Persuasion and Dissuasion in Political Campaigns:

Political Communication and Media Coverage in Senate Races

Camilo García-Jimeno and Pinar Yildirim

January 31, 2024

WP 2024-04

https://doi.org/10.21033/wp-2024-04

FEDERAL RESERVE BANK *of* CHICAGO

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

Camilo García-Jimeno[1] and Pinar Yildirim[2]

[1]Federal Reserve Bank of Chicago
[2]Wharton School, University of Pennsylvania

This Version: January 31, 2024

Abstract

We study the strategic interaction between candidates to office and the print media, exploring the following tension: while the media is instrumental for candidates to communicate with voters, candidates and media outlets have conflicting preferences over the contents of media reporting. We propose a model of bipartisan races where candidates make decisions over the type of constituencies to target with their statements along the campaign trail and media outlets make decisions over how intensely to report about the candidates based on those statements. Different kinds of media reports may persuade or dissuade voters. We develop a methodology to classify news content as suggestive of the target audience of candidate speech, and show how data on media reports and poll results, together with the behavioral implications of the model, can be used to estimate its parameters. We implement this methodology on US Senatorial races for the period 1980-2012, and find that Democratic candidates had stronger incentives to target their messages towards turning out their core supporters than Republicans. We also find that the cost in swing-voter support from targeting core supporters was larger for Democrats than for Republicans. These effects balanced each other, making media outlets willing to cover candidates from both parties at similar rates.

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

JEL Codes: C3, D72

*Contact information: García-Jimeno: cgarcia@frbchi.org, 230 S. LaSalle Street, Chicago, IL 60603. Yildirim: pyild@wharton.upenn.edu, 3620 Locust Walk, Philadelphia, PA 19104. We thank Jeff Groesback, Scott Wang, and Shawn Zamechek for excellent research assistance, and Noah Veltman for sharing with us the data on NFL fandom. We are also grateful to Daron Acemoglu, Frank DiTraglia, Wes Hartmann, Horacio Larreguy, Gregory Martin, Harikesh Nair, Maria Petrova, Carlo Prato, Subrata Sen, Jesse Shapiro, Noam Yuchtman, and to seminar participants at Tufts University, CEMFI, Pompeu Fabra, SICS, Stockholm University, the Wharton School, Princeton University, NYU Abu Dhabi, UC Berkeley, the Wallis Political Economy conference at the University of Rochester, the Southern Economic Association 2015 Conference, and the Stanford University SITE conference for their valuable comments. We gratefully acknowledge the financial support of the NET Institute, the Dean's Research Fund at the Wharton School, and the Hal Varian Visiting Assistant Professorship research fund at MIT. The opinions expressed in this article are those of the authors and do represent the views of the Federal Reserve Bank of Chicago or the Federal Reserve System. All authors declare that they have no conflicts of interest. Data used in this study come from a combination of proprietary and public sources. Data from the public sources can be requested from the authors.

1 Introduction

Does candidate speech and the associated media reporting on it matter for electoral performance? Political scientists and political economists are interested in the factors shaping electoral outcomes (Abramowitz, 1988; Dorn et al., 2020; Enikolopov et al., 2011). Marketing scholars are similarly interested in measuring the effects of earned media (e.g., Lovett and Staelin, 2016; Seiler et al., 2015; Stephen and Galak, 2012). Yet measurement of such *persuasive effects* is empirically challenging for several reasons. First, target audiences have heterogeneous beliefs, preferences, and values. On the campaign trail, candidates must communicate with a heterogeneous electorate and express ideas that may appeal to some but not to others. Similar trade-offs exist in other persuasive communication settings –for instance, a set of product attributes highlighted in advertising may attract some consumers, while making the product less appealing to others[1]–. Depending on the nature of the data available, researchers may only be able to recover the *net effects* of communication, limiting our understanding of the underlying trade-offs.

Second, heterogeneous audiences create incentives for *targeted* messaging. In the case of political campaigns, candidates have strong reasons to tailor their speeches and statements towards the preferences of the audiences they face along the campaign trail. Their ability to do so, however, is limited by a key constraint: the media covers and reports on the campaigns, reducing the candidates' ability to narrowly target their speech. Moreover, the preferences of candidates and the media over the content of media reporting can be directly in conflict: the media is often uninterested in covering speech that candidates may want widely covered, while it is often eager to cover and report on speech that candidates would prefer not covered[2]. This environment raises additional empirical challenges. When measuring candidate speech using media reporting, selection considerations arise; the content and amount of information will be selected on the media's preferences and behavior. Information will also be selected on the candidates' strategic campaigning choices because candidates are keenly aware of the intervening role of the media into what messages the public receives.

In this paper we study U.S. senatorial campaigns between 1980 and 2012 –before social media's consolidation as the main conduit of information on politics– to tackle these empirical challenges. Senate races offer a convenient empirical setting because they are high profile and enjoy ample media and polling coverage. Following ideas in Gentzkow and Shapiro (2010), we rely on an intensive text analysis of written media articles reporting on these campaigns to extract signals about the broad target audience of a candidate's speech along the campaign trail: centrist (swing) or partisan (core) voters. Relying on polling data over the course of the campaigns as measures of relative electoral support for the candidates, our media-based measures of target audience allow us to tackle the first

[1]For instance, a product that is 'unsweetened' may appeal to some consumers but not to others.

[2]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 core 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.

empirical challenge, namely to decompose net poll changes over time into persuasive and dissuasive margins from the different types of voters.

To address the selective reporting of campaign speech in the press (the media does not cover all candidate speech that takes place), we propose a simple strategic model of the interaction between candidates and the press (e.g., Bajari et al. (2010)). In this model, candidates decide what type of statements to make at every period of the campaign (core or swing-voter targeted), and media outlets decide on the intensity with which they will cover each candidate. Our main insight is that while candidates would prefer their core-targeted messages not to be widely covered by the media, the media strongly prefers to report on such messages. And while candidates would prefer their swing-targeted messages to be widely covered by the media, the media shows little interest in reporting on those types of messages. A setting like this one results in a strategic environment resembling a matching-pennies game: the equilibrium strategies of the players (the likelihood of a swing-targeted statement by the candidate, and the likelihood of coverage by the media) pin down the fraction of campaign statements reported, and among reported speech, the share that signal swing-voter targeting. Through the lens of this model we control for selection in the media reports we observe.

Controlling for selection considerations relying on the restrictions from this model is insufficient to deal with other unobservables that may drive both the types of statements candidates make, and their electoral (polling) performance. By pinning down equilibrium behavior by candidates and the media, however, the model of the campaign trail suggests that shifters to the media's payoffs that do not also shift the candidates incentives, will be appropriate instruments for our measures of media-reported candidate speech. Following Eisensee and Strömberg (2007), we collected high frequency data on sports events from the four most important sports leagues in the US (*NCAA*, *NBA*, *MLB*, and *NFL*). We use these data to build instrumental variables for the media's willingness to cover and report on politics during campaigns. Overall these instruments yield strong first stages.

We find a large asymmetry in the strategic environment faced by Democratic and Republican Senate candidates and on the persuasive (and dissuasive) effects of their speech. We estimate that Democratic Senate candidates, on average, engage in persuasive speech targeting their core supporters with 0.56 probability, while Republican Senate candidates do so with 0.45 probability. Moreover, the gain from engaging in persuasive speech targeting core voters is higher for Democratic candidates. A 10% increase in persuasive core-targeting leads to a 3.3 percentage points gain in vote share for the Democratic candidate, but only to a 0.8 percentage points gain for the Republican candidate. These gains are not trivial; historically, the margin of victory in Senate races is close to 5 percentage points.

On average, the persuasive responsiveness of Democratic core supporters is much higher than that of the Republican ones possibly owing to the lower turnout rates traditionally associated with Democratic voters.[3] This gives strong incentives for the media to cover Democratic candidates more intensely. Swing-voters punish Democratic candidates more severely for widely reported campaign

[3]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)).

speech targeting the Democratic core, a significant dissuasion effect. As a result, Democratic candidates' speech is sufficiently disciplined that, in equilibrium, Democratic and Republican candidates face similar rates of media coverage and reporting.

We explore the extent of heterogeneity in these persuasion and dissuasion effects along four dimensions. First, we explore if they vary across states with differing partisan compositions. Swing voters appear to be more persuadable by centrist reports of Democratic candidates in states with relatively few Democratic voters. Second, we explore if they vary with time to election day, and find no significant heterogeneity. Third, we explore if they vary as a function of the state of the electoral race, as measured by the gap in poll support for the candidates. The persuasion effect on swing voter-targeted speech by Republicans grows as the races become more competitive. Finally, we find no heterogeneity in electoral responses when an incumbent candidate is running.

The model we estimate also allows media outlets to exhibit asymmetric payoffs from covering the statements from Republican and Democratic candidates. We call this differential treatment *media bias* and measure the average impact that different types of statements and media reports have on the poll standings and electoral performance of candidates.[4] We find little evidence of significant preference, across all media outlets, for reporting on candidates of one party over the other.

Our findings are robust to a number of specifications, as reported in Appendix A.5. Results remain qualitatively similar if we use two or three-week intervals to define poll-to-poll periods. They are also similar if we use different article score cutoffs to classify articles as suggestive of core or swing-voter targeting. Additional robustness checks include: i) excluding sporting events happening very close to election day as they may violate our exclusion restriction, ii) using various subsets of the sporting events to construct our instruments, and iii) allowing for differential effects during the primary period.

Although we are unaware of other studies modeling the relationship between politicians and the media in the way we do here, or estimating the effect of media campaign coverage on electoral outcomes within a structural model, 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 also 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 organizations seek to spoon-feed the press in order to control the news

[4] The literature has emphasized how media bias or slant affect the media market (e.g.,Baron (2006); Mullainathan and Shleifer (2005)). In these papers, media bias refers to an outlet's preference for 'spinning' the information it receives when reporting on it. Here, our definition of media bias refers only to the media's relative preference for the extent of reporting about either political party.

coverage their candidates receive. Journalists react by striving to keep candidates off balance through independent reporting" (pg. 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 to the public. 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 speech targeted to core supporters leads to more media scrutiny and thus, to more information production. More information, thus, may be correlated with more extreme platform choices by politicians. 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 that has empirically studied 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.

2 A Simple Model of the Campaign Trail

In this section we describe the simple model of political campaigns and media coverage that will allow us to separately measure persuasive and dissuasive effects of campaign speech, and to address the econometric challenges we outlined in the introduction. The model captures what we consider are key features of the interaction between two candidates $p \in \{D, R\}$ running against each other, and the distribution of media outlets m covering the race. Candidates make statements over time that can be targeted to core 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 core supporters. Candidates benefit electorally (in their poll standing) from media reports on their swing voter-targeted statements, as this may persuade some centrist voters. Moreover, although core voter-targeted speech may persuade some partisan voters, it will also dissuade centrist voters if such speech is covered by the press. 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.

Players' Actions To increase the support of voters, candidates make a statement every period. The underlying environment is such that candidates do not fully converge to the median voter's ideological stance.[5] To persuade *core* voters, candidates make ideological statements ($a^p = c$) directly targeted to this audience, but those statements may dissuade swing voters. Candidates may, instead, make relatively centrist, *swing* voter-targeted statements ($a^p = s$), which generate little excitement among the core, but increase or maintain the electoral support in the center. Simultaneously, 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 successfully reports on candidate p (denoted by $\chi = 1$) with probability $\mathbb{P}(\chi = 1|p) = \eta_p$. Inclusion of η_p allows us to keep the action space of the media three-dimensional, while still allowing for periods without observed news reports. Moreover, it allows us to directly capture the media's overall propensity to report differentially about candidates from either party. When $\eta_D \neq \eta_R$, we refer to this as "media bias." Candidate statements and media reports determine, period-by-period, the evolution of poll standings.[6]

Payoffs Every period, the media, m, must pay a cost k per candidate followed. The per-period gains from reporting on candidate p are:

[5] This setting can easily be micro-founded in a model where the turnout of voters in the extremes of the ideological distribution (core supporters) is sensitive to their distance to the candidates' position, and the density of 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.

[6] As our focus is not on voters in this paper, we deliberately maintain 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.

$$\pi_p(a^p) = \begin{cases} 0 & if\ a^p = s \\ \pi_p & if\ a^p = c, \end{cases} \tag{1}$$

where we have chosen to normalize the gain from reporting a swing voter-targeted statement to zero. Nevertheless, we allow the gain to differ between a report about the Democrat or the Republican.

To simplify the payoff structure of the game, we make some behavioral assumptions about 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 core voters only react on the turnout margin, and never switch party allegiances. In contrast, centrist swing voters only react on the party support margin, and do not react on the turnout margin (their turnout rate is constant). We assume voters report truthfully to pollsters.

Candidates care about their poll standing, and players' actions directly map onto changes in electoral and poll support. Their payoffs depend on whether the media covers their statements or not, and on whether these are targeted to swing voters or to core supporters. More concretely, the change in poll support for candidate $p \in \{D, R\}$ between periods t and $t+1$ can be decomposed as:

$$\begin{aligned} V_p(t+1) - V_p(t) = \quad & \underbrace{\Delta^T_{cp}\mathbf{1}\{a^p(t) = c, \chi(t) = 0\}}_{\text{Candidate makes statement } c \text{, Media does not report}} + \underbrace{\left(\Delta^T_{cp} - \Delta^S_{cp}\right)\mathbf{1}\{a^p(t) = c, \chi(t) = 1\}}_{\text{Candidate makes statement } c \text{, Media reports}} \\ & + \underbrace{\Delta^S_{c\sim p}\mathbf{1}\{a^{\sim p}(t) = c, \chi(t) = 1\}}_{\text{Opponent makes statement } c \text{, Media reports}} + \underbrace{\Delta^S_{sp}\mathbf{1}\{a^p(t) = s, \chi(t) = 1\}}_{\text{Candidate makes statement } s \text{, Media reports}} \\ & - \underbrace{\Delta^S_{s\sim p}\mathbf{1}\{a^{\sim p}(t) = s, \chi(t) = 1\}}_{\text{Opponent makes statement } s \text{, Media reports}} + \epsilon^p_{t+1}, \qquad p = D, R, \end{aligned} \tag{2}$$

where Δ^T_{ap} is the average change in electoral support to candidate p on the Turnout margin when choosing action a^p, and Δ^S_{ap} is the average change in electoral support to candidate p on the Swing-voter margin when choosing action a^p. While the Δ^T_{cp} and Δ^S_{sp} are persuasion effects, the Δ^S_{cp} are dissuasion effects. $(\epsilon^D_{t+1}, \epsilon^R_{t+1})$ are other unobserved shocks to the change in electoral support.

Equation 2 incorporates our key assumptions: i) unreported swing voter-targeted statements have no effect on either core 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 his opponent. ii) Core voter-targeted statements increase the turnout of core constituencies. When such statements are unreported, they do not have an effect on swing voters. When reported, in contrast, they turn centrist voters away from the candidate making these statements and towards his opponent. We maintain (although we do not impose in estimation) the following joint parameter restrictions:

Assumption 1. *The following inequalities hold:*

$$\Delta^T_{cD} < \eta_D \left(\Delta^S_{cD} + \Delta^S_{sD}\right), \quad \Delta^T_{cD} > 0, \quad \Delta^S_{cD} > 0, \quad \Delta^S_{sD} > 0$$
$$\Delta^T_{cR} < \eta_R \left(\Delta^S_{cR} + \Delta^S_{sR}\right), \quad \Delta^T_{cR} > 0, \quad \Delta^S_{cR} > 0, \quad \Delta^S_{sR} > 0$$

Under Assumption 1, the expected swing-voter loss from making a core-targeted statement is larger than the expected gain on the turnout margin. In such case, the net effect from a core-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 take into account the zero-sum nature of swing support, they make explicit that unreported statements by a candidate do not have an effect on his opponent's poll standings, and that unreported centrist statements do not have any effect on his own poll standings. They also imply that candidates gain support from core-targeted statements that go unreported, but expect to lose support when these are reported. Finally, they imply that 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).

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 speeches. The model just described gives rise to a strategic environment resembling a matching-pennies game between each candidate and the media: if a candidate sends a core-targeted signal, the media will want to cover it. If the media covers a core-targeted signal, the candidate will prefer to send a centrist signal. If a candidate sends a centrist 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 $\eta_p \pi_p > k$. The normal form game described above does not have a pure-strategy equilibrium. The unique mixed strategy equilibrium is given by:*

$$\gamma^*_R = 1 - \frac{\Delta^T_{cD}}{\eta_D \left[\Delta^S_{cD} + \Delta^S_{sD}\right]} \tag{3}$$

$$\gamma^*_D = 1 - \frac{\Delta^T_{cR}}{\eta_R \left[\Delta^S_{cR} + \Delta^S_{sR}\right]} \tag{4}$$

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

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

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 core-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. $\square$

As is standard in a matching pennies-type environment, mixing probabilities are pinned down by indifference. This makes them a function only of the opponents' payoffs. In our application, this consequence of equilibrium has a subtle testable implication. If we want to study candidate campaign speech, we must do comparative statics on the media's payoffs. Candidates' payoffs are in fact irrelevant to explain their own equilibrium behavior. As a result, the media's payoff from reporting on core-targeted statements will be negatively correlated with the equilibrium rate at which candidates make such statements. In this sense, the media can constrain candidates' behavior in our setting. Moreover, the poll gains from a given campaign statement should have no predictive power for the rate at which candidates make such statements. Conversely, the frequency with which the media reports on the candidates should be independent of how profitable it is to report. It should depend only on the candidates' payoffs.

3 Data

3.1 Senate Races

There are 100 U.S. Senate seats, 2 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.[7] As in most other elections for public office in the U.S., Senate elections are preceded by a period of campaigning, which in practice begins well before each party in each state has chosen its candidate in either a primary election or a convention. Pollsters, however, track electoral support for the general election, even during the primary season.

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.[8] 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

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

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

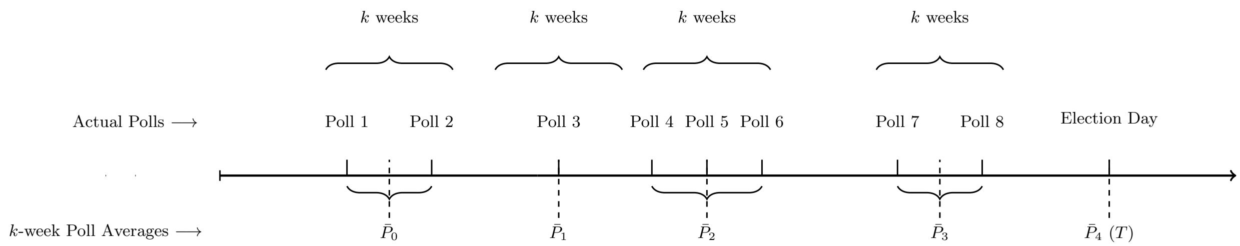


Figure 1: Construction of the poll-to-poll intervals.

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 all polling reported within a one-year window before election day.[9] We collected 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 Senate race. Naturally, the frequency of Senate race polls becomes higher in more recent years and in states with larger populations.

Our empirical strategy also requires computing frequencies of news reporting over time. To do this, we rely poll dates to construct what we call "poll-to-poll" intervals, effectively creating the time dimension of our panel. Subsequently, we use the dates of the news articles to assign them to their corresponding poll-to-poll interval, within which we measure the different news article statistics required by our empirical strategy (desceribed below). Because the definition of these periods is arbitrary, we explore two alternative criteria for the construction of the intervals grouping nearby polls using two-week or three-week windows, and averaging (weighting by poll sample size) all polls falling within the time window. We then assign the median date among the polls in the window as the period marker. This strategy is convenient because the frequency and spacing of polls is uneven across states and years, and because aggregating nearby polls helps us average out the measurement error

[9]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.

inherent in the polls. Figure 1 graphically illustrates the construction of the poll-to-poll intervals.[10]

3.3 Measuring News Reporting

Our methodology demands we classify news articles related to the campaigns as indicative of different types of candidate speech. 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 core-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 to centrist voters when expressed by a Democratic candidate in Massachusetts, but it may only appeal to the core 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 core-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 news articles mentioning either candidate in a given race. 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 implemented a text search algorithm to parse the HTML tags and gather information about the articles (publication date, source, subjects, and people mentioned in the article). These tags allowed us to further weed out irrelevant articles and omit repeated articles. 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.[11] We then computed the

[10] The construction of time periods in this way introduces an unavoidable precision/bias trade-off because the statistics we construct are based on the observed news article relative frequencies. On the one hand, the longer a poll-to-poll interval, the smaller the sampling error in the measured statistics of news reports falling within this interval, and the closer these statistics will be to the probabilities with which they are generated. On the other hand, if the actual probabilities change significantly over time,—for example because payoff parameters depend on a time-varying state variable–, the longer a poll-to-poll period, the larger the bias from a statistic based on frequency counts within the interval. To deal with this issue, we explore the robustness of our results to alternative definitions of a poll-to-poll interval, and we perform a robustness exercise where we estimate a version of the model where the game is not repeated but dynamic. In that case, we allow the payoff parameters to evolve as a function of a state variable, namely the current relative poll standing of the candidates.

[11] 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.

candidate assignment statistic τ_i:

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

where x_i^p is the count of party p's candidate 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 τ_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 ($\tau_i < 0$) and Republican ($\tau_i > 0$) 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 τ_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,

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

Here f_{ij} represents the frequency with which phrase j appears in article i. For example, if a given 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. Formally 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 being self-referential: 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 core supporter or swing voter-targeted speech by the candidates. σ_i is a continuous index which we use together with τ_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 core supporter targeted –*c*–. Figure 2 presents the distribution of the article scores σ_i for our sample of news pieces. Our benchmark specification classifies articles as signaling core supporter-targeted speech when $\sigma_i < -0.25$ for the Democrat and

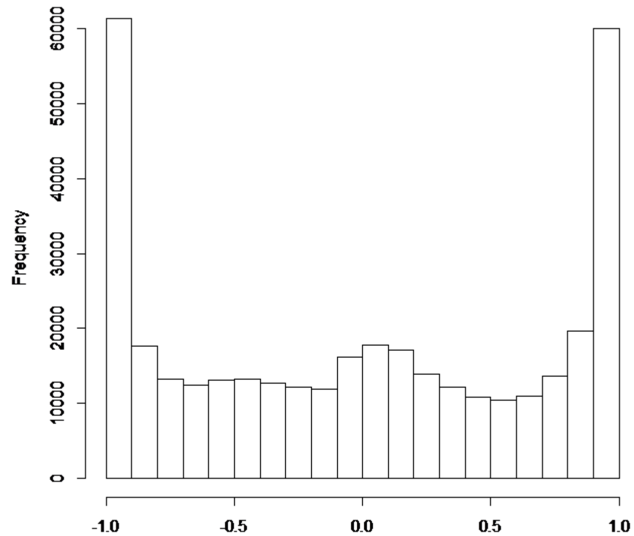


Figure 2: Distribution of articles scores σ_i.

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 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 leagues 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 obtain exogenous variation in media campaign coverage also for these states, we additionally collected information from *Facebook*.[13]

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 and dissuasive effects of candidate speech on polling performance: $(\Delta^T_{cp}, \Delta^S_{cp}, \Delta^S_{sp})$. This is despite our inability to observe a subset of the equilibrium outcomes of the game, namely realizations in which the media does not report on the campaigns.

4.1 Identification of Persuasion and Dissuasion Effects

We first introduce some notation: $X^a_{p,r}(t, t+\tau)$ is the count of type $a \in \{c, s\}$ media reports on candidate $p \in \{D, R\}$ in race r, appearing between t and $t+\tau$. $N^a_{p,r}(t, t+\tau)$ is the count of type a campaign-trail statements by candidate p in race r between t and $t+\tau$ that do not get reported by the media. While we observe $X^a_{p,r}(t, t+\tau)$ (with error), we do not observe $N^a_{p,r}(t, t+\tau)$. If within a time interval $[t, t+\tau)$ payoff parameters are constant, equilibrium of the repeated matching pennies game –equations (3)-(6)– pins down $(X^c_{p,r}(t, t+\tau), X^s_{p,r}(t, t+\tau), N^c_{p,r}(t, t+\tau), N^s_{p,r}(t, t+\tau))$ to be a draw from a multinomial distribution with success and failure probabilities determined by the equilibrium mixing strategies of candidates and media outlets.

[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.

We proceed by writing down the net change in the poll standing of a given candidate between t and $t+\tau$ from (2), as a function of the counts of realizations of game actions that affect electoral support $(X^c_{p,r}, X^c_{\sim p,r}, X^s_{p,r}, X^s_{\sim p,r} N^c_{p,r})$ in that interval. Our first observation is that by *adding* the net changes for both candidates, all terms related to swing voters cancel by their zero-sum nature, allowing us to isolate the core-voter persuasion effects. As we show in Appendix A (see (A.6)), this yields an expression that depends only on $[N^c_{p,r}(t,t+\tau) + X^c_{p,r}(t,t+\tau)]/\tau$ for $p \in \{D, R\}$ and on the average of the shocks in the time interval. We further show that the equilibrium probability of a core-targeted statement $\hat{q}^*_{p,r} = \mathbb{E}\left[(N^c_{p,r}(t,t+\tau) + X_{,r}p^c(t,t+\tau))/\tau\right]$, can be estimated within a time interval[14] as

$$\hat{q}^*_p(t,t+\tau) = \frac{X^c_p(t,t+\tau)}{X^s_p(t,t+\tau) + X^c_p(t,t+\tau)}.$$

This is very convenient, as it allows us to obtain an expression for the evolution of the sum across candidates of net poll changes that does not depend on the unobservables $N^c_{p,r}$. The proposition below establishes how the core-supporter persuasion effects $(\Delta^T_{cD}, \Delta^T_{cR})$ can be recovered.

Proposition 2. (Identification of Core-supporter Persuasion Effects) *Consider the linear specification:*

$$\frac{V_D(t+\tau) - V_D(t) + V_R(t+\tau) - V_R(t)}{\tau} = \Delta^T_{cD}\frac{1}{\tau}\frac{X^c_D}{X^c_D + X^s_D} + \Delta^T_{cR}\frac{1}{\tau}\frac{X^c_R}{X^c_R + X^s_R} + \omega(t,t+\tau) \tag{8}$$

where $\omega(t,t+\tau)$ is an error term derived in Appendix A. If instrumental variables $\mathbf{z}(t,t+\tau)$ are available, such that, (i) $\pi_p(\mathbf{z})$ vary with $\mathbf{z}$, (ii) $Cov(\mathbf{z},\omega) = 0$, and (iii) the dimension of $\mathbf{z}$ is at least 2, an IV regression of equation (8) using $\mathbf{z}$ as instruments for $\frac{X^c_D}{X^c_D+X^s_D}$ and $\frac{X^c_R}{X^c_R+X^s_R}$ identifies the persuasion effects $(\Delta^T_{cD}, \Delta^T_{cR})$.

Proof. See Appendix A. □

The dependent variable in equation (8) is the net change in the fraction of polled individuals reporting support for Neither the Democratic nor the Republican candidate. In most polls, these are people who have not made up their mind about whether to turn out or about which candidate they prefer. Proposition 2 shows that the covariation in these changes with the ratios of news reports indicative of core-targeted statements to all news reports for each candidate can identify the average turnout persuasion response of the polled electorate to core voter-targeted statements.

A key identification challenge with estimating equation (8) is the endogeneity of the relative share of news stories with core- and swing-voter targeted policy coverage $\left(\frac{X^c_D}{X^c_D+X^s_D}, \frac{X^c_R}{X^c_R+X^s_R}\right)$. Each of these shares is likely to be correlated with other unobservables that also determine the evolution of electoral support during a campaign, so we require at least two instrumental variables. These need to be sources

[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, choosing the panel periods this way will introduce no additional sources of bias when estimating equation A.5. In section A.5.1 we test the plausibility of this assumption.

of variation for the relative frequencies of core-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 equations (5) and (6), the mixing probabilities chosen by the candidates are pinned down by the media's payoffs from reporting: $q_p^*(\mathbf{z}) = \frac{k}{\eta_p \pi_p(\mathbf{z})}$. 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 reporting on politics, this should increase the rate at which the candidates target their core constituencies with their statements: 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.

While Proposition 2 allows us to recover the core-voter persuasion effects Δ_{cD}^T and Δ_{cR}^T by adding the changes in poll standings of both candidates, the proposition below shows that given knowledge of these persuasion effects, subtracting the changes in poll standings of both candidates allows us to recover the swing-voter persuasion effects Δ_{sD}^S and Δ_{sR}^S. Finally, it also shows that given knowledge of all four persuasion effects, we can then recover the swing-voter dissuasion effects Δ_{cD}^S and Δ_{cR}^S.

Proposition 3. (Identification of Swing-voter Persuasion and Dissuasion Effects) *Consider the linear specification:*

$$\frac{\hat{D}(t,t+\tau) - \hat{R}(t,t+\tau)}{2} = \Delta_{sD}^S \frac{[X_D^c + X_D^s]}{\tau} - \Delta_{sR}^S \frac{[X_R^c + X_R^s]}{\tau} + \zeta(t,t+\tau) \qquad (9)$$

[15] The exclusion restriction may fail if the occurrence of these sports events directly either 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 exclusion restriction may rise if the fanhood-weighted sporting events alter the opportunities for other political communication, e.g., political advertising.

where

$$\hat{p}(t,t+\tau) \equiv [V_p(t+\tau) - V_p(t)] - \hat{\Delta}^T_{c\sim p}\frac{X^c_{\sim p}}{X^c_{\sim p} + X^e_{\sim p}}\tau$$

is the change in electoral support for candidate $p \in \{D, R\}$ *net of the core-voter persuasion effects of the opposing candidate, and* $\zeta(t, t+\tau)$ *is an error term derived in Appendix A. If instrumental variables* $\mathbf{z}(t, t+\tau)$ *are available, such that, (i)* $\tau(\mathbf{z})$ *varies with* $\mathbf{z}$*, (ii) Cov*$(\mathbf{z}, \zeta) = 0$*, and (iii) the dimension of* $\mathbf{z}$ *is at least* 2*, an IV regression of equation (9) using* $\mathbf{z}$ *as instruments for* $\frac{[X^c_D + X^s_D]}{\tau}$ *and* $\frac{[X^c_R + X^s_R]}{\tau}$ *identifies the persuasion effects* $(\Delta^S_{sD}, \Delta^S_{sR})$*. The dissuasion effects* $(\Delta^S_{cD}, \Delta^S_{cR})$ *are identified from*

$$\Delta^S_{cp} = \frac{\Delta^T_{cp}}{\frac{[X^c_p + X^s_p]}{\tau}} - \Delta^S_{sp} \tag{10}$$

Proof. See Appendix A. □

Proposition 3 shows that the covariation between appropriately "corrected" changes in the competitiveness of the race over time and the rate at which candidates are covered about any type of statements can identify the average persuasion effect to swing voter-targeted statements. The correction entails using the estimates of $(\Delta^T_{cD}, \Delta^T_{cR})$ from Proposition 2 to account for the poll changes stemming from core-targeted candidate speech. As equation (10) shows, the swing-voter dissuasion effects –the poll gains to a candidate from core supporter-targeted statements by his opponent, Δ^S_{cp}–, are fully pinned down by equilibrium play and all four persuasion effects. Crucially, as we show in Appendix A, the error term in (10) does not depend on τ.

Proposition 3 also requires the use of instrumental variables, because the total number of reports in a period $\left(\frac{[X^c_D + X^s_D]}{\tau}, \frac{[X^c_R + X^s_R]}{\tau}\right)$ will be correlated with other unobservables in $\zeta(t, t+\tau)$ 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, however. In contrast to the identification idea for in Proposition 2, where we leveraged the dependence of q^*_p on the media's payoff from reporting on politics, π_p, our model implies that the equilibrium reporting rate of a candidate, $\mathbb{E}\left[\frac{X^c_p + X^s_p}{\tau}\right] = \eta_p(1 - \gamma_{\sim p})$, is independent of the media's payoff. As equations (3) and (4) show, in equilibrium the reporting rate 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 variation across media outlets in their willingness to report on politics, however, then sports events can be valid shifters of $\tau(\mathbf{z})$, and thus valid instruments. Sports events induce no intensive-margin response by a given media outlet (whose reporting strategy is pinned down by indifference). They can, nevertheless, induce an extensive margin response across the distribution of media outlets covering a race.

Figure 3 illustrates how variation in sports events can lead marginal outlets to begin or drop out from covering the campaigns. We plot 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

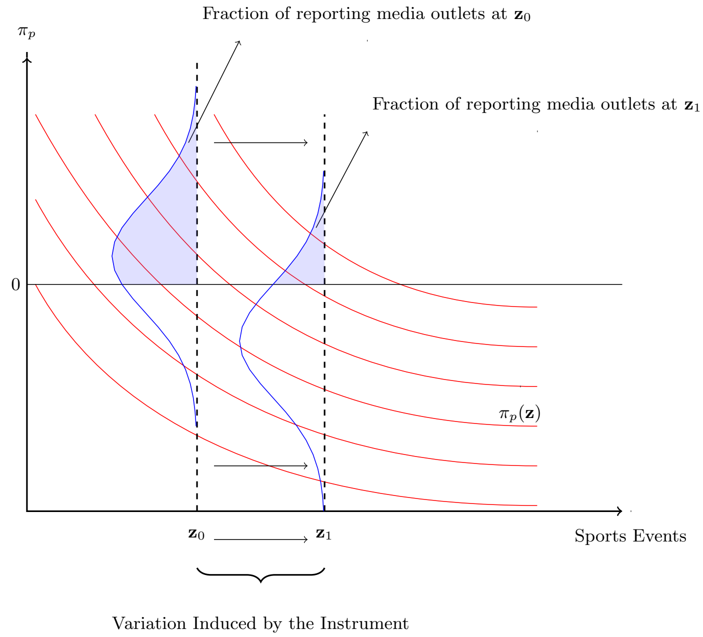


Figure 3: Instrument variation and media coverage in the extensive margin.

the campaign, effectively lowering the number of stage games τ being played. We exploit this source of variation to instrument for the endogenous variables in (9). As this discussion points out, our model once again makes an unambiguous prediction about the expected sign of the first stages for (9). In this case, the model predicts a *negative* relationship between the intensity of sports events and the two endogenous variables in the structural equation. The model also predicts a *positive* estimate for the IV second-stage coefficient on the number of reports for the Democratic candidate $\left(\frac{X_D^c+X_D^s}{\tau}\right)$, and a *negative* estimate for the coefficient on the number of reports for the Republican candidate $\left(\frac{X_R^c+X_R^s}{\tau}\right)$. 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 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 on the extensive margin.

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.

5 Estimation Results

In this section we present our main empirical findings for the persuasion and dissuasion effects $\mathbf{\Delta}$, and discuss several robustness exercises. Overall, we find that the persuasion effects on core supporters in response to core-targeted speech are larger for Democratic candidates, and that the persuasion effects on swing voters in response to swing-targeted speech are quantitatively similar for candidates from both parties. We also find that the persuasion effects on swing voters are lower in states with a more uneven partisan distribution of voters. We do not find, however, evidence suggesting that voter responsiveness to media coverage significantly changes as the campaigns develop. Our results also indicate that Democratic candidates suffer larger dissuasion effects than Republican candidates. This is, in response to relatively extreme candidate speech covered by the press, swing voters turn away more quickly from Democratic candidates than from Republican ones.

5.1 The Persuasion and Dissuasion Margins

We compute the average counts of reported core-targeted statements for each candidate, $\frac{X^c_{p,r,t}}{\tau_{r,t}}$, and the average counts of total reported statements for each candidate, $\frac{X^c_{p,r,t}+X^s_{p,r,t}}{\tau_{r,t}}$, within each poll-to-poll interval. Following Proposition 2, we recover the persuasion effects of core-targeted statements estimating (8) by IV, including race fixed effects to capture constant within-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. We also include month-of-the-year fixed effects. These are important in this setting because the sports events we use as instruments are highly seasonal. As a robustness exercise, we also estimate (8) with a full set of state, year, and state-x-year fixed effects instead of race fixed effects.

Estimation of (8) requires, for both right-hand side regressors, instruments that vary across poll-to-poll intervals within a race. As mentioned above, we rely on the occurrence of major sports events. 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 $w^{NCAA}_{rr} = 1$.[16]

Table 2 presents our main estimates of equation (8) together with the coefficients on our four instruments in each of the two first stages. Recall that our model predicts that the occurrence of sports events, by lowering the profitability of campaign reporting, should lead to an *increase* in core-targeted reported statements relative to total reported statements. Reassuringly, there is a systematically positive first-stage relationship between our instruments and each endogenous right-hand side variable in the main equation.[17] The first stage diagnostic statistics reveal that sports events are jointly good predictors of the fraction of core-targeted to total news articles on a candidate.

Table 2 reports estimates based on the 2-week poll-to-poll interval dataset in the first four columns, and on the 3-week poll-to-poll interval dataset in the last four columns. In both cases we report results using the ± 0.25 article score cutoff classification described in section 3.3. We also present estimates from OLS models which illustrate the importance of appropriately controlling for the endogeneity of equilibrium news coverage. Columns (1), (2), (5) and (6) present results that include race fixed effects,

[16] 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 $\frac{X^c_{R,r,t}}{X^c_{R,r,t}+X^s_{R,r,t}}$ is negative. Nevertheless, the unconditional correlation (without controlling for the remaining sports) is positive.

Persuasion Effects on Core Supporters (0.25 score cutoff)

Panel A: Structural equation		Dependent variable: $(\Delta V_D + \Delta V_R)/\tau$							
		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)
$X_D^c/(X_D^c + X_D^s)$	Δ_{cD}^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)
$X_R^c/(X_R^c + X_R^s)$	Δ_{cR}^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: $R_D^c/(R_D^c + R_D^s)$							
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: $R_R^c/(R_R^c + R_R^s)$							
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 Core Supporters (0.25 score cutoff). The table presents OLS and 2SLS estimates of the persuasion effects from equation (8) 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.

while columns (3), (4), (7) and (8) present results that include the state, year, and state-x-year fixed effects instead. In practice, results are unchanged when using either set of fixed effects. The standard errors we present throughout allow for heteroskedasticity and serial autocorrelation of up to order two, which we believe is important given the nature of our data. Because we measure the end-of-period electoral support for the last poll-to-poll interval of each race using the election outcome instead of a poll, we additionally include a dummy variable for the last poll-to-poll interval in each race. All of our estimated regressions are also weighted by the square root of the length in days of the poll-to-poll interval because longer intervals contain more information than shorter ones and there is significant variation in poll-to-poll interval sizes in our data.

All of our IV estimates for the Democratic persuasion effect on core voters, Δ^T_{cD}, are positive and significant. Although the IV estimates for the Republican persuasion effect, Δ^T_{cR}, are systematically positive across all of our specifications and robustness exercises, they are considerably smaller than those for the Democratic candidates (and their standard errors are larger). This is not too surprising given the large amount of measurement error in our dependent variable, which relies on noisy polls. Our estimates are also very similar when using the 2-week and the 3-week poll-to-poll intervals. This first result points out that Republican core supporters are much less persuaded by campaigning targeted towards them than Democratic core supporters. This may be because solidly Republican constituencies exhibit high baseline turnout rates. It is well known, for example, that senior white men in rural areas, who tend to favor the Republican Party, turn out at higher rates than other demographic groups. As a result, Republican candidates' incentives to target those sectors of the electorate may be weaker. Democratic campaigns, in contrast, often appear focused on mobilizing turnout among younger and minority demographic groups, possibly because these groups have lower average turnout rates, making the potential gains on this margin large. Our results suggest these voters are highly persuadable by core-targeted campaigning.

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 candidates' mixing strategies q_p, as measured by the ratio of core-targeted news reports to all news reports. 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 core 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.

With our estimates for $(\Delta^T_{cD}, \Delta^T_{cR})$ at hand and Proposition 3, we now describe our estimates of the persuasion effects on swing-voters from swing voter-targeted candidate speech. We estimate (9) by IV, once again including race fixed effects and month-of-the-year fixed effects. Through the lens of

[18] $(0.1 \times 0.56) \times (0.16/1000) \times 124$ 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.

our model, the regressors in (9) are the sample analogues of $\tau\eta_p(1-\gamma_{\sim p})$. Total observed news reports on a candidate should not vary as a function of changes in the media's payoff –from equations (3)-(4), these conditional probabilities only depend on candidates' payoffs–. Our model suggests that a media outlet's reporting strategy is pinned down by indifference, and thus, is independent of its own payoff. Nevertheless, for the distribution of media outlets as a whole, a shift in the profitability of reporting on political campaigns can lead to an extensive margin response by outlets entering into or dropping out from coverage (see Figure 3). Following this idea, we use sports events as exogenous sources of variation for the two endogenous regressors in equation (9). In this case, the model predicts sports events should be *negatively* correlated with $[X^c_{p,r,t} + X^s_{p,r,t}]$. This is exactly the pattern we find in the first stage estimates, which we present in Table 3.

Table 3 presents our estimates of equation (9). The table has the same structure as that of Table 2. Its first four columns are based on the 2-week poll-to-poll interval dataset, and the last four are based on the 3-week poll-to-poll interval dataset. All models in the table are also based on the ± 0.25 article score cutoff classification. As discussed above, 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. Quite reassuringly, across all models estimated by 2SLS we obtain a positive coefficient on $[X^c_{D,r,t}+X^s_{D,r,t}]$ corresponding to Δ^S_{sD}, and a negative coefficient on $[X^c_{R,r,t} + X^s_{R,r,t}]$ corresponding to $-\Delta^S_{sR}$, exactly as implied by equation (9) and our structural model. We consider this pattern of resulting signs to suggest the mechanism we propose. These IV estimates show that the persuasion effects over swing voters are remarkably similar in magnitude for Democratic and Republican candidates. Column (4), for example, shows our estimates for both parameters to be 0.0018. Both Δ^S_{sD} and Δ^S_{sR} are significant at the 5% level. Across specifications, both the magnitudes and significance of the parameter estimates are very similar.

We can also undertake a quantitative exercise based on our benchmark estimates of $(\Delta^S_{sD}, \Delta^S_{sR})$. In the bottom panel of Table 4 we report the average estimates of the unconditional probabilities of observing a news piece, $\eta_p(1-\gamma_{\sim p})$, as measured by the ratio of observed news pieces relative to the number of relevant stage games. Based on the 0.25 article score cutoff criterion, $\mathbb{E}[\eta_D(1-\gamma_R)] \approx 0.018$, and $\mathbb{E}[\eta_R(1-\gamma_D)] \approx 0.014$. A ten percent increase in these probabilities sustained during a month would translate, on average, into a 1.2 percentage point gain to the Democratic candidate, and a 1 percentage point gain to the Republican candidate, stemming from increased swing voter support. These would be losses for the opposing candidate[19].

The next step in our empirical strategy is to back out estimates of the dissuasion effects of core-targeted campaign speech using the equilibrium mixing strategies of the media in equations (3)-(4), together with our estimates $[X^c_{p,r,t} + X^s_{p,r,t}]$ of the conditional reporting probabilities $\eta_p(1-\gamma_{\sim p})$ as

[19] $(0.1 \times 0.018) \times (0.18/100) \times 124$ 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.

Persuasion Effects on Swing Voters (0.25 score cutoff)

Panel A: Structural equation		Dependent variable: $\tau(\hat{D}-\hat{R})/2$							
		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)
$X_D^c + X_D^s$	Δ_{sD}^S	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)
$X_R^c + X_R^s$	$-\Delta_{sR}^S$	−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: $R_D^c/(R_D^c + R_D^s)$							
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: $R_R^c/(R_R^c + R_R^s)$							
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 (9) 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_{cD}	0.016 (0.006)	0.011 (0.005)
Δ^T_{cR}	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_{cD}	0.69 (0.15)	0.50 (0.10)
Δ^S_{cR}	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 (8) and (9). Dissuasion effects in Panel A are computed according to equation (11) 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.

described in Proposition 3. We obtain average effects by integrating over our sample as follows:

$$\hat{\Delta}^S_{cp} = \frac{\hat{\Delta}^T_{cp}}{\frac{1}{N}\sum_r \sum_{t=1}^{T_r} \frac{(X^c_{p,r,t}+X^s_{p,r,t})}{\tau}} - \hat{\Delta}^S_{sp}. \tag{11}$$

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, both using the ± 0.25 article cutoff classification in column (1), and the ± 0.5 cutoff in column (2). The magnitude of the estimates is very similar for both cutoffs, showing that the specific criterion chosen to classify articles as c or s is not critical for our results. The full set of parameters is also similar when using the 3-week poll-to-poll intervals. These results are omitted to save space. As the table illustrates, the dissuasive effects of core-targeted statements over swing voters is much larger for Democratic candidates than for Republican candidates. Using the ± 0.25 cutoff estimates, $\Delta^S_{cD} = 0.69$, $\Delta^S_{cR} = 0.18$. These results suggest that swing voters are on average very sensitive to media content that signals relatively core-mobilizing campaign speech by Democrats. This difference in persuasion and dissuasion effects across parties has substantial implications for the dynamics of the Senate races: although the persuasion gains of core-targeted statements are larger for Democrats, the dissuasion cost on the swing voter margin is even larger for them. Our results suggest that swing voters are especially important in fulfilling the role of moderating Democratic candidates' campaign trail speech, while the media is relatively more important in moderating the Republican candidates' campaign trail speech. The equilibrium implication of this pattern of parameters is that candidates from both parties are covered by the media at similar rates. Our 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).

5.2 Payoff Heterogeneity

The IV estimates of the persuasion and dissuasion parameters $(\Delta^T_{cD}, \Delta^T_{cR}, \Delta^S_{sD}, \Delta^S_{sR}, \Delta^S_{cD}, \Delta^S_{cR})$ 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 $K_{r,t}$: $\Delta^T_{cp} = \alpha^T_{cp} + \beta^T_{cp} K_{r,t}$ and $\Delta^S_{sp} = \alpha^S_{sp} + \beta^S_{sp} K_{r,t}$ for $p \in \{D, R\}$.[20] We estimate (8) and (9) by IV including the relevant interaction terms, instrumenting them with the respective interactions between our sports events instruments and the source of heterogeneity in each case.[21]

5.2.1 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 5 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

[20] 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 $\boldsymbol{\Delta}$'s are constant within a time interval. This is an unavoidable bias-precision trade-off.

[21] 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 (11) restricted to the set $\Gamma_K = \{(r,t) : K_{r,t} \in K\}$ of observations in each decile:

$$\hat{\Delta}^S_{cp}(K) = \frac{\hat{\Delta}^T_{cp}(K_{p,r})}{\frac{1}{|\Gamma_K|}\sum_r \sum_{t=1}^{T_r} \frac{(X^c_{p,r,t} + X^s_{p,r,t})}{\tau}} - \hat{\Delta}^S_{sp}(K_{p,r}), \qquad (r,t) \in \Gamma_K.$$

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

			Interaction term (K):			
Panel A Parameter	Regressor	Coefficient	Dem. registration (1)	Log days to election (2)	Race tightness (3)	Incumbent running (4)
			Dependent variable: $(\Delta V_D + \Delta V_R)/\tau$			
Δ^T_{cD}	$X^c_D/(X^c_D + X^s_D)$	α^T_{cD}	0.075 (0.037)	0.001 (0.025)	0.019 (0.010)	0.018 (0.009)
	$X^c_D/(X^c_D + X^s_D) \times K$	β^T_{cD}	−0.13 (0.074)	0.001 (0.005)	−0.031 (0.039)	−0.003 (0.011)
Δ^T_{cR}	$X^c_R/(X^c_R + X^s_R)$	α^T_{cR}	−0.060 (0.048)	0.047 (0.041)	0.004 (0.009)	0.005 (0.011)
	$X^c_R/(X^c_R + X^s_R) \times K$	β^T_{cR}	0.14 (0.10)	−0.011 (0.009)	0.008 (0.032)	0.00 (0.014)
Panel B			Dependent variable: $\tau(\hat{D} - \hat{R})/2$			
Δ^S_{sD}	$X^c_D + X^s_D$	α^S_{sD}	0.037 (0.009)	0.0028 (0.008)	0.0014 (0.001)	0.0007 (0.001)
	$(X^c_D + X^s_D) \times K$	β^S_{sD}	−0.078 (0.018)	−0.0001 (0.001)	−0.002 (0.002)	0.0008 (0.001)
$-\Delta^S_{sR}$	$X^c_R + X^s_R$	α^S_{sR}	0.0020 (0.014)	−0.0163 (0.014)	0.0009 (0.002)	0.000 (0.002)
	$(X^c_R + X^s_R) \times K$	β^S_{sR}	−0.007 (0.028)	0.003 (0.003)	−0.014 (0.005)	−0.0015 (0.002)
	$\mathbb{E}[K]$		0.47	4.56	0.17	0.76

Table 5: 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.

of sports events with the corresponding heterogeneity variable as instruments. Panel A presents the estimates for the core-voter persuasion effects from equation (8)), while panel B presents the estimates for the swing voter persuasion effects from equation (9). Although the pattern of signs implies that Δ^T_{cD} decreases while Δ^T_{cR} 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.

5.2.2 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 5 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.

5.2.3 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.[22]

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

[22] 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.

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 5 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^S_{sR}, 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. 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.

5.2.4 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 5 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.

6 Concluding Remarks

We develop a framework to study how the interaction between the media's incentives to cover electoral campaigns and candidates' incentives to target different groups of voters shape both campaign trail speech, and the evolution of the races. Candidates strategically target their messages, and must rely on the news media to deliver them to heterogeneous constituencies. Political campaigns are, without doubt, among the most sophisticated marketing efforts, and their marketing often takes place through the media. While the literature in marketing has studied various aspects of electoral campaigns such as advertising, the role and impact of the news media in shaping constituency targeting and in brand differentiation have been largely overlooked. We propose a game-theoretic model of the interaction between the media and candidates, where the media prefers to report on core-supporter targeted campaign speech from candidates, while candidates prefer to be reported about swing voter-targeted messages. Because candidates have incentives to target both types of constituencies, this strategic environment is similar to a standard matching pennies game. While others have studied bias in framing and language (e.g., Baron, 2006; Gentzkow and Shapiro, 2010; Mullainathan and Shleifer, 2005), we instead focus on bias in the intensity of coverage.

The simple structure of the game allows us to propose an empirical strategy to estimate persuasion and dissuasion effects of media reporting on the evolution of political campaigns. We do so using information on U.S. Senate races over a 32 year period. These are salient races and thus, systematically covered by the media and by pollsters. Our results suggest the mechanism we propose here is important for understanding the nature of bipartisan electoral competition in settings with ample media presence.

Moreover, our model and results provide a novel way of thinking about how and why the media matters in politics, by highlighting not only that the media shapes candidate behavior, but also that candidates shape the way the media reports about politics.

Our empirical findings suggest a large asymmetry across Democratic and Republican candidates in their incentives to target core supporters. While turnout appears more responsive to core-targeted speech by Democrats, swing-voters also appear more willing to change allegiance towards Republicans when the media reports widely on core-targeted messaging by Democrats. In any election where the objective is mobilizing core constituencies, targeting is more effective for Democratic candidates. When the objective is to gain swing voter support, targeting core constituencies is costlier for candidates from this party, however, because it hurts them at the margin more than it hurts Republican candidates. Our findings suggest, perhaps surprisingly, that overall media coverage is not systematically biased towards candidates from either party. Exploring the nature of the differential responses of the electorate to targeted campaign messages may be a fruitful area for future research. Our findings may be informative more broadly for scholars interested in political campaigns and the influence of the media in politics.

References

Abramowitz, A. I. (1988): "Explaining Senate election outcomes," *The American Political Science Review*, 385–403.

Ansolabehere, S., R. Behr, and S. Iyengar (1992): *The Media Game: American Politics in the Television Age*, Longman.

Bajari, P., H. Hong, and S. Ryan (2010): "Identification and Estimation of a Discrete Game of Complete Information," *Econometrica*, 78, 1529–1568.

Baron, D. (2006): "Persistent Media Bias," *Journal of Public Economics*, 90, 1–36.

Berry, S. (1992): "Estimation of a Model of Entry in the Airline Industry," *Econometrica*, 60, 889–917.

Bresnahan, T. and P. Reiss (1990): "Entry in Monopoly Markets," *Review of Economic Studies*, 57, 531–553.

——— (1991): "Empirical Models of Discrete Games," *Journal of Econometrics*, 48, 57–81.

Budge, I. and R. Hofferbert (1990): "Mandates and Policy Outputs: U.S. Party Platforms and Federal Expenditures," *The American Political Science Review*, 84, 111–131.

Chevalier, J. A. and D. Mayzlin (2006): "The effect of word of mouth on sales: Online book reviews," *Journal of marketing research*, 43, 345–354.

Chiappori, P., S. Levitt, and T. Groseclose (2002): "Testing Mixed-Strategy Equilibria When Players are Heterogeneous: The Case of Penalty Kicks in Soccer," *American Economic Review*, 92, 1138–1151.

Dorn, D., G. Hanson, K. Majlesi, et al. (2020): "Importing political polarization? The electoral consequences of rising trade exposure," *American Economic Review*, 110, 3139–83.

Egorov, G. (2015): "Single-Issue Campaigns and Multidimensional Politics," Northwestern.

Eisensee, T. and D. Strömberg (2007): "News Droughts, News Floods, and U.S. Disaster Relief," *Quarterly Journal of Economics*, 122, 693–728.

Enikolopov, R., M. Petrova, and E. Zhuravskaya (2011): "Media and political persuasion: Evidence from Russia," *American Economic Review*, 101, 3253–85.

Fonseca, A., J. M. S. Jr., and B. K. Song (2014): "Newspaper Market Structure and Behavior: Partisan Coverage of Political Scandals in the U.S. from 1870 to 1910," .

Gentzkow, M. and J. Shapiro (2006): “Media Bias and Reputation,” *Journal of Political Economy*, 114, 280–316.

——— (2010): “What Drives Media Slant? Evidence from U.S. Daily Newspapers,” *Econometrica*, 78, 35–71.

George, L. and J. Waldfogel (2006): “The New York Times and the Market for Local Newspapers,” *The American Economic Review*, 96, 435–447.

Hartmann, W. R. and D. Klapper (2017): “Super bowl ads,” *Marketing Science, forthcoming.*

Healy, A., N. Malhotra, and C. H. Mo (2010): “Irrelevant Effects Affect Voter's Evaluations of Government Performance,” *Proceedings of the National Academy of Sciences*, 107, 12804–12809.

Knowles, J., N. Persico, and P. Todd (2001): “Racial Bias in Motor Vehicle Searches: Theory and Evidence,” *Journal of Political Economy*, 109, 203–229.

Kurkones, M. (1984): *Promises and Performance: Presidential Campaigns as Policy Predictors*, University Press of America.

Lovett, M. J. and R. Staelin (2016): “The role of paid, earned, and owned media in building entertainment brands: Reminding, informing, and enhancing enjoyment,” *Marketing Science*, 35, 142–157.

Manchanda, P., Y. Xie, and N. Youn (2008): “The role of targeted communication and contagion in product adoption,” *Marketing Science*, 27, 961–976.

Maskin, E. and J. Tirole (2004): “The Politician and the Judge: Accountability in Government,” *American Economic Review*, 94, 1034–1054.

Mayzlin, D. (2006): “Promotional chat on the Internet,” *Marketing science*, 25, 155–163.

Mullainathan, S. and A. Shleifer (2005): “The Market for News,” *American Economic Review*, 95, 1031–1053.

Newey, W. and K. West (1987): “A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix,” *Econometrica*, 55, 703–708.

Oberholzer-Gee, F. and J. Waldfogel (2009): “Media Markets and Localism: Does Local News en Espanol Boost Hispanic Voter Turnout?” *The American Economic Review*, 99, 2120–2128.

Palacios-Huerta, I. (2003): “Professionals Play Minimax,” *Review of Economic Studies*, 70, 395–415.

Prat, A. (2005): “The Wrong Kind of Transparency,” *American Economic Review*, 95, 862–877.

Puglisi, R. and J. Snyder (2008): “Media Coverage of Political Scandals,” Mimeo.

Seiler, S., S. Yao, and W. Wang (2015): “The impact of earned media on demand: Evidence from a natural experiment,” .

Shapiro, B. T., G. J. Hitsch, and A. E. Tuchman (2021): “TV Advertising Effectiveness and Profitability: Generalizable Results from 288 Brands,” *Econometrica*.

Snyder, J. and D. Strömberg (2010): “Press Coverage and Political Accountability,” *Journal of Political Economy*, 118.

Spenkuch, J. L. and D. Toniatti (2018): “Political advertising and election results,” *The Quarterly Journal of Economics*, 133, 1981–2036.

Stephen, A. T. and J. Galak (2012): “The effects of traditional and social earned media on sales: A study of a microlending marketplace,” *Journal of Marketing Research*, 49, 624–639.

Strömberg, D. (2004a): “Mass Media Competition, Political Competition, and Public Policy,” *Review of Economic Studies*, 71, 265–284.

——— (2004b): “Radio's Impact on Public Spending,” *Quarterly Journal of Economics*, 119, 189–221.

Walker, M. and J. Wooders (2001): “Minimax Play at Wimbledon,” *American Economic Review*, 91, 1521–1538.

A Appendix A

A.1 Figures and Tables

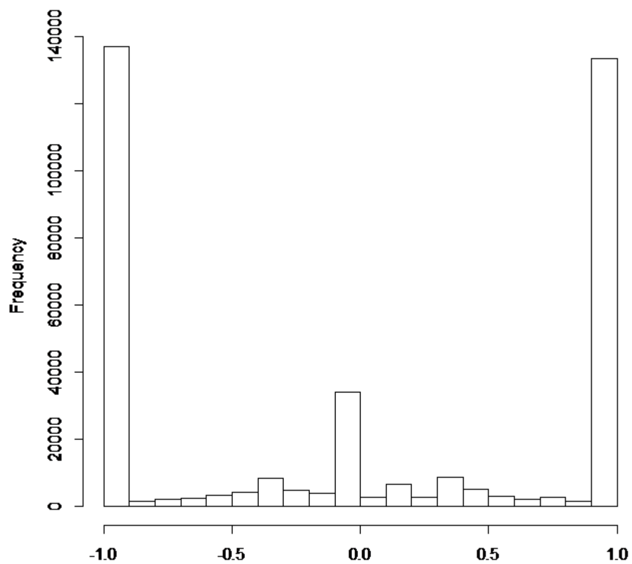


Figure A.1: Distribution of article name assignments τ_i.

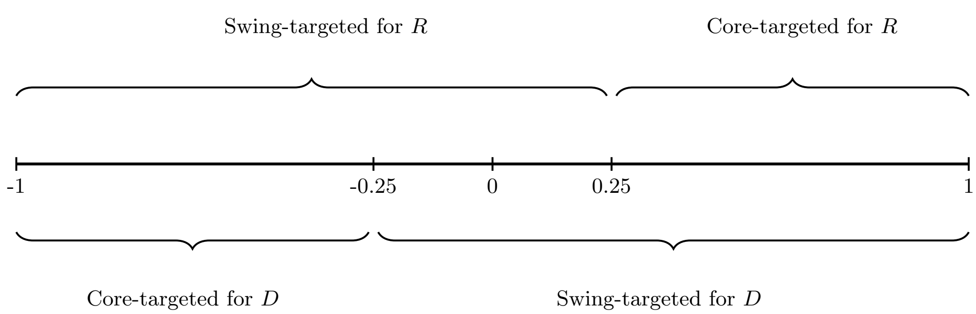
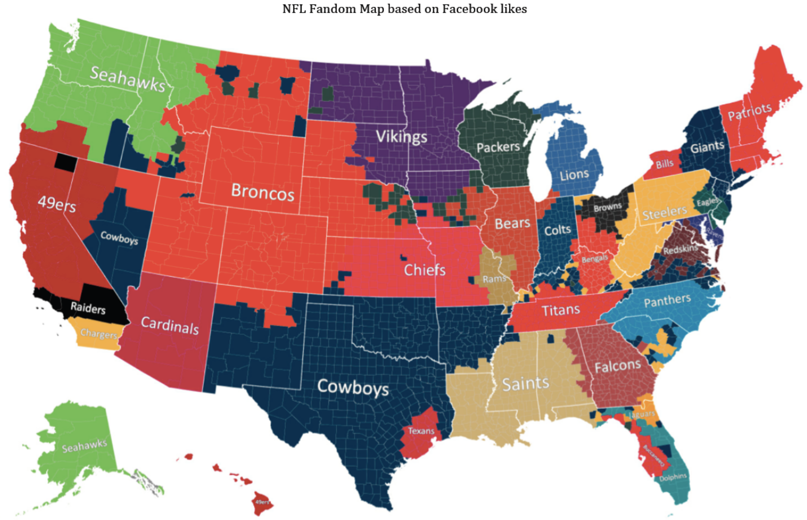


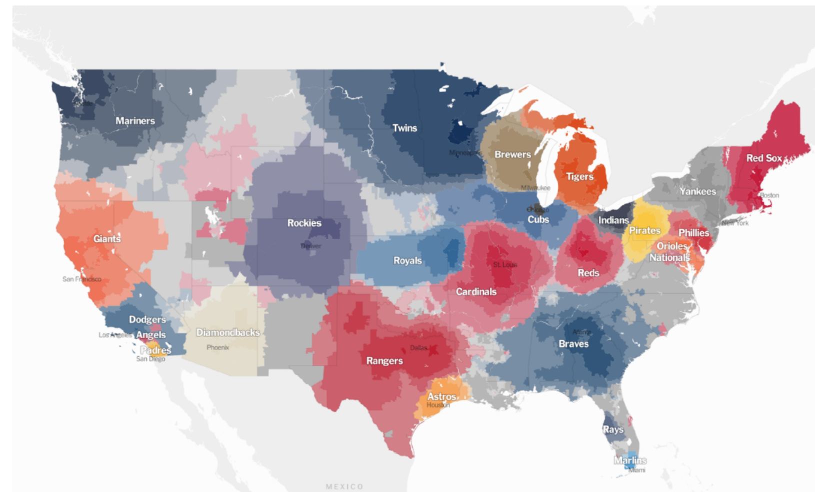
Figure A.2: Illustration of the Article Type Classification (0.25 score cutoff case).

NFL Fandom Map based on Facebook likes



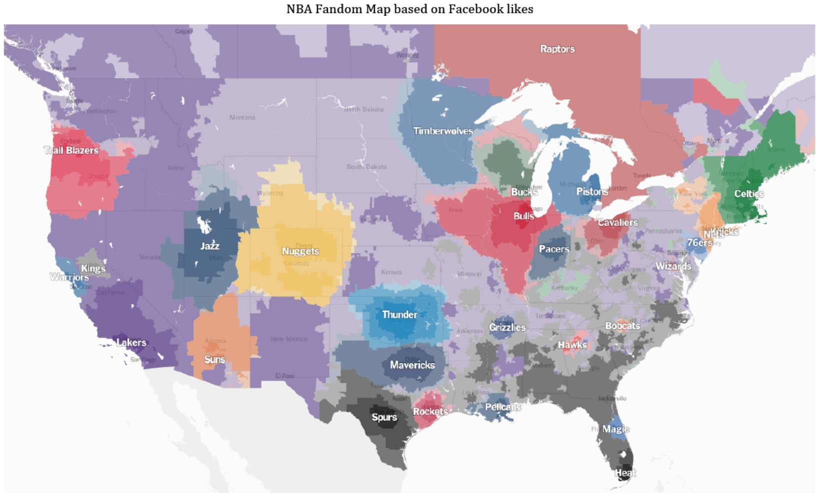
Source: The Atlantic online at: http://www.theatlantic.com/technology/archive/2014/09/the-geography-of-nfl-fandom/379729/

MLB Fandom Map based on Facebook likes



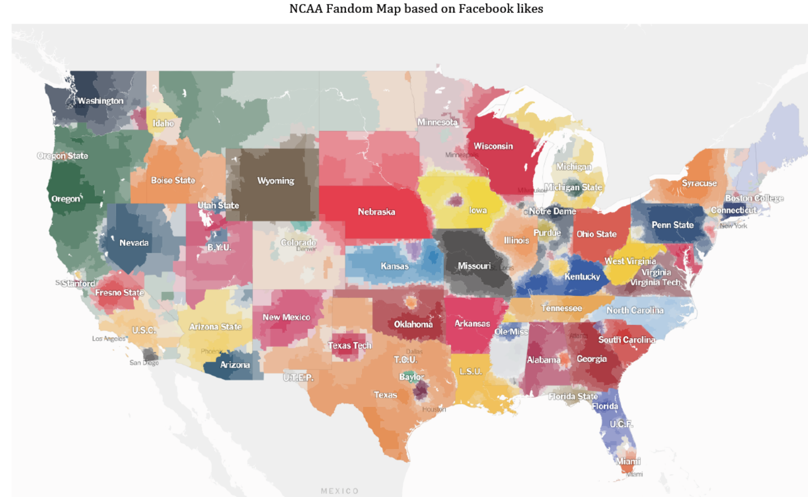
Source: New York Times online at: http://www.nytimes.com/interactive/2014/04/24/upshot/facebook-baseball-map.html

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:

$$\triangle_1 \equiv \Delta^T_{cD} - \eta_D \Delta^S_{cD} + \eta_R \Delta^S_{cR} \qquad \triangle_{13} \equiv \Delta^T_{cD} - \eta_D \Delta^S_{cD} - \eta_R \Delta^S_{sR}$$

$$\triangle_2 \equiv \Delta^T_{cR} - \eta_R \Delta^S_{cR} + \eta_D \Delta^S_{cD} \qquad \triangle_{14} \equiv \eta_R \Delta^S_{sR} + \eta_D \Delta^S_{cD}$$

$$\triangle_3 \equiv \Delta^T_{cD} - \eta_D \Delta^S_{cD} \qquad \triangle_{15} \equiv \Delta^T_{cD} - \eta_D \Delta^S_{cD}$$

$$\triangle_4 \equiv \Delta^T_{cR} + \eta_D \Delta^S_{cD} \qquad \triangle_{16} \equiv \eta_D \Delta^S_{cD}$$

$$\triangle_5 \equiv \Delta^T_{cD} + \eta_R \Delta^S_{cR} \qquad \triangle_{17} \equiv \Delta^T_{cD} - \eta_R \Delta^S_{sR}$$

$$\triangle_6 \equiv \Delta^T_{cR} - \eta_R \Delta^S_{cR} \qquad \triangle_{18} \equiv \eta_R \Delta^S_{sR}$$

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

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

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

$$\triangle_{10} \equiv \Delta^T_{cR} - \eta_D \Delta^S_{sD} \qquad \triangle_{22} \equiv -\eta_D \Delta^S_{sD}$$

$$\triangle_{11} \equiv \eta_R \Delta^S_{cR} \qquad \triangle_{23} \equiv -\eta_R \Delta^S_{sR}$$

$$\triangle_{12} \equiv \Delta^T_{cR} - \eta_R \Delta^S_{cR} \qquad \triangle_{24} \equiv \eta_R \Delta^S_{sR}$$

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, followinf 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 $a^D = c$ and $a^D = s$:

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

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

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

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

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

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

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

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

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

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

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

Thus, the mixed-strategy Nash equilibrium is unique.

A.3 Proof of Proposition 2

Consider taking the difference between the poll outcomes for a candidate between stage games $t+\tau$ and t. From equation (2) across τ stage games, the change in electoral support to candidate $p \in \{D, R\}$ is given by

$$v^p(t+\tau) - v^p(t) = \Delta_{cp}^T N_p^c(t, t+\tau) + \left(\Delta_{cp}^T - \Delta_{cp}^S\right) X_p^c(t, t+\tau)$$

$$+ \Delta_{c\sim p}^S X_{\sim p}^c(t, t+\tau) + \Delta_{sp}^S X_p^s(t, t+\tau) - \Delta_{s\sim p}^S X_{\sim p}^s(t, t+\tau) + \epsilon^p(t, t+\tau) \tag{A.5}$$

where $\epsilon^p(t,t+\tau) = \sum_{\iota=t+1}^{t+\tau} \epsilon^p(\iota)$. Now add together the equations for each candidate, and divide by the number of stage games in the interval. The zero-sum nature of swing-voter support implies all swing voter effects cancel out, and we are left with an expression that only depends on the counts of events that generate electoral responses on the turnout margin:

$$\frac{v^D(t+\tau) - v^D(t) + v^R(t+\tau) - v^R(t)}{\tau} =$$

$$\Delta^T_{cD} \frac{N^c_D(t,t+\tau) + X^c_D(t,t+\tau)}{\tau} + \Delta^T_{cR} \frac{N^c_R(t,t+\tau) + X^c_R(t,t+\tau)}{\tau} + \tilde{\omega}(t,t+\tau) \tag{A.6}$$

where $\tilde{\omega}(t,t+\tau) \equiv \frac{\epsilon^D(t,t+\tau)}{\tau} + \frac{\epsilon^R(t,t+\tau)}{\tau}$. This specification cannot be estimated because the (N^c_D, N^c_R) are unobserved. Even if an instrument $\mathbf{z}$ that satisfies the exclusion restriction of being uncorrelated with other determinants of the evolution of electoral support $\tilde{\omega}$ is available, it will necessarily be correlated with N^c_p as long as it is correlated with X^c_p. This implies that it is not possible to leave N^c_D and N^c_R in the error term of equation (A.6) if we want to implement an instrumental variables strategy. Instead, notice that equilibrium play implies $q^*_p = \mathbb{E}_\tau \left[\frac{N^c_p(t,t+\tau)+X^c_p(t,t+\tau)}{\tau}\right]$, and thus, we can express each of the (endogenous and unobserved) regressors in equation (A.6) as the equilibrium mixing strategy of the candidate plus sampling noise $\xi_p(t,t+\tau)$ that converges in probability to zero at rate $\sqrt{\tau}$ and is uncorrelated with $\mathbf{z}$:

$$\frac{N^c_p(t,t+\tau) + X^c_p(t,t+\tau)}{\tau} = q^*_p(t,t+\tau) + \frac{1}{\tau}\xi_p(t,t+\tau),$$

where $\omega(t,t+\tau) \equiv \tilde{\omega}(t,t+\tau) + \Delta^T_{cD}\frac{1}{\tau}\xi_D(t,t+\tau) + \Delta^T_{cR}\frac{1}{\tau}\xi_R(t,t+\tau)$ as a composite error term that includes all the shocks in the interval and the sampling error.

Finally, notice that

$$\frac{(1-q^*_p)[1-\gamma^*_{\sim p}]\eta_p}{q^*_p[1-\gamma^*_{\sim p}]\eta_p} = \frac{X^s_p(t,t+\tau)/\tau}{X^c_p(t,t+\tau)/\tau} \Rightarrow \hat{q}^*_p(t,t+\tau) = \frac{X^c_p(t,t+\tau)}{X^s_p(t,t+\tau) + X^c_p(t,t+\tau)} \tag{A.7}$$

to obtain equation (8).

A.4 Proof of Proposition 3

The equilibrium mixing strategies for the media in equations (3) and (4) allow us to solve for the dissuasion effects from core-targeted statements for each candidate Δ^S_{cp} as functions only of observables and the estimated $\hat{\Delta}^T_{cp}$'s from the estimation of equation (8):

$$\Delta^S_{cp} = \frac{\hat{\Delta}^T_{cp}}{(X^c_p(t,t+\tau) + X^s_p(t,t+\tau))/\tau} - \Delta^S_{sp} \tag{A.8}$$

To save space, denote $\phi_p = (X^c_p(t,t+\tau) + X^s_p(t,t+\tau))/\tau$. Using equation (A.8) we can now eliminate the Δ^S_{cp} from equation (A.5) to obtain:

$$v^p(t+\tau) - v^p(t) - \hat{\Delta}^T_{cp}[X^c_p(t,t+\tau) + N^c_p(t,t+\tau)] =$$

$$\left(\Delta_{sp}^{S}-\frac{\hat{\Delta}_{cp}^{T}}{\hat{\phi}_p}\right)X_p^c(t,t+\tau)+\left(\frac{\hat{\Delta}_{c\sim p}^{T}}{\hat{\phi}_{\sim p}}-\Delta_{s\sim p}^{S}\right)X_{\sim p}^{c}+\Delta_{sp}^{S}X_p^s(t,t+\tau)-\Delta_{s\sim p}^{S}X_p^s(t,t+\tau)+\epsilon^p(t,t+\tau)$$

Grouping terms,

$$[v^p(t+\tau)-v^p(t)]-\hat{\Delta}_{cp}^{T}[X_p^c(t,t+\tau)+N_p^c(t,t+\tau)]+\hat{\Delta}_{cp}^{T}\frac{X_p^c(t,t+\tau)}{\hat{\phi}_p}-\hat{\Delta}_{c\sim p}^{T}\frac{X_{\sim p}^{c}(t,t+\tau)}{\hat{\phi}_{\sim p}}=$$

$$\Delta_{sp}^{S}[X_p^c(t,t+\tau)+X_p^s(t,t+\tau)]-\Delta_{s\sim p}^{S}[X_p^s(t,t+\tau)+X_{\sim p}^{c}(t,t+\tau)]+\epsilon^p(t,t+\tau)$$

Multiplying and dividing by τ the second and third terms in the left-hand side of this expression, we have that

$$\frac{X_p^c(t,t+\tau)+N_p^c(t,t+\tau)}{\tau}\tau=\frac{\hat{\varphi}_p^c(t,t+\tau)}{\hat{\phi}_p(t,t+\tau)}\tau+\xi_p(t,t+\tau)$$

and

$$\frac{X_p^c(t,t+\tau)}{\hat{\phi}_p}\frac{\tau}{\tau}=\frac{\hat{\varphi}_p^c(t,t+\tau)}{\hat{\phi}_p(t,t+\tau)}\tau$$

so that these terms in the left-hand side cancel. Similarly, multiplying and dividing by τ the fourth term in the left-had side can be re-expressed as

$$\frac{X_{\sim p}^{c}(t,t+\tau)}{\hat{\phi}_{\sim p}}\frac{\tau}{\tau}=\frac{\hat{\varphi}_{\sim p}^{c}(t,t+\tau)}{\hat{\phi}_{\sim p}(t,t+\tau)}\tau$$

Now multiply and divide by τ the first and second terms of the right-hand side, to obtain:

$$[v^p(t+\tau)-v^p(t)]-\hat{\Delta}_{c\sim p}^{T}\frac{\hat{\varphi}_{\sim p}^{c}(t,t+\tau)}{\hat{\phi}_{\sim p}(t,t+\tau)}\tau=$$

$$\Delta_{sp}^{S}\hat{\phi}_p(t,t+\tau)\tau-\Delta_{s\sim p}^{S}\hat{\phi}_{\sim p}(t,t+\tau)\tau+\overline{\varpi}^p(t,t+\tau) \tag{A.9}$$

where $\overline{\varpi}^p(t,t+\tau)\equiv\epsilon^p(t,t+\tau)+\hat{\Delta}_{cp}^{T}\xi_p(t,t+\tau)$. Crucially, notice that the error term in this equation *does not* depend on τ. The left-hand side term in equation (A.9) is defined in Proposition 3 as $\hat{p}(t,t+\tau)$. Because equation (A.9) depends on the same slope parameters and observables for both parties, it is convenient to subtract the equation for candidate D from the equation for candidate R, which directly gives the result of the proposition by defining $\zeta(t,t+\tau)\equiv(1/2)\left[\varpi^D(t,t+\tau)-\varpi^R(t,t+\tau)\right]$.

With estimates of $(\Delta_{cD}^{T},\Delta_{cR}^{T},\Delta_{sD}^{S},\Delta_{sR}^{S})$ at hand, equation (A.8) uniquely pins down the remaining two elasticities $(\Delta_{cD}^{S},\Delta_{cR}^{S})$.

A.5 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 (8)-(9) 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.[23] Excluding these observations reduces the sample size from 2134 to 1871. 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 core-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 (8). Panel BI presents the parameter estimates for equation (9). 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, 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.

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

A.5.1 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 A.5 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 5.2. 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.

B Data Appendix

B.1 News Processing

We followed several steps to process the news article texts. The data collection was conducted in *Lexis Nexis* and *Factiva*.[24] 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.[25] 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.[26] 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

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

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

[26] 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.

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).

B.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 core 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 B.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 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 B.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.

B.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 B.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 (4.55)			4.86 (3.62)	
Length of poll-to-poll interval (days)		30.51 (34.32)			35.16 (35.47)	
Number of polls per interval		1.74 (1.66)			2.01 (2.12)	
Electoral support (poll results)	0.44 (0.11)		0.42 (0.11)	0.44 (0.12)		0.42 (0.11)
Number of articles per interval	56.11 (101.7)	90.22 (127.42)	41.50 (62.49)	61.98 (112.53)	98.83 (138.0)	45.43 (67.63)
Number of core-targeted articles per interval (0.25 cutoff)	35.82 (91.09)	58.79 (102.6)	22.97 (45.92)	41.75 (101.52)	68.43 (113.89)	26.67 (52.28)
Number of swing-targeted articles per interval (0.25 cutoff)	20.29 (30.21)	38.82 (57.67)	18.53 (30.52)	20.23 (30.75)	38.98 (59.30)	18.76 (31.17)
Number of core-targeted articles per interval (0.5 cutoff)	29.05 (89.46)	45.8 (97.95)	16.75 (43.50)	34.07 (98.21)	54.12 (107.93)	20.05 (50.83)
Number of swing-targeted articles per interval (0.5 cutoff)	27.07 (40.23)	51.81 (77.23)	24.75 (40.81)	27.12 (42.40)	52.58 (82.64)	25.46 (43.78)
Number of core-targeted articles per interval (0.75 cutoff)	21.18 (63.21)	33.41 (69.67)	12.23 (31.81)	25.86 (77.21)	40.87 (84.21)	15.02 (38.08)
Number of swing-targeted articles per interval (0.75 cutoff)	33.92 (49.91)	63.01 (87.93)	29.09 (46.03)	35.33 (51.11)	65.82 (90.85)	30.49 (46.88)
Number of NFL games per interval (fan weighted)		4.22 (6.34)			4.91 (6.98)	
Number of MLB games per interval (fan weighted)		14.91 (25.43)			17.17 (27.12)	
Number of NBA games per interval (fan weighted)		8.91 (27.65)			10.15 (28.62)	
Number of NCAA games per interval (playoffs)		0.04 (0.29)			0.05 (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 (488.13)	508.07 (687.04)	233.70 (358.47)
Article score	-0.52 (0.44)	-0.005 (0.70)	0.52 (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)

Panel A		Robustness exercise:			
		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: $(\Delta V_D + \Delta V_R)/\tau$			
Δ^T_{cD}	$X^c_D/(X^c_D + X^s_D)$	0.015	0.014	0.011	0.015
		(0.005)	(0.005)	(0.005)	(0.006)
Δ^T_{cR}	$X^c_R/(X^c_R + X^s_R)$	0.003	0.008	0.004	0.005
		(0.005)	(0.006)	(0.005)	(0.006)
Panel B		Dependent variable: $\tau(\hat{D} - \hat{R})/2$			
Δ^S_{sD}	$X^c_D + X^s_D$	0.21	0.13	0.12	0.12
		(0.08)	(0.056)	(0.056)	(0.06)
$-\Delta^S_{sR}$	$X^c_R + X^s_R$	−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 (8) and (9). 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: $(\Delta V_D + \Delta V_R)/\tau$									
$X_D^c/(X_D^c + X_D^s)$	Δ_{cD}^T	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)
$X_R^c/(X_R^c + X_R^s)$	Δ_{cR}^T	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: $X_D^c/(X_D^c + X_D^s)$									
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: $X_R^c/(X_R^c + X_R^s)$									
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: $\tau(\hat{D} - \hat{R})/2$									
$X_D^c + X_D^s$	Δ_{sD}^S	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)
$X_R^c + X_R^s$	$-\Delta_{sR}^S$	−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: $X_D^c + X_D^s$									
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: $X_R^c + X_R^s$									
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 thepersuasion effects from equations (8) in Panel A, and (9)) 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 structural equation in Panel BI is constructed using the benchmark parameter estimates from the structural equation (**??**). 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.

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

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

Testing 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 ($\lvert V_D - V_R \rvert$)	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 A.5: 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 ($\lvert\sigma_i\rvert$)	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 B.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 B.2: Dropped Senate Races.