Who let the dogs out? News media attention stimulates negative political advertising

Abstract

This paper demonstrates that media attention has a meaningful impact on candidates' strategies in political campaigns. This finding adds a critical dynamic overlooked in previous studies of political campaigns.

To illustrate the critical role of media on candidates, we (1) focus on one of the most pivotal decisions candidates make—whether and when to "go negative," and (2) analyze a period during which the influence of news media can be clearly distinguished. Our dataset comprises a daily panel of Congressional races in the USA.

A key challenge in identifying the impact of the news media on tone is the potential endogeneity of news coverage. To resolve this challenge, we identify two sets of instrumental variables. The first involves the observed ownership of local newspapers by media conglomerates. Ownership shifts some of the editorial decisions (such as how much attention to pay to politics) from the local level to the national level, which is exogenous to daily tone decisions. The second exploits variables that capture newsworthy events at the daily and local levels–severe weather events, sporting contests, and major crime stories. These events can crowd-out the space allocated for political reporting.

Using a 2SLS approach (with fixed-effects and clustered standard-errors) we find that the attention of the news media encourages the candidates to employ negative ads. When the media turns its attention to a race, the candidates' likelihood of going negative increases meaningfully.

Keywords: advertising tone, negative advertising, news media, instrumental variables, dynamics, politics, panel data.

1 Introduction

The story we, as scholars, tell about political campaigns overlooks a crucial chapter: the impact of the news media on candidates. Typically, our story centers on three main characters: (i) the candidates and their strategies, (ii) the voters and their choices, and (iii) the media and its coverage. While previous studies have examined the interactions between (a) candidates and voters, and (b) media and voters, they have ignored the strategic relationship between candidates and the media.[1] This study provides empirical evidence that the media has a critical role in shaping candidates' strategies and thus omitting the news media from the analysis of political campaigns results in a misspecification.

To illustrate the critical role of media on candidates we (1) focus on one of the most important decisions of candidates – whether and when to "go negative", and (2) return to a period in which the role of the news media can be disentangled clearly. Specifically, today, it is complex to isolate the influence of the news media due to its interplay with social media. Therefore, as a first step in this journey, we turn back the clock to before Facebook and other social media platforms played a meaningful role (a recent example of this is Petrova, Sen and Yildirim 2021, which shows having twitter account helps U.S. congress candidates getting more campaign contributions), two decades ago. This historical perspective allows us to isolate the role of the news media more effectively. Moreover, the mechanism we propose in subsection 2.5 for understanding the news media's role is not confined to the political context of the early 21st century, suggesting that our findings are relevant today.

Political advertising is often negative, and this negativity is on the rise (e.g. Figure 2 in Ridout, Franz and Fowler 2014). By "negative" we refer to cases in which an ad

[1]1. This oversight is not a criticism of previous work—as starting the analysis with these two pairs (candidates and voters, and media and voters) is a sensible approach. Instead, this observation serves as a suggestion for refining our understanding of political campaigns. It proposes the next step in the analysis should include the active role of the news media in shaping the campaign. 2. As discussed below, previous scholars have studied how news media cover advertising, but to our knowledge the active role of the news media in shaping the campaign has not been studied empirically. 3. There is another interesting strategic interaction – between the two candidates. This interaction was also examined theoretically and empirically (e.g., Gordon and Hartmann 2016 and Li, Rao, Narasimhan and Gao 2022).

discusses the competitor. In our data, described below, 59 percent of ads are negative. Negativity is rarely scattered evenly over the campaign. In most cases it is concentrated in two to four distinct timespans (see Web appendix). Therefore, it is interesting not only to examine whether candidates go negative or not, but also when exactly they choose to do so. Thus, we focus our investigation on the role media plays in shaping the *dynamics* of negative advertising in political campaigns.

We collect data on 248 congressional races for the U.S. House of Representatives in 2000, 2002, and 2004. The data include daily information on both the tone of the campaign (i.e., positive or negative) and its media coverage (i.e., whether the local media covered the campaign in each specific day). We find that negativity and coverage tend to go together. Specifically, we follow tone and media coverage in the 69 days between Labor Day and Election Day, and find that in 55 percent of the occasions either the tone is negative and the coverage is high, or the tone is not negative and the coverage is low. Section 2 describes (i) the data, (ii) the time series of negativity and media coverage, (iii) their correlation, (iv) the coverage of political ads, and (v) the proposed mechanism underlying the effect of coverage on tone. In this last subsection we discuss the theoretical mechanisms and provide support for an assumption (used later) that candidates have the flexibility to decide on the tone of their ads on a daily basis.

We wish to evaluate whether increased media coverage causes negativity to increase. This hypothesized causal relationship is not necessarily implied by the simple correlation described above. In addition to potential market and time of election omitted variables, the literature has offered an alternative explanation to this correlation – reverse causality: i.e., that media is more interested in negative ads than in positive ones (Patterson 1994, Ansolabehere and Iyengar 1995, Geer 2006, Ridout and Smith 2008, Fowler and Ridout 2009, Geer 2012, West 2018). This explanation portrays media as an active participant with incentives to attend to the spectacle of negative advertising. In subsection 2.4 we provide evidence consistent with the prior research showing (using analysis of the content of more than 1000 articles) that news coverage of congressional campaign ads is heavily slanted towards echoing negative rather than positive advertising. The empirical support for this explanation and other potential threats to the validity of the estimates require that we carefully disentangle the role of media coverage in shaping negativity. To do so, we need appropriate instrumental variables to establish the hypothesized causal relationship.

In Section 3 we introduce and discuss two sets of IVs in order to handle the endogeneity of the media coverage. First, we leverage the fact that (i) in the US a small number of big media holding companies (MHCs, hereafter) own a large proportion of local newspapers, and (ii) more than one-half of the districts in our data are covered by one of the top 11 media holding companies. These MHCs tend to differ, along many dimensions, in their editorial policies including their interest in politics and in sensational news. Such policies, set at the national level, are exogenous to the daily variation in local political campaigns, and thus can serve as IVs. Furthermore, since it is likely that the editorial policies depend on the time distance from Election day, we allow the interest of MHCs to vary over time, yielding daily variation in this instrumental variable (IV).

Second, we collected data on local news-worthy events (e.g., a major crime) for each day in our sample. Such events can serve as IVs for the coverage of the political campaign because they can crowd-out the space allocated for political reporting in the relevant congressional district. The three types of events included in our data are severe weather conditions, sporting events and major crime stories. Furthermore, we distinguish among three types of sporting events (e.g., an event in the neighboring district is treated separately than one in the focal district).

Section 3 reports the results of the first stage regression – i.e., the dependent variable is the media coverage and the independent variables include (1) the instruments, (2) congressional district fixed effects, (3) days until the election fixed effects (4) year fixed effects, (5) lagged negativity, and (6) characteristics of the race, candidate, and district (e.g., whether the incumbent is running). We find that the instruments are related to media coverage as expected (e.g., political coverage is lower when there is a local sports event) and that their interaction assists in explaining the variation in coverage (e.g., the effect of crime stories is especially high among newspapers owned by the media holding company CNHI). We also find, using a partial F-test, that the instruments are relevant (not weak). To the best of our knowledge, this interim result is the first finding on the dependence of political media coverage on these variables (MHCs and crowding out).

Section 4 presents the main result of this study – the dependence of candidates' tone on media coverage. The analysis includes the controls and instruments indicated above and uses 2SLS regression, with clustered standard errors (at the district level), we find that, as expected, media coverage is an important factor in candidates' decisions to go negative. On average, when the media turns its attention to the campaign, shifting our measure of media coverage from no newspaper articles to 10 articles per day, the candidates' likelihood of going negative shifts from 50% of the ads to 67% on days when candidates advertise. This shift from no articles to 10 per day is based on the empirical distribution of media coverage, as explained in section 4.

In the robustness subsection 4.2 we show that the results hold for alternative (1) formulations of the media attention variables (e.g., continuous versus median split), (2) ways of defining the dependent variable, (3) formulations of the fixed effects (e.g., congressional district fixed effect versus race fixed effect), and (4) formulations including rival negativity. Furthermore, we also show that the results are robust to outliers.

While previous studies demonstrated that the attention of the news media is slanted toward negative ads over positive, the current study brings novel causal evidence that the attention of the media encourages the candidates to go negative. In other words, rather than just being responsive to campaign negativity, news media have an active and critical role in political campaigns that should not be ignored.

In the concluding section, we speculate on the rationale behind this result, tying together previous accounts with our new findings. For example, it is quite possible that candidates dig for dirt on their rival all the time, but wait with their findings until the media turns its attention to the race. Some accounts of campaigns suggest exactly this pattern, such as Mary Landrieu's 2008 campaign which went as far as shooting multiple ads including negative ones in February, but waited until late summer to air them (Feltus, Goldstein, and Dallek 2018). Waiting is likely to be an optimal strategy since, because the news media is more likely to amplify negative rather than positive ads (as we show in section 2).

The rest of the paper is organized as follows. Section 2 describes the data and the empirical challenge. Section 3 presents the instruments and the first stage regression. Section 4 includes the main results and various sensitivity analyses and section 5 concludes.

2 Data, challenges and mechanism

This section describes our two main data sets: (1) the tone of political advertising, and (2) the extent of media coverage. Then it describes their basic statistics and time series properties, and the correlation between negativity and coverage.

2.1 Tone and coverage

Our analysis focuses on U.S. Congressional (House of Representatives) races held in three election years: 2000, 2002, and 2004. Because our focus is on political advertising, we set the time frame of our analysis to be the 69 days leading up to Election Day (Labor Day is the traditional kickoff point for electoral advertising campaigns). To simplify the analysis, we include only those races in which just the two major parties are relevant to the contest and each candidate advertises at least once. This results in 248 races and 496 candidate/campaign level observations. Throughout we use as an observation a race-candidate-day combination. Since we follow candidates' behavior over 69 days, and in some of the analyses we use a lag of the variables, the number of sample observations in our main analysis (if there are no missing observation) is $496 \times 68 = 33{,}728$.

Using data from the beginning of the millennium has an advantage. Facebook was created exactly at the end of the studied period and over the last two decades it, and the other social media outlets, became meaningful players in the media market. The data from the beginning of the millennium enable us to estimate the role of the news media cleanly without worrying about its interaction with social media. That said, using this data also has a disadvantage – it cannot capture the interactions between the players in the media market. Accordingly, we return to discussing this issue in the concluding section.

2.1.1 Tone

The tone data are based on a methodology developed by the Campaign Media Analysis Group (CMAG) that records every ad on broadcast TV and some cable channels in a storyboard format. The CMAG data include advertising for all candidates in the races taking place in the top 75 Nielsen designated media areas (DMAs): in 2000 and the top 100 DMAs in 2002 and 2004.

The raw CMAG data contain thousands of unique advertisements. This information is coded by the Wisconsin Advertising Project (WAP) along various dimensions. Central to our study, the data include information on who the ad supports, when it was aired, and what tone it took. The original tone categories are "promote," "attack," and "contrast." We follow the prior literature (Lovett and Shachar 2011; Spenkuch and Toniatti 2018; Wang, Lewis, and Schweidel 2018; Gordon, Lovett, Luo, and Reeder 2021) and code each ad as either negative (contrast or attack) or positive (promote). Lumping "attack," and "contrast" together makes sense both theoretically and empirically. Theoretically, both attack and contrast ads are meant to undermine the rival, representing different techniques to achieve the same result.[2] It makes sense to lump them together also for empirical reasons. Specifically, the findings in Ridout and Smith (2008) illustrate that the effects of attack and contrast are almost identical in their

[2]To illustrate the negativity of a contrast ad, consider the commercial "Down" by Al Gore in 2000. Here is the text said by the narrator in the ad:

"The facts on George W. Bush's 1.6 TRILLION dollar tax cut promise. Almost half goes to the richest one percent. What trickles down? An average of 62 cents a day for most taxpayers. Bush gives almost half to the richest 1 percent, leaving 62 cents to trickle down to us.

Al Gore builds on a foundation of fiscal discipline. Pay down the nation's debt. Protect Social Security and Medicare. 10,000 dollar a year deduction for college tuition. Because the middle classes earn more than trickle down."

magnitude (1.3 and 1.437).

Candidates do not always advertise, especially at the beginning of the election cycle. In particular, while candidates show no ads 52% of the time, 85% of these ad-free days occur before the candidate airs their first ad of the campaign. After airing the first ad, days without ads are infrequent (only 15% of days). Among all days in our data, including those without ads, on average 28% of days have negative ads.

Candidates sometimes show more than one ad creative on a particular day. They also mix tones. On 29% of days in which candidates air ads, they air both positive and negative ads. In other words, on some days all ads are positive, in others all of them are negative and in the rest of the days some ads are negative and some are positive. On such mixed days (i.e., both positive and negative ads), the composition of ads is tilted towards negative (60% negative). Furthermore, in 41% of the days in which candidates' air ads, all the ads are positive, compare with only 30% of the days in which all ads are negative. The 2000 elections were the most negative (only 28% of the days were all positive) and those in 2002 the most positive (50 percent of the days were all positive). We note that, in many of our descriptive results and our main analyses, we define our negativity measures as equal to one if any of the ads aired by a candidate on that day were negative (i.e., combining negative and mixed) and term this variable $NegMix$. In the robustness subsection (section 4.2) we show that the findings are not sensitive to this formulation choice.

2.1.2 Media Coverage

To quantify the degree of media attention focused on a given race, we assemble a dataset of news articles (print or digital) that discuss the race and/or its participants. Obviously, newspapers are not the only media entity that covers political campaigns and elections, but it seems reasonable to expect that when the news media develop an interest in a congressional campaign, the interest and attention will be shared by all types of media, not just one of them. Furthermore, Schaffner (2006) demonstrated that newspapers tend to devote far more attention to members of Congress than local television stations, supporting our use of newspapers as a leading proxy.

Our data collection started with newslibrary.com. This web-based resource includes detailed news data from local newspapers. Using a variety of queries, we recorded the total number of articles in local newspapers pertaining to each candidate on a given day in the 69 days leading up to Election Day. To bolster the precision of our measure (i.e., to ensure all relevant articles are included) we used various alternative spellings for each candidate in the search tool. For example, Thaddeus McCotter, the Republican Congressman from the 11th district of Michigan, was referred to, in some articles, as Thad McCotter. We ended-up considering 243,343 articles. The average number of articles about a candidate per day is 7.21 (14.4 for the race). Not surprisingly, the off-year election (2002) received the most media attention with a daily average of 11.95 articles per candidate.

Despite our efforts, it seems reasonable to expect that the media coverage is measured with noise. Accordingly, we account for it in the estimation. Furthermore, most of our analysis is not conducted with the continuous and crude measure of media coverage, but rather with a binary variable, termed $MediaHigh$, that is based on a median split of this continuous measure. This can be justified both theoretically and empirically. Theoretically we wish to distinguish between two states: (1) media paying attention to the campaign, and (2) media not paying attention. Unlike presidential elections, Congressional elections are not as engaging for the media and thus the default coverage is very low. Our approach is meant to distinguish between those regular days and special days in which the media turns its attention to the race. This approach makes sense empirically as well since, as noted above, it is reasonable to expect that the continuous measure is too crude and a median split will have less noise. Finally, to illustrate the robustness of our result, we demonstrate, in the empirical analysis, that the results are not sensitive to our choice of using a binary variable as a measure. Specifically, we present the estimation results also when media attention is measured by the number of articles about the race on any specific day, denoted as $MediaArticles$.

Characterizing empirically the two categories of $MediaHigh$ provides additional support for the usefulness of this median split in capturing the theoretical considerations. Specifically, focusing on the observations for which $MediaHigh = 0$ we find that the mean number of articles is 0.6 and the median is zero. In other words, this captures well the state of things when the media does not pay attention to the race. On the other hand, when we focus on the observations for which $MediaHigh = 1$ we find that the mean number of articles is 28.6 and the median is 10. The differences are quite meaningful. Thus, our concept of media paying attention matches very well to $MediaHigh$. In the low group for most cases the media pays no attention. In the high group, the level of attention is quite high at ten articles a day at the median. We are contrasting between media not (really) paying attention and media paying (substantial) attention.

2.1.3 Summary Statistics

Table 1 below provides summary statistics for the data. The table includes all variables used in the analysis, some of which (control variables and instruments) will be introduced and discussed later in the paper.

2.2 Dynamics of tone and coverage

Given our interest in the dynamics of political campaigns, it makes sense to describe some of the basic time series patterns they exhibit. We first examine how candidate negativity and news media coverage vary over the 69 days leading up to each election. The left panel of Figure 1 presents the proportion of days that $NegMix$ equals one. The clear overall trend progresses steadily from low negativity to high. Campaigns generally start on a positive note, but become more and more negative as the election nears. This finding is consistent with Goldstein and Freedman (2002).

Turning to the temporal pattern of media coverage, the right panel of Figure 1 displays the variable $MediaHigh$, averaged across races for each day. As with negativity, news media coverage clearly increases over time, though with a more marked acceleration in the last twenty days of the contest. Indeed, the day with the lowest

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
NegMix	33,728	0.281	0.450	0	0	1	1
NegMix_Lagged	33,728	0.272	0.445	0	0	1	1
OnlyNegative	33,728	0.143	0.350	0	0	0	1
OnlyNegative_Lagged	33,728	0.139	0.346	0	0	0	1
MediaHigh	33,728	0.493	0.500	0	0	1	1
MediaArticles	33,728	14.430	37.442	0	0	9	1,400
TossUps	33,728	0.129	0.335	0	0	0	1
OpenSeat	33,728	0.274	0.446	0	0	1	1
SameOpponent	33,728	0.105	0.306	0	0	0	1
PercentWhite	33,728	0.787	0.153	0.180	0.700	0.903	0.970
PercentBachelorsDegree	33,728	0.235	0.083	0.060	0.170	0.280	0.560
MeanHouseholdIncome	33,728	0.438	0.112	0.272	0.360	0.483	0.916
Frontrunner	33,728	0.304	0.460	0	0	1	1
Incumbent	33,728	0.373	0.484	0	0	1	1
Weather	33,728	0.010	0.102	0	0	0	1
Sport	33,728	0.050	0.219	0	0	0	1
SportSameState	33,728	0.039	0.193	0	0	0	1
SportNextDistrict	33,728	0.096	0.295	0	0	0	1
NewsCrime	33,728	0.008	0.089	0	0	0	1
MHC_Gannet	33,728	0.218	0.413	0	0	0	1
MHC_CNHI	33,728	0.206	0.404	0	0	0	1
MHC_Lee.Enterprises	33,728	0.065	0.246	0	0	0	1
MHC_Ogden	33,728	0.073	0.259	0	0	0	1
MHC_Boone	33,728	0.024	0.154	0	0	0	1
MHC_Landmark	33,728	0.117	0.321	0	0	0	1
MHC_Paxton	33,728	0.081	0.272	0	0	0	1
MHC_Knight.Ridder	33,728	0.052	0.223	0	0	0	1
MHC_New.Media.Corp	33,728	0.044	0.206	0	0	0	1
MHC_Hearst.Newspapers	33,728	0.032	0.177	0	0	0	1
MHC_Pulitzer.Inc	33,728	0.032	0.177	0	0	0	1

Table 1: Summary Statistics

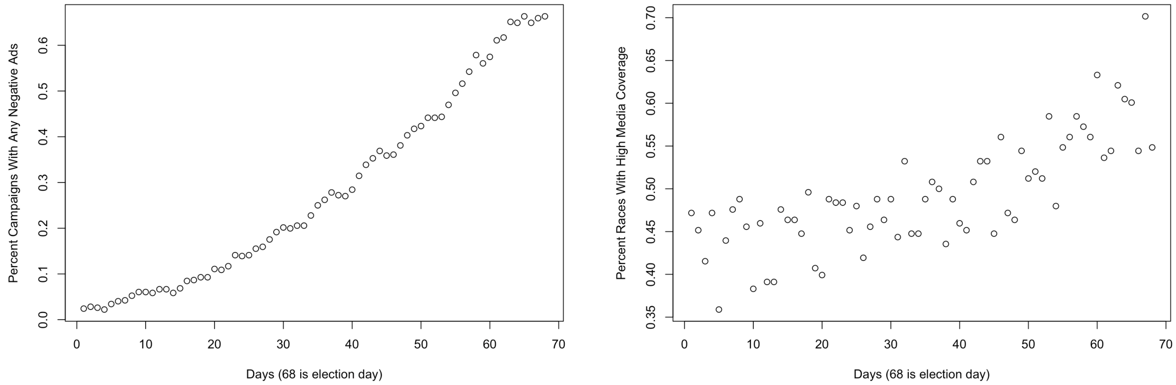

Figure 1: Time Series of $NegMix$ and $MediaHigh$ Daily Averages (Across Races)

media coverage is in the first week of the campaign (five days after Labor Day) and the highest arrives two days before Election Day. Specifically, on the fifth day of the race, the news media in most districts hardly covers the race (only 36 percent of them have a high coverage), while two days before the election almost three quarters of them (70 percent) provide high coverage. Another way to look at this is as follows: while the news media hardly cover the race in the first three weeks of the campaign, it almost always covers it in the last three weeks.

Thus, there are two takeaways from Figure 1: (i) media coverage and negativity exhibit clear dynamism, and (ii) there appears to be a correlation between these variables.

2.3 The correlation between tone and coverage

The correlation between media coverage and negativity is not very large, 0.11, but is highly significant ($p < .0001$), and as illustrated later, quite meaningful. The correlation is the highest in the 2004 elections (0.17) compared with only 0.08 in 2000 and 0.07 in 2002. Recall that our measure of negativity includes both days with only negative ads and days with a mixture of negative and positive ads. If we do not consider days with mixture of tones as "negative," the correlation decreases to 0.07 ($p < .0001$).

On days in which the media coverage is low and the candidates air ads, the share of negativity is 55 percent. On days in which the coverage is high, the share of negativity increases to 62 percent. Looking at the other side of the coin, we find that, on days that a candidate goes negative, the prospect of high coverage is 58 percent compared with only 46 percent if she does not. All in all, these statistics suggest that negativity and coverage tend to go together. However, so far, we have not examined causality.

2.4 The effect of tone on coverage

Previous studies have examined how media coverage depends on the campaign's tone. The theoretical argument is intuitive: the news media's success depends on attracting readers, and sensational news does a better job in this task than standard news (Bennett 2003; Patterson 1994). Since attack and comparison ads bring any controversy in the campaign to the forefront, the news media is more likely to echo and amplify negative ads in comparison to positive ones.

Existing empirical work supports this idea (Ridout and Smith 2008, Fowler and Ridout 2009, Geer 2012, and West 2018). West (2018), for example, evaluates the negativity of TV news coverage of presidential advertising on CBS Evening News from 1972 to 2008. He finds that 66% of the ads discussed were negative. Ridout and Smith (2008) use content analysis of news coverage in ten Senatorial races in 2004 to show that attack and contrast ads are more likely to receive media attention than positive ads. In their analysis, the dependent variable is the number of newspapers mentions of each ad, while the explanatory variables are various characteristics of the ad, the race, and the newspaper. One of the attributes of the advertising is tone. The authors found that both attack and contrast ads are likely to be mentioned more than positive ads, and their effect was quite similar (the coefficient of attack ads was 1.437 and the one for contrast ad was 1.3).

In Appendix A we show that similar patterns arise in our sample. Specifically, using content analysis of newspapers articles about ads, following Ridout and Smith (2008), we show that a negative ad is more likely (than a positive ad) to appear in the news. In other words, free media focuses on negative ads more than paid media.

The evidence so far demonstrates that a negative ad is more likely to be reported in the news than a positive one. There are several mechanisms that might lead to this result. One hypothesis is that media coverage increases during times of the race when tone is negative. In other words, the media pay more attention to the race when it is nasty and thus a negative ad has a better chance to be covered than a positive one. This hypothesis is examined in Table 2, which reports regression results explaining media attention. Column one focuses on the hypothesis that media attention is high when a candidate becomes negative. In this regression, the focal explanatory variable is lagged negativity, $NegMix_{i,t-1,k}$ for candidate i, at time $t-1$, and congressional district $k \in \kappa$, where κ is the set of all congressional districts. The dependent variable is $MediaHigh_{t,k(i)}$.[3] This estimation, and every analysis in this paper, also include fixed effects for (1) year, (2) days to election, and (3) congressional districts. In order to define the estimated equation, let $d(t)$ be the number of days until the election at time t so that $t = 1, ..., 207$; $Y2002(t)$ and $Y2004(t)$ be dummy variables indicating the election years 2002 and 2004. Accordingly, the estimated equation is:

$$MediaHigh_{t,k(i)} = \alpha_1 NegMix_{i,t-1,k} + \mu_t + \delta_k + \epsilon_{i,t,k} \tag{1}$$

where

$$\mu_t = \mu^y_{2002} Y2002(t) + \mu^y_{2004} Y2004(t) + \mu^d_{d(t)} \tag{2}$$

for all t; the congressional districts are indexed by k so that $k \in \kappa$; where κ is the set of all congressional districts; and $\epsilon_{i,t,k}$ is an iid unobserved shock at the level of a day, district, and candidate. The congressional district fixed effects is represented by δ_k while the time fixed effect is captured by μ_t which accounts for both the variation over years as well as variation over days in the race (see equation (2)). Notice that the equation assumes that the pattern of media attention in the 69 days until the election

[3]The theoretical framework presented above distinguishes between times in which the media pay (versus do not pay) attention to the *race*, but relates this race-level variable with *candidate* negativity. Because our main interest is on the effect of media attention on candidate negativity (see section 4), we operationalize our analyses throughout at the candidate level. In section 4.2, we test the robustness of our findings against alternatives to our endogenous regressor, $MediaHigh_{t,k(i)}$, that vary at the candidate level, e.g., $MediaHighCandidate_{i,t,k}$. It turns out that the findings are not sensitive to this operational decision.

is expected to be the same over the three elections (e.g., $\mu^d_{d(1)} = \mu^d_{d(70)}$).

The estimate of α_1 is 0.039 (with standard error of .006; $p < .01$). Thus, the estimation results is consistent with the hypothesis that the media is more likely to cover the race following days in which the tone is negative than after days in which it is not.

The evidence in this subsection illustrates consistency between our setting and prior evidence about negativity affecting media coverage that could also be a source of reverse causality. Of course, for our focal question, there are additional potential sources for such endogeneity – e.g., an unobserved variable that is correlated with both media coverage and negativity. Whatever the reason, to get a consistent estimate of the role of media in the choice of tone, one needs to resolve the endogeneity concern.

2.5 The effect of coverage on tone: mechanism

The primary goal of this study is to demonstrate that news media affects candidate strategies, in particular negativity. While previous papers have demonstrated that voters are influenced by news media (for example, DellaVigna and Kaplan 2007, Martin and Yurukoglu 2014) and by the campaign's advertisments (e.g., Spenkuch and Toniatti 2018, Wang, Lewis and Schweidel 2018, Gordon, Lovett, Luo, and Reeder 2021), we are interested in the effect of the media on candidate ad choices. For our purposes, the specific nature of this effect—whether it increases or decreases campaign negativity—and the precise mechanisms involved are less important. Our main concern is whether we can obtain a reliable estimate of the effect of media coverage on the tone of the discourse. That said, the evidence presented above suggests a mechanism by which the effect of media coverage on negativity would be positive, as explained below.

First, we operate under the assumption that at any given time, candidates possess a repertoire of advertisements, some positive and others negative. This assumption aligns with descriptions of the political landscape (Feltus, Goldstein, and Dallek 2018). Thus, under this assumption, candidates are free to choose the tone of their advertisements on a daily basis.

	Dependent variable:		
	MediaHigh		
	(1)	(2)	(3)
NegMix_Lagged	0.039***	0.033***	0.032***
	(0.006)	(0.006)	(0.006)
Weather			−0.008
			(0.021)
SportSameState			−0.135***
			(0.017)
Sport			−0.088***
			(0.012)
SportNextDistrict			0.007
			(0.012)
NewsCrime			−0.046*
			(0.024)
DaysUntilElection:MHC_Gannet		0.002***	0.001***
		(0.0002)	(0.0002)
DaysUntilElection:MHC_CNHI		−0.002***	−0.002***
		(0.0003)	(0.0003)
DaysUntilElection:MHC_ LeeEnterprises		0.002***	0.002***
		(0.0004)	(0.0004)
DaysUntilElection:MHC_ Ogden		0.002***	0.002***
		(0.0004)	(0.0004)
DaysUntilElection:MHC_ Boone		0.001*	0.001*
		(0.001)	(0.001)
DaysUntilElection:MHC_ Landmark		−0.001***	−0.001***
		(0.0003)	(0.0003)
DaysUntilElection:MHC_Paxton		0.002***	0.002***
		(0.0004)	(0.0004)
DaysUntilElection:MHC_KnightRidder		0.0004	0.001
		(0.0005)	(0.0005)
DaysUntilElection:MHC_NewMediaCorp		−0.001**	−0.001**
		(0.001)	(0.001)
DaysUntilElection:MHC_HearstNewspapers		−0.003***	−0.003***
		(0.001)	(0.001)
DaysUntilElection:MHC_PulitzerInc		0.0005	0.0004
		(0.001)	(0.001)
Year Effects	Y	Y	Y
Days to Election Effects	Y	Y	Y
District Fixed Effects	Y	Y	Y
Observations	33,728	33,728	33,728
R^2	0.412	0.416	0.418
Adjusted R^2	0.408	0.411	0.414
Residual Std. Error	0.385 (df = 33492)	0.384 (df = 33481)	0.383 (df = 33476)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 2: Descriptive Regressions on Media Coverage

Second, consider our earlier finding that the news media tends to echo negative over positive advertisements. This tendency clearly encourages candidates to prefer airing their negative advertisements when the media focuses on their race. In essence, the behavior of the media provides a straightforward mechanism for its role in political campaigns: its attraction to negativity means that when it turns its attention to a race, the candidates are likely to respond with negativity.

This is not the sole mechanism that could lead candidates to adopt a negative stance when media attention intensifies (echoing campaign advertisements). Another possibility involves two alternative conditions. The first is based on the evidence that negative ads are generally more effective than positive ones for persuading voters to choose one candidate over another (Gordon, Lovett, Luo, and Reeder 2021). The second is that messages wear out so that candidates are limited in their negative content about their opponent. Thus, if negative ads are more effective, but limited, then candidates will want to save them to leverage the further enhancement of negative ads when media coverage is high.

Both of these mechanisms suggest that when media focuses on a race, candidates are more likely to use negative ads. Such an increase could result from reallocating ads to existing media slots already purchased by the campaign or acquiring additional slots on the spot market. Importantly, these mechanism do not involve *creating* negative ads in response to the increased media coverage, but rather shifting the media allocation from available positive ads to available negative ads. Thus, under these potential mechanism, candidates can respond rapidly to an increase in media coverage. In our empirical analyses we focus on responses within a day, which aligns with these mechanisms.[4]

Lastly, the discussion here overlooks the interactions between candidates. In the robustness section of the results it is illustrated empirically that the inclusion of rival's reaction does not alter our main results and insights.

[4]Note that another mechanism would be that media coverage presents a new negative trait of the opponent, which the candidate then develops into an ad that is aired. Due to the technological constraints related to ad production in our period, we find it unlikely that this mechanism is a major part of the effect we measure.

3 Instruments and first stage results

The core focus of this study is on demonstrating that the news media plays an important and significant role in political campaigns. For this purpose, we wish to show that one of the critical decisions made by candidate – when to “go negative” – is affected by the attention that the news media pay to the campaign. As just discussed, such an empirical question raises an immediate endogeneity concern, since it is unreasonable to assume media coverage is exogeneous to the candidates’ tone.

To address these concerns, we estimate the effect of coverage on tone using 2SLS regression. Note that using 2SLS also assists in resolving the potential measurement error in the media coverage variable noted in section 2. The 2SLS analysis will be presented in the next section. This current section introduces two sets of potential instrumental variables (IVs) – ownership by media holding companies and events that crowd out political news – and then presents the dependence of media coverage on these IVs and the control variables.

3.1 Media holding companies

Not all media outlets are highly interested in politics. Variation in coverage among news media (not just in politics) is the norm. Each newspaper has an editorial policy that governs its interest in various topics. For example, while some news media elaborate and intensely cover crime stories (e.g., *New York Post*), others focus more intently on business news (e.g., *Wall Street Journa*l).

Such heterogeneity in interest can provide us with exogeneous variation in media coverage. For example, if we know that the news media that operates in district A is more interested in politics than the one that exists in district B, we would expect to find that the media coverage of the race in district A is more intense than that of B.

The editorial policy is arguably determined a long time before each specific political campaign, and it is, thus, likely to be a good instrument for particular tone decisions during the campaign. To ensure even further that the editorial policy is exogeneous to each specific district, we leverage on the ownership structure of newspapers in the USA.

In the United States, a small number of large media holding companies own a large proportion of local newspapers. Such media holding companies have editorial policies. Consider, for example, the sensationalist focus of newspapers in the Murdoch portfolio. Such policies are followed, at least to some degree, by their local newspapers. Indeed, Eshbaugh-Soha (2010) find that the tone of local newspaper coverage of presidential races depends on the corporate ownership. The ownership structure of local newspapers is not expected to directly influence campaign decisions making it a valid instrument for us.

We collect information about the structure of these MHCs from historical information drawn from news articles and websites. We examine the top eleven MHCs, which include Gannet, CNHI, Lee Enterprises, Ogden, Boone, Landmark, Paxton, Knight Ridder, News Media Corp, Hearst Newspapers, and Pulitzer, Inc. For each entity, we identify the districts that are covered by the newspapers owned by the MHC. Some districts have multiple newspapers held by one or more MHCs. Of the 248 races we study, 147 are covered by at least one newspaper controlled by a MHC, and 59 by at least two. The dominant MHC in our sample is Gannet, whose newspapers cover 22% of the races. See Table 1 for descriptives of the coverage of races by the MHCs.

There are a few changes in ownership within district between years (13 out of 166 distinct congressional districts), but there is no change in ownership during the 69 days of any of the campaigns in our data. Hence, MHCs have limited useful variation within a district. However, while the editorial policy is mostly fixed over time, its daily execution is not. For example, the evidence above demonstrated that the interest of the media in local politics grows as Election Day comes close. Of course, this increase in interest is not identical for all MHCs; some might focus only on the last week, while others might raise their interest much earlier. To capture this variation, we allow the MHCs variables to interact with a time trend (i.e., number of days until Election Day) in constructing our instruments. Specifically, we add to equation 4 the element $MHC_{t,k}d(t)\alpha_2$ where

$MHC_{t,k}$ is a *1x11* row vector that captures the 11 MHCs in our data, and α_2 is a *11x1* parameters vector. The inclusion of these interactions have another advantage highlighted by Angrist and Krueger (1991), who justified the inclusion of very similar interaction terms by pointing out that these interactions improve the precision of the focal estimate by increasing the first-stage R^2.

In what follows, we present preliminary results intended only to illustrate the potential of the relevant variables as instruments. The results of the estimation that includes the MHC variables are presented in the second column of Table 2. While preliminary, the estimates demonstrate the vast heterogeneity in the interest of the MHCs over the days of the campaign. To get a sense of the meaning of these estimates, recall that the estimation already includes year and "day to election" fixed effects. In other words, the estimation already captures the average increase in interest in politics as Election Day gets closer. Compared with this average trend, some MHCs pay more attention to the early days of the campaign (e.g. Hearst Newspapers), while others (e.g., Paxton) focus on the days closer to Election Day.

3.2 Crowding out variables

The daily attention given by the local media to a congressional race depends on the other topics that make the news. Some days are slow, with very few things happening, while others are crowded with newsworthy events. When things are slow, the news media is likely to "fill up" the space with anything, including, of course, reporting on the local campaign. On the other hand, on busy days, news on congressional races is likely to be crowded out.

In order to measure the daily interest of the media in news regarding the campaigns, we identified three types of events that are likely to draw the media's attention and crowd-out reporting on anything else. They are severe weather conditions, a major crime story, and sporting events. It is reasonable to expect that, for example, a major local crime story would attract the attention of the local news media and crowd-out any news on the local congressional race, but such an event is not likely to have a direct effect on the decisions of the candidates to go negative on that day. Thus, the crowding-out variables are valid instruments for us and can serve as good IVs.

The category of "severe weather" includes tropical storms and hurricanes, but also natural disasters such as earthquakes and floods ($Weather$). "Major crime" includes mass killings, terror attacks, killings by serial killers, and other criminal cases that would receive broad media coverage and public attention ($NewsCrime$). "Sport events" includes major league sporting events: NHL, NFL, MLB, and the NBA. The data was collected from local and national online sources. Given the variety of sporting events, we have split them into three categories: events in the focal district ($Sport$), in the neighboring district ($SportNextDistrict$), and in the state ($SportSameState$). Table 1 presents some basic statistics about these data.

To get a preliminary sense of the role that this set of variables might play, they were added to the estimation model reported in the previous subsection. Specifically, we add an element (on the top of $MHC_{t,k}d(t)\alpha_2$) to equation (4) – $CrowdOut_{t,k}\alpha_3$, where $CrowdOut_{t,k}$ is a *1x5* row vector that captures the five crowding out variables, and α_3 is a *5x1* parameters vector.

The estimates (presented in column 3 of Table 2) demonstrate that four of the five variables have the expected negative sign and three of those are significant ("sport events in the district" and "sport events in the state" are significant at $p < .0001$ and "major crime" stories at $p < .1$).

3.3 Interactions

Another set of variables that can potentially serve as instruments are interactions between the two sets of IVs just discussed (MHCs and crowding out). It makes sense to include this set of variables for two reasons: theoretical and empirical. Theoretically, these interactions seem relevant because all of them reflect editorial policy considerations. For example, it seems likely that newspapers that belong to different MHCs will adjust their coverage of political issues differently when there is a major crime story. The reasoning is as follows: MHCs' editorial policies are relevant not only to political reporting, but to all news categories. In other words, if two MHCs differ in their treatment of political topics they are likely to differ also in their coverage of most other issues as well. The second reason to include the interaction is simple – empirically there is some chance that the interactions improve the fit of the model and thus will assist us in the 2SLS analysis.

To get a preliminary sense of the role that this set of variables might play, they were also added to the estimation model reported in the previous subsection. Specifically, we add another element (on the top of the above) to equation (4) – $e_1[CrowdOut'_{t,k}MHC_{t,k}\alpha_4]e_2$, where α_4 is a *5x11* parameter matrix, e_1 is a *1x5* vector of 1s, and e_2 is a *11x1* vector of 1s. Thus, the estimated equation is:

$$\begin{aligned} MediaHigh_{t,k(i)} =& \alpha_1 NegMix_{i,t-1,k} \\ & + MHC_{t,k}d(t)\alpha_2 + CrowdOut_{t,k}\alpha_3 + e_1[CrowdOut'_{t,k}MHC_{t,k}\alpha_4]e_2 \\ & + \mu_t + \delta_k + \epsilon_{i,t,k} \end{aligned} \tag{3}$$

The estimates are presented in column 1 of Table 6 in Appendix B. These results are included in the Appendix due to the large number of coefficient estimates (especially in α_4). The estimates demonstrate that these interactions add richness to the analysis. For example, we find that the crowding out effect of sport events (in the district) is weakest for the newspapers owned by the MHC Gannet, and that crime stories have an extra crowding out effect for newspapers owned by the MHC CNHI.

3.4 Testing the instruments

Finally, we test for the relevancy of the variables above as excluded instruments in the 2SLS reported in the next section. To do so, we need to add variables to media regression that are expected to have a direct effect on negativity in the second stage of the estimation (i.e., the included instruments). These variables can be categorized into three straightforward groups: (1) race characteristics, (2) candidates' attributes, and

(3) demographics of the district.

The race characteristics variables are (i) whether the race was defined as "toss-up" (i.e., closely contested) by Cook's Political Report ($TossUp$), (ii) a binary variable that equals one if neither one of the candidates is an incumbent (i.e. $OpenSeat$), and (iii) a binary variable that equals one if the two candidates competed in the same race two years earlier ($SameOpponent$). The candidate-specific variables are whether she is: (i) the $Frontrunner$, (ii) the $Incumbent$, and (iii) a $Republican$. The demographic variables are: (i) the proportion of white voters in the district ($PercentWhite$), (ii) the share of individuals with a Bachelor degree ($PercentBachelorsDegree$), and (iii) the mean income of a household in the district ($MeanHouseholdIncome$). Let the $1x9$ row vector, $X_{i,t,k}$ captures these nine variables for candidate i at time t in congressional district k.

When including these variables in the estimation, the resulting equation is:

$$\begin{aligned} MediaHigh_{t,k(i)} =& \alpha_1 NegMix_{i,t-1,k} + X_{i,t,k}\alpha_5 \\ &+ MHC_{t,k}d(t)\alpha_2 + CrowdOut_{t,k}\alpha_3 + e_1[CrowdOut'_{t,k}MHC_{t,k}\alpha_4]e_2 \\ &+ \mu_t + \delta_k + \epsilon_{i,t,k} \end{aligned} \tag{4}$$

where α_5 is a $9x1$ parameters vector. The estimation results, reported in the second column of Table 6 in Appendix B, also account for clustering the standard errors by district. Note that these results correspond to the first stage estimates for the causal model that is discussed in the next section.

The question of whether the instrumental variables (i.e., the interaction between the MHCs and time, the crowding out variables and the interaction between the crowding out and the MHCs) provide sufficient power can be addressed by the partial F-test (Kleibergen-Paap Wald) of the variables in the regression. This result is reassuring with a value of 14.332, supporting the use of these variables as instruments in the 2SLS analysis.

4 Results: media attention encourages negativity

We approach the empirical question – does media coverage affect candidates' tone – without a specific theory in hand.

On the one hand, it seems reasonable to expect that media attention encourages negativity. Two related rationales are available. The first is that media, due to its commercial considerations (Patterson 1994), are biased toward negative ads versus positive ones. As mentioned above, this idea is consistent with the evidence in previous studies. If the media is more likely to echo negative ads, candidates should air more negative ads, when media coverage is high. The second is that negative ads are more effective than positive ads in convincing consumers (Gordon, Lovett, Luo, and Reeder 2021) or in building up knowledge about candidates (Lovett and Shachar 2011). In this case, when media coverage is high and there is a good chance that ads will be echoed by the press, candidates should air more negative ads. In either case, as accounts of campaigns suggest (Feltus, Goldstein, and Dallek 2017, p. 139), candidates might hold on to damaging material in anticipation of the right moment.

On the other hand, previous findings have also suggested that, in some cases, media coverage of a negative ad can backfire (see Kahn and Kenney 1999; Ridout and Fowler 2012 and Pedersen 2014 who discuss the framing effect, and Phillips, Urbany, and Reynolds 2007 and Major and Andersen 2016 that highlight the potential backfire). Therefore, while we expect media coverage to lead to higher negativity, the opposite is also possible.

In this section, we report the results of a two-stage least squares (2SLS) analysis in which tone is the focal dependent variable and media coverage is an endogenous regressor. The other variables in the estimation include lagged negativity, the fixed effects and the set of race and candidates' characteristics variables. The standard errors are clustered at the congressional district level. Specifically, the estimated equation is:

$$NegMix_{i,t,k} = \beta_1 NegMix_{i,t-1,k} + X_{i,t,k}\beta_2 + \beta_3 \widehat{MediaHigh}_{t,k(i)} + \eta_t + \gamma_k + \nu_{i,t,k}. \quad (5)$$

where $k \in \kappa$, the parameters β_1 and β_3 are scalars, β_2 is a $9x1$ parameter vector, $\nu_{i,t,k}$ is an iid unobserved shock, and

$$\eta_t = \eta^y_{2002} Y2002(t) + \eta^y_{2004} Y2004(t) + \eta^d_{d(t)} \quad (6)$$

The estimates are presented in Table 3. The findings provide a solid support for the main theme presented here. Specifically, they demonstrate that media coverage encourages candidates to adopt a negative tone – i.e., media attention encourages negativity.

Before discussing the magnitude of the effect, it is worth recalling the operationalization of the media coverage variable. It is a binary variable ($MediaHigh$) that distinguishes between times in which the media pay attention to the race (i.e., the media coverage of the race is above the median) and times in which it does not. This is exactly the distinction that we are looking for – between regular days and those in which the media pay substantial attention to the race. Further, recall, that our variable captures this well. When $MediaHigh$ equals zero the median number of articles is zero, and when it equals 1 the median is 10.

The estimated coefficient, $\widehat{\beta}_3$, is 0.079 (s.e.= 0.018) and it is significantly different from zero at $p < .001$. To assess the magnitude of this estimate we calculate the model's predictions under two different scenarios. First, when the media pays attention to all races at all times, and second, when it never pays attention. With no media attention, the average percent of days (including those without ads) in which the candidates air negative ads is 24%. With media attention, the percentage is 32%. When we restrict our attention only to days in which there are ads we find that the proportion of ads with a negative tone increases from 50% to 67%. Thus, on average, shifting media coverage from low to high increases the probability of airing negative ads in a meaningful way.

Media coverage has quite a meaningful role in the negativity of political campaigns.

	Dependent variable:		
	NegMix		
	(1)	(2)	(3)
NegMix_lagged	0.887***	0.876***	0.866***
	(0.006)	(0.006)	(0.006)
TossUps	0.015		
	(0.011)		
OpenSeat	0.045***		
	(0.011)		
SameOpponent	0.007		
	(0.009)		
Frontrunner	−0.0004	0.002	
	(0.004)	(0.003)	
Incumbent	0.012***	0.010***	
	(0.003)	(0.003)	
Republican	0.002	0.002	
	(0.002)	(0.002)	
PercentWhite	0.022		
	(0.085)		
PercentBachelorsDegree	0.308		
	(0.213)		
MeanHouseholdIncome	−0.263		
	(0.173)		
‘medHigh(fit)‘	0.079***	0.100**	0.104**
	(0.018)	(0.049)	(0.051)
Year Effects	Y	Absorbed	Absorbed
Days to Election Effects	Y	Y	Y
Level of Fixed Effects	District	Race	Race-Candidate
Kleibergen-Paap F statistics	14.332	20.082	20.095
Overidentification Test P Value	0.521	0.466	0.479
Observations	33,728	33,728	33,728
R^2	0.875	0.875	0.876
Adjusted R^2	0.874	0.874	0.873
Residual Std. Error	0.160 (df = 33482)	0.160 (df = 33408)	0.160 (df = 33163)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3: Results from 2SLS Analysis

4.1 The selection of the level of fixed effects

Next we discuss the choice of fixed effect level. So far we estimated the model with congressional district fixed effects. We can adopt finer fixed effects either at the level of the race or at the level of the race and candidate. This is done in columns 2 (race) and 3 (race and candidate) of Table 3. Interestingly, in both cases the estimates reflect a larger effect of media attention on negativity. While in the default setting the coefficient is 0.079 in column 2 it is 0.100 and in the third column it is 0.104, though these three coefficient values have overlapping confidence intervals.

Moving to finer fixed effects requires that these fixed effects have sufficient explanatory power in the data to warrant their use. For this evaluation we use the standard information criteria (Yum 2022). The number of fixed effect parameters is 165 at the district level, 247 at the race level, and 495 at the race and candidate level. We compared the model fits by calculating AIC and BIC values. The AIC and BIC values for the congressional district fixed effect model are -27861.57 and -25780.32. For the race fixed effect models they are -27770.02 and -25065.24. For the candidate fixed effect model they are -27385.36 and -22616.19. Thus, our main model has the smallest AIC and BIC values suggesting that congressional districts is the appropriate level of fixed effect.

Thus, our preferred model is with the congressional district fixed-effect which has the most conservative estimate of the effect of media attention on negativity.

4.2 Robustness

Here we examine the robustness of the finding to a large variety of other alternative formulations. We start with the operationalization of the media coverage and the negativity variables. As explained above, the variable that we use to represent the media coverage captures the theoretical framework well. Specifically, the media is rarely interested in congressional races, and thus it is important to distinguish between regular days (i.e., no media coverage) and those in which the media pay attention. That said, it is worth checking whether the finding is sensitive to our operationalization choice. This is done in Table 4. In the first column we are still using a median split, but in this case the variable is candidates specific – i.e., it is not the coverage of the race but rather the coverage of the particular candidate. It turns out that the estimate and its standard error hardly change as a result of switching the operationalization ($\widehat{\beta}_3$, is 0.076 instead of 0.079).[5]

In columns (2) and (3) we are moving from a median split to continuous measures of media coverage. In column (2) it is the natural log of the number of articles on both

[5] We prefer to use our default version of $MediaHigh$ because it best captures the theoretical construct of media paying attention or not to the race.

candidates on each day and in column (3) the number of articles is specific to each candidate. The main qualitative result holds in both cases and both are statistically significant, demonstrating that the finding is robust to the operationalization of the media coverage measure.

Next, we consider the operationalization of negativity. As mentioned above, the negativity measure lumps together days in which all the ads aired by the candidate are negative with those in which some of the ads are negative. Recall that when a candidate airs both negative and positive ads, the majority of the ads (60%) are negative. In the last column of Table 4 we restrict the dependent variable to take a value of one only on days in which all the ads by a candidate are negative. Once again, the findings do not change as a result of this restriction.

Table 5 examines the sensitivity of the results with respect to (1) outliers and (2) the inclusion of the rival's negativity. In the first three columns of the table we test the sensitivity of the main finding with respect to outliers. First, we calculate the first stage estimate of $\widehat{MediaHigh}_{i,t,k}$. We then calculate the 0.5%, 1%, and 2.5% threshold values on both ends of the estimated values. By excluding these values, we examine whether our effect is robust to the extreme situations in the data. Column (1), (2), and (3) correspond to these three thresholds. It is reassuring that the effect of media attention increases as more extreme values of $\widehat{MediaHigh}_{i,t,k}$ are excluded.

Next in the last column of the table we add an interesting regressor – the lagged tone choice of the rival candidate. While the theoretical framework presented above does not account directly for the interaction between the candidates, it makes sense to examine empirically whether the inclusion of such a variable affects the results. The estimation shows that, to some degree, candidates follow the tone choices of their rival – i.e., the coefficient of the lagged rival's negativity on the previous day ($NegMix\_Lagged\_Opponent$) is positive. The effect is minor – the coefficient on the lagged negativity of the candidate is 25 times bigger than the coefficient of the rival's lagged negativity – but statistically significant at the 0.001 level. However, most importantly, the coefficient of the media attention is still positive and highly significant

	Dependent variable:			
	NegMix			OnlyNegative
	(1)	(2)	(3)	(4)
negMix_lagged	0.887^{***}	0.888^{***}	0.888^{***}	
	(0.006)	(0.006)	(0.006)	
TossUps	0.022^{**}	0.028^{***}	0.029^{***}	0.003
	(0.010)	(0.010)	(0.010)	(0.011)
OpenSeat	0.031^{***}	0.030^{***}	0.026^{***}	0.035^{***}
	(0.009)	(0.010)	(0.008)	(0.011)
SameOpponent	0.004	0.007	0.005	0.002
	(0.009)	(0.007)	(0.008)	(0.009)
Frontrunner	0.005	0.003	0.004	0.005
	(0.004)	(0.003)	(0.004)	(0.004)
Incumbent	0.001	0.009^{***}	0.004	0.016^{***}
	(0.004)	(0.003)	(0.004)	(0.003)
Republican	0.002	0.002	0.003	0.005^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
PercentWhite	0.099	0.073	0.107	0.017
	(0.070)	(0.069)	(0.072)	(0.064)
PercentBachelorsDegree	0.332^{*}	0.357^{**}	0.342^{*}	0.417^{**}
	(0.174)	(0.175)	(0.177)	(0.188)
MeanHouseholdIncome	-0.295^{**}	-0.348^{**}	-0.345^{**}	-0.365^{***}
	(0.147)	(0.144)	(0.142)	(0.134)
‘MediaHighCandidate(fit)‘	0.076^{***}			
	(0.020)			
‘log(MediaArticles + 1)(fit)‘		0.014^{**}		
		(0.006)		
‘log(MediaArticlesCandidate + 1)(fit)‘			0.018^{**}	
			(0.007)	
‘medHigh(fit)‘				0.069^{***}
				(0.023)
OnlyNegative_lagged				0.843^{***}
				(0.007)
Year Effects	Y	Y	Y	Y
Days to Election	Y	Y	Y	Y
District Fixed Effects	Y	Y	Y	Y
Kleibergen-Paap F statistics	40.806	33.325	41.898	17.21
Overidentification Test P Value	0.451	0.265	0.27	0.859
Observations	33,727	33,728	33,728	33,728
R^2	0.874	0.878	0.877	0.762
Adjusted R^2	0.873	0.877	0.877	0.761
Residual Std. Error	0.160 (df = 33481)	0.157 (df = 33482)	0.158 (df = 33482)	0.171 (df = 33482)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4: Robustness against different operationalizations

with a similar magnitude to previous formulations.

	Dependent variable:			
	NegMix			
	(1)	(2)	(3)	(4)
NegMixed_lagged	0.887***	0.887***	0.888***	0.876***
	(0.006)	(0.006)	(0.006)	(0.006)
NegMix_lagged_opp				0.035***
				(0.005)
TossUps	0.013	0.013	0.009	0.011
	(0.008)	(0.008)	(0.009)	(0.009)
OpenSeat	0.045***	0.047***	0.048***	0.040***
	(0.009)	(0.009)	(0.009)	(0.009)
SameOpponent	0.007	0.008	0.006	0.006
	(0.006)	(0.006)	(0.006)	(0.007)
Frontrunner	−0.0005	−0.001	−0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.004)
Incumbent	0.012***	0.013***	0.012***	0.014***
	(0.003)	(0.003)	(0.003)	(0.003)
Republican	0.002	0.003	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
PercentWhite	0.024	0.018	0.022	0.013
	(0.045)	(0.046)	(0.043)	(0.071)
PercentBachelorsDegree	0.291**	0.285**	0.322**	0.260
	(0.141)	(0.143)	(0.145)	(0.177)
MeanHouseholdIncome	−0.256**	−0.244**	−0.263**	−0.215
	(0.113)	(0.115)	(0.115)	(0.143)
‘medHigh(fit)‘				0.067***
				(0.015)
medHigh_fitted (outliers)	0.082***	0.086***	0.088***	
	(0.019)	(0.019)	(0.020)	
Year Effects	Y	Y	Y	Y
Days to Election Effects	Y	Y	Y	Y
District Fixed Effects	Y	Y	Y	Y
Dropping Outliers	.5%	1%	2.5%	
Observations	33,387	33,055	32,045	33,728
R^2	0.879	0.879	0.879	0.877
Adjusted R^2	0.878	0.878	0.878	0.876
Residual Std. Error	0.157 (df = 33141)	0.157 (df = 32809)	0.156 (df = 31799)	0.158 (df = 33481)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 5: Robustness against Outliers and Lagged Opponent Decision

Finally, since we use fixed effects, we performed a Hausman test for the possibility of endogeneity due to Nickell Bias. The test is based on the Arellano and Bond (1991) GMM estimator (see Nickell 1981 and Hausman 1978). We find no evidence of endogeneity in the lagged dependent variable due to Nickell Bias, i.e., we do not reject the null of no endogeneity bias with chi-squared value of 6.99 (p = 1.00) and the lagged dependent variable coefficient is estimated to be similar in the instrumented model (coefficient on the lagged negativity is 0.893).

Overall, these results indicate a robust, statistically significant finding that higher media coverage causes an increase in candidates airing negative ads. The magnitudes are substantial and suggest that media plays an important role in shaping the negativity of races. It implies that the news media play an important and even critical role in political campaigns and should not be ignored. We already knew that the news media cover negative ads more than positive which could amplify the effect of negative ads more than positive. The evidence in this section illustrates that it has another role in advancing and strengthening the negativity in political campaigns – its attention encourages the candidates to escalate the negativity of their messages and ads. This portrays an interesting picture of negativity in political campaigns. Each race has intense and mild periods. In the intense (mild) periods the tone of the ads is negative (not negative) and the media coverage is high (low). Furthermore, one of the reasons that the candidate airs negative ads in these period is the attention of the media.

5 Conclusion

This study shows that the news media play a meaningful role in political campaigns. Using data on the congressional races of 2000, 2002 and 2004 we find that when the news media turn their attention to one of the races, the tone of the candidates in this race is more likely to become negative (i.e., the candidates stop focusing their advertising messages solely on themselves and start talking about their rivals). To our knowledge, this is the first causal evidence of the media's role in setting the tone of political advertising.

This study addresses the challenge of endogeneity in media coverage by identifying two new instruments. First, we exploit the ownership of local newspaper by media conglomerates. Such ownership moves some of the editorial decisions (such as, how much attention to pay to politics) from the local level to the national level, which is clearly exogenous to the daily tone decisions of congressional candidates. We interact the media holding company variables with time effects (i.e., number of days until the election) in order to capture variation in the interest of such conglomerates over the course of the race.

Our second set of instruments include variables that capture newsworthy events at the daily and local levels. These events – severe weather, sporting events, and major crime stories – can crowd-out the space allocated for political reporting in the relevant congressional district. Of course, these events do not depend on the daily tone decisions of the candidates and are not expected to have a direct effect on these decisions. That is, these events are expected to affect tone decisions through their impact on media coverage.

Using 2SLS (with fixed-effects for congressional districts and clustered standard errors), we find that the attention of the news media encourages the candidates to be negative in their ads. In other words, the news media have a role in political campaigns and they are responsible, at least partially, for the negativity in political campaigns.

The obvious limitation of our results is that they are based on a period in which social media was not a factor. This is both an advantage and a disadvantage. It is an advantage in the sense that the effect of the news media can be estimated cleanly without worrying about its interaction with social media. It is a disadvantage in the sense that the role of the news media might be (at least partially) different when social media is in play. However, we note that given the ample evidence that social media exhibits the same attraction to negativity (Brady et al., 2017, Schöne et al., 2023 and Fine and Hunt 2023), its influence on the tone of the race is expected to be similar to news media. Future research should further explore the interaction between social and news media in such a setting.

We believe that the findings reported here can encourage research in additional directions. The theoretical framework suggested here does not distinguish between the actions of the two candidates, and empirically we allow for an interaction between the candidates only as a robustness test. The finding in this test suggests that it might be interesting to consider not only the dynamic interaction between the candidates and the news media, but also (at the same time) the daily interaction between the candidates. Such examination can be both empirical and theoretical. Furthermore, in the current study the budget of the candidates is exogenous. In practice, both the tone of the race and the media coverage might affect the success of fundraising efforts, and thus, total spending on ads.

Another direction that one can take, following the findings here, relates to the content of the ads. While the tone of the candidates is the most interesting and important aspect of the ads' content, recent advances in text and video analysis tools can allow future research to shed a more precise light on the strategies of the candidates.

Finally, while political advertising is of interest to marketers per se, our findings might encourage scholars to examine the role of news media in a commercial setting. There are significant differences between the political and commercial settings that makes such an "extension" both interesting and challenging. Unlike political campaigns, commercial campaigns are not limited in time (by something like Election Day), and thus, it is possible that the coverage of a specific industry or market does not come in spikes, but rather it is at a modest level continuously. If this is the case, it would be interesting to examine the impact of a permanent increase in the coverage of an industry on the tone of advertising of the players in this market. For example, what if Huffpost started covering the automobile industry extensively? Will that have an effect on the commercials of car makers and distributors?

This study demonstrates the meaningful role that the news media play in political setting. This should encourage us to introduce the news media in other fronts of marketing, both theoretically and empirically, not only as a direct effect on consumer actions (Stephen and Galak 2012; Lovett and Staelin 2016), but also on the resulting firm actions.

6 References

Angrist, J. D., and Krueger, A. B. (1991). "Does Compulsory School Attendance Affect Schooling and Earnings?" *The Quarterly Journal of Economics.* 106 (4), 979-1014.

Ansolabehere, S. and Iyengar, S. (1995). Going Negative: How Political Advertisements Shrink & Polarize the Electorate. The Free Press.

Arellano, M. and Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies*, *58*(2), pp.277-297.

Bennett, W. L. (2003). News: The politics of illusion. New York: Longman.

Brady, W.J., Wills, J.A., Jost, J.T., Tucker, J.A. and Van Bavel, J.J., 2017. Emotion shapes the diffusion of moralized content in social networks. *Proceedings of the National Academy of Sciences*, *114(28)*, pp.7313-7318.

DellaVigna, S. and Kaplan, E., 2007. The Fox News effect: Media bias and voting. *The Quarterly Journal of Economics*, *122(3)*, pp.1187-1234.

Eshbaugh-Soha, M. (2008). Local Newspaper Coverage of the Presidency. The International Journal of Press/Politics, 13(2), 103-119.

Feltus, W. J., Goldstein, K. M., and Dallek, M. (2018). Inside campaigns: elections through the eyes of political professionals. CQ Press.

Fine, J.A. and Hunt, M.F., 2023. Negativity and elite message diffusion on social media. *Political Behavior*, *45(3)*, pp.955-973.

Fowler, E. F., and Ridout, T. N. (2009). Local television and newspaper coverage of political advertising. Political Communication, 26(2), 119-136.

Geer, J. G. (2006). In Defense of Negativity: Attack Ads in Presidential Campaigns. University of Chicago Press.

Geer, J. G. (2012). The news media and the rise of negativity in presidential campaigns. PS: Political Science & Politics, 45 (3), 422-427.

Goldstein, K., & Freedman, P. (2002). Campaign advertising and voter turnout: New evidence for a stimulation effect. Journal of Politics, 64(3), 721-740.

Gordon, B. R., and Hartmann, W. R. (2016). Advertising competition in presidential elections. Quantitative Marketing and Economics, 14 (1), 1-40.

Gordon, B. R., and Hartmann, W. R. (2013). Advertising effects in presidential elections. Marketing Science, 32 (1), 19-35.

Gordon, B, Lovett, M. Luo, B. and J. Reeder (2021) “Disentangling the Effects of Ad Tone on Voter Turnout and Candidate Choice in Presidential Elections”, forthcoming

Management Science.

Hausman, J.A., 1978. Specification tests in econometrics. *Econometrica: Journal of the econometric society*, pp. 1251-1271.

Hedgcock, W., Rao, A. R., and Chen, H. (2009). Could Ralph Nader's entrance and exit have helped Al Gore? The impact of decoy dynamics on consumer choice. Journal of Marketing Research, 46 (3), 330–343.

Hoegg, M. and M. Lewis (2012). The impact of candidate appearance and advertising strategies on election outcomes? Journal of Marketing Research, 48 (5), 895–909.

Kahn, K. F. and Kenney, P. J. (1999) The Spectacle of U.S. Senate Campaigns. The Princeton University Press.

Kim, H., Rao, A. R., and A. Y. Lee, (2009). It's time to vote: the effect of matching message orientation and temporal frame on political persuasion. Journal of Consumer Research, 35 (April), 877–888.

Klein, J. and R. Ahluwalia (2005). Negativity in the evaluation of political candidates. Journal of Marketing, 69 (1), 131–142.

Li, X., Rao, R.S., Narasimhan, O. and Gao, X., 2022. Stay positive or go negative? Memory imperfections and messaging strategy. International Journal of Research in Marketing, 39(4), pp.1127-1149.

Lovett, M., and Peress, M. (2015). Targeting Political Advertising on Television. Quarterly Journal of Political Science, 10(3), 391-432.

Lovett, M., and R. Shachar (2011). The seeds of negativity: knowledge and money. *Marketing Science*, 30 (3), 430–446.

Lovett, Mitchell J., and Richard Staelin. "The role of paid, earned, and owned media in building entertainment brands: Reminding, informing, and enhancing enjoyment." *Marketing Science* 35, no. 1 (2016): 142-157.

Major, M., and D. J. Andersen (2016). Polls and elections: Swift boating reconsidered: News coverage of negative Presidential ads. Presidential Studies Quarterly, 46 (4), 891-910.

Martin, G.J. and Yurukoglu, A., 2017. Bias in cable news: Persuasion and polarization. *American Economic Review*, *107(9)*, pp.2565-2599.

Nickell, S., 1981. Biases in dynamic models with fixed effects. *Econometrica: Journal of the econometric society*, pp. 1417-1426.

Ogburn, W. F., and L. C. Coombs (1940). The economic factor in the Roosevelt elections. American Political Science Review, 34 (4), 719-727.

Patterson, Thomas E. (1994). Out of order. New York: Vintage Books.

Pedersen, R. T. (2014). News media framing of negative campaigning. Mass Communication and Society, 17 (6), 898-919.

Phillips, J., Urbany, J., and T. Reynolds (2008). Confirmation and the effects of valenced political advertising: a field experiment. Journal of Consumer Research, 34 (6), 794–806.

Pollock, J. K. (1930). The German Reichstag Elections of 1930. American Political Science Review, 24 (4), 989-995.

Ridout, T. N., and Smith, G. R. (2008). Free advertising: How the media amplify campaign messages. *Political Research Quarterly*, *61*(4), 598-608.

Ridout, T. N., Franz, M. M., and Fowler, E. F. (2014). Advances in the study of political advertising. Journal of Political Marketing, 13 (3), 175-194.

Schaffner, B. F. (2006). Local News Coverage and the Incumbency Advantage in the U.S. House. Legislative Studies Quarterly, 31(4), 491-511.

Schöne, J.P., Garcia, D., Parkinson, B. and Goldenberg, A., 2023. Negative expressions are shared more on Twitter for public figures than for ordinary users. *PNAS nexus*, *2(7)*, p.pgad219.

Shachar, R. (2009). The political participation puzzle and marketing. Journal of Marketing Research, 46 (6), 798–815.

Soberman, D. A., and L. Sadoulet (2007). Campaign spending limits and political advertising. Management Science, 53 (10), 1521–1532.

Spenkuch, J. L., and Toniatti, D. (2018). Political advertising and election results. The Quarterly Journal of Economics, 133 (4), 1981-2036.

Stephen, Andrew T., and Jeff Galak. "The effects of traditional and social earned media on sales: A study of a microlending marketplace." *Journal of marketing research* 49, no. 5 (2012): 624-639

Wang, Y., Lewis, M., and Schweidel, D. A. (2018). A border strategy analysis of ad source and message tone in senatorial campaigns. Marketing Science, 37 (3), 333-355.

West, D. M. (2018) Air Wars: Television Advertising and Social Media in Election Campaigns 1952-2016. Sage CQ Press.

Yum, M. (2022). Model selection for panel data models with fixed effects: a simulation study. *Applied Economics Letters*, 29(19), pp.1776-1783.

A Following Ridout and Smith (2008) with Congressional races (2000-2004)

In this Appendix we wish to examine whether the news media tend to echo negative ads more than positive ads. For this purpose we needed to determine for each newspaper article in our data (i) whether it is about advertising or not and (ii) if it is about advertising, does it echo a negative or a positive ad. This required us to conduct a detailed manual data collection and analysis.

To cleanly identify media mentions specifically about advertising, we focused attention on the 50 races in our overall sample that exhibited the most news media coverage. (Recall that we have collected data on media coverage for our entire sample.) For each race we searched newslibrary.com for local news articles that contain either of the candidates' names and the term "ad*", which nests additional terms like "advertising" and "advertisements". We tried various alternative terms, and found the term "ad" provided a large degree of precision than others (e.g., "media"), while avoiding too small of a sample (e.g., "advertisement"). We also found that most articles that covered advertising in a race mentioned both candidates. Each such search produces an ordered list of articles for each race from which we randomly selected articles to examine manually. This random selection provides a representative sample that is feasible to analyze given the manual process that is required.

We start from a sample of 1119 articles across the 50 races. Two judges evaluated each of the articles. Their first task was to determine whether the article is about an advertisement.

Part of the judgment related to whether the article was relevant to our study. Considerable effort was taken to avoid evaluating the tone of non-advertising content (e.g., a campaign speech) and to ensure that the evaluation was specifically about ads in that race (many articles cover multiple local races). Specifically, the articles were filtered for four conditions. First, that the article mentioned political advertising. Second, that the political advertising was on TV. Third, that the TV ads were aired by the candidates or the party (i.e., not independent groups or political action committees (PACs)). Fourth, that the TV ads could be identified as positive, negative, or both.

We coded up to 10 articles per race that met these criteria. The minimum, median, and maximum number of articles used to evaluate tone per race are 1, 4, and 10, respectively. Through the selection process described above, our final sample includes 41 races and 197 articles. This number may appear small. Our filtering criteria are quite strict in the sense that we require the content of the articles to clearly indicate that they are about political advertising on TV by the candidate or party. There are many more articles that could be construed as about advertising, but we exclude them because they do not specifically indicate so. We also analyzed the data with less strict filtering and found similar conclusions. Out of all cases, these independent evaluations were in agreement 87.71% of the time. The discrepancies were then resolved by joint re-evaluation.

In order to examine whether the media focuses on negative messaging, we construct two variables for each race: (1) the percentage of articles about negative advertising (vs. positive advertising) out of all the ads that were covered by the news media, and (2) the proportion of advertising (by both candidates) that is spent on negative ads. The percent of advertising spending that is negative is calculated using the 69 days leading up to the election for each of the relevant races and comes from the CMAG/WAP advertising data. The two variables are positively and significantly correlated ($\rho = 0.34$, $p = .03$), providing face validity to our manual data collection effort.

Figure 2 addresses the question of whether the media is more likely to echo a negative versus a positive ad. Each point represents a particular race. The x-axis represents the proportion of ads that are negative (out of all the ads aired in this race). The y-axis represents the proportion of articles that discuss negative ads (out of all the ads covered by the media). If the news media does not prefer one type of tone over the other (e.g., negative over positive), we should expect that the observations would be close to the 45 degree line. If the observations are above (below) the 45 degree line, the media prefer negative over positive ads (positive over negative ads. It is easy to see that most races

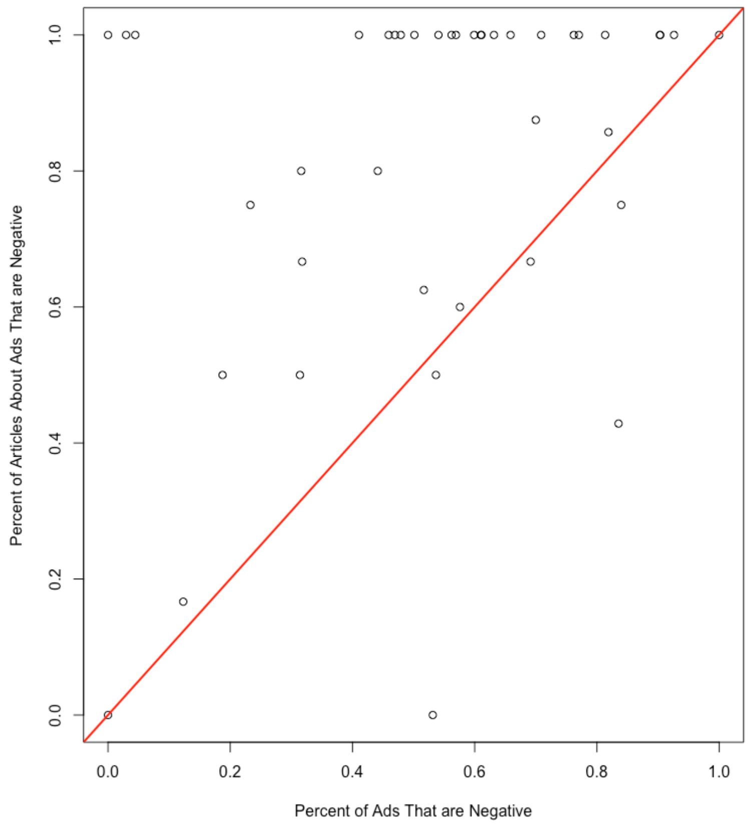

Figure 2: Plot of Media Coverage of Negative Ads vs. Actual Negative Ads

fall above the 45 degree line. In fact, 83% of the races have more reporting of negative ads than airing of these ads.

While the figure illustrates this result visually, it can be also tested statistically. Aggregating the data, the mean difference between the percent of media coverage of negative advertisements and the percent of negative advertisements is 28.16% (t-stat = 5.71, $p < .001$). This result clearly indicates that news media coverage slants heavily toward negative advertisements.

The evidence in this Appendix is somewhat similar to that of Ridout and Smith (2008) who already illustrated this point with ten U.S. Senate campaigns in 2004.

B First stage: the effect of the instruments on media coverage

	Dependent variable:	
	MediaHigh	MediaHigh
	(1)	(2)
NegMix_Lagged	0.031^{***} (0.006)	0.011 (0.022)
DaysUntilElection:MHC_Gannet	0.002^{***} (0.0003)	0.001^{*} (0.001)
DaysUntilElection:MHC_CNHI	-0.002^{***} (0.0003)	-0.001 (0.001)
DaysUntilElection:MHC_ LeeEnterprises	0.002^{***} (0.0004)	0.001 (0.001)
DaysUntilElection:MHC_ Ogden	0.002^{***} (0.0004)	0.002 (0.001)
DaysUntilElection:MHC_ Boone	0.001 (0.001)	0.001 (0.001)
DaysUntilElection:MHC_ Landmark	-0.001^{***} (0.0003)	-0.001 (0.001)
DaysUntilElection:MHC_Paxton	0.003^{***} (0.0004)	0.002^{*} (0.001)
DaysUntilElection:MHC_KnightRidder	0.002^{***} (0.0005)	0.001 (0.002)
DaysUntilElection:MHC_NewMediaCorp	-0.001 (0.001)	-0.001 (0.001)
DaysUntilElection:MHC_HearstNewspapers	-0.003^{***} (0.001)	-0.003^{***} (0.001)
DaysUntilElection:MHC_PulitzerInc	0.00005 (0.001)	0.0001 (0.001)
Weather	-0.011 (0.030)	0.019 (0.042)
SportSameState	-0.049^{**} (0.024)	-0.044 (0.181)
Sport	-0.083^{***} (0.017)	-0.057 (0.042)
SportNextDistrict	0.018 (0.016)	0.026 (0.097)
NewsCrime	-0.055 (0.035)	-0.053 (0.061)
Weather:MHC_Gannet	-0.086 (0.064)	-0.102 (0.068)
Weather:MHC_CNHI	0.008 (0.059)	0.015 (0.084)
Weather:MHC_ LeeEnterprises	0.080 (0.165)	0.053 (0.203)
Weather:MHC_ Ogden	-0.024 (0.103)	-0.050 (0.072)
Weather:MHC_ Boone	0.176 (0.125)	0.121 (0.076)
Weather:MHC_ Landmark	-0.071 (0.058)	-0.109 (0.077)
Weather:MHC_Paxton	-0.022 (0.082)	-0.038 (0.147)
Weather:MHC_KnightRidder	0.277^{***} (0.099)	0.236 (0.259)
Weather:MHC_NewMediaCorp	0.051 (0.399)	-0.140 (0.111)
Weather:MHC_HearstNewspapers	0.113 (0.097)	0.090 (0.157)
Weather:MHC_PulitzerInc	-0.142 (0.291)	-0.166^{**} (0.082)
Sport:MHC_Gannet	0.181^{***} (0.032)	0.141^{**} (0.056)
Sport:MHC_CNHI	-0.137^{***} (0.047)	-0.174^{***} (0.059)
Sport:MHC_ LeeEnterprises	-0.075 (0.429)	-0.061 (0.101)
Sport:MHC_ Ogden	-0.036 (0.066)	-0.037 (0.074)
Sport:MHC_ Landmark	0.138 (0.108)	0.164 (0.108)
Sport:MHC_Paxton	0.186^{***} (0.061)	0.193^{***} (0.065)
Sport:MHC_KnightRidder	-0.157^{***} (0.034)	-0.100 (0.156)
Sport:MHC_NewMediaCorp	-0.006 (0.539)	-0.007 (0.005)
Sport:MHC_PulitzerInc	-0.095 (0.382)	-0.121^{**} (0.047)
SportNextDistrict:MHC_Gannet	-0.181^{***} (0.034)	-0.189^{*} (0.109)
SportNextDistrict:MHC_CNHI	0.041 (0.043)	0.013 (0.071)
SportNextDistrict:MHC_ LeeEnterprises	0.119 (0.073)	0.145^{**} (0.065)
SportNextDistrict:MHC_ Ogden	0.008 (0.042)	0.010 (0.187)
SportNextDistrict:MHC_ Landmark	0.249^{***} (0.040)	0.119 (0.165)
SportNextDistrict:MHC_Paxton	-0.107^{**} (0.052)	-0.117 (0.073)
SportNextDistrict:MHC_KnightRidder	-0.087 (0.056)	-0.115 (0.090)
SportNextDistrict:MHC_NewMediaCorp	-0.213 (0.385)	0.159 (0.137)
SportNextDistrict:MHC_PulitzerInc	-0.058 (0.276)	0.067 (0.155)
SportSameState:MHC_Gannet	0.191^{***} (0.044)	0.141 (0.198)
SportSameState:MHC_CNHI	0.101 (0.066)	0.127 (0.146)
SportSameState:MHC_ Ogden	-0.105 (0.122)	-0.143 (0.254)
SportSameState:MHC_ Landmark	-0.600^{***} (0.050)	-0.417^{*} (0.216)
SportSameState:MHC_Paxton	-0.027 (0.073)	0.024 (0.158)
SportSameState:MHC_KnightRidder	-0.583^{***} (0.194)	-0.430^{**} (0.210)
SportSameState:MHC_NewMediaCorp	0.039 (0.384)	-0.069 (0.080)
SportSameState:MHC_PulitzerInc	0.083 (0.274)	0.138 (0.207)
NewsCrime:MHC_Gannet	0.059 (0.055)	0.044 (0.084)
NewsCrime:MHC_CNHI	-0.124^{*} (0.068)	-0.114 (0.091)
NewsCrime:MHC_ LeeEnterprises	0.185^{*} (0.101)	0.179^{*} (0.094)
NewsCrime:MHC_ Ogden	-0.022 (0.085)	-0.036 (0.085)
NewsCrime:MHC_ Boone	0.172 (0.205)	0.154^{*} (0.089)
NewsCrime:MHC_ Landmark	-0.047 (0.069)	-0.059 (0.096)
NewsCrime:MHC_Paxton	0.039 (0.196)	0.018 (0.186)
NewsCrime:MHC_KnightRidder	0.281^{**} (0.128)	0.324^{***} (0.106)
NewsCrime:MHC_NewMediaCorp	-0.137 (0.122)	-0.167 (0.157)
NewsCrime:MHC_PulitzerInc	-0.094 (0.314)	-0.005 (0.204)
Year Effects	Y	Y
Days to Election Effects	Y	Y
District Fixed Effects	Y	Y
Race Characteristics Variables	N	Y
Observations	33,728	33,728
R^2	0.425	0.454
Adjusted R^2	0.420	0.449
Residual Std. Error	0.381 (df = 33429)	0.371 (df = 33420)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6: Media Coverage Regressions (Column 2 is 1st Stage Regression of 2SLS)

C WebAppendix: Negativity Spans

Campaigns tend to air ads of the same tone for a few days or more at a time. To capture the tendency to continue with the same tone over few days, we describe these events as "spans" and provide a statistical description of their properties here. We jointly consider both candidates' tones so that there are nine possible tone-pairs per race-day, corresponding to the two candidates' choices (e.g., positive-positive, negative-positive, no ads-positive). The longest spans (23 days on average) are ones with no ads, which are largely early in the race when many campaigns do not air ads. To describe negativity spans, we pool over any spans that contain negative ads from either candidate. The average length of these negativity spans is 8.9 days. Of races that ever go negative, on average, they include 3.8 such spans (3.3 if considering all races). We plot the histogram of the number of these negativity spans per campaign in Figure 3. The modal case is two negativity spans (32%), with most of the mass centered closely around this mode as 56% of races have between 2 and 4 negativity spans. Races with only one such negativity span occur in only 12.5% of the total cases. Further, negativity spans are spread across the campaign, with 44% of the spans with some negativity occurring prior to the last 30 days of the campaign. Taken together, these features suggest that the dynamics of negativity are an important feature of the decision to go negative.

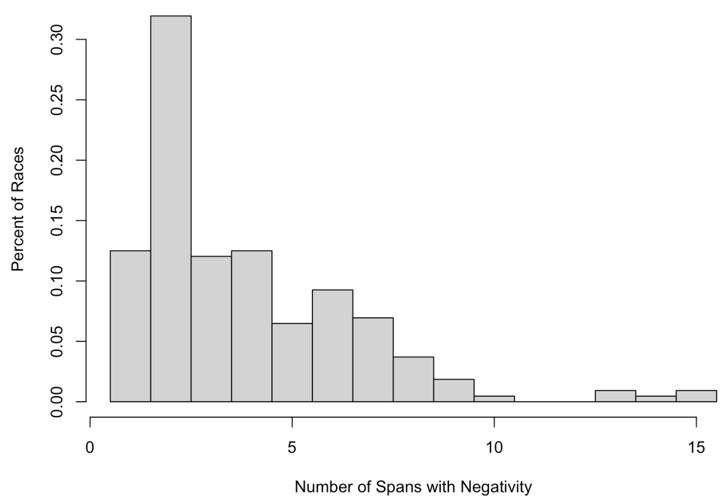

Figure 3: Distribution of the Number of Spans of Negativity per Race