Exposure to Negative Advertising Contributes to Affective Polarization*

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Abstract

The use of negative advertising in American election campaigns, along with partisan hostility toward political opponents, has increased over the past several decades. We argue that these parallel trends are causally linked. To estimate the effects of exposure to negative campaign advertising in presidential races, we employ a within-election-cycle difference-in-differences design along media market borders. We find that exposure to negative—but not positive—advertisements significantly increased political polarization in the early 2000s. The magnitude of this effect is substantial: a typical increase in negative advertising during the 2000 election accounts for roughly one-quarter of the affective polarization observed that year. Across the 2000, 2004, and 2008 campaigns, exposure to negative ads not only heightened animus toward the out-party but also strengthened favorable evaluations of the in-party. We further show that the polarizing effect of advertising has diminished in more recent election cycles, consistent with increased partisan sorting or the possibility that measures of out-party animus have approached a ceiling. These findings highlight a contextual mechanism of polarization and suggest that efforts to reduce polarization should focus on incentives shaping elite behavior, rather than the predispositions of partisans. (186 words)

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1 Introduction

There is now ample evidence documenting the phenomenon of affective polarization. Democrats and Republicans habitually treat their opponents as a stigmatized out group. Partisan animus manifests itself in the form of unfavorable evaluations of the opposition party and its leaders, aversion to social contact with partisans from the other side, and in indicators of implicit or sub-conscious prejudice. Most tellingly, partisans subject their opponents to discrimination in a variety of behavioral settings (Iyengar and Westwood 2015; Gift and Gift 2015; Sinclair, Nilsson, and Agerström 2023).

Intensified hostility across the political divide is a relatively recent development. The American National Election Studies feeling thermometer time series shows that between the mid-1970s and 1990, the average rating of the out-party hovered around 50 (the midpoint), suggesting that partisans felt either neutral or ambivalent toward opponents. The thermometer scores began a slow but steady decline in the 1990s, with the average rating of the out-party falling to 40 in 2000. Since 2000, the trend accelerated significantly, with the average out-party rating dropping from 40 to 20 by 2024. Since 2012, the modal thermometer score for the out-party has plummeted to zero.

The onset of increased partisan animus closely tracks another well-documented trend in American politics corresponding to the advent of large-scale televised negative campaigning. At the dawn of the broadcast era, as candidates and their consultants discovered the power of television advertising, campaign ads tended to mimic product ads, with messages extolling the virtues and strengths of the sponsoring candidate. Positive appeals made up around two-thirds of presidential ads that aired between 1960 and 1984 (Geer 2012).[1] The turning point in the trajectory of advertising tone occurred in 1988 when the infamous "Willie Horton" and "Boston Harbor" attacks directed at Democrat Michael Dukakis enabled George Bush to neutralize Dukakis' early lead in the polls, leading consultants to conclude that negative

[1] This tabulation is based on a classification of presidential ads collected by the advertising archive at the University of Oklahoma.

appeals were especially persuasive (for discussions of the 1988 advertising campaign, see Jamieson 1993; Mendelberg 1997).

The proportion of negative ads in presidential campaigns nearly doubled between 1992 and 2008 (Geer 2012) exceeding 60 percent. For the post-2008 period, for which there is more reliable and precise data on advertising buys and airings, the move toward negativity has continued – attack and contrast ads took up more than 70 percent of the advertising budget in congressional and gubernatorial elections held in 2012 and 2014 (Wesleyan Media Project 2014)). In 2024, based on a database of all televised ads that aired before Election Day, the level of negativity reached 82 percent.[2] In the case of the Trump campaign, virtually every ad attacked Kamala Harris (see Wesleyan Media Project 2024. Clearly, "going negative" is a dominant strategy in modern campaigns.

The correspondence between the onset of increased out-party animus and the widespread adoption of negative campaigning can hardly be coincidental. In this paper, we argue that there are strong theoretical reasons to expect that amplified negativity in campaign discourse is causal to increased partisan animus. Decades of research into the origins of public opinion demonstrates that partisan voters take on the views of their leaders (Zaller 1992). When Kamala Harris exclaims that Donald Trump "is unstable and unfit for office" and Trump counters with "she is a radical left lunatic," partisans naturally conclude that their opponents are scurrilous. Although name calling and personal abuse have been fixtures of American politics dating back to the early days of the Republic, these modern rhetorical signals travel more rapidly today and reach a much larger audience. Despite well-intentioned efforts to make campaign advertising more civil (e.g., by requiring candidates to appear in their ads and acknowledge their sponsorship of the message), the trajectory of advertising tone remains almost exclusively negative.

We test the causal impact of exposure to negative campaigning on affective polarization using a series of large-scale cross-sectional surveys that track the level of partisan animus

[2]In Appendix Figure A2, we visualize some of these trends in recent election cycles.

over five election cycles. We extend previous designs used in the literature estimating the effect of campaign advertisements (Huber and Arceneaux 2007; Spenkuch and Toniatti 2018; Sides, Vavreck, and Warshaw 2022) by isolating within-county and within-election-cycle variation. We show that residents of media markets who are exposed to a greater barrage of negative messages tend to be more polarized than residents of markets less exposed to the ad campaign. The effect is substantively important: over the course of these campaigns, the average within-unit change in negative advertising accounts for approximately 24.1%, 12.9%, and 12.0% of changes in affective polarization in the 2000, 2004, and 2008 election cycles, respectively. However, this effect has substantially diminished by 2020 and 2024, a pattern we attribute to increased partisan sorting and ceiling effects in the indicators of partisan animus.

In what follows, we first survey the literature on the use of negative campaigning and its effects on voter attitudes. Next, we describe our research design, sources of data, and analysis strategy. We then present our findings with an accompanying discussion of their implications for the study of affective polarization and American politics more generally.

2 Causes and Effects of Negative Campaigning

A large body of scholarship documents the growing use of negative appeals in American politics. Numerous studies examine both the underlying causes of this trend and its attitudinal and behavioral consequences for voters. We review each of these literatures in turn.

Proposed Explanations

Scholars have advanced several explanations for the prevalence of negative messaging in the political arena. One account is psychological: experimental research demonstrates that negative stimuli leave stronger imprints in human information processing. Individuals are more likely to attend to and retain negative, rather than positive, information (Baumeister et al. 2001; Bradley, Angelini, and Lee 2007; Soroka, Fournier, and Nir 2019). In addition, negative traits are weighted more heavily than positive traits in impression formation (Fiske 1980; Klein 1991). For campaigns seeking to break through a highly cluttered information environment, harsh attacks on opponents are therefore more likely to be noticed and remembered by target audiences.

A second factor underlying the rise of negative campaigning is candidates' need to attract news coverage. The audience for campaign communications includes not only voters but also journalists. In high-profile races, "free media" in the form of news coverage is at least as important—if not more so—than paid advertising as a channel of communication (see Iyengar 2022). Consistent with the journalistic maxim "if it bleeds, it leads," editorial judgments of newsworthiness exhibit a pronounced negativity bias (for evidence in the domain of economic news, see Soroka 2006). Accordingly, messages emphasizing conflict and controversy tend to generate more press coverage than those highlighting civility and cooperation on the campaign trail.

In fact, the available evidence indicates that negative ads are substantially more likely to receive press coverage than positive ads. During the 1988 campaign, for example, attacks launched by groups affiliated with George H. W. Bush against Michael Dukakis received front-page coverage in major newspapers. Coverage of presidential campaign advertising in the New York Times and the Washington Post reached approximately 200 stories in 1988––more than double the number in 1984 (Geer 2012).

By 2004, the newsworthiness of negative ads had increased by an additional 25 percent, yielding roughly 250 stories. Trends in broadcast news were similar: by 2008, network coverage of campaign advertising focused disproportionately on attack ads (Geer 2012). In short, negative ads are aired "not so much with an eye to influencing voters directly, but with the hope of altering the news media's narrative in the campaign" (p. 9).

A third explanation for the emergence of negative campaigning is strategic. Ever since the 1988 campaign, when the Dukakis team simply ignored the barrage of attacks that came their way, it has become ingrained in the consultants' playbook that the attacked candidate must immediately rebut the attack, typically in the form of a counter-attack. As a result, most ad campaigns converge to a negative equilibrium (for efforts to model this spiral of negativity, see Skaperdas and Grofman 1995; Ansolabehere and Iyengar 1995).

Consumer demand constitutes a final contributing factor. In an era of heightened polarization, partisans who strongly dislike their opponents are more likely to reward candidates who engage in attack messaging. Moreover, one consequence of intensified partisan animus is increased electoral loyalty. In the past three election cycles, rates of partisan defection have fallen into the single digits, with defection among strong partisans remaining especially rare (see Jacobson 2023). Consistent with this pattern, a large-scale analysis of partisan defection in the 2020 election found that a substantial majority of Republicans remained loyal—voting for Trump despite holding opposing positions on several salient issues (Tyler, Iyengar, and Wilkins, n.d.).

As the rarity of defection illustrates, in the current polarized environment, it is very difficult to persuade partisans (see Kalla and Broockman 2018 for evidence of null effects in contemporary campaigns). Campaigns therefore may be more inclined to pursue changes in turnout, either by mobilizing their base, or demobilizing their opponents. Raising doubts about a candidate's fitness for office may do little to dissuade supporters of that candidate but might be sufficient to discourage some of them from voting. It is this potential for campaign demobilization to which we turn next.

Effects of Negative Campaigns

In a series of carefully controlled experiments carried out during the 1990 and 1992 election cycles, Ansolabehere and Iyengar (1995) showed that exposure to a single negative ad was sufficient to depress intention to vote by around 4.5 percentage points among California voters. Participants exposed to the negative ad treatment also expressed more cynicism about the electoral process and their own ability to make a difference (Ansolabehere and

Iyengar 1995, 103–104).

While the Ansolabehere-Iyengar experiments achieved strong control in the form of content equivalence across the positive and negative ad conditions, the experimental ads necessarily differed from actual ads in several respects. For instance, the treatment ads lacked background music and sound bites from the sponsoring candidate.

Studies that have investigated the effects of actual ads on voter engagement typically find null effects (for a review, see Lau, Sigelman, and Rovner 2007). The question of whether negative campaigns demobilize voters thus remains open. Moreover, given what we know about the level of out-party animus today, it seems quite plausible that negative messages will actually work to mobilize rather than demobilize partisans (for evidence that out-party animus is positively correlated with turnout, see Ahn and Mutz 2023).

Another set of studies has pursued the "backlash" hypothesis on the grounds that civility is normatively appropriate, leading voters to sanction candidates who attack. Tests of this hypothesis have yielded mixed findings. A handful of studies show some traces of backlash, but this evidence comes from overseas elections featuring multi-party systems that make it possible for a third-party candidate to gain support, when the two major parties engage in attacks and counter-attacks (for instance, Roese and Sande 1993; Walter and Eijk 2019; Galasso, Nannicini, and Nunnari 2023). Studies with American voters, however, generally find only weak traces of backlash (see Lau et al. 1999; Fridkin and Kenney 2004; Jasperson and Fan 2002.

Quite surprisingly, only a handful of studies have investigated the causal impact of negative campaigns on partisan animus. In the first study to document the phenomenon of affective polarization, the authors tracked changes in polarization over the course of the 2004 and 2008 campaigns. In both cases, they found that exposure to the campaign increased out-party animus, that voters living in states with higher levels of campaign advertising were more polarized, and that state-level exposure to negative ads was a contributory factor (Iyengar, Sood, and Lelkes 2012).

On the basis of time series data from 2000, 2004, and 2008, Sood and Iyengar (2016) reported similar results. Using both feeling thermometers and candidate trait ratings to measure affective polarization, the authors documented substantial increases in out-party animus over the course of the campaign. In both 2004 and 2008 (but not 2000), they found that voters in battleground states, who received significantly larger doses of negativity, registered significantly greater over-time increases in polarization. We replicate these analyses here as part of our observational survey databases.

In a cross-national extension, Martin and Nai (2024) found that in multi-party elections, supporters of parties that engage in or are targets of negative campaigning express higher levels of partisan animus. Their results held up across the introduction of multiple covariates including voter ideology and strength of partisanship.

Of course, the time series evidence is correlational, making it difficult to draw firm conclusions about the causal impact of campaign negativity. Small-scale experiments that manipulate the tone of campaign ads tend to bolster the observational evidence. In an experiment administered during the 2012 campaign (Lau et al. 2017) the researchers found increased polarization among participants assigned to view a negative ad, but the effect was conditional on participants' access to partisan news sources. The authors theorized that exposure to attack ads on polarization was indirect; supporters of the attacked candidate would be motivated to seek out supportive information refuting the attack from partisan providers and that this conjunction of exposure to campaign attacks and access to supportive partisan information would fuel out-party animus. In support of this expectation, they detected a significant interaction between access to partisan news and exposure to negative advertising (Lau et al. 2017).[3]

The most recent experimental study, based on a large-scale field experiment (Weiss,

[3]We limit our attention in this literature review to negativity in advertising campaigns. There is a parallel literature addressing the effects of negative news coverage. Consistent with the demobilization hypothesis, this literature generally shows that exposure to incivility and conflict in news reports fosters cynicism and distrust toward politicians and government (see Patterson 1994; Cappella and Jamieson 1997; Mutz and Reeves 2005; Valentino, Beckmann, and Buhr 2001).

Green, and Willer 2025), tested the depolarizing effects of public service ads (sponsored by the National Governor's Association) that called for civility in political discourse. The treatment ads –drawn from five different states – featured prominent politicians from both parties calling for civility in campaigns. The experiment yielded mixed results. Although participants in the treated condition reported greater willingness to engage in bipartisan behaviors, their level of animus toward the opposing party remained unchanged. While this study addresses the potential for positive appeals to depolarize, it sheds no light on the polarizing effects of negative messages.

3 Research Design

Establishing the causal relationship between exposure to negative advertising and partisan animus at scale has proven challenging. The strongest design for estimating the effects of negative campaigning on out-party animus is a controlled experiment in which the only difference between treatment and control conditions is the tone of the message. This is the design implemented by Ansolabehere and Iyengar (1995) in a series of experiments that examined the effects of campaign negativity on voter turnout.

In their studies, the authors constructed advertisements with identical visual content but varied the voiceover to manipulate tone-—either promoting the sponsoring candidate or attacking the opponent. For example, in a negative version of an advertisement targeting Republican gubernatorial candidate Pete Wilson, the narration stated that "crime rates increased by three percent while he was mayor of San Diego." In the corresponding positive version, the narration stated that "crime rates fell by three percent . . . ." Because the advertisements were identical in all other respects, any observed differences in outcome variables across conditions could only be attributed to variation in the tone of the advertising.

Replicating such tight control over the advertising message is not possible using real-world treatments. Observational designs are thus limited to comparisons of residents from geographic locations characterized by high or low levels of campaign advertising. In the U.S. context, given the state-by-state allocation of electoral votes, presidential campaigns limit their advertising to "battleground" states in which support for the major candidates is relatively even (Shaw 2006).

However, simply using residents of high exposure battleground media markets as the treated group is problematic. As prior studies on campaign advertisements have noted, areas targeted for advertising are also targeted for other forms of campaigning (e.g., appearances by the candidate, interviews on local media, and canvassing), which introduces any number of campaign-related confounded variables. More importantly, campaigns behave strategically in the allocation of their advertising budgets, targeting areas in which the audience for the ads is likely to respond favorably to their message. In 2024, Harris ads targeted Harris-leaning voters, while the Trump campaign tried to reach MAGA-inclined voters. Exposure to advertising is thus not only non-random, but also correlated with the political predispositions of the targeted audience. In the case of our outcome variable of interest—affective polarization—comparing residents of battleground and non-battleground states would confound exposure to advertising with voters' partisan preferences, the key driver of out-party animus.

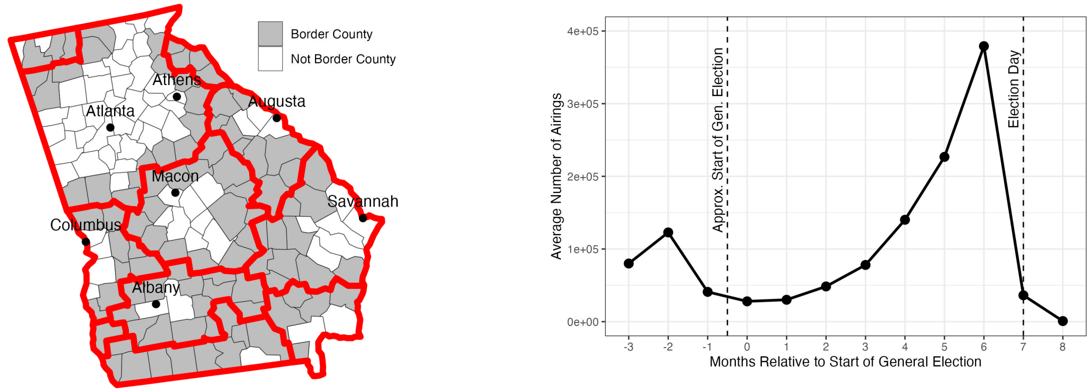
Given these identification challenges, Huber and Arceneaux (2007) show that the closest observational approximation to an experimental treatment assigns counties that fall within a battleground media market, but lie across the state border and therefore outside of the battleground state itself, as treated units. Voters in these areas receive broadcast programming from battleground media, but are not exposed to broader campaign activities that typically accompany heavy ad spending. Moreover, unlike residents of battleground DMAs, they have not been targeted on the basis of their candidate preferences. In short, the design estimates an average effect for the treated counties in a non-battleground state that happen to belong to "saturated" DMAs by comparing them against counties in the same non-battleground state that belong to lower exposure markets.

Subsequent work has built and extended this approach in three ways. First, scholars have noted that substantial non-random variation in advertising intensity exists within non-battleground states, and have sought to further refine the control group by re-weighting observations (Urban and Niebler 2014) or restricting comparisons to geographically adjacent counties (Spenkuch and Toniatti 2018). Second, the original Huber and Arceneaux design is geographically limiting by construction, as it relies exclusively on counties in non-battleground states that happen to fall within battleground DMAs. Subsequent work has argued that the core identifying assumption—that campaigns do not explicitly target individual border counties—holds more broadly, even when the sample is expanded to include all counties along media market boundaries regardless of whether the DMA is a battleground (Spenkuch and Toniatti 2018; Sides, Vavreck, and Warshaw 2022). For example, Spenkuch and Toniatti (2018) find that border counties constitute on average only 5% of a DMA's population, suggesting these areas are peripheral not only geographically but also to campaign strategy. Third, cross-sectional or single-election comparisons of narrow geographic regions risk conflating advertising differentials with long-term residential sorting or shifts driven by electoral coalition trends. To guard against this, Yamaya (2026) exploits within-election variation to study patterns in campaign contributions, using a difference-in-differences design that differences out election-specific geographic confounds. The present paper adopts a similar identification strategy, applying it to the question of affective polarization across five election cycles.

The design conducts paired comparisons across neighboring counties in the same state that straddle a DMA boundary. We illustrate this in Figure 1, using the state of Georgia. Counties in the sample are shaded in gray and largely fall outside of major metropolitan areas. Following previous work, we enumerate all possible pairs of counties that share a border (Spenkuch and Toniatti 2018; Sides, Vavreck, and Warshaw 2022; Yamaya 2026). These county pairs serve as the basic comparison groups, with variation in advertising within these pairs providing the identifying contrast.

Figure 1: Research Design: Georgia DMA Boundaries and Variation in Ad Exposure

(a) Border counties in GA (b) Ad Airings Within Election Cycle



Note: Panel A displays a map of Georgia with DMA boundaries outlined in red. Counties that straddle a DMA boundary and enter our sample are shaded. Major cities are indicated for reference. Panel B plots the monthly average number of presidential campaign advertisement airings relative to the start of the general election campaign, averaged across the five election cycles in our sample.

Figure 1b shows how advertising intensity varies within the election cycle. Advertising in presidential campaigns intensifies as the election approaches. There is typically a modest bump during the primaries, followed by a sharp increase through the general election. We use this within-election change in advertising exposure as the treatment, and compare it against changes in partisan animus for our research design.

4 Empirical Approach

Implementing the design described above requires granular data on the volume of televised advertising across U.S. media markets over the course of a campaign, as well as repeated, large-scale measures of affect toward political parties and candidates drawn from a sufficiently broad set of designated market areas (DMAs). Such data are available for the 2000, 2004, 2008, 2020, and 2024 election cycles; comparable data are not available for 2012 and 2016. We next describe the three primary data sources used in our empirical analysis and then outline our estimation strategy.

Data

Advertising data: We draw our campaign advertising data from two sources. For the 2000, 2004, and 2008 presidential election cycles, we use the Wisconsin Advertising Project (Goldstein, Franz, and Ridout 2002; Goldstein and Joel Rivlin 2007; Goldstein et al. 2011) to measure exposure to political advertising. These data cover all presidential campaign ads that aired on traditional network and cable broadcasts. In 2000, the dataset covers the 75 largest DMAs; coverage expanded to the 100 largest DMAs in 2004 and to all 210 DMAs in 2008. The Wisconsin Advertising Project database includes the precise number of airings per ad, the media market location, and human-coded categorization of ads based on their tone.

For the 2020 and 2024 presidential elections, we use advertising data provided by AdImpact, a private consulting firm that tracks political advertising across national TV and cable networks in all 210 DMAs. AdImpact monitors broadcasts airing weekdays between 7 a.m. and 1 a.m. and on weekends between 7 a.m. and midnight. The firm transcribes each ad and codes the transcripts for tone (as negative, contrast, or positive) and issue content. The data are validated in three ways: AdImpact cross-checks advertisements against scraped FCC public records and manually reviews any discrepancies, records are further verified against sources reporting directly from advertising agencies, and expected airing dates are continuously monitored with discrepancies manually reviewed. For each ad, AdImpact provides multiple indicators of exposure, including gross rating points (GRPs) and total number of airings.

Our analysis of advertising tone collapses contrast and negative ads into a single category. This decision is based on a content analysis of all presidential ads aired in 2024 using Stanford undergraduates as coders. The results showed that, on average, the ratio of negative to positive information in contrast ads was disproportionately negative—around 80:20.

GRPs—the most precise indicator of ad exposure—are only available for the 2020 and 2024 cycles. For earlier cycles, we rely on total number of airings. The high correlation between weekly GRPs and airings in 2020 and 2024 validates using the number of airings as an exposure measure (Appendix A reports a linear relationship and correlations of .69 and .67, respectively). For consistency across all five election cycles, we use total airings as our primary measure of ad exposure, though we report results for both measures wherever relevant and find that differences in operationalization do not affect our substantive conclusions.

Survey data: Our survey data come from four sources covering the 2000 to 2024 election cycles: the National Annenberg Election Surveys (NAES), Nationscape Insights, the Polarization Research Lab's America's Political Pulse survey, and aggregated 2024 surveys from the YouGov-administered Stanford-Arizona State-Yale study. Across these sources, the survey instruments used to measure affective polarization differ modestly, as we document below. To facilitate comparisons of effect sizes across elections, we standardize all outcomes relative to their within-unit variation (Mummolo and Peterson 2018).

For the 2000, 2004, and 2008 elections, we use the National Annenberg Election Surveys (Annenberg Public Policy Center 2000, 2004, 2008)—large-scale rolling cross-sections of daily phone interviews with American voters (N = 100,626, 98,711, and 57,967, respectively). Respondents rate their affect toward presidential candidates on a 101-point feeling thermometer scale in 2000, and a 11-point scale in 2004 and 2008.

For 2020, we merge the advertising data with Nationscape (Vavreck and Tausanovitch 2021), a large-scale rolling cross-section online survey administered by researchers at UCLA (N = 494,796). Nationscape conducted weekly, nationally representative surveys via Lucid. The surveys measure affect toward Democrats, Republicans, and major presidential candidates on a 4-point Likert scale.

For 2024, we draw on two separate sources. First, we use the Polarization Research Lab's America's Political Pulse survey (Westwood and Lelkes 2024), which measures Americans' affect toward the two major parties on a 101-point feeling thermometer scale (N = 157,954). Second, we use the Stanford-Arizona State-Yale (SAY) rolling cross-section survey from YouGov that interviewed approximately 797750 Americans at seven points during the campaign between December 2023 and the weeks immediately following the election. The SAY surveys record favorability toward Joe Biden, Kamala Harris, and Donald Trump on a bipolar 4-point scale, including an option of no opinion; we treat no opinion as the midpoint.

In all surveys, we compute respondents' average rating toward in-party candidates and subtract their average rating toward out-party candidates. Because we focus on respondents residing in counties that straddle a media market boundary, we retain only approximately 40% of respondents in each dataset. We report sample characteristics and their differences from the general U.S. population in Appendix B. We also run balance tests on various demographic covariates from the surveys. While we retain a number of covariates across all surveys, such as race, party affiliation, and family income, some variables are not available.

Supplemental data: To match survey respondents to their DMA, we construct a county-to-DMA crosswalk using Capital IQ Pro's MediaCensus data, which reports all U.S. broadband and video operators by ZIP code, county, and DMA. We extract unique county-DMA pairings from the broadcaster geographies to build the crosswalk. Counties that fall into multiple DMAs are excluded from the analysis, since our public opinion surveys do not provide sufficiently precise location data to determine which portion of such counties respondents inhabit. We merge respondent locations with county geographies using shape files from the Census Bureau.

For our placebo tests, we utilize turnout data using David Leip's United States Election Atlas (Leip 2023). This dataset contains county-level total votes, population, and voter registration figures for all presidential elections since 1912. We calculate lagged changes in turnout by taking the difference in turnout between the previous two election cycles.

Estimation

We estimate the design using a stacked two-way fixed effect model. In the model we interact the county and primary/general fixed effects with the aforementioned county border pair indicators, such that the identifying variation comes from comparing advertising intensity across geographically adjacent counties over the course of a single election cycle. The estimating equation is given below:

$$Y_{itcp} = \theta_{c\times p} + \eta_{t\times p} + \tau_1 Negative_{ctp} + \tau_2 Positive_{ctp} + X\beta_{itcp} + \varepsilon_{itcp} \tag{1}$$

Where Y_{itcp} is the level of affective polarization for respondent i at time t, living in county c pair p. Location fixed effects (θ) are defined at the county-pair level and time fixed effects (η) are dummies for the primary and general season interacted with the county pair fixed effects. In some specifications, we add individual-level controls for party identification, race, age group, household income, and education levels.

Our primary treatment variable ($Negative_{ctp}$) represents total negative ad airings at time t in county c pair p. We regress this with $Positive_{ctp}$ (positive ad airings) to isolate the effect of negative advertising from overall campaigning.

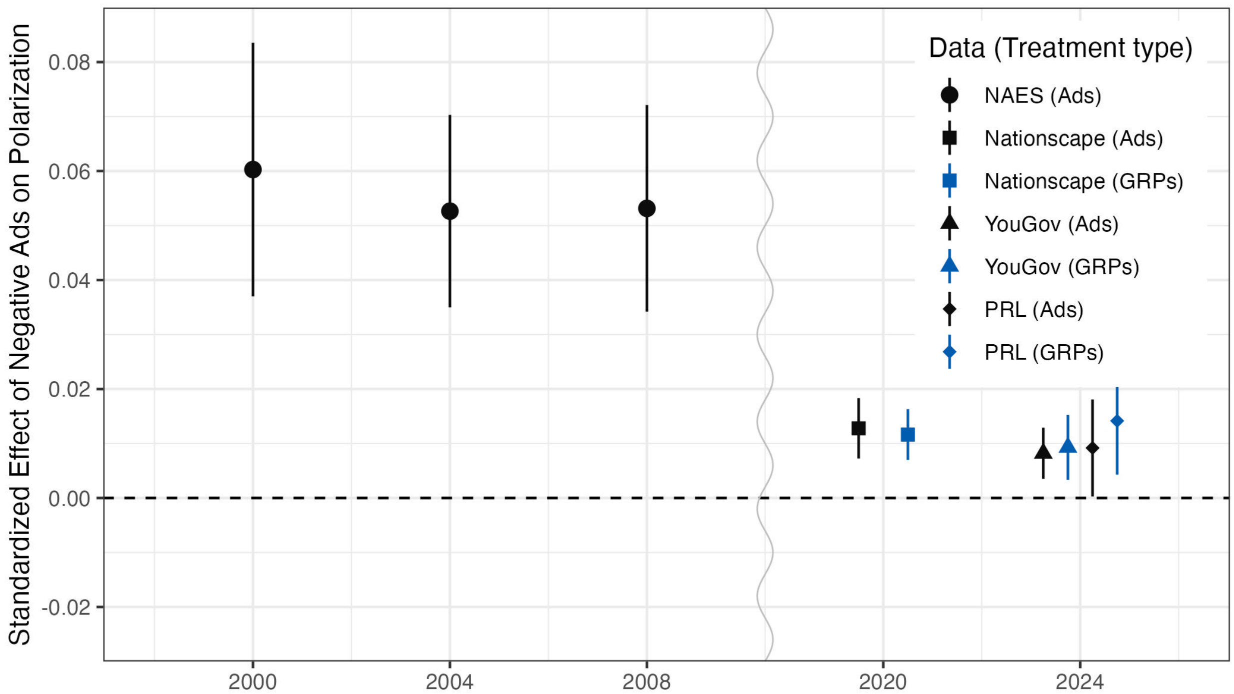
5 Results

We begin by presenting election-specific estimates of the effects of exposure to negative advertising. Figure 2 plots the effect of exposure to negative ads on affective polarization in the five election cycles. To facilitate comparisons over years, both outcome and treatment variables are standardized, so coefficients can be interpreted as changes in standard deviation units. Each point corresponds to a separate regression for that year, with the treatment operationalized as either negative ad airings or GRPs, depending on data availability.

As shown in Figure 2, televised advertising in the 2000s reliably shifted voters' evaluations of candidates and parties. A one-standard deviation change in the within-unit treatment leads to a 0.06, 0.05, and 0.05 standard deviation change in affective polarization for 2000, 2004, and 2008, respectively. All these coefficients are statistically significant, suggesting that negative advertising has a meaningful polarizing effect.

To put these numbers in perspective, first consider the year 2000. The 2000 NAES

Figure 2: Effect of Negative Advertising on Affective Polarization Across Election Cycles



Note: Each point plots the estimated coefficient on negative advertising from Equation 1, with a separate regression estimated for each election year. The treatment variable is either number of ad airings or gross rating points (GRP), depending on data availability. The dependent variable is the level of affective polarization reported by the survey respondent. Both treatment and outcome are standardized by their within-unit standard deviation. Standard errors are clustered at the DMA level, and error bars represent 95% confidence intervals.

measures partisan affect on a 101-point feeling thermometer, and on that scale our estimates imply that every additional 1000 negative ad airings are associated with roughly 3 points of polarization. Affective polarization in our sample peaked at 35.4 points in December 2000 and bottomed at 19.4 points in June 2000. Our estimates imply, the typical within-election increase in negative ad airings between the primary and general election periods corresponds to approximately 24.1% of this bottom-to-peak swing — a substantial share of within-year movement attributable to negative advertising alone.

This effect is roughly comparable in the 2004 and 2008 elections. Starting in 2004, the NAES measures partisan affect on an 11-point feeling thermometer scale. On this scale, our estimates for both 2004 and 2008 imply that every additional 1,000 airings of negative ads are associated with approximately 0.16 points of polarization. For 2004 and 2008 respectively, the average increase in ad airings between the primary and general election periods accounts for approximately 12.9% and 12.0% of the bottom-to-peak swing in affective polarization. This indicates a substantive, though slightly smaller, effect of negative ads on polarization compared to the 2000 election.

By the 2020s, however, the polarizing effects of advertising have declined significantly. The 2020 election cycle is the first year where we have both GRPs and the number of airings. Both measures yield standardized coefficients of 0.01. Using the same back-of-the envelope calculations, this means that a typical within-election increase in negative ad airings corresponds to approximately 0.98% of overall variation in affective polarization. Regardless of whether we use negative ad airings or GRPs, negative advertising no longer elicits the shifts in partisan animus recorded in earlier cycles.

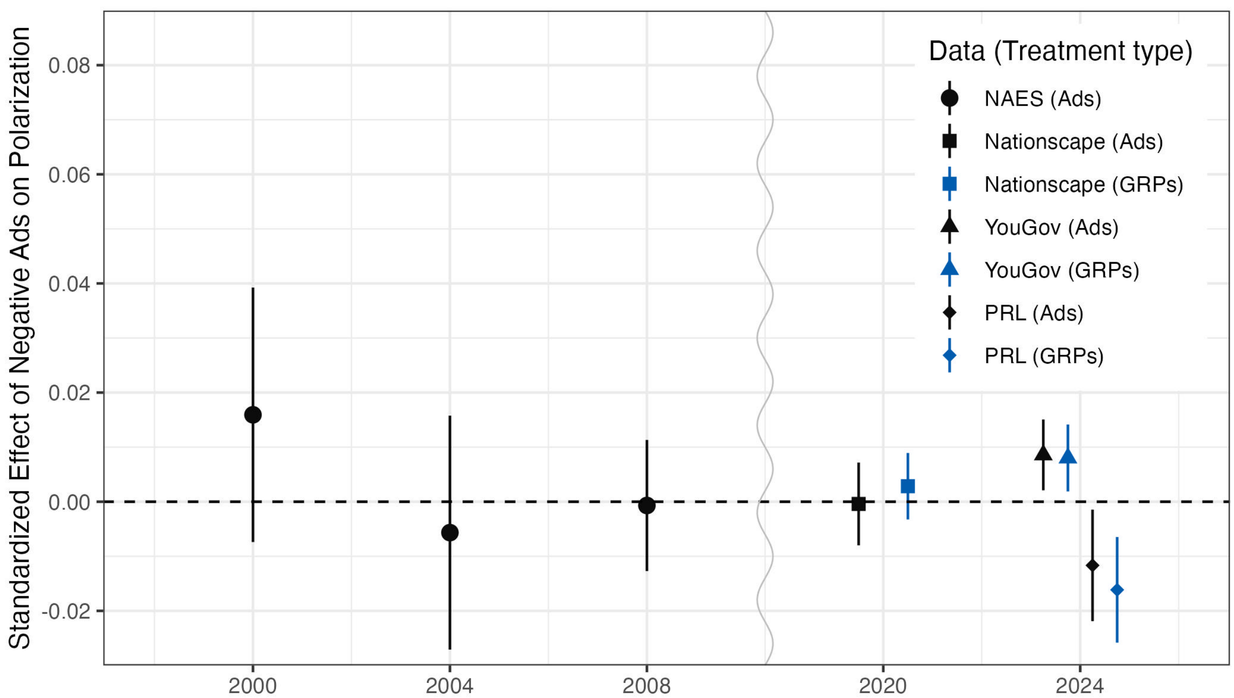
The results are no different for 2024, when using the SAY dataset from YouGov (0.008 for negative airings and 0.009 for negative GRPs) or the data from PRL (0.009 for negative airings and 0.014 for negative GRPs). The estimates using the PRL data are particularly useful because that survey also use a 101-point thermometer scale, facilitating direct comparisons to estimates in the 2000 NAES. The 2024 estimates suggest that an additional 1,000 negative airings are associated with an approximately 0.15 unit increase in polarization—a 95% decrease from 2000. As we will elaborate later, an important finding is that the movement in polarization over the entire election cycle has become much smaller over time. In 2024, polarization moved from its lowest point in November 2023 at 49.7 to a peak of 56.2 in August 2024, a mere difference of 6.5 points. Given the stability of partisan attitudes, fluctuations in advertising are less likely to contribute to polarization today.

This decline is not simply a function of advertising scale or volume; the same holds for proportional effort. To take into account the fact that total presidential advertising volume has increased almost seven fold between 2000 and 2024, we can compare changes in the raw scale against within-unit standard deviation changes in the treatment. A 1 standard deviation change in ad volume in 2000 leads to a 1.92 change in the 101-point scale, while the same 1 standard deviation change in 2024 leads only to a 0.28 change.

We can further document the polarized effects of negative advertising by benchmarking them against the effects of positive advertising. As shown in Figure 3 below, positive ads do not polarize. The coefficients for positive advertisements are consistently small and statistically indistinguishable from zero, underscoring that the polarizing effects of political campaigns derive primarily from negative advertising. The pattern is consistent with our broader argument that the decades-long rise in affective polarization is tied, in part, to the parallel growth in negative presidential advertising.

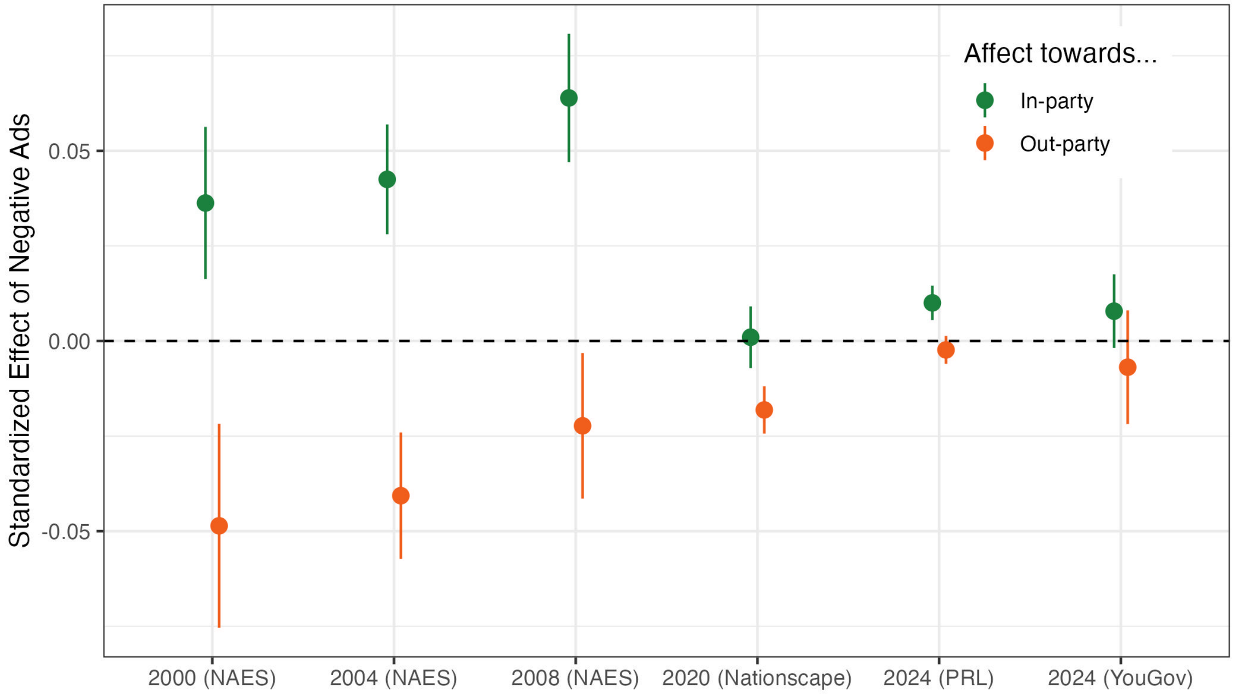
Why are negative advertisements more polarizing? Most directly, they denigrate the opposing candidate by criticizing issue positions, past performance in office, and often personal character. In contrast, positive advertisements emphasize the sponsoring candidate's credentials and accomplishments, providing little basis for viewers to update their evaluations of the opponent. Negative ads may also elevate in-group evaluations by articulating substantive contrasts between the sponsoring and targeted candidates. Whereas positive appeals are one-sided, negative advertisements foreground differences between parties and candidates across salient policy domains and character traits. Taken together, these features

Figure 3: Effect of Positive Advertising on Affective Polarization Across Election Cycles



Note: Each point plots the estimated coefficient on positive advertising from Equation 1, with a separate regression estimated for each election year. The treatment variable is either number of ad airings or gross rating points (GRP), depending on data availability. The dependent variable is the level of affective polarization reported by the survey respondent. Both treatment and outcome are standardized by their within-unit standard deviation. Standard errors are clustered at the DMA level, and error bars represent 95% confidence intervals.

Figure 4: Decomposing Affective Polarization: In-Party Versus Out-Party Affect



Note: Each point plots the estimated coefficient on negative advertising for either in-party or out-party affect, with a separate regression estimated for each outcome and election year. The treatment variable is the number of ad airings. Both treatment and outcome are standardized by their within-unit standard deviation. Standard errors are clustered at the DMA level, and error bars represent 95% confidence intervals.

make negative advertising particularly well suited to widening the affective gap between partisans.

We can assess the extent to which negative advertising influences both components of affective polarization (in-party approval, out-party disapproval). As shown in Figure 4, when we separate the in and out party evaluations, the effects of exposure to negative advertising is symmetric. In the 2000s, negative advertising improved evaluations of in-party candidates and degraded evaluations of out-party candidates. In 2000, negative advertising hurt the opponent more than helped the sponsor, while in 2008 this relationship was reversed. By 2020, however, negative advertising no longer meaningfully moves either component of affective polarization.

The declining role of campaign advertising as a polarizing force likely reflects two interconnected features of contemporary American politics. First, the electorate has become increasingly socially sorted, such that partisan identity now aligns with a range of other salient social identities (Mason, 2016). This alignment is widely understood to be a central driver of affective polarization (Iyengar et al. 2019). By contrast, in the 2000s, social and ideological cleavages were less tightly aligned, producing greater identity cross-pressures that tempered hostility toward the out-party (see Cassese 2020; Brader, Tucker, and Therriault 2014. Under these less sorted conditions—–and in the presence of comparatively weaker baseline animus—–short-term campaign forces, such as negative advertising, had greater capacity to intensify affective polarization. Today, however, given the level of social sorting and the highly elevated state of out-party animus (the median thermometer score for the opposing party in the past two cycles of the ANES is 0), partisans have much stronger priors regarding their evaluations of the in and out party. The effects of short-term cues such as exposure to campaigns are therefore weakened.

A more mechanical explanation for diminishing returns to negative advertising lies in the distribution of partisans' prior attitudes. Contemporary partisans enter campaign season with out-party evaluations already at or near their lower bound, leaving limited scope for further decline (see Fasching et al. 2024). As a result, the polarizing effects of campaign communication are likely to operate primarily through shifts in in-party evaluations. However, given the extensive time-series evidence demonstrating the relative stability of in-party affect (Iyengar, Sood, and Lelkes 2012), variation in advertising tone is unlikely to be a principal driver of in-group favoritism.

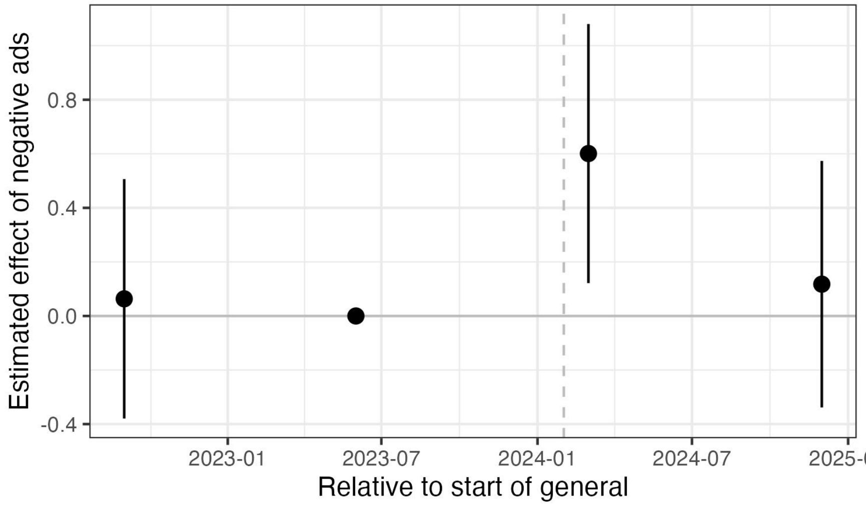
We conclude by documenting several robustness checks on our empirical approach, organized around three forms of threats to inference. The first is that the results are confounded by strategic placement of advertising. To address this, we adopt a first-differences framework and test whether changes in advertising volume predict prior changes in turnout. Using a concrete example, this means we examine whether changes in primary to general advertising swings in the 2024 election correlate with the change in turnout between the 2016 and

2020 presidential election. Appendix Table D9 reports these estimates using all years and county pairs for total votes, turnout as a share of total population, and turnout as a share of registered voters as the dependent variables. The estimates are precise nulls across all measures.

The second threat to inference concerns changes in survey composition. Since our surveys consist of repeated cross sections, we want to ensure that our estimates are not driven by systematic changes in the types of people answering the survey. Appendix Figures D5a to D6b report a series of balance tests where we regress a set of demographic variables (characteristics that should not change within a year, as a result of ad exposure) on ad volume. In most surveys and years, airings do not correlate with most survey demographics. Two exceptions are the 2000 NAES and 2020 Nationscape, where we find evidence of imbalance across multiple variables. To guard against the possibility that these imbalances drive our results, Appendix C reports two additional regression specifications for each year: one adding individual-level demographic controls from the survey data, and one interacting these controls with primary/general election period indicators to allow different demographic groups to follow different within-election time trends. The same appendix also reports specifications that re-cluster standard errors at the state level and re-weight observations by the inverse of the number of times each county appears in the sample to account for the stacked structure of the data. None of these alternative specifications alter our conclusions.

The third concern involves unobserved, time-varying confounds that are specific to county-pair and election year. The standard diagnostic is the pre-trends test, but this is difficult to implement in most election years in our sample given the coarseness of the time units available (surveys spanning only the primary and general election periods). This reflects two constraints: the need to avoid underpowered cells when partitioning the sample by county and time period, and the fact that most surveys do not interview respondents sufficiently far in advance of the election. Fortunately, one exception is the Polarization Research Lab's 2024 survey which provides repeated measurements over an extended pre-election period.

Figure 5: Placebo Test: Pre-Election Trends in Affective Polarization (2024)



Note: This figure plots coefficients from a dynamic specification of the panel regression, in which negative advertising exposure in gross rating points (GRP) is interacted with a set of nine-month period indicators spanning before and after the start of the general election. The omitted reference period is the period immediately preceding the general election. Standard errors are clustered at the DMA level and error bars represent 95% confidence intervals.

We exploit this feature of the PRL data, and the fact that most of presidential advertising intesity comes during the general election, to estimate a dynamic model. We divide the sample into four periods: two pre-election periods (2022–2023 and 2023–February 2024), one general election period (March–November 2024), and one post-election period (after November 2024). We interact the total negative general election GRPs with indicators for each period, using the immediate pre-period as the reference category. Figure 5 plots the resulting coefficients. We find no evidence of differential pre-trends, and the effect does not persist into the post-election period. We caution, however, that the main 2024 effect is itself small, so it remains unclear whether the absence of persistence reflects a general pattern or is specific to the 2024 cycle.

6 Discussion & Conclusion

Our results show that the conduct of political campaigns has repercussions for voter attitudes. Exposure to hateful speech from presidential candidates can make partisan voters more hateful toward their opponents. The effect is stronger in the elections that occurred relatively early in the development of affective polarization and tapers off in recent campaigns. We surmise that this trend is attributable to more ingrained feelings of out-party animus caused by social sorting and other historical forces (e.g., the development of social media and providers of partisan news) that have contributed to the growth of affective polarization.

While our results are limited to presidential campaigns, given the widespread adoption of negative advertising in statewide and local races, we anticipate similar polarizing effects in these campaigns. Consider the recent gubernatorial elections in Virginia and New Jersey. More than 70 percent of the ads that aired in these races offered negative rather than positive cues. Unsurprisingly, Virginia and New Jersey residents surveyed immediately after the election expressed very high levels of out-party animus (Wu and Iyengar 2026).

As we noted at the outset, the persuasive effects of elite rhetoric on public opinion are well documented. In a polarized environment, partisans will be more receptive to messages from copartisan candidates that demean the opposing candidate than to messages promoting the candidacy of the sponsor. Given the surge in the level of negative advertising over the past few cycles, it appears that campaign consultants are well aware of this generalization. Along with the factors we noted earlier, the greater persuasiveness of negative advertising is a strong incentive for candidates to adopt a harsh tone in their advertising.

We note that our findings have implications for ongoing efforts to "depolarize" the electorate. The elevated level of out-party animus has set off alarm bells within the academy, civil society organizations, and major foundations. The pressing concern appears to be that partisan animus can motivate anti-democratic behaviors such as denying the results of legitimate elections, approval of the use of violence as a means of advancing partisan interests, and the strategic spreading of misinformation. The fear is that polarization and such related changes in behavioral norms present an imminent threat to democratic institutions and norms.

These concerns have led to an outpouring of interventions designed to mitigate polarization. These interventions include facilitating interpersonal contact across party lines, correcting misperceptions of opposing partisans, and making non-partisan identities more salient (see Voelkel et al. 2024 for evidence of the efficacy of such treatments). Our results suggest that such interventions, by focusing on voter predispositions rather than elite behavior, are misplaced. To the extent that societal or contextual forces are responsible for the spread of polarization, treatments should seek to weaken these forces rather than focusing on the symptoms of the underlying problem.

One such potentially effective treatment is the "Disagree Better" initiative developed by Governor Spencer Cox of Utah and recently endorsed by the National Governor's Association. In the 2020 Utah gubernatorial election, Republican Cox and his Democratic opponent appeared in joint ads outlining their positions on major issues and making no critical reference to their opponent. Similar efforts to make campaigns more civil may break the spiral of negativity and animus so characteristic of the current state of American campaigns. However, given the powerful incentives underlying the strategy of "going negative," the prospects for such reform efforts seem, at best, less than promising.

More generally, we reiterate that understanding the origins of a societal condition is a necessary precondition for being able to treat that condition. Our findings suggest that affective polarization has worsened partly through elite communication. The fact that this effect has attenuated in recent cycles does not undermine the underlying relationship; if anything, the decline suggests that the electorate has become so polarized that sustained elite messaging can no longer move the needle. Effective interventions should therefore address the incentive structures that govern the content and tone of elite political communication rather than delivering behavioral or informational nudges aimed at curbing the symptoms of polarized individuals.

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Appendix

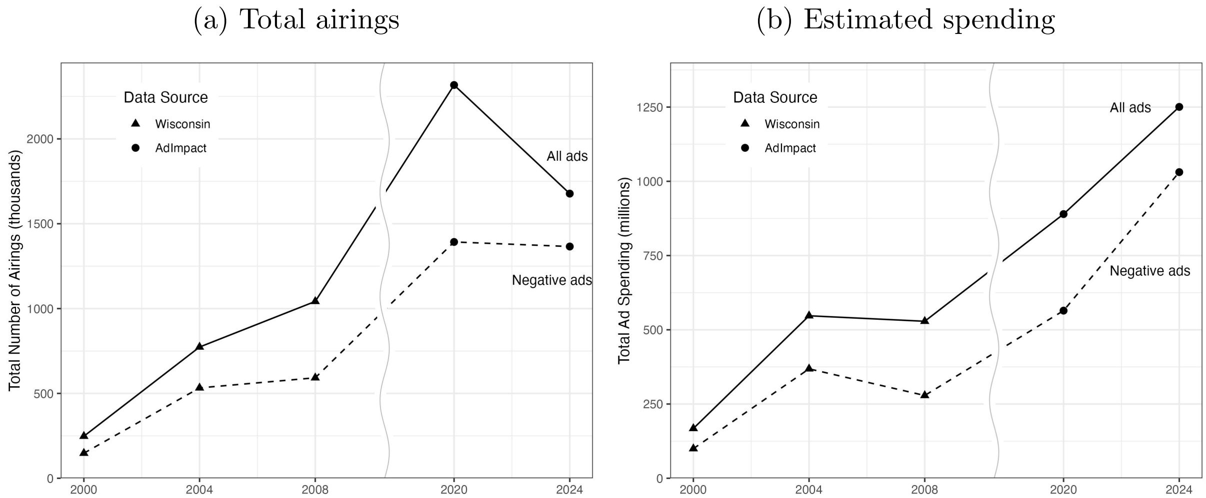
A Descriptive of ads & Validation of Number of ads against GRPs

The current literature on political campaigning argues that advertising volume has gradually increased over the past several years (Geer 2012). At the same time, political campaigns have also grown increasingly negative in both tone and substance. To better illustrate this, figure A2 plots the movement of presidential TV advertising over the five election cycles in our study. We quantify ad volume using two metrics: total airings and estimated spending. Since 2000, total presidential TV advertising volume has increased roughly by a factor of 7 by the 2024 election. Campaigns have also become more negative by a little over 20 percentage points over the same time frame. Negative ads constituted approximately 60% of total ad spending and airings in 2000 but grew to account for over 80% of all ad volume by 2024.

Measurements for ad GRPs are only available for the 2020 and 2024 cycles from the AdImpact dataset. For the elections during the 2000s, we rely on total number of airings as a proxy for ad exposure. One common criticism of using ad volume for this purpose is that ad volume fails to account for viewer engagement with the advertisement. To further validate our usage of total ad airings as a proxy for exposure in the 2000s, we measure the correlaton between GRPs and airings in the 2020 and 2024 elections. Figure A2 implies that the relationship between weekly number of ads and GRPs is strongly positive and linear. This assuages concerns that our results are being primarily driven by a poor measurement of ad exposure, and is further evidenced by the similar effects of both measures on affective polarization.

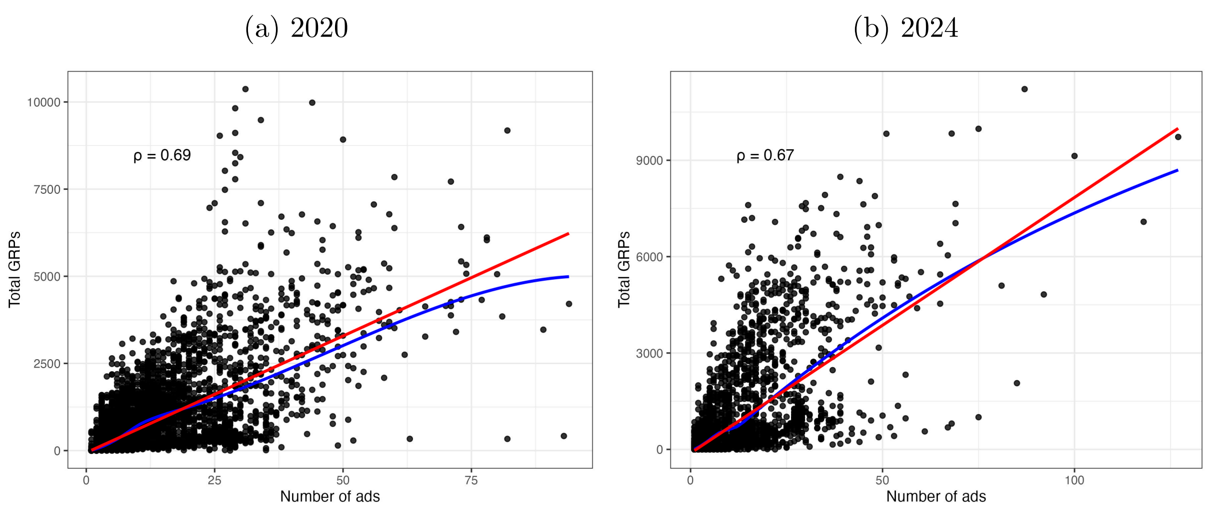
While scholars have found ample evidence to support the cyclical nature of political advertising over the course of the campaign (see Geer 2012; Iyengar 2022, there is less documentation on the within-election trends in affective polarization. According to data from the ANES, levels of affective polarization has risen consistently across election cycles since the 1990s (Iyengar, Sood, and Lelkes 2012; Iyengar et al. 2019). We leverage data from the Polarization Research Lab's America's Political Pulse survey to plot within-election trends in affective polarization. In figure A3, we see that affective polarization gradually increases over the course of the general election: beginning at the trough near the start of the general election and peaking just before election day. Polarization decreases quite sharply after election day.

Figure A1: Trends in Presidential TV Advertising



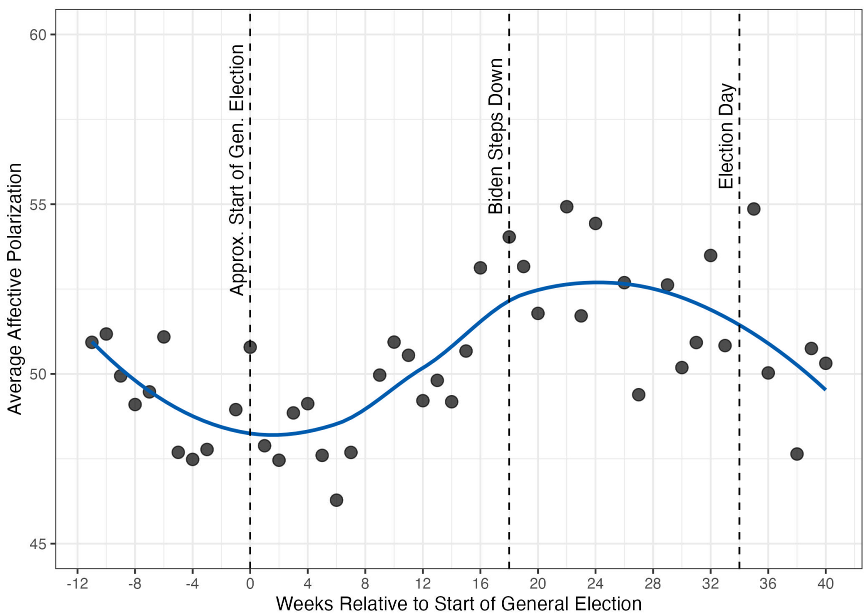
Note: This figure plots trends in presidential TV advertising across election cycles. Panel A shows the total number of airings for all ads and for negative ads separately, where negative ads combine the "negative" and "contrast" categories. Panel B plots estimated total spending for each election cycle.

Figure A2: Correlation Between Weekly Ad Airings and GRPs



Note: This figure compares the weekly sum of campaign advertisement gross rating points (GRP) against the number of airings, separately for 2020 and 2024. Each observation is a DMA-week. The red line shows a linear fit and the blue line shows a LOESS curve.

Figure A3: Trends in Affective Polarization During the 2024 Election



Note: Data are from the Polarization Research Lab's (PRL) America's Political Pulse surveys. Affective polarization is measured as each respondent's in-party thermometer rating minus their out-party rating. Each point plots the weekly average level of affective polarization across the 2024 election cycle. The blue line shows a LOESS curve.

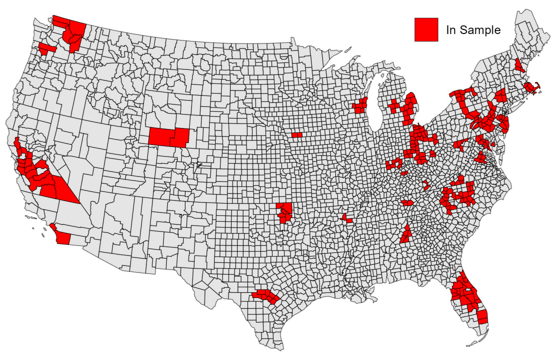
B Sample Selection

In Figure B4, we depict which counties appear in our sample for each respective election cycle. Our sampling criteria proceeds in two steps. First, we filter for counties that are included in our border-pair design. Next, we only take counties that have a minimum of five observations in both the primary and general election period during each respective election year. 2000 and 2004 are especially sparse since the Wisconsin Ad Project only covers the largest 50 and 75 DMAs respectively.

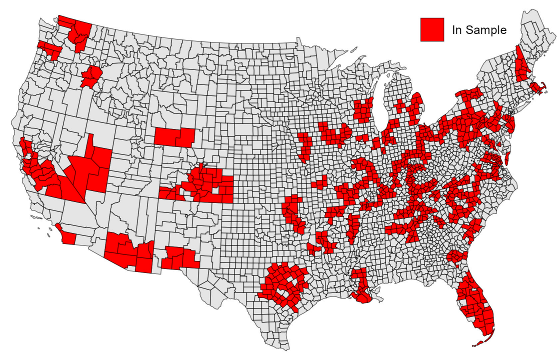
Tables B1 and B2 describes how our sampled counties differ from the rest of the counties in the United States. We regress an indicator variable for county sampling on various demographic variables from the U.S. census data. Table B2 includes state fixed effects to show how border counties differ relative to other counties in the same state. We can see that the sampled counties differ from the general population on a number of demographic variables. In particular, the education and age are especially imbalanced across all five election cycles. These results do caution us to consider potential demographic factors that could impact the generalizability of our results.

Figure B4: In-Sample Counties Across Election Years

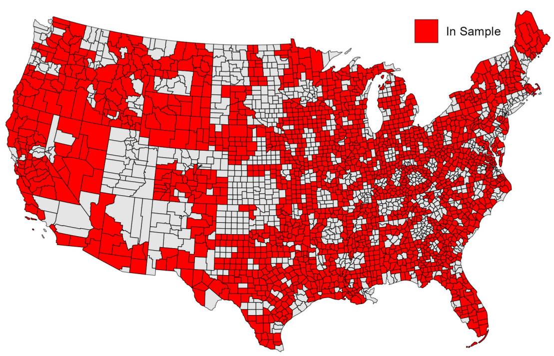
(a) 2000



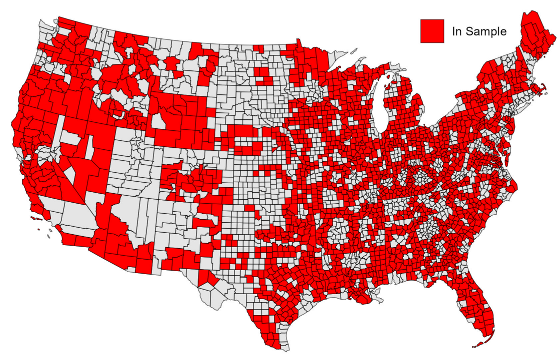
(b) 2004



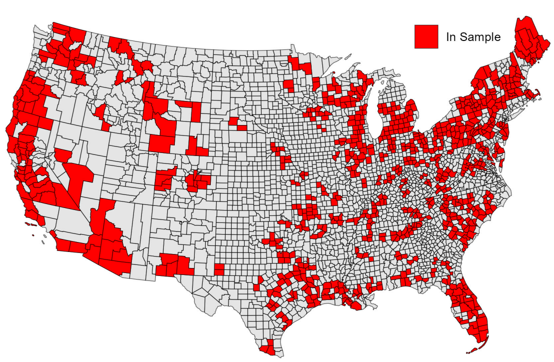
(c) 2008



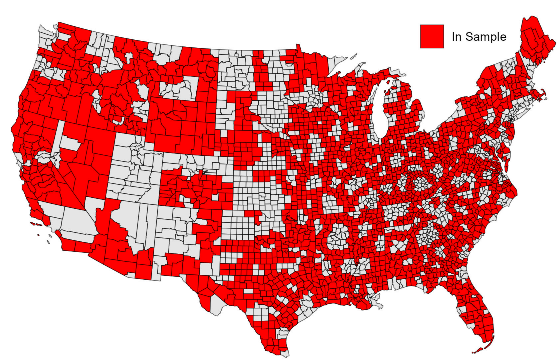
(d) 2020



(e) 2024 – PRL



(f) 2024 – YouGov



Note: This figure depicts in-sample counties across all five election years.

Table B1: Balance Tests on Sampled Counties (No Fixed Effects)

	2000	2004	2008	2020	2024: PRL	2024: YouGov
Constant	-0.21	-1.86***	-0.33	0.06	1.61***	-0.10
	(0.21)	(0.34)	(0.35)	(0.33)	(0.25)	(0.28)
Total Population	4.73**	5.17	-4.87	-0.22	7.18**	-2.53
	(1.73)	(2.78)	(2.94)	(2.83)	(2.44)	(2.75)
Median Household Income	0.96***	1.50***	-0.44**	-0.19	0.00	-0.00
	(0.12)	(0.19)	(0.15)	(0.11)	(0.00)	(0.00)
Proportion Male	-1.15***	-1.15**	0.46	-1.06**	-2.26***	-0.08
	(0.25)	(0.41)	(0.40)	(0.39)	(0.33)	(0.37)
Proportion White	-0.10	-0.15	0.19	0.65***	0.23***	0.38***
	(0.07)	(0.11)	(0.10)	(0.10)	(0.06)	(0.07)
Proportion Black	-0.18**	-0.14	0.33**	0.58***	-0.25***	-0.35***
	(0.06)	(0.10)	(0.10)	(0.10)	(0.07)	(0.08)
Proportion Above 18	1.18***	2.96***	1.41***	1.50***	0.78***	1.04***
	(0.18)	(0.29)	(0.29)	(0.28)	(0.22)	(0.25)
Proportion College Degree	-0.47***	-1.22***	-1.04***	-1.39***	-0.32***	-1.23***
	(0.09)	(0.14)	(0.15)	(0.14)	(0.10)	(0.11)
Proportion Have Married	-0.24*	0.37	0.03	-0.49**	-1.15***	0.12
	(0.12)	(0.19)	(0.19)	(0.18)	(0.16)	(0.17)
Unemployment Rate	0.21	-0.43	0.95**	0.31	1.60***	0.55
	(0.23)	(0.37)	(0.33)	(0.39)	(0.36)	(0.41)
Poverty Rate	0.27	1.06***	-1.14	-0.45*	-1.05***	0.47**
	(0.16)	(0.26)	(0.22)	(0.23)	(0.15)	(0.17)
N	3,139	3,139	3,221	3,220	3,222	3,222

Note: This table presents regression results where the dependent variable indicates whether the county is sampled for the respective election cycle. Total population is factored by 100,000,000 and median household income is factored by 100,000 for ease of comparison. The dependent variables are an array of census demographics. Each column represents a different election year cycle. The unit of observation is a county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed test)

Table B2: Balance Tests on Sampled Counties (State Fixed-Effects)

	2000	2004	2008	2020	2024: PRL	2024: YouGov
Total Population	-0.16	0.59	-14.14***	-9.66***	-3.22	-12.69***
	(1.70)	(2.75)	(2.90)	(2.81)	(2.40)	(2.72)
Median Household Income	0.49***	0.44*	-0.61***	-0.07	0.00	-0.00
	(0.14)	(0.22)	(0.17)	(0.12)	(0.00)	(0.00)
Proportion Male	-0.76**	-0.40	1.01*	0.16	-1.31***	0.13
	(0.26)	(0.42)	(0.41)	(0.40)	(0.33)	(0.37)
Proportion White	-0.12	-0.33*	-0.11	0.27*	0.10	-0.02
	(0.08)	(0.14)	(0.13)	(0.12)	(0.08)	(0.09)
Proportion Black	-0.25**	-0.38**	-0.09	0.17	-0.50***	-0.17
	(0.08)	(0.13)	(0.14)	(0.13)	(0.10)	(0.12)
Proportion Above 18	0.41	1.43***	0.83*	0.59	-0.52*	1.15***
	(0.21)	(0.35)	(0.33)	(0.31)	(0.25)	(0.29)
Proportion College Degree	-0.28**	-0.64***	-0.43*	-0.58***	-0.01	-0.85***
	(0.10)	(0.17)	(0.17)	(0.16)	(0.10)	(0.12)
Proportion Have Married	-0.12	0.50*	0.59**	0.31	-0.65***	0.52**
	(0.14)	(0.22)	(0.19)	(0.19)	(0.16)	(0.18)
Unemployment Rate	-0.29	-0.89*	0.46	0.26	0.36	0.14
	(0.25)	(0.41)	(0.36)	(0.39)	(0.35)	(0.40)
Poverty Rate	0.15	0.43	0.24	0.84**	-0.07	0.91***
	(0.18)	(0.29)	(0.26)	(0.26)	(0.19)	(0.21)
N	3,138	3,138	3,220	3,219	3,221	3,221
State FE	✓	✓	✓	✓	✓	✓

Note: This table presents regression results where the dependent variable indicates whether the county is sampled for the respective election cycle. Total population is factored by 100,000,000 and median household income is factored by 100,000 for ease of comparison. The dependent variables are an array of census demographics. Each column represents a different election year cycle. The unit of observation is a county. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed test)

C Year by year analyses

In appendix C, we present the raw coefficients of alternative models on the effect of campaign ads on affective polarization. We present five different models. First, we present the coefficients for the model using the non-standardized, original scale for advertising volume and polarization. Second, we cluster standard errors at the state level. Third, we re-weight the model by the inverse propensity of each county in the sample. Fourth, we include individual-level demographic controls in the model. Finally, we interact these demographic controls with the primary/general election period indicators to account for demographic within-election time trends. We find that the statistical and substantive interpretations of the coefficients for each election year remains largely the same. For 2020 and 2024, We also find that number of airings and GRPs have similar directional effects on polarization.

Table C3: The Effect of Campaign Ads (2000)

	Original scale	Clustered	Re-weighted	Controls	Interacted controls
N Negative Ads	2.99***	2.99***	3.21***	3.01***	3.00***
	(0.58)	(0.62)	(0.40)	(0.50)	(0.50)
N Positive Ads	2.27	2.27	4.47*	2.16	2.16
	(1.84)	(2.09)	(1.70)	(1.92)	(1.94)
N	15,516	15,516	15,516	13,721	13,721
SE Clustered by	DMA	State	DMA	DMA	DMA
County × Pair FE	✓	✓	✓	✓	✓
General × Pair FE	✓	✓	✓	✓	✓
Controls				✓	✓
General × Controls					✓

Note: This table presents regression results where the dependent variable is respondent-level affective polarization in the 2000 election cycle. The treatment variables are the number of negative and positive presidential campaign advertisement airings (in thousands). Column 1 shows the baseline specification from Equation 1 with the outcome on its original scale. Column 2 adjusts the clustering structure. Column 3 reweights observations by the number of times each enters the dataset, reflecting the stacked structure of the data. Column 4 adds individual-level demographic controls, including party identification, race, age group, household income, and education. Column 5 interacts these controls with the time indicators to allow for demographic-specific time trends. The unit of observation is a respondent-county pair. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed test)

Table C4: The Effect of Campaign Ads (2004)

	Original scale	Clustered	Re-weighted	Controls	Interacted controls
N Negative Ads	0.16***	0.16**	0.14***	0.14***	0.14***
	(0.03)	(0.05)	(0.03)	(0.04)	(0.04)
N Positive Ads	-0.04	-0.04	-0.02	0.02	0.03
	(0.14)	(0.20)	(0.10)	(0.16)	(0.16)
N	37,793	37,793	37,793	32,557	32,557
SE Clustered by	DMA	State	DMA	DMA	DMA
County × Pair FE	✓	✓	✓	✓	✓
General × Pair FE	✓	✓	✓	✓	✓
Controls				✓	✓
General × Controls					✓

Note: This table presents regression results where the dependent variable is respondent-level affective polarization in the 2004 election cycle. The treatment variables are the number of negative and positive presidential campaign advertisement airings (in thousands). Column 1 shows the baseline specification from Equation 1 with the outcome on its original scale. Column 2 adjusts the clustering structure. Column 3 reweights observations by the number of times each enters the dataset, reflecting the stacked structure of the data. Column 4 adds individual-level demographic controls, including party identification, race, age group, household income, and education. Column 5 interacts these controls with the time indicators to allow for demographic-specific time trends. The unit of observation is a respondent-county pair. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed test)

Table C5: The Effect of Campaign Ads (2008)

	Original scale	Clustered	Re-weighted	Controls	Interacted controls
N Negative Ads	0.16***	0.16***	0.19***	0.16***	0.16***
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
N Positive Ads	-0.00	-0.00	-0.00	0.02	0.01
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
N	50,150	50,150	50,150	43,773	43,773
SE Clustered by	DMA	State	DMA	DMA	DMA
County $\times$ Pair FE	✓	✓	✓	✓	✓
General $\times$ Pair FE	✓	✓	✓	✓	✓
Controls				✓	✓
General $\times$ Controls					✓

Note: This table presents regression results where the dependent variable is respondent-level affective polarization in the 2008 election cycle. The treatment variables are the number of negative and positive presidential campaign advertisement airings (in thousands). Column 1 shows the baseline specification from Equation 1 with the outcome on its original scale. Column 2 adjusts the clustering structure. Column 3 reweights observations by the number of times each enters the dataset, reflecting the stacked structure of the data. Column 4 adds individual-level demographic controls, including party identification, race, age group, household income, and education. Column 5 interacts these controls with the time indicators to allow for demographic-specific time trends. The unit of observation is a respondent-county pair. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed test)

Table C6: The Effect of Campaign Ads (2020)

Panel A: Number of Ad Airings

	Original scale	Clustered	Re-weighted	Controls	Interacted controls
N Negative Ads	0.01***	0.01**	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N Positive Ads	-0.00	-0.00	-0.00	0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	330,230	330,230	330,230	315,112	315,112
SE Clustered by	DMA	State	DMA	DMA	DMA
County × Pair FE	✓	✓	✓	✓	✓
General × Pair FE	✓	✓	✓	✓	✓
Controls				✓	✓
General × Controls					✓

Panel B: Gross Rating Points (GRPs)

	Original scale	Clustered	Re-weighted	Controls	Interacted controls
GRP Negative Ads	0.10***	0.10***	0.11***	0.08***	0.08***
	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)
GRP Positive Ads	0.03	0.03	-0.00	0.03	0.03
	(0.03)	(0.06)	(0.02)	(0.03)	(0.03)
N	330,230	330,230	330,230	315,112	315,112
SE Clustered by	DMA	State	IID	DMA	DMA
County × Pair FE	✓	✓	✓	✓	✓
General × Pair FE	✓	✓	✓	✓	✓
Controls				✓	✓
General × Controls					✓

Note: This table presents regression results where the dependent variable is respondent-level affective polarization in the 2020 election cycle. The treatment variables are the number of negative and positive presidential campaign advertisement intensity. Panel A measures treatment by ad count and Panel B by GRP exposure. Column 1 shows the baseline specification from Equation 1 with the outcome on its original scale. Column 2 adjusts the clustering structure. Column 3 reweights observations by the number of times each enters the dataset, reflecting the stacked structure of the data. Column 4 adds individual-level demographic controls, including party identification, race, age group, household income, and education. Column 5 interacts these controls with the time indicators to allow for demographic-specific time trends. The unit of observation is a respondent-county pair. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed test)

Table C7: The Effect of Campaign Ads (PRL 2024)

Panel A: Number of Airings

	Original scale	Clustered	Re-weighted	Controls	Interacted controls
N Negative Ads	0.15*	0.15*	0.15*	0.12	0.12
	(0.08)	(0.08)	(0.07)	(0.08)	(0.09)
N Positive Ads	-0.87*	-0.87*	-0.86*	-0.74	-0.70
	(0.39)	(0.40)	(0.35)	(0.43)	(0.43)
N	62,534	62,534	62,534	62,534	62,534
SE Clustered by	DMA	State	DMA	DMA	DMA
County × Pair FE	✓	✓	✓	✓	✓
General × Pair FE	✓	✓	✓	✓	✓
Controls				✓	✓
General × Controls					✓

Panel B: Gross Rating Points (GRPs)

	Original scale	Clustered	Re-weighted	Controls	Interacted controls
GRP Negative Ads	2.26**	2.26**	1.97**	2.09*	2.02*
	(0.84)	(0.72)	(0.67)	(0.91)	(0.91)
GRP Positive Ads	-12.67**	-12.67**	-11.11***	-11.87**	-11.34**
	(4.04)	(4.05)	(3.27)	(4.31)	(4.36)
N	62,534	62,534	62,534	62,534	62,534
SE Clustered by	DMA	State	IID	DMA	DMA
County × Pair FE	✓	✓	✓	✓	✓
General × Pair FE	✓	✓	✓	✓	✓
Controls				✓	✓
General × Controls					✓

Note: This table presents regression results where the dependent variable is respondent-level affective polarization in the 2024 election cycle, using data from the Polarization Research Lab. The treatment variables are the number of negative and positive presidential campaign advertisement intensity. Panel A measures treatment by ad count and Panel B by GRP exposure. Column 1 shows the baseline specification from Equation 1 with the outcome on its original scale. Column 2 adjusts the clustering structure. Column 3 reweights observations by the number of times each enters the dataset, reflecting the stacked structure of the data. Column 4 adds individual-level demographic controls, including party identification, race, age group, household income, and education. Column 5 interacts these controls with the time indicators to allow for demographic-specific time trends. The unit of observation is a respondent-county pair. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed test)

Table C8: The Effect of Campaign Ads (YouGov 2024)

Panel A: Number of Ads

	Original scale	Clustered	Re-weighted	Controls	Interacted controls
N Negative Ads	0.01***	0.01*	0.01***	0.01**	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N Positive Ads	0.05*	0.05*	0.04*	0.04*	0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	464,478	464,478	464,478	461,313	461,313
SE Clustered by	DMA	State	DMA	DMA	DMA
County × Pair FE	✓	✓	✓	✓	✓
General × Pair FE	✓	✓	✓	✓	✓
Controls				✓	✓
General × Controls					✓

Panel B: Gross Rating Points (GRPs)

	Original scale	Clustered	Re-weighted	Controls	Interacted controls
GRP Negative Ads	0.09**	0.09*	0.12**	0.08**	0.08**
	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
GRP Positive Ads	0.36*	0.36*	0.23	0.26	0.26
	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)
N	464,478	464,478	464,478	461,313	461,313
SE Clustered by	DMA	State	IID	DMA	DMA
County × Pair FE	✓	✓	✓	✓	✓
General × Pair FE	✓	✓	✓	✓	✓
Controls				✓	✓
General × Controls					✓

Note: This table presents regression results where the dependent variable is respondent-level affective polarization in the 2024 election cycle, using data from the Stanford-Arizona State-Yale rolling cross-section survey from YouGov. The treatment variables are the number of negative and positive presidential campaign advertisement intensity. Panel A measures treatment by ad count and Panel B by GRP exposure. Column 1 shows the baseline specification from Equation 1 with the outcome on its original scale. Column 2 adjusts the clustering structure. Column 3 reweights observations by the number of times each enters the dataset, reflecting the stacked structure of the data. Column 4 adds individual-level demographic controls, including party identification, race, age group, household income, and education. Column 5 interacts these controls with the time indicators to allow for demographic-specific time trends. The unit of observation is a respondent-county pair. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed test)

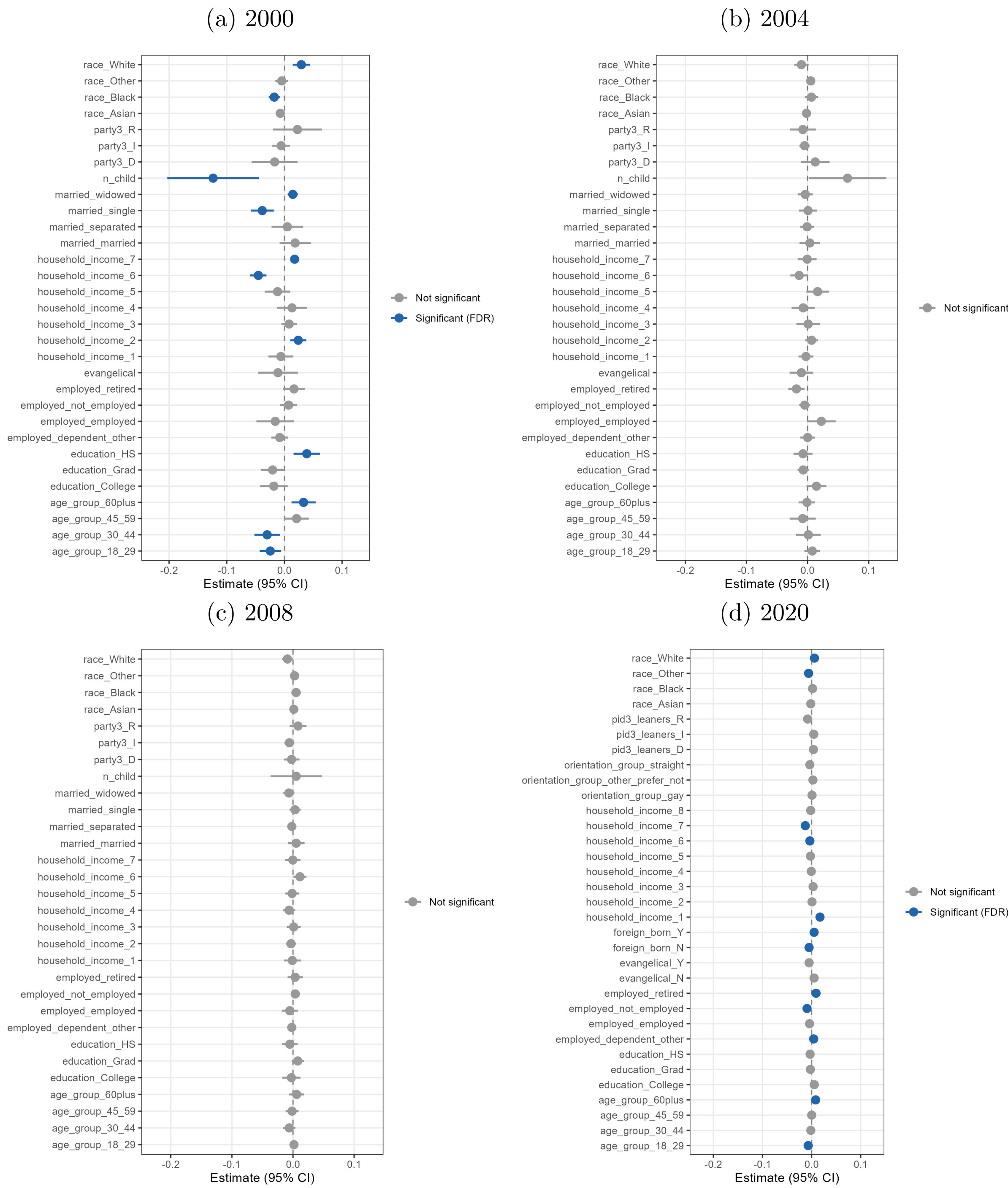
D Placebo tests

Table D9: Placebo Test: Ad Volume and Lagged Turnout Changes

	Total votes	Total votes	Turnout (Pop.)	Turnout (Pop.)	Turnout (Reg.)	Turnout (Reg.)
Change Total Ads	139.43		0.00		-0.00	
	(127.59)		(0.00)		(0.00)	
Change Negative Ads		240.47		0.00		-0.00
		(190.46)		(0.00)		(0.00)
Change Positive Ads		-168.13		-0.00		-0.00
		(114.36)		(0.00)		(0.00)
N	15,046	15,046	15,046	15,046	14,028	14,028
SE Clustered by	DMA	DMA	DMA	DMA	DMA	DMA
Election year × Pair FE	✓	✓	✓	✓	✓	✓

Note: This table presents a placebo test in which lagged changes in turnout are regressed against changes in ad volume (in thousands). Lagged changes mean that, for example, the change in turnout between 2016 and 2020 is regressed against the change in ad volume in the 2024 election. Columns 1–2 use the total number of votes cast, Columns 3–4 use turnout as a share of county population, and Columns 5–6 use turnout as a share of registered voters. Turnout figures are drawn from Dave Leip's United States Election Atlas. The unit of observation is a county pair in a election year. Standard errors are clustered at the DMA level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed test)

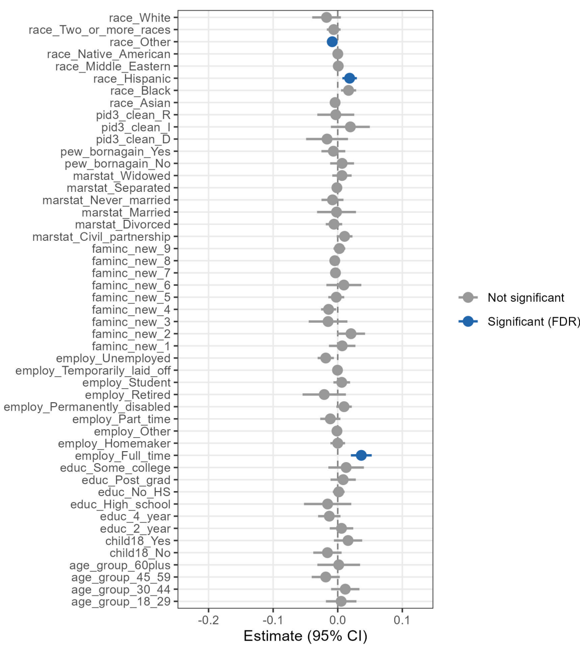
Figure D5: Covariate Balance



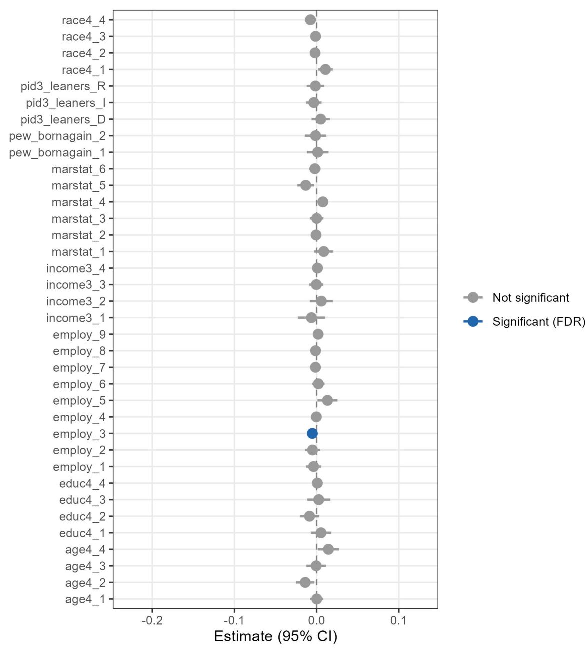
Note: This figure plots covariate balance tests across elections. Each panel indicates shows the residualized coefficient of the treatment on various demographic variables. We highlight covariates that are significant after correcting the p-values.

Figure D6: Covariate Balance Cont.

(a) 2024 – PRL



(b) 2024 – YouGov



Note: This figure plots covariate balance tests across elections. Each panel indicates shows the residualized coefficient of the treatment on various demographic variables. We highlight covariates that are significant after correcting the p-values.