Matching Pennies on the Campaign Trail: An Empirical Study of Senate Elections and Media Coverage*

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September, 2015

Abstract

We study empirically the strategic interaction between the media and candidates in a bipartisan election. We suggest that the relationship between the media and candidates in a campaign is shaped by both a dimension of alignment of preferences, and a dimension of misalignment, which leads to a strategic environment resembling a matching pennies game. As a result, making inferences about politicians' ideologies or policy stances based on media reports is not possible without taking explicit account of how each player's behavior affects the other. Based on this observation, we develop a simple structural model of bipartisan races where the media makes reports about the candidates, and candidates make decisions along the campaign trail regarding the type of constituencies to target with their statements and speeches. We show how data on media reports, electoral results, and poll results, together with the behavioral implications of the model, can be used to estimate its structural parameters. We implement this methodology on US Senatorial races for the period 1980-2012. These parameters are useful, among other things, to predict the evolution of races during the campaign trail, and to understand the forces shaping candidates' speech during campaigns. Moreover, our results suggest a novel interpretation for how the media constrains politicians' behavior in an democracy.

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

JEL Codes: C3, D72

Preliminary, comments welcome.

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1 Introduction

The importance of the media for the well-functioning of democracies is widely accepted. One of the key roles attributed to the media is to monitor leaders' behavior while in office. The media also plays a significant role in shaping the actions or statements that politicians make during electoral campaigns. In fact, during campaign periods the media is especially involved in reporting about politics, and invest heavily in covering campaigns. On the other hand, candidates are particularly aware of the way and extent to which the media reports on them. Most modern campaigns invest heavily in media relations, and hire specialized staff who focus on dealing and communicating with reporters and media outlets. Politicians are escorted into campaign locations with political consultants, who curate speeches by choosing or omitting words, phrases, and issues.

In short, candidates use the media to communicate with their constituencies, and the media uses candidates to produce and sell news (Bartels (1996); Prat and Stromberg (2013)). However, this relationship is not purely symbiotic. On the contrary, electoral campaigns are not just a game between candidates, but a highly strategic one between candidates and the media. Although candidates and media outlets both share the objective of being reported and reporting, respectively, their preferences are misaligned regarding the contents of such reporting. First, there are scandals, which candidates do not want to be reported, while the media is particularly eager to report about. The breaking of such events depends on the previous history of the candidates, together with the increased spotlight at which the campaign itself puts them. More importantly, though, during campaigns candidates need to target a heterogeneous electorate. Particularly in competitive and bipartisan races, candidates require the support of both relatively extreme and centrist voters. This gives them incentives to differentiate their message as long as it can actually be targeted. The media, on the other hand, produces public information which constrains the ability of candidates to target different audiences. A key idea we explore in this paper is that relatively extreme messages that happen to be widely reported may significantly hurt candidates among centrist voters, even if it benefits them among more ideologically extreme ones. A recent example of this was 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 very narrow audience of wealthy individuals, its public revelation led to a significant backlash and widespread media coverage.

In this paper, we argue that these considerations make bipartisan campaigns closely resemble the strategic environment of a classic matching pennies game between each candidate and the media. Regardless of whether they desire to inform the public or simply earn revenue, as long as media outlets profit more by reporting or covering less centrist candidate statements and candidates benefit by not being reported on such kinds of statements, candidates' incentives to target extreme constituencies will be determined by how profitable it is for the media to report on them. Likewise, the media's incentives to invest in covering the campaigns will be determined by how profitable it is for candidates to make more or less extreme statements along the campaign trail. Both players will need to behave over time in an as unpredictable (to the other player) way as possible.

Thus, we develop a simple model of bipartisan electoral races with media coverage and unidimensional policy that can be taken to the data. In the model, differences in the turnout and swing-vote responses of different voters put a limit to full policy convergence. Policy positioning by candidates happens through their campaign statements. Voters perceive a candidate as more or less centrist as a function of the cumulative statements they have had access to, either through the media or through direct contact with the candidate. Voters express their preferences throughout the campaign by answering to pollsters, and lastly, by voting on election day. The media (as a whole) decides on the intensity with which it will cover each candidate, and candidates decide the type of statements to make at every date during the campaign.

We show how data on media reports, electoral results, and poll results, together with the behavioral implications of the model, can be used to estimate its structural parameters. Modeling electoral races in this way, and differently from all the previous literature, we provide a novel interpretation of the media's role in constraining politicians' behavior outside the standard political agency framework. Moreover, we suggest a novel channel through which politicians can influence the media's behavior that is unrelated to the corruption or influence-buying channels emphasized in the literature.

We implement this methodology looking at U.S. Senatorial races for the period 1980-2012. U.S. Senate races are ideal due to their high profile, and thus, ample media and polling coverage. In practice, we estimate a discrete game of complete information (see Bajari et al. (2010)) with several novelties. First, the nature of the environment allows us to study a repeated (and subsequently dynamic) game in a very parsimonious way. This is because matching pennies games have a unique Nash equilibrium in mixed strategies, and naturally, electoral campaigns are finite in time as they end on election day. Thus, an unraveling argument implies that the repeated (and dynamic) game will also have a unique subgame perfect equilibrium, hugely simplifying estimation. Second, our empirical strategy allows us to overcome a pervasive problem faced by the literature interested in estimating payoff parameters in discrete games of this nature, when frequencies for a subset of game outcomes is unobserved. For example, in entry games data on the number of firms which, in a given period, decide not to enter, is necessarily unobserved. Similarly, in our model the media chooses whether or not to cover a given candidate. In periods when the media does not report, we do not observe the type of statement made by the candidate. As a result, we observe the frequencies for different types of statements only conditional on the media reporting. Nevertheless, we overcome this difficulty using changes in poll data over the campaign, which we argue are responsive to the full distribution of statements made, and thus, allow us to to recover all relevant payoff parameters.

The data and modeling assumptions allow us to estimate the payoff parameters governing this game, which directly express the average impact that different types of statements and media reports have on polling and electoral performance of candidates. Furthermore, we also are able to estimate the relative bias in payoffs for the media from covering Republican vs. Democratic candidates. Our identification strategy closely depends on mapping conditional probabilities to observed frequencies, and thus, depends on some modeling assumptions about other conditional probabilities. In practice, we estimate first a linear model where the relative media bias in coverage is only partially identified, but which makes our identification arguments transparent. Subsequently, we estimate a more general model that fully respects the nature of the data, which allows us to point identify relative media bias parameters through its non-linearities.

Our model and estimation require data classifying news coverage during an electoral campaign as reporting more or less centrist statements by the candidates. Thus, our paper also contributes to the literature by developing and implementing a novel text-analysis methodology to assess the extent to which the contents of a given news piece mentions relatively centrist or relatively extreme statements made by the candidates. The key idea is to create a self-referential measure. We first compute the more and less frequent phrases related to policy issues found within a set of news articles for both candidates in a particular Senate race (state-x-year) across media outlets. We also compute the relative counts of candidate names mentioned in the articles, to measure the extent to which it reports coverage of a given candidate. We then assign a score to each article based on the frequency with which it contains phrases that are relatively commonly used in articles that mention more heavily one or the other candidate. We can then use this index to classify each news piece as being either centrist-reporting or extreme-reporting, and use different classification criteria to ensure the robustness of our results.

Finally, using our parameter estimates, we can perform some counterfactual exercises that allow us to assess the impact of partisan bias in the media, race characteristics such as the ideological distribution of voters, and technological innovations altering the cost of media reporting. Additionally, our methodology lends itself for the prediction of campaign outcomes.

Although we are unaware of any other study modeling the relationship between politicians and the media in the way we do here, nor estimating the effect of media campaign coverage on electoral outcomes within a structural model, our paper relates to several literatures. Foremost, this paper is related to the literature on media coverage

(Gentzkow and Shapiro (2006); Puglisi and Snyder (2008); Stromberg (2004a)). Although most of it does endogenize policy choices by politicians and coverage decisions by the media, unlike the previous literature we allow politicians' choices to respond to the coverage strategies of the media. On the other hand, the empirical literature has measured the impact of media coverage on policy outcomes (Snyder and Stromberg (2010); Stromberg (2004b)). Instead we focus on the impact of media coverage on candidate behavior. 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 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 their results are partial equilibrium, here we model and estimate both the media's coverage choices as well as the equilibrium responses of candidates and campaigns to them. In contrast to the partisan biases of 19th Century periodicals, Gentzkow et al. (2006) emphasize how the growth od the media market size led to more independent and "informative" media throughout the 20th Century in the U.S., which is closer to the period we study here.

Second, our paper relates to the literature on transparency, which asks how increased information affects policy outcomes (Maskin and Tirole (2004); Prat (2005)). Most insights in this literature follow closely those from the contract-theory literature on agency. In our model, an increase in the amount of information generated in equilibrium can only come from the media reporting more intensely, which can happen only when candidate's payoffs from (unreported) extreme statements are higher. Thus, somewhat counterintuitively, more information may be correlated with politicians choosing more extreme platforms. 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. Nevertheless, the fact that voters seem to care significantly about what candidates say does suggest there must be a close relationship between campaign speech and policy choices.

Also within the tradition of political agency, Besley and Prat (2006) develop a model where the media plays the key role of supplying to voters the information on incumbent behavior they use when deciding whether to retain or dismiss him. When the leader is able to influence the media's information supply decision, it can undermine democracy's ability to exert agency control. In this literature, competition in the media market limits the extent of media capture, and thus, of selection on the information supplied to the public (See for example Chiang and Knight (Forthcoming); Corneo (2006)). Although Gentzkow et al. (2014b) find little evidence of elected officials manipulating the competitiveness of the media market in early 20th century America, in contrast, we show that selected media content can arise even in highly competitive media markets, but for very different reasons than those suggested by models of capture.

Our paper also directly fits within the the literature studying how the media affects citizens' opinions and electoral choices (e.g.,DellaVigna and Kaplan (2007); Enikolopov et al. (2011); Campante and Hojman (2010)), and is related to the strand of the literature measuring the media's ideological positions (Gentzkow and Shapiro (2010); Puglisi (2006)). Instead of attempting to measure the ideological positions of different media outlets, we measure the extent of reporting on more or less centrist issues by the media as a whole. Although our paper does not directly study voter learning and the extent to which voters react to new information during campaigns, our ability to establish an empirical link between overall news reports and poll changes indirectly suggests voter responsiveness to information, similar to the findings in Hirano et al. (2015) who study voter learning during primaries and find strong effects for statewide offices. In recent work, Gentzkow et al. (2011) have shown that in the extensive margin, the existence of a newspaper market is robustly associated with higher turnout. Here we complement finding showing important effects on turnout on the intensive margin of media reporting.

Third, since we model the interaction between politicians and the media as a matching pennies game, our paper also is related to the literature that has empirically studied this kind of strategic environment and the mixed-strategy equilibria it is associated with. Walker and Wooders (2001) were the first to look for empirical evidence on 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 also 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. To the best of our knowledge, our paper is the first to use this game-theoretic framework for empirical analysis in a 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 Bresnahan and Reiss (1990, 1991); Berry (1992)). In contrast, we estimate a model where only mixed strategies are economically meaningful, and propose a different identification strategy.

The rest of the paper proceeds as follows. Section 2 provides a brief overview of electoral campaigns in the U.S. focused on Senate races. Section 3 presents our benchmark (linear) model of the campaing trail, Section 4 describes the data, and Section 5 discusses identification, the empirical strategy, and main results. Section 6 then presents a more general (non-linear) version of our model, describe its estimation results and presents some counterfactual exercises. Section 7 concludes, and Appendices A, B and C contain proofs and a detailed description of data sources.

2 Context

In this section we briefly discuss our focus on U.S. Senate races and some institutional background on them. The U.S. Senate has been democratically elected for a century now, after the 17th Amendment to the Constitution was passed in 1913. Previous to the amendment, State Legislatures elected U.S. Senators. The Senate is composed of 2 senators per state; hence, 100 senate seats currently exist. Senate elections are held every two years 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. As a result, there are around 33 elections taking place every electoral cycle[1].

As in most other elections for public office in the U.S., general elections are preceded by a period of campaigning, which comes after each party in each state has chosen its candidate in either a primary election or a convention. Most states hold primaries, which vary in how close to the general election they happen. Interestingly, even during the primaries pollsters track hypothetical electoral outcomes for the general election. This is facilitated by the fact that a large fraction of Senate races include an incumbent senator, who is very likely to become his party's candidate in the general election, and often even runs unopposed in the primary.

Technological change in the media industry has transformed in major ways how electoral politics operates in the U.S. As access to newspapers first, later television, and more recently, the internet, have arisen and deepened, not only the quantity but also the kind of information received by voters has changed. First, direct contact between candidates and voters was reduced. Printed news and television made the media an unavoidable middleman in the transmission of political messages. Direct contact between politicians and voters, for example through town-hall meetings and campaign-trail speeches, allowed candidates great control over the exact contents of their messages. Moreover, during the 19th and early 20th Centuries, the extent of direct control of media outlets by politicians' families also contributed to their ability to determine which constituencies were reached by different messages. In contrast, candidates now have little direct control over how the media will report on their actions and statements, both because of competition in the media market and the reduced extent of direct media control by politically

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

involved families. Second, information has become increasingly public. Before the advent of these new information technologies, candidates had the ability to target their messages narrowly to specific groups. This ability has been significantly undermined by the broad reach that modern media technologies have. According to Ansolabehere et al. (1992, , p. 71), "The importance of the mass media and the growth of television in particular have forced candidates to respond to the routines and incentives of news organizations. Candidates and their staffs devote a great deal of energy to influencing the decisions of reporters and editors. Successful candidates and campaigns also adjust their behavior to exploit the media environment in which they operate."

The importance of these changes manifest themselves in the key role that public and media relations play within the organizational structure of political campaigns. This is especially so in U.S. Senate races, which by their nature are quite salient and are thus intensely covered by both state and national-level media outlets. Interestingly, the very recent emergence of social media may be allowing candidates to have more direct access to their constituencies once again. They may also partially allow increased message differentiation and targeting. In practice, the different technological changes have altered both the costs of campaign coverage by the media, and the costs and benefits for candidates of producing differentiated messages.

This discussion also motivates our focus on U.S. Senate races. While the number of U.S. House races is significantly larger, House electoral districts are small relative to most media markets. This limits the extent to which the media will be directly following individual races. Furthermore, data on polls for House races is very scarce. On the other hand, U.S. presidential races have extensive media and poll coverage, but there are too few of them for a satisfactory statistical analysis. Senate races are, thus, an ideal compromise. Moreover, their state-level nature implies that the electorate is diverse enough for candidates to have incentives to send differentiated messages.

3 A Simple Model of the Campaign Trail

In this section, we describe the simple model of campaign speech and media coverage that we subsequently estimate. The model captures what we consider are key features of the interaction between two candidates running against each other, $p \in \{D, R\}$, and the distribution of media outlets m covering the race. In the model, candidates make statements over time that can be more or less ideologically centrist, with the purpose of attracting political support from more or less centrist voters. The media decides about coverage of the campaigns every period, and perceives a higher payoff from reporting news about relatively more extreme candidate statements. Candidates' electoral performance benefits from media reporting on their relatively centrist statements, and although it may also benefit from unreported relatively extreme statements, it is harmed by media reporting on these kinds of statements.

We assume time is discrete $t = 0, ..., T$, where $t = T$ is the election day and $t = 0$ is the beginning of the campaign. For the purposes of the model we will assume that both candidates begin their campaigning on the same date. We also assume that every period each candidate makes a campaign statement. Each media outlet decides on whether to follow the Democratic candidate D, the Republican candidate R, or both. Conditional on following a candidate, the media successfully reports on their statements with an exogenous probability that may vary across parties. Candidate statements and media reports then translate period by period onto changes in electoral support from voters. Since our focus on this paper is not on voters, we model their behavior in the simplest possible way, assuming their electoral support decisions respond period by period to the amount of information they receive during the campaign, either directly from candidates or through the media.

Players' Choices

Candidates make statements every period with the purpose of increasing their electoral support. The underlying environment is such that (for an un-modeled reason) candidates do not fully converge to the unidimensional median voter's ideological stance. For example, this could be because the turnout of voters in the extremes of the ideological distribution is sensitive to their distance to the candidates' position, and the density of voters is high in the extremes. To capture the electoral support of relatively extreme voters, candidates are tempted to make relatively extreme statements e, directly targeted to those audiences. Nevertheless, relatively extreme statements may decrease the electoral support of centrist voters. Candidates may, instead, make relatively centrist statements c, which generate little excitement in the extremes, but may increase or maintain the electoral support in the center.

Candidates and the media have partially aligned preferences: Candidates benefit from being reported about in the media, and the media profits from reporting news about candidates. Nevertheless, preferences of candidates and the media are also partly misaligned: candidates benefit from the media reporting on their relatively centrist statements, and are possibly hurt when the media reports on their relatively extremist statements. Nevertheless, the media profits more from reporting on extremist statements than from reporting on centrist ones. This gives rise to a matching-pennies strategic environment between each politician and the media. Candidates also take each others' strategies as given when deciding what types of statements to express.

Candidates can take two possible actions every period. Either to make a non-controversial/centrist statement or a relatively controversial/extreme statement: $s^p \in \{c, e\}$. Simultaneously, we assume the media can take one of three possible actions: to follow both candidates, to follow only D, and to follow only R: $s^m \in \{(F_D F_R), (F_D N_R), (N_D F_R)\}$. In either case, we further assume that after having taken its action, the media successfully reports (denoted by $\chi = 1$) with probability $\mathbb{P}(\chi = 1|p) = \eta_p$. This modeling choice allows us to keep the action space of the media three dimensional, while still allowing for realizations where no reports are observed.

Payoffs

We assume a very simple structure for payoffs. Every period, the media must pay a cost k per candidate followed. Also, we assume the following per-period gains from reporting on candidate p:

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

Thus, for simplicity we normalize the gain from reporting a non-controversial statement or action to zero. Nevertheless, we are allowing the gain for the media to differ between a report about D and a report about R.

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 make them change their turnout decision. This distinction is important because the first margin leads to a zero-sum setting from the point of view of the candidates, while the second margin does not. The payoff structure we present below implicitly assumes that voters in the extremes of the ideological distribution only react on the turnout margin, and never switch party allegiances, whereas voters in the center of the distribution only react on the party support margin (they are swing voters), and do not react on the turnout margin (their turnout rate is constant). We also assume that individuals report truthfully to pollsters.

For candidates, instantaneous payoffs depend on whether their statements/actions are reported or not, and whether these are targeted to the center or to the extremes. Candidates care about their electoral support, and players' actions directly map into changes in political support. Thus, we assume that centrist statements that are not reported by the media have no effect on either extremist or centrist voters. Centrist statements that are reported, in contrast, have an effect on centrist voters. They shift support from the candidate not reported to the candidate reported. Because the turnout rate for centrist voters is unaffected, the gain for one candidate is exactly the loss for his opponent. On the other hand, we assume extreme statements increase the turnout of extreme constituencies. When they are unreported, they do not have an effect on centrist voters. When they are reported, in contrast, they also swing centrist voters away from the candidate making the statement and towards his opponent. This loss is assumed to be larger than the gain on the turnout margin, so that the net effect from a reported extreme statement on political support is negative for the candidate making it.

We denote by $\Delta^T_{s^p p}$ the change in electoral support to candidate p when he chooses action s^p due to the turnout effect, and by $\Delta^S_{s^p p}$ the change in electoral support when candidate p chooses action s^p due to the swing voter effect. Thus we can express the change in political support for each candidate $p \in \{D, R\}$ between period t and period $t+1$ as:

$$v^p(t+1) - v^p(t) = \Delta^T_{ep}\mathbf{1}\{s^p(t) = e, \chi(t) = 0\} + \left(\Delta^T_{ep} - \Delta^S_{ep}\right)\mathbf{1}\{s^p(t) = e, \chi(t) = 1\}$$

$$+\Delta^S_{e\sim p}\mathbf{1}\{s^{\sim p}(t) = e, \chi(t) = 1\} + \Delta^S_{cp}\mathbf{1}\{s^p(t) = c, \chi(t) = 1\} - \Delta^S_{c\sim p}\mathbf{1}\{s^{\sim p}(t) = c, \chi(t) = 1\} + \epsilon^p \tag{2}$$

Above, (ϵ^D, ϵ^R) are other unobserved shocks to the change in electoral support of D and R. We impose the following parameter restrictions:

Assumption 1. *The following inequalities hold:*

$$\begin{array}{llll} \Delta^T_{eD} < \eta_D\left(\Delta^S_{eD} + \Delta^S_{cD}\right), & \Delta^T_{eD} > 0, & \Delta^S_{eD} > 0, & \Delta^S_{cD} > 0 \\ \Delta^T_{eR} < \eta_R\left(\Delta^S_{eR} + \Delta^S_{cR}\right), & \Delta^T_{eR} > 0, & \Delta^S_{eR} > 0, & \Delta^S_{cR} > 0 \end{array}$$

These inequalities are sufficient for the game to have a unique Nash equilibrium in mixed strategies on the stage game. Equations (1) and (2) and the parameter restrictions in Assumption 3 are fairly natural. They take into account the zero-sum nature of swing support, and also make explicit the assumptions that (i) unreported actions by a candidate do not have an effect on his opponent's support, and (ii) unreported c statements by a candidate do not have any effect on his own support. They also imply that candidates gain support from extreme statements that go unreported, but expect to lose support when these are reported. Finally, they assume that own centrist statements that are reported increase own support (at the expense of the opponent), and opponent's centrist statements that are reported decrease own support (and are a gain to the opponent). We further assume that candidates maximize their electoral support (which, in a bipartisan race, is equivalent to maximizing the winning probability). In summary, we have a total of eleven structural parameters in this model: $\boldsymbol{\theta} = (\Delta^T_{eD}, \Delta^S_{eD}, \Delta^S_{cD}, \Delta^T_{eR}, \Delta^S_{eR}, \Delta^S_{cR}, \eta_D, \eta_R, \pi_D, \pi_R, k)$ determining the payoffs of all players.

The above payoff structure gives rise to a stage game G that has a matching pennies structure. It's normal form representation is presented in Appendix A.

Proposition 1. *Assume $\eta_p\pi_p > k$. The normal form game described above does not have a pure-strategy equilibrium. The unique mixed strategy equilibrium is given by:*

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

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

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

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

where γ_D denotes the probability that m plays $F_D N_R$, γ_R denotes the probability that m plays $N_D F_R$, q_D denotes the probability that D plays e, and q_R denotes the probability that R plays e. Furthermore, because the stage-game *has a unique Nash equilibrium, the only Subgame Perfect Equilibrium of the finitely repeated game G^T is to play the unique stage-game Nash equilibrium every period.*

Proof. See Appendix A.

□

As is standard in a matching pennies environment, mixing probabilities of a given player are pinned down by indifference, and thus, are a function only of the opponents' payoffs. In this context, this implication of equilibrium has an interesting interpretation. It suggests that if we want to study the statements and actions of candidates, we must do comparative statics relative to the media's payoffs. Candidates' payoffs are in fact irrelevant to explain their equilibrium behavior. For example, the more the media profits from reporting on an extremist statement, the lower will have to be the rate at which the candidate makes such statements. This is the sense in which, in our setting, the media can constrain candidates' behavior. More importantly, the electoral gain from a given statement should have no predictive power for the rate at which the candidate makes such statements. Conversely, the frequency with which the media reports on the candidates is independent of how profitable such action is, and depends only on the candidates' payoffs. Notice also that the ratio $q_D^*/q_R^* = \eta_R\pi_R/\eta_D\pi_D$ does not depend on k.

4 Data

This section describes our data and the construction of our main variables and data structure. First, we discuss the information on all senate races included in our dataset, the poll and election outcomes data collected, and how we rely on poll availability to construct the time dimension of our panel. We then introduce our news coverage data and describe in detail the construction of our news article scores measuring the type of content reported in them. We conclude discussing the sports events data which we will rely upon for our identification strategy.

4.1 Senate Races

For our empirical implementation, we gathered and put together data from several sources, and built a dataset of all ordinary competitive races to the U.S. Senate taking place between 1980 and 2012 for which a Democrat and a Republican candidate ran[2]. This makes a total of 427 races in our sample, out of the around 561 (=17 election cycles×33 races) total races that could have taken place in this 32 year period. For each senate race, we have data on its outcome (share Democrat and share Republican) from the Federal Elections Commission, the date and outcomes of the primaries for each party whenever a primary took place -or whether the candidate was chosen at a party convention for states electing their candidates that way-, information on whether the 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 Democrat and Republican of registered voters in the state (for states without party registration, we use the vote share for president in the most recent election). Table 1 presents summary statistics for all the variables in our study.

4.2 Polls

Our empirical strategy requires that we have data on the evolution of partisan support during the campaign. Thus, we additionally made an effort to collect as detailed as possible polling data on the races. The data on polls was

[2] 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 C contains a list of dropped races.

gathered 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. We focused on obtaining poll reports for a one-year window before the election (for example, for the 1998 election we began our search on November 1, 1997). Any polls found through the articles were recorded, and the accompanying article(s) saved for verification. If any discrepancies were found between two articles about the same poll, other articles (from different newspaper sources) were searched to verify which information was correct, if possible. We used Factiva for 1998, in addition to PollingReport.com because the PollingReport data for 1998 was sparse. For both PollingReport.com and Dow Jones/Factiva, some assumptions were necessary. For example, sometimes poll dates were not exactly given (e.g. only the month of the poll or "over the weekend" was reported). If only the month of the poll was reported, we assumed it took place on the fifteenth day of the month unless it refers to a poll in November, in which case we assume it happened on the first day of the month. We collected a total of 4,076 polls. Naturally, the frequency of Senate race polls becomes higher in more recent years and in states with larger populations.

Our empirical strategy relies on our ability to compute frequencies of news reporting over time, and the subsequent changes in electoral/poll support. Thus, we rely on our dataset of polls to construct what we call "poll-to-poll" intervals, within which we measure the reporting frequencies. Because the definition of these periods is arbitrary, we use two alternative definitions, by grouping nearby polls, using two-week or three-week windows, and averaging -weighting by poll sample size- all polls falling within the window. We then assign the average date among the polls in the window as the period marker. Put together, the poll data points implicitly define poll-to-poll intervals within each race, which we use as the time units in our panel. We follow this strategy given that the frequency and spacing of polls is uneven across states and years, and because aggregating nearby polls helps us average out the inherent measurement error in poll reports. Figure 1 graphically illustrates the construction of the poll-to-poll intervals.

The construction of time periods in this way introduces an unavoidable precision/bias trade-off. The longer a poll-to-poll interval, the smaller the sampling error for the measured ratios of frequencies of news reports falling within it, and thus, the closer these relative frequencies 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, where we allow the payoff parameters to evolve as a function of a state variable, namely the current relative poll standing of the candidates.

4.3 Measuring News Reporting

One key innovation in this paper relies on our ability to construct measures of the types of content in news articles covering political campaigns, which are necessary to establish a link between candidate speech and electoral performance. More specifically, we require a classification of media coverage as reporting more or less centrist candidate statements. Of course, the definition of more or less centrist/extreme positions is only meaningful relative to the ideological distribution of the state. For example, it is possible that a given statement by a democrat is considered centrist in Massachusetts but extremely leftward in Utah. Moreover, the ideological distribution of the population within a state may change over time, making a statement that could be considered extremist in 1980 relatively centrist in 2012. Thus, any classification of the reporting content of media news must be race-specific.

Measuring the type of media coverage and taking these issues into account is non-trivial. With this in mind, we follow some of the ideas in the seminal work of Gentzkow and Shapiro (2010) for computing measures of media slant, to develop a novel 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 was based on the names of both candidates for each race. The news articles were downloaded in HTML (for Lexis Nexis) and .rtf (for Factiva) formats. We collected all news articles mentioning either candidate in a given race, during the one year period prior to the election date for each state. Our initial search recovered more than 300,000 articles covering 560 races and 1,120 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 persons mentioned in the article). These tags allowed us to further weed out irrelevant articles and omit repeated articles. Our estimation sample contains information from 210,848 news articles. Although articles often mention both candidates, the average article is usually centered on reporting about just 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. We rely on the candidate name information in the articles themselves for the construction of our media index.

We proceed in the following way. First, to assess the extent to which an article reports on the Democratic or the Republican candidate, we count the number of times the name of each appears in each article. We then compute the 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. Of course, 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 2 presents the distribution of τ_i across all articles and races. The distribution is strongly multi-modal, with most articles referring heavily to either one or the other candidate. There is also some significant density of articles mentioning both candidates evenly (with scores close to 0). The τ_i provides us with a continuous measure that will allow us to classify the contents of all articles in each race.

With this purpose, within the set of all articles corresponding to a given race, we identify the 1,000 most commonly used 2 word phrases (2-grams) and 3-word phrases (3-grams) -500 of each-. We then proceed by giving 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. Formally, 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 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,

$$a_i = \frac{\sum_j s_j f_{ij}}{\sum_j f_{ij}} \in [-1, 1]$$

Thus, 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 completely self-referential, in the sense that we do not use any information from outside the coverage of the specific race to assess the extent to which a given news piece is likely to be reporting more or less centrist statements or actions by the candidates. a_i is a continuous index which, together with τ_i, we use to classify each article both as covering either the Democrat or the Republican (depending on whether τ_i is negative or positive respectively), and whether the content is more centrist c or extremist e (depending on the value of a_i). Figure 3 presents the distribution of the article scores for all of our sample. Our benchmark specification classifies extreme-content articles (e) as those with $a_i < -0.25$ for the Democrat and those with $a_i > 0.25$ for the Republican, and as centrist-contents articles (c) as the remaining articles in the range $[-0.25, 1]$ for the Democrat and in the range $[-1, 0.25]$ for the Republican among the articles assigned to each candidate. Thus, for example, if the threshold is set to 0.25, then all articles assigned to the Democrat with $a_i \in (-0.25, 1]$ are considered c articles, and all articles with $a_i \in [-1, -0.25]$ are considered e articles. Similarly, all articles assigned to the Republican with $a_i \in [-1, 0.25)$ are considered c articles, and all articles with $a_i \in [0.25, 1]$ are classified as e articles. Figure 4 illustrates graphically the article classification criterion for the ± 0.25 cutoff. In our robustness analysis we present additional results that reclassify all articles using alternative cutoffs $a_i = \pm 0.5$ and $a_i = \pm 0.75$.

Our collection of news articles also allowed us to obtain information on the number of different media outlets covering each race. We obtained this information based on the media outlet name and date tags in the articles. As a result, we have data on the count of different outlets reporting on a race within each poll-to-poll interval[3]. 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 for each media outlet every day during the campaign.

4.4 Sports news data as media-payoff shifters

In our empirical strategy we exploit the observed correlations between frequencies of news reporting and changes in poll support for both candidates to back up the payoff parameters of the matching pennies game. Because changes in electoral support along the campaign may be due to a host of unobservables (to the econometrician) which may, in turn, be correlated with candidates' incentives to make different kinds of statements and the media's incentives to cover electoral campaigns, we rely on the occurrence of major sports events as exogenous shifters of the media's attention similarly to Eisensee and Stromberg (2007). More specifically, we collected daily information on all games from the NFL, MLB, and NBA, and all playoffs games from the NCAA between 1979 and 2012. 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, which are likely unrelated to any strategic behavior by the candidates. Because most games for each sport take place during a specific season of the year (football is concentrated in the winter, and baseball in the summer, for example), having information from these four sports provides us with year-round variation.

Some states do not have teams making it to the playoffs with enough frequency or at all during the 33 year period, so we additionally collected information from Facebook. Among all of its users, 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

[3] In order to remove misclassifications due to the occasional use of 'the' in front of an outlet name (e.g., "The New York Times" could occasionally be classified as "New York Times"), we processed the text to remove the word "the" in front of all outlet names.

vary its behavior in response to salient sports events from teams of other states, which have a significant support in the state where the race is taking place. Specifically, we computed the matrices $\mathbf{W}^{NFL}$, $\mathbf{W}^{MLB}$, and $\mathbf{W}^{NBA}$, where entry w_{ij}^{l}, $l \in \{NFL, MLB, NBA\}$ 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 those states without teams in our data, this matrix provides us with variation in media payoffs, coming from the fact that a large fan base rooting for out-of-state sports teams may lead the media's attention towards covering those events. Under the assumption that the media will differentially focus its attention on teams from other states with a significant support base in the state, we are able to obtain some variation in the media's attention for our full sample of states[4]. Figure 5 presents Facebook "likes" maps for each of these four sports leagues in the US, illustrating the straddling of fans across states which we exploit.

5 Identification, Empirical Strategy, and Results

5.1 The Repeated Game in the Linear Case

In this section we present and discuss our empirical strategy to recover the payoff parameters governing the matching pennies game described above. Our empirical strategy has several components. We first discuss the non-parametric identification of the equilibrium mixing strategies of all players based on the counts of the different types of news articles in our dataset. We then show how relying on these mixing strategies, on poll data, and on an appropriate exogenous source of variation for news article frequencies we can identify the electoral response elasticities that map directly into the game's payoff parameters for the candidates. We also show how the media's partisan coverage biases are only partially identified in the linear model, and how to compute their identified set. We then present our findings based on an instrumental variables estimation strategy and explore additional robustness exercises. Overall, we find that the turnout margin is more responsive for Democratic candidates, that the swing voter margin is similarly responsive for Democrats and Republicans, and that a large partisan bias of the media in either direction is unlikely. We also find that the responsiveness of centrist voters to centrist statements falls rapidly as states' constituencies become less evenly balanced between parties, but do not find evidence suggesting that voter responsiveness to media coverage significantly changes as the campaigns develop.

5.1.1 Identification of the mixing strategies

Our first task is to propose a methodology that allows us to identify the model parameters $\boldsymbol{\theta}$ using the equilibrium conditions (3)-(6), and the data on media reports, poll results, and electoral results. The main difficulty in identifying payoff parameters from behavior reflecting mixed strategies in a setting such as this one is that the nature of the game implies that we do not observe counts of type e or c candidate statements in periods when the media does not report. We first introduce some notation. Define $X_p^s(t, t+\tau)$ as the count of type $s \in \{e, c\}$ media reports on candidate $p \in \{D, R\}$ between time t and time $t+\tau$. Also define $N_p^s(t, t+\tau)$ as the count of type s statements by candidate p between time t and time $t+\tau$ that do not get reported by the media. Of course, while the latter are unobservables, the former are observed (with error). Assuming for the time being that payoff parameters $\boldsymbol{\theta}$ are constant within the time interval $[t, t+\tau)$, the repeated matching pennies game directly gives us the joint distribution for the four observables and the four unobservables $(X_D^c, X_D^e, X_R^c, X_R^e, N_D^c, N_D^e, N_R^c, N_R^e)$. In particular for each p, $(X_p^c(t, t+\tau), X_p^e(t, t+\tau), N_p^c(t, t+\tau), N_p^e(t, t+\tau))$ is drawn from a multinomial distribution where the probabilities of success and failure are determined by the equilibrium mixing strategies of the candidates and the

[4] 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. As a result, we do not weight NCAA sports events by the cross-state fandom weights.

media. Thus, $(X_p^c(t,t+\tau), X_p^e(t,t+\tau))$ each have a binomial marginal distribution, given by:

$$\mathbb{P}(X_p^e(t,t+\tau)=k) = \left(\begin{array}{c}\tau\\ k\end{array}\right)\left(q_p^*[1-\gamma_{\sim p}^*]\eta_p\right)^k\left(1-q_p^*[1-\gamma_{\sim p}^*]\eta_p\right)^{\tau-k} \tag{7}$$

$$\mathbb{P}(X_p^c(t,t+\tau)=k) = \left(\begin{array}{c}\tau\\ k\end{array}\right)\left((1-q_p^*)[1-\gamma_{\sim p}^*]\eta_p\right)^k\left(1-(1-q_p^*)[1-\gamma_{\sim p}^*]\eta_p\right)^{\tau-k} \tag{8}$$

which follow from the fact that q_p^* is the probability that candidate p chooses an extreme statement each period, and $[1-\gamma_{\sim p}^*]\eta_p$ is the total probability that the media reports on candidate p each period. Because $(X_p^c(t,t+\tau), X_p^e(t,t+\tau))$ are observed we can also express the conditional (on (X_p^e, X_p^c)) marginal distribution of N_p^e, which is a binomial and takes the following form[5]:

$$\mathbb{P}(N_p^e(t,t+\tau)=k|X_p^e(t,t+\tau), X_p^c(t,t+\tau)) =$$

$$\left(\begin{array}{c}\tau-X_p^e(t,t+\tau)-X_p^c(t,t+\tau)\\ k\end{array}\right)\left[\frac{q_p^*[1-(1-\gamma_{\sim p}^*)\eta_p]}{(1-\gamma_{\sim p}^*)\eta_p}\right]^k\left[1-\frac{q_p^*[1-(1-\gamma_{\sim p}^*)\eta_p]}{(1-\gamma_{\sim p}^*)\eta_p}\right]^{\tau-X_p^e(t,t+\tau)-X_p^c(t,t+\tau)-k} \tag{9}$$

which follows from the fact that $1-(1-\gamma_{\sim p}^*)\eta_p$ is the total probability that the media does not report on candidate p each period. Because the X_p^s are observable, equations (7) and (8) allow us to non-parametrically identify the conditional probabilities generating the observed media reports. The MLE estimator for a binomial random variable is simply its sample analogue. Defining $\varphi_p^e \equiv q_p^*[1-\gamma_{\sim p}^*]\eta_p$ and $\varphi_p^c \equiv (1-q_p^*)[1-\gamma_{\sim p}^*]\eta_p$, we obtain for $p\in\{D,R\}$:

$$\hat{\varphi}_p^e(t,t+\tau) \equiv \frac{X_p^e(t,t+\tau)}{\tau} \tag{10}$$

$$\hat{\varphi}_p^c(t,t+\tau) \equiv \frac{X_p^c(t,t+\tau)}{\tau} \tag{11}$$

Equations (10) and (11) give us four equations in six unknowns $(q_D^*, q_R^*, \gamma_D^*, \gamma_R^*, \eta_D, \eta_R)$. Nevertheless, by taking the quotients of these conditional probabilities for each p, we can identify the equilibrium mixing strategies of both candidates:

$$\frac{\hat{\varphi}_p^c}{\hat{\varphi}_p^e} = \frac{(1-q_p^*)[1-\gamma_{\sim p}^*]\eta_p}{q_p^*[1-\gamma_{\sim p}^*]\eta_p} \Rightarrow q_p^*(t,t+\tau) = \frac{\hat{\varphi}_p^e(t,t+\tau)}{\hat{\varphi}_p^c(t,t+\tau)+\hat{\varphi}_p^e(t,t+\tau)} \tag{12}$$

The efficient estimator of the $q_p^*(t,t+\tau)$'s will be the one with that takes $t=0$, $\tau=T$. Moreover, from equations (12) for $p\in\{D,R\}$ and the definition of the φ_p^s's, we can also identify the conditional probabilities

$$\hat{\phi}_p(t,t+\tau) \equiv [1-\gamma_{\sim p}^*]\eta_p = \hat{\varphi}_p^c(t,t+\tau)+\hat{\varphi}_p^e(t,t+\tau) \tag{13}$$

Although it is not possible to separately identify the η_p's and the γ_p's just based on the observed article counts, below we show it is still possible to estimate the candidates' payoff parameters. The reason is that expressions (12) imply that we directly observe the parameters governing the DGP for the unobserved counts $(N_D^c, N_D^e, N_R^c, N_R^e)$ even though we do not observe their realizations. Furthermore, as we will show below, exploiting the variation in polls and electoral results, we will be able not only to directly identify the payoff parameters of the game, but also, as a result, to provide an identified set for the γ_p's, the η_p's, and relative media profits π_R/π_D.

[5] There is an analogous expression for the conditional distribution of $N_p^c(t,t+\tau)$ which we omit here to save space, and because given our model assumptions, electoral support is independent of the realizations of unreported centrist statements.

5.1.2 Identification of the electoral performance technology for the linear case

We begin by discussing our empirical strategy on the linear model for electoral support, which makes the identification arguments very transparent and illustrates clearly what are the sources of variation we exploit to identify the different payoff parameters of the game. In section 6 we will describe our estimation strategy on the general model that relaxes local linearity. Recall that in our data we observe poll outcomes at different points in time along the campaign. Within each of the poll-to-poll time intervals we constructed, candidates and the media make sequences of choices which we partially observe. Thus, consider taking the difference between the poll outcomes at times $t+\tau$ and t, at which we observe (an average of) polls. From equation (2) across τ periods, the change in electoral support to candidate $p \in \{D, R\}$ from t to $t+\tau$ is given by

$$v^p(t+\tau) - v^p(t) = \Delta^T_{ep} N^e_p(t, t+\tau) + \left(\Delta^T_{ep} - \Delta^S_{ep}\right) X^e_p(t, t+\tau)$$

$$+\Delta^S_{e\sim p} X^e_{\sim p}(t, t+\tau) + \Delta^S_{cp} X^c_p(t, t+\tau) - \Delta^S_{c\sim p} X^c_{\sim p}(t, t+\tau) + \epsilon^p(t, t+\tau) \quad (14)$$

where $\epsilon^p(t, t+\tau) = \sum_{\iota=t+1}^{t+\tau} \epsilon^p(\iota)$. In practice, the length of a given period will be determined by the frequency of polls for the race, which means we must assume that pollsters poll-timing decisions are not dependent on how the media is covering the campaigns or how the campaign is developing. Below we will perform a test of this assumption. Equation (14) shows that the change in electoral support for each candidate will depend on the frequency of the different possible game outcomes during that interval of time. Notice in particular the zero-sum nature of swing-voter support. This observation implies that by adding the change in electoral support of both candidates, all changes coming from 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:

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

$$\Delta^T_{eD}\left[N^e_D(t, t+\tau) + X^e_D(t, t+\tau)\right] + \Delta^T_{eR}\left[N^e_R(t, t+\tau) + X^e_R(t, t+\tau)\right] + \tilde{\omega}(t, t+\tau) \quad (15)$$

where $\tilde{\omega}(t, t+\tau) \equiv \epsilon^D(t, t+\tau) + \epsilon^R(t, t+\tau)$. Equation (15) makes it clear that variation in the counts of extreme statements of both candidates can be used to identify the response of voter support to this kind of campaign speech (Δ^T_{eD} and Δ^T_{eR}). There are two issues with estimation of equation (15). First, the obvious endogeneity of the extent of extreme statements, which are likely correlated with other unobservables that also determine the evolution of electoral support during a campaign. Second, the counts of extreme unreported statements N^e_D and N^e_R are unobservable. We tackle both of these issues.

First, notice that estimation of the parameters in this equation will require instruments for the report counts. Any instrument that is valid though, and thus satisfies the exclusion restriction of being uncorrelated with other determinants of the evolution of electoral support $\tilde{\omega}$, will necessarily be correlated with N^e_p as long as it is correlated with X^e_p. This implies that it is not possible to leave N^e_D and N^e_R in the error term of equation (15) if we want to implement an instrumental variables strategy. Luckily, here we can make use of our knowledge of the distribution of the unobserved counts (N^e_D, N^e_R). The mean of a binomial random variable is equal to its success probability times the number of trials, which means we can always express the unobserved counts within a poll-to-poll interval as $N^e_p(t, t+\tau) = \tau q^*_p[1 - \eta_p(1 - \gamma^*_{\sim p})] + \xi_p(t, t+\tau)$ where $\xi_p(t, t+\tau)$ is mean-zero sampling error. Additionally, we can divide both sides of equation (15) by the number of periods in the poll-to-poll interval. Notice that $\frac{1}{\tau}\sum_\tau \xi_p(t, t+\tau) \to 0$ as the length of the poll-to-poll interval grows. Expressing the N^e_p's in this way in equation (15) amounts in practice to including an explanatory variable with classical measurement error, which should create no additional issues as long as our instruments are valid. Thus, we obtain an expression that depends on the equilibrium conditional probabilities that we identified in section 5.1.1:

$$\frac{v^D(t+\tau)-v^D(t)+v^R(t+\tau)-v^R(t)}{\tau}=\Delta^T_{eD}\left[q^*_D[1-\eta_D(1-\gamma^*_R)]+\frac{X^e_D(t,t+\tau)}{\tau}\right]$$

$$+\Delta^T_{eR}\left[q^*_R[1-\eta_R(1-\gamma^*_D)]+\frac{X^e_R(t,t+\tau)}{\tau}\right]+\tilde{\omega}(t,t+\tau)+\Delta^T_{eD}\frac{\xi_D(t,t+\tau)}{\tau}+\Delta^T_{eR}\frac{\xi_R(t,t+\tau)}{\tau}$$

or, in terms of our notation in section 5.1.1,

$$\frac{v^D(t+\tau)-v^D(t)+v^R(t+\tau)-v^R(t)}{\tau}=\Delta^T_{eD}\frac{\hat{\varphi}^e_D(t,t+\tau)}{\hat{\phi}_D(t,t+\tau)}+\Delta^T_{eR}\frac{\hat{\varphi}^e_R(t,t+\tau)}{\hat{\phi}_R(t,t+\tau)}+\omega(t,t+\tau) \tag{16}$$

where $\omega(t,t+\tau)\equiv\frac{\tilde{\omega}(t,t+\tau)}{\tau}+\Delta^T_{eD}\frac{\xi_D(t,t+\tau)}{\tau}+\Delta^T_{eR}\frac{\xi_R(t,t+\tau)}{\tau}$ is a composite error term that includes all the shocks and the sampling error. Equation (16) can be estimated to recover $(\Delta^T_{eD},\Delta^T_{eR})$ with appropriate instruments. These need to be sources of variation for the frequency of counts of extreme statements made by candidates, which do not, simultaneously, covary with any other determinants of the evolution of electoral support during the campaign. Our model suggests what the natural instruments for these variables should be. From the equilibrium mixing probabilities in equations (5) and (6), the mixing probabilities chosen by the candidates are pinned down by the media's payoffs from reporting. Thus, a shifter of the media's payoffs to reporting on the campaign, which is otherwise unrelated to other campaign outcome determinants, will generate variation in the candidates' choices, that can be used to identify the parameters of interest. Such an instrument needs to vary across poll-to-poll intervals.

Here we follow the idea of looking at events that may crowd out the media's attention (thus, lowering its payoff from reporting on the campaigns), such as in Eisensee and Stromberg (2007) who use time variation generated by the occurrence of the Olympic Games to study how the media covers natural disasters. In a similar vein, we use daily data on the occurrence of games in any of the four major sports leagues in the U.S. ($MBL, NFL, NBA, NCAA$) including teams from the race's state or from other states with a significant local fan base as proxied by the Facebook fan data discussed in section 4.4 which we match to each poll-to-poll interval in our sample. The exclusion restriction is thus, that games in any of these sports are uncorrelated to any unobserved determinants of the evolution of electoral support besides how they alter the media's relative payoffs from covering the campaigns. We believe this is a very plausible exclusion restriction[6].

As noted above, if the $\boldsymbol{\Delta}$ payoff parameters are not constant over time, the sample analogue estimators of the conditional 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 the interval. This is an unavoidable bias-precision trade-off. Nevertheless, our framework allows us to introduce time-varying parameters, which can be relevant if, for example, there is a state-variable such as the current relative performance of the candidates over which payoff parameters change. As a robustness check in section 5.4 we allow for the payoff parameters to vary over time, effectively making the game a dynamic one.

Equipped with estimates of Δ^T_{eD} and Δ^T_{eR}, we can go back to equation (14). Notice that from the equilibrium mixing strategies for the media (equations (3) and (4)) we can express the Δ^S_{ep}'s as functions of the estimated $\hat{\Delta}^T_{ep}$'s:

$$\Delta^S_{ep}=\frac{\hat{\Delta}^T_{ep}}{\hat{\phi}_p}-\Delta^S_{cp} \tag{17}$$

[6]One possible channel through which the exclusion restriction may fail to hold is if the occurrence of these sports events lowers turnout during or around election day. This effect, if present, is likely to be small as it is restricted to matter only around the election day, thus only for the last of the poll-to-poll intervals in each race. Nevertheless, as a robustness check we estimate our model excluding the last period of each race.

Replacing for Δ^S_{eD} and Δ^S_{eR} from equation (17) above, and defining

$$\hat{p}(t,t+\tau) \equiv \frac{v^p(t+\tau)-v^p(t)}{\tau} - \hat{\Delta}^T_{e\sim p}\frac{\hat{\varphi}^e_{\sim p}(t,t+\tau)}{\hat{\phi}_{\sim p}(t,t+\tau)} \tag{18}$$

as the change in electoral support for party p net of the turnout effects of the opposing party, equation (14) can be conveniently rewritten as

$$\hat{p}(t,t+\tau) = \Delta^S_{cp}\hat{\phi}_p(t,t+\tau) - \Delta^S_{c\sim p}\hat{\phi}_{\sim p}(t,t+\tau) + \varpi^p(t,t+\tau) \tag{19}$$

where $\varpi^p(t,t+\tau) \equiv \frac{\epsilon^p(t,t+\tau)}{\tau} + \Delta^T_{ep}\frac{\xi_p(t,t+\tau)}{\tau}$. Finally, because the equation (19) above 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 and scale the whole equation by the size of the poll-to-poll interval:

$$\frac{\hat{D}(t,t+\tau)-\hat{R}(t,t+\tau)}{2}\tau = \Delta^S_{cD}\hat{\phi}_D(t,t+\tau)\tau - \Delta^S_{cR}\hat{\phi}_R(t,t+\tau)\tau + \zeta(t,t+\tau) \tag{20}$$

where $\zeta(t,t+\tau) \equiv \frac{1}{2}\tau\left[\varpi^D(t,t+\tau)-\varpi^R(t,t+\tau)\right]$. Equation (20) illustrates that the regression of an appropriately "corrected" difference between the change in electoral support of both candidates on the estimated conditional probabilities of all realized reports about the candidates can identify the payoff parameters related to the gains in electoral support stemming from centrist statements reported by the media. Naturally, both $\hat{\phi}_p(t,t+\tau)\tau$'s will be correlated with other unobservables in $\zeta(t,t+\tau)$, and thus, we require the use of appropriate instruments once more. In contrast to the identification argument for equation(16), the variation in the right-hand side variables induced by sports events is of a different nature. While the equilibrium mixing probabilities of the candidates, $q^*_p = \mathbb{E}\left[\frac{\hat{\varphi}^e_p(t,t+\tau)}{\hat{\phi}_p(t,t+\tau)}\right]$, directly depend on the media's reporting payoff π_D, the equilibrium reporting rate $\eta_p(1-\gamma_{\sim p}) = \mathbb{E}\left[\hat{\phi}_p(t,t+\tau)\right]$ does not. 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. Nevertheless, the right-hand side variables in equation (20) are scaled by the size of the poll-to-poll interval. If the occurrence of sports events leads to variation across media outlets in their willingness to report on politics, then sports events can be valid shifters of τ, and thus valid instruments for the right-hand side variables in equation (20)[7]. Even though sports events induce no intensive-margin response by a given media outlet (whose reporting strategy is pinned down by indifference), they can induce an extensive margin response across the distribution of media outlets covering a race. Figure 7 illustrates how variation in sports events can lead to infra-marginal outlets (those barely not covering the race) to enter coverage, or to supra-marginal outlets (those barely covering the race) to drop out from coverage. We exploit this source of variation to instrument for the endogenous variables in equation (20). In section 5.5 we will be able to provide an empirical test for this mechanism. The estimation of equation (20) implies that all six payoff parameters governing the electoral support technology can be identified from the the covariation between the electoral support slopes and the appropriate relative counts of different types of media reports.

5.1.3 Identification of the media coverage bias and payoffs for the linear case

Although our identification strategy allows us to recover all of the payoff parameters governing the electoral support technology ($\Delta^T_{eD}, \Delta^T_{eR}, \Delta^S_{eD}, \Delta^S_{eR}, \Delta^S_{cD}, \Delta^S_{cR}$) and to identify the conditional probabilities of a media report about D ($\eta_D(1-\gamma_R)$) and a media report about R ($\eta_R(1-\gamma_D)$), we cannot separately identify the η_p's from the γ_p's.

[7] Notice that in equation (20) $\zeta(t,t+\tau)$ is independent of τ.

The reason is that observed counts of reports are the outcome of both media coverage and successful reporting, and these events are indistinguishable from observed reports only. In equilibrium, observed media reporting on a given candidate results from the interaction between the reporting bias and the media's mixing strategy. But the equilibrium mixing strategy in the linear model moves inversely to the reporting bias making it impossible to disentangle their effects separately. Nevertheless, the model does provide additional structure that allows us to partially identify the η_p's (and thus the γ_p's from equations (3)-(4)). Recall that $\mathbb{E}\left[\hat{\phi}_p\right] \equiv \frac{\hat{\Delta}^T_{ep}}{\hat{\Delta}^S_{ep}+\hat{\Delta}^S_{cp}}$ for $p \in \{D, R\}$. The media's mixing probabilities can be expressed as

$$\gamma_p = 1 - \frac{1}{\eta_{\sim p}}\hat{\phi}_{\sim p}$$

Since $\gamma_p \in (0,1)$, it must be that $\eta_D > \hat{\phi}_D$ and $\eta_R > \hat{\phi}_R$. Furthermore, $\gamma_D + \gamma_R < 1$, which implies that

$$\eta_R < \frac{\hat{\phi}_R}{1 - \frac{1}{\eta_D}\hat{\phi}_D}$$

These three inequalities give us an identified set for (η_D, η_R), which is illustrated in Figure 6 at the estimated values. The hyperbola represents the shape of the constraint in the right-hand side of the inequality above. Finally, we can exploit the candidates' equilibrium mixing probabilities from equations (5)-(6) together with our identified set for the η_p's to obtain an identified set for the relative payoff to the media from reporting about R and D:

$$\frac{\pi_R}{\pi_D} = \frac{\eta_D}{\eta_R}\frac{\hat{q}^*_D}{\hat{q}^*_R} \tag{21}$$

which we can trace on the identified set for (η_D, η_R) at the estimated q_p's. These can be interpreted as bounds on the relative media payoffs from Democratic versus Republican coverage.

5.2 Results for the Linear Case

To sum up, our empirical strategy consists of several steps. On our state-x-race-x-poll-to-poll interval dataset, we first compute the average counts of reported extreme statements for each candidate within a poll-to-poll interval $\hat{\varphi}^e_{p,r,t} \equiv \frac{X^e_{p,r,t}}{\tau_{r,t}}$, and the average counts of total reported statements for each candidate within a poll-to-poll interval $\hat{\phi}_{p,r,t} \equiv \frac{X^e_{p,r,t}}{\tau_{r,t}} + \frac{X^c_{p,r,t}}{\tau_{r,t}}$, where $p \in \{D, R\}$ denotes the candidate's party, r denotes the race, $t \in \{1, 2, ...T_r\}$ denotes the poll-to-poll interval, T_r is the last poll-to-poll interval of race r, and $\tau_{r,t}$ denotes the number of stage games within poll-to-poll interval t for race r -days in the poll-to-poll interval times number of total media outlets ever reporting on the race-. We then estimate the turnout effects of extreme statements by IV on the following linear regression:

$$\frac{\triangle v^D_{r,t} + \triangle v^R_{r,t}}{\tau_{r,t}} = \Delta^T_{eD}\frac{X^e_{D,r,t}}{X^e_{D,r,t} + X^c_{D,r,t}} + \Delta^T_{eR}\frac{X^e_{R,r,t}}{X^e_{R,r,t} + X^c_{R,r,t}} + \delta_r + \sum_{m=1}^{12}\varrho^m_{r,t} + \omega_{r,t} \tag{22}$$

Here the δ_r are race fixed effects. These will capture any unobservable systematic differences that are constant within state or within election year, 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 year. Thus, here we are exploiting exclusively within-race variation, this is, variation in media reporting and electoral support changes along the campaign trail. The $\varrho^m_{r,t}$ are month-of-the-year fixed effects, which are important in this setting given the seasonal nature of the sports data which we use as instruments. As a robustness exercise, we also estimate equation (22) above with a full set of state, year, and state-x-year fixed effects, instead of race fixed effects. Equation (22) shows that to estimate the responsiveness of the turnout margin in these elections we need to look at the total change in electoral support for both candidates. This is natural given that voters that switch allegiances between D and R will not show up in the sum $\triangle v^D_{r,t} + \triangle v^R_{r,t}$. Only voters that switch from not voting (or supporting a third party) to supporting D or R, or the opposite, will show up in the dependent variable of equation (22).

Estimation of equation (20) requires instruments for both right-hand side regressors, that vary across poll-to-poll intervals within a race. As mentioned above, we rely on the occurrence of major sports events. More specifically, 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:

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

where the w^l_{rj} are the fraction of state r's population in counties where a plurality of Facebook users are fans of a team from state j playing in sports league l. Since we do not use the Facebook fan weights for $NCAA$ games, this amounts to the assumption that $w^{NCAA}_{rj} = 0$ if $r \neq j$, and $w^{NCAA}_{rr} = 1$[8]. According to our model, the regressors in equation (22) are the sample analogues for the candidates' mixing probabilities q^*_p, which in equilibrium depend inversely on the media's profitability of reporting on the respective party (see equations (5)-(6)). Thus, our model predicts that the occurrence of sports events, by lowering the profitability of political reporting for the media, should lead to an *increase* in q^*_p, and thus, a relatively larger fraction of extreme reported statements relative to total reported statements. Table 2 presents our main estimates of equation (22) together with the coefficients on our four instruments in each of the two first stages. Reassuringly, there is a systematically positive first-stage relationship between our instruments and each endogenous right-hand side variable in the main equation[9]. The first stage diagnostic statistics reveal that sports events are jointly good predictors of the fraction of extreme to total news articles on a candidate.

Table 2 reports estimates based on the 2-week poll-to-poll interval dataset, and also on the 3-week poll-to-poll interval dataset for comparison, in both cases using our ± 0.25 article score cutoff classification. We also present estimates from OLS models which illustrate the importance of appropriately controlling for the endogeneity of news coverage with other unobserved determinants of electoral support evolution. Columns (1), (2), (5) and (6) present results that include race fixed effects, 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 2, which we believe is important given the nature of our data. In all of our benchmark models, we additionally include a dummy variable for the last poll-to-poll interval in each race, given that we measure the end-of-period electoral support for the last period of each race directly with the election outcome instead of a poll. All of our estimated regressions are also weighted by the square root of the length in days of the poll-to-poll interval, since 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 turnout elasticity Δ^T_{eD} are positive and significant. Interestingly, although the IV estimates for the Republican turnout elasticity Δ^T_{eR} are systematically positive across all of our robustness exercises, they are significantly smaller than the Democratic turnout elasticity, and their standard errors are large. This is not too surprising given the large amount of measurement error in our dependent variable which relies on arguably quite noisy polls. Our estimates are also very similar when using the 2-week and the 3-week poll-to-poll intervals. We believe this first result is important, as it points out that right-wing extreme voters are much less responsive on the turnout margin to campaigning targeted towards them than left-wing extreme voters. The

[8] As additional robustness exercises available upon request, we estimated our main equations using the number of games per day as instruments instead of the log. Results are unchanged.

[9] The partial correlation coefficient for NCAA games on the first stage for $\frac{X^e_{R,r,t}}{X^e_{R,r,t}+X^c_{R,r,t}}$ is negative. Nevertheless, the unconditional correlation (without controlling for the remaining sports) is positive.

reason may be that relatively right-wing citizens across the board already report high turnout margins, especially in comparison to relatively left-wing citizens. It is well known, for example, that senior white males in rural areas, who tend to favor Republicans, have much higher average turnout rates than other demographic groups. As a result, Republican candidates' incentives to target those sectors of the electorate are weak. Democratic campaigns often appear very 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.

With our estimates for $(\Delta^T_{eD}, \Delta^T_{eR})$, we then construct $\hat{D}_{r,t}$ and $\hat{R}_{r,t}$ defined in equation (18). We then estimate the swing voter effects of centrist statements by IV on the regression below:

$$\frac{\hat{D}_{r,t} - \hat{R}_{r,t}}{2}\tau_{r,t} = \Delta^S_{cD}[X^e_{D,r,t} + X^c_{D,r,t}] - \Delta^S_{cR}[X^e_{R,r,t} + X^c_{R,r,t}] + \tilde{\delta}_r + \sum_{m=1}^{12} \tilde{\varrho}^m_{r,t} + \zeta_{r,t} \tag{23}$$

Once again, the $\tilde{\delta}_r$ are race fixed effects, and $\varrho^m_{r,t}$ are month-of-the-year fixed effects. In contrast to equation (22), according to our model the regressors in equation (23) are the sample analogues of $\tau\eta_p(1 - \gamma_{\sim p})$. Thus, total observed news reports on a candidate should not vary as a function of changes in a given media outlet's payoff (recall from equations (3)-(4) that these conditional probabilities only depend on candidates' payoffs). Nevertheless, even if the reporting strategy of a media outlet is pinned down by indifference and thus does not respond to changes in its own payoff, for the distribution of media outlets as a whole, a shift to the profitability of reporting on political campaigns may lead to some outlets to drop out or enter into coverage. Thus, even if the intensive margin of reporting is invariant to media payoff shocks, the extensive margin is likely to respond to sufficiently large shocks. Figure 7 illustrates this idea graphically, by plotting a hypothetical distribution of media outlets potentially covering a Senate race. Outlets are heterogeneous in the payoff they perceive from reporting, and the payoff for each outlet is decreasing in the occurrence of sports events. At any point in time, only outlets with a positive payoff will be active on the race. As salient sports events take place, marginal outlets may drop out from coverage reducing the observed news reports. As a result, sports events can be used as exogenous sources of variation for the two endogenous regressors in equation (23). In this case, the prediction is that sports events should be *negatively* correlated with $[X^e_{p,r,t} + X^c_{p,r,t}]$. Perhaps surprisingly, this is exactly the pattern we find in the first stage estimates, which we present in Table 3.

Table 3 presents our benchmark estimates of equation (23). The table has the same structure as Table 2, with the first four columns based on the 2-week poll-to-poll intervals, and the last four based on the 3-week poll-to-poll intervals. 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 our instruments are systematically negatively correlated with both the Democratic and the Republican total news reports counts, consistent with our discussion above. Panel a then presents our main estimates of the Democratic and Republican swing-voter elasticities in response to centrist media contents. Quite reassuringly, across all models estimated by IV we obtain a positive coefficient on $[X^e_{D,r,t} + X^c_{D,r,t}]$ corresponding to Δ^S_{cD}, and a negative coefficient on $[X^e_{R,r,t} + X^c_{R,r,t}]$ corresponding to Δ^S_{cR}, exactly as implied by equation (23). We consider this pattern of resulting signs to very strongly suggest the validity of our proposed model. The IV estimates in the table show that for the case of the swing centrist electoral support elasticities, these are remarkably similar for Democrats and Republicans. The estimates in column (4), for example, estimate both parameters to be 0.0018, although the one for the Democratic candidate is more precisely estimated. Nevertheless, both Δ^S_{cD} and Δ^S_{cR} are significant at the 5% significance level. Across specifications both the magnitudes and significance of the parameter estimates are very similar, including the OLS estimates.

The next step in our empirical strategy is to back up estimates of the swing voter responses to extreme statements using the equilibrium mixing strategies of the media in equations (3)-(4), together with our estimates $\hat{\phi}_p$ of the conditional reporting probabilities $\eta_p(1 - \gamma_{\sim p})$. We obtain average elasticities by integrating over all our sample as follows:

$$\hat{\Delta}^S_{ep} = \frac{\hat{\Delta}^T_{ep}}{\frac{1}{N}\sum_r \sum_{t=1}^{T_r} \hat{\phi}_{p,r,t}} - \hat{\Delta}^S_{cp} \tag{24}$$

Panel a in Table 4 presents the estimates of all six candidate payoff parameters in our model. The table presents estimates using the 2-week poll-to-poll interval dataset, 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 e 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 swing voter responsiveness to extreme statements is significantly larger for the Democratic candidate than for the Republican candidate. Using the ± 0.25 cutoff estimates, while $\Delta^S_{eD} = 0.0069$, $\Delta^S_{eR} = 0.0018$. This difference in electoral support elasticities across parties has important implications for the dynamics of the Senate races, as it implies that although the turnout gains of extreme statements are larger for Democrats than for Republicans, the cost on the swing voter margin is even larger. Our estimates suggest that centrist voters are on average very sensitive to media contents suggesting relatively extreme Democratic statements. In equilibrium, the implication of this pattern of parameters is that candidates from both parties are covered by the media at similar rates. Panel b presents our non-parametric estimates of the implied average (across all races) equilibrium mixing probabilities of candidates, and the conditional probabilities of media reporting.

5.3 LDA Score Article Classification

[Results here will be table 5]

5.4 Payoff Heterogeneity

The IV estimates of the payoff parameters $(\Delta^T_{eD}, \Delta^T_{eR}, \Delta^S_{cD}, \Delta^S_{cR}, \Delta^S_{eD}, \Delta^S_{eR})$ described above are average effects across states, 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 payoff parameters across different races. We do so in a straightforward parametric way by allowing the payoff parameters we recover from equations (22) and (23) to depend on race characteristics, which we consider may be important sources of heterogeneity. We explore four sources of variation in candidate payoff parameters across races. Differences in 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 running. More specifically, we assume that each of the payoff elasticities is a linear function of one of these four characteristics: $\Delta^T_{ep} = \alpha^T_{ep} + \beta^T_{ep} K_{r,t}$ and $\Delta^S_{cp} = \alpha^S_{cp} + \beta^S_{cp} K_{r,t}$ for $p \in \{D, R\}$. We estimate equations (22) and (23) by IV including the interaction terms that arise by allowing the payoff parameters to depend on these characteristics, instrumenting the interaction terms with the respective interactions between our sports events instruments and $K_{r,t}$ in each case. We subsequently recover the respective estimates for the $\Delta^S_{ep}(K)$, making decile bins for $K_{p,r}$ and computing the integration in equation (24) restricted to the set $\Gamma_K = \{(r,t) : K_{r,t} \in K\}$ of observations falling in each decile:

$$\hat{\Delta}^S_{ep}(K) = \frac{\hat{\Delta}^T_{ep}(K_{p,r})}{\frac{1}{|\Gamma_K|}\sum_r \sum_{t=1}^{T_r} \hat{\phi}_{p,r,t}} - \hat{\Delta}^S_{cp}(K_{p,r}), \qquad (r,t) \in \Gamma_K.$$

5.4.1 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 the distribution using the average of the democratic registration share of the electorate and the most recent Democratic presidential election results. For states without partisan registration, we use only the presidential election results. The results for this exercise are presented in column (1) of Table 6, and graphically in panel a of Figure 8, which plots the coefficients along the deciles of the distribution of the Democratic voter registration. These and all other estimates in the table use our benchmark 2-week poll-to-poll interval dataset based on the ± 0.25 article score cutoff and are estimated by IV using all sports and interactions of sports and voter registration as instruments. Panel a presents the estimates for the turnout elasticities from equation (22), while panel b presents the estimates for the swing voter elasticities from equation (23). Although the patter of signs implies that Δ^T_{eD} decreases while Δ^T_{eR} increases with democratic registration, we cannot estimate this effect precisely. In contrast, there appears to be a strong and significant decreasing relationship between Democratic registration and Δ^S_{cD}. This is, in states with relatively few Democratic voters, these voters appear to be much more responsive to centrist media coverage favoring the Democratic candidates. Except for this result, the partisan distribution of the electorate does not appear to be a major source of heterogeneity in electoral response elasticities across states or over time.

5.4.2 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 payoff parameters in equations (22) and (23) to depend on the time between the initial date of the poll-to-poll interval and the day of the general election. Because the time to election day varies within race, we also include the time to election as a covariate in the equation. Our main results for this exercise are presented in column (2) of Table 6. They show no statistically significant evidence for this possibility. Overall, the Δ's appear to be stable along the campaign trail.

5.4.3 State of the Race: A Dynamic Game

Another way of relaxing the assumption that payoff parameters are constant over time is by exploring the possibility that they depend on an endogenous state variable, making the game in practice a dynamic one rather than a repeated one. In an electoral campaign setting, it is possible that both candidates' and the media's incentives change along the campaign, 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 make risky statements when he is performing badly in the polls. Similarly, it may be that the electoral cost of bad press grows as election day approaches, making politicians more cautions in the final days of the campaign. Similarly, the media's profitability of covering political campaigns may be higher as the election day approaches. To explore this possibility and its implications regarding the robustness of our results, we allow for payoff parameters to depend on a state variable. In principle, this state variable could be a high dimensional object including many possible characteristics of the environment that may change over time and alter incentives. In practice, the finite nature of our data requires us to limit the dimensionality of the state variable.

Thus, we assume that payoff parameters are a function of the current state of the race as measured by the margin between candidates in the polls at the beginning of the poll-to-poll interval. 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. Given the finite horizon of the game and the unique stage-game Nash equilibrium, analogously to the repeated game, the dynamic game only has one Subgame Perfect Equilibrium that prescribes playing the mixed-strategy Nash equilibrium of the stage game given the value of the state variable at every period. As a result, equilibrium play is independent across periods conditional on the state variable, and we can replicate our estimation strategy above. Similar to the time-to-election exercise above, the race tightness varies over time within a race, so we also include it separately as a covariate.

Results for this exercise are presented in column (3) of Table 6 and in panel b of Figure 8. Overall, we do not find a strong relationship between the state of the race and the electoral support elasticities, except for the centrist swing response for Republicans Δ^S_{cR}, which appears to be higher in more competitive periods of a race. This suggests that Republicans may have stronger incentives that Democrats to send more centrist messages as races become closer. Nevertheless, the results from this exercise should be taken with caution given that race tightness is an endogenous outcome, and we are including it as a covariate in our econometric exercise.

5.4.4 Incumbent Running

Our final exercise looking at payoff heterogeneity explores whether electoral support sensitivity is different in races where incumbents are running. Thus, we allow the Δ's to depend on a dummy variable for elections with a running incumbent. Results for this exercise are presented in column (4) of table 6. We find no evidence of differences in candidate payoff parameters in races with or without incumbents. We should notice, nevertheless, that this test may not have much power given that 75% of all senate races in our sample are races with a running incumbent.

5.5 Robustness Exercises and Specification Tests

5.5.1 Robustness Exercises

In Tables 7 and 8 we present a subset of additional econometric exercises on the linear model showing the robustness of our main findings to several variations. Table 7 reports IV results for alternative specifications based on the 2-week poll-to-poll interval dataset. First, we estimate equations (22)-(23) 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 electoral support, in contrast to all other periods in which beginning and end-of-period electoral support are measured with polls. Any systematic biases in polls would be reflected in the electoral support changes for the last poll-to-poll intervals. 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. Although unlikely given that poll-to-poll intervals cover an average of 30 days, if sports events that happen very near the 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. This is, of course, a problem only for the last poll-to-poll interval in each race. Excluding these observations reduces the sample size from 2134 to 1871. As column (1) in Table 7 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 that include days 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 of importance to distinguish between both regimes. Notice that for most races, even during primary campaign days pollsters are already collecting polls asking about electoral support for the candidates, which eventually become the Democratic and Republican nominees, suggesting that in most cases the bipartisan race is already implicitly being played even before the primary outcome is known. As column (2) in table 7 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 7 we estimate our main linear 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. Given the relatively arbitrary nature of our classification of centrist versus extreme article contents, it is reassuring that our main results are unaltered.

In table 8 we then look at the sensitivity of our estimates to using alternative subsets of our sports events instruments in what amounts to over-identification exercises. We do this both on the 2-week poll-to-poll interval dataset (columns (1)-(5)) and in the 3-week poll-to-poll interval dataset (columns (6)-(10)), always using the ± 0.25 article score cutoff classification. Panel Ia presents the parameter estimates for equation (22), while panel Ib presents the parameter estimates for equation (23). Panels IIa and IIb present diagnostic statistics for the respective first stages, using the different subsets of instruments. In the table we present results that omit one by one each of the four sports events from the instrument set, and also include an even more demanding specification where we omit both MLB and NBA games simultaneously, making the models in columns (5) and (10) 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, and in fact, we cannot reject the null of no joint significance in 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 remains unchanged relative to our baseline model estimates.

5.5.2 Testing Assumptions

Tables 9 and 10 present further estimation results where we probe some of the key assumptions behind our matching pennies game. Table 9 presents evidence suggesting that, as implied by our discussion about media coverage changes in the extensive-margin illustrated in Figure 7, the number of media outlets covering a senate race does vary systematically with sports events. We are able to test this assumption relying on the articles data collected, which also includes the outlet names for each news piece, allowing us to compute the number of different outlets producing news for a given race over time. Table 9 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, on each of our sports events instruments. The table presents results both for the 2-week and 3-week poll-to-poll interval datasets. All regressions show evidence of a significant and negative within-race correlation between game frequencies and media outlet coverage.

Finally, we are also able to indirectly test the assumption that the timing of polls can be considered exogenous relative to the evolution of each senate race. Recall this is a key assumption we rely on to justify the construction of our poll-to-poll intervals. We test this assumption by exploring the correlation between the frequency of actual polls in our dataset with how tight the race is at any given point in time. In Table 10 we run OLS regressions of the number of actual polls we use to construct the average end-poll of each poll-to-poll interval, with or without normalizing it by the length of the interval in days, on the measure of race tightness that we used in the exercise described in section 5.4. We do this both in the 2-week and 3-week poll-to-poll interval datasets. As the table shows, we find no correlation between poll frequencies and the state of the race, suggesting that in the aggregate, pollsters are not releasing polls as a function of how the race is evolving. We see these results, together with our use of alternative poll-to-poll windows, as reassuring.

6 The Repeated Game in the General Case

The empirical strategy developed above focused on a linear technology. This allows us to illustrate in a transparent way the sources of variation we exploit to identify the different types of voter responses to candidate statements and media coverage. Nevertheless, this linear technology can only be a locally linear approximation of the DGP for the evolution of poll or vote shares. Thus, to assess the validity of our previous findings as well as to provide a more general analysis, in this section we model the distribution of electoral support shares (v_{t+1}^D, v_{t+1}^R) as a random vector drawn from a Dirichlet distribution every period, that depends on the actions of candidates and the media. This allows us to restrict the support of the electoral support shares to the unit simplex. We then develop a minimum-distance estimator based on the moments of the marginal distributions of the electoral support shares that allows us to recover all the payoff parameters for the candidates that map into elasticities that can be compared with the ones we recovered in section 5.2. Formally, we assume that the electoral support shares are drawn every period from a Dirichlet distribution with density function

$$f(v_{t+1}^D, v_{t+1}^R|\mathbf{s}) = \frac{1}{B(\alpha_t^D, \alpha_t^R, \alpha^O)} \left(v_{t+1}^D\right)^{\alpha_t^D - 1} \left(v_{t+1}^R\right)^{\alpha_t^R - 1} \left(v_{t+1}^O\right)^{\alpha_t^O - 1} \tag{25}$$

where $v_{t+1}^O = 1 - v_{t+1}^D - v_{t+1}^R$, $B(\alpha_t^D, \alpha_t^R, \alpha^O)$ is the Beta function, and

$$\alpha_t^p \equiv v_t^p + \tilde{\Delta}_{ep}^T \mathbf{1}\{s^p(t) = e, \chi^p(t) = 0\} + \left(\tilde{\Delta}_{ep}^T - \tilde{\Delta}_{ep}^S\right) \mathbf{1}\{s^p(t) = e, \chi^p(t) = 1\}$$

$$+\tilde{\Delta}_{e\sim p}^S \mathbf{1}\{s^{\sim p}(t) = e, \chi^{\sim p}(t) = 1\} + \tilde{\Delta}_{cp}^S \mathbf{1}\{s^p(t) = c, \chi^p(t) = 1\} - \tilde{\Delta}_{c\sim p}^S \mathbf{1}\{s^{\sim p}(t) = c, \chi^{\sim p}(t) = 1\}$$

We additionally assume that $\alpha_t^O = 1 - v_t^D - v_t^R$. Because the marginal distributions of a Dirichlet are Beta distributions, this amounts to assuming that in the absence of any actions by candidates or the media, the expected vote share for each candidate at time $t+1$ would be the observed vote share at time t (See Appendix B). In the general case, the stage game G has a unique mixed-strategy equilibrium, which we characterize below.

Proposition 2. *Assume $\eta_p \pi_p > k$. The normal form game between candidates and the media does not have a pure-strategy equilibrium. The unique mixed strategy equilibrium is given by:*

$$\gamma_R^*(\eta_D, \eta_R; \tilde{\Delta}, v_{t-1}^D, v_{t-1}^R) = \frac{(D+F)A - (A+B)D}{(A+C)(D+F) - (A+B)(D+E)} \tag{26}$$

$$\gamma_D^*(\eta_D, \eta_R; \tilde{\Delta}, v_{t-1}^D, v_{t-1}^R) = \frac{(A+C)D - (D+E)A}{(A+C)(D+F) - (A+B)(D+E)} \tag{27}$$

where A, B, C, D, E, F are defined in Appendix A, and (q_D^*, q_R^*) are given by equations (5) and (6) in Proposition 1. Furthermore, because the stage-game has a unique Nash equilibrium, the only Subgame Perfect Equilibrium of the finitely repeated game G^T is to play the unique stage-game Nash equilibrium every period.

Proof. See Appendix A.

□

Proposition 2 makes it explicit that differently from the linear case, in the more general model the equilibrium mixing probabilities for the media depend on both reporting biases and on the current state of electoral support. Although the interpretation of the $\tilde{\Delta}$'s as the responses of the electoral support to different outcomes is similar to the linear model, the exact interpretation (and thus, the magnitudes of these parameters) is different, given that the marginal effects on the expected voter shares are no longer the Δ's themselves. It is for this reason that we denote the parameters in the general model with a $\sim$ superscript.

6.1 Identification of the electoral performance technology in the general model

We proceed similarly to section 5.2, and use the law of iterated expectations recursively to first obtain an expression for the sum of Democratic and Republican electoral support, which does not depend on parameters related to the swing voter margin. This allows us to obtain a moment condition that only depends on the parameters related to the turnout margin (See Appendix B):

$$\mathbb{E}[v_{r,t}^D + v_{r,t}^R | v_{r,t-1}^D, v_{r,t-1}^R] = 1 - \frac{1 - v_{t-1}^D - v_{t-1}^R}{(1+\tilde{\Delta}_{eD}^T)^{X_{D,r,t}^e + N_{D,r,t}^e}(1+\tilde{\Delta}_{eR}^T)^{X_{R,r,t}^e + N_{R,r,t}^e}} \tag{28}$$

Notice the above equation is exact only under the assumption that in no period a simultaneous realization of an e statement by both candidates is realized. This would require a slight modification of the condition above, but would also require us to observe the counts of joint realizations of outcomes for both candidates each period. The computational burden would increase dramatically, and given that the number of observed statements is small relative to the size of the average poll-to-poll interval, our assumption is of little consequence. Denote the right-hand side of equation (28) by $m_{r,t}^T(\boldsymbol{v}_{r,t-1}, \boldsymbol{X}_{r,t}, \boldsymbol{N}_{r,t}; \tilde{\boldsymbol{\Delta}}^T)$, and $\tilde{\boldsymbol{\Delta}}^T = (\tilde{\Delta}_{eD}^T, \tilde{\Delta}_{eR}^T)$. $\mathbb{E}\left[\mathbf{z}_{r,t}' \mathrm{g}_{r,t}^T(\boldsymbol{y}_{r,t}, \boldsymbol{N}_{r,t}; \tilde{\boldsymbol{\Delta}}^T)\right] = \mathbf{0}$ is thus a valid moment condition for a minimum distance estimator, where $\mathrm{g}_{r,t}^T(\boldsymbol{y}_{r,t}, \boldsymbol{N}_{r,t}; \tilde{\boldsymbol{\Delta}}^T) = v_{r,t}^D + v_{r,t}^R - m_{r,t}^T(\boldsymbol{v}_{r,t-1}, \boldsymbol{X}_{r,t}, \boldsymbol{N}_{r,t}; \tilde{\boldsymbol{\Delta}}^T)$, $\boldsymbol{y}_{r,t} = (\boldsymbol{v}_{r,t}, \boldsymbol{v}_{r,t-1}, \boldsymbol{X}_{r,t})$ is all the observed data, and $\mathbf{z}_{r,t} = [z_{r,t}^{NFL}, z_{r,t}^{NLB}, z_{r,t}^{NBA}, z_{r,t}^{NCAA}]$ is our instruments vector. This moment condition provides the main source of variation for identifying the turnout effects. We can additionally construct moments to estimate the swing voter parameters in a similar way. Appendix B shows we can express the expected electoral support share of each candidate $p \in \{D, R\}$ at the end of the poll-to-poll interval t, conditional on the electoral support share at the beginning of the interval, and realizations of candidates and media actions during the interval up to a second order error:

$$\mathbb{E}[v_{r,t}^p | v_{r,t-1}^p] = \frac{v_{t-1}^p + \left(\tilde{\Delta}_{ep}^T - \tilde{\Delta}_{ep}^S\right) X_{p,r,t}^e + \tilde{\Delta}_{e\sim p}^S X_{\sim p,r,t}^e + \tilde{\Delta}_{cp}^S X_{p,r,t}^c - \tilde{\Delta}_{c\sim p}^S X_{\sim p,r,t}^c + \tilde{\Delta}_{ep}^T N_{p,r,t}^e}{(1+\tilde{\Delta}_{eD}^T)^{X_{D,r,t}^e + N_{D,r,t}^e}(1+\tilde{\Delta}_{eR}^T)^{X_{R,r,t}^e + N_{R,r,t}^e}} + O\left(\tilde{\Delta}^2\right) \tag{29}$$

where $\tilde{\Delta} = max\{\tilde{\Delta}_{eD}^T, \tilde{\Delta}_{eD}^S, \tilde{\Delta}_{eR}^T, \tilde{\Delta}_{eR}^S, \tilde{\Delta}_{cD}^S, \tilde{\Delta}_{cR}^S\}$. Equation (29) shows that in the general model, which fully respects the $[0, 1]$ range for the electoral support random variables, changes in electoral support for party p naturally can no longer be independent of the turnout responses for the opposing party. Based on the two expectations above, we can recover the remaining four swing-voter electoral support elasticities $\tilde{\boldsymbol{\Delta}}^S = (\tilde{\Delta}_{eD}^S, \tilde{\Delta}_{eR}^S, \tilde{\Delta}_{cD}^S, \tilde{\Delta}_{cR}^S)$. Denoting the right-hand side of equations (29) by $m_{p,r,t}(v_{r,t-1}^p, \boldsymbol{X}_{r,t}, \boldsymbol{N}_{r,t}; \tilde{\boldsymbol{\Delta}})$ respectively, $\mathbb{E}\left[(\mathbf{I}_2 \otimes \mathbf{z}_{r,t})' \mathbf{g}_{r,t}^S(\boldsymbol{y}_{r,t}, \boldsymbol{N}_{r,t}; \tilde{\boldsymbol{\Delta}})\right] = \mathbf{0}$ are valid moment conditions, where

$$\mathbf{g}_{r,t}^S(\boldsymbol{y}_{r,t}, \boldsymbol{N}_{r,t}; \tilde{\boldsymbol{\Delta}}) = \left[\begin{array}{c} v_{r,t}^D - m_{D,r,t}(v_{r,t-1}^D, \boldsymbol{X}_{r,t}, \boldsymbol{N}_{r,t}; \tilde{\boldsymbol{\Delta}}),\ v_{r,t}^R - m_{R,r,t}(v_{r,t-1}^R, \boldsymbol{X}_{r,t}, \boldsymbol{N}_{r,t}; \tilde{\boldsymbol{\Delta}}) \end{array}\right]'.$$

We can stack all these residuals into the vector

$$\mathbf{g}_{r,t}(\boldsymbol{y}_{r,t}, \boldsymbol{N}_{r,t}; \tilde{\boldsymbol{\Delta}}) = \begin{bmatrix} \mathrm{g}_{r,t}^T(\boldsymbol{y}_{r,t}, \boldsymbol{N}_{r,t}; \tilde{\boldsymbol{\Delta}}^T) \\ \mathbf{g}_{r,t}^S(\boldsymbol{y}_{r,t}, \boldsymbol{N}_{r,t}; \tilde{\boldsymbol{\Delta}}) \end{bmatrix} \tag{30}$$

In equation (30) above, the N_p^e 's are unobserved. Nevertheless, the conditional probability distributions for extreme unobserved statements are given by equation (9), which we use to integrate over the conditional distribution of $\boldsymbol{N}_{r,t}$:

$$\hat{\mathbf{g}}_{r,t}(\boldsymbol{y}_{r,t};\tilde{\boldsymbol{\Delta}}) = \sum_k \hat{\mathbb{P}}(N^e_{D,r,t}=k|X^e_{D,r,t},X^c_{D,r,t})\sum_l \hat{\mathbb{P}}(N^e_{R,r,t}=l|X^e_{R,r,t},X^c_{R,r,t})\mathbf{g}_{r,t}(\boldsymbol{y}_{r,t},k,l;\tilde{\boldsymbol{\Delta}})$$

Our minimum distance estimator takes the form

$$min_{\tilde{\boldsymbol{\Delta}}}\left(\sum_{r=1}^N\sum_{t=1}^{T_r}\mathbf{Z}'_{r,t}\hat{\mathbf{g}}_{r,t}(\boldsymbol{y}_{r,t};\tilde{\boldsymbol{\Delta}})\right)'\left(\sum_{r=1}^N\sum_{t=1}^{T_r}\left(\frac{\tau_{r,t}}{\tau_{max}}\right)^{\frac{1}{2}}\mathbf{Z}'_{r,t}\mathbf{W}_{r,t}\mathbf{Z}_{r,t}\right)^{-1}\left(\sum_{r=1}^N\sum_{t=1}^{T_r}\mathbf{Z}'_{r,t}\hat{\mathbf{g}}_{r,t}(\boldsymbol{y}_{r,t};\tilde{\boldsymbol{\Delta}})\right) \tag{31}$$

where the $\left(\frac{\tau_{r,t}}{\tau_{max}}\right)^{\frac{1}{2}}$ are weights analogous to those employed for the estimation of the linear model, giving more importance to longer poll-to-poll intervals, and defining $\mathbf{Z}_{r,t} = \mathbf{I}_3 \otimes \mathbf{z}_{r,t}$. The weighting matrix in expression (31) is given by $\mathbf{W}_{r,t} = \hat{\mathbf{g}}^0_{r,t}(\boldsymbol{y}_{r,t};\hat{\tilde{\boldsymbol{\Delta}}}_0)\hat{\mathbf{g}}^0_{r,t}(\boldsymbol{y}_{r,t};\hat{\tilde{\boldsymbol{\Delta}}}_0)'$, and $\hat{\mathbf{g}}^0_{r,t}(\boldsymbol{y}_{r,t};\hat{\tilde{\boldsymbol{\Delta}}}_0)$ are residuals coming from a first-stage estimation, thus allowing for arbitrary correlation across the errors for each candidate within a race[10]. Different from the linear model strategy, here we can identify all the swing voter response parameters simultaneously without relying on the implied equilibrium mixing strategies. Rather, the identification comes directly from the covariation in counts of extreme and centrist reports for each candidate with the slope of the electoral support of both candidates within poll-to-poll intervals[11]. In practice, we allow the $\tilde{\boldsymbol{\Delta}}$'s to depend linearly on the Democratic registration share as in section 5.4 which allows us to obtain a better model fit, and to perform counterfactual exercises of interest regarding changes in the partisan distribution of voters.

6.2 Identification of the media coverage bias and payoffs on the general model

As a final step in our empirical strategy on the general model, we use the equilibrium mixing probabilities defined in Proposition 2, evaluated at our estimated $\tilde{\boldsymbol{\Delta}}$ to point identify (η_D, η_R). The identification of these media reporting biases follows a similar logic to the one developed for the linear case, except that in this case we achieve point identification. Of course, this result illustrates that identification of the media coverage biases comes exclusively from the nonlinearities in the equilibrium mixing probabilities for the media in the general model. Using the fact that $\hat{\phi}_{p,r,t} = \eta_p(1-\gamma^*_{\sim p})$, equations (26)-(27) imply that

$$\hat{\phi}_{p,r,t} = \eta_p\left[1-\gamma^*_{\sim p}(\eta_D,\eta_R;\hat{\tilde{\Delta}},v^D_{r,t},v^R_{r,t})\right]$$

This is a system of two non-linear equations in two unknowns (η_D, η_R), which we can average across all races and poll-to-poll intervals and invert to obtain the estimated media coverage biases. $(\hat{\eta}_D, \hat{\eta}_R)$ are given by the root of the system

$$\sum_{r=1}^N\sum_{t=1}^{T_r}\begin{bmatrix}\hat{\phi}_{D,r,t}-\hat{\eta}_D\left[1-\gamma^*_R(\hat{\eta}_D,\hat{\eta}_R;\hat{\tilde{\Delta}},v^D_{r,t},v^R_{r,t})\right]\\ \hat{\phi}_{R,r,t}-\hat{\eta}_R\left[1-\gamma^*_D(\hat{\eta}_D,\hat{\eta}_R;\hat{\tilde{\Delta}},v^D_{r,t},v^R_{r,t})\right]\end{bmatrix}=\begin{bmatrix}0\\0\end{bmatrix} \tag{32}$$

Finally, we can go back to equation (21) to point identify the relative payoffs for the media:

$$\frac{\pi_R}{\pi_D} = \frac{\hat{\eta}_D}{\hat{\eta}_R}\frac{\hat{q}^*_D}{\hat{q}^*_R} \tag{33}$$

[10]In practice,

$$\hat{\tilde{\boldsymbol{\Delta}}}_0 = argmin_{\tilde{\boldsymbol{\Delta}}}\left(\sum_{r=1}^N\sum_{t=1}^{T_r}\mathbf{Z}'_{r,t}\hat{\mathbf{g}}_{r,t}(\boldsymbol{y}_{r,t};\tilde{\boldsymbol{\Delta}})\right)'\left(\sum_{r=1}^N\sum_{t=1}^{T_r}\left(\frac{\tau_{r,t}}{\tau_{max}}\right)^{\frac{1}{2}}\mathbf{Z}'_{r,t}\mathbf{Z}_{r,t}\right)^{-1}\left(\sum_{r=1}^N\sum_{t=1}^{T_r}\mathbf{Z}'_{r,t}\hat{\mathbf{g}}_{r,t}(\boldsymbol{y}_{r,t};\tilde{\boldsymbol{\Delta}})\right)$$

[11]Although a consistent estimator can also be derived by first estimating the turnout extreme elasticities based on equation (28) and then estimating the swing-voter centrist elasticities based on equation (29) using the estimates from (28), the efficient estimator estimates all parameters simultaneously as described above.

6.3 Results for the General Case

Our minimum distance estimates of the general model are presented in Table 11, using our two alternative article score cutoff classifications. Column (1) presents estimates for the ±0.25 cutoff, and column (2) presents estimates for the ±0.5 cutoff. Standard errors are computed using the delta method based on the analytic variance-covariance matrix of the Minimum Distance Estimator. The magnitudes of the estimates are remarkably similar between them. Instead of presenting the $\tilde{\Delta}$ parameters directly, which are not directly comparable with the Δ's from the linear model, we present the comparable average marginal effects of different kinds of stage-game outcomes. Each of the rows in panel a of Table 10 reports the marginal change in the expected voter share of a given candidate, from an extreme unreported statement, a centrist reported statement, and an extreme reported statement, respectively. These are similar in magnitude to the analogous estimates for the linear model presented in Table 4, suggesting that the local linear model is a reasonable approximation to the DGP for the electoral support evolution. Turnout effects are smaller for the Republican candidate, swing-voter centrist effects are of similar magnitude across candidates, and swing-voter extreme effects are almost three times larger for the Democratic candidates.

As mentioned in the previous section, the non-linearities in the equilibrium mixing strategies of the media that arise in the general model are sufficient to point identify the media biases (η_d, η_R). Panel b in Table 11 presents these estimates. Reassuringly, using either article score cutoff definition, these parameters fall inside the identified set for them we obtained from the linear model (see Figure 6). Although similar in magnitude for the Democratic and the Republican reporting, η_D is estimated to be larger than η_R (we cannot reject the hypothesis that they are equal). Nevertheless, recall the observed differences in our estimates of the candidates' equilibrium mixing strategies q_p^* imply the Democratic candidates on average play e with a higher frequency than the Republican candidates (see panel b in Table 4). This fact together with our estimates of media payoff bias imply, using equation (33), that the media's relative payoff from reporting on the republican candidates is lower than when reporting on the Democratic candidate (our estimate of π_R/π_D is 0.72). Recall that in our model, the π_p's represent the profitability of reporting about extreme statements by candidates from party p. One possible reason why our estimates suggest that $\pi_D > \pi_R$ is that Republican audiences, which are known to be wealthier on average, have a higher willingness to pay for news that are likely to hurt Democratic candidates, than Democratic audiences who may consume less news. This is, of course, just one possible interpretation of the finding.

6.4 Some Counterfactual Exercises

Our parameter estimates allow us to explore the equilibrium implications of several different changes in the economic environment, which may prove of interest. Here we propose exploring two counterfactual exercises. First, we estimate the effect on the whole distribution of election outcomes of a change in the partisan distribution of the electorate, as proxied by an increase in the fraction of registered democrats and a concomitant decrease in the fraction of registered Republicans. This experiment is of particular interest given the recent demographic trends in the U.S. population, which some argue are favoring the Democratic party in the medium run. In a second experiment, we explore the impact over the distribution of election outcomes, of a change in relative media profitability that makes it more profitable to cover one party relative to the other.

We perform these counterfactual exercises through a simulation algorithm based on our parameter estimates. First, notice that we have only identified the relative media payoffs, and that k is not identified within our estimation. Thus, we require an additional normalization to be able to simulate senate races. We do so by normalizing $\pi_R = 1$, which immediately implies that $k = \eta_R q_R$ from the equilibrium mixing strategy for candidate R. We then use the parameter estimates in Table 10, together with this value for k, to perform the simulation exercises. For each state we fix the number of media outlets O_s covering the race to be equal to the average number of media outlets for that state across years in our data. We additionally fix the number of campaign days to be 300. Thus, for each state, there are $300O_r$ sequential stage games being played. Using the equilibrium mixing strategies implied by the game's structural parameters, we then draw sequences of actions $(s_D, s_R, s_m) \in \{c, e\}^2 \times \{F_D F_R, F_D N_R, N_D F_R\}$ and sequences of media reporting success indicators (χ_D, χ_R) that induce realized outcome paths, which period by period determine the evolution of electoral support for each candidate. We obtain the electoral support realizations for every stage game by drawing from the Dirichlet distribution in equation (25), at the realized actions for that period and the current electoral support vector. We simulate 1000 sequences for each race, assuming that the initial electoral support $v^p_{r,0}$ is given by the average electoral support of party p in state r across all election cycles in our data. This allows us to compute an average time-T election outcome for each state, averaging the end date electoral support over the 1000 simulations. We do this at the sample data and re-do the simulation under the counterfactual scenario. This allows us to compare the expected election outcomes predicted by the model in both situations.

6.4.1 A Change in the Partisan Distribution of the Electorate

In our first simulation exercise we assume that Democratic voter registration increases by 10 percentage points (and concomitantly the republican registration decreases by 10 percentage points) in each state. This directly maps into a change in the $\tilde{\mathbf{\Delta}}$'s under which we run the simulation. In particular, it implies a decrease in $\tilde{\Delta}^T_{eD}$ $\tilde{\Delta}^S_{cD}$, and an increase in $\tilde{\Delta}^T_{eR}$ and $\tilde{\Delta}^S_{cR}$. Figure 9 presents a scatterplot illustrating the main results from this exercise. The x-axis plots the (average across simulations) Democratic margin at time T across the races for all 50 states at the observed voter registration. The y-axis plots the corresponding (average across simulations) Democratic margin at time T at the higher Democratic registration assumed by the counterfactual. The figure illustrates a compression in the distribution of the democratic electoral performance relative to the benchmark. In the most Republican states, Democratic candidates do better under the counterfactual, while in the most Democratic states they do worse. This is driven by the equilibrium implications of the model.

The increase in the Democratic fraction of voters leads to a lower electoral support elasticity to centrist statements from Democrats, and a higher electoral support elasticity to extreme statements by Republicans (see Table 11). In turn, this implies that for both Republican and Democratic candidates, incentives to shift their attention towards their more extreme constituencies becomes stronger. For the former the reason is that extreme constituencies deliver a larger marginal payoff from extreme statements; for the latter the reason is that centrist-targeted statements are now less effective. In equilibrium, this does not alter the rates at which candidates send differentiated messages, but it does alter the rates at which the media reports on them. In particular, it requires the media to cover at higher rates both Republican and Democratic candidates (as to maintain the candidates' indifference). In initially more republican states, the increased media attention to the Democratic candidates is counterbalanced by a relatively large increase in the fraction of Democratic voters. In contrast, in initially more Democratic states, while the proportional increase in democratic voters is relatively small, the responsiveness of Republican voters becomes larger at both the turnout and swing-voter margins, leading to improved performance by Republican candidates.

Of course, it is hard to argue that in the face of a significant increase in the fraction of democratic voters and its implied change in the electoral support elasticities, the media's relative payoffs to covering democratic versus republican candidates would remain unchanged. This is a maintained assumption in the counterfactual, as we are not allowing the π_p's to depend on the partisan distribution of voters. As such, this exercises must be interpreted taking this limitation into account.

6.4.2 A Change in Relative Media Payoffs

In an additional exercise, we explore the implications of an exogenous change in the relative media payoffs, captured by the π_p's in our model. Our counterfactual exercise will assume that π_D increases by 25%. Given our payoff normalization $\pi_R = 1$, from Table 11 and our estimates for (η_D, η_R) and (q_D, q_R), the implied π_D given $\pi_R = 1$ from equation(33) is 1.4. Thus, a 25% increase in the relative profitability of reporting on the Democratic candidates would imply a $\pi'_D = 1.75$. In contrast to the previous counterfactual, in this case the media's mixing strategies are unaltered. The only change in equilibrium behavior is a fall in the Democratic candidate's mixing strategy q_D, which we use for the simulation of senate races across all states. Figure 10 presents a scatterplot illustrating the results for this exercise. In this case, the increased profitability of Democratic coverage disciplines the Democratic candidates by reducing the rate at which they target extreme audiences. Because the rate at which the media is reporting is unaltered, this translates into an increase in media reports of centrist statements by Democrats that yields electoral gains on the swing voter margin that are larger than the losses associated with the lower frequency of extreme statements on the turnout margin. As a result, Democratic candidates improve their electoral prospects across the board, which can be seen in the figure. The gains for Democrats are larger in initially less Democratic states.

7 Concluding Remarks

In this paper we develop a framework to study how the interaction between the media's incentives to cover and report on electoral campaigns, and candidates' incentives to target different groups of voters, shape both the kinds of statements and policy positions that politicians adopt when running for office, and the evolution of the campaigns themselves. We do this by proposing a very simple game-theoretic model of the interaction between the media and candidates, where the media gains from reporting relatively extreme statements made by candidates on the campaign trail, while candidates benefit from being reported by the media when making statements targeted towards the center of the ideological spectrum. Nevertheless, because candidates have incentives to target relatively extreme constituents, this strategic environment forces both the media and the candidates to play mixed strategies. The media randomizes on its coverage decision, while candidates randomize on the type of statements made along the campaign trail.

The simple structure of the game allows us to propose a strategy for the estimation of this discrete game of complete information, and to test for the empirical relevance of this strategic environment. We do so using information on U.S. Senate races in the last 30 years, which are politically salient and thus, systematically covered by the media. We show how data on the evolution of the campaigns (poll data), together with election results and media coverage information, can be used to estimate the key parameters of the game. We estimate both a linear approximation and a more general version of the game, exploiting exogenous variation in media coverage incentives coming from the occurrence of salient sports events. The estimated parameters can then be used to explore the effects of different counterfactual policies and scenarios. Our results are broadly consistent with the mechanism we propose as being important for understanding the nature of bipartisan electoral competition in a setting where the media plays a key role. Moreover, our model and results provide a novel way of thinking about how and why the media matters in politics, and a specific channel for how it can shape politicians' behavior.

References

Agranov, Marina, Jacob Goeree, Julian Romero, and Leeat Yariv, "What Makes Voters Turn Out: The Effects of Polls and Beliefs," October 2013. Caltech.

Alesina, Alberto and Richard Holden, "Ambiguity and Extremism in Elections," June 2008.

Ansolabehere, Stephen, Roy Behr, and Shanto Iyengar, *The Media Game: American Politics in the Television Age*, Longman, 1992.

Aragones, Enriqueta and Thomas Palfrey, "Mixed Equilibrium in a Downsian Model with a Favored Candidate," *Journal of Economic Theory*, 2002, *103*, 131–161.

— , — , **and Andrew Postlewaite**, "Political Reputations and Campaign Promises," *Journal of the European Economic Association*, June 2007, *5* (4), 846–884.

Bajari, Patrick, Han Hong, and Stephen Ryan, "Identification and Estimation of a Discrete Game of Complete Information," *Econometrica*, 2010, *78* (5), 1529–1568.

Bartels, Larry, "Politicians and the Press: Who Leads, Who Follows," September 1996. Princeton.

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

Besley, Timothy and Andrea Prat, "Handcuffs for the Grabbing Hand? Media Capture and Government Accountability," *American Economic Review*, 2006, *96* (3), 720–736.

Boleslavsky, Raphael and Christopher Cotton, "Information and Extremism in Elections," *American Economic Journal: Microeconomics*, 2015, *7* (1), 165–207.

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

— **and** — , "Empirical Models of Discrete Games," *Journal of Econometrics*, 1991, *48* (1), 57–81.

Campante, Filipe and Daniel Hojman, "Media and Polarization," 2010. Harvard.

Chiang, Chun-Fang and Brian Knight, "Media Bias and Influence: Evidence from Newspaper Endorsements," *Review of Economic Studies*, Forthcoming.

Chiappori, Pierre, Steven Levitt, and Tim Groseclose, "Testing Mixed-Strategy Equilibria When Players are Heterogeneous: The Case of Penalty Kicks in Soccer," *American Economic Review*, 2002, *92* (4), 1138–1151.

Corneo, Giacomo, "Media Capture in a Democracy: The Role of Wealth Concentration," *Journal of Public Economics*, 2006, *90* (1), 37–58.

DellaVigna, Stefano and Ethan Kaplan, "The Fox News Effect: Media Bias and Voting," *Quarterly Journal of Economics*, 2007, *122*, 1187–1234.

Eguia, Jon and Antonio Nicolo, "On the Efficiency of Partial Information in Elections," June 2012.

Eisensee, Thomas and David Stromberg, "News Droughts, News Floods, and U.S. Disaster Relief," *Quarterly Journal of Economics*, 2007, *122* (2), 693–728.

Enikolopov, Ruben, Maria Petrova, and Ekaterina Zhuravskaya, "Media and Political Persuasion: Evidence from Russia," *American Economic Review*, 2011, *111* (7), 3253–3285.

Fonseca, Angela, James M. Snyder Jr., and B. K. Song, "Newspaper Market Structure and Behavior: Partisan Coverage of Political Scandals in the U.S. from 1870 to 1910," October 2014.

Gentzkow, Matthew and Jesse Shapiro, "Media Bias and Reputation," *Journal of Political Economy*, 2006, *114* (1), 280–316.

— **and** — , "What Drives Media Slant? Evidence from U.S. Daily Newspapers," *Econometrica*, 2010, *78* (1), 35–71.

— **, Edward Glaeser, and Claudia Goldin**, "The Rise of the Fourth Estate. How Newspapers Became Informative and Why it Mattered," in Edward Glaeser and Claudia Goldin, eds., *Corruption and Reform: Lessons from America's Economic History*, University of Chicago Press, 2006, chapter 6, pp. 187–230.

_ **, Jesse Shapiro, and Michael Sinkinson**, "The Effect of Newspaper Entry and Exit on Electoral Politics," *American Economic Review*, 2011, *101* (7), 2980–3018.

_ **,** _ **, and** _ , "Competition and Ideological Diversity: Historical Evidence from US Newspapers," *American Economic Review*, 2014, *104* (10), 3073–3114.

_ **, Nathan Petek, Jesse Shapiro, and Michael Sinkinson**, "Do Newspapers Serve the State? Incumbent Party Influence on the US Press, 1869-1928," *Journal of the European Economic Association*, 2014, *13* (1), 29–61.

Hansen, Stephen, Michael McMahon, and Andrea Prat, "Transparency and Deliberation within the FOMC: A Computational Linguistics Approach," Technical Report, Centre for Economic Policy Research, London 2014.

Hirano, Shigeo, Gabriel Lenz, Maksim Pinkovskiy, and James Snyder, "Voter Learning in State Primary Elections," *American Journal of Political Science*, 2015, *59* (1), 91–108.

Knowles, John, Nicola Persico, and Petra Todd, "Racial Bias in Motor Vehicle Searches: Theory and Evidence," *Journal of Political Economy*, 2001, *109* (1), 203–229.

Maskin, Eric and Jean Tirole, "The Politician and the Judge: Accountability in Government," *American Economic Review*, 2004, *94* (4), 1034–1054.

Mullainathan, Sendhil and Andrei Schleifer, "The Market for News," *American Economic Review*, 2005, *95* (4), 1031–1053.

Palacios-Huerta, Ignacio, "Professionals Play Minimax," *Review of Economic Studies*, 2003, *70*, 395–415.

Prat, Andrea, "The Wrong Kind of Transparency," *American Economic Review*, 2005, *95* (3), 862–877.

_ **and David Stromberg**, "The Political Economy of Mass Media," November 2013.

Puglisi, Riccardo, "Being the New York Times: The Political Behavior of a Newspaper," 2006. LSE.

_ **and James Snyder**, "Media Coverage of Political Scandals," 2008. Mimeo.

Snyder, James and David Stromberg, "Press Coverage and Political Accountability," *Journal of Political Economy*, 2010, *118* (2).

Stromberg, David, "Mass Media Competition, Political Competition, and Public Policy," *Review of Economic Studies*, 2004, *71* (1), 265–284.

_ , "Radio's Impact on Public Spending," *Quarterly Journal of Economics*, 2004, *119* (1), 189–221.

Walgrave, Stefaan, Stuart Soroka, and Michiel Nuytemans, "The Mass Media's Political Agenda-Setting Power: A longitudinal Analysis of Media, Parliament, and Government in Belgium," *Comparative Political Studies*, 2008, *41* (6), 814–836.

Walker, Mark and John Wooders, "Minimax Play at Wimbledon," *American Economic Review*, 2001, *91* (5), 1521–1538.

Figures

Figure 1: Creation of the poll-to-poll intervals

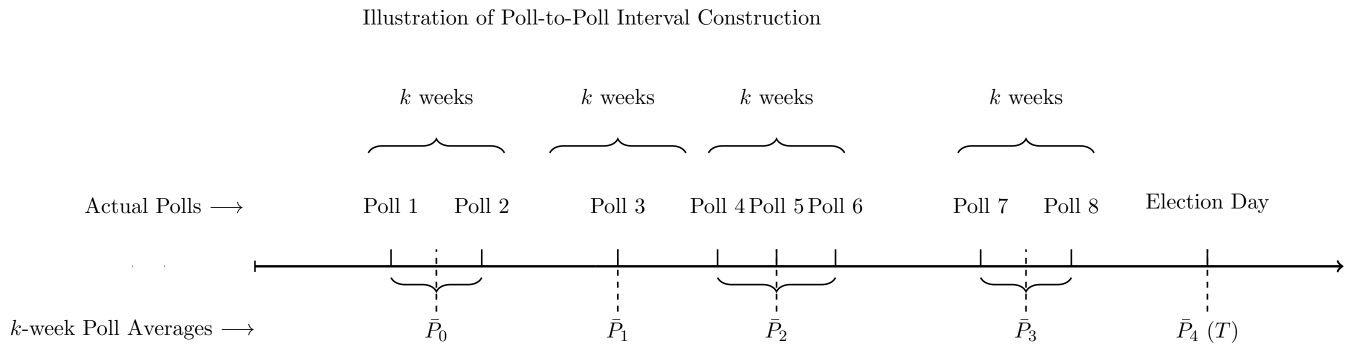


Figure 2: Distribution of article name assignments τ_i

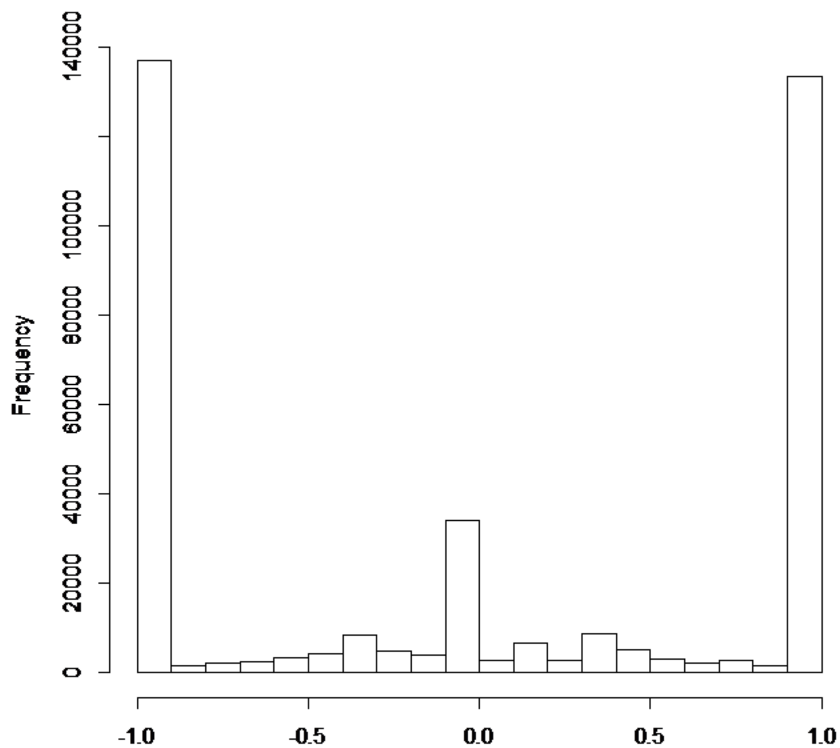


Figure 3: Distribution of articles scores a_i

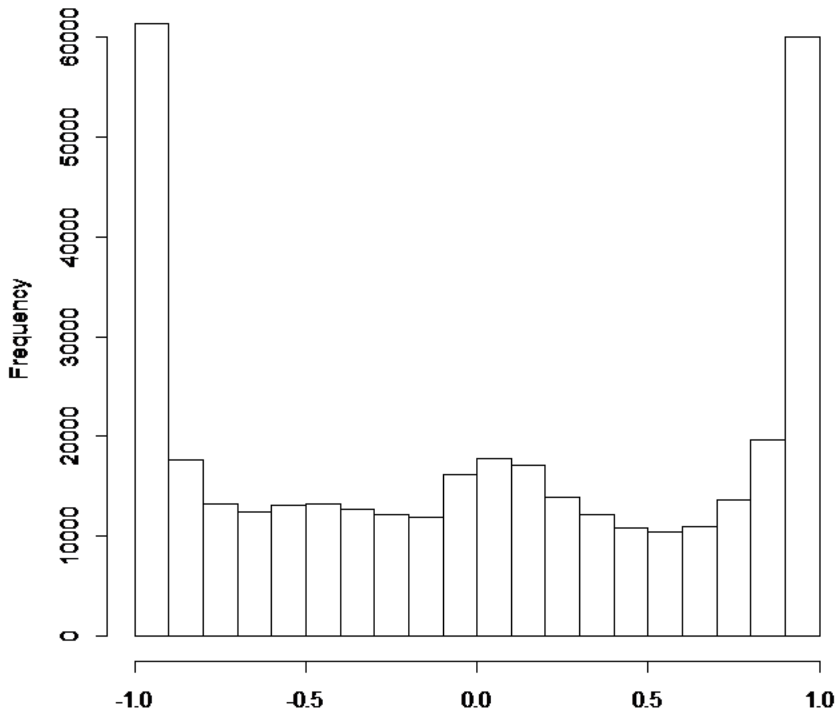


Figure 4: Classification of article types

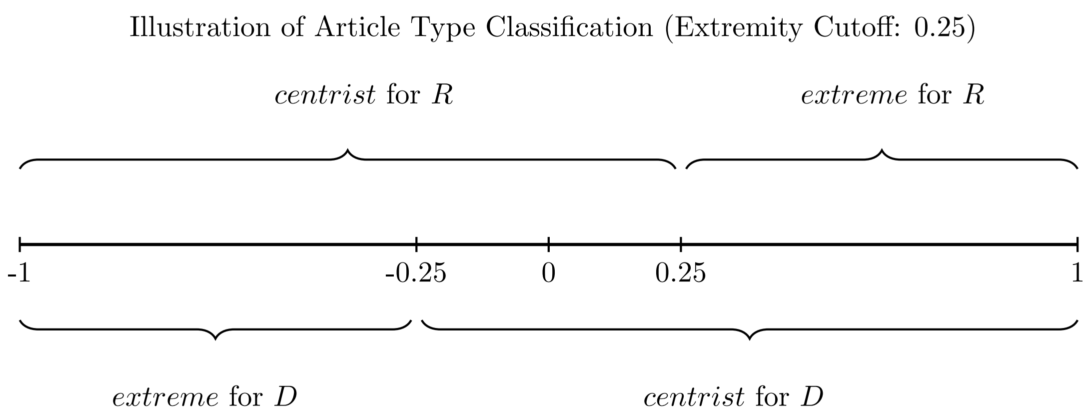
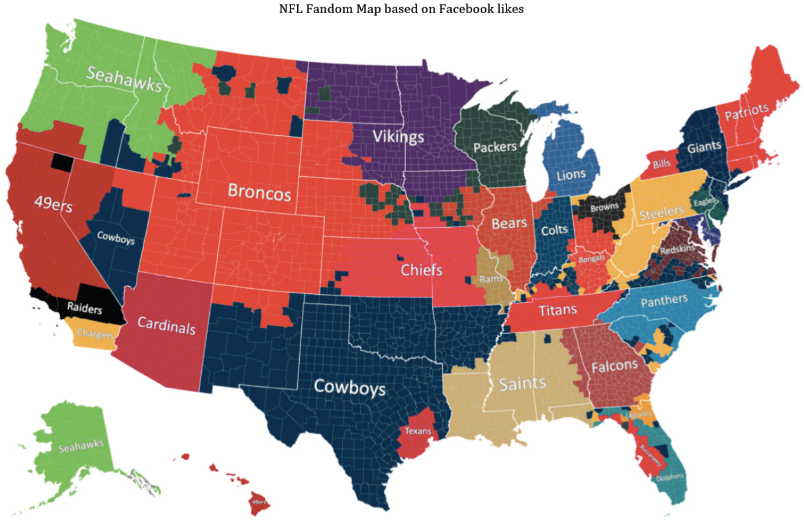


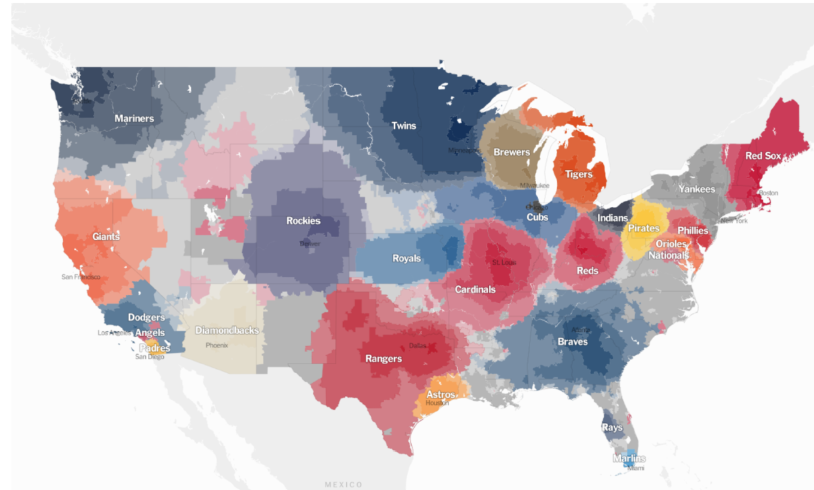
Figure 5: Facebook sports-fans maps

NFL Fandom Map based on Facebook likes



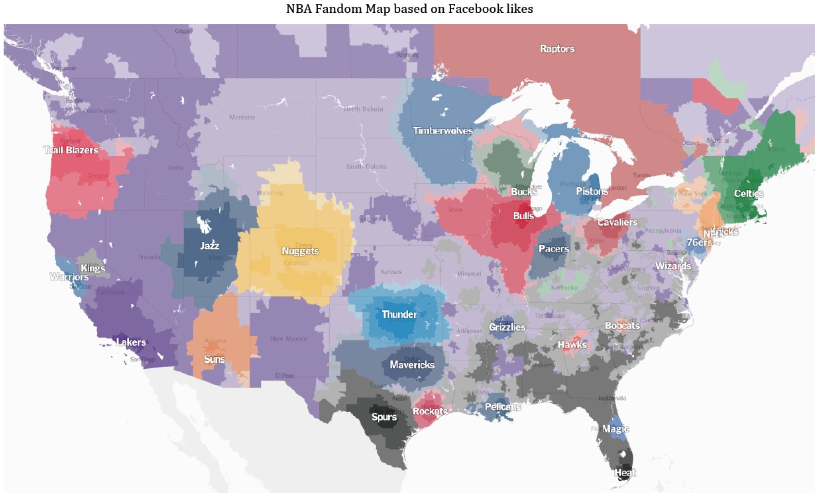
Source: The Atlantic online at: http://www.theatlantic.com/technology/archive/2014/09/the-geography-of-nfl-fandom/379729/

MLB Fandom Map based on Facebook likes



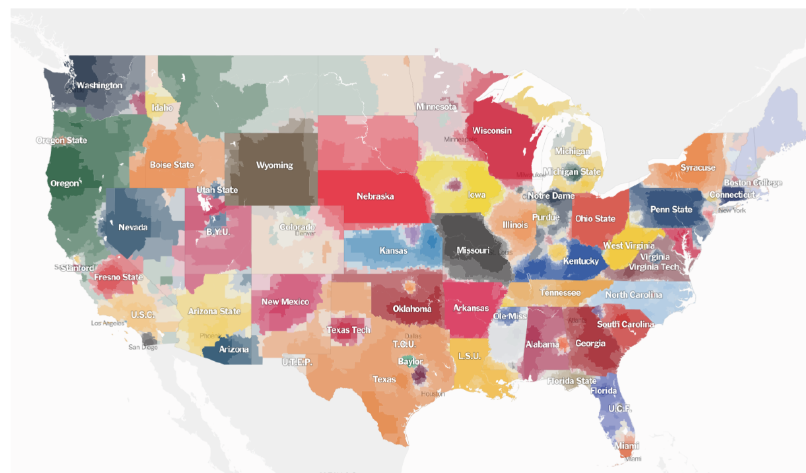
Source: New York Times online at: http://www.nytimes.com/interactive/2014/04/24/upshot/facebook-baseball-map.html

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 6: Identified set for eta's in the linear model

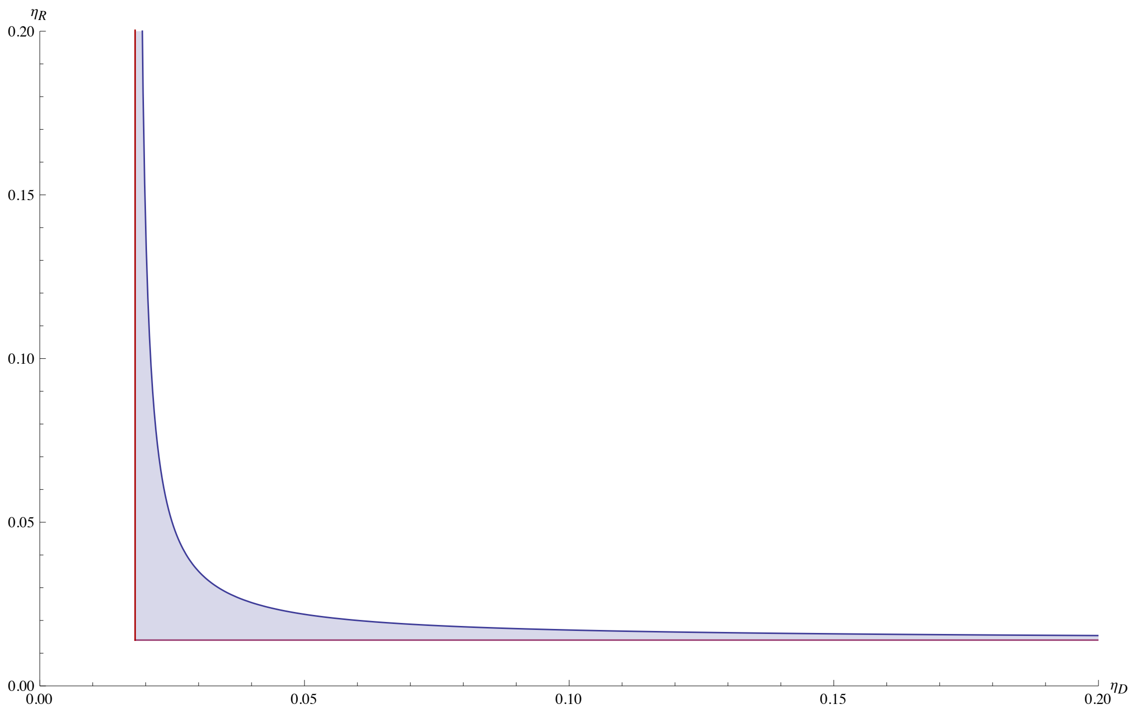


Figure 7: Instrument variation and media coverage in the extensive margin

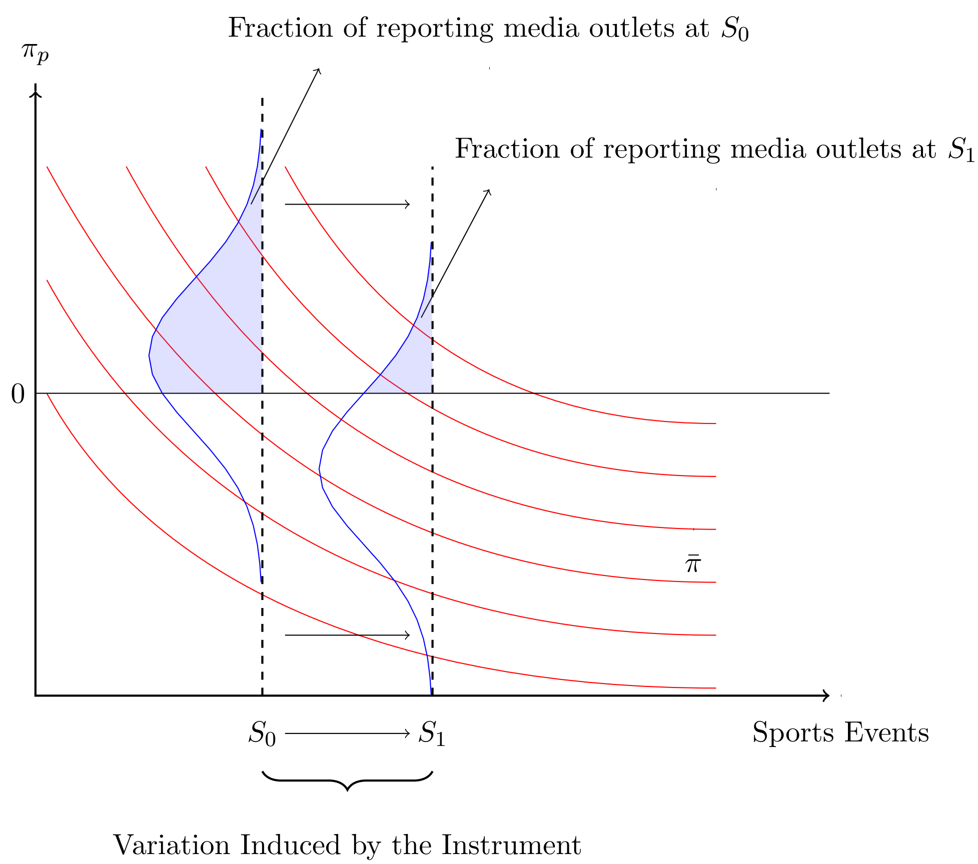
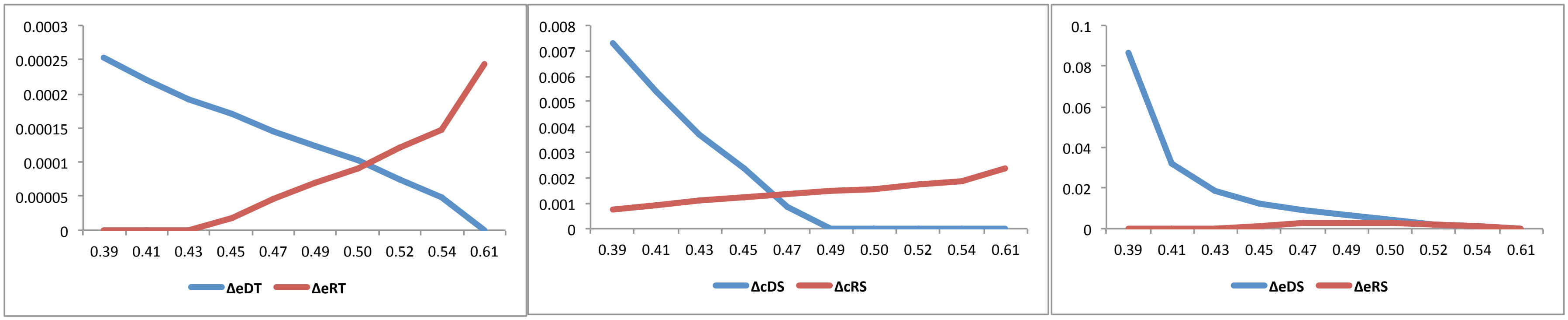


Figure 8: Heterogeneity in Electoral Response Elasticities

Figure 8: Heterogeneity in Electoral Response Elasticities

Panel a: Along the Distribution of the Democratic Registration Share



Panel b: Along the Distribution of Race Competitiveness

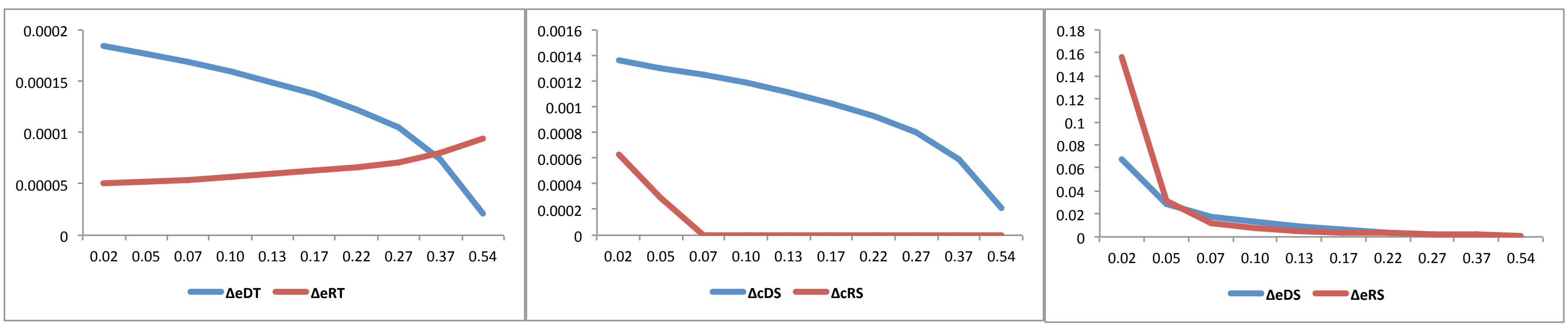


Figure 9: Counterfactual Change in the Partisan Distribution of the Electorate

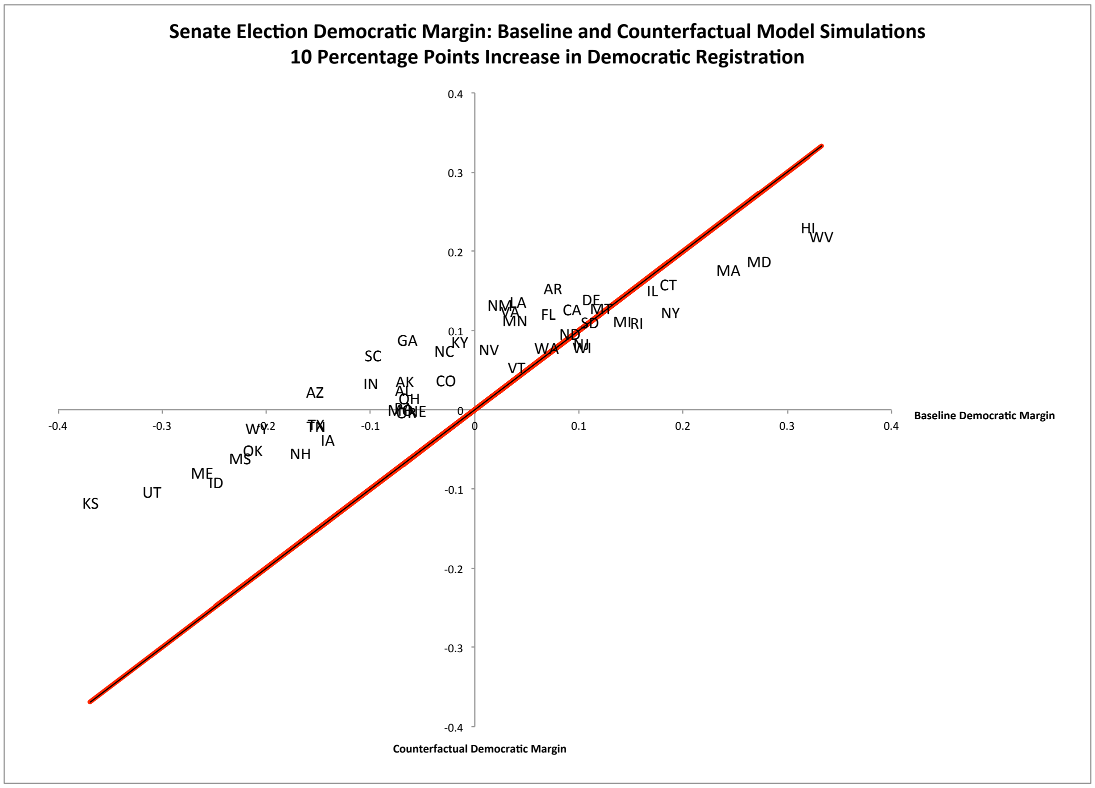
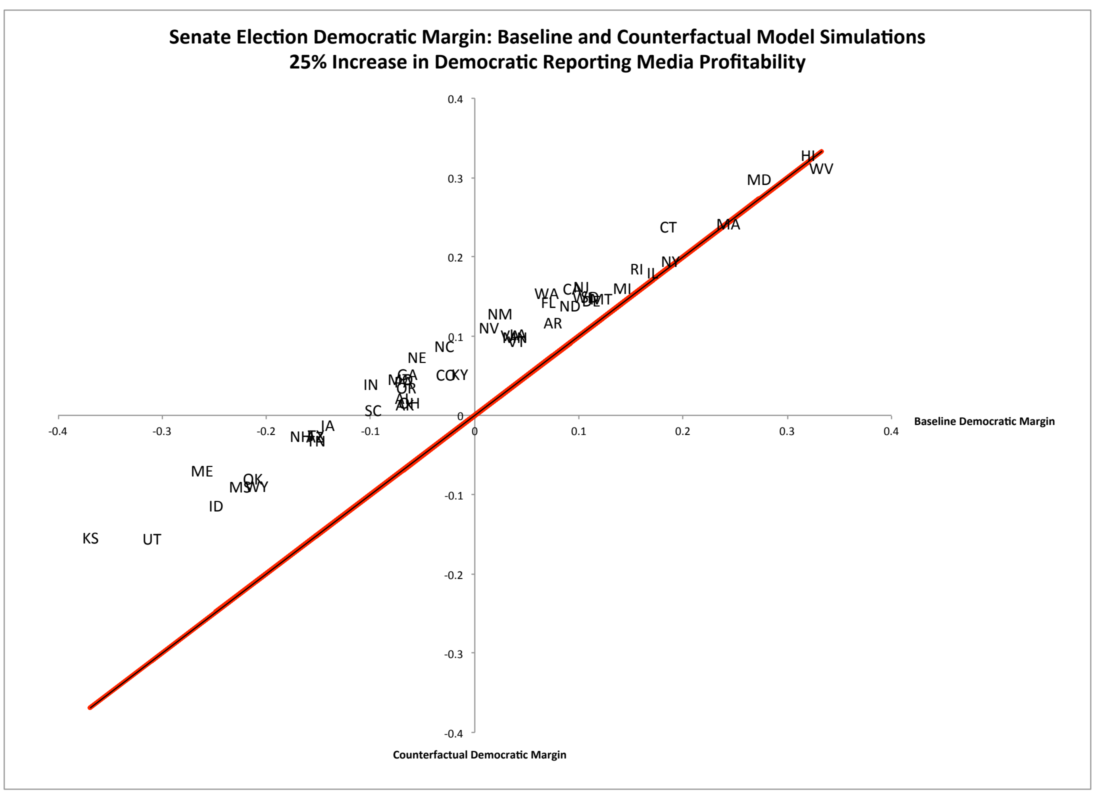


Figure 10: Counterfactual Change in Relative Media Payoffs



Tables

Table 1: Descriptive Statistics

Table 1: Descriptive Statistics

Panel a	2-week Intervals			3-week Intervals		
	Democrat	All	Republican	Democrat	All	Republican
Number of poll-to-poll intervals per race		5.63			4.86	
		(4.55)			(3.62)	
Length of poll-to-poll interval (days)		30.51			35.16	
		(34.32)			(35.47)	
Number of polls per interval		1.74			2.01	
		(1.66)			(2.12)	
Electoral support (poll results)	0.44		0.42	0.44		0.42
	(0.11)		(0.11)	(0.12)		(0.11)
Number of articles per interval	56.11	90.22	41.50	61.98	98.83	45.43
	(101.70)	(127.42)	(62.49)	(112.53)	(138.00)	(67.63)
Number of extreme articles per interval	35.82	58.79	22.97	41.75	68.43	26.67
(0.25 cutoff)	(91.09)	(102.60)	(45.92)	(101.52)	(113.89)	(52.28)
Number of centrist articles per interval	20.29	38.82	18.53	20.23	38.98	18.76
(0.25 cutoff)	(30.21)	(57.67)	(30.52)	(30.75)	(59.30)	(31.17)
Number of extreme articles per interval	29.05	45.80	16.75	34.07	54.12	20.05
(0.5 cutoff)	(89.46)	(97.95)	(43.50)	(98.21)	(107.93)	(50.83)
Number of centrist articles per interval	27.07	51.81	24.75	27.12	52.58	25.46
(0.5 cutoff)	(40.23)	(77.23)	(40.81)	(42.40)	(82.64)	(43.78)
Number of extreme articles per interval	21.18	33.41	12.23	25.86	40.87	15.02
(0.75 cutoff)	(63.21)	(69.67)	(31.81)	(77.21)	(84.21)	(38.08)
Number of centrist articles per interval	33.92	63.01	29.09	35.33	65.82	30.49
(0.75 cutoff)	(49.91)	(87.93)	(46.03)	(51.11)	(90.85)	(46.88)
Number of NFL games per interval		4.22			4.91	
(fan weighted)		(6.34)			(6.98)	
Number of MLB games per interval		14.91			17.17	
(fan weighted)		(25.43)			(27.12)	
Number of NBA games per interval		8.91			10.15	
(fan weighted)		(27.65)			28.62	
Number of NCAA games per interval		0.04			0.05	
(playoffs)		(0.29)			(0.31)	

Panel b	Democrat	All	Republican
Number of races		415	
Number of races per election cycle		24.41	
		(7.91)	
Number of polls		4076	
Number of polls per election cycle		239.76	
		(208.15)	
Number of polls per race		10.01	
		(11.93)	
Number of news articles	131131	210848	96984
Number of news articles per race	315.97	508.07	233.70
	(488.13)	(687.04)	(358.47)
Article Score	-0.52	-0.005	0.52
	(0.44)	(0.70)	(0.43)
Number of media outlets per race		124.17	
		(85.40)	

	2-week Intervals	3-week Intervals
Observations	2337	2033

Notes: The table reports means and standard deviations for our main variables. Panel a reports summary statistics for the 2-week poll-to-poll interval dataset and the 3-week poll-to-poll interval dataset. Panel b reports overall summary statistics. Please see the text and the data description Appendix C for variable definitions and sources.

Table 2: Estimates of Equation (22)

Table 2: Electoral Share Response Elasticities in the Linear Model (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	**Parameter**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$R_D^e/(R_D^e + R_D^c)$	Δ_{eD}^T	0.000024	0.00016	0.000026	0.00016	0.000032	0.00015	0.000032	0.00018
		(0.000006)	(0.00006)	(0.000006)	(0.00006)	(0.000006)	(0.00008)	(0.000007)	(0.000089)
$R_R^e/(R_R^e + R_R^c)$	Δ_{eR}^T	-0.000003	0.00005	-0.000003	0.00005	-0.000005	0.00009	-0.000004	0.00009
		(0.0000048)	(0.000058)	(0.0000048)	(0.000059)	(0.000005)	(0.00008)	(0.000005)	(0.000088)
Panel b: First Stages		**Dependent Variable: $R_D^e/(R_D^e + R_D^c)$**							
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-squared			0.95		0.95		0.96		0.95
F test for excluded instruments (p value)			0.001		0.001		0.006		0.003
		Dependent Variable: $R_R^e/(R_R^e + R_R^c)$							
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-squared			0.93		0.93		0.94		0.94
F test for excluded instruments (p value)			0.000		0.000		0.050		0.042
Month Fixed Effects		YES	YES	YES	YES	YES	YES	YES	YES
Race Fixed Effects		YES	YES	NO	NO	YES	YES	NO	NO
Year-x-State Fixed Effects		NO	NO	YES	YES	NO	NO	YES	YES
Races		415	415	415	415	415	415	415	415
Observations		2134	2134	2134	2134	1865	1865	1865	1865

Notes: The table presents OLS and 2SLS estimates of the extreme turnout elasticities from equation (22) using the article score cutoff of 0.25. Even columns present OLS estimates, and odd 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 ratios of extreme to total news reports. The first four columns in the table are estimated on the 2-week poll-to-poll interval dataset. The last four columns are estimated on the 3-week poll-to-poll interval dataset. 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. Standard errors are robust to arbitrary heteroskedasticity and to arbitrary serial correlation of up to order 2 following Newey and West (1987).

Table 3: Estimates of Equation (23)

Table 3: Electoral Share Response Elasticities in the Linear Model (0.25 score cutoff)

Panel a: Structural Equation		Dependent Variable: $\tau(D+R)/2$							
		2-week poll-to-poll intervals				3-week poll-to-poll intervals			
Explanatory variable	Parameter	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)	OLS (7)	2SLS (8)
$R_D^e + R_D^c$	Δ_{cD}^S	0.0015	0.0018	0.0015	0.0018	0.0015	0.002	0.0015	0.002
		(0.0004)	(0.0009)	(0.0004)	(0.00087)	(0.0003)	(0.0010)	(0.0003)	(0.0010)
$R_R^e + R_R^c$	$-\Delta_{cR}^S$	-0.0008	-0.0018	-0.0008	-0.0018	-0.0010	-0.0027	-0.0010	-0.0029
		(0.0002)	(0.0010)	(0.0002)	(0.0011)	(0.0002)	(0.00136)	(0.0002)	(0.0014)
Panel b: First Stages		Dependent Variable: $R_D^e + R_D^c$							
Log NFL games/τ			1.73		1.80		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		-1348.2		-1347.5
			(410.13)		(410.02)		(503.09)		(504.20)
R-squared			0.70		0.70		0.72		0.72
F test for excluded instruments (p value)			0.007		0.007		0.029		0.028
		Dependent Variable: $R_R^e + R_R^c$							
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		-7.352		-6.765
			(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-squared			0.73		0.73		0.76		0.76
F test for excluded instruments (p value)			0.000		0.000		0.000		0.000
Month Fixed Effects		YES	YES	YES	YES	YES	YES	YES	YES
Race Fixed Effects		YES	YES	NO	NO	YES	YES	NO	NO
Year-x-State Fixed Effects		NO	NO	YES	YES	NO	NO	YES	YES
Races		415	415	415	415	415	415	415	415
Observations		2134	2134	2134	2134	1865	1865	1865	1865

Notes: The table presents OLS and 2SLS estimates of the centrist swing-voter elasticities from equation (23) using the article score cutoff of 0.25. Even columns present OLS estimates, and odd 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 dataset, 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 dataset, 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. Standard errors are robust to arbitrary heteroskedasticity and to arbitrary serial correlation of up to order 2 following Newey and West (1987).

Table 4: Identified Parameter Estimates and Equilibrium Mixing Strategies in the Linear Model

Table 4: Electoral Share Response Elasticities and Equilibrium Mixing Strategies in the Linear Model

	2-week poll-to-poll intervals	
	0.25 article score cutoff	0.5 article score cutoff
	(1)	(2)
Panel a	**Parameters**	
Δ_{eD}^{T}	0.00016	0.00011
Δ_{eR}^{T}	0.00005	0.00004
Δ_{cD}^{S}	0.0018	0.0012
Δ_{cR}^{S}	0.0018	0.0015
Δ_{eD}^{S}	0.0069	0.0050
Δ_{eR}^{S}	0.0018	0.0015
Panel b	**Average Equilibrium Mixing Strategies**	
$E[q_D]$	0.557	0.414
$E[q_R]$	0.449	0.299
$E[\eta_D(1-\gamma_R)]$	0.018	0.018
$E[\eta_R(1-\gamma_D)]$	0.014	0.014

Notes: The table presents all the identified parameters (panel a) and equilibrium probabilities (panel b) in the model estimated using the 2-week poll-to-poll interval dataset. Electoral support change elasticities in panel a are taken from the estimation of equations (22) and (23). Extreme swing support parameters are computed according to equation (24) in the text. Column (1) is based on the 0.25 article score cutoff dataset 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 dataset. Estimates in panel b are computed directly from the sample analogues as weighted averages using relative interval lengths as weights.

Table 5: Estimates of Equation (22) under Alternative LDA Article Score Classification

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Table 6: Heterogeneity in Electoral Response Elasticities

Table 5: Heterogeneity in Electoral Response Elasticities (2-week poll-to-poll intervals, 0.25 article score cutoff)

			Interaction term (K):			
Panel a			**Democratic registration**	**Log days to election**	**Race tightness**	**Incumbent running**
Parameter	**Explanatory variable**	**Coefficient**	**(1)**	**(2)**	**(3)**	**(4)**
			Dependent Variable: $(\Delta V_D+\Delta V_R)/\tau$			
Δ_{eD}^{T}	$R_D^e/(R_D^e + R_D^c)$	α_{eD}^{T}	0.00075	0.00001	0.00019	0.00018
			(0.00037)	(0.00025)	(0.00010)	(0.00009)
	$(R_D^e/(R_D^e + R_D^c))\times K$	β_{eD}^{T}	-0.0013	0.00001	-0.00031	-0.00003
			(0.00074)	(0.00005)	(0.00039)	(0.00011)
Δ_{eR}^{T}	$R_R^e/(R_R^e + R_R^c)$	α_{eR}^{T}	-0.00060	0.00047	0.00004	0.00005
			(0.00048)	(0.00041)	(0.00009)	(0.00011)
	$R_R^e/(R_R^e + R_R^c)\times K$	β_{eR}^{T}	0.0014	-0.00011	0.00008	0.0000
			(0.0010)	(0.00009)	(0.00032)	(0.00014)
Panel b						
Parameter	**Explanatory variable**	**Coefficient**	**Dependent Variable: $\tau(D+R)/2$**			
Δ_{cD}^{S}	$R_D^e + R_D^c$	α_{cD}^{S}	0.037	0.0028	0.0014	0.0007
			(0.009)	(0.008)	(0.001)	(0.001)
	$(R_D^e + R_D^c)\times K$	β_{cD}^{S}	-0.078	-0.0001	-0.002	0.0008
			(0.018)	(0.001)	(0.002)	(0.001)
$-\Delta_{cR}^{S}$	$R_R^e + R_R^c$	α_{cR}^{S}	0.0020	-0.0163	0.0009	0.0000
			(0.014)	(0.014)	(0.002)	(0.002)
	$(R_R^e + R_R^c)\times K$	β_{cR}^{S}	-0.007	0.003	-0.014	-0.0015
			(0.028)	(0.003)	(0.005)	(0.002)
	E[K]		0.47	4.56	0.17	0.76

Notes: The table presents coefficient and parameter estimates from 2SLS models that include an interaction between a race characteristic and the endogenous explanatory variables. All models are estimated on the 2 week poll-to-poll interval dataset 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 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 in the beginning of the poll-to-poll interval. Because this variable varies across 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 on 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).

Table 7: Robustness Exercises

Table 6: Robustness Exercises (2-week poll-to-poll intervals)

Panel a		Robustness Exercise: Excluding last poll-to-poll interval (1)	Controlling for post-primary dummy (2)	0.5 article score cutoff (3)	0.75 article score cutoff (4)
Parameter	**Explanatory variable**	**Dependent Variable: $(\Delta V_D+\Delta V_R)/\tau$**			
Δ_{eD}^{T}	$R_D^e/(R_D^e + R_D^c)$	0.00015	0.00014	0.00011	0.00015
		(0.00005)	(0.00005)	(0.00005)	(0.00006)
Δ_{eR}^{T}	$R_R^e/(R_R^e + R_R^c)$	0.00003	0.00008	0.00004	0.00005
		(0.00005)	(0.00006)	(0.00005)	(0.00006)
Panel b					
Parameter	**Explanatory variable**	**Dependent Variable: $\tau(D+R)/2$**			
Δ_{cD}^{S}	$R_D^e + R_D^c$	0.0021	0.0013	0.0012	0.0012
		(0.0008)	(0.00056)	(0.00056)	(0.00060)
$-\Delta_{cR}^{S}$	$R_R^e + R_R^c$	-0.0024	-0.0016	-0.0015	-0.0014
		(0.0012)	(0.00082)	(0.00076)	(0.00078)
	Races	415	415	415	415
	Observations	1871	2134	2134	2134

Notes: The table presents 2SLS estimates of the electoral support elasticities from equations (22) and (23). All models are estimated on the 2 week poll-to-poll interval dataset, and include a full set of senate race fixed effects, and month fixed effects. The dependent variable for 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 that consist 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 the log of NFL games per day, the log of MLB games per day, the log of NBA games per day, and the 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).

Table 8: Overidentification Exercises

Table 7: 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 Ia: Main Equation		**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Explanatory variable	**Parameter**	**Dependent Variable: $(\Delta V_D+\Delta V_R)/\tau$**									
$R_D^e/(R_D^e + R_D^c)$	$\mathbf{\Delta_{eD}^T}$	0.00014	0.00019	0.00011	0.00024	0.00015	0.00009	0.00018	0.00020	0.0002	0.00021
		(0.00006)	(0.00008)	(0.00006)	(0.00010)	(0.00009)	(0.00007)	(0.00010)	(0.00010)	(0.00007)	(0.00012)
$R_R^e/(R_R^e + R_R^c)$	$\mathbf{\Delta_{eR}^T}$	0.00003	0.00013	0.00004	0.0000	0.00013	0.00005	0.00013	0.00009	0.0001	0.00012
		(0.00006)	(0.00010)	(0.00004)	(0.0001)	(0.00009)	(0.00007)	(0.00012)	(0.00008)	(0.0001)	(0.00012)
Panel IIa: First Stages		**Dependent Variable: $R_D^e/(R_D^e + R_D^c)$**									
R-squared		0.78	0.78	0.78	0.78	0.78	0.80	0.80	0.80	0.80	0.80
F test for excluded instruments (p value)		0.014	0.011	0.058	0.011	0.037	0.071	0.015	0.082	0.014	0.042
		Dependent Variable: $R_R^e/(R_R^e + R_R^c)$									
R-squared		0.80	0.80	0.80	0.80	0.80	0.82	0.82	0.82	0.82	0.82
F test for excluded instruments (p value)		0.002	0.076	0.000	0.001	0.032	0.021	0.067	0.019	0.166	0.053
Panel Ib: Main Equation											
Explanatory variable	**Parameter**	**Dependent Variable: $\tau(D+R)/2$**									
$R_D^e + R_D^c$	$\mathbf{\Delta_{cD}^S}$	0.0010	0.0024	0.0018	0.0010	0.0030	0.0012	0.0027	0.0019	0.0015	0.0032
		(0.0007)	(0.0010)	(0.0008)	(0.0011)	(0.0014)	(0.0007)	(0.0011)	(0.0009)	(0.0012)	(0.0017)
$R_R^e + R_R^c$	$\mathbf{-\Delta_{cR}^S}$	-0.0002	-0.0021	-0.0020	-0.0019	-0.0033	-0.0015	-0.0030	-0.0029	-0.0027	-0.0046
		(0.0016)	(0.0011)	(0.0012)	(0.0011)	(0.0017)	(0.0013)	(0.0014)	(0.0017)	(0.0012)	(0.0028)
Panel IIb: First Stages		**Dependent Variable: $R_D^e + R_D^c$**									
R-squared		0.60	0.60	0.60	0.60	0.60	0.63	0.63	0.63	0.63	0.63
F test for excluded instruments (p value)		0.062	0.095	0.046	0.495	0.047	0.090	0.134	0.088	0.672	0.062
		Dependent Variable: $R_R^e + R_R^c$									
R-squared		0.60	0.61	0.60	0.60	0.60	0.64	0.64	0.64	0.64	0.64
F test for excluded instruments (p value)		0.009	0.001	0.003	0.013	0.001	0.016	0.006	0.048	0.037	0.023
Races		415	415	415	415	415	415	415	415	415	415
Observations		2134	2134	2134	2134	2134	1865	1865	1865	1865	1865

Notes: The table presents 2SLS estimates of the electoral support elasticities from equations (22) (panel a) and (23) (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 Ib is constructed using the benchmark parameter estimates from the structural equation (22) (column (4) in table 2 for panel b columns (1)-(5), and column (8) in table 2 for panel b columns (6)-(10)). Panels Ia and Ib presents estimates for the structural equations (second stages), and panels IIa and IIb report the corresponding R squared and p value for the F tests on the excluded instruments of each first stage. The dependent variables in the first stages of Panel IIa are the Democratic and Republican ratios of extreme to total news reports. The dependent variables in the first stages of Panel IIb 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 dataset. The last five columns are estimated on the 3-week poll-to-poll interval dataset. 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).

Table 9: Testing Model Assumptions: Media Coverage and Sports Events on the Extensive Margin

Table 8: Testing Model Assumptions. Media Coverage and Sports Events on the Extensive Margin

	Dependent Variable: Number of reporting outlets in poll-to-poll interval/Total Number of reporting outlets in race									
	2-week poll-to-poll intervals					3-week poll-to-poll intervals				
Explanatory Variable	**(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-squared	0.69	0.69	0.69	0.70	0.70	0.70	0.70	0.70	0.70	0.70
Races	415	415	415	415	415	415	415	415	415	415
Observations	2134	2134	2134	2134	2134	1865	1865	1865	1865	1865

Notes: The table presents OLS regressions. The dependent variable in all columns is the number media outlets reporting on a race in a poll-to-poll interval as a fraction of all media outlets ever reporting on a 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 a race, and a constant. The first five columns in the table are estimated on the 2-week poll-to-poll interval dataset. The last five columns are estimated on the 3-week poll-to-poll interval dataset. 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, 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.

Table 10: Testing Model Assumptions: Poll Coverage Intensity and Race Competitiveness

Table 9: Testing Model Assumptions. Poll Timing and Race Tightness

Dependent Variable:	**Number of polls in poll-to-poll interval**		**Number of polls in poll-to-poll interval/Length of poll-to-poll interval**	
Poll-to-poll intervals:	**2 week**	**3 week**	**2 week**	**3 week**
Explanatory Variable	**(1)**	**(2)**	**(6)**	**(7)**
Race tightness (abs(V_D-V_R))	0.041	0.100	0.001	0.025
	(0.506)	(0.697)	(0.066)	(0.077)
R-squared	0.39	0.48	0.42	0.47
Races	415	415	415	415
Observations	2134	1865	2134	1865

Notes: The table presents OLS regressions of a measure if poll coverage intensity on the tightness of the senate race as measured by the absolute value of the difference between the Democrat's electoral support and the Republican'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.

Table 11: Heterogeneity in Media Biases

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Table 12: Identified Parameter Estimates and Marginal Effects in the General Model

Table 10: Electoral Share Response Elasticities and Parameters in the General Model

	2-week poll-to-poll intervals	
	0.25 article score cutoff (1)	**0.5 article score cutoff (2)**
Panel a	**Average Marginal Effects**	
$dE[v_t^D \mid v_{t-1}^D]/d(s^D{=}e,\chi^D{=}0)$	0.00027	0.00022
	(0.00006)	(0.00005)
$dE[v_t^R \mid v_{t-1}^R]/d(s^R{=}e,\chi^R{=}0)$	0.00013	0.00010
	(0.00008)	(0.00005)
$dE[v_t^D \mid v_{t-1}^D]/d(s^D{=}c,\chi^D{=}1)$	0.0025	0.0017
	(0.0009)	(0.0068)
$dE[v_t^R \mid v_{t-1}^R]/d(s^R{=}c,\chi^R{=}1)$	0.0031	0.0024
	(0.0003)	(0.0006)
$dE[v_t^D \mid v_{t-1}^D]/d(s^D{=}e,\chi^D{=}1)$	0.0086	0.0086
	(0.004)	(0.005)
$dE[v_t^R \mid v_{t-1}^R]/d(s^R{=}e,\chi^R{=}1)$	0.0032	0.0038
	(0.0012)	(0.0016)
Panel b	**Media Bias and Relative Payoff Parameters**	
η_D	0.030	0.038
	(0.009)	(0.012)
η_R	0.025	0.026
	(0.012)	(0.012)
π_R/π_D	0.720	0.750
	(0.410)	(0.430)

Notes: The table presents marginal effects for average electoral support analogous to those in Table 4 (panel a) and the estimated media bias and relative payoff parameters (panel b) in the general model estimated using the 2-week poll-to-poll interval dataset. Electoral support change elasticities in panel a are computed from equation (29) at the parameters estimated by Minimum Distance and the sample averages in the data. Media bias parameters are estimated as the root of the system in equation (32), and the relative media payoffs are computed from equation (33). Column (1) is based on the 0.25 article score cutoff dataset. Column (2) is based on an analogous estimation using the 0.5 article score cutoff dataset. Standard errors are computed using the delta method based on the analytic variance-covariance matrix of the minimum distance estimator.

Appendix A

Derivation of the unique Nash equilibrium of the stage game G:

The normal form game is (in each cell the payoffs are written in the order D, R, M):

$$\begin{array}{c} \\ D \end{array} \begin{array}{c} M \\ \left[\begin{array}{ccccccccccc} & & & s^M = F_D F_R & & & s^M = F_D N_R & & & s^M = N_D F_R \\ s^D = e & \triangle_1 & \triangle_2 & \eta_D \pi_D + \eta_R \pi_R - 2k & \triangle_3 & \triangle_4 & \eta_D \pi_D - k & \triangle_5 & \triangle_6 & \eta_R \pi_R - k \\ s^D = c & \triangle_7 & \triangle_8 & \eta_R \pi_R - 2k & \triangle_9 & \triangle_{10} & -k & \triangle_{11} & \triangle_{12} & \eta_R \pi_R - k \end{array}\right] \end{array} \begin{array}{c} \\ s^R = e \end{array}$$

$$R$$

$$D \quad \left[\begin{array}{ccccccccccc} & & & s^M = F_D F_R & & & s^M = F_D N_R & & & s^M = N_D F_R \\ s^D = e & \triangle_{13} & \triangle_{14} & \eta_D \pi_D - 2k & \triangle_{15} & \triangle_{16} & \eta_D \pi_D - k & \triangle_{17} & \triangle_{18} & -k \\ s^D = c & \triangle_{19} & \triangle_{20} & -2k & \triangle_{21} & \triangle_{22} & -k & \triangle_{23} & \triangle_{24} & -k \end{array}\right] \quad s^R = c$$

Linear Case:

$$\begin{array}{cc}
\triangle_1 \equiv \Delta^T_{eD} - \eta_D \Delta^S_{eD} + \eta_R \Delta^S_{eR} & \triangle_{13} \equiv \Delta^T_{eD} - \eta_D \Delta^S_{eD} - \eta_R \Delta^S_{cR} \\
\triangle_2 \equiv \Delta^T_{eR} - \eta_R \Delta^S_{eR} + \eta_D \Delta^S_{eD} & \triangle_{14} \equiv \eta_R \Delta^S_{cR} + \eta_D \Delta^S_{eD} \\
\triangle_3 \equiv \Delta^T_{eD} - \eta_D \Delta^S_{eD} & \triangle_{15} \equiv \Delta^T_{eD} - \eta_D \Delta^S_{eD} \\
\triangle_4 \equiv \Delta^T_{eR} + \eta_D \Delta^S_{eD} & \triangle_{16} \equiv \eta_D \Delta^S_{eD} \\
\triangle_5 \equiv \Delta^T_{eD} + \eta_R \Delta^S_{eR} & \triangle_{17} \equiv \Delta^T_{eD} - \eta_R \Delta^S_{cR} \\
\triangle_6 \equiv \Delta^T_{eR} - \eta_R \Delta^S_{eR} & \triangle_{18} \equiv \eta_R \Delta^S_{cR} \\
\triangle_7 \equiv \eta_D \Delta^S_{cD} + \eta_R \Delta^S_{eR} & \triangle_{19} \equiv \eta_D \Delta^S_{cD} - \eta_R \Delta^S_{cR} \\
\triangle_8 \equiv \Delta^T_{eR} - \eta_R \Delta^S_{eR} - \eta_D \Delta^S_{cD} & \triangle_{20} \equiv \eta_R \Delta^S_{cR} - \eta_D \Delta^S_{cD} \\
\triangle_9 \equiv \eta_D \Delta^S_{cD} & \triangle_{21} \equiv \eta_D \Delta^S_{cD} \\
\triangle_{10} \equiv \Delta^T_{eR} - \eta_D \Delta^S_{cD} & \triangle_{22} \equiv -\eta_D \Delta^S_{cD} \\
\triangle_{11} \equiv \eta_R \Delta^S_{eR} & \triangle_{23} \equiv -\eta_R \Delta^S_{cR} \\
\triangle_{12} \equiv \Delta^T_{eR} - \eta_R \Delta^S_{eR} & \triangle_{24} \equiv \eta_R \Delta^S_{cR}
\end{array}$$

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. Conditions for such an equilibrium are:

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

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

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

$$\Leftrightarrow q^*_R = \frac{k}{\eta_R \pi_R} \tag{34}$$

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

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

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

$$\Leftrightarrow q_D^* = \frac{k}{\eta_D \pi_D} \tag{35}$$

3. D must be indifferent between $s^D = e$ and $s^D = c$:

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

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

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

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

$$\Leftrightarrow \gamma_R^* = 1 - \frac{\Delta_{eD}^T}{\eta_D\left[\Delta_{eD}^S + \Delta_{cD}^S\right]} \tag{36}$$

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

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

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

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

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

$$\Leftrightarrow \gamma_D^* = 1 - \frac{\Delta_{eR}^T}{\eta_R\left[\Delta_{eR}^S + \Delta_{cR}^S\right]} \tag{37}$$

Thus, the mixed-strategy Nash equilibrium is unique.

General Case:

In the general case, the payoff parameters on the normal-form game G are given by:

$$\begin{array}{cc}
\triangle_1 \equiv \frac{\Delta_{eD}^T - \eta_D\Delta_{eD}^S + \eta_R\Delta_{eR}^S}{1+\Delta_{eD}^T+\Delta_{eR}^T} - \frac{\Delta_{eD}^T+\Delta_{eR}^T}{1+\Delta_{eD}^T+\Delta_{eR}^T} v_{t-1}^D & \triangle_{13} \equiv \frac{\Delta_{eD}^T - \eta_D\Delta_{eD}^S - \eta_R\Delta_{cR}^S}{1+\Delta_{eD}^T} - \frac{\Delta_{eD}^T}{1+\Delta_{eD}^T} v_{t-1}^D \\
\triangle_2 \equiv \frac{\Delta_{eR}^T - \eta_R\Delta_{eR}^S + \eta_D\Delta_{eD}^S}{1+\Delta_{eR}^T+\Delta_{eD}^T} - \frac{\Delta_{eR}^T+\Delta_{eD}^T}{1+\Delta_{eR}^T+\Delta_{eD}^T} v_{t-1}^R & \triangle_{14} \equiv \frac{\eta_R\Delta_{cR}^S + \eta_D\Delta_{eD}^S}{1+\Delta_{eD}^T} - \frac{\Delta_{eD}^T}{1+\Delta_{eD}^T} v_{t-1}^R \\
\triangle_3 \equiv \frac{\Delta_{eD}^T - \eta_D\Delta_{eD}^S}{1+\Delta_{eD}^T+\Delta_{eR}^T} - \frac{\Delta_{eD}^T+\Delta_{eR}^T}{1+\Delta_{eD}^T+\Delta_{eR}^T} v_{t-1}^D & \triangle_{15} \equiv \frac{\Delta_{eD}^T - \eta_D\Delta_{eD}^S}{1+\Delta_{eD}^T} - \frac{\Delta_{eD}^T}{1+\Delta_{eD}^T} v_{t-1}^D \\
\triangle_4 \equiv \frac{\Delta_{eR}^T + \eta_D\Delta_{eD}^S}{1+\Delta_{eR}^T+\Delta_{eD}^T} - \frac{\Delta_{eR}^T+\Delta_{eD}^T}{1+\Delta_{eR}^T+\Delta_{eD}^T} v_{t-1}^R & \triangle_{16} \equiv \frac{\eta_D\Delta_{eD}^S}{1+\Delta_{eD}^T} - \frac{\Delta_{eD}^T}{1+\Delta_{eD}^T} v_{t-1}^R \\
\triangle_5 \equiv \frac{\Delta_{eD}^T + \eta_R\Delta_{eR}^S}{1+\Delta_{eD}^T+\Delta_{eR}^T} - \frac{\Delta_{eD}^T+\Delta_{eR}^T}{1+\Delta_{eD}^T+\Delta_{eR}^T} v_{t-1}^D & \triangle_{17} \equiv \frac{\Delta_{eD}^T - \eta_R\Delta_{cR}^S}{1+\Delta_{eD}^T} - \frac{\Delta_{eD}^T}{1+\Delta_{eD}^T} v_{t-1}^D \\
\triangle_6 \equiv \frac{\Delta_{eR}^T - \eta_R\Delta_{eR}^S}{1+\Delta_{eR}^T+\Delta_{eD}^T} - \frac{\Delta_{eR}^T+\Delta_{eD}^T}{1+\Delta_{eR}^T+\Delta_{eD}^T} v_{t-1}^R & \triangle_{18} \equiv \frac{\eta_R\Delta_{cR}^S}{1+\Delta_{eD}^T} - \frac{\Delta_{eD}^T}{1+\Delta_{eD}^T} v_{t-1}^R \\
\triangle_7 \equiv \frac{\eta_D\Delta_{cD}^S + \eta_R\Delta_{eR}^S}{1+\Delta_{eR}^T} - \frac{\Delta_{eR}^T}{1+\Delta_{eR}^T} v_{t-1}^D & \triangle_{19} \equiv \eta_D\Delta_{cD}^S - \eta_R\Delta_{cR}^S \\
\triangle_8 \equiv \frac{\Delta_{eR}^T - \eta_R\Delta_{eR}^S - \eta_D\Delta_{cD}^S}{1+\Delta_{eR}^T} - \frac{\Delta_{eR}^T}{1+\Delta_{eR}^T} v_{t-1}^R & \triangle_{20} \equiv \eta_R\Delta_{cR}^S - \eta_D\Delta_{cD}^S \\
\triangle_9 \equiv \frac{\eta_D\Delta_{cD}^S}{1+\Delta_{eR}^T} - \frac{\Delta_{eR}^T}{1+\Delta_{eR}^T} v_{t-1}^D & \triangle_{21} \equiv \eta_D\Delta_{cD}^S \\
\triangle_{10} \equiv \frac{\Delta_{eR}^T - \eta_D\Delta_{cD}^S}{1+\Delta_{eR}^T} - \frac{\Delta_{eR}^T}{1+\Delta_{eR}^T} v_{t-1}^R & \triangle_{22} \equiv -\eta_D\Delta_{cD}^S \\
\triangle_{11} \equiv \frac{\eta_R\Delta_{eR}^S}{1+\Delta_{eR}^T} - \frac{\Delta_{eR}^T}{1+\Delta_{eR}^T} v_{t-1}^D & \triangle_{23} \equiv -\eta_R\Delta_{cR}^S \\
\triangle_{12} \equiv \frac{\Delta_{eR}^T - \eta_R\Delta_{eR}^S}{1+\Delta_{eR}^T} - \frac{\Delta_{eR}^T}{1+\Delta_{eR}^T} v_{t-1}^R & \triangle_{24} \equiv \eta_R\Delta_{cR}^S
\end{array}$$

In this general case, conditions for the unique mixed-strategy equilibrium identical to those for the linear case regarding the media's indifference conditions:

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

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

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

$$\Leftrightarrow q_R^* = \frac{k}{\eta_R\pi_R} \tag{38}$$

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

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

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

$$\Leftrightarrow q_D^* = \frac{k}{\eta_D\pi_D} \tag{39}$$

The conditions for candidates' indifference, in contrast, are given by:

3. D must be indifferent between $s^D = e$ and $s^D = c$:

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

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

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

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

$$\Leftrightarrow \gamma_R = \frac{A}{A+C} - \frac{A+B}{A+C}\gamma_D \tag{40}$$

with $A \equiv q_R(\triangle_1 - \triangle_7) + (1-q_R)(\triangle_{13} - \triangle_{19})$, $B \equiv q_R(\triangle_9 - \triangle_3) + (1-q_R)(\triangle_{21} - \triangle_{15})$, and $C \equiv q_R(\triangle_{11} - \triangle_5) + (1-q_R)(\triangle_{23} - \triangle_{17})$.

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

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

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

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

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

$$\Leftrightarrow \gamma_D = \frac{D}{D+F} - \frac{D+E}{D+F}\gamma_R \tag{41}$$

with $D \equiv q_D(\triangle_2 - \triangle_{14}) + (1-q_D)(\triangle_8 - \triangle_{20})$, $E \equiv q_D(\triangle_{18} - \triangle_6) + (1-q_D)(\triangle_{24} - \triangle_{12})$, and $F \equiv q_D(\triangle_{16} - \triangle_4) + (1-q_D)(\triangle_{22} - \triangle_{10})$.

Equations (40) and (41) form a system of two linear equations in two unknowns, whose unique solution is given by:

$$\gamma_R^*(\eta_D, \eta_R; \tilde{\Delta}, v_{t-1}^D, v_{t-1}^R) = \frac{(D+F)A - (A+B)D}{(A+C)(D+F) - (A+B)(D+E)}$$

$$\gamma_D^*(\eta_D, \eta_R; \tilde{\Delta}, v_{t-1}^D, v_{t-1}^R) = \frac{(A+C)D - (D+E)A}{(A+C)(D+F) - (A+B)(D+E)}$$

where we make explicit their dependence on the media coverage biases (η_D, η_R).

Appendix B

Marginal distributions for the electoral support shares

The marginal distribution for each of the vote shares is given by a beta density:

$$f(v_{t+1}^D|\mathbf{s}) = \frac{1}{B(\alpha_t^D, \alpha_t^R + \alpha^O)} \left(v_{t+1}^D\right)^{\alpha_t^D - 1} \left(1 - v_{t+1}^D\right)^{\alpha_t^R + \alpha^O - 1}$$

$$f(v_{t+1}^R|\mathbf{s}) = \frac{1}{B(\alpha_t^R, \alpha_t^D + \alpha^O)} \left(v_{t+1}^R\right)^{\alpha_t^R - 1} \left(1 - v_{t+1}^R\right)^{\alpha_t^D + \alpha^O - 1}$$

$$f(v_{t+1}^O|\mathbf{s}) = \frac{1}{B(\alpha_t^O, \alpha_t^D + \alpha^R)} \left(v_{t+1}^O\right)^{\alpha_t^O - 1} \left(1 - v_{t+1}^O\right)^{\alpha_t^D + \alpha^R - 1}$$

so the conditional means under no actions by any player are

$$\mathbb{E}[v_{t+1}^D] = \frac{\alpha_t^D}{\alpha_t^D + \alpha_t^R + \alpha_t^O}$$

$$\mathbb{E}[v_{t+1}^R] = \frac{\alpha_t^R}{\alpha_t^D + \alpha_t^R + \alpha_t^O}$$

$$\mathbb{E}[v_{t+1}^O] = \frac{\alpha_t^O}{\alpha_t^D + \alpha_t^R + \alpha_t^O}$$

When $\alpha_t^O = 1 - v_t^D - v_t^R$, we get

$$\mathbb{E}[v_{t+1}^D] = v_t^D$$

$$\mathbb{E}[v_{t+1}^R] = v_t^R$$

$$\mathbb{E}[v_{t+1}^O] = 1 - v_t^D - v_t^R$$

Derivation of Equation (28)

Assume poll-to-poll interval t contains k stage games. If in period $k-1$ candidate p chooses $s^p = e$,

$$\mathbb{E}[v_k^D + v_k^R | v_{k-1}^D, v_{k-1}^R] = \frac{\alpha_k^D + \alpha_k^R}{\alpha_k^D + \alpha_k^R + 1 - v_k^D + v_k^R}$$

$$\mathbb{E}[v_k^D + v_k^R | v_{k-1}^D, v_{k-1}^R] = \frac{v_{k-1}^D + v_{k-1}^R + \tilde{\Delta}_{ep}^T}{1 + \tilde{\Delta}_{ep}^T}$$

Taking the expectation conditioning on period $k-2$, if in period $k-2$ candidate $\sim p$ chooses $s^{\sim p} = e$,

$$\mathbb{E}[v_k^D + v_k^R | v_{k-2}^D, v_{k-2}^R] = \frac{\frac{v_{k-2}^D + v_{k-2}^R + \tilde{\Delta}_{e\sim p}^T}{1 + \tilde{\Delta}_{e\sim p}^T} + \tilde{\Delta}_{ep}^T}{1 + \tilde{\Delta}_{ep}^T}$$

$$\mathbb{E}[v_k^D + v_k^R | v_{k-2}^D, v_{k-2}^R] = \frac{v_{k-2}^D + v_{k-2}^R + \tilde{\Delta}_{e\sim p}^T + \left(1 + \tilde{\Delta}_{e\sim p}^T\right)\tilde{\Delta}_{ep}^T}{\left(1 + \tilde{\Delta}_{e\sim p}^T\right)\left(1 + \tilde{\Delta}_{ep}^T\right)}$$

$$\mathbb{E}[v_k^D + v_k^R | v_{k-2}^D, v_{k-2}^R] = \frac{v_{k-2}^D + v_{k-2}^R - 1 + \left(1 + \tilde{\Delta}_{e\sim p}^T\right)\left(1 + \tilde{\Delta}_{ep}^T\right)}{\left(1 + \tilde{\Delta}_{e\sim p}^T\right)\left(1 + \tilde{\Delta}_{ep}^T\right)}$$

$$\mathbb{E}[v_k^D + v_k^R | v_{k-2}^D, v_{k-2}^R] = 1 - \frac{1 - v_{k-2}^D - v_{k-2}^R}{\left(1 + \tilde{\Delta}_{ep}^T\right)\left(1 + \tilde{\Delta}_{e\sim p}^T\right)}$$

Iterating backwards up to period 0, at which point the poll results are observed, noticing that all terms related to swing voter support cancel from the conditional expectations, we obtain

$$\mathbb{E}[v_k^D + v_k^R | v_0^D, v_0^R] = 1 - \frac{1 - v_0^D - v_0^R}{\left(1 + \tilde{\Delta}_{eD}^T\right)^{X_D^e + N_D^e}\left(1 + \tilde{\Delta}_{eR}^T\right)^{X_R^e + N_R^e}}$$

Derivation of Equations (29)

Define

$$\Delta_j^T = \begin{cases} 0 & if \quad s_j^D \neq e \quad and \quad s_j^R \neq e \\ \tilde{\Delta}_{eD}^T & if \quad s_j^D = e \quad and \quad s_j^R \neq e \\ \tilde{\Delta}_{eR}^T & if \quad s_j^D \neq e \quad and \quad s_j^R = e \end{cases}$$

and

$$\Delta_j^p = \tilde{\Delta}_{ep}^T \mathbf{1}\{s^p(j) = e, \chi^p(j) = 0\} + \left(\tilde{\Delta}_{ep}^T - \tilde{\Delta}_{ep}^S\right)\mathbf{1}\{s^p(j) = e, \chi^p(j) = 1\}$$

$$+\tilde{\Delta}_{e\sim p}^S \mathbf{1}\{s^{\sim p}(j) = e, \chi^{\sim p}(j) = 1\} + \tilde{\Delta}_{cp}^S \mathbf{1}\{s^p(j) = c, \chi^p(j) = 1\} - \tilde{\Delta}_{c\sim p}^S \mathbf{1}\{s^{\sim p}(j) = c, \chi^{\sim p}(j) = 1\}$$

Using iterated expectations period by period, it follows that

$$\mathbb{E}[v_k^p | v_0^p] = \frac{v_0^p}{\prod_{i=1}^{k-1}\left(1 + \tilde{\Delta}_i^T\right)} + \sum_{i=1}\left[\frac{\Delta_i^p}{\prod_{j=i}^{k-1}\left(1 + \tilde{\Delta}_j^T\right)}\right]$$

$$= \frac{v_0^p}{\prod_{i=1}^{k-1}\left(1 + \tilde{\Delta}_i^T\right)} + \frac{\sum_{i=1}\Delta_i^p}{\prod_{i=1}^{k-1}\left(1 + \tilde{\Delta}_i^T\right)} + O(\Delta^2)$$

Appendix C

News Coverage

In processing the article texts, we have followed several steps. The data collection was conducted in Lexis Nexis, and then for a subset of the years, we also conducted search in Factiva. (Due to the limits of search and downloads on Factiva, we could not execute a broader search for all of the 30 year election periods.) Our search terms included the name of the candidate (e.g. “Alan Kenneth Smith”) as well as the abbreviations or versions of the name that we were able to consider as alternatives for how the senate candidate might have been mentioned (examples may be “Senator Smith”, “Al Smith”, “Al K. Smith”). We have downloaded all articles which hit either of the two words in the downloads. We followed a clean up procedure for defining the articles about a candidate in the following fashion. We first remove all the common English words from the article (before the words are stemmed). Then using the Porter Stemming algorithm, we stem 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 data, we first conduct a pass for cleaning the articles which may be irrelevant to the political context that we are using them for. In the first pass, after stemming the articles, we look for the names of the candidate in the article. Here we look for the whole name, excluding any middle names or abbreviations (e.g., Jr.). If the name of the candidate is mentioned in the article, we consider the article to be relevant to our data analysis. If there is no mention of the article, we remove these articles into a bin for a secondary search to prevent any unintentional removal of relevant articles. We find that the first pass categorizes about 25% of the articles as irrelevant. Here, we are concerned that some of the articles that are relevant may be removed unintentionally. For example, a common reason to fail the first pass for an article may be 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.) To reduce similar Type-II errors, we conduct a second manual search on the articles that failed the first pass. A research assistant investigated the common reasons for error on articles where there is a mistake by looking at 10% of articles. We then updated our algorithm to account for these common errors. This second pass reduced the percent of articles removed to 20%.

We carry out our search algorithm for the common words using the articles that passed our second test. For each set of candidate articles, after removal of the 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 for another example of a similar choice).

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 D and and R running against each other), or because a candidate died during the race.

3-way races dropped:
AK 2010
LA 1992
LA 2002
CT 2006
FL 2010
ME 2012
Unopposed races:
ID 2004
SD 2010
AR 1990
GA 1990
MS 1990
KS 2002
In practice unopposed races:
VA 1990
AZ 2000
MA 2002
MS 2002
VA 2002
IN 2006
AR 2008
Not bipartisan races:

LA 1990
VT 2006
VT 2012
Candidate died:
MN 2002
Others:
NE 1988
IN 1990
ND 1992
TN 1994
KS 1996
GA 2000
MO 2002
WY 2008
CO 2010
DE 2010
LA 2010
WV 2010