Persuasion and Dissuasion in Political Campaigns: Communication and Media Coverage in Senate Races

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Abstract

We estimate the persuasive and dissuasive effects of media-reported campaign-trail speech on candidate electoral performance using a model in which, during each bipartisan race, candidates choose whether to address partisan supporters or swing voters, newspapers choose whether to cover each remark, and reported speech moves turnout and voter support. The model captures a core tension: while candidates seek selective media amplification of their messages, media outlets chase the most polarizing content. Using text analysis to label more than 200,000 newspaper stories from 1980-2012 as partisan or swing voter-oriented, and linking those labels to high-frequency polls of U.S. Senate races, we estimate the model parameters that allow us to recover persuasive and dissuasive effects of campaign speech. We rely on instruments that exploit sports-driven crowding-out of political coverage. The estimates reveal that Democratic appeals to their base are approximately four times more effective at mobilizing partisan turnout than Republican appeals, but also provoke twice the level of backlash from swing voters. These offsetting forces moderate Democratic rhetoric and, because media outlets prefer partisan content, yield near-symmetric coverage of the two parties despite asymmetric mobilization returns.

Keywords: Matching Pennies, Political Campaigns, Senate Elections, Media, Persuasion

JEL Codes: C3, D72

1 Introduction

Throughout political campaigns, candidates often oscillate between partisan rhetoric and measured centrist appeals. Whether those pivots help or hurt them electorally depends not only on who hears them, but on which remarks the news media choose to amplify. In this paper, we ask how candidates' incentives to target different audiences, and the media's incentives to cover political campaigns, interact to shape campaign speech and campaign performance.

Answering this question is empirically challenging for two reasons. First, electorates are heterogeneous. A remark that appeals to some voters –*persuasive effects*– can simultaneously alienate others –*dissuasive effects*–, similar to how an advertised product attribute may attract one consumer segment while repelling another. Depending on the data available, researchers may only be able to recover the *net effects* of communication, limiting our understanding of the underlying trade-offs that candidates face. Second, the preferences of candidates and the media often diverge. This is because heterogeneous audiences create incentives for *targeted* messaging by candidates. Their ability to target campaign communication, however, is limited by a key constraint: media outlets determine which messages are amplified or ignored.[1] Thus, campaign speech observed through media coverage is shaped both by the media's coverage choices and by candidates' strategic anticipation of those choices—complicating efforts to identify the causal effect of campaign rhetoric on electoral outcomes.

We develop a methodology that allows us to measure and separate the polling and electoral impacts of the persuasive and dissuasive margins of campaign speech, examining U.S. Senate campaigns from 1980 to 2012 –before social media became the principal conduit of political news. Senate races are well suited to the task because they attract heavy press attention and frequent polling. We bring together several sources of information and a theoretical framework that guide the empirical analysis. First, following ideas in Gentzkow and Shapiro (2010), we parse thousands of newspaper stories to infer whether each reported remark was aimed at swing or partisan voters. Second, we collected rich polling data over the course of the campaigns as measures of candidate electoral support. These data alone cannot identify either the average impact of campaign speech on electoral support or its separate persuasive and dissuasive components. Two hurdles stand in the way. The first is endogeneity: candidates tailor their rhetoric in response to events arising during the campaign, and journalists decide when and what to cover, so both speech content and coverage intensity co-move with unobserved factors that also influence the race. The second is what we will refer to as *net effects*. Even if endogeneity were absent, polling shifts reflect only the aggregate change in support: gains from persuasion minus losses from dissuasion. To disentangle these, we develop a simple strategic model of candidate-media interaction, inspired by Bajari et al. (2010), that explicitly models voter responses to different types of messaging. This framework allows us to decompose poll shifts into persuasive

[1] A recent example of this trade-off is Mitt Romney's "the other 47%" statement during a private fundraiser in Boca Raton during the 2012 U.S. presidential election. Although intended for a narrow partisan electorate audience, the statements were secretly recorded by a waitress in the event and then revealed to the media. Revelation of the statements led to a major backlash for Romney.

and dissuasive components. Crucially, we exploit two pieces of information embedded in the polling time series: (i) changes in the share of respondents backing neither candidate and (ii) changes in the relative standing of candidates. Our empirical strategy exploits each of these two margins separately, and shows how they are each informative about the persuasive and dissuasive margins of change in voter support.

In the model, each candidate chooses every period between a partisan or a swing-oriented statement, and the media chooses how intensely to cover each candidate. Voters react differently to the two message types. Our main insight is that candidates would like partisan appeals to fly under the media's radar while the media prefers to report them; candidates, in contrast, would welcome broad coverage of their swing appeals, which the media largely ignores. Such a setting results in a strategic environment resembling a matching-pennies game: The equilibrium probabilities of issuing a swing-targeted statement and receiving coverage determine both the overall share of campaign remarks the press reports and, within that subset, the share aimed at swing voters. Those rates expose the selection built into reported speech and let us infer how much campaign rhetoric goes unreported.

Although the model yields equilibrium implications that allow us to address selection into reporting, unobserved shocks could still influence both candidate rhetoric and polling changes. The model points to a solution: shocks that shift media payoffs without affecting candidate incentives are valid instruments for reported speech. Daily schedules of the *NCAA*, *NBA*, *MLB*, and *NFL* games satisfy this criterion. Packed sports line-ups crowd out political media coverage while leaving the campaign behavior of candidates unchanged (see Eisensee and Strömberg (2007)), giving us plausibly exogenous variation in coverage. These crowd-out instruments provide strong first stages and, paired with the model's equilibrium implications, let us recover average persuasive and dissuasive effects as closed-form functions of the estimated parameters of our model.

We find that Democratic and Republican campaigns confront markedly different strategic incentives. A 10-point rise in reported partisan speech raises Democratic support by about 3 points –more than four times the corresponding gain observed for Republican candidates.[2] At the same time, this increase in partisan rhetoric triggers a swing-voter backlash that is twice as large for Democrats as for Republicans. While Democrats face a sharper trade-off where partisan rhetoric energizes their base yet invites heavier media scrutiny and stronger swing-voter punishment, we estimate that, on average, 56% of Democratic remarks –but only 45% of Republican ones–, aim to mobilize partisan supporters. Media coverage, in contrast, is evenly balanced even though partisan mobilization returns are asymmetric. Indeed, the model we estimate allows media outlets to exhibit asymmetric payoffs from covering the statements from Republican and Democratic candidates. We refer to this differential

[2] That Democratic partisan supporters are considerably more responsive than Republican ones on the persuasion margin may be the result of the lower turnout rates traditionally associated with Democratic voters. This finding is consistent with previous empirical studies showing the effect of the media on voting behavior through increased turnout (see George and Waldfogel (2006); Oberholzer-Gee and Waldfogel (2009); Strömberg (2004a)).

treatment as *media bias*.[3] We find little evidence of systematic preference across outlets for covering candidates of one party over the other. Because the typical margin of victory in U.S. Senate races is 5 percentage points, the estimated effects we document are likely to have a meaningful electoral impact.

Overall, our results provide a decomposition of campaign speech into turnout and swing components, quantify the news media's role in magnifying or muting the effects of those components, and offer a framework for thinking about the trade-off between base activation and swing attrition whenever campaign speech is mediated by earned media. They also highlight the crucial role that the media plays in shaping candidates' communication incentives during the campaign season.

To explore heterogeneity in our findings, we next examine whether persuasion and dissuasion vary across four salient contexts. State partisanship matters: in states where Democrats make up a smaller share of the electorate, swing voters reward Democratic centrist appeals more strongly, whereas Republican effects do not shift with party balance in the state. Competitiveness matters as well: as the poll gap between candidates narrows, Republican swing-targeted speech becomes more effective at moving swing voters, perhaps because tighter races heighten attention. In contrast, we find little heterogeneity by time to election day and by whether one of the candidates is an incumbent senator. The size of both persuasive gains and dissuasive losses are similar from the early campaign through election day, and between races with and without a sitting senator on the ballot.

These findings are robust to a battery of alternative specifications. They hold when we shorten or lengthen the polling windows used to compute poll-share changes, and when we tighten or loosen the thresholds that label news stories as partisan or swing-oriented. They are also stable if we (i) drop sports events towards the end of the campaigns, (ii) build instruments from any single sport or from different sport combinations, and (iii) allow the effects of campaign speech to differ between the primary season and the post-primary weeks.

1.1 Related Literature

Our paper relates to several research areas. Foremost, to the literature on media coverage (Gentzkow and Shapiro, 2006; Puglisi and Snyder, 2008; Strömberg, 2004a), which separately studies policy choices by politicians or coverage decisions by the media. In contrast, we explore the simultaneous determination of candidates' choices and media coverage strategies. The theoretical literature on issue selection has emphasized how informational frictions between voters and candidates may affect campaign message choices (Egorov (2015)). The empirical literature, in turn, has measured the impact of media coverage on policy outcomes (Snyder and Strömberg (2010); Strömberg (2004b)). Instead, we focus on the impact of media coverage on candidate behavior, and indirectly, on electoral outcomes. Thus, our model is close in spirit to the ideas in Ansolabehere et al. (1992), according to whom "... some of the most crucial interactions in campaigns are those between candidates and reporters... campaign

[3] In contrast to prior literature, where media bias is typically defined as the ideological slant or framing of news content (e.g., Baron (2006); Mullainathan and Shleifer (2005)), our definition of media bias refers only to the media's relative preference for the extent of reporting about either political party.

organizations seek to spoon-feed the press in order to control the news coverage their candidates receive. Journalists react by striving to keep candidates off balance through independent reporting" (p.72). Another related paper is Fonseca et al. (2014), who study the partisan bias in newspaper coverage of political scandals in the late 19th Century U.S. They find significant bias in reporting depending on newspaper partisanship. While they focus on political scandals only, here we focus on the media's coverage choices over any candidate-related content.

This study is also related to the literature estimating the effects of communication by advertisers (Shapiro et al., 2021; Spenkuch and Toniatti, 2018), by experts such as sales people (Manchanda et al., 2008), by consumers of a brand (Chevalier and Mayzlin, 2006; Mayzlin, 2006), and by friends and family (Chevalier and Mayzlin, 2006) through persuasion via word of mouth. We instead focus on persuasive or dissuasive political communication, as delivered by media. Our paper also relates to the literature on transparency that studies how communication in principal-agent settings affects policy outcomes (Maskin and Tirole, 2004; Prat, 2005). In our model, an increase in candidates' payoffs from persuasive speech targeted to partisan supporters leads to more media scrutiny and thus, to more information production. More information, thus, may be observed when platform choices by politicians are more ideologically extreme. Of course, if there is no relationship between what candidates say during campaigns and what they do while in office, understanding the forces shaping campaign speech would be uninformative about the media's role in shaping policy. Voters appear to care about what candidates say, however, and the literature does suggest there is a close relationship between campaign speech and policy choices (Budge and Hofferbert, 1990; Kurkones, 1984).

This study is also related to the literature studying matching-pennies-type strategic environments and the mixed-strategy equilibria associated with them. Walker and Wooders (2001) were the first to look for empirical evidence of mixed-strategy behavior by studying serving on Wimbledon tennis matches. In a very different context, Knowles et al. (2001) developed a test for racial profiling in motor vehicle searches. In their model, policemen randomize over searching and not searching potential suspects. Palacios-Huerta (2003) and Chiappori et al. (2002) similarly studied penalty kick data in soccer to look for evidence of mixing behavior. In contrast, we use this game-theoretic framework in a persuasion and political economy context.

Lastly, our paper contributes to the literature estimating discrete games of complete information. Most of these have been Industrial Organization applications focused on the problem of entry, and on pure strategy equilibria (see Berry (1992); Bresnahan and Reiss (1990, 1991)). In contrast, we estimate a model where only mixed strategies are economically meaningful, and propose a different identification strategy. Moreover, for games where a subset of outcomes is unobserved (such as the tax auditing game), Bresnahan and Reiss (1990) pointed out a negative identification result for the game's payoff parameters. Our methodology shows how this issue can be overcome empirically.

While marketing scholars have measured the effects of earned media (e.g., Lovett and Staelin, 2016; Seiler et al., 2015; Stephen and Galak, 2012), we are unaware of other studies modeling the relationship between candidates to elected office and the media in the way we do here, or estimating the effect of media campaign coverage on electoral outcomes leveraging the implications of a structural model.

2 A Simple Model of the Campaign Trail

In this section we describe the simple model of political campaigns and media coverage that allows us to separately measure persuasive and dissuasive effects of campaign speech, and to address the econometric challenges we outlined above. The model captures what we consider are key features of the interaction between two candidates $c \in \{D, R\}$ running against each other, and the distribution of media outlets m covering the race. Because our main purpose is to estimate persuasion and dissuasion effects from candidate speech, we begin by describing the framework linking the electoral performance of the candidates along the campaign trail to the campaign speech they produce. We incorporate the following mechanisms: i) Campaign speech targeted towards partisan voters can persuade them to turn out. ii) Campaign speech targeted towards centrist voters can persuade them to support the candidate engaging in it. iii) Media-reported campaign speech targeted towards partisan voters dissuades centrist voters. Being centrist, these voters are likely to be swing voters; this is, if persuaded or dissuaded, they take their support away from one candidate and give it to the opponent. Thus, on the swing-voters margin, one candidate's gain is the other's loss. This strategic environment involves a trade-off for candidates: partisan-targeted speech may induce turnout among partisans, but if covered widely by the media, it can sway swing voters towards the opponent.

Candidates make statements over time that can be targeted to partisan or swing voter constituencies. The media decides on the coverage of the campaigns every period and obtains different payoffs from reporting on either type of campaign speech. The key assumption we maintain (and implicitly test) is that payoffs to the media are higher when reporting news on campaign speech targeted to partisan voters. For example, if partisan-targeted speech is more controversial or more informative about the candidates' actual views, it may induce more attention by the public. Time is discrete, $t = 0, ..., T$, where $t = 0$ is the beginning of the campaign and $t = T$ is election day, and both candidates begin their campaigning on the same date.

2.1 Players' Actions and payoffs.

Candidates Candidates make a campaign statement a^c every period. Statements can be targeted to more ideological, *partisan* voters ($a^c = p$). Such statements, however, may dissuade swing voters. Statements may instead be targeted to *swing* voters ($a^c = s$). These will generate little excitement among partisans, but will increase or maintain the electoral support among the swing voters. The environment we have in mind, thus, is one where candidates do not converge (in their campaign speech) to the median voter's ideological stance.[4] More precisely, the payoff environment incorporates the following assumptions about the behavior of potential voters: the arrival of media reports can have two effects on voters' decisions. First, it can make them shift support from one candidate to the other. Second, it can alter their turnout decision. This distinction is important because the first margin leads to a zero-sum setting from the candidates' point of view, while the second margin does not. The payoff structure we present below assumes that partisan voters only react on the turnout margin (they do not switch party allegiance). In contrast, swing voters only react on the party support margin. We assume voters report truthfully to pollsters. Naturally, these assumptions do not hold perfectly in practice. We believe they are, to first order, plausible in the partisan setting we study, while allowing us to make considerable empirical progress.

Candidates care about their poll standing, and their actions directly map onto changes in electoral and poll support. Their payoffs depend on whether the media covers their statements, and on whether these statements are targeted to swing voters or to partisan supporters. More precisely, the change in poll support for candidate $c \in \{D, R\}$ between periods t and $t+1$ can be decomposed as:

$$\begin{aligned}\Delta V_c(t+1) = \quad & \underbrace{\Delta^T_{pc}\mathbf{1}\{a^c(t)=p, \chi^c(t)=0\}}_{\text{Candidate makes statement } p\text{, Media does not report}} \quad + \underbrace{\left(\Delta^T_{pc}-\Delta^S_{pc}\right)\mathbf{1}\{a^c(t)=p, \chi^c(t)=1\}}_{\text{Candidate makes statement } p\text{, Media reports}} \\ & + \underbrace{\Delta^S_{p\sim c}\mathbf{1}\{a^{\sim c}(t)=p, \chi^{\sim c}(t)=1\}}_{\text{Opponent makes statement } p\text{, Media reports}} + \underbrace{\Delta^S_{sc}\mathbf{1}\{a^c(t)=s, \chi^c(t)=1\}}_{\text{Candidate makes statement } s\text{, Media reports}} \\ & - \underbrace{\Delta^S_{s\sim c}\mathbf{1}\{a^{\sim c}(t)=s, \chi^{\sim c}(t)=1\}}_{\text{Opponent makes statement } s\text{, Media reports}} \quad + \epsilon^c(t+1), \end{aligned} \tag{1}$$

where Δ^T_{ac} is the average change in electoral support to candidate c on the Turnout margin when choosing action a, and Δ^S_{ac} is the average change in electoral support to candidate c on the Swing-voter margin when choosing action a. $\sim c$ denotes candidate c's opponent, and $\chi^c(t) = 1$ denotes the event that the media reports on candidate c. While Δ^T_{pc} and Δ^S_{sc} are persuasion effects, Δ^S_{pc} are dissuasion effects. (ϵ^D, ϵ^R) are other unobserved shocks to the change in electoral support.

Equation 1 incorporates our key assumptions. i) Swing voter-targeted statements that go unreported by the media have no effect on either partisan or swing voters. When reported, these statements shift support from the candidate not reported to the candidate reported. Because the turnout rate for swing voters is unaffected, the gain for one candidate is exactly the loss for the opponent. ii) Partisan voter-targeted statements increase the turnout of partisan constituencies. When such statements are unreported, they do not have an effect on swing voters. We believe this is plausible in the context of Senate races, where voters can hear candidate messages directly in rallies or town halls –relatively more likely attended by partisan voters–, or indirectly through the media. When reported, in contrast,

[4] This setting can be micro-founded in a model where the turnout of voters in the extremes of the ideological distribution (partisans) is sensitive to their distance to the candidates' position, and the density of partisan voters is high in the extremes. Standard incentives to move towards the median must be traded-off against the loss in turnout from the margins of the distribution of voters.

they turn swing voters away from the candidate making these statements and towards the opponent.

The media Simultaneously, every period the media takes one of three possible actions: to follow both candidates, to follow only D, or to follow only R. In either case, after having taken its action, the media outlet reports on candidate c with probability $\eta_c \leq 1$. This probability intends to capture non-modeled reasons why the media as a whole may be more or less likely to report on different candidates. It also allows the model to predict periods without observed news reports, while keeping the strategy space for the media only trinary. When $\eta_D \neq \eta_R$, we refer to this as "coverage media bias." Candidate statements and media reports determine, period-by-period, the evolution of poll standings.[5] Media outlets pay a cost k per candidate followed. The per-period gains from reporting on candidate c are:

$$\pi_c(a^c) = \begin{cases} 0 & if\ a^c = s \\ \pi_c & if\ a^c = p, \end{cases} \tag{2}$$

Notice that the media's relative payoff from partisan speech coverage is allowed to differ across candidates, and that the media maximizes these payoffs given their coverage bias.

2.2 Equilibrium

Candidates maximize their poll standing (in a bipartisan race this is equivalent to maximizing the winning probability every period), and take each other's strategies as given when deciding their campaign-trail speech. Equilibrium in this simple model naturally depends on the payoff parameters. We maintain (although we do not impose in estimation) the following joint parameter restrictions:

Assumption 1. *The following inequalities hold:*

$$\begin{array}{llll} \Delta^T_{pD} < \eta_D \left(\Delta^S_{pD} + \Delta^S_{sD}\right), & \Delta^T_{pD} > 0, & \Delta^S_{pD} > 0, & \Delta^S_{sD} > 0 \\ \Delta^T_{pR} < \eta_R \left(\Delta^S_{pR} + \Delta^S_{sR}\right), & \Delta^T_{pR} > 0, & \Delta^S_{pR} > 0, & \Delta^S_{sR} > 0 \end{array}$$

Under Assumption 1, the expected gain on the turnout margin –which includes the opportunity cost of foregoing gain in support from a swing-targeted statement–, is less than expected swing-voter loss from making a partisan-targeted statement. In this case, the net effect from a partisan-targeted statement reported by the media is negative for the candidate making the statement. Equations (1) and (2) and the parameter restrictions in Assumption 1 are fairly natural. They make explicit that unreported statements by a candidate do not have an effect on his opponent's poll standings, and that unreported swing-voter targeted statements do not have any effect on the candidate's own poll standings. They also imply that candidates gain support from partisan-targeted statements that go

[5] As our focus is not on voters in this paper, we deliberately keep their decisions simple: their support at any point in time responds to the changes in the information they receive during the campaign, either directly from the candidates or from the media.

unreported, but expect to lose support when these statements are reported. Finally, they take into account the zero-sum nature of swing support: reported own swing voter-targeted statements increase own support (at the expense of the opponent), and reported opponent's swing-targeted statements decrease own support (and are a gain to the opponent).

This strategic environment resembles a matching-pennies game between each candidate and the media: if a candidate sends a partisan-targeted signal, the media will want to cover it. If the media covers a partisan-targeted signal, the candidate will prefer to send a swing-voter targeted signal. If a candidate sends a swing-voter targeted signal, the media will not want to cover it. If the media does not cover it, the candidate will prefer to send a partisan signal. As a result, both the candidates and the media have strong incentives to play a mixed strategy over the course of the campaign to appear unpredictable in their action choices. The uniqueness of equilibrium we establish below allows us to pin down the joint distribution of players' actions and poll changes over time.

Proposition 1. (Equilibrium Strategies) *Suppose $\eta_c \pi_c > k$. The game described above does not have a pure-strategy equilibrium. The unique mixed strategy equilibrium is given by:*

$$\gamma_R^* = 1 - \frac{\Delta_{pD}^T}{\eta_D \left[\Delta_{pD}^S + \Delta_{sD}^S\right]} \tag{3}$$

$$\gamma_D^* = 1 - \frac{\Delta_{pR}^T}{\eta_R \left[\Delta_{pR}^S + \Delta_{sR}^S\right]} \tag{4}$$

$$q_D^* = \frac{k}{\eta_D \pi_D} \tag{5}$$

$$q_R^* = \frac{k}{\eta_R \pi_R} \tag{6}$$

where γ_D is the probability that the media follows D but not R, γ_R is the probability that the media follows R but not D, and q_D and q_R are the probabilities that candidates D and R make partisan-targeted statements. Because the stage-game has a unique Nash equilibrium, the only sub-game perfect equilibrium of the finitely repeated game is to play the unique stage-game Nash equilibrium every period.

Proof. See Appendix A. □

As is the case in a standard matching-pennies environment, the equilibrium mixing probabilities are determined by players' indifference conditions. This implies that each player's strategy depends only on the payoffs of their opponent, not their own. In our setting, this leads to a testable implication: to understand a candidate's equilibrium campaign speech behavior, one must examine how changes in the media's payoffs affect it. The candidate's own payoffs do not influence their equilibrium strategy. As a result, when the media derives greater benefit from reporting on partisan-targeted statements, candidates respond by making such statements less frequently. In this sense, the media constrains candidate's speech in our setting. Conversely, the media's reporting frequency depends only on the candidates' payoffs and not on the media's own reporting returns.

3 Data

We now briefly describe our data and approach for measuring the the likely candidate covered, and type of campaign speech reported in media articles.

3.1 Senate Races

There are 100 U.S. Senate seats, two per state. Senate elections are held in November of even years, and senators are elected by plurality within each state. Under the current system, a third of the seats are up for election on each 2-year cycle and each seat has a six-year term, so there are about 33 elections every electoral cycle.[6] As with most U.S. elections, Senate races are preceded by an extended period of campaigning that typically begins well before parties formally nominate their candidates through primaries or conventions. Nevertheless, pollsters begin tracking general election support even during this pre-nomination phase.

We built a data set of all ordinary competitive races to the U.S. Senate taking place between 1980 and 2012 for which a Democrat and a Republican ran.[7] Our final sample includes 415 races (out of the $561 = 17$ election cycles $\times$ 33 races that could have taken place in this 32-year period). For each Senate race we have information on its outcome (Democratic share and Republican share) from the Federal Elections Commission, the date, and outcomes of the primaries for each party whenever a primary took place –or whether the candidate was chosen at a party convention for states electing their candidates that way–, information on whether an incumbent senator was running, and characteristics of the political environment such as the party of the President, the party of the incumbent senators in the state, and the share of Democratic and Republican registered voters in the state. For states without party registration, we use the vote share for President in the most recent election. Table A.1 in the online appendix presents summary statistics for all variables.

3.2 Polls

We collected detailed polling data for Senate races from a variety of sources. To the best of our knowledge, the earliest systematic compilation of polls goes back to 1998. We obtained polls from PollingReport.com for 1998-2004, and from Pollster.com for 2006-2012. For pre-1998 poll data, we did an exhaustive newspaper search using the Dow Jones/Factiva news database, focusing on polling

[6] After the resignation or death of an incumbent senator, special elections can be held at different times.

[7] We excluded races with three prominent candidates, races where a candidate ran unopposed, non-bipartisan races, and races where either candidate died or quit during the campaign. Appendix C contains a list of the races we dropped.

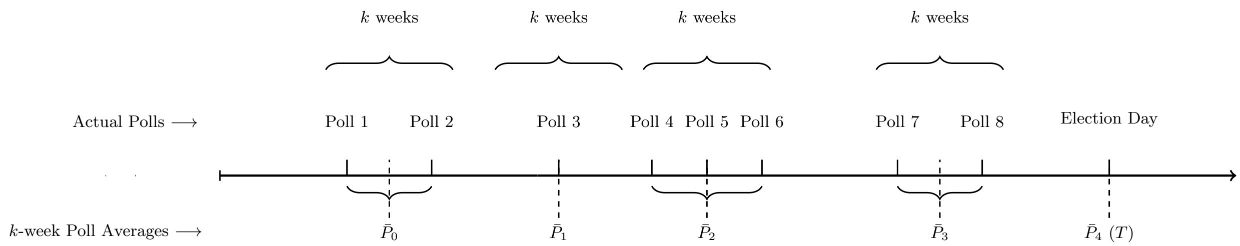

Figure 1: Construction of the poll-to-poll intervals.

reported within a one-year window before election day.[8] We obtain a total of 4076 polls. As Table A.1 illustrates, we obtain an average of 240 polls per election cycle, and of 10 polls per race. Naturally, the frequency of Senate race polls becomes higher in more recent years and in more populous states.

Our empirical strategy requires that we align news coverage with polling periods. We treat the span between successive polls as a "poll-to-poll" interval, which becomes the time unit of our panel. Each newspaper story is dated and assigned to the interval that contains that date. We then compute the article counts statistics needed for our empirical analysis (described below) within that same interval. Because polling cadence is uneven across states and years, we form two alternative intervals. One specification groups polls whose dates fall inside a rolling two-week window; an alternative one uses a three-week window. Within each window we average poll results—weighting by sample size—and stamp the interval with the median poll date. Bundling proximate polls regularizes the timeline and attenuates the sampling error of individual surveys. Figure 1 illustrates how the windows segment a campaign and how stories are slotted into their corresponding poll-to-poll intervals.[9]

3.3 Measuring News Reporting

Our methodology requires us to classify campaign-related news articles based on the type of candidate speech they reflect. This allows us to establish a link between reported candidate speech and electoral performance. More specifically, we need a criterion to classify each news piece as suggestive of partisan-targeted or swing voter-targeted campaign speech. Naturally, such a distinction is empirically meaningful only in relation to the ideological distribution of the relevant population of potential voters –the state in our setting–. For example, the same statement may be considered moderate and targeted

[8]For example, for the 1998 election we began our search on November 1, 1997. In a few cases we encountered discrepancies in the reported polling results across articles from different newspaper sources referring to the same poll, in which case we averaged the results. The 1998 poll data from PollingReport.com was sparse, so we also did an online newspaper search for polls for that year. When only the month of the poll was reported we imputed the date to be the fifteenth of the month except for November polls, in which case we imputed the date to be the first of the month.

[9]Choosing the width of a poll-to-poll interval poses a precision–bias trade-off. Longer intervals pool more articles, so the relative- frequency measures we compute suffer less sampling noise and better approximate the true reporting probabilities. Yet if those probabilities shift over the campaign—for instance, because pay-offs vary with the candidates' current standing—long intervals blur that variation and introduce bias. We probe both margins. First, we rerun the analysis with alternative interval definitions (two-week and three-week windows). Second, we estimate a dynamic version of the model in which pay-off parameters evolve with a state variable: the candidates' real-time poll gap. Results remain stable across these specifications.

to swing voters when expressed by a Democratic candidate in Massachusetts, but it may only appeal to partisan Democratic voters when expressed by a Democratic candidate in Utah. Moreover, the ideological distribution of the population within a state may change over time, making a statement that could be considered partisan-targeted in 1980, appealing to swing voters in 2012. A sensible classification criterion for the reported content of media reports must be race-specific.

With this in mind, we follow Gentzkow and Shapiro (2010) to compute media slant and to develop an index of media content. For each race, we conducted a comprehensive search of news reporting from two major news databases, *Lexis Nexis* and *Factiva*, which cover national and local newspapers. The search criteria involved the names of the Democratic and Republican candidates in each race during the year prior to election day. We collected all articles mentioning either candidate. Our initial search recovered more than 300,000 articles covering 560 races and 1120 candidates. For the set of articles mentioning either candidate in a given race, we gather information about the articles (publication date, source, subjects, and people mentioned in the article). As Table A.1 illustrates, our estimation sample contains information from 210,848 news articles, with an average of 508 articles per race.

To assess the extent to which an article reports on the Democratic or the Republican candidate, we counted the number of times the name of each appears in the article.[10] We then computed the candidate assignment statistic κ_i:

$$\kappa_i = \frac{g_i^R - g_i^D}{g_i^R + g_i^D} \in [-1, 1]$$

where g_i^c is the count of candidate c's name in article i. Values closer to $+1$ imply the article is more heavily reporting on the Republican, and values closer to -1 imply the article is more heavily reporting on the Democrat. Figure A.1 in the online Appendix presents the distribution of κ_i across all articles and races. The distribution is multi-modal, with most articles referring heavily to just one candidate. There is also some density of articles mentioning both candidates evenly (with scores close to 0). Table A.1 reports the number of articles we classify as referring to the Democratic ($\kappa_i < 0$) and Republican ($\kappa_i > 0$) candidates.

Within the set of articles corresponding to a race, we identify the 500 most commonly used 2 word phrases (2-grams), and the 500 most commonly used 3-word phrases (3-grams). We then give a score $s_j \in [-1, 1]$ to each phrase $j \in \{1, 2, ..., 1000\}$, related to how Republican-specific vs. Democratic-specific the phrase is within the set of articles covering the race. We do this by computing a weighted average of the κ_i's corresponding to articles containing phrase j, where the weights are the frequencies with which each phrase appears in each article, relative to all articles covering the race. For each j,

$$s_j = \frac{\sum_i \kappa_i f_{ij}}{\sum_i f_{ij}} \in [-1, 1].$$

Here f_{ij} represents the frequency with which phrase j appears in article i. For example, if a given

[10] Although articles often mention both candidates, the average article is usually centered on reporting about one of them. The name of the opponent is reported as part of the context only. A few articles, of course, discuss the race as a whole and would be harder to classify as reporting about the Democrat or the Republican.

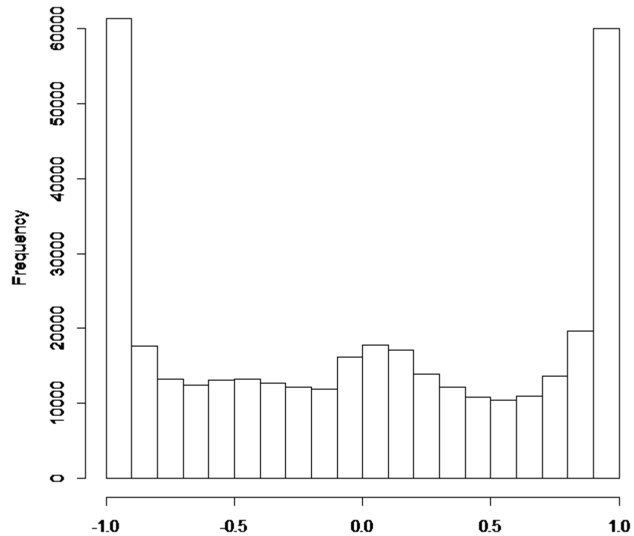

Figure 2: Distribution of articles scores σ_i.

phrase appears only in articles that only mention the Republican candidate, then that phrase will have a score of $s_j = 1$. s_j gives us information regarding the extent to which phrase j is more commonly associated to one candidate or to the other. Endowed with the score s_j for each phrase in the race, we then compute a score for each news article in the race, building a weighted average of the scores of phrases appearing in the article, where the weights are the frequencies with which each phrase appears in each article, relative to all phrases in the article. For each i,

$$\sigma_i = \frac{\sum_j s_j f_{ij}}{\sum_j f_{ij}} \in [-1, 1]. \tag{7}$$

Articles with more phrases which, within the race coverage, are more closely associated with articles more heavily covering the Republican (Democratic) candidate will get higher (lower) scores.

This measure has the advantage of relying solely on information from the relevant race: we do not use any information from outside the coverage of the specific race to assess whether a news piece is likely to be reporting about partisan supporter or swing voter-targeted speech by the candidates. σ_i is a continuous index which we use together with κ_i, to classify each article both as covering either the Democrat or the Republican, and whether the content is more swing voter targeted –s– or partisan supporter targeted –p–.[11] Figure 2 presents the distribution of the article scores σ_i for our sample of news pieces. Our benchmark specification classifies articles as signaling partisan-targeted speech when $\sigma_i < -0.25$ for the Democrat and when $\sigma_i > 0.25$ for the Republican. It classifies the remaining articles as signaling swing voter-targeted speech (those with scores $\sigma_i \in [-0.25, 1]$ for the Democrat

[11] Although this measure only uses information from reported campaign speech, an implication of our model is that candidates cannot condition on being covered or not. As a result, the distribution of types of speech is the same among reported and unreported speech.

and with scores $\sigma_i \in [-1, 0.25]$ for the Republican). Figure A.2 in Appendix A illustrates graphically the article classification criterion for the ± 0.25 cutoff. For robustness, we present additional results that reclassify all articles using alternative cutoffs $\sigma_i = \pm 0.5$ and $\sigma_i = \pm 0.75$.

Using our collection of news articles we also obtain information on the number of different media outlets covering each race, based on the news outlets' names and date tags. As a result, we have data on the count of different outlets reporting on a race within each poll-to-poll interval. Finally, to compute overall reporting frequencies, we defined the total effective number of periods or stage games within each poll-to-poll interval as the number of days between polls times the total number of media outlets ever reporting on the particular race. This is equivalent to assuming that the candidates play a stage game against each media outlet every day during the campaign.

3.4 Sports news data as media-payoff shifters

Our empirical strategy exploits the correlations between frequencies of news reporting and changes in poll support for both candidates. A host of unobservables can lead to changes in electoral support along the campaign. These may be correlated with candidates' incentives to make different kinds of statements and the media's incentives to cover them. To overcome this difficulty, we rely on the occurrence of major sports events as exogenous shifters of the media's attention, similar to Eisensee and Strömberg (2007) and Hartmann and Klapper (2017). More specifically, we collected daily information on all games from the *NFL*, *MLB*, and *NBA*, and all playoff games from the *NCAA* between 1979 and 2012.[12] This constitutes a dataset with more than 600,000 observations. For each day, we have information on whether a team played or not, and won or lost the game. We then match teams to their respective states, which gives us daily state-level variation in the media's payoff from reporting on political campaigns. This source of variation is unlikely to be related to unobservables driving candidate behavior along the campaign trail. Because most games for each sports league take place during a specific season of the year (e.g., football is concentrated in the winter, and baseball in the summer), having information from the four major league sports provides us with year-round variation. Some states do not have teams in these leagues, or their teams seldom make it to the playoffs with enough frequency. To also obtain exogenous variation in media campaign coverage for these states, we additionally collected information from *Facebook*.[13]

[12] *NFL* is the National Football League, *MLB* is the Major League Baseball, *NBA* is the National Basketball Association, and *NCAA* is the National Collegiate Athletic Association.

[13] *Facebook* collected county-level information on the distribution of "likes" among its users in 2013, for each *NFL*, *MLB*, *NBA*, and *NCAA* team. We use this information as a proxy for the extent to which the media covering a race in a given state may vary its behavior in response to salient sports events from teams of other states, which have a major support in the state where the race is taking place. We computed the matrices $\mathbf{W}^{NFL}$, $\mathbf{W}^{MLB}$, and $\mathbf{W}^{NBA}$, where entry w^l_{ij}, $l \in \{NFL, MLB, NBA\}$ records the total population of counties in state i, as a fraction of total state population, where a plurality of *Facebook* users supports a team from state j in the sports league l. For states without teams in our data, these matrices provide us with variation in media payoffs, coming from a large fan base rooting for out-of-state sports teams that may lead to local media attention. Figure A.3 illustrates the geographic distribution of fans of the teams in these four leagues, illustrating the straddling of fans across states that we rely on. The *Facebook* fan map for the *NCAA* reveals that fandom for College Football is very highly correlated with state boundaries, thus giving us no additional variation. For this reason, we do not weight *NCAA* sports events by the cross-state fandom weighs.

4 Empirical Strategy and Identification

We now describe our empirical strategy, bringing together the model of the campaign trail from section 2 and the data from section 3. Relying on our classification of news articles, on polling data, and on the exogenous source of variation in campaign news coverage induced by sports events, we can identify the persuasive, $(\Delta^T_{pc}, \Delta^S_{sc})$, and the dissuasive, (Δ^S_{pc}), effects of candidate speech on polling performance: This is despite our inability to observe a subset of the equilibrium outcomes of the game, namely campaign speech unreported by the media.

4.1 Identification of Persuasion and Dissuasion Effects

4.1.1 Persuasion effects on the partisan-voter margin

Consider the change in poll support for candidate c during a poll-to-poll interval t, of length τ. Throughout, by length of an interval we mean the number of instances of candidate speech within a given poll-to-poll interval indexed by t. From (1), if we add up the poll changes of both candidates, conveniently, all terms involving swing-voter effects cancel out:

$$\Delta V_R(t+1) + \Delta V_D(t+1) = \Delta^T_{pR} \sum_\tau \mathbf{1}\{a^R(\tau) = p\} + \Delta^T_{pD} \sum_\tau \mathbf{1}\{a^D(\tau) = p\} + \sum_\tau (\epsilon^R(\tau) + \epsilon^D(\tau))$$

Thus, the covariation between changes in the margin of voters not supporting either candidate over a given time period, and the number of partisan-targeted statements of each candidate over the same period, can inform us about the persuasion effects of that kind of speech on the turnout margin. One challenge in estimating this equation is that we observe only the reported fraction of partisan-targeted speech. However, notice that

$$q^*_c(t) = \mathbb{E}\left[\frac{1}{\tau}\sum_\tau \mathbf{1}\{a^c(\tau) = p\}\right] \tag{8}$$

since $q^*_c(t)$ is the equilibrium probability that candidate c makes a partisan-targeted statement. Similarly, equilibrium strategies from Proposition 1 also imply that

$$q^*_c(t)(1-\gamma^*_{\sim c}(t))\eta_c = \mathbb{E}\left[\frac{1}{\tau}\sum_\tau \mathbf{1}\{a^c(\tau) = p, \chi^c(\tau) = 1\}\right] \tag{9}$$

$$(1-q^*_c(t))(1-\gamma^*_{\sim c}(t))\eta_c = \mathbb{E}\left[\frac{1}{\tau}\sum_\tau \mathbf{1}\{a^c(\tau) = s, \chi^c(\tau) = 1\}\right] \tag{10}$$

are the equilibrium fractions of partisan-targeted statements reported by the media, and of swing-voter targeted statements reported by the media, respectively. Since we measure these with the number of partisan $(Articles^p_c(t))$ or swing-voter targeted news articles $(Articles^s_c(t))$ for candidate c, both are observed. Solving for $q_c^*(t)$ from (9) and (10),

$$\hat{q}_c^*(t) = \frac{Articles_c^p(t)}{Articles_c^s(t) + Articles_c^p(t)}. \tag{11}$$

The intuition here is simple: in equilibrium, the likelihood of media reporting on the candidate does not depend on the type of statement made by the candidate, so the share of partisan-targeted statements reported is an unbiased estimate of the overall rate at which the candidate makes such statements. Thus, we obtain an estimating equation that depends only on observables:[14]

$$\frac{\Delta V_D(t+1) + \Delta V_R(t+1)}{\tau} = \Delta_{pD}^T \frac{Articles_D^p(t)}{Articles_D^s(t) + Articles_D^p(t)} + \Delta_{pR}^T \frac{Articles_R^p(t)}{Articles_R^s(t) + Articles_R^p(t)} + \omega(t) \tag{12}$$

where $\omega(t) = \frac{1}{\tau}\sum_\tau(\epsilon_R(\tau) + \epsilon_D(\tau))$ is a composite error.

A key identification challenge with estimating equation (12) is the endogeneity of the shares of news stories with partisan-targeted content. Each of these shares may be correlated with other unobservables that also determine the evolution of electoral support during a campaign, so we need at least two instrumental variables. These need to be sources of variation for the relative frequencies of partisan-targeted statements made by candidates, which do not also covary with other determinants of the evolution of electoral support during the campaign. Our model suggests what the natural instruments for these variables should be. From (5) and (6), the mixing probabilities chosen by the candidates are pinned down by the media's payoffs from reporting: $q_c^*(\mathbf{z}_t) = \frac{k}{\eta_c \pi_c(\mathbf{z}_t)}$. A shifter of the media's payoffs to reporting on the campaign, otherwise unrelated to other campaign outcome determinants, will generate variation in the candidates' choices. If larger values of the instrument reduce the media's profitability of covering politics, this should increase the rate at which the candidates engage in partisan-targeted speech: we expect a positive *sign* for the first stage.

As described in section 3.4, we rely on salient sports events as shifters of the media's attention (lowering its payoff from reporting on the campaigns). Eisensee and Strömberg (2007) use variation generated by the occurrence of the Olympic Games to study media coverage of natural disasters. In a similar spirit, we use daily data on the occurrence of games in any of the four major sports leagues in the U.S. (MBL, NFL, NBA, $NCAA$). We match the games to the poll-to-poll intervals where they occur and the states where their fan bases are, including games with teams from the race's state or from other states with a significant local fan base as proxied by the *Facebook* fandom data (see section 3.4). The exclusion restriction is that the occurrence and outcomes of the games in any of these leagues are uncorrelated with any unobserved determinants of the evolution of electoral support, other than by altering the media's relative payoffs from covering the campaigns. We believe this is a plausible exclusion restriction.[15] Moreover, because the model predicts the sign of the first stages, we consider the first stages as implicit specification tests of our model.

[14] In practice, the length of a panel period, τ, will be determined by the frequency of polls for the race as we described in section 3.2. As long as pollsters' poll-timing decisions are not dependent on how the media is covering the campaigns or how the campaign is developing, defining the time periods this way will introduce no additional sources of bias when estimating equation 12. In section B.2.1 we test the plausibility of this assumption.

[15] The exclusion restriction may fail if the occurrence of these sports events directly lowers the turnout or changes the voters' electoral choices. Healy et al. (2010), for example, find that college football wins around election day increase the vote share of incumbent Senators. This effect is restricted to matter only around election day, thus only for the last poll-to-poll interval in each race. As robustness checks, we estimate the model excluding the last period of each race, and using only variation in games won instead of variation in games taking place. A similar violation of the exclusion restriction may arise if the sporting events alter the opportunities for other political communication, e.g., political advertising.

4.1.2 Persuasion effects on the swing-voter margin

While adding the changes in poll standings of both candidates within a poll-to-poll interval allows us to recover the partisan-voter persuasion effects Δ^T_{pD} and Δ^T_{pR}, taking the difference between them, we can recover the swing-voter persuasion effects Δ^S_{sD} and Δ^S_{sR}. In Appendix A we show that using the equilibrium strategies (3)-(4),

$$\Delta V_D(t+1) - \Delta V_R(t+1) = \Delta^T_{pR} \sum_\tau \mathbf{1}\{a^R(\tau) = p\} - \Delta^T_{pD} \sum_\tau \mathbf{1}\{a^D(\tau) = p\} + 2\Delta^S_{sD} \sum_\tau \mathbf{1}\{\chi^D(\tau) = 1\} - 2\Delta^S_{sR} \sum_\tau \mathbf{1}\{\chi^R(\tau) = 1\} + \sum_\tau (\epsilon^D(\tau) - \epsilon^R(\tau)). \quad (13)$$

We can then normalize by the size of the poll-to-poll interval, and notice that

$$(1 - \gamma^*_{\sim c}(t))\eta_c = \mathbb{E}\left[\frac{1}{\tau}\sum_\tau \mathbf{1}\{\chi^c(\tau) = 1\}\right]$$

is the equilibrium share of news reports of any type about candidate c, the empirical analogue being simply

$$(1 - \widehat{\gamma^*_{\sim c}(t)})\eta_c = \frac{Articles^s_c(t) + Articles^p_c(t)}{\tau} \quad (14)$$

This expression follows from the equilibrium implications of Proposition 1: the probability with which the media covers a candidate does not depend on the type of speech of the candidate so the share of news report (which we measure with article counts) directly estimates the rate at which the media covers the candidate. Because during the campaign candidates make pronouncements every day, the empirical analogue to the number of periods τ in a poll-to-poll interval is the number of days in it times the number of media outlets covering the race. The first two terms in (13) have their empirical analogues given by (11), while we recover their coefficients, Δ^T_{pR} and Δ^T_{pD}, from estimating (12). Thus, these terms are observed and we can subtract them from both sides of (13) to obtain the estimating equation that allows us to recover the swing-voter persuasion effects:

$$\frac{1}{2}\frac{\Delta V_D(t+1) - \Delta V_R(t+1)}{\tau} - \frac{1}{2}\left[\Delta^T_{pR}\hat{q}^*_R(t) - \Delta^T_{pD}\hat{q}^*_R(t)\right] = \Delta^S_{sD}\frac{Articles^D_s(t) + Articles^D_p(t)}{\tau} - \Delta^S_{sR}\frac{Articles^R_s(t) + Articles^R_p(t)}{\tau} + \zeta(t) \quad (15)$$

where $\zeta(t) = \frac{1}{2\tau}\sum_\tau(\epsilon^D(\tau) - \epsilon^R(\tau))$ is a composite error.

The covariation between the differential improvement in the polls of the Democratic candidate over the Republican candidate within a given period of time (i.e., how the competitiveness of the race is changing) after appropriately correcting for the partisan-voter effects, and the overall intensity with which the media reports on the candidates, identifies the persuasion effects on the swing-voter margin. The intuition behind the estimating equation (15) is as follows: although only reported swing-targeted speech moves voters positively on the swing-voter margin, the media's equilibrium reporting strategy, which is indifferent to the type of speech, implies that all types of news reports reflect the marginal gains from additional swing-voter targeted speech.

Estimating the swing-voter persuasion effects from (15) also requires instrumental variables because the total news reporting intensity may be correlated with other unobservables driving the evolution of the campaign. We again rely on exogenous variation induced by sports events. The variation in this case is of a different nature,

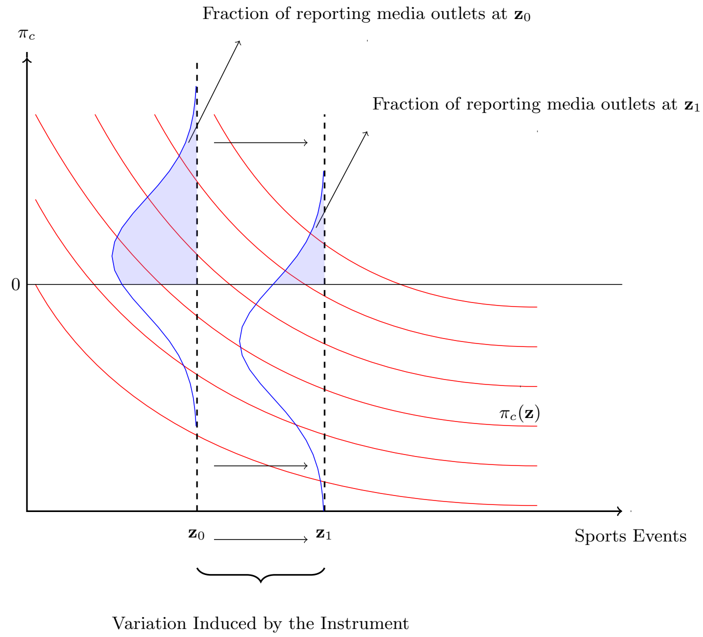

Figure 3: Instrument variation and media coverage in the extensive margin.

however. In contrast to the identification idea for equation (12), where we leveraged the dependence of $q_c^*(t)$ on the media's payoff from reporting on politics, π_c, our model implies that the equilibrium reporting rate on a candidate, $(1-\gamma_{\sim c})\eta_c$, is independent of the media's payoff. As equations (3) and (4) show, it depends only on the candidates' payoff parameters, which are unlikely to respond to variation in sports events. If the occurrence of sports events leads to differences across media outlets in their willingness to report on politics, however, then sports events can be shifters of $\tau(\mathbf{z})$, and thus relevant instruments. Sports events induce no intensive-margin response by a given media outlet (whose reporting strategy is pinned down by indifference). They can induce an extensive margin response across the distribution of media outlets covering a race, however.

Figure 3 illustrates how variation in sports events can lead marginal outlets to begin covering or dropping coverage of the campaigns. The figure plots a hypothetical distribution of media outlets with heterogeneous payoffs from campaign coverage. Overall, their payoff from campaign coverage is decreasing in the occurrence of relevant sports events, and only those outlets with a positive payoff invest in covering the campaign. When more sports events take place in a given period, some media outlets stop covering the campaign, lowering the total reporting. We exploit this source of variation to instrument for the endogenous variables in (15).

As this discussion points out, our model once again makes an unambiguous prediction about the expected sign of the first stages for (15). In this case, the model predicts a *negative* first stage relationship between the intensity of sports events and the two endogenous variables in (15). Because we chose to subtract the Republican candidate's poll gain from the Democratic candidate's gain, the model also predicts a *positive* estimand of the coefficient on the media reporting intensity on the Democrat, and a *negative* estimand on the corresponding coefficient on Republican. These sign predictions are further specification tests of our model.

In Table 1 we directly test this mechanism in our data, by looking at the correlation between sports events and the number of distinct media outlets from which we observe news pieces over time. We find evidence that the number of media outlets covering a senate race does vary systematically with sports events relevant to the race's state. The table reports OLS results of a regression where the dependent variable is the number of

Testing Model Assuptions: Media Coverage and Sports Events on the Extensive Margin

Dependent variable:	No. of reporting media outlets in poll-to-poll interval / Total no. of reporting media outlets in the race									
	2 week poll-to-poll intervals					3 week poll-to-poll intervals				
Regressor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log NFL games/τ	−0.008					−0.005				
	(0.029)					(0.036)				
Log MLB games/τ		−0.021					−0.042			
		(0.019)					(0.021)			
Log NBA games/τ			−0.035					−0.041		
			(0.018)					(0.021)		
Log NCAA games/τ				−2.335					−2.046	
				(0.609)					(0.658)	
Log all games/τ					−0.062					−0.085
					(0.017)					(0.020)
R^2	0.69	0.69	0.69	0.70	0.70	0.70	0.70	0.70	0.70	0.70
No. of Races	415	415	415	415	415	415	415	415	415	415
No. of Observations	2134	2134	2134	2134	2134	1865	1865	1865	1865	1865

Table 1: Testing Model Assumptions: Media Coverage and Sports Events on the Extensive Margin. The table presents OLS panel regressions. The dependent variable in all columns is the number of media outlets reporting on a race in a poll-to-poll interval as a fraction of all media outlets ever reporting on the race. All models include a full set of Senate-race fixed effects, month fixed effects, a dummy variable for the last poll-to-poll interval in the race, and a constant. The first five columns of the table are estimated on the 2 week poll-to-poll interval panel. The last five columns of the table are estimated on the 3-week poll-to-poll interval panel. Columns (1) and (6) include the log number of NFL games per day, columns (2) and (7) include the log number of MLB games per day, columns (3) and (8) include the log number of NBA games per day columns (4) and (9) include the log number of $NCAA$ games per day, and columns (5) and (10) include the log number of NFL, MLB, NBA, and $NCAA$ games per day. All regressions are weighted by the square root of the length in days of the poll-to-poll interval (relative to the longest interval). Standard errors are robust to arbitrary heteroskedasticity.

distinct media outlets reporting on a senate race in a given poll-to-poll interval as a fraction of all media outlets ever reporting on that race, and the right-hand-side variables are our sports events instruments. These models include Senate-race fixed effects, exploiting only within-race variation. The table presents results both for the 2-week and 3-week poll-to-poll interval datasets we described in section 3. All regressions show evidence of a significant and negative within-race correlation between game frequencies and media outlet coverage.

4.1.3 Dissuasion effects

Once we have recovered estimates for the turnout and swing-voter margin persuasion effects, the media's equilibrium strategies in (3) and (4) from Proposition 1 allow us to directly solve for the swing-voter margin persuasion effects Δ^S_{pD} and Δ^S_{pR} using (14). These are the poll gains to a candidate from media reported partisan voter-targeted statements by his opponent:

$$\Delta^S_{pc} = \frac{\Delta^T_{pc}}{(1-\widehat{\gamma^*_{\sim c}(t)})\eta_c} - \Delta^S_{sc}, \quad c \in \{D, R\} \tag{16}$$

5 Estimation Results

We now present our main empirical findings for the persuasion and dissuasion effects $\mathbf{\Delta}$, and probe their robustness. Three findings stand out. First, base mobilization: partisan rhetoric moves Democratic supporters more than Republican supporters; the estimated $\mathbf{\Delta}$ for Democratic partisans is noticeably larger. Second, swing-voter persuasion: centrist appeals shift swing voters by similar magnitudes for both parties, but those gains shrink in states with a more uneven partisan distribution of voters. Third, temporal stability: voter responsiveness to press coverage is flat over the course of the campaign; we see no systematic rise or fade as Election Day approaches. A final asymmetry concerns backlash: when the press highlights partisan speech, swing voters desert Democrats faster than Republicans, giving Democratic rhetoric a larger dissuasion component.

5.1 Partisan-voter persuasion estimates

To estimate the persuasion effect of partisan appeals, we estimate (12) by two-stage least squares. The first stage instruments media-reported partisan speech with the sport-based crowd-out shocks. The second stage relates the fitted speech measure to changes in partisan turnout. We include race fixed effects to absorb state and election year unobservables such as the state's average ideology, or any specific features of a given electoral year such as the party in power, or whether it is a midterm election. As such, we exploit exclusively within-race variation in media reporting and electoral support changes along the campaign trail. Month fixed effects further control for the strong seasonality of our sports instruments. As a robustness check we replace the single race fixed effect with the full set of separate state, year, and state-by-year dummies.[16]

Table 2 reports the 2SLS estimates for equation (12) and the first-stage coefficients on the four sports-event instruments. The model predicts that when a busy sports schedule crowds politics out of media reporting, the mix of reported campaign stories should tilt toward partisan rhetoric. Consistent with that prediction, every instrument enters the first stage with a positive and significant coefficient: more sports events raise the share of partisan-targeted articles in total coverage.[17] The first stage diagnostic statistics reveal that sports events are jointly good predictors of the fraction of partisan-targeted to total news articles on a candidate.

Table 2 compares estimates across two timing schemes and two identification strategies. Columns 1–4 use the 2-week poll intervals; columns 5–8 switch to 3-week intervals. All columns classify articles with the ± 0.25 score cut-off described in Section 3.3. Within each timing scheme we report OLS and 2SLS results. Specifications with race fixed effects appear in columns (1), (2), (5) and (6); the alternative set with separate state, year, and state-by-year dummies appears in columns (3), (4), (7) and (8). Estimates are virtually identical across the two fixed-effect structures. Standard errors are heteroskedasticity-robust and correct for up to two

[16] Estimation of (12) requires, for both right-hand side regressors, instruments that vary across poll-to-poll intervals within a race. We compute our instruments $z^l_{r,t}$ as the fan-weighted log number of games per day from sports league $l \in \{NFL, MLB, NBA, NCAA\}$ relevant to state r falling within the poll-to-poll interval t:

$$z^l_{r,t} = \log\left[\frac{1}{\tau_{r,t}} \sum_j w^l_{rj} l_{r,t}\right],$$

where w^l_{rj} is the fraction of state r's population in counties where a plurality of *Facebook* users supports a team from state j playing in sports league l. We do not use the *Facebook* fan weights for $NCAA$ games (see subsection 3.4). This amounts to making the $w^{NCAA}_{rj} = 0$ if $r \neq j$, and $w^{NCAA}_{rr} = 1$. As additional robustness exercises, we estimated our main equations using the number of winning games per day as instruments instead. Results are very similar.

[17] The partial correlation coefficient for $NCAA$ games on the first stage for $\frac{Articles^p_R(t)}{Articles^p_R(t)+Articles^s_R(t)}$ is negative. Nevertheless, the unconditional correlation (without controlling for the remaining sports) is positive.

Persuasion Effects on Partisan Voters (0.25 score cutoff)

Panel A: Structural equation		Dependent variable: Average sum of poll changes for D and R							
		2 week poll-to-poll intervals				3 week poll-to-poll intervals			
Explanatory variable	Param.	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)	OLS (7)	2SLS (8)
$\frac{\text{Articles}_D^p}{\text{Articles}_D^s+\text{Articles}_D^p}$	Δ_{pD}^T	0.024	0.16	0.026	0.16	0.032	0.15	0.032	0.18
		(0.006)	(0.06)	(0.006)	(0.06)	(0.006)	(0.08)	(0.07)	(0.089)
$\frac{\text{Articles}_R^p}{\text{Articles}_R^s+\text{Articles}_R^p}$	Δ_{pR}^T	−0.003	0.05	−0.003	0.05	−0.005	0.09	−0.004	0.09
		(0.005)	(0.058)	(0.005)	(0.059)	(0.005)	(0.08)	(0.005)	(0.088)
Panel B: First Stages		Dependent variable: $\frac{\text{Articles}_D^p}{\text{Articles}_D^s+\text{Articles}_D^p}$							
Log NFL games/τ			0.076		0.077		0.104		0.119
			(0.034)		(0.035)		(0.041)		(0.041)
Log MLB games/τ			0.049		0.048		0.034		0.032
			(0.024)		(0.025)		(0.026)		(0.027)
Log NBA games/τ			0.060		0.060		0.058		0.058
			(0.020)		(0.020)		(0.022)		(0.022)
Log NCAA games/τ			1.112		1.135		0.695		0.722
			(0.588)		(0.590)		(0.674)		(0.685)
R^2			0.95		0.95		0.96		0.95
F test (p-value)			0.001		0.001		0.006		0.003
		Dependent variable: $\frac{\text{Articles}_R^p}{\text{Articles}_R^s+\text{Articles}_R^p}$							
Log NFL games/τ			0.088		0.089		0.033		0.014
			(0.034)		(0.034)		(0.041)		(0.042)
Log MLB games/τ			0.087		0.086		0.048		0.050
			(0.024)		(0.024)		(0.026)		(0.027)
Log NBA games/τ			0.023		0.023		−0.010		−0.012
			(0.020)		(0.020)		(0.022)		(0.022)
Log NCAA games/τ			−1.234		−1.234		−1.339		−1.352
			(0.579)		(0.579)		(0.673)		(0.688)
R^2			0.93		0.93		0.94		0.94
F test (p-value)			0.000		0.000		0.05		0.042
Race fixed effects		Y	Y	N	N	Y	Y	N	N
Year×State fixed effects		N	N	Y	Y	N	N	Y	Y
No. of Races		415	415	415	415	415	415	415	415
No. of Observations		2134	2134	2134	2134	1865	1865	1865	1865

Table 2: Persuasion Effects on Partisan Supporters (0.25 score cutoff). The table presents OLS and 2SLS estimates of the persuasion effects from equation (12) using a 0.25 article score cutoff. Even-numbered columns present OLS estimates and odd-number columns present 2SLS estimates. Panel A present estimates for the structural equation (second stage), and panel B presents estimates of the coefficients for the instruments in both the first stages for the Democratic and the Republican ratios of turnout-targeted to total news reports. The first four columns in the table are estimated on the 2-week poll-to-poll interval panel. The last four columns are estimated on the 3-week poll-to-poll interval panel. All regressions are weighted by the square root of the length in days of the poll-to-poll interval (relative to the longest interval). Columns (1), (2), (5), and (6) include Senate-race fixed-effects. Columns (3), (4), (7), and (8) include a full set of year, state, and year-x-state fixed effects. All models include a dummy variable for the last poll-to-poll interval in a race and month fixed effects. Standard errors are robust to arbitrary heteroskedasticity and to arbitrary serial correlation of up to order 2 following Newey and West (1987). Coefficients and standard errors in Panel A are multiplied by 1000.

lags of autocorrelation. We include a dummy for the final poll interval—where election returns replace polling data—and weight each regression by the square root of the days spanned by the interval to reflect the greater information content of longer spans.

In every specification the IV coefficient on the Democratic partisan-persuasion parameter, Δ^T_{pD}, is positive and statistically significant. The Republican counterpart, Δ^T_{pR}, is also positive but smaller and less precisely estimated, implying that Republican partisan voters respond less to appeals aimed at them than do Democratic partisans. A plausible reason is baseline turnout: core Republican constituencies—older white voters in rural areas—already vote at high rates, so additional mobilization yields limited returns. Democrats, conversely, concentrate on younger and minority voters whose turnout is lower and therefore more elastic; our estimates confirm that these groups are readily persuaded by partisan-targeted campaigning. The pattern persists when the analysis is repeated with three-week poll intervals.

Our estimates from Table 2 are informative about the partial equilibrium effects of candidate behavior on poll changes. In the bottom panel of Table 4 we report the average estimates of the candidates' fraction of partisan-targeted statements, q_c. Based on the 0.25 article score cutoff criterion, $\mathbb{E}[q_D] \approx 0.56$, and $\mathbb{E}[q_R] \approx 0.45$. A ten percent increase in these probabilities, which is within the range of variation induced by the sports events, if sustained during a month would translate, on average, into a 3.3 percentage point gain to the Democratic candidate, and a 0.8 percentage point gain to the Republican candidate stemming from their partisan supporters' increased turnout.[18] Because the margin of victory for most Senate races is around 5 percentage points, this simple exercise illustrates the importance of media coverage incentives on election outcomes.

5.2 Swing-voter persuasion effects

To identify persuasion effects from swing voters we estimate equation (15) by 2SLS, again absorbing race fixed effects and month dummies. The model implies that a media outlet's coverage rule is pinned down by an indifference condition, and thus, independent of its own payoffs. Aggregate coverage, however, can still shift on the extensive margin as outlets enter or exit campaign coverage when outside opportunities improve (see Figure 3). Sports events create exactly such payoff shocks: they crowd politics out of the news hole without affecting campaign strategy. We therefore instrument both endogenous regressors with the sports schedule. The first stage confirms the model's prediction: more games reduce total coverage of each candidate. Coefficient estimates appear in Table 3.

Table 3 mirrors the layout of Table 2. Columns (1)–(4) use the two-week poll windows; columns (5)–(8) use three-week windows. All specifications rely on the ± 0.25 article-score cutoff. the first-stage estimates in panel B show that our instruments are systematically negatively correlated with both the Democratic and the Republican total news reports counts. Panel A then presents our main estimates of the Democratic and Republican swing-voter elasticities in response to swing voter-targeted media contents. Across every 2SLS specification the coefficient on Democratic coverage, Δ^S_{pD}, is positive, while the coefficient on Republican coverage enters with the opposite sign, $-\Delta^S_{sR}$, exactly as equation (15) implies. Magnitudes are almost identical for the two parties: in column 4 we estimate both at 0.0018, and both are significant at the 5 percent level. The size and significance of these effects remain stable across interval definitions and fixed-effect choices, indicating that persuasion of swing voters is symmetric between parties.

[18] We consider a 10% increase over the average number of outlets (124) for the average poll-to-poll interval (approximately 30 days): $(0.1 \times 0.56) \times (0.16/1000) \times 124$ media outlets on average $\times$ 30 days ≈ 0.033 for Democrats, and $(0.1 \times 0.45) \times (0.05/1000) \times 124$ media outlets on average $\times$ 30 days ≈ 0.008 for Republicans.

Persuasion Effects on Swing Voters (0.25 score cutoff)

Panel A: Structural equation		Dependent variable: Adjusted difference of poll changes for D and R							
		2 week poll-to-poll intervals				3 week poll-to-poll intervals			
Explanatory variable	Param.	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)	OLS (7)	2SLS (8)
$(\text{Articles}^p_D + \text{Articles}^s_D)/\tau$	Δ^S_{sD}	0.15	0.18	0.15	0.18	0.15	0.2	0.15	0.2
		(0.04)	(0.09)	(0.04)	(0.087)	(0.3)	(0.10)	(0.03)	(0.10)
$(\text{Articles}^p_R + \text{Articles}^s_R)/\tau$	$-\Delta^S_{sR}$	−0.08	−0.18	−0.08	−0.18	−0.10	−0.27	−0.10	−0.29
		(0.02)	(0.10)	(0.02)	(0.11)	(0.02)	(0.136)	(0.02)	(0.14)
Panel B: First Stages		Dependent variable: $(\text{Articles}^s_D + \text{Articles}^p_D)/\tau$							
Log NFL games/τ			1.73		1.08		19.47		18.30
			(24.07)		(24.05)		(30.50)		(30.48)
Log MLB games/τ			−34.72		−34.62		−36.12		−36.00
			(17.06)		(17.06)		(19.58)		(19.59)
Log NBA games/τ			−12.82		−12.82		−17.99		−19.60
			(13.93)		(13.93)		(16.43)		(16.45)
Log NCAA games/τ			−1322.8		−1321.3		−1348		−1347.5
			(410.13)		(410.02)		(503.09)		(504.2)
R^2			0.70		0.70		0.72		0.72
F test (p-value)			0.007		0.007		0.029		0.028
		Dependent variable: $(\text{Articles}^s_R + \text{Articles}^p_R)/\tau$							
Log NFL games/τ			−34.52		−34.44		−28.01		−29.04
			(12.93)		(12.92)		(16.24)		(16.19)
Log MLB games/τ			−6.99		−7.02		−7.35		−6.77
			(9.16)		(9.17)		(10.42)		(10.41)
Log NBA games/τ			−22.17		−22.13		−31.59		−31.88
			(7.49)		(7.48)		(8.75)		(8.74)
Log NCAA games/τ			−663.0		−663.8		−582.2		−581.7
			(220.34)		(220.31)		(267.91)		(267.84)
R^2			0.73		0.73		0.76		0.76
F test (p-value)			0.000		0.000		0.000		0.000
Race fixed effects		Y	Y	N	N	Y	Y	N	N
Year×State fixed effects		N	N	Y	Y	N	N	Y	Y
No. of Races		415	415	415	415	415	415	415	415
No. of Observations		2134	2134	2134	2134	1865	1865	1865	1865

Table 3: Persuasion Effects on Swing Voters (0.25 score cutoff). The table presents OLS and 2SLS estimates of the persuasion effects on swing-voters from equation (15) using a 0.25 article score cutoff. Even-numbered columns present OLS estimates, and odd-number columns present 2SLS estimates. Panel A presents estimates for the structural equation (second stage), and panel B presents estimates of the coefficients for the instruments in both the first stages for the Democratic and the Republican total news reports. The first four columns in the table are estimated on the 2-week poll-to-poll interval panel, and the dependent variable is constructed using the parameter estimates from the model in Panel A, column (4) of Table 2. The last four columns are estimated on the 3-week poll-to-poll interval panel, and the dependent variable is constructed using the parameter estimates from the model in Panel A, column (8), of Table 2. All regressions are weighted by the square root of the length in days of the poll-to-poll interval (relative to the longest interval). Columns (1), (2), (5), and (6) include Senate-race fixed-effects. Columns (3), (4), (7), and (8) include a full set of year, state, and year-x-state fixed effects. All models include a dummy variable for the last poll-to-poll interval in a race and month fixed effects. Standard errors are robust to arbitrary heteroskedasticity and to arbitrary serial correlation of up to order 2 following Newey and West (1987). Coefficients and standard errors in Panel A are multiplied by 100.

Persuasion and Dissuasion Effects and Equilibrium Mixing Strategies

Dependent variable:	2 week poll-to-poll intervals			
	0.25 article score cutoff (1)		0.5 article score cutoff (2)	
Panel A	Parameters (s.e.)			
Δ^T_{pD}	0.016	(0.006)	0.011	(0.005)
Δ^T_{pR}	0.005	(0.005)	0.004	(0.005)
Δ^S_{sD}	0.18	(0.060)	0.12	(0.046)
Δ^S_{sR}	0.18	(0.081)	0.15	(0.062)
Δ^S_{pD}	0.69	(0.15)	0.50	(0.10)
Δ^S_{pR}	0.18	(0.076)	0.15	(0.083)
Panel B	Average Equilibrium Mixing Strategies			
$\mathbb{E}[q_D]$	0.557		0.414	
$\mathbb{E}[q_R]$	0.449		0.299	
$\mathbb{E}[\eta_D(1-\gamma_R)]$	0.018		0.018	
$\mathbb{E}[\eta_R(1-\gamma_D)]$	0.014		0.014	

Table 4: Parameter Estimates and Equilibrium Mixing Strategies. The table presents the Persuasion and Dissuasion parameters (Panel A) and average equilibrium mixing probabilities (Panel B) in the model estimated using 2-week poll-to-poll intervals. Persuasion effects in Panel A are taken from the estimation of equations (12) and (15). Dissuasion effects in Panel A are computed according to equation (17) in the text. Column (1) is based on the 0.25 article score cutoff and the estimates in column (4) of Table 2 and column (4) of Table 3. Column (2) is based on analogous models using the 0.5 article score cutoff. Estimates in Panel B are computed directly from the sample analogues as weighted averages using relative interval lengths as weights. Parameter estimates reported in Panel A are multiplied by 100.

We also undertake a quantitative exercise based on our benchmark swing-voter elasticities ($\Delta^S_{sD}, \Delta^S_{sR}$) to gauge how shifts in overall coverage move the polls. The bottom panel of Table 4 reports the unconditional probability that the media reports a story on candidate c: $(1-\gamma_{\sim c})\eta_c$. Based on the 0.25 article score cutoff criterion, $\mathbb{E}[\eta_D(1-\gamma_R)] \approx 0.018$ for Democrats, and $\mathbb{E}[\eta_R(1-\gamma_D)] \approx 0.014$ for Republicans. If either probability rose by 10 percent for a full month, the model predicts a 1.2-percentage-point swing toward the Democrat or a 1.0-point swing toward the Republican, respectively— and equally large losses for the rival.[19]

5.3 Swing-voter dissuasion effects

The final step of our empirical strategy is to back out estimates of the dissuasion effects of partisan-targeted campaign speech using (16). We obtain average effects by integrating over our sample as follows:

$$\hat{\Delta}^S_{pc} = \frac{\hat{\Delta}^T_{pc}}{\frac{1}{N}\sum_r \sum_{t=1}^{T_r} \frac{(Articles^p_c(t)+Articles^s_c(t))}{\tau(t)}} - \hat{\Delta}^S_{sc}, \tag{17}$$

[19]Consider a 10% increase over the average number of outlets (124) over the average poll-to-poll interval days (approximately 30 days): $(0.1 \times 0.018) \times (0.18/100) \times 124$ media outlets on average $\times$ 30 days ≈ 0.012 for Democrats, and $(0.1 \times 0.014) \times (0.18/100) \times 124$ media outlets on average $\times$ 30 days ≈ 0.010 for Republicans.

where N is the number of races in our data, and T_r is the number of poll-to-poll intervals in race r.

Panel A in Table 4 presents the estimates of all six effects in our model. The table presents estimates using 2-week poll-to-poll intervals, using both the ± 0.25 and ± 0.5 article cutoff classifications. We find a striking asymmetry in the swing-voter backlash to partisan rhetoric. Under the ± 0.25 cut-off, we obtain $\Delta_{pD}^{S} = 0.69$ for Democrats versus $\Delta_{pR}^{S} = 0.18$ for Republicans, implying that swing voters punish partisan Democratic speech nearly four times harder. This difference in persuasion and dissuasion effects across parties has substantial implications for the dynamics of the Senate races. Because Democratic turnout mobilization gains are larger but their swing-voter losses are larger still, swing voters—not the press—are the main moderating force on Democratic rhetoric. For Republicans, the pattern reverses: the media's lower appetite for Republican partisan stories does more to curb their rhetoric than swing-voter reactions do. The equilibrium implication of these offsetting pressures is that candidates from both parties are covered by the media at similar rates. The average estimates of the equilibrium probabilities that a given media outlet generates a news piece on a candidate in a given day during the campaign are 0.018 for Democrats and 0.014 for Republicans (panel B of Table 4).

5.4 Payoff Heterogeneity

We probe how persuasion and dissuasion vary across four settings—state partisanship, time remaining until election day, race competitiveness, and whether the race includes an incumbent candidate. We report these results in the online appendix B.1 of the paper.

Overall, we find limited heterogeneity. Swing voters are especially responsive to Democratic centrist appeals in states where Democrats are numerically weak. Republican swing-targeted messages grow more persuasive as races tighten, measured by a smaller poll gap. In contrast, we detect no systematic variation in persuasion or dissuasion with time remaining until election day or with an incumbent candidate running in the race. However, the incumbency test may be underpowered because three-quarters of the contests feature a sitting senator. The corresponding appendix provides a more detailed discussion.

6 Concluding Remarks

Political campaigns are among the most sophisticated marketing efforts. These efforts are primarily channeled through earned media. Yet, while marketing scholarship has scrutinized paid campaign ads, it has paid less attention to how news coverage itself impacts electoral campaign outcomes by shaping constituency targeting and brand differentiation. We contribute to answering this question by estimating persuasion and dissuasion effects of U.S. Senate campaign speech over 1980-2012, a period when newspapers and television still served as the principal gatekeepers of political information.

Leveraging plausibly exogenous shifts in the profitability of political reporting—fluctuations in major-league sports schedules—and a simple structural model that treats candidate–media interaction as a matching-pennies game, we recover separate elasticities for partisan mobilization and swing-voter conversion. Candidates wish to publicize centrist appeals; the media, chasing audience interest, prefer to spotlight partisan rhetoric. The equilibrium mapping of those conflicting incentives guides an econometric strategy that disentangles persuasion from dissuasion despite endogenous coverage.

We highlight three core findings. First, Democratic partisan voters respond more strongly to partisan rhetoric than Republican voters do, but swing voters penalize Democrats more heavily for it. Second, asymmetry moderates Democratic speech: because the backlash risk outweighs the mobilization gain, Democrats temper partisan appeals, which in turn dulls the media's incentives to cover them. Third, the resulting equilibrium yields nearly symmetric coverage rates across parties, even though mobilization returns are asymmetric.

Although our study covers only the pre-social media period (before 2012), the mechanism illuminates forces that may be relevant in the social-media era. Algorithmic curation on social media platforms, for example, while still filtering messages, is primarily driven by engagement, not newsworthiness. By allowing candidates to microtarget supporters without broad exposure, these platforms may lower the swing-voter backlash that disciplined Democratic rhetoric during our period of study, while simultaneously eroding the advantage Republicans once enjoyed from relatively insulated conservative-leaning media networks. At the same time, if social media-driven polarization is shrinking the pool of persuadable swing voters, future campaigns may tilt even further toward pure turnout strategies—a shift our model predicts would amplify partisan mobilization effects and weaken the moderating role of the press.

The mechanism we propose is important for understanding the nature of bipartisan electoral competition in settings with ample media presence and where earned media is a main communication channel for candidates to elected office. But even in the current environment, persuasion and dissuasion margins are still of considerable importance for political campaigns. Future work might extend the framework to post-2012 elections, integrate platform-specific audience measures, or exploit exogenous shocks to online engagement as instruments. More broadly, exploring how heterogeneous electorates respond to increasingly personalized political messaging remains an open and pressing question.

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A Appendix

A.1 Figures and Tables

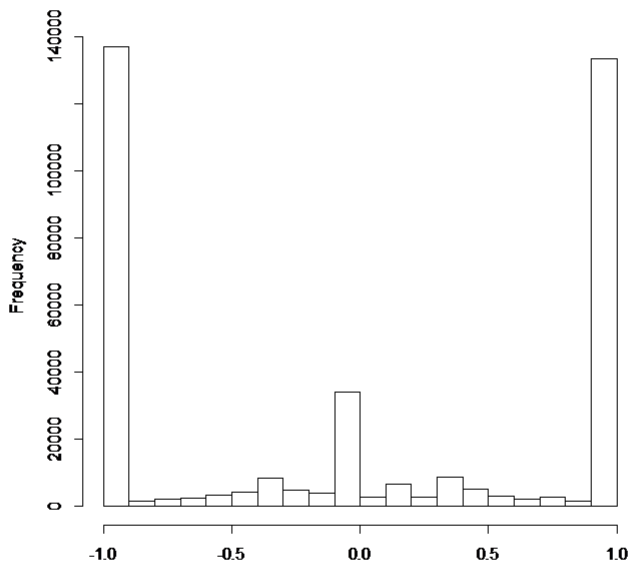


Figure A.1: Distribution of article name assignments κ_i.

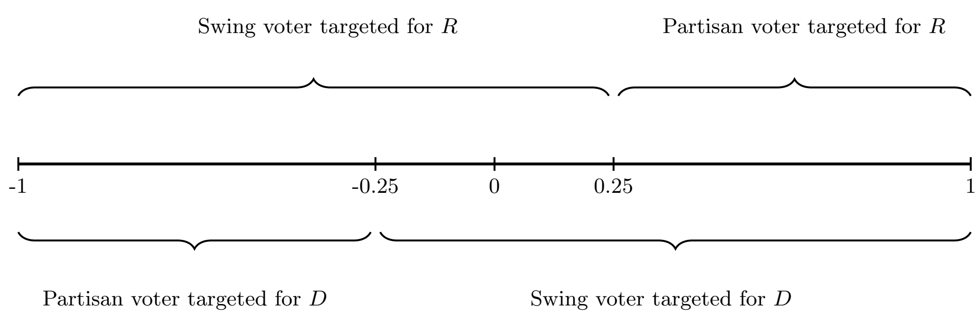
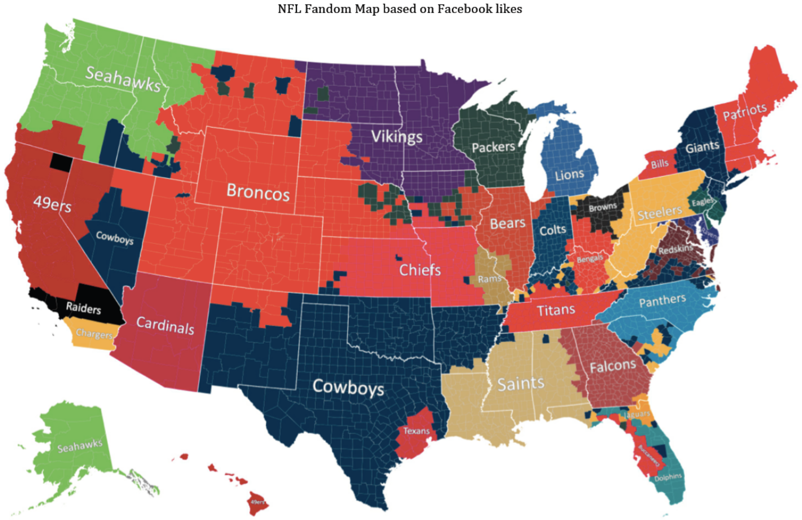


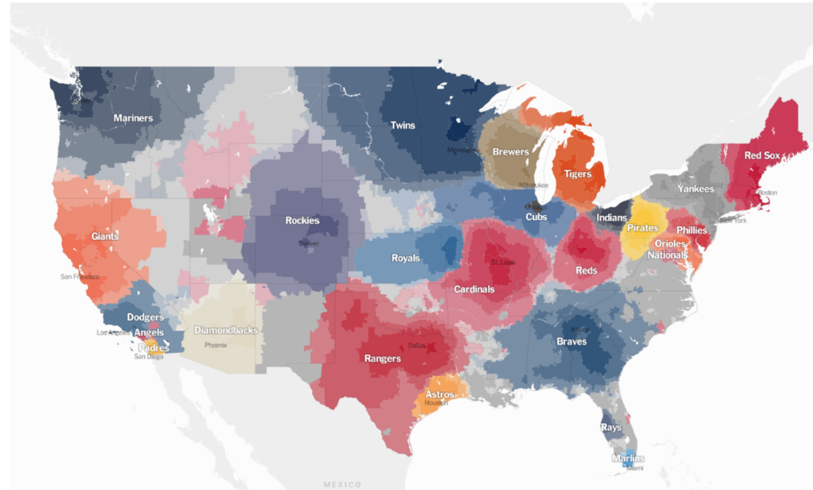
Figure A.2: Illustration of the Article Type Classification (0.25 score cutoff case).

NFL Fandom Map based on Facebook likes



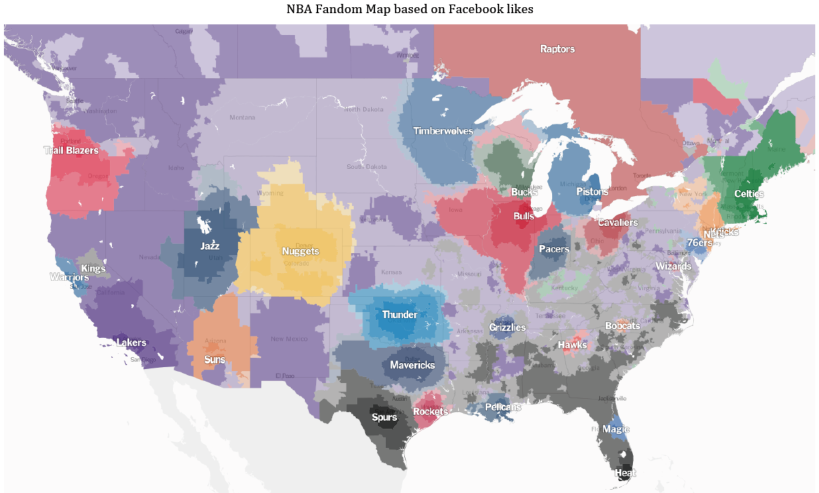
Source: The Atlantic online at: http://www.theatlantic.com/technology/archive/2014/09/the-geography-of-nfl-fandom/379729/

MLB Fandom Map based on Facebook likes



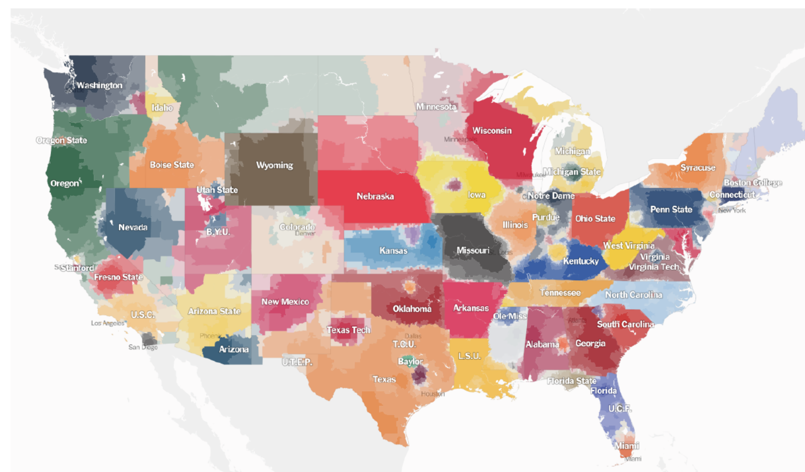
Source: New York Times online at: http://www.nytimes.com/interactive/2014/04/24/upshot/facebook-baseball-map.html

NBA Fandom Map based on Facebook likes



Source: The New York Times online at: http://www.nytimes.com/interactive/2014/05/12/upshot/12-upshot-nba-basketball.html?abt=0002&abg=1

NCAA Fandom Map based on Facebook likes



Source: The New York Times at: http://www.nytimes.com/interactive/2014/10/03/upshot/ncaa-football-fan-map.html?abt=0002&abg=1

Figure A.3: *Facebook* Sport-Team Fans Distribution Maps.

A.2 Proof of Proposition 1

The normal form game G is presented in Table A.4 below. In each cell, the payoffs are written in the order (D, R, m).

Existence and Uniqueness:

Define the following parameters:

$$\triangle_1 \equiv \Delta^T_{pD} - \eta_D\Delta^S_{pD} + \eta_R\Delta^S_{pR} \quad \triangle_{13} \equiv \Delta^T_{pD} - \eta_D\Delta^S_{pD} - \eta_R\Delta^S_{sR}$$

$$\triangle_2 \equiv \Delta^T_{pR} - \eta_R\Delta^S_{pR} + \eta_D\Delta^S_{pD} \quad \triangle_{14} \equiv \eta_R\Delta^S_{sR} + \eta_D\Delta^S_{pD}$$

$$\triangle_3 \equiv \Delta^T_{pD} - \eta_D\Delta^S_{pD} \quad \triangle_{15} \equiv \Delta^T_{pD} - \eta_D\Delta^S_{pD}$$

$$\triangle_4 \equiv \Delta^T_{pR} + \eta_D\Delta^S_{pD} \quad \triangle_{16} \equiv \eta_D\Delta^S_{pD}$$

$$\triangle_5 \equiv \Delta^T_{pD} + \eta_R\Delta^S_{pR} \quad \triangle_{17} \equiv \Delta^T_{pD} - \eta_R\Delta^S_{sR}$$

$$\triangle_6 \equiv \Delta^T_{pR} - \eta_R\Delta^S_{pR} \quad \triangle_{18} \equiv \eta_R\Delta^S_{sR}$$

$$\triangle_7 \equiv \eta_D\Delta^S_{sD} + \eta_R\Delta^S_{pR} \quad \triangle_{19} \equiv \eta_D\Delta^S_{sD} - \eta_R\Delta^S_{sR}$$

$$\triangle_8 \equiv \Delta^T_{pR} - \eta_R\Delta^S_{pR} - \eta_D\Delta^S_{sD} \quad \triangle_{20} \equiv \eta_R\Delta^S_{sR} - \eta_D\Delta^S_{sD}$$

$$\triangle_9 \equiv \eta_D\Delta^S_{sD} \quad \triangle_{21} \equiv \eta_D\Delta^S_{sD}$$

$$\triangle_{10} \equiv \Delta^T_{pR} - \eta_D\Delta^S_{sD} \quad \triangle_{22} \equiv -\eta_D\Delta^S_{sD}$$

$$\triangle_{11} \equiv \eta_R\Delta^S_{pR} \quad \triangle_{23} \equiv -\eta_R\Delta^S_{sR}$$

$$\triangle_{12} \equiv \Delta^T_{pR} - \eta_R\Delta^S_{pR} \quad \triangle_{24} \equiv \eta_R\Delta^S_{sR}$$

G is a game with finite action space, which is sufficient for existence of a Nash equilibrium. Checking the non-existence of a Nash equilibrium in pure strategies is straightforward. Thus, any equilibria must be in mixed strategies. Define the media's action space to be $a^m \in \{F_D N_R, N_D F_R, F_D F_R\}$, denoting, in turn, following D but not R, following R but not D, and following both D and R.

Conditions for such an equilibrium are:

1. M must be indifferent between playing $a^M = F_D F_R$ and $a^M = F_D N_R$:

$$\mathbb{E}[U_M|F_D F_R] = q_D q_R(\eta_D\pi_D + \eta_R\pi_R - 2k) + (1-q_D)q_R(\eta_R\pi_R - 2k) + q_D(1-q_R)(\eta_D\pi_D - 2k) + (1-q_D)(1-q_R)(-2k)$$

$$= q_D q_R(\eta_D\pi_D - k) + (1-q_D)q_R(-k) + q_D(1-q_R)(\eta_D\pi_D - k) + (1-q_D)(1-q_R)(-k) = \mathbb{E}[U_M|F_D N_R]$$

$$\Leftrightarrow q_R^* = \frac{k}{\eta_R\pi_R} \tag{A.1}$$

2. M must be indifferent between $a^M = F_D F_R$ and $a^R = N_D F_R$:

$$\mathbb{E}[U_M|F_D F_R] = q_D q_R(\eta_D\pi_D + \eta_R\pi_R - 2k) + (1-q_D)q_R(\eta_R\pi_R - 2k) + q_D(1-q_R)(\eta_D\pi_D - 2k) + (1-q_D)(1-q_R)(-2k)$$

$$= q_D q_R(\eta_R\pi_R - k) + (1-q_D)q_R(\eta_R\pi_R - k) + q_D(1-q_R)(-k) + (1-q_D)(1-q_R)(-k) = \mathbb{E}[U_M|N_D F_R]$$

$$\Leftrightarrow q_D^* = \frac{k}{\eta_D\pi_D} \tag{A.2}$$

3. D must be indifferent between $a^D = p$ and $a^D = s$:

$$\mathbb{E}[U_D|p] = (1-\gamma_D-\gamma_R)q_R\triangle_1 + \gamma_D q_R\triangle_3 + \gamma_R q_R\triangle_5$$

$$+(1-\gamma_D-\gamma_R)(1-q_R)\triangle_{13} + \gamma_D(1-q_R)\triangle_{15} + \gamma_R(1-q_R)\triangle_{17}$$

$$= (1-\gamma_D-\gamma_R)q_R\triangle_7 + \gamma_D q_R\triangle_9 + \gamma_R q_R\triangle_{11}$$

$$+(1-\gamma_D-\gamma_R)(1-q_R)\triangle_{19} + \gamma_D(1-q_R)\triangle_{21} + \gamma_R(1-q_R)\triangle_{23} = \mathbb{E}[U_D|s]$$

$$\Leftrightarrow \gamma_R^* = 1 - \frac{\Delta_{pD}^T}{\eta_D\left[\Delta_{pD}^S + \Delta_{sD}^S\right]} \tag{A.3}$$

4. R must be indifferent between $a^D = p$ and $a^D = s$:

$$\mathbb{E}[U_R|p] = (1-\gamma_D-\gamma_R)q_D\triangle_2 + \gamma_D q_D\triangle_4 + \gamma_R q_D\triangle_6$$

$$+(1-\gamma_D-\gamma_R)(1-q_D)\triangle_8 + \gamma_D(1-q_D)\triangle_{10} + \gamma_R(1-q_D)\triangle_{12}$$

$$= (1-\gamma_D-\gamma_R)q_D\triangle_{14} + \gamma_D q_D\triangle_{16} + \gamma_R q_D\triangle_{18}$$

$$+(1-\gamma_D-\gamma_R)(1-q_D)\triangle_{20} + \gamma_D(1-q_D)\triangle_{22} + \gamma_R(1-q_D)\triangle_{24} = \mathbb{E}[U_R|s]$$

$$\Leftrightarrow \gamma_D^* = 1 - \frac{\Delta_{pR}^T}{\eta_R\left[\Delta_{pR}^S + \Delta_{sR}^S\right]}. \tag{A.4}$$

Thus, the mixed-strategy Nash equilibrium is unique.

A.3 Derivation of equation (13)

Taking the difference between the change in support for the Republican and the change in support for the Democrat candidate within a poll-to-poll interval from (1),

$$\begin{aligned}
\Delta V_D(t) - \Delta V_R(t) = &\left[\Delta^T_{pD} \sum_\tau \mathbf{1}\{a^D(\tau) = p\} - \Delta^T_{pR} \sum_\tau \mathbf{1}\{a^R(\tau) = p\}\right] \\
&+ 2\left[\Delta^S_{sD} \sum_\tau \mathbf{1}\{a^D(\tau) = s, \chi^D(\tau) = 1\} - \Delta^S_{pD} \sum_\tau \mathbf{1}\{a^D(\tau) = p, \chi^D(\tau) = 1\}\right] \\
&- 2\left[\Delta^S_{sR} \sum_\tau \mathbf{1}\{a^R(\tau) = s, \chi^R(\tau) = 1\} - \Delta^S_{pR} \sum_\tau \mathbf{1}\{a^R(\tau) = p, \chi^R(\tau) = 1\}\right] \\
&+ \sum_\tau (\epsilon^D(\tau) - \epsilon^R(\tau))
\end{aligned} \tag{A.5}$$

The next observation is that equilibrium strategies from (3) and (4) imply that

$$\Delta^S_{pD} = \frac{\Delta^T_{pD}}{(1-\gamma^*_R)\eta_D} - \Delta^S_{sD}$$

and

$$\Delta^S_{pR} = \frac{\Delta^T_{pR}}{(1-\gamma^*_D)\eta_R} - \Delta^S_{sR}.$$

We can use (9) and (10) to substitute $(1-\gamma^*_{\sim c})\eta_c$ in each of these expressions. Replacing them in (A.5) and collecting terms,

$$\begin{aligned}
\Delta V_D(t) - \Delta V_R(t) = &\left[\Delta^T_{pD} \sum_\tau \mathbf{1}\{a^D(\tau) = p\} - \Delta^T_{pR} \sum_\tau \mathbf{1}\{a^R(\tau) = p\}\right] \\
&+ 2\left[\Delta^S_{sD} \sum_\tau \mathbf{1}\{\chi^D(\tau) = 1\} - \Delta^T_{pD} \frac{\sum_\tau \mathbf{1}\{a^D(\tau) = p, \chi^D(\tau) = 1\}}{\frac{1}{\tau}\sum_\tau \mathbf{1}\{a^D(\tau) = p, \chi^D(\tau) = 1\}} q^*_D(t)\right] \\
&- 2\left[\Delta^S_{sR} \sum_\tau \mathbf{1}\{\chi^R(\tau) = 1\} - \Delta^T_{pR} \frac{\sum_\tau \mathbf{1}\{a^R(\tau) = p, \chi^R(\tau) = 1\}}{\frac{1}{\tau}\sum_\tau \mathbf{1}\{a^R(\tau) = p, \chi^R(\tau) = 1\}} q^*_R(t)\right] \\
&+ \sum_\tau (\epsilon^D(\tau) - \epsilon^R(\tau))
\end{aligned}$$

Recall from (8) that $q^*_c(t)\tau = \sum_\tau \mathbf{1}\{a^c(\tau) = p\}$. This gives us

$$\begin{aligned}
\Delta V_D(t) - \Delta V_R(t) = &\left[\Delta^T_{pR} \sum_\tau \mathbf{1}\{a^R(\tau) = p\} - \Delta^T_{pD} \sum_\tau \mathbf{1}\{a^D(\tau) = p\}\right] \\
&+ 2\left[\Delta^S_{sD} \sum_\tau \mathbf{1}\{\chi^D(\tau) = 1\} - \Delta^S_{sR} \sum_\tau \mathbf{1}\{\chi^R(\tau) = 1\}\right] \\
&+ \sum_\tau (\epsilon^D(\tau) - \epsilon^R(\tau)).
\end{aligned}$$

B Heterogeneity Analysis and Robustness Checks

B.1 Payoff Heterogeneity

The IV estimates of the persuasion and dissuasion parameters are average effects across states and three decades, identified off the variation in media coverage and poll changes within races over time. In this section, we explore the extent of heterogeneity in these parameters across races. We do so in a straightforward parametric way by allowing them to depend on race characteristics, which may be important sources of heterogeneity. Here we discuss four sources of heterogeneity: the partisan distribution of voters across states and time, the time to election day, the competitiveness of the election at a given point in time, and the presence of an incumbent senator in the race. Specifically, we allow the persuasion effects to be linear functions of one of these four characteristics $K_{r,t}$: $\Delta^T_{pc} = \alpha^T_{pc} + \beta^T_{pc} K_{r,t}$ and $\Delta^S_{sc} = \alpha^S_{sc} + \beta^S_{sc} K_{r,t}$ for $c \in \{D, R\}$.[B.1] We estimate (12) and (15) by 2SLS including the relevant interaction terms, instrumenting them with the respective interactions between our sports events instruments and the source of heterogeneity in each case.[B.2]

B.1.1 The partisan distribution of voters

We first explore heterogeneity in electoral responses as a function of the partisan distribution of the electorate, which varies considerably across states. We proxy this distribution using the average of the Democratic registration share of the electorate and the most recent presidential election results. For states without partisan registration, we use only the presidential election returns. Column (1) of Table B.1 presents the results. These and all other estimates in the table use our benchmark 2-week poll-to-poll intervals based on the ± 0.25 article score cutoff and use all sports events and interactions of sports events with the corresponding heterogeneity variable as instruments. Panel A presents the estimates for the partisan-voter persuasion effects from equation (12)), while panel B presents the estimates for the swing voter persuasion effects from equation (15). Although the pattern of signs implies that Δ^T_{pD} decreases while Δ^T_{pR} increases with Democratic registration, we cannot estimate these effects precisely. In contrast, we find a significant decreasing relationship between Democratic registration and Δ^S_{sD}. In states with relatively few Democratic voters, these voters appear to be more persuaded by swing voter-targeted media coverage favoring the Democratic candidates. Except for this result, the partisan distribution of the electorate is not a major source of heterogeneity.

[B.1] An additional reason to explore heterogeneity in this context is the potential bias of our estimates if parameters vary substantially over time because we base our empirical strategy on the computation of probabilities based on relative frequencies. On the one hand, if the underlying probabilities vary substantially over time, the sample analogue estimators of the mixing probabilities will be biased. This would make shorter poll-to-poll intervals preferable. On the other hand, longer poll-to-poll intervals reduce sampling error, as long as the $\mathbf{\Delta}$'s are constant within a time interval. This is an unavoidable bias-precision trade-off.

[B.2] To recover the remaining dissuasion effects $\Delta^S_{cp}(K)$ when allowing for heterogeneity, we construct decile bins for $K_{p,r}$ and compute the integration in equation (17) restricted to the set $\Gamma_K = \{(r,t) : K_{r,t} \in K\}$ of observations in each decile:

$$\hat{\Delta}^S_{pc}(K) = \frac{\hat{\Delta}^T_{pc}(K_{p,r})}{\frac{1}{|\Gamma_K|}\sum_r \sum_{t=1}^{T_r} \frac{Articles^p_c(t) + Articles^s_c(t)}{\tau(t)}} - \hat{\Delta}^S_{sc}(K_{p,r}), \qquad (r,t) \in \Gamma_K.$$

B.1.2 Days to Election

In a second exercise, we explore the possibility that the electoral responsiveness of voters varies along the campaign. For example, if voters pay more attention to media coverage as November approaches, they may become more responsive to the news over time. We explore this possibility by allowing the persuasion effects to depend on the time between the initial date of the poll-to-poll interval and the general election date. Because the time to election day varies across poll-to-poll intervals within each race, we also include the time to election as a covariate. Column (2) of Table B.1 reports the main results for this exercise. They show no statistically significant evidence of heterogeneity in time to election day. Overall, the Δ's are stable over time.

B.1.3 State of the Race: A Dynamic Game

We also explore whether persuasion and dissuasion effects vary as a function of the political environment and the previous evolution of the race itself. For example, we may expect a candidate to become more willing to take risks when he is behind in the polls. On the other hand, the electoral cost of bad press may grow as election day approaches, making politicians more cautions late in the race. Similarly, the media's campaign coverage profitability may grow as election day approaches. The state of the race is an endogenous state variable, making the game in practice a dynamic one rather than a repeated one. To explore this possibility and its implications for the robustness of our results, we allow the payoff parameters to depend on the current state of the race, measured by the poll margin between candidates at the beginning of the corresponding poll-to-poll interval.[B.3]

We now have a dynamic game where payoffs depend on a state variable, and where the state variable itself evolves over time as a function of the players' previous choices. Even in this case, the finite horizon of the game and the uniqueness of Nash equilibrium in its stage game imply that the dynamic game only has one sub-game perfect equilibrium. It prescribes playing the mixed-strategy Nash equilibrium of the stage game given the value of the state variable at every period. As a result, the equilibrium play is independent across periods conditional on the state variable, and we can replicate our estimation strategy from above. Similarly to the time-to-election exercise, the poll margin varies over time within a race, so we also include it separately as a covariate.

Column (3) of Table B.1 presents these results. Overall, we do not find a strong relationship between the state of the race and the electoral responsiveness effects. The only exception arises for the persuasion response to swing-targeted speech for Republicans, Δ_{sR}^{S}, which is higher in more competitive periods of a race. This suggests that incentives to target swing voters become stronger for Republican candidates as races become tighter. While we cannot single out the mechanism that generates this finding, it is possible that voters respond differently to similar campaign speech as the races become more competitive. For example, voters, and in particular swing voters, may devote more time and attention to the campaigns. The results from this exercise should be taken with caution because the poll margin is an endogenous outcome which we are including as a covariate.

[B.3] In principle, the relevant state variable may be a high-dimensional vector of time-varying characteristics. In practice, our sample size requires us to limit the dimensionality of the state variable we consider.

B.1.4 Incumbent Running

Our final exercise looking at payoff heterogeneity explores whether poll responsiveness differs in races where incumbents are running. We allow the Δ's to depend on a dummy variable for elections with a running incumbent. Column (4) of Table B.1 reports the results. We find no evidence of differences in candidate payoff parameters in races with or without incumbents. This test may not have much power, however: 75% of all Senate races in our sample have an incumbent running.

B.2 Robustness Exercises and Specification Tests

In Tables A.2 and A.3 we present a subset of additional econometric exercises exploring the robustness of our main findings. Table A.2 reports IV results for alternative specifications based on 2-week poll-to-poll intervals. First, we estimate equations (12)-(15) excluding the last poll-to-poll interval for each race. We do this for two reasons. First, our last poll-to-poll interval for each race is constructed using the general election result as the end-of period value. This is in contrast to all other periods in which beginning and end-of-period electoral support are measured using averages of polls. Second, the validity of our instruments relies on the assumption that sports events are shifters of the media's reporting payoffs, but do not otherwise affect the evolution of the polls. If sports events that happen very near election day –thus falling on the last poll-to-poll interval– directly lead to lower turnout in elections, the exclusion restriction would not be satisfied.[B.4] Excluding these observations reduces the sample size from 2,134 to 1,871. As column (1) in Table A.2 shows, the magnitude and significance of the estimated parameters is almost unchanged relative to our baseline estimates.

In column (2) we then include a dummy variable for poll-to-poll intervals after the primary election for the race. If the strategic environment is significantly different before and after the primaries have taken place, it may be important to distinguish between both regimes. For most races, even during primary campaign days, pollsters are already collecting polls asking for the candidates who eventually become the Democratic and Republican nominees. This suggests that in most cases, the bipartisan race is already implicitly taking place before the primary outcome is known. As column (2) in Table A.2 shows, controlling for a post-primary dummy variable does not alter any of our benchmark estimates either.

Finally, in columns (3) and (4) of Table A.2 we estimate our main specification using two alternative article score cutoffs. Column (3) presents estimates using a ± 0.5 cutoff, and column (4) presents estimates using a quite extreme $\pm .75$ cutoff. Because our classification cutoff for partisan-targeted versus swing-targeted news content is arbitrary, it is reassuring that our main results are unaltered.

In Table A.3 we turn to a sensitivity analysis of our estimates to the inclusion of alternative subsets of our sports events instruments. These, in practice, amount to over-identification exercises. We report the results from models using the 2-week (columns (1)-(5)) and the 3-week (columns (6)-(10)) poll-to-poll interval datasets, using the ± 0.25 article score cutoff classification. Panel AI presents the parameter estimates for equation (12). Panel BI presents the parameter estimates for equation (15). Panels AII and BII present diagnostic statistics for the respective first stages that include different subsets of instruments. We present results that omit one by one each of the four sports events from the instrument set in columns (1)-(4) and (6)-(9). In columns (5) and (10) we also include a more demanding specification where we omit both MLB and NBA games simultaneously,

[B.4] We believe this is unlikely given that poll-to-poll intervals cover an average of 30 days.

making these models exactly identified. The F-tests for the excluded instruments across the table do suggest that we lose some of the joint predictive power of our instruments when excluding some of them. However, we fail to reject the null of no joint significance in only 4 out of the 40 first stages reported in the Table. Standard errors for the parameter estimates are also somewhat larger, but in most cases the parameter estimates that are significant in our benchmark specification using all instruments remain significant at the 5% level when using only a subset of them. More importantly, the table shows that the magnitude and pattern of signs for the estimated parameters remain unchanged relative to our baseline model estimates.

B.2.1 A Test for Poll Timing Independence

Finally, we are also able to indirectly test whether the timing of polls appears to be uncorrelated with the evolution of the Senate races. Recall from our discussion in subsection 3.2 that this underlies the validity of our method for building the poll-to-poll intervals which determine the panel structure of our dataset. We do this by exploring the correlation between the frequency of actual polls in our dataset and the competitiveness of the race at any given point in time. In Table B.2 we report results from OLS regressions of the number of actual polls used to construct the average end-poll of each poll-to-poll interval, on the measure of race competitiveness we introduced in subsection B.1. We present results with or without normalizing by the length of the interval in days, and for both the 2-week and the 3-week poll-to-poll interval datasets. As the table illustrates, we find no correlation between poll frequencies and the state of the race. Pollsters do not appear to be releasing polls as a function of how the race is evolving. We see these results, together with those using alternative poll-to-poll windows, as reassuring.

C Data Appendix

C.1 News Processing

We followed several steps to process the news article texts. The data collection was conducted in *Lexis Nexis* and *Factiva*.[C.1] Our search terms included the name of the candidate (e.g., "Alan Kenneth Smith") as well as common abbreviations of the names (examples include "Senator Smith", "Al Smith", "Al K. Smith"). We downloaded all articles which with a succesfull hit for either search criterion.[C.2] We followed a clean-up procedure before computing our classification scores as follows: first we removed all common English words from the article (before the words are stemmed). Then using the Porter Stemming algorithm, we stemmed the words to their linguistic roots. The benefit of the stemming algorithm is that it allows us to reduce the words to workable roots which eliminate differentiations due to tense or subject.

To reduce the Type-I and Type-II error in the algorithm, we then eliminated articles irrelevant to our setting. In the first pass, after stemming the articles, we searched for candidate names (Here we looked for complete names, excluding any middle names or abbreviations) If the name of the candidate was mentioned in the article, we considered the article to be relevant to our data analysis. If there was no mention of the name in the article, we removed it into a secondary group over which we undertook a secondary search to prevent the unintentional removal of relevant articles.[C.3] We found our first pass categorizes about 25% of the articles as irrelevant. To reduce the potential for Type-II errors, we conducted a second manual search on the articles that failed the first pass. A research assistant investigated the common reasons for error on articles where a mistake arose, by looking at 10% of all removed articles. We then updated our algorithm to account for these common errors. This second pass reduced the percent of articles removed to 20%.

We carried out our search algorithm for the common words on the set of articles that passed our second test. For each set of candidate articles, after removal of common English words, punctuation, and stemming, we sought for the most commonly used two-word and three-word phrases. Single words may result in a high number of uninformative words and therefore they were not preferred for analysis here (see Gentzkow and Shapiro (2010) for another example of a similar choice).

C.1.1 A Validation Exercise

Our theoretical model of campaign-trail speech is based on the premise that the media profits relatively more from reporting on candidate speech targeted to partisan supporters. To the extent that this premise is correct, a revealed-preference argument would suggest that written media outlets should be willing to allocate more space to news pieces covering these kinds of campaign speech. As a validation exercise of our index of media content σ_i, in Table C.1 we look at the relationship between the number of words in an article in our sample, and the absolute value of its score σ_i. The table presents results from OLS specifications using either the number of words or its log, with and without race fixed effects. All specifications control for the article's candidate

[C.1] Due to the limits of search and downloads imposed on us by *Factiva*, we could not rely exclusively on this database.

[C.2] The article texts themselves are proprietary of these two companies.

[C.3] For example, a common failure reason in the first pass is a mis-typed character or string (e.g., instead of "Senator Elizabeth", the article would be stored in the newspaper database as "SenatorElizabeth". The missing character can prevent our algorithm from picking up the name of the candidate.

assignment score τ_i, a quadratic in the article's date, and year fixed effects. The conditional correlation between article length and σ_i is always positive, and is highly significant in the models including race fixed effects which exploit within-race variation only. The mean word count of articles in our sample is around 800 words. From column (2) in Table C.1, moving from a score of 0 to a score of 1 increases the article's length by 40 words, or around 5% of the average article length. This suggests that our proposed index is a reliable signal of the article content relevant to our model.

C.2 Senate Race Data: Dropped Senate Races

We drop from our analysis some senate races either because they were 3-way races, unopposed races, in practice unopposed races (more than one candidate ran, but other candidates were from third parties), not bipartisan races (not a Democrat and a Republican running against each other), or because a candidate died during the race. Table C.2 presents a list of races for which data was available, but which we excluded from the analysis for the aforementioned reasons.

Descriptive Statistics

Panel A	2-Week Intervals			3-Week Intervals		
	Dem.	All	Rep.	Dem.	All	Rep.
Number of poll-to-poll intervals per race		5.63			4.86	
		(4.55)			(3.62)	
Length of poll-to-poll interval (days)		30.51			35.16	
		(34.32)			(35.47)	
Number of polls per interval		1.74			2.01	
		(1.66)			(2.12)	
Electoral support (poll results)	0.44		0.42	0.44		0.42
	(0.11)		(0.11)	(0.12)		(0.11)
Number of articles per interval	56.11	90.22	41.50	61.98	98.83	45.43
	(101.7)	(127.42)	(62.49)	(112.53)	(138.0)	(67.63)
Number of core-targeted articles per interval (0.25 cutoff)	35.82	58.79	22.97	41.75	68.43	26.67
	(91.09)	(102.6)	(45.92)	(101.52)	(113.89)	(52.28)
Number of swing-targeted articles per interval (0.25 cutoff)	20.29	38.82	18.53	20.23	38.98	18.76
	(30.21)	(57.67)	(30.52)	(30.75)	(59.30)	(31.17)
Number of core-targeted articles per interval (0.5 cutoff)	29.05	45.8	16.75	34.07	54.12	20.05
	(89.46)	(97.95)	(43.50)	(98.21)	(107.93)	(50.83)
Number of swing-targeted articles per interval (0.5 cutoff)	27.07	51.81	24.75	27.12	52.58	25.46
	(40.23)	(77.23)	(40.81)	(42.40)	(82.64)	(43.78)
Number of core-targeted articles per interval (0.75 cutoff)	21.18	33.41	12.23	25.86	40.87	15.02
	(63.21)	(69.67)	(31.81)	(77.21)	(84.21)	(38.08)
Number of swing-targeted articles per interval (0.75 cutoff)	33.92	63.01	29.09	35.33	65.82	30.49
	(49.91)	(87.93)	(46.03)	(51.11)	(90.85)	(46.88)
Number of NFL games per interval (fan weighted)		4.22			4.91	
		(6.34)			(6.98)	
Number of MLB games per interval (fan weighted)		14.91			17.17	
		(25.43)			(27.12)	
Number of NBA games per interval (fan weighted)		8.91			10.15	
		(27.65)			(28.62)	
Number of NCAA games per interval (playoffs)		0.04			0.05	
		(0.29)			(0.31)	

Descriptive Statistics (cont.)

Panel B	Dem.	All	Rep.
Number of races		415	
Number of races per election cycle		24.41	
		(7.91)	
Number of polls		4076	
Number of polls per election cycle		239.76	
		(208.15)	
Number of polls per race		10.01	
		(11.93)	
Number of news articles	131131	210848	96984
Number of news articles per race	315.97	508.07	233.70
	(488.13)	(687.04)	(358.47)
Article score	-0.52	-0.005	0.52
	(0.44)	(0.70)	(0.43)
Observations	2337		2033

Table A.1: Descriptive Statistics: The table reports means and standard deviations for our main variables. Panel a reports summary statistics for the 2-week poll-to-poll interval panel and the 3-week poll-to-poll interval panel. Panel b reports overall summary statistics. Please see the text and the data description Appendix B for variable definitions and sources.

Robustness exercises (2 week poll-to-poll intervals)

		Robustness exercise:			
Panel A		Excluding last poll-to-poll interval	Controlling for post-primary dummy	0.5 article score cutoff	0.75 article score cutoff
Parameter	Regressor	(1)	(2)	(3)	(4)
		Dependent variable: Average sum of poll changes for D and R			
Δ^T_{pD}	$\frac{\text{Articles}^p_D}{\text{Articles}^p_D+\text{Articles}^s_D}$	0.015	0.014	0.011	0.015
		(0.005)	(0.005)	(0.005)	(0.006)
Δ^T_{pR}	$\frac{\text{Articles}^p_R}{\text{Articles}^p_R+\text{Articles}^s_R}$	0.003	0.008	0.004	0.005
		(0.005)	(0.006)	(0.005)	(0.006)
Panel B		Dependent variable: Adjusted difference of poll changes for D and R			
Δ^S_{sD}	$(\text{Articles}^p_D + \text{Articles}^s_D)/\tau$	0.21	0.13	0.12	0.12
		(0.08)	(0.056)	(0.056)	(0.06)
$-\Delta^S_{sR}$	$(\text{Articles}^p_R + \text{Articles}^s_R)/\tau$	−0.24	−0.16	−0.15	−0.14
		(0.12)	(0.082)	(0.076)	(0.078)
No. of races		415	415	415	415
No. of observations		1871	2134	2134	2134

Table A.2: Robustness Exercises. The table presents IV estimates of the persuasion effects from equations (12) and (15). All models are estimated on the 2 week poll-to-poll interval panel, and include a full set of Senate-race fixed effects, and month fixed effects. The dependent variable in Panel B is constructed using the parameter estimates from Panel A. All regressions are weighted by the square root of the length in days of the poll-to-poll interval (relative to the longest interval). Column (1) excludes all observations consisting of the last poll-to-poll interval in a race. Columns (2), (3), and (4) include a dummy variable for the last poll-to-poll interval in a race. All models use log of NFL games per day, log of MLB games per day, log of NBA games per day, and log of $NCAA$ games per day as instruments. Standard errors are robust to arbitrary heteroskedasticity and to arbitrary serial correlation of up to order 2 following Newey and West (1987). Coefficients and standard errors in Panels A and B are multiplied by 100.

Overidentification Exercises

		2 week poll-to-poll intervals					3 week poll-to-poll intervals				
Excluded Instruments:		NFL	MLB	NBA	NCAA	MLB, NBA	NFL	MLB	NBA	NCAA	MLB, NBA
Panel AI: Structural Equation		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Regressor	Param.	Dependent variable: Average sum of poll changes for D and R									
$\frac{\text{Articles}^p_D}{\text{Articles}^p_D+\text{Articles}^s_D}$	Δ^T_{pD}	0.014	0.019	0.011	0. 024	0.015	0.009	0.018	0.020	0.02	0.021
		(0.006)	(0.008)	(0.006)	(0.010)	(0.009)	(0.007)	(0.010)	(0.010)	(0.007)	(0.012)
$\frac{\text{Articles}^p_R}{\text{Articles}^p_R+\text{Articles}^s_R}$	Δ^T_{pR}	0.003	0.013	0.004	0.00	0.013	0.005	0.0013	0.009	0.01	0.012
		(0.006)	(0.010)	(0.004)	(0.01)	(0.009)	(0.007)	(0.012)	(0.008)	(0.01)	(0.012)
Panel AII: First Stages		Dependent variable: $\frac{\text{Articles}^p_D}{\text{Articles}^p_D+\text{Articles}^s_D}$									
R^2		0.78	0.78	0.78	0.78	0.78	0.80	0.80	0.80	0.80	0.80
F test (p-value)		0.014	0.011	0.058	0.011	0.037	0.071	0.015	0.082	0.014	0.042
		Dependent variable: $\frac{\text{Articles}^p_R}{\text{Articles}^p_R+\text{Articles}^s_R}$									
R^2		0.80	0.80	0.80	0.80	0.80	0.82	0.82	0.82	0.82	0.82
F test (p-value)		0.002	0.076	0.000	0.001	0.032	0.021	0.067	0.019	0.166	0.053
Panel BI: Structural Equation											
Regressor	Param.	Dependent variable: Adjusted difference of poll changes for D and R									
$(\text{Articles}^p_D + \text{Articles}^s_D)/\tau$	Δ^S_{sD}	0.10	0.24	0.18	0.10	0.30	0.12	0.27	0.19	0.15	0.32
		(0.07)	(0.10)	(0.08)	(0.11)	(0.14)	(0.07)	(0.11)	(0.09)	(0.12)	(0.17)
$(\text{Articles}^p_R + \text{Articles}^s_R)/\tau$	$-\Delta^S_{sR}$	−0.02	−0.21	−0.20	−0.19	−0.33	−0.15	−0.30	−0.29	−0.27	−0.46
		(0.16)	(0.11)	(0.12)	(0.11)	(0.17)	(0.013)	(0.14)	(0.17)	(0.12)	(0.28)
Panel BII: First Stages		Dependent variable: $(\text{Articles}^p_D + \text{Articles}^s_D)/\tau$									
R^2		0.60	0.60	0.60	0.60	0.60	0.63	0.63	0.63	0.63	0.63
F test (p-value)		0.062	0.095	0.046	0.495	0.047	0.090	0.134	0.088	0.672	0.062
		Dependent variable: $(\text{Articles}^p_R + \text{Articles}^s_R)/\tau$									
R^2		0.60	0.60	0.60	0.60	0.60	0.64	0.64	0.64	0.64	0.64
F test (p-value)		0.009	0.001	0.003	0.013	0.001	0.016	0.006	0.048	0.037	0.023
No. of races		415	415	415	415	415	415	415	415	415	415
No. of observations		2134	2134	2134	2134	2134	1865	1865	1865	1865	1865

Table A.3: Overidentification Exercises. The table presents IV estimates of the persuasion effects from equations (12) in Panel A, and (15) in Panel B. All models are estimated using the 0.25 article score cutoff, and include a full set of Senate-race fixed effects, month fixed effects, and a dummy variable for the last poll-to-poll interval in a race. The dependent variable for the equation in Panel BI is constructed using the benchmark parameter estimates from equation (12). Columns (1)-(5) are based on the estimate from column (4) of Table 2. Columns (6)-(10) are based on the estimate from column (8) in Table 2. Panels AI and BI present estimates for the structural equations (second stages), and Panels AII and BII report the corresponding R-squared and p-value for the F-tests on the excluded instruments for each first stage. The dependent variables in the first stages of Panel AII are the Democratic and Republican ratios of turnout-targeted to total news reports. The dependent variables in the first stages of Panel BII are the Democratic and Republican total news reports. The first five columns in the table are estimated on the 2 week poll-to-poll interval panel. The last five columns are estimated on the 3 week poll-to-poll interval panel. All regressions are weighted by the square root of the length in days of the poll-to-poll interval (relative to the longest interval). Columns (1) and (6) exclude the log number of NFL games per day from the instrument set. Columns (2) and (7) exclude the log number of MLB games per day from the instrument set. Columns(3) and (8) exclude the log number of NBA games per day from the instrument set. Columns (4) and (9) exclude the log number of $NCAA$ games per day from the instrument set. Columns (5) and (10) present a just-identified model excluding the log number of MLB games per day and the log number of NBA games per day from the instrument set. Standard errors are robust to arbitrary heteroskedasticity and to arbitrary serial correlation of up to order 2 following Newey and West (1987). Coefficients and standard errors in Panels AI and BI are multiplied by 100.

Republican's Action	Democrat's Action	Media's action: $a^M = F_D F_R$	Media's action: $a^M = F_D N_R$	Media's action: $a^M = N_D F_R$
$a^R = p$	$a^D = p$	$(\Delta_1, \Delta_2,\ \eta_D \pi_D + \eta_R \pi_R - 2k)$	$(\Delta_3, \Delta_4,\ n_D \pi_D - k)$	$(\Delta_5, \Delta_6,\ n_R \pi_R - k)$
$a^R = p$	$a^D = s$	$(\Delta_7, \Delta_8,\ n_R \pi_R - 2k)$	$(\Delta_9, \Delta_{10},\ -k)$	$(\Delta_{11}, \Delta_{12},\ n_R \pi_R - k)$
$a^R = s$	$a^D = p$	$(\Delta_{13}, \Delta_{14},\ \eta_D \pi_D - 2k)$	$(\Delta_{15}, \Delta_{16},\ n_D \pi_D - k)$	$(\Delta_{17}, \Delta_{18},\ -k)$
$a^R = s$	$a^D = s$	$(\Delta_{19}, \Delta_{20},\ -2k)$	$(\Delta_{21}, \Delta_{22},\ -k)$	$(\Delta_{23}, \Delta_{24},\ -k)$

Table A.4: Normal Form of the Stage Game.

Testing for Heterogeneity in Persuasion and Dissuasion Effects (2 week poll-to-poll intervals, 0.25 article score cutoff)

Panel A Parameter	Regressor	Coefficient	Interaction term (K): Dem. registration (1)	Log days to election (2)	Race tightness (3)	Incumbent running (4)
			Dependent variable: Average sum of poll changes for D and R			
Δ_{pD}^{T}	$\frac{\text{Articles}_D^p}{\text{Articles}_D^p+\text{Articles}_D^s}$	α_{pD}^{T}	0.075	0.001	0.019	0.018
			(0.037)	(0.025)	(0.010)	(0.009)
	$\frac{\text{Articles}_D^p}{\text{Articles}_D^p+\text{Articles}_D^s} \times K$	β_{pD}^{T}	-0.13	0.001	-0.031	-0.003
			(0.074)	(0.005)	(0.039)	(0.011)
Δ_{pR}^{T}	$\frac{\text{Articles}_R^p}{\text{Articles}_R^p+\text{Articles}_R^s}$	α_{pR}^{T}	-0.060	0.047	0.004	0.005
			(0.048)	(0.041)	(0.009)	(0.011)
	$\frac{\text{Articles}_R^p}{\text{Articles}_R^p+\text{Articles}_R^s} \times K$	β_{pR}^{T}	0.14	-0.011	0.008	0.00
			(0.10)	(0.009)	(0.032)	(0.014)
Panel B			Dependent variable: Adjsuted difference of poll changes for D and R			
Δ_{sD}^{S}	$(\text{Articles}_D^p + \text{Articles}_D^s)/\tau$	α_{sD}^{S}	0.037	0.0028	0.0014	0.0007
			(0.009)	(0.008)	(0.001)	(0.001)
	$(\text{Articles}_D^p +$ $\text{Articles}_D^s)/\tau \times K$	β_{sD}^{S}	-0.078	-0.0001	-0.002	0.0008
			(0.018)	(0.001)	(0.002)	(0.001)
$-\Delta_{sR}^{S}$	$(\text{Articles}_R^p + \text{Articles}_R^s)/\tau$	α_{sR}^{S}	0.0020	-0.0163	0.0009	0.000
			(0.014)	(0.014)	(0.002)	(0.002)
	$(\text{Articles}_R^p +$ $\text{Articles}_R^s)/\tau \times K$	β_{sR}^{S}	-0.007	0.003	-0.014	-0.0015
			(0.028)	(0.003)	(0.005)	(0.002)
	$\mathbb{E}[K]$		0.47	4.56	0.17	0.76

Table B.1: Heterogeneity in Persuasion and Dissuasion Effects. The table presents parameter estimates from IV models that include an interaction between race characteristics and the endogenous explanatory variables. All models are estimated on 2-week poll-to-poll intervals using 2134 observations from 415 Senate races. Models in column (1) allow for an interaction with the Democratic registration in the state as defined in the text. Models in column (2) allow for an interaction with the log of days to the general election. Because this variable varies across poll-to-poll intervals and races, log days to the general election is also included as a covariate. Models in column (3) allow for an interaction with a proxy for the competitiveness of the race, measured as the absolute value of the difference between the Democratic and Republican poll results at the beginning of the poll-to-poll interval. Because this variable varies across poll-to-poll intervals and races, race competitiveness is also included as a covariate. Models in column (4) allow for an interaction with a dummy variable for races where an incumbent senator is running. The dependent variable for the equation in Panel B uses the parameter estimates from the corresponding column of Panel A. All models include Senate-race fixed effects, month fixed effects, and a dummy variable for the last poll-to-poll interval in a race. The set of instruments includes the log of NFL games per day, the log of MLB games per day, the log of NBA games per day, the log of $NCAA$ games per day, and interactions of each of these variables with the corresponding interaction variable. All regressions are weighted by the square root of the length in days of the poll-to-poll interval (relative to the longest interval). Standard errors are robust to arbitrary heteroskedasticity and to arbitrary serial correlation of up to order 2 following Newey and West (1987). Coefficients and standard errors in Panel A are multiplied by 100.

Testing Model Assuptions: Poll Timing and Race Tightness

Dependent variable:	Polls in poll-to-poll interval		$\frac{\text{Polls in poll-to-poll interval}}{\text{Length of poll-to-poll interval}}$	
Poll-to-poll interval size:	2 week	3 week	2 week	3 week
	(1)	(2)	(3)	(4)
Race tightness ($\|V_D - V_R\|$)	0.041	0.100	0.001	0.025
	(0.506)	(0.697)	(0.066)	(0.077)
R^2	0.39	0.48	0.42	0.47
No. of Races	415	415	415	415
No. of Observations	2134	1865	2134	1865

Table B.2: Testing Model Assumptions: Poll Coverage Intensity and Race Competitiveness: The table presents OLS panel regressions of a measure of poll coverage intensity on the tightness of the Senate race as measured by the absolute value of the difference between the Democratic candidate's electoral support and the Republican candidate's electoral support. The dependent variable in columns (1) and (2) is the number of polls in the poll-to-poll interval. The dependent variable in columns (3) and (4) is the number of polls per day in the poll-to-poll interval. All models include a full set of Senate-race fixed effects, month fixed effects, a dummy variable for the last poll-to-poll interval in a race, and a constant. All regressions are weighted by the square root of the length in days of the poll-to-poll interval (relative to the longest interval). Standard errors are robust to arbitrary heteroskedasticity.

Conditional Correlations of Article Word Counts and Article Scores

Dependent variable:	Number of Words		Log Number of Words	
	(1)	(2)	(3)	(4)
Absolute value of article score ($\|\sigma_i\|$)	36.83	40.10	0.052	0.036
	(29.98)	(17.69)	(0.031)	(0.016)
Race Fixed Effects	N	Y	N	Y
R^2	0.02	0.06	0.09	0.29
No. of Races	417	417	417	417
No. of Observations	176034	176034	176034	176034

Table C.1: Article Word Counts: The table presents OLS panel regressions of a measure of article word count on the absolute value of the article's score σ_i. The dependent variable in columns (1) and (2) is the word count of the article. The dependent variable in columns (3) and (4) is the log of the word count of the article. All models control for the article candidate assignment score τ_i, the article's days to election and its square, and include year fixed effects and a constant. Columns (2) and (4) include race fixed effects. Standard errors are robust to arbitrary heteroskedasticity and clustered at the Senate-race level.

Dropped Senate Races

Candidate Died	Non-bipartisan Races	3-way Races	Unopposed Races	Unopposed Race (in practice)	Other Reason
MN 2002	LA 1990	AK 2010	ID 2004	VA 1990	NE 1988
	VT 2006	LA 1992	SD 2010	AZ 2000	IN 1990
	VT 2012	LA 2002	AR 1990	MA 2002	ND 1992
		CT 2006	GA 1990	MS 2002	TN 1994
		FL 2010	MS 1990	VA 2002	KS 1996
		ME 2012	KS 2002	IN 2006	GA 2000
				AR 2008	MO 2002
					WY 2008
					CO 2010
					DE 2010
					LA 2010
					WV 2010

Table C.2: Dropped Senate Races.