) Cons. Strong Cons.	(10) Cons. Strong Cons.	(11) Cons. Strong Cons.
	Income < \$50,000 ≥ \$50,000		Age < 50 ≥ 50		Education No College College		Gender Male Female		White	Race Black	Hispanic
$HHIacc_{c,s}$	-2.0966* (1.1305)	-3.8085*** (1.2999)	-2.5836* (1.5156)	-2.6551** (1.0313)	-2.2627 (2.2503)	-3.3335*** (0.7736)	-3.7439*** (1.3005)	-2.1008 (1.3851)	-1.4015 (1.1461)	-1.0333 (4.1964)	-1.8381 (3.0478)
$HHIacc_{c,s} \times Rep_i$	2.4228* (1.4702)	4.5035*** (1.5319)	2.6993 (2.1352)	2.8016** (1.2766)	2.5909 (2.3476)	3.8869*** (1.1722)	6.0872*** (1.5447)	0.4651 (1.8109)	1.5164 (1.3514)	-1.3061 (12.1671)	6.8338* (3.6207)
$HHIall_{c,s}$	0.5013* (0.2976)	0.1639 (0.2942)	0.0445 (0.3615)	0.5581** (0.2506)	0.3986 (0.4106)	0.2473 (0.2753)	0.2650 (0.2925)	0.3485 (0.2759)	0.2365 (0.2535)	0.1930 (0.5743)	-1.5018 (0.9382)
Observations	113,638	166,428	109,226	170,840	71,772	208,293	135,496	144,570	218,206	27,160	18,743
Geographic Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Demographic Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Rep	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is a binary indicator equalling to one if the respondent's political views are conservative/strong conservative. All estimates include geographic (county area, elevation and ruggedness) and demographic (total population, population shares for White, Black, Asian, Hispanic and above 50 year categories, median earnings, Gini coefficient, poverty rate, unemployment, farming area, number of churches, average nighttime lights, internet connectivity and non-Rush Limbaugh AM count) controls, as well as individual controls in the form of the respondent's age, race, gender, educational status, family income and marital status. Rep_i is a binary indicator equalling to 1 if the respondent voted for the Republican party at the previous presidential election, and zero otherwise. The sample is limited to respondents identifying as Republican/Democratic voters. Standard errors, clustered at the county level, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table B.13: Estimates based on RL listenership as per ANES 1996

	(1)	(2)
	Listening to the Show	Listening to the Show
$HHIacc_{c,s}$	8.3866 (11.0681)	12.7608 (17.0160)
Observations	557	517
Geographic Controls	NO	YES
Demographic Controls	NO	YES
Individual Controls	YES	YES
State FE	YES	YES

Notes: The dependent variable is a binary indicator equalling to 1 if the respondent listens to the show, and 0 otherwise. Geographic controls include county area, elevation and ruggedness. Demographic controls include total population, population shares for White, Black, Asian, Hispanic and above 50 year categories, median earnings, Gini coefficient, poverty rate, unemployment farming area, number of churches, nighttime lights, and internet connectivity. Individual controls include the respondent's age, age squared, gender, race, marital status, education, income and occupation. Standard errors, clustered at the county level, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1