Which Political Ads Work?

Evidence from Campaign TV Ads during US Congressional Elections

Adlai Newson* †

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Abstract

The spending on political advertising during campaigns in the US has increased more than five-fold over the past twenty years, yet our understanding of the causal effect of these ads is still incomplete. This paper exploits discontinuities in advertising at geographic media market boundaries that partition Congressional districts to causally estimate the effects of the ad sponsor (candidates, outside groups, party committees), ad content, and the ad tone of political advertising on Congressional candidate vote shares over the period 2004-2018. I find that advertising is indeed a powerful tool of persuasion, but that these effects are conditional on the sponsor and content of the advertisement. Voters sharply discount ads from presidential and senatorial races, but are persuaded by ads which target their local Congressional candidates and weakly by other Congressional candidates. Candidates are the most effective ad sponsors, followed by outside groups, while ads from party committees have a precisely-estimated null effect. Negative advertising is particularly effective, and does not appear to demobilize the electorate.

*Affiliation: UBC **Contact**: adlai.newson@gmail.com

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Candidates' ability to persuade voters is the cornerstone of every democratic system. In the United States, massive media campaigns are waged by Federal election candidates every two years expressly for this purpose. These media campaigns have been expanding rapidly in scale, with millions of ads run and billions of dollars spent on campaign battlegrounds that twenty years ago saw little mass media usage.[1] As the scale of these campaigns has increased, so too has the interest among scholars as to their effects. Although the academic literature on the effects of mass media communication is long indeed,[2] the fundamental question of how persuasive media works, and in which contexts, is still largely unresolved. In political settings, the primary challenge faced by researchers is the difficulty of employing convincing empirical designs. With some exceptions, extant studies have been in laboratory settings with simulated campaigns and voting behaviour or, alternatively, observational studies "which for the most part lacks compelling strategies for identifying causal effects" (DellaVigna and Gentzkow, 2010).

To contribute to this literature, I employ a quasi-experimental design that exploits discontinuities in ad viewership at 'media market' boundaries during Congressional elections to the United State House of Representatives over the period 2004-2018. Due to Federal Communications Commission regulations, cable providers are required to include all broadcast stations within a geographic region called a media market. These markets were defined by the Nielsen Company with the intention of creating contiguous groups of similar viewers, and are typically centred around large municipalities. To estimate voters' exposure to political advertisements, each ad airing is matched with viewership data corresponding to the time of day and station the ad was aired on. The result is a market-level measure of viewership, also called impressions, for each advertisement. Because the media market is a regulated border for cable provider content, counties on either side of a media market

[1] See opensecrets.org/campaign-expenditures for access to these data. An estimated \$2.83B was spent on political broadcast and national cable ads in 2016 (Franklin Fowler, Ridout and Franz, 2016), seven times the total amount raised for all purposes by presidential candidates in 1996.

[2] See, for example, Bernays (1928) and Downs (1957)

boundary are exposed to different local broadcast stations. Figure 1 shows how this strategy matches media market border-counties with each neighbouring county in a different media market but within the same Congressional district. The differences in ad exposure between these media market border counties provide the identifying variation used to estimate the effects of advertising on vote share.

The strength of this strategy is twofold. First, this approach has the virtue of using real-world advertising and voting outcomes. Experimental studies typically rely on soliciting participants intention to vote in simulated campaign settings (e.g., Ansolabehere et al. (1994); Dowling and Wichowsky (2015); Brooks and Murov (2012)). This is problematic both because stated intent in a laboratory setting may be a poor measure of voting behaviour, and because in laboratory settings ads are viewed in isolation rather than as part of an overall campaign, where candidates may choose ads strategically according to the actions of their opponent. In contrast, studying the effect of advertising exposure on vote shares in real-world campaigns both allows for candidates to choose their ads strategically at the media market level, and ensures that these effects are on the ultimate object of candidates' interest: vote shares. Compared with extant work observational work, the strength of this strategy the match between neighbouring counties that are similar but for their membership in different media markets. Because media markets are typically centered on municipalities, counties along a media market border represent 3.5% of the population of the congressional district at the median. Voters in these rural counties are members of the same Congressional district voting for the same Congressional candidate, and as such make for a more realistic counterfactual for advertising exposure than counties which are less geographically or politically proximate.

Using this design, I establish that these ads do in fact work to increase candidates' vote shares: in the baseline specification, a one standard deviation in advertising exposure (roughly sixty advertisement views per citizen across the electoral cycle) nets the candidate

0.4% in vote share. I show robustness of this persuasive effect to several measures of ad exposure and functional forms, representing differing assumptions about how ad exposure affects voters. Next, I turn to the features of ads which appear most effective. In particular, I contribute to several recurrent themes in the literature on political advertising: 1) how voters account for the sponsor of ads, between candidates, party committees, and outside groups; 2) the strength of vertical and horizontal spillover effects from other races (e.g., ads run for presidential candidates); 3) the effectiveness of negative/attack advertisements; 4) the relevance of policy-oriented versus more personal ads run by candidates; and 5) partisan difference in the use and effectiveness of advertising.

I find that voters largely discount ads for presidential and senatorial elections when deciding which Congressperson to vote for (vertical spillover). Similarly but to a lesser degree, voters discount ads for Congressional candidates which they cannot vote for, but whose ads they are directly exposed to because they share the same media market (horizontal spillover). Taken together, these results suggest presidential and senatorial media campaigns do not assist down-ballot co-partisans, and that the electorate is able to distinguish ads based on the *specificity* of ad content to the campaigning candidates. Next, I find large heterogeneity in ad effectiveness by the sponsor of the ad. Ads run by candidates have large effects on the electorate, followed by ads run by third parties, which I refer to as *outside groups*. Ads run by party committees (e.g., the Democratic Congressional Campaign Committee) have little to no effect. Negative advertising is particularly effective, and when compared to the Democratic party, Republican party negative ads are more effective at decreasing the vote share of the Democratic candidate and increasing the vote share of the Republican candidate.

These results touch on several strains of research across marketing, political economy, and political science. The effect of media on political outcomes has been studied at least since Klapper (1960) who argued that persuasive media accounted for very little in political outcomes[3]. Perhaps it is surprising, then, that many of the original questions remain. While many modern scholars argue that political advertising does have persuasive effects (Jacobson, 2015), the Klapper's 'minimal effects' hypothesis survives to this day[4]. Even where scholars agree that advertising is effective, they disagree about the features of ads which make them so. Some scholars find little evidence that negative campaigning works or demobilizes the electorate (Lau and Rovner, 2009; Lau, Sigelman and Rovner, 2007; Krasno and Green, 2008; Goldstein and Freedman, 2002), while others find it effective and demobilizing (Ansolabehere, Iyengar and Simon, 1999; Ansolabehere et al., 1994). Some research finds that ads sponsored by outside groups are particularly effective (Dowling and Wichowsky, 2015; Brooks and Murov, 2012), while other research finds it ineffective (Wang, Lewis and Schweidel, 2018). Some studies find informing voters about policy persuasive (Kendall, Nannicini and Trebbi, 2015; Cruz et al., 2018; Bidwell, Casey and Glennerster, 2020), while others argue the persuasive effect of informational treatments are zero (Dunning et al., 2019). I review these cleavages in the literature in the context of this article's contribution to these debates.

The first strain of research is concerned with how voters respond based on the source of political messages. In a formal model of the effects of media on the electorate, Prat (2002) argues that voters may insufficiently discount ads from candidates funded by interested third parties, while in the formal work of Bernhardt, Krasa and Polborn (2008), rational voters with partisan news preferences distort electoral outcomes through media bias. In more empirical work, Chiang and Knight (2011) find that the most persuasive newspaper endorsements of candidates come from the least-biased sources, and DellaVigna and Kaplan (2007) find that the introduction of Fox News increased Republican vote shares. All else equal, the predictions from this branch of literature is that voters should find outside group ads relatively more persuasive than ads run by candidates, who are the most-biased source

[3]See McQuail (1987) for a history of ideas with respect to mass media

[4]See, for example, Kalla and Broockman (2018), who conduct a meta-analysis of informational treatments and find no evidence of effectiveness.

of information. In line with this prediction, both Brooks and Murov (2012) and Dowling and Wichowsky (2015) find that attack ads by outside groups are more effective than those run by candidates in laboratory settings. In contrast, however, Wang, Lewis and Schweidel (2018) finds little effect of outside-group ads run in Senate races. I contribute to this debate by showing that outside group spending is indeed effective, but with an effect roughly half the size of that for candidate-sponsored ads[5]. This discrepancy between experimental and observational evidence may point to differing strategic roles played by outside groups in campaigns, a discussion I defer to later in this paper.

This work also engages with the academic literature on the effectiveness of negative campaigning, typically defined as ads where the political affiliation of the ad's sender is at odds with the affiliation of the ad's subject. In a recent field experiment, Galasso, Nannicini and Nunnari (2020) find that negative advertising is effective, but in races with more than two candidates, benefits accrue most to the uninvolved party. Lau and Rovner (2009); Lau, Sigelman and Rovner (2007); Krasno and Green (2008); Goldstein and Freedman (2002) find that there is little evidence to substantiate that negative advertising is effective, nor that it depresses aggregate turnout, while earlier work on negative campaigning found strong persuasive and demobilizing effects (Ansolabehere, Iyengar and Simon, 1999; Ansolabehere et al., 1994). In line with the former assessment, I am able to reject large effects of negative advertising on turnout. However, I also find that negative campaigning is indeed a persuasive tool - estimated effects on negative campaigning are stronger and statistically more precise than those for positive ads.

Next there is the question of how persuaded voters are by the informational content of ads. Kendall, Nannicini and Trebbi (2015) run a large-scale field experiment during an Italian mayoral election. In addition to estimating the effectiveness of their randomly allocated campaign media, the authors vary the informational content of their messages and find that

[5]This is especially surprising because the marginal cost of political advertising is far higher for outside groups than for candidates: see Moshary (2020).

voters cross-update their beliefs about candidates based on policy and valence information. Similarly, Cruz et al. (2018) find that informing voters about incumbent policy changes their beliefs about the valence characteristics of candidates. This literature suggests that both emotive and informational content is informative, and that effects along one dimension can spill over into the other. [6]

This use of media market boundaries to identify the causal effect of advertising has been used to identify the spillover effects of commercial advertising (Shapiro, 2018; Shapiro, Hitsch and Tuchman, 2020), the effect of negative campaigning in senatorial campaigns (Wang, Lewis and Schweidel, 2018), and the effect of advertising at the presidential on vote shares and turnout (Spenkuch and Toniatti, 2018). Spenkuch and Toniatti (2018) find no effect on turnout, but a robust effect vote share per standard deviation increase in the partisan difference in advertising impressions. They reconcile the surprising result of finding effects on vote shares but not on turnout by arguing that advertising works by persuading opposing groups of partisans to turn out or stay home in roughly equal measure. More recently, Sides, Vavreck and Warshaw (2021) apply a similar border discontinuity approach to many Federal races. They find that effect sizes increase in down-ballot races, and they similarly estimate little vertical spillover. Unlike this paper, their primary objective is to establish the effect of advertising across different races, and do not examine the effects of ad source or content. In addition, they do not restrict their analysis to remain within Congressional districts, which as I will discuss, may contribute to the larger effect sizes in their work. The modern border-discontinuity strategy is preceded by Huber and Arceneaux (2007), who use the media markets which cross borders to estimate the effect of swing-state presidential advertising on non-swing-state voters' preferences, and Ashworth (2007), who similarly use

[6] In contrast, in field studies conducted across six developing countries, Dunning et al. (2019) find little evidence for the effectiveness of informing voters about incumbent performance. For the effect of providing information to voters on incumbency advantage, see also Larreguy, Marshall and Snyder (2018); Kam and Newson (2016); Ansolabehere, Snowberg and Snyder (2006). Similarly, media may spur electoral contestation (Fergusson, Riaño and Song, 2020; Kam and Newson, 2021)

non-battleground states to find no effect of advertising on aggregate turnout.

The remainder of the article is as follows. Section 2 introduces the datasets used in the analysis. Section 3 develops a simple model and discusses identification in the framework of an optimizing candidate. Section 4 presents the results and discussion. The conclusion follows.

1 Data

Because it is crucial for identification that media market borders are drawn between otherwise-similar counties, a discussion of how these market definitions arise is in order. Nielsen Media Market definitions were adopted by the FCC in 1992 to implement a regulatory requirement designed to protect local broadcast stations. The regulation stipulates that a cable provider which intends to sell a subscription to residents in a county must include in their subscription the county's local broadcast stations, and Nielsen market definitions were adopted by the FCC to define which local broadcast stations should be included by cable providers to which county. Figure 2 shows the geography of these markets on the mainland United States. Each cable subscriber within a given media market is thus exposed to the same set of advertisements from the local broadcast stations associated with that market. These markets typically feature at least ten counties, typically centered around an urban area. The median county interior to a media market has a 50% higher population than the median county along a market border.

The data for political advertising were obtained from the Wesleyan Media Project (WMP)[7]. These data digitally fingerprint political ads across all 210 Nielsen media markets, and in addition to data on the occurrence of these ads, the data provides information on the tone, sponsor (candidate, interest group, party, or candidate-party collaboration), and affiliation

[7]WMP is a collaboration between Wesleyan University, Bowdoin College, and Washington State University, and includes media tracking data from Kantar/Campaign Media Analysis Group (CMAG) in Washington, D.C.

(democrat, republican, etc.) of each ad. Although these data represent the universe of political ad airings run across the media markets covered during each election cycle, they only capture ads run on national cable, national network, and local broadcast television. When considering the universe of paid [8] campaign media, the three key omissions from these data are local cable advertising, radio, and online advertising. While itemized data on these additional advertising expenditures are hard to come by there, it is estimated that broadcast television spot ads are far and away the largest component of candidates' media expenditures. I will discuss the possible biases from the omission of these missing data sources in the identification section. Both Canen and Martin (2021) and Gerber et al. (2011) find that the effect of advertising is short-lived (on the order of days or weeks), and as such I follow other papers in the literature in restricting the sample to ads in the 60-day window immediately preceding the election day.

Simply counting the number of ads run in a media market makes for a poor measure of ad exposure because of the large variance in ad viewership across different stations and times within the media market. To compensate for this, I aggregate these aid airings data within 30-minute blocks for each channel on each media market, then merged with viewership data from Nielsen made available to researchers through through the Kilts marketing center at the University of Chicago. The Nielsen data tracks viewership at a high frequency throughout the year in a limited number of media markets, and in all markets covered by the CMAG data for several months. For markets which are covered at the time of the election I match the Nielsen viewership data (called *impressions*) for the time window and media market station with the ad airing observation from the CMAG data. For ads run in markets not tracked by Nielsen during the election period, I impute impressions using viewership records from the same year, including from the same market where the ads are run (during periods when the market is tracked by Nielsen). As the viewership data is only avail-

[8] As opposed to 'earned media' - coverage of candidate activities, interviews, etc by media organizations of their own accord, without paid endorsement.

able post-2006, I impute viewership data entirely for years 2004 and 2006 using population trends and Nielsen viewership data from 2008. Although the imputation for these two years bring additional estimation error into the analysis, all that is required is for this procedure to deliver an improvement in the measurement of ad exposure is that the imputed viewership figures are more accurate than using the simple count of ad airings.

Once the Nielsen AdIntel data are matched with CMAG ad airings records, the result is a 'weight' between zero and one corresponding to the average political ad impressions within each 30-minute window on each station in a media market, as a fraction of the total number of voting-age viewers across all stations in the market. This weight is then aggregated across the two months leading up to the campaign, and across the stations in market, to arrive at a single measure of ad exposure for each market, for each category of political ad, for each ad sponsor. For example, all positive ads run on all stations in a given market by Democrat-leaning outside groups which support a particular Democratic candidate are aggregated over the 60-day window preceding the election. This measure is then used as-is, or differenced across party to create a measure of relative ad exposure. For example, letting $\text{DemImp}_{k,m,\tau}(s,t)$ represent the sum of Democrat-favouring ad impressions from sponsor s (e.g., Congressional candidates) to target t (e.g., Congressional election) in airtime block a, year y, on station k airing on market m, and similar for RepImp, we have that

$$\text{Dem. Ad. Advantage}_{y,m}(s,t) = \sum_k \sum_\tau \frac{\text{DemImp}_{k,m,\tau,y}(s,t) - \text{RepImp}_{k,m,\tau,y}(s,t)}{\text{Population}_{m,y}}$$

where τ identifies the airtime of the ad, aggregated to 30-minute blocks, and k indicates a specific station in market m.

Finally, these data are combined with county-level vote data from Congressional elections 2004-2018, from uselectionatlas.org. These data provide county-level vote counts for Democratic and Republican congressional elections. These partisan vote counts are normalized by the county population to get partisan vote shares, using the 2010 census data and Census Bureau estimates for other years[9]. I refer to the difference in these two shares as the Democratic vote margin.

2 Identification and Empirical Strategy

2.1 Identification

The main specification identifies the effect of ads using variation in the relative strength of Democrat advertising induced by crossing a media market border within a congressional district. The strength of this strategy is that it is able to flexibly control for all shocks common to a pair of adjacent market-border counties within a Congressional district. To the extent that these market-border counties are similar to each other, this amounts to holding fixed a wide range of time-varying factors might otherwise confound the results. Such factors include, for instance, a preference shock for a particular party or candidate, changing economic conditions, and beliefs about government or expectations of the future. It is crucial to restrict the sample of border-counties to those that belong to the same Congressional district because quantity of advertising is likely positively correlated with candidate characteristics (e.g., fundraising ability). Table 4 shows that when market border-pairs belonging to different Congressional districts are included, the magnitude of the estimated effect of advertising increases dramatically. Because of the flexibility of this approach in controlling for all shocks common to observably-similar counties, this empirical design represents a significant improvement over designs that require differences between counties to be fixed, or to vary parametrically.

Relative to studies which use presidential advertising, using Congressional elections has several advantages. First, because there are a large number of elections and candidates,

[9]Available at http://data.gov/

results in this setting are significantly less susceptible to biases from the characteristics of a small set of candidates. For example, if television ad campaign strategy accounts for, say, the peculiar personal charisma of a particular presidential candidate by running more (or fewer) ads that highlight these qualities, estimates of ad effectiveness may be similarly peculiar. Secondly, the value of a Congressional to candidates seat should, in principle, be equal across races. A significant concern at the presidential level is that, due to the electoral college system, candidates value voters based in different states differently, and overall ad strategy may reflect what is most appealing to swing-state voters. Because Congressional ad campaigns are (at least to candidates) fought only within Congressional district boundaries, the effectiveness of advertising should be estimated from many ad campaigns targeted to a broad spectrum of people.

The key requirement in the media market border identification strategy is that latent election-relevant variables are not discontinuous at these boundaries. One important place where this requirement may fail is when candidates explicitly take the media market boundary into account when implementing their campaign strategies. I will refer to this potential source of endogeneity as *strategic endogeneity*, as opposed to the sources endogeneity discussed at the outset that do not derive from candidate campaign decisions.

One immediate source of strategic endogeneity arises from counties that border media markets but each belong to different congressional districts. To mistakenly compare border counties that cross district boundaries means that the estimates are subject to bias from comparing races that differ in many ways besides advertising exposure (candidate valence, the issues of the campaign, etc). When these cross-district borders are included in the analysis, estimates increase dramatically in magnitude, which accords with the well-established endogeneity of the field: candidates who are likely to win the election are also likely to have robust media campaigns.

Another source of this strategic endogeneity may be non-television activities of candidate's campaigns, such as online advertising. While online advertising is unlikely to affect the results for most of the sample periods, it has been on the rise. There is, however, reason to believe that online advertising campaigns are not a significant confounder of the results. Firstly, despite its looming presence in popular media, digital ad expenditure remains a "relatively low" when compared with traditional broadcast media Fowler, Franz and Ridout (2018). In Fowler, Franz and Ridout (2020), the authors note that in 2014 candidate spending on online advertising was less than 1% of their spending on broadcast media ads, and in 2016, a massive year for online advertising which saw the Trump campaign spend nearly half of its media budget on online ads, Senate candidates spending only 11% of their media budget on Google and Facebook ads, with House candidates in competitive races spending only 8%. Next, Fowler et al. (2021) find that expenditure on Facebook ads during campaigns by Congressional candidates remains essentially constant in the 25 weeks leading up to the election, whereas television expenditure rises dramatically, beginning roughly at 10 weeks before election day. They argue that Facebook ads may be used for a "more diverse range of goals," such as fundraising and recruiting volunteers, and less as a direct means of persuasion. Finally, if we suppose that online advertising is used more by candidates who cannot afford traditional media campaigns (as is argued in Fowler et al. (2021)), the estimates of the effect of broadcast media would be downward biased.

Finally, it remains to address the possible confounding effects of direct campaign outreach through canvassing and mailers. In a meta-analysis of the literature on political persuasion activities undertaken by campaigns with a focus on direct-contact, Kalla and Broockman (2018) find that the "best estimate for the persuasive effects of campaign contact and advertising-such as mail, phone calls, and canvassing-on Americans' candidate choices in general elections is zero." Nonetheless, the confidence intervals reported in these studies are typically large, and average effects may mask heterogeneous effects. Barton, Castillo and Petrie (2014), for example, in a field experiment conducted during a campaign for local office, finds no effect of direct canvassing by the candidate on partisan voters (those who would likely vote for the candidate in any case), but a large[10] effect on non-partisan voters. While the effect of meeting directly with the candidate seeking election to a local office is likely not directly comparable to Congressional elections, to the extent that Congressional campaigns use canvassing in border counties to compliment their market-wide media strategy, effects here may be overstated.

However, if a candidate accounts for latent (to the econometrician) characteristics of border-counties when she deciding how to allocate her ad purchases across the two media markets that bisect her district, the resulting estimates will likely be biased.[11] In order to better understand the source of this strategic bias, I develop a simple model to illustrate the problem and provide insight on how this bias can be quantified.

2.2 Empirical Model

Suppose the Democratic candidate utility is given by

$$U = \sum_m \lambda_m \sum_i C_i(\mu_m + f(a_m, X_i)) - \sum_m \gamma_m a_m$$

where i indexes a county with market$\times$district population share C_i, and this market$\times$district subregion m has λ_m population share of the district, and f maps a relative measure (i.e., Democrat vs. Republican) market-level advertising exposure a_m and latent county characteristic X_i into a county vote share. Parameter μ_m represents the market-level bias in vote-share for Democratic candidates, and γ_m the cost of advertising. For a stylized example, consider Figure 4.

[10] 20% increase in probability of supporting the candidate, conditional on voting

[11] Spenkuch and Toniatti (2018) argues that this is less of a concern in presidential elections because border counties are typically small, but this is potentially misleading because if border-counties are similar to each other, the sum of all such districts for a media market may represent a sizable portion of the electorate.

Candidates choose ads for each market to satisfy the optimality condition

$$\lambda_m \sum_i C_i f_1(a_m^*, X_i) = \gamma_m$$

For simplicity, let us suppose that candidates choose advertising according to the population-weighted average of these latent characteristics across the overlap between the media market and their Congressional district. A simple way to operationalize this assumption is multiplicative separability of $f(\cdot,\cdot)$, but in general this assumption may be satisfied with a wide range of functions. Letting $f_a(a_m, X_i) = g(a_m)h(X_i)$, with $g(\cdot)$ strictly monotonic, the ads policy function satisfies

$$a_m^* = g^{-1}\left(\frac{\lambda_m}{\gamma_m}\left(\sum_i C_i h(X_i)\right)^{-1}\right)$$

where $h(\cdot)$ measures the how the effectiveness of ads responds to latent favourability.

In a linear regression of vote share (the first summation in candidate utility) on advertising advantage a_m, the bias due to candidates strategically choosing ads according to unobserved border-county characteristics can be represented as $\mathrm{Cov}[X_b a_m^*]$, where X_b represents the latent characteristic in the border county. The direction of the bias will depend on two factors: 1) how the optimal ad policy responds to changes in market characteristics, and 2) the market characteristics of border counties relative to interior counties. As the strategic value of a county falls its importance in determining the advertising strategy falls, which reduces the magnitude of the bias. By observing the direction of the change in the coefficients as we consider less-strategic counties we can draw conclusions about the direction of this bias.

For example, suppose that relative to a central county c, ads run in a border county b are more effective for the Republican candidate. Although we cannot observe the magnitude of this difference $h(X_b) - h(X_c)$, simply by observing that the coefficient on a_m increases when reducing the strategic value of the county, we can conclude that the effectiveness of ads for Democratic candidates is increasing in this latent characteristic. This is, in fact, what we find in Table 5. When estimating the effectiveness of ads using counties with relatively higher strategic value (defined as the county population divided by the population of the overlap between the media market and congressional district to which the county belongs) the estimated effect *decreases*, suggesting that (under our assumption about X_b, X_c) candidates target their ads to places they expect to do worse.

In addition, by decreasing the strategic value of border counties and tracing the changes in the coefficients I can estimate the amount of bias induced by this endogeneity. As the strategic importance of a county is driven not by its population but by its population as a proportion of the market-district subregion one can vary this parameter without mechanically changing county population or other characteristics.

2.3 Empirical Strategy

The main specification identifies the effect of ads using variation in the relative strength of Democrat advertising induced by crossing a media market border within the congressional district. For each election year t, each county c appears in the data once for each cross-border pair c' in the data.

$$\text{DemCongrVoteshare}_{c,y} = \delta_c + \delta_{(c',c),y} + \beta \sum_{s,t} \text{DemAdAdvantage}_{m,y}(s,t) + \varepsilon_{c,y} \tag{1}$$

where (c, c') identifies a particular border-county pair which includes c. Observations are county-years. To build intuition for how this design works, suppose a county has exactly one neighbour that spans a media-market boundary within its Congressional district. Then this county observation appears in the data once (each year). See Figure 1 for an example with multiple counties. Each pair of cross-border counties contributes the difference in

DemAdAdvantage and *DemCongrVoteshare* between them to the estimation of β. Counties with no border-pairs are dropped from the analysis entirely. To account for this duplication of observations, and the measurement error in estimating voters' county-level advertising exposure from market-level impressions data, standard errors are clustered at the media market level. In addition, because some media cross state boundaries, I cluster at the state level, to allow correlated errors within state, so that standard errors are two-way clustered by media market and state. See Colin Cameron, Gelbach and Miller (2011) for a reference on multi-way clustering. Finally, note that each county has a fixed effect δ_c to account for persistent differences between counties across market borders.

The dependent variable *DemCongrVoteshare* is the county votes for the democratic candidate divided by the population of the county[12], and the independent variable *DemAdAdvantage*(s,t) is the standardized difference in ad count between Democrats and Republicans in ads with targeting election t from ad sponsor type s[13] For example, one such explanatory variable could be the Democratic advantage in ads run by third parties in support of a presidential election candidate. I exclude counties which belong to more than one congressional district, and analyses are robust to excluding such (possibly gerrymandered) congressional districts entirely.

3 Results

The first set of results in Table 2 confirms that political ads have an effect on election outcomes. Border-pair and county fixed effects are included, along with a four-year lag of the dependent variable, in order to control for the past election's vote outcomes of the same type (presidential or midterm). Using a two-election lag also avoids dynamic panel regression

[12]Using the population of the county instead of registered voters avoids endogeneity concerns with voter registration. All results are robust to using the two-party vote share instead.

[13]Alternatively, the proportion of all ad impressions that are favourable to the Democratic target t from source s.

bias from using the past election (Nickell, 1981). The dependent variable is the standardized difference in impressions favouring the Democratic Congressperson. The effect of this relative Democrat advantage are shown on Democratic and Republican vote-share, as well as on the difference of the two measures.

The results suggest that a one standard deviation change in the Democratic impressions advantage (about 22 ad views per voter) results in a 0.47% increase in vote share for the Democratic candidate. This result mirrors the result obtained by Spenkuch and Toniatti (2018) for the effectiveness of presidential advertising in the years 2004, 2008, and 2012, who finds that a standard deviation increase in impressions favouring the Democrat increase vote-share by 0.4%. Table 3 shows that the effects for Democrats and Republicans are symmetric, with a standard deviation of Democrat (Republican) ad impressions increasing Democrat (Republican) vote share by between 0.5 and 0.7%, and decreasing Republican (Democrat) vote share by 0.5-0.6%. These effects are somewhat larger in magnitude than but statistically indistinguishable from the estimated effect of relative ad exposure (Democrat net Republican impressions) in Table 2, which is reassuring that the relative advertising strength measure does not obscure important heterogeneity across party lines.

3.1 Ad Target

Now we move to investigate the importance election targeting. The two types of spillover possible from non-targeted ads are horizontal and vertical spillover, where horizontal refers to ads for or against Congressional candidates that are not running in the voters district, but to which the voter is exposed by sharing a media market, and vertical spillover refers to ads that target senatorial or presidential candidates[14]. To investigate these spillover effects I estimate Specification 3.

[14]For further ”downstream” spillover effects onto gubernatorial and attorneys general elections see Sides, Vavreck and Warshaw (2021)

$$\text{DemCongrVoteshare}_{c,y} = \delta_c + \delta_{(c',c),y} + \sum_{t \in P,S,M,C} \beta_t \sum_s \text{DemAdAdvantage}(s,t)_{m,y} + \varepsilon_{c,y} \quad (2)$$

Compared with Specification 1, this specification tests seperately for the effects of ads which target a presidential race (P), senatorial race (S), races for Congressional candidates who share the voters media market (M), and ads which target the voters' own congressional candididate (C). The results are shown in Table 6 . The first two columns of Table 6 use all biennial elections 2004-2018, while the last two use only the presidential elections across the same period. There are several interesting observations to make here. Firstly, and perhaps surprisingly, the largest and most significant effect by far is the effect of ads run by congressional candidates that are most pertinent to the voter's decision. Second, on observes a large increase in the effectiveness of ads irrespective of their target in presidential election years. Indeed, there is even a limited spillover effect from other congressional candidates detectable at the 10% level. One plausible explanation for this change in effect size can be found in Huber and Arceneaux (2007), who find that less-partisan and lower-information voters are more persuaded by political ads. As presidential elections have higher turnout and therefore possibly more of these low-information, less-partisan voters, voter heterogeneity is one candidate explanation for this finding. In keeping with these findings, measures of ad exposure henceforth will use only ads which are targeted for or against one of the voter's congressional district candidates.

3.2 Ad Sponsor

Moving from the importance of target to the importance of ad sponsor, Table 7 shows the effect of a partisan ad impressions difference within each type of ad sponsor: Congressional candidates (C), Congressional Party committees (P), and outside groups (O), the last of which includes independent expenditure groups.

$$\text{DemCongrVoteshare}_{c,y} = \delta_c + \delta_{(c',c),y} + \sum_{s \in C,P,O} \beta_s \text{DemAdAdvantage}_{m,y}(s, C) + \varepsilon_{c,y} \quad (3)$$

The effectiveness of ads run by party committees can be thought of along two lines of reasoning: first, voters may not strongly associate ads run by a party committee to the candidate. This may allow the candidate to 'offload' ads to the party committee which might otherwise provoke backlash among voters if aired by the candidate. Second, the party may take into account spillover effects of its own advertising onto other congressional races, whereas in principle a candidate's only concern is their own (re)election. Perhaps surprisingly, Table 7 shows that these party committee ads have little discernible effect on voters. If the reason for this weak effect is that party committees account for spillover effects onto neighbouring congressional district races, Table 6 offers little encouragement.

Two notable members of the outside expenditure group are "SuperPACs" and 501(c)(4) "dark money" groups. A number of judicial rulings in 2010, including Citizens United v. Federal Election Commission, lifted fundraising and expenditure limitations by these types of organization, and the majority of these expenditures are in media. The funding source for these outside ads is typically impossible to identify from the ad itself, leading to widespread concerns that these ads reduce the accountability of the democratic process by giving anonymous actors the ability to sway elections. In a laboratory setting, Brooks and Murov (2012) find that attack ads by outside groups are more effective than candidates. In contrast, Wang, Lewis and Schweidel (2018) finds little effect of these ads in Senate races. To my knowledge this is among the first to estimate the effectiveness of these groups in Congressional races. The results are something of a compromise between Brooks and Murov (2012) and Wang, Lewis and Schweidel (2018). Outside group ads are effective, but voters appear to discount such ads significantly relative to candidate ads. There are (at least) two ways to view the heterogeneity in these effects. Firstly, non-candidate entities may be pursuing slightly different objectives than directly electing the candidate they support. For example, party committees may account for spillover effects into other Congressional districts, and outside groups may aim to increase support for specific policies in addition to increasing their favoured candidate's vote-share. A second possibility for this heterogeneity is that entities fulfill different roles in campaign strategy. For example, about ninety percent of outside group ads are negative, with little difference between Democrats and Republicans, compared with only twenty to thirty percent negative ads for candidates.

3.3 Ad Tone

The results of the previous section suggest that an important reason for the difference in the efficacy of ads may be how voters respond to the tone of advertising. The most frequent definition of negative advertising is simply the mismatch between the partisan affiliation of the source and affiliation of the target of the ad. If a candidate runs an ad which exclusively discusses her opponent, the argument goes, it is unlikely to be a flattering portrait. Using this definition of tone, researchers have established a body of work, both theoretical and empirical, on tone's possible effects on voter behaviour.

The first of these two camps, championed by Lau and Rovner (2009), views negative advertising as a crucial means of informing the electorate about candidates. A candidate can likely be counted on to advertise her strengths, but is much less likely to divulge her mistakes, and as such attack advertising provides voters with the information required to make an informed choice.

I test whether the volume of negative ad impressions has consequences for current or future turnout. I also explore the persuasive effect of negative advertising by estimating the marginal effect of an additional negative ad impression, and the effect of a maginal change in the overall race tone. In order to test for robustness I use three distinct measures of ad negativity: the traditional definition of mismatch between affiliation of ad sender and ad target, the binary response of human coders asked to state whether the primary tone of the advertisement is Positive, Negative, or Contrast[15], and finally, a principal component analysis at the ad level which includes a large set of dummies about primarily affective features of the advertisement.

Included in the CMAG data are a suite of dummy variables corresponding to each ad, covering features of the ad that are primarily affective. For each year I take the first principal component at the ad airing level, orient this vector according to the coder's definition of ad tone, then aggregate the ads across the campaign period at the market level. As a result, I am left with a measure of the positivity of each sponsor's overall campaign in each market they runs ads in. This measure strongly tracks the binary human-coded measure of tone (similarly aggregated to the market-sponsor level), but may represent a more granular measure, and is hopefully immune to the possible biases of human coders.

4 Conclusion

In conclusion, I contribute to the literature on the effect of advertising on political outcomes by exploiting the discontinuities in advertising at geographic media market boundaries that lie within congressional districts. First, I find that advertising is indeed a powerful tool for influencing vote shares; a standard deviation in advertising exposure increases a candidates' vote share by 0.4%. Voters sharply discount ads for "up-ticket" elections (presidential and senatorial), but ads for other congressional candidates are roughly half as influential as ads for the voters' own Congressional candidate during presidential election years. I find that ads run by candidates are far more effective than those run by outside groups or party committees. I further find that while both positive and negative ads are effective, results strongly

[15]Contrast ads represent a small minority of ads, and results are insensitive to dropping these ads

indicate that negative advertising is the driving persuasive force. I find little evidence for a demobilizing effect of negative advertising.

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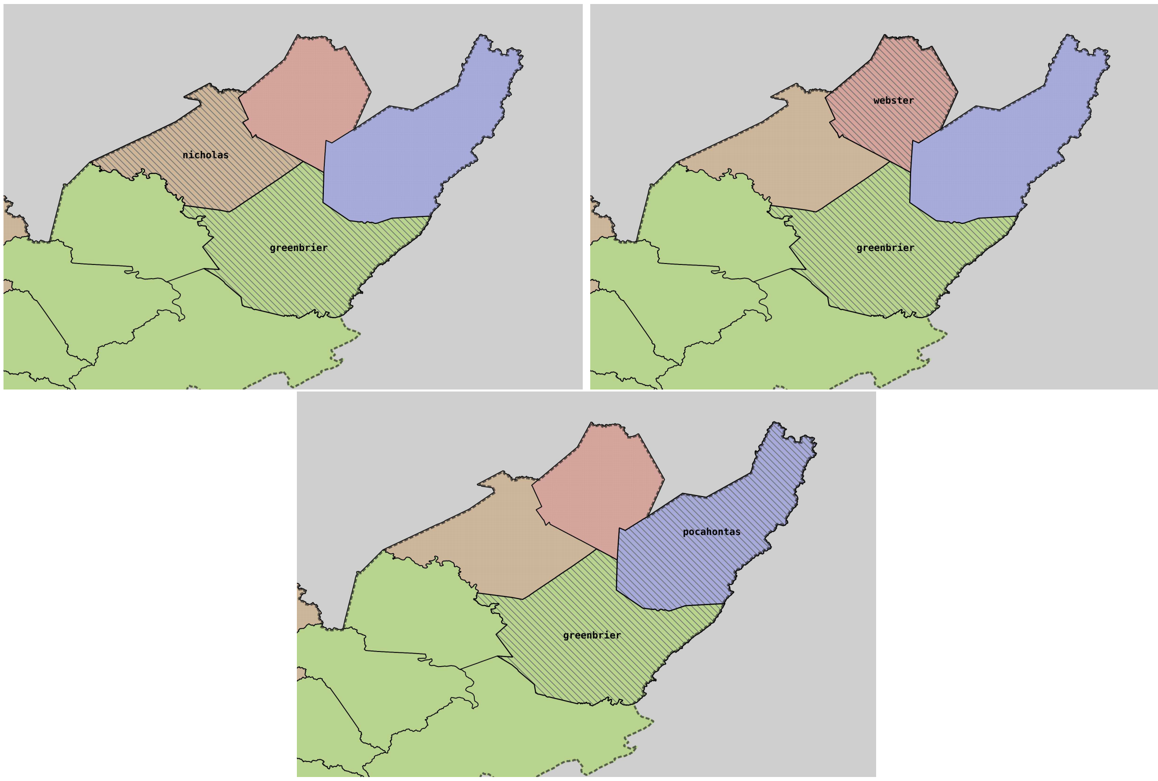
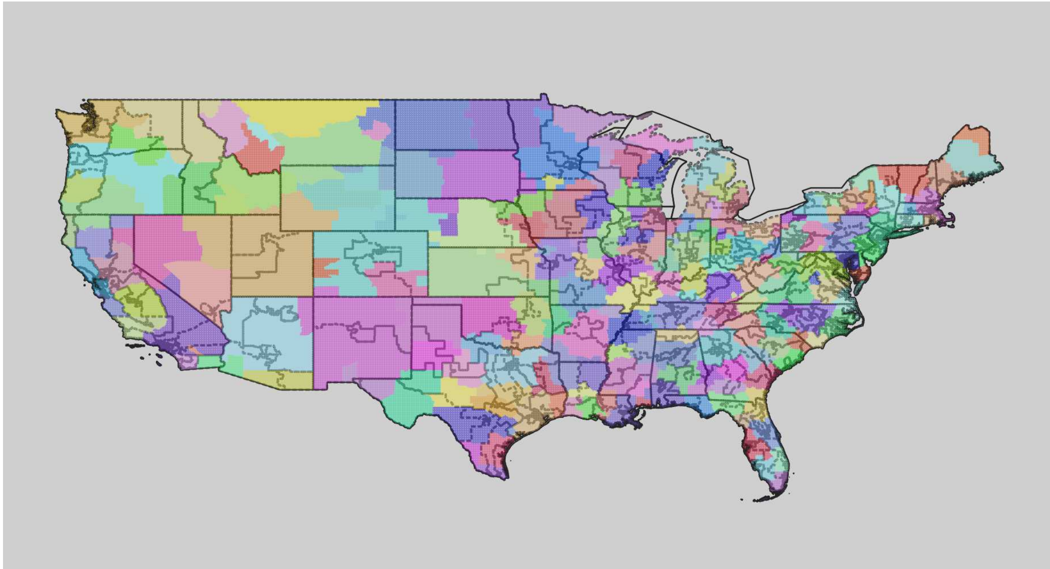
A Figures

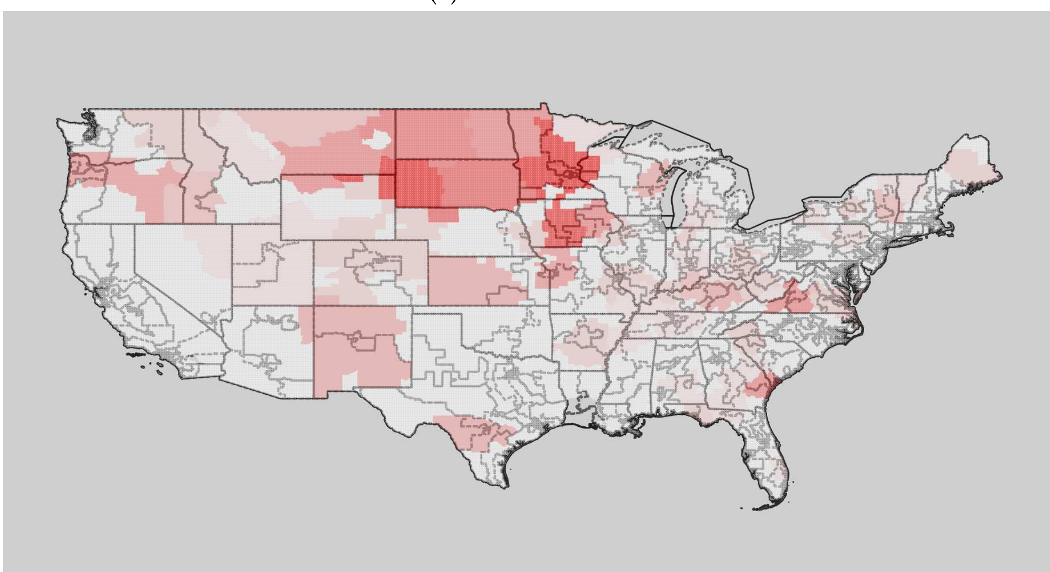


Above is an example of how the border-pair identification strategy works, using a section of West Virginia's 3rd Congressional District (WV3). There are four media markets which intersect WV3, represented by the four colours on the map. For each electoral cycle, the county of Greenbrier is included as an observation once for each neighbour it has in a different media market. Thus, Greenbrier appears three times in each year: once each for Nicholas, Webster, and Pocahontas, but not for its neighbours within the same Media Market, or with an counties outside the Congressional District.

Figure 1: Identification using Market-Border Counties



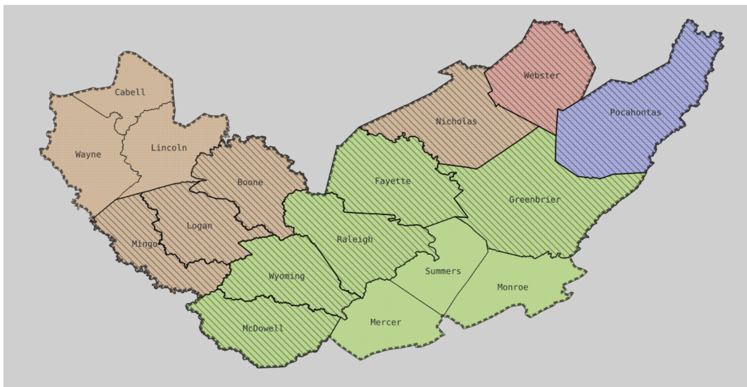
(a) Media Markets



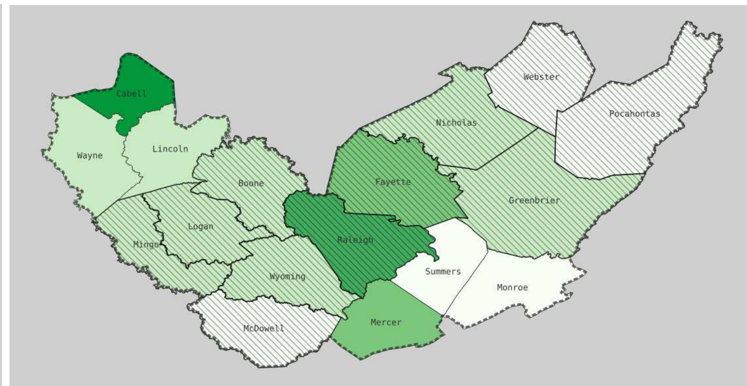
(b) Advertising Intensity, 2010

Figure 2: Nielsen Media Markets

Shown are the Nielsen Media Markets and Congressional districts for the United States. Congressional outlines are in gray. Figure a) colour-codes the 210 media markets used in the sample, and Panel b) shows the distribution of advertising intensity (measured by the total number of air airings) by Congressional Candidates across these media markets during the 2010 Congressional election, using intervals of 500 ad airings, from 0 (white) to 6,000 (dark red).



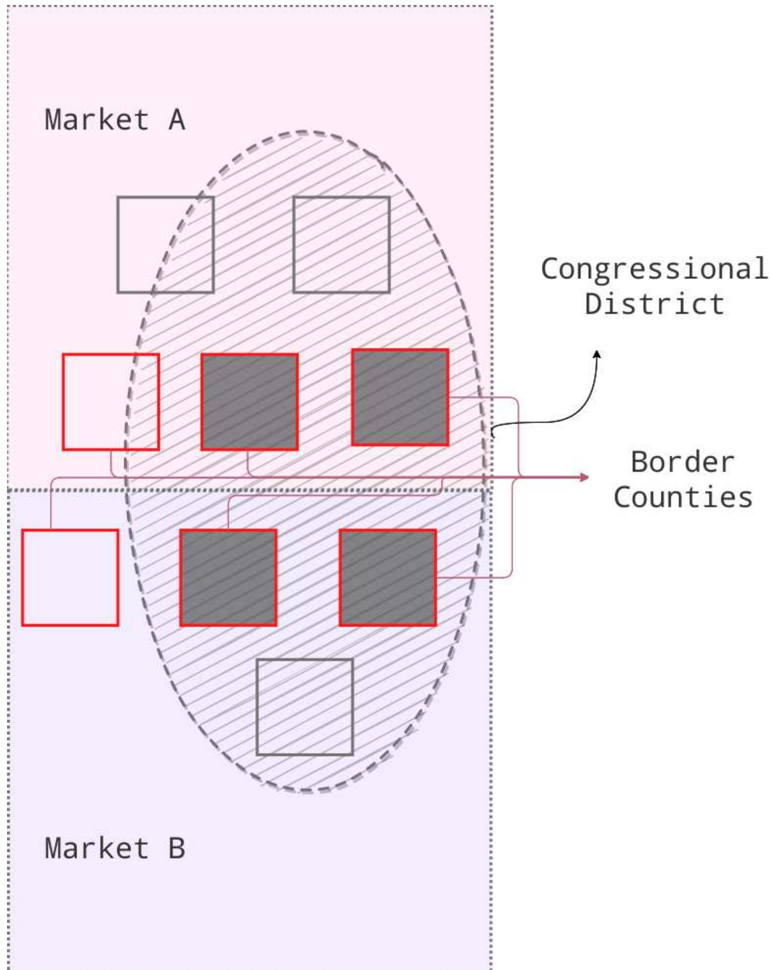
(a) Media Markets



(b) Population

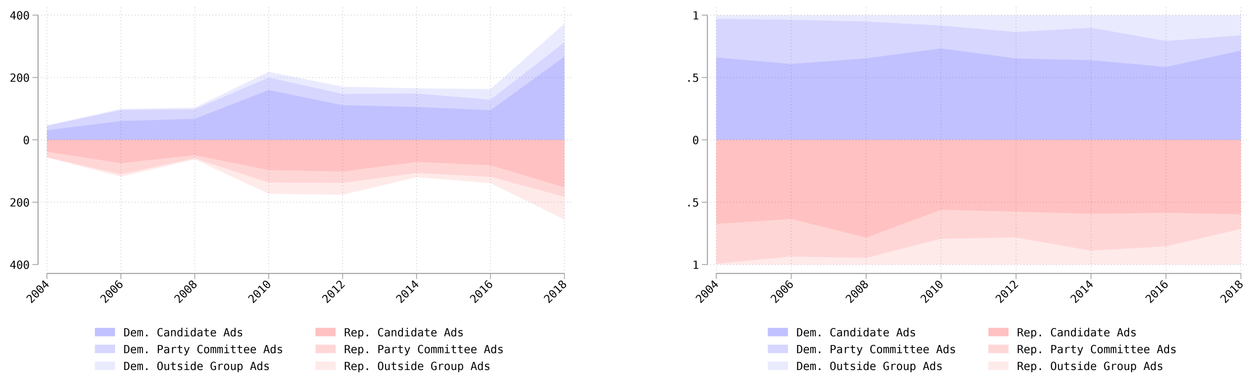
Shown are the media market border counties of the third Congressional District in Virginia. Counties along media market borders are patterned with stripes. Panel a) shows the overlap between the four media markets and the Congressional district counties, with each colour representing a different market. Figure b) shows the distribution of the county population across the Congressional district, in increments of approximately 20,000 residents, between 8,300 (white) and 93,000 (dark green). Note in b) that while two of the three populous counties of the district are not along a media market border, one (Raleigh) is.

Figure 3: W. Virginia 3rd Congressional District



Shown is a stylized example of how counties, markets, and congressional districts interact. The ovular Congressional district spans two media markets, A and B. The sum of the population of the counties (squares) that lie within the district-market intersection represent the number of voters for that candidate residing in a particular media market, i.e., the strategic value of the market to the candidate. The population of these subregions are represented by λ_m in the empirical model. Here there are two such subregions, each with three counties (for estimation, the counties partially overlapping the Congressional district in Market A are either individually excluded, or for robustness, all Congressional districts with overlapping counties are excluded).

Figure 4: Markets, Counties, Congressional Districts



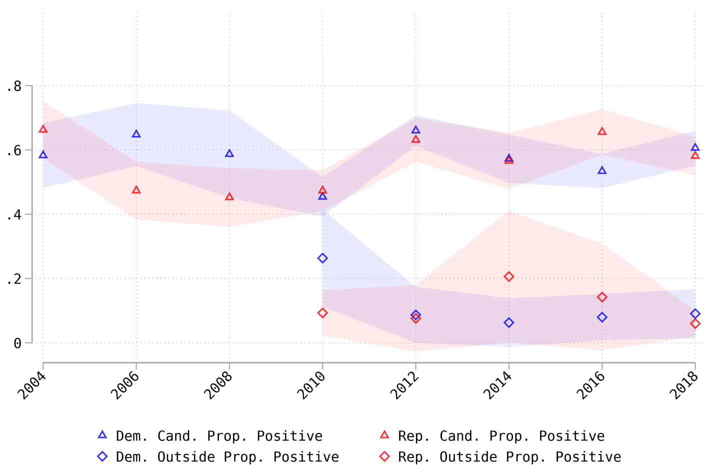
(a) Total Number of Ads

(b) Proportion of Ads by Ad Sponsor

The figures above show the trends in aid airings targeted to Congressional races across time. The left figure shows the total number of Congressional ads by all sponsors (Candidates, Outside Groups, and Party Committees) stacked vertically, and the right figure shows the proportion of total ads run by each sponsor.

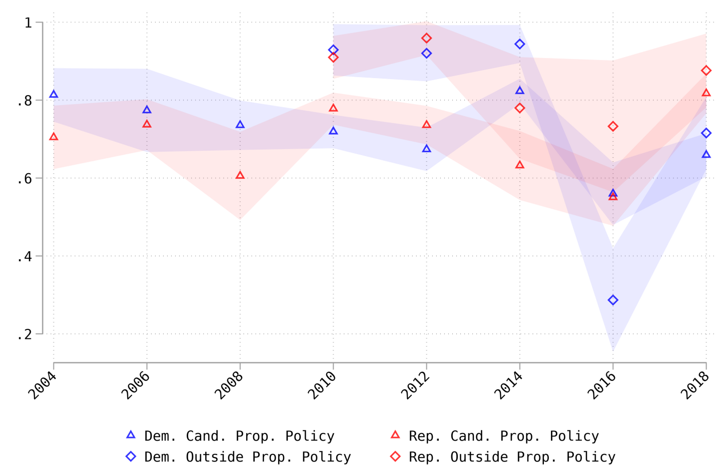
Figure 5: Total Number of Ads (in thousands)

(a) **Tone**



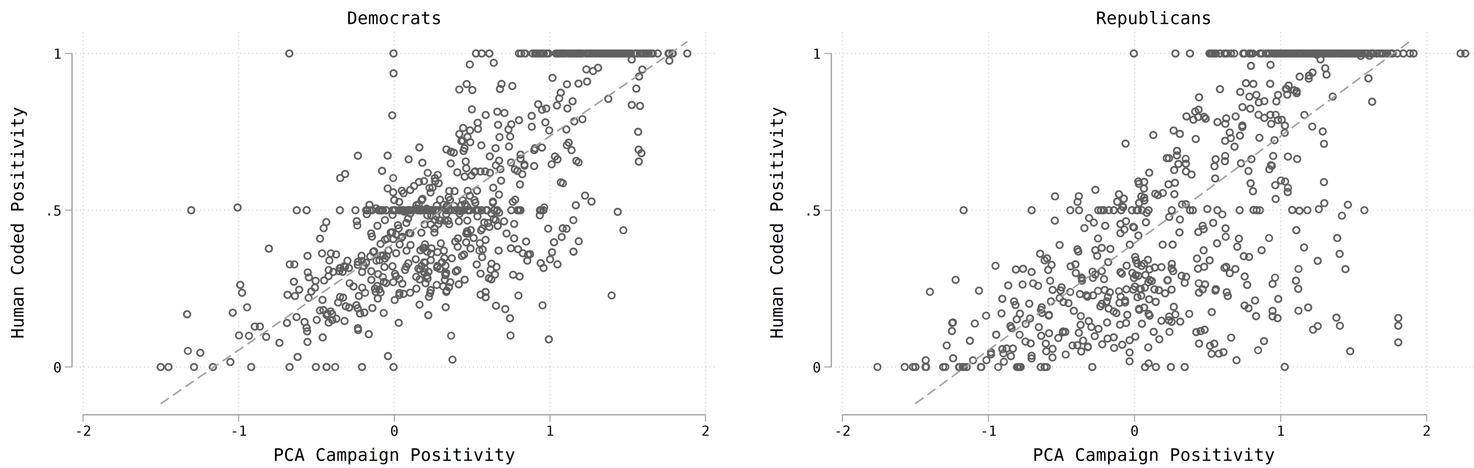
(b) Figure show the proportion of positive ad exposures by Democrats, Republicans including all campaign actors (Candidates, Outside Groups, and Party Committees). The proportion is obtained by aggregating the human-coded response to the question: *In your judgment, is the primary purpose of the ad to promote a specific candidate, attack a candidate, or contrast the candidates?* Contrast ads are treated as half positive and half negative, but results are not sensitive to this assumption.

(c) **Policy**



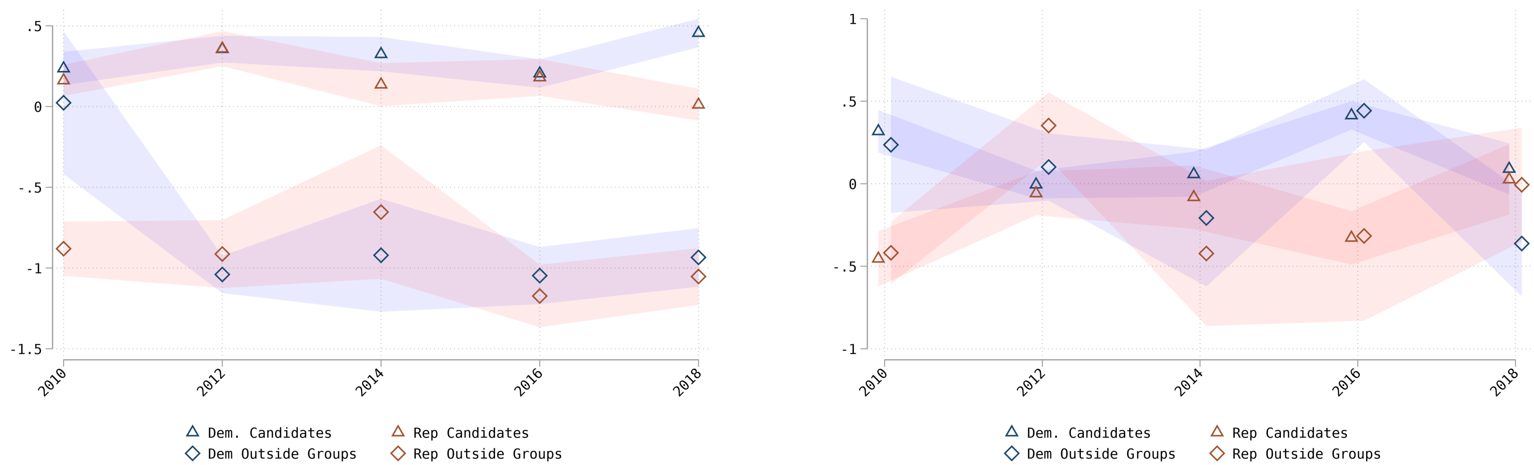
(d) Figure show the proportion of policy ad exposures run by Democrats, Republicans including all campaign actors (Candidates, Outside Groups, and Party Committees). The proportion is obtained by aggregating the human-coded response to the question: *In your judgment, is the primary focus of the ad personal characteristics of either candidate or policy matters?*

Figure 6: Ad Content: Prop. Policy and Prop. Positive



This figure shows the relationship between the aggregated human-coded response to the question *In your judgment, is the primary purpose of the ad to promote a specific candidate, attack a candidate, or contrast the candidates?*, the the first principal component of a set of emotive dummy variables (eg: is there music playing, does the candidate appear in the ad, does the ad make an appeal to fear,etc).

Figure 7: Tone Measures: Human vs. PCA



(a) Tone

(b) Issues

This figure shows the relationship candidates and outside groups, by party affiliation, in the use of negative campaigning and ad content. For panel b), each ad has a set of dummy variables indicating whether the ad discussed a particular issue (eg, Taxes, Healthcare, Poverty, etc). Figure b) plots the average within each of the four groups of the issues vector projected on to the first principle component of the matrix $X'X$, where X is of size (Number of Ads)$\times$(Number of Issues). This is done within each year, and the oriented within-year to positively predict affiliation with Democrats (i.e., higher values of the PCA projection scalar should indicate policies mentioned more often by Democrats). These issue data are only available in the Wesleyan data, which are only provided contiguously after 2008.

Figure 8: Tone and Content: Candidates and Outside Groups

B Tables

	Democrats		Republicans	
	Mean	Std. Dev.	Mean	Std. Dev.
Votes As Share Of County Population	14	8	22	9
Total Ads (Count)/100	14	18	11	14
Total Ads (Impressions/100,000)	22	49	18	43
Candidate Ads (Impressions/100,000)	16	34	12	25
Party Committee Ads (Impressions/100,000)	14	22	14	27
Outside Group Ads (Impressions/100,000)	9	20	10	22

Table 1: Summary Statistics

	(1)	(2)	(3)
	Dem. Vote Share	Rep. Vote Share	Dem. Vote Margin
Dem Ad Adv.	0.258***	-0.205**	0.459**
	(0.095)	(0.093)	(0.174)
County FE	X	X	X
Border-pair x Year FE	X	X	X
Lagged Dep. Var	Yes	Yes	Yes
N	15656	15656	15656
R2	0.981	0.984	0.981

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Dem. Ad. Adv.* is the difference in all ads run by Democratic ad sponsors and all ads run by Republican ad sponsors, and this difference is standardized to have unit variance. The dependent variable *Dem. (Rep) Vote Share* is the number of votes for the Democratic (Republican) Congressional candidate, divided by county population, *Dem. Vote Margin* is the difference in the two previous dependent variables, and *Turnout* is the total number of votes, divided by county population. Standard errors are two-way clustered at the $\mathrm{MediaMarket} + \mathrm{State}$ level. An observation is a county, and ad exposure is measured at the media market level. Each county$\times$year is observed once for each pair it has across a media-market boundary within the congressional district.

Table 2: Effectiveness of Advertising Exposure

	(1) Dem. Vote Share	(2) Rep. Vote Share	(3) Dem. Vote Margin	(4) Turnout
Dem. Ad Impressions	0.394***	-0.292**	0.681***	0.098
	(0.117)	(0.112)	(0.212)	(0.083)
Rep. Ad Impressions	-0.371***	0.338***	-0.709***	-0.018
	(0.098)	(0.113)	(0.199)	(0.073)
County FE	X	X	X	X
Border-pair x Year FE	X	X	X	X
Lagged Dep. Var	Yes	Yes	Yes	Yes
N	15656	15656	15656	15656
R2	0.981	0.984	0.981	0.985

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Dem. (Rep) Ad Impressions* measures the number of views of Democratic (Republican) ads by county residents of voting age, as a proportion of county population. *Dem. (Rep) Vote Share* is the number of votes for the Democratic (Republican) Congressional candidate, divided by county population, *Dem. Vote Margin* is the difference in the two previous dependent variables. Standard errors are two-way clustered at the $\mathrm{MediaMarket} + \mathrm{State}$ level. An observation is a county, and ad exposure is measured at the media market level. Each county$\times$year is observed once for each pair it has across a media-market boundary within the congressional district.

Table 3: Partisan Effectiveness of Advertising Exposure

	(1)	(2)	(3)
	Dem. Vote Share	Rep. Vote Share	Dem. Vote Margin
Dem Ad Adv.	0.360***	-0.291**	0.653***
	(0.100)	(0.119)	(0.204)
County FE	X	X	X
Border-pair x Year FE	X	X	X
County Sample	Within-State	Within-State	Within-State
Lagged Dep. Var	Yes	Yes	Yes
N	25902	25902	25902
R2	0.968	0.972	0.968

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors are two-way clustered at the $\mathrm{MediaMarket} + \mathrm{State}$ level. The table shows that compared with the baseline estimates in Table 2, when border-pair counties are included which belong to different Congressional districts, the magnitude of the estimates increase dramatically. This suggests that a candidate's advertising advantage is positively correlated with latent positive characteristics (for example, fundraising ability). An observation is a county, and ad exposure is measured at the media market level. Each county$\times$year is observed once for each pair it has across a media-market boundary within the congressional district.

Table 4: Using Within-Race versus Within-State Boundaries

	(1) Dem. Vote Share	(2) Rep. Vote Share	(3) Dem. Vote Margin
County Strategic Value $\leq$ 10%=0 $\times$ Dem. Ad Adv.	0.626**	-0.681**	1.295**
	(0.261)	(0.282)	(0.513)
County Strategic Value $\leq$ 10%=1 $\times$ Dem. Ad Adv.	0.895**	-1.288***	2.180***
	(0.371)	(0.345)	(0.655)
County FE	X	X	X
Border-pair x Year FE	X	X	X
Lagged Dep. Var	Yes	Yes	Yes
N	15656	15656	15656
R2	0.981	0.984	0.981

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors are two-way clustered at the $\mathrm{MediaMarket} + \mathrm{State}$ level. An observation is a county, and ad exposure is measured at the media market level. Each county$\times$year is observed once for each pair it has across a media-market boundary within the congressional district. County strategic value is defined as the county population divided by the population of the overlap of the Media Market and congressional district - it thus represents the importance of a county (in terms of potential voter share) in the candidate's decision to run an ad in the media market.

Table 5: Effectiveness of Ad Impressions: Bias

	(1) Dem. Vote Margin	(2) Dem. Vote Margin	(3) Dem. Vote Margin	(4) Dem. Vote Margin
Dem Ad Adv. in				
Ads Targeting All Races	0.104			
	(0.066)			
Dem Ad Adv. in				
Ads Targeting Congr. Race		0.459^{**}	0.450^{**}	0.453^{**}
		(0.174)	(0.168)	(0.171)
Dem Ad Adv. in				
Ads Targeting Other Congr. Race			0.070	0.074
			(0.088)	(0.087)
Dem Ad Adv. in				
Ads Targeting Senatorial Race				0.063
				(0.121)
County FE	X	X	X	X
Border-pair x Year FE	X	X	X	X
Sample	All Years	All Years	All Years	All Years
SE Cluster	State + Mkt	State + Mkt	State + Mkt	State + Mkt
Lagged Dep. Var	Yes	Yes	Yes	Yes
N	15656	15656	15656	15656
R2	0.981	0.981	0.981	0.981

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Dem Ad Adv* is the standardized difference between Democratic and Republican ad impressions which target the given race. Standard errors are two-way clustered at the $\mathrm{MediaMarket} + \mathrm{State}$ level. An observation is a county, and ad exposure is measured at the media market level. Each county$\times$year is observed once for each pair it has across a media-market boundary within the congressional district.

Table 6: Effectiveness by Advertisement Target

	(1)	(2)	(3)
	Dem. Vote Share	Rep. Vote Share	Dem. Vote Margin
Candidate Sponsored			
Dem Ad Adv.	0.129^{**}	-0.129^{***}	0.256^{**}
	(0.057)	(0.047)	(0.099)
Party Committee Sponsored			
Dem Ad Adv.	0.056^{*}	0.012	0.043
	(0.029)	(0.038)	(0.056)
Outside Group Sponsored			
Dem Ad Adv.	0.078^{**}	-0.078^{**}	0.159^{**}
	(0.037)	(0.034)	(0.062)
County FE	X	X	X
Border-pair x Year FE	X	X	X
Lagged Dep. Var	Yes	Yes	Yes
N	15656	15656	15656
R2	0.981	0.984	0.981

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Candidate Sponsored Dem Ad Adv* is the difference between the number of impressions of ads run by the Democratic Congressional candidate and the Republican Congressional Candidate, and similar for party committee and outside group sponsored ads. Standard errors are two-way clustered at the $\mathrm{MediaMarket} + \mathrm{State}$ level. An observation is a county, and ad exposure is measured at the media market level. Each county$\times$year is observed once for each pair it has across a media-market boundary within the congressional district.

Table 7: Effectiveness by Advertisement Sponsor

	(1) Turnout	(2) Turnout	(3) Turnout	(4) Turnout $t+2$	(5) Turnout $t+4$
Prop. Positive	0.193	0.299	0.471	0.723	-2.019
	(0.384)	(0.415)	(0.426)	(0.756)	(2.898)
Total Impressions		0.156	0.269*	0.046	-0.254
		(0.111)	(0.146)	(0.162)	(0.201)
Prop. Positive × Total Impressions			-0.741	0.265	0.724
			(0.479)	(0.650)	(1.381)
County FE	X	X	X	X	X
Border-pair x Year FE	X	X	X	X	X
Turnout Control	Prev. Cycle	Prev. Cycle	Prev. Cycle	Curr. Cycle	Curr. Cycle
Lagged Dep. Var	Yes	Yes	Yes	Yes	Yes
N	2984	2984	2984	2046	638
R2	0.992	0.992	0.992	0.992	0.996

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors are two-way clustered at the $\mathrm{MediaMarket{+}State}$ level. An observation is a county, and ad exposure is measured at the media market level. Each county×year is observed once for each pair it has across a media-market boundary within the congressional district.

Table 8: Effect of Tone on Next-Cycle Turnout

	(1) Dem. Vote Share	(2) Rep. Vote Share	(3) Dem. Vote Margin	(4) Dem. Vote Margin	(5) Dem. Vote Margin
Dem Ad Adv.					
in Positive Ads	0.156	-0.150	0.301	0.272	0.333
	(0.100)	(0.110)	(0.199)	(0.230)	(0.336)
Dem Ad Adv.					
in Negative Ads	0.245**	-0.175*	0.425**	0.166	0.708**
	(0.114)	(0.090)	(0.179)	(0.202)	(0.319)
County FE	X	X	X	X	X
Border-pair x Year FE	X	X	X	X	X
Years	All Years	All Years	All Years	Midterms	Pres. Elections
N	15656	15656	15656	7790	7866
R2	0.981	0.984	0.981	0.981	0.985

Standard errors in parentheses. ${}^{*}p < 0.10$, ${}^{**}p < 0.05$, ${}^{***}p < 0.01$. Standard errors are two-way clustered at the $\mathrm{MediaMarket} + \mathrm{State}$ level. Tone is measured at the ad level by human coders who respond to the question: *In your judgment, is the primary purpose of the ad to promote a specific candidate, attack a candidate, or contrast the candidates?*. Contrast ads are treated as half-positive and half-negative, but can also be dropped without influencing the results. An observation is a county, and ad exposure is measured at the media market level. Each county$\times$year is observed once for each pair it has across a media-market boundary within the congressional district.

Table 9: Effectiveness of Campaign Tone