# Polarization in Less than Thirty Seconds: Continuous Monitoring of Voter Response to Campaign Advertising 

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[^0]American political campaigns activate and reinforce rather than alter voters' basic partisan predispositions. Both aggregate and individual-level studies demonstrate that exposure to campaign communication strengthens the correspondence between partisan predispositions and voting choice (for a recent review, see lyengar and Simon, 2000).

At the aggregate level of analysis, the reinforcement effect appears over time, as voters gradually align their voting intention with the so-called "fundamentals": e.g., partisanship, retrospective assessments of the state of the economy, and approval of presidential performance (Gelman and King, 1993; Iyengar and Petrocik, 1998). By Election Day, the electorate is almost perfectly polarized, with the competing candidates enjoying near-unanimous support from the ranks of their respective partisans.

Individual-level studies of campaign effects also document reinforcement or polarization effects. These studies demonstrate that voters do not react to campaign messages as dispassionate observers, but as biased partisans (Schmitt et al., 2004; Lord, Ross, and Lepper, 1979; Eveland and Shah, 2003). For instance, no matter how flawed the actual performance of candidates during televised debates, in-partisans are quick to declare "their" candidate as the winner (Sigelman and Sigelman, 1984). In the most glaring example of such partisan filtering, Republicans felt that President Ford had out-debated Jimmy Carter despite Ford's repeated gaffes concerning the autonomy of Eastern Europe (Sears and Chaffee, 1979).

A second strand of individual-level evidence demonstrates the reinforcing effects of campaign advertising on partisan predispositions. Of the many forms of campaign communication, television advertising is especially likely to exert a polarizing effect among partisan viewers -- both because the audience for advertisements consists disproportionately of partisans and also because advertising is transparently one-
sided, making it relatively easy for partisans to recognize their position vis-à-vis the source and react accordingly. Party identification is such an important ingredient of the voter's attitudinal endowment that voters are motivated to resist persuasion (for the classic discussion of acceptance factors in the persuasion process, see McGuire, 1985).

Experiments provide the most direct evidence of advertising-induced partisan polarization. The key indicator of polarization is asymmetric persuasion in response to specific ads. In a series of experiments spanning both presidential and state-level campaigns, Ansolabehere and lyengar demonstrated that ads proved persuasive only among voters who shared the partisanship of the sponsoring candidate. Exposure to a single advertisement boosted support for the sponsor by 14 percent among inpartisans, but by only 3 percent among independents and out-partisans (Ansolabehere and lyengar, 1995, p. 76). In the particular case of relatively weak in-partisans (defined as those with little interest in politics), the sponsor's share of the vote actually increased by 25 percent (p. 80). Similar experimental findings emerged in studies of the 1992 and 1996 presidential campaigns which confirmed that the reinforcing effect of exposure to campaign ads was especially pronounced among younger voters, who are typically less partisan in inclination (see Iyengar and Petrocik, 1998). In short, as the scope and volume of ad campaigns increases, partisans of either side are more likely to line up in their respective corners.

In the present study, we attempted to model the polarizing effects of campaign ads using a novel methodology. We continuously monitored voters' reactions over the course of a thirty second ad. As they watched a pair of target ads from a 2006 Senate race, study participants moved a slider to indicate their general approval or disapproval of what they saw or heard during the playing of each ad. The pattern of change in the position of the slider demonstrates the reinforcing effects of advertising
quite clearly; Democrats and Republicans moved toward the opposite extremes as they watched the ads. The most effective senatorial ads polarized partisans quite rapidly, well before the closing display of the sponsor's identity. The least effective ads elicited longer periods of ambivalence from both Republicans and Democrats.

We compared rates of polarization across Democratic and Republican sponsors, and the tone (positive versus negative) of the message. In general, Democrats responded more quickly than Republicans to their respective ads suggesting a contextual advantage for the former. Polarization was also accelerated in the case of positive ads; partisans' dial scores generally took longer to converge in the case of negative ads. Finally, as anticipated, we found that the rate of polarization was significantly higher for the more strongly partisan of voters.

## Research Design

During the closing weeks of the 2006 Senate campaign, approximately 1,900 registered voters from the seven battleground states of Ohio, Pennsylvania, Maryland, Tennessee, Missouri, Montana, and Virginia participated in an online study in which they watched a pair of either negative or positive ads from the race for US Senate (one for each candidate). Study participants were selected from the Polimetrix online research panel. The number of participants from each state varied from a low of 80 in Montana to a high of 530 in Pennsylvania. Each participant was assigned to his or her home state condition, e.g., Montana residents only watched ads from the Montana Senate race. Across the entire sample, Democrats outnumbered Republicans by five percentage points (44 versus 39 percent). Participants were split evenly by gender, and their median age was 49. Twenty percent of the participants had a high school education or less, $35 \%$ had some college, and $45 \%$ were college graduates.

Non-whites accounted for 12 percent of the sample.

## Experimental Procedure

A novel feature of this experiment was the use of an online "dial" to monitor voters' reactions to advertising. Instead of asking for a summary evaluation of the ad, participants reacted continuously while the ad was playing. They were instructed (and given a practice task) on how to move a slider located immediately below the video in accordance with their feelings about the content of the ad. The specific instruction was:

If what you see or hear makes you feel good, or you agree with the speaker, indicate this by moving the slider towards the green end. If, however, your reaction is negative, and you dislike what you see or hear, then move the slider to the red zone.

Special software recorded the position of the slider once a second at quite a high level of resolution, by evenly dividing the range of dial positions into 100 intervals, with zero indicating the left or negative end of the dial, and 100 the right or positive end. Thus, as the ad played, we could monitor voters' reactions from beginning to end. At the start of each ad, the slider begins at the neutral or " 50 " position, and this is the first dial value recorded for each ad view. Figure 1 displays a pair of screenshots from one of the Tennessee conditions, with two hypothetical settings of the dial (not at the start of the ad).

After completing the practice trial, participants were shown a pair of Senate ads. They were assigned at random to either a positive or negative tone condition. The order in which the ads appeared was also randomized. The positive tone condition featured two positive ads, while the negative condition featured two negative ads (in either


Figure 1: Screenshots from On-Line Dial Experiment. As the ad played, subjects could move the slider (or "dial") to indicate their feelings about the content of the ad, with the position of the dial being recorded once a second.
case, one ad from each candidate). The treatment spots themselves were selected primarily from ads produced by the individual candidates, but in some instances we included ads aired on behalf of the candidates by the Democratic or Republican Senate campaign committees. Table 1 provides a full list of the Senate candidates and the ads used in this study.

|  | State | Candidate | Ad Title | Tone | Party |
| ---: | :--- | :--- | :--- | :--- | :--- |
| 1 | MD | Ben Cardin-D | Post | Positive | D |
| 2 | MD | Ben Cardin-D | Dogs | Negative | D |
| 3 | MD | Michael Steele-R | Real Ideas for Change | Positive | R |
| 4 | MD | Michael Steele-R | Taking out the Trash | Negative | R |
| 5 | MO | Claire McCaskill-D | Divide-Stem | Positive | D |
| 6 | MO | Claire McCaskill-D | Big Oil | Negative | D |
| 7 | MO | Jim Talent-R | Security | Positive | R |
| 8 | MO | Jim Talent-R | Again | Negative | R |
| 9 | MT | Jon Tester-D | Creating a Buzz | Positive | D |
| 10 | MT | Jon Tester-D | Numbers Game | Negative | D |
| 11 | MT | Conrad Burns-R | Conrad Burns 100\% | Positive | R |
| 12 | MT | Conrad Burns-R | Repeal It | Negative | R |
| 13 | OH | Sherrod Brown-D | Family Doctor | Positive | D |
| 14 | OH | Sherrod Brown-D | Critical | Negative | D |
| 15 | OH | Mike DeWine-R | Independent Fighter | Positive | $R$ |
| 16 | OH | Mike DeWine-R | Weakening Security | Negative | $R$ |
| 17 | PA | Bob Casey-D | Vote for our Dad | Positive | D |
| 18 | PA | Bob Casey-D | Debbie's Story | Negative | D |
| 19 | PA | Rick Santorum-R | Candles | Positive | $R$ |
| 20 | PA | Rick Santorum-R | Casey's Campaign Team | Negative | $R$ |
| 21 | TN | Harold Ford, Jr.-D | Partners | Positive | D |
| 22 | TN | Harold Ford, Jr.-D | Big Oil | Negative | D |
| 23 | TN | Bob Corker-R | A few Words | Positive | $R$ |
| 24 | TN | Bob Corker-R | Playboy | Negative | R |
| 25 | VA | Jim Webb-D | Gipper | Positive | D |
| 26 | VA | Jim Webb-D | 97 Percent | Negative | D |
| 27 | VA | George Allen-R | McCain | Positive | $R$ |
| 28 | VA | George Allen-R | Fiction | Negative | R |
|  |  |  |  |  |  |

After reacting to the two ads, participants completed a brief online survey including questions about their intended vote in the senate election. They also rated the two
candidates on a "feeling thermometer" from 0 (cold) to 100 (warm).

## Content Analysis

We classified each 30 second ad in accordance with several characteristics of the message, including partisanship of the sponsor and advertising tone (positive or negative). In addition, we carried out a more finely-grained content analysis in which we recorded the presence or absence of various messages during each second of the advertisement.

One set of message attributes concerned the visibility of the candidates in campaign ads. We recorded how frequently the sponsoring candidate or opponent was identified. (On average, references to the sponsor and opponent took up 13.893 and 7.607 seconds per ad respectively.) We also recorded for how long the sponsoring candidate ( 7.321 seconds per ad) or opponent ( 1.750 seconds per ad) appeared on screen or were mentioned in the voiceover ( 14.357 seconds for the sponsor, 10.607 seconds for the opponent).

Finally, we coded the ads for their issue content. Thirty-five distinct policy issues were referenced across the sample of 28 ads. Two issues stood out in terms of their salience. In the aftermath of the Abramoff scandal, candidates from both parties (incumbents and challengers alike) devoted significant attention to influence peddling and their commitment to reform ( 3.821 seconds per ad). References to national security/terrorism were almost as prominent ( 3.571 seconds per ad). As expected, Republicans were more likely to focus on terrorism than Democrats. In comparison with lobbying and terrorism, other issues paled in visibility; for instance, references to education, immigration, and health care amounted to $1.071,1.000$, and .929 seconds per ad respectively.

## Descriptive Analysis

We begin by plotting the dial scores (Figures 2 to 8 ) for all 28 ads used in the study. Red, blue and black lines show the dials series for Republicans, Democrats, and independents respectively. The lighter lines represent the time trends at the level of individual viewers, while the more heavily shaded lines capture the average trend for the three groups. Vertical lines indicate the inter-quartile range of dial scores at a particular second, by partisan group.

At the individual level, although there is considerable variability in the evolution of the dial scores, partisans do tend to polarize over time. Using the partisan means produces much smoother trajectories than inspecting the individual-level trajectories, and reveals a striking consistency of results across all 28 ads.

A compact, graphical summary of the trajectories of the party-specific, mean dial scores appear in Figure 9. Again, we see quite large and consistent disparities in the mean trajectories, by party of the subject, and party of the candidate. In short, Republicans tend to like the messages in Republican ads, and tend to dislike the messages in Democratic ads, and conversely for Democrats. Figure 9 provides a visual hint that Republican ads are generating faster and larger responses from Republican partisans, and possibly from Democratic partisans, and this is a point we explore with the statistical modeling reported below.

Responsiveness to advertising is limited to partisans: while Republicans and Democrats inevitably move in opposing directions, independents are more likely to be unmoved by the ads, and are considerably more likely to remain ambivalent over the entire playing of the ad. Two insights into this are presented in Figures 10 and 11. Figure 10 shows the percentage of partisans who have the slider set to the highest or lowest possible positions, second-by-second, and by party. Since each ad view



Figure 4: Dial Scores Trajectories, by Second and Partisanship of Subject, Montana. Red trajectories indicate Republican subjects; blue for Democrats, and black for independents. The trajectories shown with heavier lines are the second-by-second means for each party groups, with the vertical lines corresponding to the second-by-second party-specific inter-quartile ranges.


Figure 5: Dial Scores Trajectories, by Second and Partisanship of Subject, Ohio. Red trajectories indicate Republican subjects; blue for Democrats, and black for independents. The trajectories shown with heavier lines are the second-by-second means for each party groups, with the vertical lines corresponding to the second-by-second party-specific inter-quartile ranges.


Figure 6: Dial Scores Trajectories, by Second and Partisanship of Subject, Pennsylvania. Red trajectories indicate Republican subjects; blue for Democrats, and black for independents. The trajectories shown with heavier lines are the second-by-second means for each party groups, with the vertical lines corresponding to the second-by-second party-specific inter-quartile ranges.




Figure 9: Average Partisan Response to Republican Ads, by Partisan Group. Red lines indicate second-by-second mean dial scores of Republican subjects; blue lines for Democrat subjects and black lines for Independents.


Figure 10: Percentage of Subjects Recording 0 or 100 Dial Scores, by Second and Subjects' Partisanship.
begins with the slider at 50 , no one records the maximum or minimum score at the start of the ad view. But as the ads proceed, partisans are gradually finding their way to the extreme positions such that by the end of the ads, roughly $1 / 3$ of partisans have indicated their like or dislike of the ad content to the maximum extent possible. The corresponding proportion for independents is just over 20\%. Clearly, independents are not as agitated by the ad content as are partisans.

A similar story emerges from Figure 11, showing the percentage of subjects who are yet to move from the initial, "neutral" dial setting of 50. Partisans are generally faster to move away the 50 mark than independents. Ten seconds into the ads, on average, only about $25 \%$ of Democratic subjects and $30 \%$ of Republican subjects are yet to have moved the dial, while the corresponding proportion among independents is 37\%. By the end of the ad, only 4\% of Democrats and 6\% of Republicans have left the dial setting unchanged, while the corresponding proportion among independent


Figure 11: Percentage of Subjects Yet to Move from Initial, Neutral Dial Score of 50, by Second and Subjects' Partisanship.
is $10 \%$.
These summaries of the data strongly suggest that partisan reaction to the partisan source of particulars ads is the most politically interesting feature of the data. One more descriptive graph helps make this point. Figure 12 shows levels of polarization, measured as the difference between the second-by-second average dial score for Republican subjects, and the corresponding quantity among Democratic subjects, ad by ad. Democratic ads are generally disliked by Republicans, but liked by Democrats, and so the Republican mean score minus the Democratic mean score for such an ad is almost always a negative quantity (a small quantity minus a larger quantity); conversely, a Republican ad generates high/low dial scores from Republicans/Democrats and almost always generate a positive polarization score. We also distinguish ads by their tone; negative ads are shown in Figure 12 with the black line, and generate trajectories in polarization that are generally indistinguishable from


Figure 12: Polarization, by Second and by Ad Type (partisan sponsor and tone)
positive ads sent by the same partisan sponsor. There is one prominent exception, a negative ad by Ben Cardin (D-MD) that produced very little polarization (the black line sitting above the pack of Democratic ads); inspection of Figure 2 shows that this ad did little to move Democrats or Republicans, on average, and in this sense is the "least effective" ad of the 28 ads analyzed here. Thus, for the remainder of the paper, we concentrate on the effects of partisan sourcing, deferring a consideration of the effects of tone to another day.

## Statistical Modeling

The series of descriptive graphs just presented are suggestive, but only that. While partisan reactions to ads appear to be the dominant pattern in the dials data, conditional on the partisanship of the candidate sponsoring the ad, we are yet to present any authoritative test of this conjecture. We are also interested in differences
across partisan groups, and across the partisanship of the candidates.
Each respondents' dials scores form a trajectory over time, $\left\{y_{t}\right\}, y_{t} \in\{1,2, \ldots, 100\}$, $t=1,2, \ldots, 30$, all constrained to start at $y_{1}=50$. We model these trajectories with a non-linear, Gompertz function in time, with a horizontal offset:

$$
y_{t}= \begin{cases}50+\beta_{1}\left(1-\exp \left[-\exp \left(\beta_{2}\right)\left(t-\beta_{3}\right)\right]\right) & \text { if } t>\beta_{3}  \tag{1}\\ 50 & \text { otherwise }\end{cases}
$$

The $\beta_{1}$ parameter defines an asymptote in for $y_{t}$; that is, as $t \rightarrow \infty, y_{t} \rightarrow 50+\beta_{1}$. The $\beta_{2}$ parameter is a growth rate, while $\beta_{3}$ is the horizontal offset: i.e., there is no growth in $y_{t}$ until $t>\beta_{3}$, since at $t=\beta_{3} \Rightarrow y_{t}=50+\beta_{1}[1-\exp (0)]=50$, and we explicitly set $y_{t}=50, \forall t<\beta_{3}$. In this way $\beta_{1}$ is a measure of the extent to which the ad influences opinion. The parameter $\beta_{2}$ is a measure of the speed with which the ad moves respondents to the $50+\beta_{1}$ asymptote (but only after opinions begin to move away from $y_{1}=50$ ); $\beta_{2}$ is actually the logarithm of the rate constant, and is related to the "half-life" $t_{0.5}=\log 2 / \exp \left(\beta_{2}\right)$, the time it takes for $y_{t}$ to travel half the distance to its asymptote of $50+\beta_{1}$, after it begins to move. $\beta_{3}$ is a measure of how long opinions remain dormant through exposure to the ad. Thus, a "powerful" ad is one that, say, has a large $\beta_{1}$ parameters (in absolute value), a large $\beta_{2}$ growth rate parameter, and small $\beta_{3}$ (dormancy period).

We fit equation 1 to the dials data by grouping respondents according to the ads they viewed, and by party identification categories. That is, let $j$ index the set

$$
\begin{equation*}
\mathcal{J}=\{\mathcal{S} \times \mathcal{P} \times \mathcal{C} \times \mathcal{T}\} \tag{2}
\end{equation*}
$$



Figure 13: Three-Parameter Non-Linear Growth Curve. $\beta_{1}$ parameterizes the vertical displacement of the asymptote in $y, 50+\beta_{1}$, as $t \infty$. $\beta_{2}$ is the logarithm of the growth rate, such that half of the growth in $y$ occurs at $t_{0.5}=\log 2 / \exp \left(\beta_{2}\right) . \beta_{3}$ is dormancy period, such that there is no movement away from $y=50$ until $t>\beta_{3}$.
where the sets

$$
\begin{aligned}
\mathcal{S} & =\{" M D ", " M O ", " M T ", " O H ", " P A ", " T N ", " V A "\} \\
\mathcal{P} & =\{\text { Democrat, Independent, Republican }\} \\
\mathcal{C} & =\{\text { Democrat, Republican }\} \\
\mathcal{T} & =\{\text { Positive, Negative }\}
\end{aligned}
$$

are (respectively), states, respondent party identification categories, candidate parties, and tone of advertisements. That is, $\#\{\mathcal{J}\}=J=7 \times 3 \times 2 \times 2=84$ is the total number of design configurations. Any particular ad view and its corresponding dial score trajectory belongs to one of these categories; we let $i=1, \ldots, n_{j}$ index the trajectories within design configuration $j=1, \ldots, J$. Within each design configuration we then fit equation 1 to each trajectory, via the following hierarchical model (momentarily suppressing the $j$ subscript indexing design configuration, for notational clarity):

$$
\begin{align*}
y_{i t} & \sim N\left(\mu_{i t}, \sigma_{t}^{2}\right)  \tag{3a}\\
\mu_{i t} & = \begin{cases}50+\beta_{i 1}\left(1-\exp \left[-\exp \left(\beta_{i 2}\right)\left(t-\beta_{i 3}\right)\right]\right) & \text { if } t>\beta_{i 3}, \\
50 & \text { otherwise }\end{cases}  \tag{3b}\\
\beta_{k i} & \sim N\left(\beta_{k}, \sigma_{k}^{2}\right), \quad k=1,2  \tag{3c}\\
\beta_{k} & \sim N\left(0,100^{2}\right), \quad k=1,2  \tag{3d}\\
\sigma_{k} & \sim \operatorname{Unif(0,100),\quad k=1,2}  \tag{3e}\\
p\left(\beta_{i 3}=t\right) & =1 / T_{j}, \forall t=1, \ldots, T_{j} . \tag{3f}
\end{align*}
$$

where equation 3c defines a hierarchical model for the individual-level asymptote and growth parameters $\beta_{i 1}$ and $\beta_{i 2}$, respectively, with equations 3d and 3e completing
the specification of the hierarchical model, giving proper prior densities over the hyperparameters $\beta_{k}$ and $\sigma_{k}^{2}$. No hierarchical structure is imposed on the dormancy parameters $\beta_{i 3}$, which are given a prior mass function placing equal prior weight on each of the discrete $T_{j}$ time periods (equation 3f).

The ideas underlying this model is that each trajectory can be reasonably approximated as a member of the family of three-parameter growth curves given in equation 1. It should be all trajectories of the form of equation 1 are monotone. Flamboyantly non-monotone dial score trajectories will not be well fit by a growth curve of the sort in equation 1. There are a reasonable number of monotone trajectories apparent in Figures 2 through 8 that will not be fit well by the model in equation 3, but they are not particular abundant; we can augment the growth curve with additional non-linear terms to capture particularly flamboyant trajectories, but refrain from doing so for now.

Within each design configuration $j \in \mathcal{J}$, we assume that trajectories are exchangeable conditional on the hierarchical model given above. That is, we assume that, say all Democrats watching the same ad will generate dial score trajectories that are sufficiently similar such that variation in trajectories is adequately captured by the hierarchical model in equation 3c. In this way, the trajectory defined by

$$
y_{t}= \begin{cases}50+\beta_{1}\left(1-\exp \left[-\exp \left(\beta_{2}\right)\left(t-\bar{\beta}_{3}\right)\right]\right) & \text { if } t>\bar{\beta}_{3}  \tag{4}\\ 50 & \text { otherwise }\end{cases}
$$

is the average dial score trajectory in a particular design configuration, where $\beta_{1}$ and $\beta_{2}$ are the means of the $\bar{\beta}_{3}=n_{j}^{-1} \sum_{i=1}^{n_{j}} \beta_{i 3}$. After estimating these hyperparameters specific to a particular design configuration $j$, we can then compare them across configurations, looking for systematic differences through the design strata: party
of the candidate, party identification of the ad viewing subjects, and tone of the ad. Alternatively, another hierarchical model for the $\beta$ parameters would be another way to test for these differences, but we defer this for a future revision of this paper.

Finally, we also specify a model for the variances $\sigma_{t}^{2}$. Since all dial score trajectories start at 50, and move away from that starting point at different rates, the variation in dial scores across subjects at any given time point is surely non-constant. Put simply, the disturbances $\varepsilon_{i t}=y_{i t}-\mu_{i t}$ are heteroskedastic, where $\mu_{i t}$ is defined as in equation 3b. We deal with this by fitting letting the variances $\sigma_{t}^{2}=\operatorname{var}\left(\varepsilon_{i t}\right)$ evolve via the following model:

$$
\begin{align*}
\log \sigma_{t} & \sim N\left(\gamma_{1}+\gamma_{2} t+\gamma_{3} \log \sigma_{t-1}, \omega^{2}\right)  \tag{5a}\\
\gamma_{k} & \sim N\left(0,10^{2}\right), \quad k=1,2,3  \tag{5b}\\
\omega & \sim \operatorname{Unif}(0,10) \tag{5c}
\end{align*}
$$

and noting that $\sigma_{1}=0$ (i.e., all dial score trajectories start at $y_{1}=50$ ).
The statistical model defined in equations 3 and 5 generates a normal likelihood, subject to the complications induced by the hierarchical model for the $\beta i 1$ and $\beta_{i 2}$ parameters, and the auto-regressive heteroskedastic component of the model given in equation 5. We adopt a Bayesian approach for inference, using Markov chain Monte Carlo (MCMC) methods to explore the joint posterior density of the model parameters, using the free software package JAGS, version 1.01. The MCMC algorithm is run for 4,000 iterations, with the first 1,000 iterations discarded as burn-in. Graphical inspection of trace plot indicate no problems with convergence, and suggest that the MCMC algorithms are mixing well.

## Results

Estimating the model described in the previous section yields $J=84$ estimates of $\beta_{1}, \beta_{2}, \beta_{3}$, which together define the average dial score trajectory for design configuration $j$. There are too many design configurations for us to report the result of the model fitting for each configuration. Some graphical summaries of the model fitting appear in Figure 14 and 15, showing the fit of the model to the data from the 12 design configurations that encompass the Maryland data: i.e., 2 candidates, 2 ad types (positive and negative), and subjects classified into three party identification categories. The colored lines indicate individual dial score trajectories (red for Republican views, violet for Independents and blue for Democrats). The dark lines summarize uncertainty as to the location of the average dial score trajectory (equation 4), with the estimated average dial scores lying in the middle of the dark lines.In some cases the dark lines are spread diffusely, indicating relatively less precision in the corresponding estimates of the average trajectories. At least for the 12 configurations shown in Figures 14 and 15, the model does a reasonable to very good job of capturing the trends in the raw data (compare the raw data for Maryland respondents in Figure 2).

Our primary interest lies in the understanding the variation in the $\beta$ parameters across design configurations. Due to constraints of time and space we focus on $\beta_{1}$, the parameter that taps how far the steady-state average dial trajectory has departed from the initial state of 50 . Figure 16 displays all 84 point estimates of $\beta_{1}$, indicating that $\beta_{1}$ varies considerably across the design configurations. Recall also that positive values of $\beta_{1}$ are consistent with average trajectories converging on a generally positive view of the ad content, and conversely for negative values of $\beta_{1}$. Partisan reactions dominate the pattern of results in Figure 16: Democrats generally like ads from



Ben Cardin (MD-D) - "Post" - Positive
Ind viewers

Figure 14: Estimated Average Dial Score Trajectories, Maryland Senate Contest, positive ads from both major party candidates. The colored lines indicate individual dial score trajectories (red for Republican views, violet for Independents and blue for Democrats). The dark lines summarize uncertainty as to the location of the average dial score trajectory (equation 4), with the estimated average dial scores lying in the middle of the dark lines.




Ben Cardin (MD-D) - "Dogs" - Negative


Time Figure 15: Estimated Average Dial Score Trajectories. Maryland Senate Contest, negative ads from both major party candidates. The colored lines indicate individual dial score trajectories (red for Republican views, violet for Independents and blue for Democrats). The dark lines summarize uncertainty as to the location of the average dial score trajectory (equation 4), with the estimated average dial scores lying in the middle of the dark lines.

Democratic candidates, Republicans generally like Republican ads, though probably not as much as Democrats like Democratic ads, which perhaps reflects the poor political environment faced by Republican candidates in 2006. Mismatches between the partisanship of sending candidate and viewing subject generally result in negative views of the ad content. Independents generally like very few ads at all: the estimated $\beta_{1}$ parameters are generally small for independents, and at least relative to partisans, save for a few negative ads that evoked considerable opprobium from independents, almost on a par with the reactions of the ad's out-partisans (e.g., the Bob Corker "Playboy" ad attacking Harold Ford Jr, and the Claire McCaskill negative ad from the Missouri Senate race). The other pattern that is visually apparent in Figure 16 is the way that all respondents appear to dislike negative ads, at least relative to positive ads from the same candidate. In all but two cases, the $\beta_{1}$ from the negative ad from a given candidate lies below the corresponding $\beta_{1}$ from that candidate's positive ad.

To more rigorously assess these conclusions about the patterns in $\beta_{1}$ across ads, we estimate a series of simple regression models. Design strata appear as predictors in these regression models. Since Figures 14 and 15 reveal variation in uncertainty around the estimates of $\beta_{1}, \beta_{2}$ and $\beta_{3}$ across design configurations, we estimate these regressions with weighted least squares, with weights $w_{j}$ equal to the reciprocal of the standard deviation of the posterior density of the respective $\beta_{1}, \beta_{2}$, and $\beta_{3}$. In this way, estimates of $\beta$ that are relatively imprecise get relatively less weight in these 2 nd stage regressions.

The set of regression models consists of a series of direct effects for the following design strata: (1) subject party identification $\mathcal{P}$; (2) candidate party $\mathcal{C}$, and (3) ad tone $\mathcal{T}$. We also consider interactions among these variables. We also consider models that include (1) fixed effects for the 28 unique ads in the study, given by crossing the design strata states $\mathcal{S}$, candidate party $\mathcal{C}$ and tone $\mathcal{T}$, and (2) fixed effects for


Figure 16: Estimates of $\beta_{1}$ (steady-state level of movement from initial dial setting of $y_{1}=50$ ), across the 84 design configurations, grouped by party identification viewing subject $(\mathcal{P})$ and tone of ad $(\mathcal{T})$.

| Model | Description | $d f$ | $r^{2}$ | AIC |
| :--- | :--- | :---: | ---: | ---: |
| Model 1: | Candidate Fixed Effects: $\mathcal{S} \times \mathcal{C}$ | 14 | .18 | 84.84 |
| Model 2: | Ad Fixed Effects: $\mathcal{S} \times \mathcal{C} \times \mathcal{T}$ | 28 | .35 | 92.66 |
| Model 3: | Direct Effects of Viewer, Sender, Tone: $\mathcal{P}+\mathcal{C}+\mathcal{T}$ | 5 | .18 | 66.64 |
| Model 4: | Viewer-Sender Interaction: $\mathcal{P} \times \mathcal{C}+\mathcal{T}$ | 7 | .89 | -101.01 |
| Model 5: | Viewer Interactions: $\mathcal{P} \times(\mathcal{C}+\mathcal{T})$ | 9 | .90 | -101.28 |
| Model 6: | Sender Interactions: $\mathcal{C} \times(\mathcal{T}+\mathcal{P})$ | 8 | .89 | -99.10 |
| Model 7: | 3-way interactions: $\mathcal{C} \times \mathcal{T} \times \mathcal{P}$ | 12 | .91 | -102.63 |


| Hypothesis Tests |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| Restricted | Unrestricted | $F$-test | df | $p$-value |
| Model 5 | Model 7 | 2.19 | 3 | .10 |
| Model 4 | Model 6 | 0.08 | 1 | .78 |
| Model 4 | Model 7 | 2.13 | 5 | .07 |
| Model 4 | Model 5 | 1.96 | 2 | .15 |

Table 1: Model Comparisons for $\beta_{1}$, steady-state, average deflection of dial from initial neutral state. Data from $J=84$ design configurations. All models estimated with weighted least squares.
candidates alone, given by the product of the design strata states $\mathcal{S}$ and candidate party $\mathcal{C}$.

Comparisons of the regression models fit to the data appear in Table 1. The simple fixed effects specifications (Models 1 and 2) soak up a lot of degrees of freedom for relatively little fit to the data. Model 3, which simply fits a series of dummy variables for the viewing subject's partisanship, the partisanship of the candidate and a dummy variable for tone consumes just 5 degrees of freedom, but produces a poor fit to the data as well. Consistent with the pattern in Figure 16, it is the partisan match (or lack thereof) between sponsoring candidate and viewing subject that produces a dramatic jump in fit: Models 4 through 7 all include the complete set of 6 interactions between $\mathcal{P}$ and $\mathcal{C}$ and have $r^{2}$ in the neighborhood of .90. Ad tone enters into various forms throughout Models 5 to 7, but with only marginal improvement in fit to Model 4; although the AIC is minimized with Model 7, we narrowly fail to reject the null
hypothesis that the restrictions in Models 4 and 5 relative to Model 7 are true, at least at conventional levels of statistical significance ( $p=.07$ and .10 , respectively). We also fail to reject Model 4 in favor of Model 5, with the latter model introducing interactions between tone and the partisanship of the viewer. Parameter estimates for Model 4 appear in Table 2.

Finally, we also estimate a series of models that augments Model 4 with a one degree of freedom interaction between each of the viewing subject partisanship categories and ad tone, testing the idea that maybe tone impacts particular partisan groups in particular ways. A summary of this additional analysis appears in Table 2. We find no support for this hypothesis, at least not at conventional levels of statistical significance. Tone of the ad does matter: the estimated negative tone offset in $\beta_{1}$ provided by Model 4 is 16 points on the 100 point dial score $(t=6.5)$, a large and important difference, and about half of the estimated 33 point difference between Independents and Democrats $\beta_{1}$ estimates, and over half the 26 point difference between Independent and Republican $\beta_{1}$ estimates (see the point estimates in Table 2). But based on these data, we cannot reject the contention that while there is a negative reaction to negative ads, this reaction does not appear to vary across partisan groups. Independents are notable for being less impressed by political ads in particular, but their relative dislike for negative ads seems no larger or smaller than that of partisans.

## Discussion

Exposure to campaign advertising inevitably polarizes partisan viewers. Voters' partisan commitment takes precedence over de novo impression formation during the course of a thirty second campaign advertisement. The onset of an ad automatically

| Model 4 |  | Estimate | Std. Error |  |
| :---: | :---: | :---: | :---: | :---: |
| Intercept |  | 20.3 |  | 2 |
| Independent Viewers |  | -33.5 | 4 | 9 |
| Republican Viewers |  | -59.3 | 4 | 1 |
| Republican Candidate |  | -65.7 | 3 | . 7 |
| Positive Tone |  | 16.0 | 2 | . 5 |
| Independent Viewer $\times$ Republican Candidate |  | 58.2 |  | 8 |
| Republican Viewers $\times$ Republican Candidate |  | 125.4 |  | . 5 |
| Restricted | Unrestricted | $F$-test |  | $p$-value |
| Model 4 | Democrat-specific reaction to tone | 3.14 | 1 | . 08 |
| Model 4 | Independent-specific reaction to tone | e 2.44 | 1 | . 12 |
| Model 4 | Republican-specific reaction to tone | 0.29 | 1 | . 59 |

Table 2: Parameter Estimates and Additional Tests of Model 4
cues voters to respond in partisan terms and in most cases they adjust their evaluations of the ad to conform to their partisan identity well before the closing screen. In this sense, the rate of change in partisan viewers' dial scores is an indicator of partisan priming. Advertising prompts the viewer to respond as a Democrat or Republican. Here, our work is closely analogous to psychological research which typically tests for priming effects through response latency: the lower the response time, the stronger the prime.

Our analysis has yet to consider several attributes of the advertising message -both verbal and visual -- that might affect the rate of partisan polarization. For instance, the early appearance on screen of the sponsoring or opposing candidate could make it easier for viewers respond in partisan terms. Conversely, messages that focus on personal attributes rather than policy issues may dampen partisan processing of the message. There may also be a learning curve to the partisan response by which ads encountered later in the campaign are processed more rapidly than those viewed at an early stage.

In closing, we acknowledge again that advertising is the most partisan form
of campaigning and thus the most likely to generate polarized responses. More "objective" messages including news reports, talk show appearances or candidate debates may well yield less polarized results and more temporal variation within partisan groups. We intend to incorporate dials data on these alternative forms of campaign communication during the 2008 cycle.

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[^0]:    ${ }^{1}$ Iyengar and Jackman, Stanford University; Hahn, UCLA. Prepared for presentation at the Annual Meeting of the Midwestern Political Science Association, Chicago, Illinois.

