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Harvard Business School

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Selling to a Moving Target: Dynamic Marketing Effects in US Presidential Elections

Doug J. Chung, Lingling Zhang

Harvard Business School, Harvard University, Boston, MA 02163, United States

dchung@hbs.edu, lzhang@hbs.edu

Abstract

We examine the effects of various political campaign activities on voter preferences in the domain of US Presidential elections. We construct a comprehensive data set that covers the three most recent elections, with detailed records of voter preferences at the state-week level over an election period. We include various types of the most frequently utilized marketing instruments: two forms of advertising—candidate’s own and outside advertising, and two forms of personal selling—retail campaigning and field operations. Although effectiveness varies by instrument and party, among the significant effects we find that a candidate’s own advertising is more effective than outside advertising, and that advertising and retail campaigning work more favorably towards Republican candidates. In contrast, we find field operations to be more effective for Democratic candidates, primarily through get-out-the-vote efforts. We do not find any between-party differences in the effectiveness of outside advertising. Lastly, we also find a moderate but statistically significant carryover effect of campaign activities, indicating the presence of dynamics of marketing efforts over time.

Key words: multi-channel marketing, personal selling, advertising, political campaigns, dynamic panel data, instrumental variables.

1. Introduction

Choosing the person who stands at the head of a country, guiding its political, social, military, and economic influence, is inarguably of great importance. Yet the success or failure of electoral campaigning has long remained a matter of some mystery, explicable—if at all—only after the dust of a surprising outcome has settled. It is tempting to seek to understand political processes by applying the principles of the market. After all, isn't a successful campaign for a presidential candidate (i.e., convincing more than half the registered voters who actually get to the polls to cast their ballot as we wish) like making a winning argument that someone should buy a BMW over a Mercedes? Well, maybe yes—and maybe no.

The most obvious difference is that when the sales figures come in, after the wind-up of expensive marketing campaigns, BMWs will either have sold better or worse than Mercedes, but presumably both will have some market share, achieving something and likely surviving through their hard work and investment. A presidential election, on the other hand, is an extraordinarily expensive winner-take-all proposition. Second place is quite literally nothing, a complete loss; and the people working in that “company,” including the CEO-candidate, are in essence then unemployed.

However, setting aside the differences in stakes and scale between the domains of US national politics and product marketing, there are striking and informative parallels that allow us to judiciously apply marketing theory to understand the best and most efficient ways to use the huge but still finite resources available to a US presidential campaign.

The skyrocketing campaign spending in recent US presidential elections has prompted intense interest among political strategists, academics, and even the general public in understanding the effects of political campaigns. For example, in the 2012 Barack Obama versus Mitt Romney election, the campaigns and their allies spent a total of \$2.3 billion, making it the most expensive US presidential election in history (Sides and Vavreck, 2013). Until the 1980s, most academic research on political elections concluded that presidential campaigns had only a “minimal effect”: they simply reinforce a voter's existing beliefs but are incapable of altering a voter's political predisposition or even convincing an intended non-voter to vote (e.g., Finkel, 1993; Klapper, 1960).

In contrast, recent studies have come to reach a different conclusion, finding evidence that political campaigns can shift voter preferences and hence make a substantial impact on election outcomes. Yet, several important questions remain unanswered: i) What are the effects of various types of campaign activities such as advertising, candidate live appearances, and field operations? ii) What are the effects of different types of advertising—a candidate’s own vs. outside advertising? iii) Do the effects of campaign activities vary by party? And importantly, iv) Are the effects contemporaneous and largely short-lived, or do they persist? If the latter is true, for how long does the effect last? Answers to these questions would provide the much-needed insights into guiding efficient allocation of campaign resources throughout an election period.

Understanding the true campaign effect is a challenging task. One difficulty is related to measuring voters’ actual exposures to various campaign activities. Many extant papers used survey-based self-reports, e.g., asking individuals how much media advertising they could recall being exposed to (Finkel, 1993). However, such measures are subject to both the selection bias (respondents and non-respondents may differ in their levels of interest in politics as well as attentiveness in campaign activities) and the measurement bias (recall accuracy may correlate with a voter’s political predisposition) (Goldstein and Ridout, 2004). With better empirical data becoming available recently, several studies have found more objective measures on campaign activities; for example, how much advertising was actually aired in each media market (e.g., Gordon and Hartmann, 2013; Shaw, 1999) and how many field offices were deployed in each county (Chung and Zhang, 2014; Darr and Levendusky, 2014).

The second challenge with examining the campaign effects is the endogeneity concern associated with the level of campaigns. Simply put, how much campaign activities are deployed to promote a candidate may be correlated with how much voter support he or she receives; however, we researchers may not be able to observe all of the underlying strategic factors, creating an endogeneity problem. There are at least two reasons why endogeneity may be present in our context. First, campaign efforts tend to be much more concentrated in the so-called “battleground states” than in other states simply because it makes little sense to campaign where the focal candidate is almost surely to win or lose. However, when all candidates shift their strategic

emphasis to the battleground states, the head-on competition there may make the winning margins even narrower in those states than in the non-battleground states. Second, the changes in campaign activities over time may also be endogenous. Intuitively, an effective campaign should monitor the voter support to their focal candidate in each state and promptly adjust the efforts accordingly. Precisely because of these two reasons, simply correlating the level of campaign activities with voter preferences would yield an inaccurate estimate of the campaign effect; in some cases we might even identify a negative association, forced to conclude that campaign activities can actually hurt the candidate.

Extant empirical studies on campaigns have largely acknowledged yet not adequately addressed the endogeneity concern on campaign planning. The few exceptions include Gordon and Hartmann (2013) and Huber and Arceneaux (2007), both of which focus exclusively on the effect of campaign advertising. Gordon and Hartmann (2013) utilized the instrumental variable approach, using advertising prices in the previous non-election year as instruments for the amount of advertising. Huber and Arceneaux (2007) exploited a natural experimental setting and examined the effect of advertising in non-battleground states, where advertising exposures were more “accidental” than strategic. However, both studies focused on identifying the overall causal effect across elections and did not address the dynamics of a campaign effect that likely exist within an election period.

The one study that allows for within-election-period dynamics is a paper by Gerber et al. (2011). By manipulating the level of a gubernatorial candidate’s own advertising in different media markets through a field experiment, the authors found that political advertising had some enduring effect over time. Although the field-experimental design offers a clean identification strategy for causal inference, it comes with a cost of external validity; such experiments are typically small in scale (both cross-sectional and longitudinal) compared to national presidential campaigns—Gerber et al. carried out their experiment in roughly 20 media markets for three weeks during the 2006 Texas Gubernatorial Election.

While the vast majority of research on political campaigns has addressed mass-media advertising, in reality, candidates have always employed multiple campaign activities—advertising,

candidate appearances, field operations—to mobilize and persuade potential voters. Because the levels of various campaign activities tend to be highly correlated, studying the effect of one without accounting for the others may lead to an estimation bias. A few papers have examined campaign activities beyond media advertising. Shaw (1999) found that television advertising and candidate appearances had substantial effects in the 1988-96 US presidential elections. Chung and Zhang (2014) studied three campaign activities—field operations, a candidate’s own advertising, and outside advertising sponsored by independent political interest groups—and found that campaign effects differed among voter segments. However, both of these studies focused on the aggregate campaign effects throughout an election period; hence they cannot address one question vital to candidates and campaigns: how best to allocate resources within an election period. Voter preferences towards a candidate fluctuate during an election year either because of external shocks or because of a candidate’s own and rival’s marketing efforts. Thus, campaigns are trying to sell their appeal to a dynamic and moving target.

While earlier studies in this field can probably help provide guidance on how to allocate campaign resources before the start of the general election, most presidential campaigns have to deal with ups and downs over an entire campaign period and, thus, need to micro-manage available resources in a time-specific manner. That is, how much and where to campaign, using which campaign activities, at which particular time during the election.

In this paper, we examine the dynamic effect of campaigns in the context of US presidential elections. In particular, we examine all of the principal campaign activities at the disposal of candidates, specifically, in the domain of mass media television advertising—both the candidate’s own and outside advertising—and that of personal selling—the candidate’s live appearances and field operations. The former involves large-scale mass-media communication while the latter generates voter contacts in a more targeted and personal manner, analogous to mass-media advertising and personal selling, respectively, in markets for products and services. While the other three activities likely take effect throughout an election period, field operations are typically believed to increase the turnout of voters who are likely to vote for that campaign’s candidate, primarily through the get-out-the-vote effects.

We use multiple sources to compile a comprehensive weekly panel data set at a grandeur scale that covers the general-election periods for the 2004, 2008, and 2012 US presidential elections. We collect detailed records on advertising—both the candidates’ own and outside advertising—and candidate live appearances during each election period. Further, we measure the scale of field operations by enumerating the field offices deployed by each party in each state for each of the three election years.

For our empirical application, we apply the dynamic panel data modeling approach (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998) and treat the campaign variables as endogenous. Our results generate several insights into understanding the dynamics of campaign effects. We find both short- and long-term effects for various campaign activities. Although both types of advertising (a candidate’s own and outside advertising) boost a candidate’s favorability while suppressing the rival’s, a candidate’s own advertising has a much greater impact. Further, live appearances increase a candidate’s favorability, and field operations boost voter turnout for the focal candidate. Interestingly, a candidate’s own advertising and live appearances seem to have a stronger effect for Republican candidates, whereas the get-out-the-vote effect seems to favor Democratic candidates. The effect of outside advertising seems to have no difference between parties.

Our paper makes two main contributions. First, using a unique and comprehensive data set, we generate new insights on the dynamic effect of political campaigns, after addressing both endogenous campaign planning and heterogeneity in voter preferences across candidates and states. Thus, our results can help campaign strategists design when, where, how—and how much—to campaign. Second, our paper jointly estimates the expected payoffs of various campaign activities. By including television advertising, candidate appearances, and field operations, the three most frequently used campaign tools that campaign strategists employ to influence voter preferences during an election, we comprehensively address the issue of campaign resource allocation. We elucidate not only the positive effects of advertising and candidate appearances but also the negative effects of campaign activities by their opponents. Furthermore, to the best of our knowledge, this paper is one of the first attempts to systematically examine the effect of outside

political ads, a force that has gained increasing importance during recent presidential elections. Knowing the “bang for the buck” of various campaign techniques will help a candidate decide when to visit a particular state and when and how much to advertise. Further, by carefully analyzing the effect of field operations on voter turnout, our research will inform the effectiveness of the get-out-the-vote efforts, which have been speculated as one of the factors in the landslide victories of Obama in the 2008 and 2012 elections (Chung and Zhang, 2014).

We believe that our findings will help inform potential presidential candidates and their political strategists on how best to utilize resources to win an election. There will always be some external factors that are utterly beyond the control of a candidate or a campaign—acts of terrorism, financial crises, and natural disasters. Nevertheless, our research will provide guidance for making the best possible use of the ones that are controllable.

The remainder of the paper is organized as follows. Section 2 describes the campaign activities and the data used for empirical analysis. Section 3 presents the model specification and the empirical estimation strategy. Section 4 discusses the results and section 5 concludes.

2. Data

To estimate the dynamic effect of campaign activities within an election period, four pieces of information are essential: (1) voter preferences towards candidates; (2) the amount of television advertising exposures for the candidates; (3) the schedules of candidate visit appearances; and (4) the scale of candidates’ campaign field operations. The first three activities vary both across elections and over time within an election period, while the fourth only varies across elections. We utilize multiple sources to construct a comprehensive and unique data set that covers the 2004, 2008, and 2012 presidential elections. Our data structure is a weekly panel with candidate-state being the cross-sectional units and the data collection period running from the first week of August to Election Day of each election. Next, we describe each of the data elements in detail.

2.1. Voter preference

Voter preference for a particular presidential candidate is the dependent variable of interest. We use the actual vote outcomes to measure the final revealed preference. The data are from the CQ Press Voting and Elections Collection, a database that tracks major US political elections. For each state in each election, we retrieve the votes cast for the Democratic, the Republican, and the independent candidates. To make the measurement consistent with the metric used for the periods during an election, we calculate, out of the total number of votes, the share of votes received by the Democratic and Republican candidates, respectively. We then use these shares as the dependent variable in the last period of each election.

For each election, we focus on the more contested or the so-called “battleground states” or “swing states,” typically the sites of the fiercest battles in presidential elections.¹ Residents of battleground states are exposed to intense campaign advertising on local television networks, repeated candidate visits, and frequent contacts by field campaign teams; whereas residents of states whose electoral outcome is a foregone conclusion usually have much less exposure to any type of campaign activity (Gimpel et al., 2007). The disparate resource allocation between battleground and non-battleground states is intuitively understandable: it makes little sense to campaign where the candidate is 1) sure to win or 2) has no chance of winning. Hence, by focusing only on battleground states, we aim to understand campaign activities where they matter the most. Therefore, any insights we gain would be all the more relevant for campaign managers in strategic planning.

¹ A formal definition of “battleground states,” “swing states” or “contested states” is lacking. Typically, a state is considered a battleground state if no party has an obvious winning margin, based on polls and election results from previous years. We used the list of battleground states defined by Real Clear Politics. In 2004, the battleground states were Arkansas, Arizona, Colorado, Florida, Iowa, Maine, Michigan, Minnesota, Missouri, Nevada, New Hampshire, New Jersey, New Mexico, Ohio, Oregon, Pennsylvania, Washington, West Virginia, and Wisconsin. In 2008, the identified battleground states were Colorado, Florida, Georgia, Indiana, Iowa, Michigan, Minnesota, Mississippi, Missouri, Montana, Nevada, New Hampshire, New Jersey, New Mexico, North Carolina, North Dakota, Ohio, Oregon, Pennsylvania, South Dakota, Virginia, and Wisconsin. In 2012, the list included Arizona, Colorado, Florida, Iowa, Michigan, Minnesota, Missouri, Nevada, New Hampshire, North Carolina, Ohio, Oregon, Pennsylvania, Virginia, and Wisconsin.

Table 1 presents the summary statistics of the actual vote shares in the three elections covered by our data. Across the battleground states in 2004, the winning candidate, George W. Bush, acquired an average of 50.0% of the votes while John Kerry acquired 48.9%. In the next two elections, the winning candidate, Barack Obama, received an average of 51.8% and 50.7% in 2008 and 2012, respectively, across the swing states.

<Table 1>

For the weeks leading to Election Day, we measure voter preference by the percent of likely voters who favor the Democratic or the Republican candidate via averaging the tracking polls conducted by various organizations. Data are acquired from Real Clear Politics (RCP), a high-quality aggregator of political news and polls. For the three elections under study, we utilize RCP’s tracking of state-level poll ratings, from which we exclude partisan polls as they may be subject to a partisan bias.² The remaining polls were conducted by a variety of agencies, including polling and consulting firms such as Gallup and SurveyUSA, as well as newspapers and television channels such as Washington Post and CNN. The polls vary in sample sizes, with an interquartile range between 580 and 800 likely voters per survey. We reduce the potential measurement error by averaging over the various polls.

We chose to focus on the period beginning in late August and early September, because this is historically regarded as the starting point of the November general election, when candidates typically start to carry out full-scale campaign operations. Thus, we end up with 1,562 weekly observations; they are from 19 states for 2004, 22 states for 2008, and 15 states for 2012. Our unit of analysis is therefore at the state-week level.

Table 2 presents the summary statistics for the constructed average poll ratings. Note that the mean poll ratings for the two parties were close for each election, confirming intense competition in the swing states. The poll ratings are interpreted as the average percent of likely voters who favor a particular candidate. For example, in the 2004 election, across the battleground states, and over the election period, an average of 46.6% of the tracking polls of likely voters

² We excluded 20 polls that were sponsored by Republican-leaning organizations such as Civitas Poll, McLaughlin & Associates, and Moore Information. We also removed 18 polls conducted by the Democratic-leaning groups such as Baydoun/Foster, Democracy Corps, and Public Policy Polling (PPP).

reported being in favor of Bush and 46.9% in favor of Kerry. The remaining 6.5% reported supporting neither.

<Table 2>

It is worth mentioning that tracking polls were much less frequently conducted in non-battleground states during an election, making the data for those states insufficient for reliable analysis or inference. Therefore, it makes empirical sense to focus on the battleground states for our analysis.

2.2. Television advertising

We acquired two types of television advertising data. The first type is advertisements made by the candidates' own campaigns and their party committees, i.e., the Democratic National Committee (DNC) or the Republican National Committee (RNC). We refer to this type as “candidate’s own advertising” or “campaign advertising.” The second type of advertisements is those sponsored by outside political groups, also known as the Political Action Committees (PACs). These groups can pull donations from both individuals and organizations, and air television advertising to promote their own candidate and attack the rival—under the condition that PACs are prohibited from coordinating directly with the candidates or their parties. PACs have arguably played a role in US presidential elections for decades, but they have taken on much greater prominence in the last several elections, mainly because in 2002 a campaign finance reform law set stricter restrictions on fund-raising and spending; hence, the PACs stepped in to fill this gap.³ Especially in the 2012 election, a relatively new form of organizations—the Super PACs—emerged as major advertisers to spend heavily on competitive advertising.⁴ Due to the large number of PACs that advertised in recent presidential elections, it is challenging to track all the advertisements they sponsored. Fortunately, we were able to obtain advertising data for the top

³ The Bipartisan Campaign Reform Act of 2002, enacted on March 27, 2002, regulates the financing of political campaigns in the U.S.—Source: http://en.wikipedia.org/wiki/Bipartisan_Campaign_Reform_Act, retrieved May 22, 2015.

⁴ Super PACs are made up of independent PACs that support a candidate with unlimited—and often anonymous donations—from unions, companies, or individuals.

spenders, which combined were responsible for more than 90% of the total ad spending made by PACs.

We measure the amount of ad exposure using gross rating points (GRPs), which quantify ad impressions as a percentage of the target audience reached in an intended market. For example, if an advertisement aired in the Des Moines-Ames area reached 25% of the target population, it received a GRP value of 25; if the same advertisement was aired ten times, the GRP value would be 250 ($= 25 \times 10$). Thus, 250% of the target audience was exposed to advertisement; or equivalently, a representative person in the market viewed the ad 2.5 times. GRPs are a more accurate measure of ad exposure than dollar spending, because the prices of advertising vary significantly across markets. For example, the same amount of ad dollars would yield much less exposure in Los Angeles than in Kansas City. Hence, GRPs provide a measure of audience exposure independent of cost.

We obtained advertising data from Nielsen Media Research, which divides the US media market into 210 designated market areas (DMA): residents throughout one DMA receive largely the same television offerings including advertising. Therefore, our advertising metrics were originally collected at the DMA level. To match advertising to the states, we construct state-level ad exposures by taking the weighted average of DMA-level GRPs across the DMAs from the same state. For instance, in Colorado there are four overlapping DMAs: Albuquerque-Santa Fe, Colorado Springs-Pueblo, Denver, and Grand Junction-Montrose. For each DMA, we calculate a weight variable that equals the percentage of Voting Age Population (VAP, i.e., resident citizens aged 18 and above) who live in the focal DMA out of the total Colorado Voting Age Population.⁵ After the weight is assigned to each DMA-Colorado pair, the GRPs for Colorado is defined as the weighted average of DMA-level GRPs across those four overlapping DMAs. In summary, the total advertising exposure for candidate i in state s at time t would be

⁵ A DMA can cross multiple state lines. Take DMA “Albuquerque-Santa Fe” for example. It consists of one county from Arizona, four from Colorado, and twenty-seven from New Mexico. When calculating the VAP-weight variable for the Albuquerque-Santa Fe-Colorado pair, we divided the sum of VAP from the 16 Colorado counties by the total Colorado VAP.

$$a_{ist} = \sum_{d=1}^{D_s} w_d a_{idt}$$

where D_s is the number of overlapping DMAs, w_d is the population weights, and a_{idt} is the advertising exposure.

The summary statistics for advertising are presented in Table 3. Across the battleground states, the Democratic candidates had more advertising than the Republicans in all three elections: on average, ad impressions from the Democratic candidates were higher by 25%, 52%, and 36% in 2004, 2008, and 2012, respectively. The Democrats also received more outside PAC ads in 2004, but had fewer than the Republicans in the next two elections. Overall, the Republican candidates received 41% more outside ads in 2008 and a whopping 708% more in the 2012 election. When we combine the ads sponsored by the candidate’s campaign with those sponsored by the PACs, we see that overall the Democratic candidates had more ad impressions in 2004 and 2008. However, in the 2012 election, ads from the PACs supporting Romney significantly outweighed the outside ads supporting Barack Obama; in the end, the Romney candidacy had 25% more ad impressions in the battleground states than Obama.

<Table 3>

To examine how advertising evolves within a single election, we plot for each year the total ad GRPs aired by the candidates and their party committees in Figure 1. There is a clear rising trend of ad intensity as Election Day approaches. For example, in 2004, the Democratic candidates and party committee bought 3.7 times as many GRPs in the last five weeks of the election as it did in the first five weeks (beginning August 1). This ratio was 5.6 and 2.9 for 2008 and 2012, respectively. The within-campaign increase in ad impressions is similar for the Republicans, with the ratios being 3.3, 3.6, and 2.9, for the three elections respectively.

<Figure 1>

Figure 2 plots the total GRPs per week for PAC ads. It is noteworthy that the PACs increased their spending in 2012 by a significant amount compared with the 2004 and 2008 presidential elections so that the three panels in Figure 2 required different scales for the y-axis.

We do not observe obvious trends for 2004 and 2008, but see a rising pattern for 2012 when the PAC ad spending was much more substantial.

<Figure 2>

2.3. Candidate appearances

In addition to television advertising, candidates also carry out on-the-ground campaigns by visiting battleground states for face-to-face contacts with voters. Candidates hold town-hall meetings, attend rallies, host fund-raising events, and sometimes make impromptu stops to simply shake hands with supporters. This is usually referred to as “retail politics” (Vavreck et al., 2002), in the sense that candidates seek to personally target and influence voters on a small and local scale. Such live appearances also generate free media coverage that may reach local residents who do not physically attend campaign rallies. We measure retail campaigning by finding out whether the presidential or vice-presidential candidates made a campaign-related appearance in a particular state during each week. The visit schedules were collected from the “Democracy in Action” project hosted by George Washington University. The project maintains detailed records of where and how the candidates spent their time during the fall campaign of most recent presidential elections. The information is based on travel announcements provided by the campaign teams, supplemented with records of news accounts.

Summary statistics of candidate appearances are reported at the bottom of Table 3. For two elections, the Republican candidates made more frequent visits to the battleground states. In the 2004 election, 48% of the state-week observations had a visit appearance from the Republican candidates compared with 45% from the Democrats. In 2012, the numbers were 44% versus 39%. In contrast, we see no differences between the parties for the 2008 election.

2.4. Field operations

In recent presidential elections, grassroots mobilization activities have seen a strong resurgence among the mix of important campaign techniques available to candidates (Darr and Levendusky, 2014). Campaigns increasingly rely on ground operations to mobilize potential voters and encourage get-out-the-vote efforts. Often referred to as the “ground game” (in contrast to

advertising on the airwaves), those grassroots activities enable the campaign to make direct voter contacts but at a much larger scale than retail campaigning. The vast majority of direct voter outreach—such as door-to-door canvassing or talking to voters in supermarket parking lots—is coordinated through campaign field offices. Therefore, we use the number of field offices per state to measure the scale of campaign field operations. This is the same measure used by several recent papers studying ground campaigning (Chung and Zhang, 2014; Darr and Levendusky, 2014; Masket, 2009).

Table 4 presents the summary statistics for field operations. Throughout all three elections under study, the Democratic candidates deployed many more field offices in battleground states than did Republicans. Among the Democratic candidates, Obama clearly placed an even stronger emphasis on field operations than Kerry did. In 2008, his campaign had more than 70 field offices in Ohio and Virginia; and in 2014, had the largest number of field offices in Florida and Ohio.

It should be noted that the raw number of field offices may not represent the true “effective reach” of field operations: the effect of an office may depend on the size of the population it targets. For example, the effective reach—e.g., the percent of target population reached as in GRP—for a field office in New Hampshire may be much higher than that in Florida, simply because the latter is much more densely populated. Therefore, we normalize the number of field offices by the inverse of the VAP for each state. The new metric is the number of field offices per 100,000 VAP (see the bottom section of Table 4 for the summary statistics). Taking the population size into account, we see that the Republican candidates consistently deployed roughly 0.2 field offices per 100,000 VAP across the three elections, while the Democratic candidates deployed a much greater number. Between the Democratic candidates, Obama’s scale of field operations roughly doubled Kerry’s (Obama had roughly 1.0 field office per 100,000 VAP in 2008 and 2012 and Kerry had 0.5). The VAP-normalized field operations are used in our analysis.

< Table 4 >

2.5. Model-free evidence

In this section we present some model-free evidence on the relation between advertising and voter preferences. To control for cross-sectional differences across states, we examine the

association between the weekly changes in advertising and the corresponding changes in poll ratings. We illustrate candidate advertising in Figure 3 and PAC advertising in Figure 4.

Figure 3a and 3b show scatter plots of the percentage change in a candidate’s own advertising and that of his rival, respectively, along with the percentage change in poll ratings and the best-fitting nonparametric smoothed polynomial with its 95-percent confidence interval shaded in gray. Thus, for Figure 3a, the horizontal axis is the percent change of candidate i ’s advertising in state s from week $t-1$ to t , i.e., $100 \times (a_{is,t}^c - a_{is,t-1}^c) / a_{is,t-1}^c$, and the vertical axis corresponds to the percentage change in poll ratings, i.e., $100 \times (y_{is,t} - y_{is,t-1}) / y_{is,t-1}$. Overall, we see a positive trend, suggesting that voter preference towards a candidate tends to rise with an increase in advertising intensity. In Figure 3b, we illustrate the rating changes against the changes in ad exposures from the rival candidates. As expected, the more a competitor advertises, the lower the focal candidate’s poll ratings. Thus, the positive own-ad effect and the negative competitive-ad effect provide initial evidence that candidate advertising seems to be effective in shifting voter preferences.

< Figure 3 >

Figure 4 depicts the relation between PAC advertising and voter preferences. Figure 4a shows PAC ads that support the focal candidate and Figure 4b presents ads in favor of the rival candidate. Again, the plot exhibits a positive own-ad effect: more PAC ads for the focal candidates are in general associated with more favorable ratings, and vice versa. However, the scatterplot does not show an obvious relation between poll favorability and PAC ads in support of rival candidates.

< Figure 4 >

To gain an initial understanding of the dynamics (or persistence) of the ad effect, we plot the changes in poll ratings against the lagged changes in advertising, that is, the percentage GRP change in the previous weeks. The top two panels in Figure 5 are for the candidate’s own ads and the bottom two are for the PAC ads in support of the focal candidate. We find a positive association between ratings and advertising from the previous week (Figures 5a and 5c),

suggesting that the ad effect may persist for at least a week. However, with a lag of two weeks, the pattern is mixed. We see a negative trend for the candidate’s own ads (Figure 5b) but a weak positive trend for PAC ads (Figure 5d). Therefore, Figure 5 does not provide sufficient evidence for whether the effect of advertising lasts more than one week.

< Figure 5 >

It is noteworthy that Figures 3 through 5 do not account for the possible endogeneity issue mentioned previously with regards to campaign activities. That is, candidates and PACs can increase advertising in anticipation of declining favorability ratings and decrease them in the opposite situation. If such a “balancing” effect is at work, tracking poll ratings could seem unchanged despite changes in advertising, whereas, in the case of declining favorability, campaigns could have prevented the ratings from dropping further. To assess the true causal effect of advertising (and other campaign activities as well), we need a formal model that carefully addresses endogeneity; we present our modeling approach in the next section.

3. Model

3.1. Dynamic Model

Let y_{ist} be the voter preference for candidate i across residents in state s at week t . Naturally, y_{ist} would be a function of the previous week’s voter preference $y_{is,t-1}$, and current campaign activities. The activities include candidate i ’s own campaign activities and those by i ’s rivals ($-i$), as well as the mobilization and persuasion efforts sponsored by PAC groups. We also allow y_{ist} to be a function of unobservable factors related to candidates, states, and time. Formally, we model candidate preference ratings in the following multiplicative specification:

$$y_{ist} = (y_{is,t-1})^\lambda (a_{ist}^c)^{\delta_1} (a_{(-i)st}^c)^{\delta_2} (a_{ist}^o)^{\eta_1} (a_{(-i)st}^o)^{\eta_2} \exp(\varphi_1 R_{ist} + \varphi_2 R_{(-i)st} + \alpha_{is} + \gamma_t + \varepsilon_{ist}) (f_{ist})^{\beta I_t} \dots (1),$$

where λ is the carryover factor that measures how much of previous week’s voter preference persists to the current week; a_{ist}^c , a_{ist}^o , and R_{ist} are the candidate’s own advertising, outside PAC advertising supporting candidate i , and the candidate’s campaign appearances in state s during

week t , respectively; $a_{(-i)st}^c$, $a_{(-i)st}^o$, and $R_{(-i)st}$ are the corresponding campaign activities for the rival party; δ , η , and φ are the marginal effect for candidate advertising, PAC advertising, and retail campaigning, respectively, where subscript 1 corresponds to the own effect and subscript 2 the competitive effect; α_{is} is the candidate-state specific effect that accounts for the time-invariant favorability towards candidate i for residents in state s ; γ_t captures the weekly shocks to voter preference that are common to candidates and states; and ε_{ist} is the idiosyncratic shock specific to each candidate, state, and week combination. The component $(f_{ist})^{\beta I_t}$ captures systematic differences in voter turnout between final poll results and the actual outcome of the election, where I_t is an indicator variable that equals one if t is Election Day and zero otherwise, f_{ist} is the intensity of field operations deployed by candidate i in state s , and β is the corresponding marginal effect of field operations.

We model voter preference in a multiplicative functional form to allow for non-linear effects of campaign activities. The clear advantage of this specification becomes apparent after we take the logarithm transformation on the two sides of equation (1), yielding the following equation used for estimation:

$$Y_{ist} = \lambda Y_{is,t-1} + \delta_1 A_{ist}^c + \delta_2 A_{(-i)st}^c + \eta_1 A_{ist}^o + \eta_2 A_{(-i)st}^o + \varphi_1 R_{ist} + \varphi_2 R_{(-i)st} + \beta I_t F_{ist} + \alpha_{is} + \gamma_t + \varepsilon_{ist} \dots \quad (2)$$

where $Y_{ist} = \log(y_{ist})$, $A_{ist} = \log(a_{ist})$, and $F_{ist} = \log(f_{ist})$.

In any attempt to predict voter preference for presidential candidates, it is critical to take into account not only the campaign activities but also the contextual factors that may shape voter preferences. Campbell (1992) proposed two sets of such variables, the first of which indicates the national political climate that functions as background for the current campaigns and includes factors such as the incumbency status of the presidential candidates and the state of the national economy. The second set, composed of characteristics of the states, includes variables like the home-state advantage for the presidential and vice-presidential candidates, and the rate of economic growth in each state. We capture all of these effects using the candidate-state fixed

effect α_{is} , which also absorbs the impacts from any other unobservable nation-wide or state-level factors, as long as the effect is time-invariant throughout the weeks of the general election.

The weekly shifts in voter preference are captured by the week fixed effect γ_t , which measures the shocks that vary over time but are homogenous across candidates and states. One example is the fact that voters tend to be more interested in candidates as Election Day approaches; in this case, γ_t would capture any common contemporaneous fluctuations in voter preference. Including the weekly fixed effects also helps to remove the interdependence among the cross-sectional units, as failure to do so may introduce autocorrelation among ε_{ist} and, thus, violate the zero serial correlation assumption required for estimation, which we will explain in the estimation section.

It is worth noting that because Barack Obama was a candidate in two of the three elections, we treat his candidacy in 2008 and 2012 as two separate cross-sectional units. Thus, α_{is} allows varying levels of preference towards him in the same state between the two elections.

3.2. Estimation

The specification in the form of equation (2) allows the distinction between the short-run dynamics and the long-run relationship, but calls for careful estimation. First, by construction, the lag of the dependent variable on the right-hand side of the equation, $Y_{is,t-1}$, is correlated with the unobserved candidate-state fixed effect, α_{is} . Because of this endogeneity concern, the ordinary least square (OLS) regression would generate biased estimates, referred to as the dynamic panel bias (Nickel, 1981). One possible approach to mitigate this problem would be to include dummy variables for each candidate-state combination and perform the so-called least-squares dummy-variable (LSDV) regression, which is equivalent to eliminating the mean differences across candidate-states and obtaining the within-groups fixed-effect (FE) estimator. However, in dynamic panel data, the within-group estimator does not eliminate the dynamic panel bias (Nickell, 1981): after the de-meaning-transformation, the new lagged dependent variable $Y_{is,t-1}^* = Y_{is,t-1} - \bar{Y}_{is}$ will still be correlated with the new error term $\varepsilon_{ist}^* = \varepsilon_{ist} - \bar{\varepsilon}_{is}$ because $Y_{is,t-1}$ in $Y_{is,t-1}^*$ will be negatively

correlated with $\varepsilon_{is,t-1}$ in ε_{ist}^* . Interestingly, in OLS, the lagged variable $Y_{is,t-1}$ and the error term $(\alpha_{is} + \varepsilon_{ist})$ will be positively correlated. Thus, the OLS and the LSDV estimator provide upper and lower bounds for the range of the true parameter value for the carryover factor λ (Bond, 2002); hence, we first perform the OLS and the LSDV regression to generate benchmark values for the carryover factor.

To address the dynamic panel bias and account for the unobservable heterogeneity across candidates and states, we apply the dynamic panel data method developed by Arellano and Bond (1991). The key concept behind this approach is to use the lagged dependent variables as instruments in a first-difference model, as introduced by Anderson and Hsiao (1981). After taking the first-difference transformation for equation (2) to subtract out the candidate-state fixed effects α_{is} , our model becomes

$$\begin{aligned} Y_{ist} - Y_{is,t-1} = & \lambda(Y_{is,t-1} - Y_{is,t-2}) \\ & + \delta_1(A_{ist}^c - A_{is,t-1}^c) + \delta_2(A_{(-i)st}^c - A_{(-i)s,t-1}^c) \\ & + \eta_1(A_{ist}^o - A_{is,t-1}^o) + \eta_2(A_{(-i)st}^o - A_{(-i)s,t-1}^o) \dots (3), \\ & + \varphi_1(R_{ist} - R_{is,t-1}) + \varphi_2(R_{(-i)st} - R_{(-i)s,t-1}) \\ & + \beta I_t F_{ist} + (\gamma_t - \gamma_{t-1}) + (\varepsilon_{ist} - \varepsilon_{is,t-1}) \end{aligned}$$

which can be rewritten as

$$\begin{aligned} \Delta Y_{ist} = & \lambda \Delta Y_{is,t-1} + \delta_1 \Delta A_{ist}^c + \delta_2 \Delta A_{(-i)st}^c + \eta_1 \Delta A_{ist}^o + \eta_2 \Delta A_{(-i)st}^o \dots (4), \\ & + \varphi_1 \Delta R_{ist} + \varphi_2 \Delta R_{(-i)st} + \beta I_t F_{ist} + \Delta \gamma_t + \Delta \varepsilon_{ist} \end{aligned}$$

where $\Delta Y_{ist} = Y_{ist} - Y_{is,t-1}$, $\Delta Y_{is,t-1} = Y_{is,t-1} - Y_{is,t-2}$, $\Delta \varepsilon_{ist} = \varepsilon_{ist} - \varepsilon_{is,t-1}$, and so on. We assume zero serial correlations between the error terms for the same cross-sectional unit, i.e., $E(\varepsilon_{ist} \varepsilon_{isr}) = 0$ for all $r \neq t$. As suggested by Arellano and Bond (1991), the levels of the dependent variable, lagged two periods or more, are valid instruments in the equation in first differences. We form the identification restriction as

$$E(Y_{is,t-q} \Delta \varepsilon_{ist}) = 0 \dots (5),$$

where $q = 2, 3, \dots, (t-1)$ and $t = 3, 4, \dots, T$, and use the generalized method of moments (GMM) (Hansen, 1982; Wooldridge, 2002) to estimate our parameters of interest. This estimator is usually referred to as the Difference GMM (DGMM) estimator.

The DGMM estimator may perform poorly if Y_{ist} is close to a random walk, so that the past levels (the instruments) convey little information about future changes (the lagged differences). To improve efficiency, Arellano and Bover (1995) and Blundell and Bond (1998) further suggested the use of lagged differences of Y_{ist} as instruments for the equation in levels. The identification restriction is expressed as

$$E(u_{ist} \Delta Y_{is,t-1}) = 0 \quad \dots (6),$$

for $t = 3, 4, \dots, T$, where $u_{ist} = \alpha_{is} + \varepsilon_{ist}$. Such instruments are valid as long as the changes in voter preference are uncorrelated with the fixed effect: $E(\alpha_{is} \Delta Y_{ist}) = 0$ for all i , s , and t . Using this additional set of instruments would require stacking the equations in differences and the equations in levels for periods 3, 4, ..., T ; hence, this is typically referred to as the System GMM (SGMM) estimator.

We have completed the specification of the instruments necessary to identify the carryover factor λ . However, we would need to consider instruments to identify the effect of campaign activities, which we have good reason to believe are endogenous. During the general election, candidates and their campaign teams closely monitor any fluctuations in voter favorability in battleground states, taking prompt actions to boost goodwill or reduce damages from negative news. For example, in September 2012, the Obama campaign launched television ads attacking Romney's November 2008 *New York Times* article, "Let Detroit Go Bankrupt," and asserted that Romney actually profited from the auto bailout. Such ads were a blow to the Romney candidacy, especially in Rust Belt states like Ohio.⁶ The effect for events like these would be captured by ε_{ist} as a negative shock in our model. Shortly after the ads were aired, the Romney campaign went into crisis-management mode to reduce the damage, more intensively in Michigan and Ohio, where

⁶ The Wall Street Journal, February 23, 2012, from <http://blogs.wsj.com/washwire/2012/02/23/obama-super-pac-air-ads-in-michigan-on-auto-bailout>.

voters' goodwill was perhaps damaged the most. Of course, this is only one of the many examples of why campaign activities may be correlated with idiosyncratic shocks: $E(M_{ist}\varepsilon_{ist}) \neq 0$ for all t , where M_{ist} represents $A_{ist}^c, A_{(-i)st}^c, A_{ist}^o, A_{(-i)st}^o, R_{ist}$, and $R_{(-i)st}$.

We again exploit the panel structure of the data to construct instrumental variables to address the endogeneity concern regarding campaign activities. The argument behind the instruments for M_{ist} is similar to that for the lagged dependent variable. In a nutshell, we use the lagged variables as instruments for differences and the lagged differences as instruments for levels. The identification restriction is written as

$$E(u_{ist}\Delta M_{is,t-1}) = 0; E(M_{is,t-q}\Delta\varepsilon_{ist}) = 0 \dots (7),$$

where $q = 2, \dots, t-1$.

Similar to within-campaign activities M_{ist} , one can argue that the intensity of field operations is endogenous and so our estimates of the parameter β will be biased. By having an extensive set of candidate-state fixed effects, we mitigate the endogeneity problem associated with field operations. Nevertheless, to address this possible endogeneity problem, we use real estate rental prices to instrument field operations. The logic is similar to that behind the use of cost shifters to instrument prices in the traditional marketing and economics literature. That is, the real estate rental price in a state is exogenously determined outside our model specification—specifically, exogenous with regards to election-specific shocks—but shifts a candidate's choice to deploy field operations in that state.

Along with using real estate rental prices to instrument the intensity of field operations, we combine the restriction conditions of (5), (6), and (7) to form a SGMM estimator with endogenous predictors, which we refer to as the SGMM-IV estimator. The parameter estimates and the standard errors follow the GMM estimation procedures.

4. Results

We first perform OLS and LSDV estimations of equation (2) and report the parameter estimates in Table 5. Columns (1) and (2) correspond to the OLS and LSDV estimators,

respectively. The carryover parameter is estimated to be high, 0.775 ($p < 0.01$), in the OLS pooled regression. This is expected, as the association between the lagged and the contemporaneous voter preference would be inflated when the candidate-state fixed effects are not accounted for. After including the candidate-state fixed effects, the carryover parameter estimate drops to 0.309 ($p < 0.01$) in the LSDV regression. As mentioned previously, these two values provide both a lower and an upper bound for the true value of the carryover parameter.

<Table 5>

We present the results of various model specifications of equation (2) in Table 6.⁷ The first column is the DGMM estimates, where lagged (second order and up) levels are used as instruments in the first-difference equation. The second column is the SGMM estimator, which adds lagged differences $\Delta Y_{is,t-1}$ as instruments in the level equation. In this estimation, we also applied the orthogonal deviations transformation as proposed by Arellano and Bover (1995). The advantage of this transformation over the first-difference transformation is that the former subtracts the average of all future observations of a variable from the contemporaneous one, so that it minimizes data loss. Indeed, using additional moment conditions of lagged differences and the orthogonal deviations transformation increased our sample size from 818 to 988. Lastly, although all of the lags of $Y_{is,t-q}$ and $M_{is,t-q}$ for $q = 2, 3, \dots, (t-1)$ are valid instruments in the differences equations, we have to be careful with choosing the number of instruments. Too many lags would lead to a large number of elements in the estimated variance-covariance matrix of the moments, which based on a finite sample like ours, may not have enough information for accurate estimation (Roodman, 2009). As a result, we retain all valid lags for Y_{ist} but only four lags for advertising and retail campaigning, to make sure that the variance-covariance matrix is of reasonable size.⁸ We report the number of instruments associated with each estimator.

We begin by assessing the zero serial correlation assumption for the idiosyncratic errors, as the error autocorrelation structure would determine the validity of the instruments used to generate

⁷ We used STATA's command `xtabond2` (Roodman 2009) to estimate the parameters.

⁸ In addition to limiting the number of lags for our endogenous campaign variables, we collapse the matrix of instruments such that the number of instruments is of reasonable size. We use the collapse option in the Stata command `xtabond2`.

Table 6. We perform the Arellano–Bond test to examine the serial correlation in the first-difference errors. Because the first differences of independently distributed errors are by definition auto-correlated, rejecting the null hypothesis of no serial correlation at order one does not imply that our estimation is misspecified. It would be problematic, however, if the hypothesis of no serial correlation was rejected at order two. In our case, the Arellano-Bond AR(2) test results do not offer evidence to reject the zero serial correlation assumption (see the bottom of columns (1) to (4) in Table 6).

<Table 6>

The first column in Table 6 shows the results of the DGMM estimator: the carryover effect is 0.238 ($p < 0.01$), which is even lower than the LSDV estimate, suggesting that the lags of the dependent variables alone may not provide enough information to accurately identify the carryover parameter. Due to gaps in our panel data, the DGMM estimator also reduced the sample size by 17%. Therefore, we applied the orthogonal deviation transformation and further added the level equation to form the SGMM estimator in column (2), where the estimate for the carryover factor increases to 0.447 ($p < 0.01$), which now falls between the OLS and the LSDV estimates. However, for both PAC ads and retail campaigning, the own effects are estimated to be negative and the competitive effects are estimated to be positive, which intuitively does not make sense. We believe these counterintuitive results may be caused by endogeneity: when PACs intensified their ads in response to a dip in their candidate’s rating, or when a candidate made more visits to a state where his or her candidacy faced more disturbing news, this negative association would be picked up by the estimator when campaign variables are treated as exogenous. In the same vein, when rival candidates or their supporting PACs strategically shifted campaign efforts away from states where they have more voter support, this would lead to a spurious positive estimate for the competitive effect, as in the case above. Based on this, we believe that it is critical to treat campaign variables as endogenous and hence re-estimated the parameters using the SGMM-IV specification (column 3). Next, we interpret the results from the SGMM-IV estimator.

The carryover factor for voter preference is estimated to be 0.471 and significant, which suggests persistence in campaign effects over time. Further, candidate advertising can significantly affect voter preferences. That is, a candidate would receive a boost in favorability if his or her own campaign increases the number of television ads and would expect a dip in rating if a rival's campaign increases its number of ads. Note that we log-transform both the dependent variable and the ad exposure measures and, hence, the parameters can be interpreted directly as elasticities. Our estimates suggest that, if a candidate increases campaign ads by 1%, he or she would expect an increase of 0.015% in favorability in the current week, 0.007% ($= \hat{\lambda} \cdot 0.015$) in the subsequent week, and 0.003% ($= \hat{\lambda}^2 \cdot 0.015$) in the week after. This implies a long-term effect of $0.015 / (1 - \hat{\lambda})$, which in the context of a candidate's own ads, the overall long-term elasticity is estimated to be 0.028. The competitive effect for a rival's campaign ads is estimated to be negative and slightly smaller. If the rival's campaign increases its advertising by 1%, the focal candidate would expect a slump in ratings of 0.011% in the current week and 0.005% in the subsequent week. The cumulative long-term elasticity for rivals' competitive ads is estimated to be -0.021 .

The magnitude of the effect of PAC ads is smaller than that for candidate's own campaign ads. The own elasticity was estimated to be 0.002 and the cross elasticity (of equal size) was -0.002 . When PACs supporting the focal candidate increase ads by 1% or when those supporting the rival decrease ads by 1%, the focal candidate would expect a boost in favorability of 0.002%, small but statistically significant.

We find a positive own effect for retail campaigning (i.e., candidate live appearances), 0.012 ($p < 0.01$). This suggests that, if a candidate visits a particular state, the average favorability for his or her candidacy would rise by approximately one percent. The competitive effect is estimated to have roughly the same magnitude but in the opposite direction, suggesting that the focal candidate would expect a dip in favorability in a state where the rival candidate appeared in person to campaign.

As mentioned previously, a campaign's field operations reflect its grassroots efforts to mobilize potential voters. Note that field operations enter our model only in the last period—Election Day.

Because there is limited variation in field operations within an election year, any state-level effect on voter preference (poll ratings) produced by field operations would be captured through the candidate-state fixed effects α_{is} . Consequently, because the parameter β is identified purely off the last period, from the difference in the final poll results to the actual election outcomes, we label the parameter as capturing the last-moment turnout effect. Overall, we find that field operations boost the turnout rate, 0.019 ($p < 0.01$). Note that our field operations are the number of field offices per 100,000 VAP. This estimate suggests that, when a campaign increases its field office density by one percent, the final vote share in that state would increase by roughly two percent, through increasing turnout.

How would these various campaign effects differ by parties? The last column in Table 6 presents this result. We performed the same SGMM-IV method as in column (3) but included interactions between the Democratic dummy and each of the campaign variables. We find some interesting patterns. First of all, several campaign activities seem to differ in effect between Democrats and Republicans. Across the elections, the effect of field operations seemed to be greater for Democratic candidates than for Republicans. In contrast, the own effects of television advertising and retail campaigning are greater for Republican candidates, suggesting that voters seem to be more responsive when the Republican candidates increase their advertising or make more appearances in the battleground states. The only campaign activity for which we see no differences between the parties is PAC ads, for which the own elasticity and the cross elasticity are comparable between the Democrats and Republicans.

5. Conclusion and Discussion

Despite the fact that electing the President of the United States is a decision that has substantial and lasting global repercussions, predicting the likelihood of success of any presidential campaign has long been an inexact science, at best. In seeking to quantify the effect of the various activities that constitute a campaign—applying established principles of statistics, logic, and marketing—it is important to remember that while the hard work and investment put into selling

a manufactured product will culminate in various companies dividing market share, a presidential election is an extraordinarily expensive winner-take-all proposition; second place is literally nothing. However, there are enough valid parallels between US presidential campaigns and product marketing to support judicious application of marketing theory to inform decisions on the best and most efficient ways to use the huge but still finite resources available to a US presidential campaign.

In this paper, we examine the effect of political campaigns, specifically their use of marketing activities, using a unique and comprehensive data set that covers the 2004, 2008, and 2012 US presidential elections. We include two types of mass-media advertising—the candidate’s own and PAC advertising—and two forms of personal selling (or ground-campaigning) efforts—retail campaigning and field operations. By considering almost all principal campaign activities, we are able to estimate the effect of each activity while controlling for others. Further, we accommodate heterogeneity and allow different states to have varying levels of political predisposition towards different candidates while at the same time addressing the endogeneity concerns associated with campaign activities.

Our results generate four main insights. First, we conclude that various campaign activities throughout an election period do indeed play a major role in shaping voter preference and, hence, reject the assertion of some past studies of the “minimal effect” of campaigns on election outcomes. Second, to the best of our knowledge, we offer one of the first analyses, at a grandeur scale, of the effects of PAC advertising, which in recent years has become a force to be reckoned with within the US political arena. Although it is smaller in magnitude than that of the candidate’s own advertising, the effect of PAC advertising is significant, intensifying a voter’s existing preference for a candidate and decreasing possible preference for the rival candidate. Third, we find evidence that the effects of political campaigns persist over time but are subject to a relatively rapid decay: only about half of the contemporaneous effect carries over to the next period. Finally, we find that the effect of various campaign activities differ between parties, suggesting that a candidate may want to sustain activities that work better for him or her and improve upon the efficiency of those

that work better for the rival. These insights together lay a foundation for more effective allocation of campaign resources in future presidential elections.

The finding that a candidate’s own ads behave differently than PAC ads is worth further discussion. In fact, PAC ads have only a fraction of the effect of a candidate’s own ads. Further, we find no differential effects between the two major parties. Although elucidating the reasons behind these results is beyond the scope of this paper, we believe that they may be due to the limited coordination of advertising among various PACs.

While a candidate’s own ads are highly coordinated, with consistent messages to efficiently target voters, PAC ads convey disparate messages based on each organization’s political agendas; hence, they will be less efficient. The lack of a coherent ad theme is apparent when we consider just three randomly selected PAC-sponsored TV ads by each party from the 2012 election. We were told by Republican PACs that Romney helped locate the missing daughter of his business partner; that Obama is misleading America about the poor state of the economy; and that Romney cares deeply about people who are struggling, including disabled veterans. On the other hand, we learned from Democratic PACs that Obama is strong on energy independence; he will protect women from a return to unsafe abortions; and former Labor Secretary Robert Reich believes Obama has the right economic plan for America.

Interestingly, field operations seem to be more effective for Democratic candidates, while candidate advertising and retail campaigning seem to be more effective for Republican candidates. Among the many factors that could influence the efficiency of field operations is location. Using geo-locations of field offices, Chung and Zhang (2014) find that Democratic candidates tended to deploy offices where they were expected to be most effective—i.e., in areas of higher partisan support. Furthermore, Democratic supporters are more likely than Republican supporters to reside in urban areas, which could also make the Democratic field offices more efficient at mobilizing potential voters. To pin down the specific reasons why Democratic field operations are more effective might require digging deeper into how their field teams operated. Did they use more door-to-door visits than phone calls? Did they have more information about potential voters and

hence could do better targeting?⁹ Along the same lines, similar analyses are required to look beyond ad exposures and visit frequencies to untangle the mechanisms by which advertising and retail campaigning succeed or fall short. Though this is beyond the scope of the current paper, we believe it is an important and exciting area deserving more exploration in future research.

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⁹ CNN, (2012). “Analysis: Obama won with a better ground game.” November 7, 2012.

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Table 1: Summary Statistics of Actual Vote Shares

Year	Party	N	Mean	SD	Min	Max
2004	Republican	19	50.0	3.3	44.6	56.1
	Democratic	19	48.9	3.1	43.2	53.6
2008	Republican	22	46.7	4.5	40.4	56.2
	Democratic	22	51.8	4.5	43.0	57.4
2012	Republican	15	47.5	3.4	42.1	55.4
	Democratic	15	50.7	3.3	42.7	54.2

Note: The observations are at the state level.

Table 2: Summary Statistics of Poll Ratings

Year	Party	N	Mean	SD	Min	Max
2004	Republican	209	46.6	2.7	40	54.0
	Democratic	209	46.9	3.0	38	54.0
2008	Republican	199	45.0	4.2	36.5	56.5
	Democratic	199	47.6	4.1	33	56.7
2012	Republican	142	45.4	2.8	39.5	54.0
	Democratic	142	47.8	2.2	42	53.0

Note: The observations are at the state-week level.

Table 3: Summary Statistics of Television Advertising and Candidate Visits

Variable	Year	Party	N	Mean	SD	Min	Max	Total
<i>Candidate advertising (GRPs)</i>								
	2004	Republican	266	504.7	421.6	8.6	1,981	134,252
		Democratic	266	633.2	520.7	6.1	2,135	168,438
	2008	Republican	308	502.7	449.5	0.8	2,328	154,832
		Democratic	308	764.0	677.4	1.5	3,059	235,300
	2012	Republican	207	531.2	505.3	0	2,588	109,950
		Democratic	207	721.0	611.0	0	2,354	149,252
<i>PAC advertising (GRPs)</i>								
	2004	Republican	266	64.6	118.5	0	448	17,176
		Democratic	266	81.3	126.5	0	551	21,621
	2008	Republican	308	37.2	71.4	0	336	11,449
		Democratic	308	26.4	68.5	0	552	8,134
	2012	Republican	207	450.4	409.9	0	2,286	93,228
		Democratic	207	63.6	100.9	0	475	13,170
<i>Candidate visits</i>								
	2004	Republican	266	0.48	0.50	0	1	128
		Democratic	266	0.45	0.50	0	1	119
	2008	Republican	308	0.32	0.47	0	1	100
		Democratic	308	0.32	0.47	0	1	99
	2012	Republican	207	0.44	0.50	0	1	91
		Democratic	207	0.39	0.49	0	1	80

Note: The observations are at the state-week level.

Table 4: Summary Statistics of Field Operations

Variable	Year	Party	N	Mean	SD	Min	Max	Total
<i>Number of field offices</i>								
	2004	Republican	19	3.7	6.2	0	19	71
		Democratic	19	15.6	11.8	0	42	297
	2008	Republican	22	7.6	7.1	0	18	167
		Democratic	22	35.2	23.7	1	82	774
	2012	Republican	15	17.7	14.0	0	48	265
		Democratic	15	44.3	35.8	2	122	665
<i>Number of field offices per 100,000 resident citizens aged 18 and above</i>								
	2004	Republican	19	0.2	0.4	0	1.9	
		Democratic	19	0.5	0.3	0	1.3	
	2008	Republican	22	0.2	0.2	0	0.7	
		Democratic	22	1.0	0.8	0.05	2.6	
	2012	Republican	15	0.3	0.2	0	0.9	
		Democratic	15	0.9	0.8	0.04	2.8	

Note: The observations are at the state level.

Table 5: Ordinary Least Squares (OLS) and Least Square Dummy Variable (LSDV)

	OLS	LSDV
Lagged poll rating	0.775*** (0.019)	0.309*** (0.029)
Candidate advertising	0.008*** (0.002)	0.008*** (0.003)
Rival candidate advertising	-0.006*** (0.002)	-0.006** (0.003)
PAC advertising	-0.0002 (0.001)	0.001 (0.001)
Rival PAC advertising	0.001 (0.001)	0.0002 (0.001)
Retail campaigning	-0.004 (0.003)	-0.004 (0.003)
Rival retail campaigning	0.001 (0.003)	-0.0005 (0.003)
Field operations	0.004 (0.008)	0.005 (0.007)
Candidate-week dummies	(omitted)	(omitted)
Number of observations	988	988

***: $p < 0.01$, **: $p < 0.05$, * $p < 0.10$

Table 6: Parameter Estimates

	(1) DGMM	(2) SGMM	(3) SGMM-IV	(4) SGMM-IV
Lagged poll rating	0.238*** (0.018)	0.447*** (0.019)	0.471*** (0.026)	0.439*** (0.033)
Candidate advertising	0.017*** (0.001)	0.011*** (0.001)	0.015*** (0.002)	0.012*** (0.003)
Rival candidate advertising	0.004*** (0.001)	-0.008*** (0.001)	-0.011*** (0.002)	-0.013*** (0.004)
PAC advertising	0.001 (0.001)	-0.0001 (0.0004)	0.002*** (0.001)	0.003*** (0.001)
Rival PAC advertising	0.002*** (0.001)	0.001 (0.000)	-0.002*** (0.000)	-0.005*** (0.001)
Retail campaigning	-0.0001 (0.002)	-0.006*** (0.001)	0.012** (0.005)	0.025*** (0.008)
Rival retail campaigning	-0.002 (0.002)	0.002** (0.001)	-0.012** (0.005)	0.0005 (0.005)
Field operations	0.005*** (0.002)	0.011*** (0.001)	0.019*** (0.005)	-0.019 (0.016)
Democratic X Candidate advertising				-0.007* (0.004)
Democratic X Rival candidate advertising				0.014** (0.005)
Democratic X PAC advertising				-0.0003 (0.001)
Democratic X Rival PAC advertising				0.002 (0.001)
Democratic X Retail campaigning				-0.023** (0.010)
Democratic X Rival retail campaigning				-0.005 (0.009)
Democratic X Field operations				0.031** (0.013)
Candidate-week dummies	(omitted)	(omitted)	(omitted)	(omitted)
Number of GMM instruments	97	110	134	165
Number of observations	818	988	988	988

Specification tests

Hansen J	Do not reject	Do not reject	Do not reject	Do not reject
Difference-in-Hansen J		Do not reject	Do not reject	Do not reject
Arellano and Bond AR(1)	Reject ***	Reject ***	Reject ***	Reject ***
Arellano and Bond AR(2)	Do not reject	Do not reject	Do not reject	Do not reject

Note. Column (1) uses the lagged levels of the dependent variable as instruments in the difference equation. Column (2) adds the lagged difference as instruments in the level equation, and also applies the orthogonal deviations transformation to the difference equation. Column (3) treats campaign variables as endogenous and uses lagged variables as instruments for advertising and retail campaigning and real estate rents for field operations. Column (4), in addition to treating campaign variables as endogenous, also adds the interactions between the Democratic dummy and each campaign activity. ***: $p < 0.01$, **: $p < 0.05$, * $p < 0.10$

Figure 1: Total Advertising GRPs by Candidates over Weeks, by Year and Party

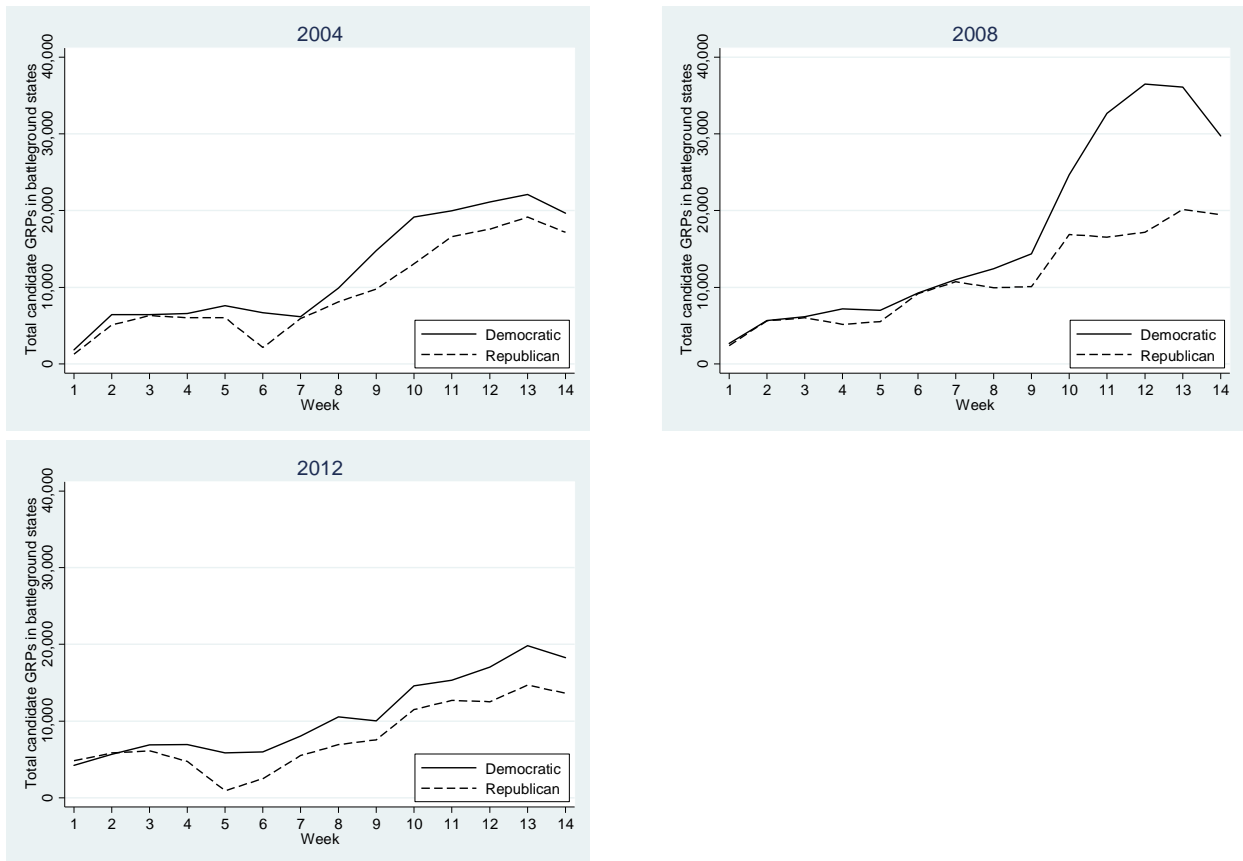


Figure 2: Total Advertising GRPs by PACs over Weeks, by Year and Party

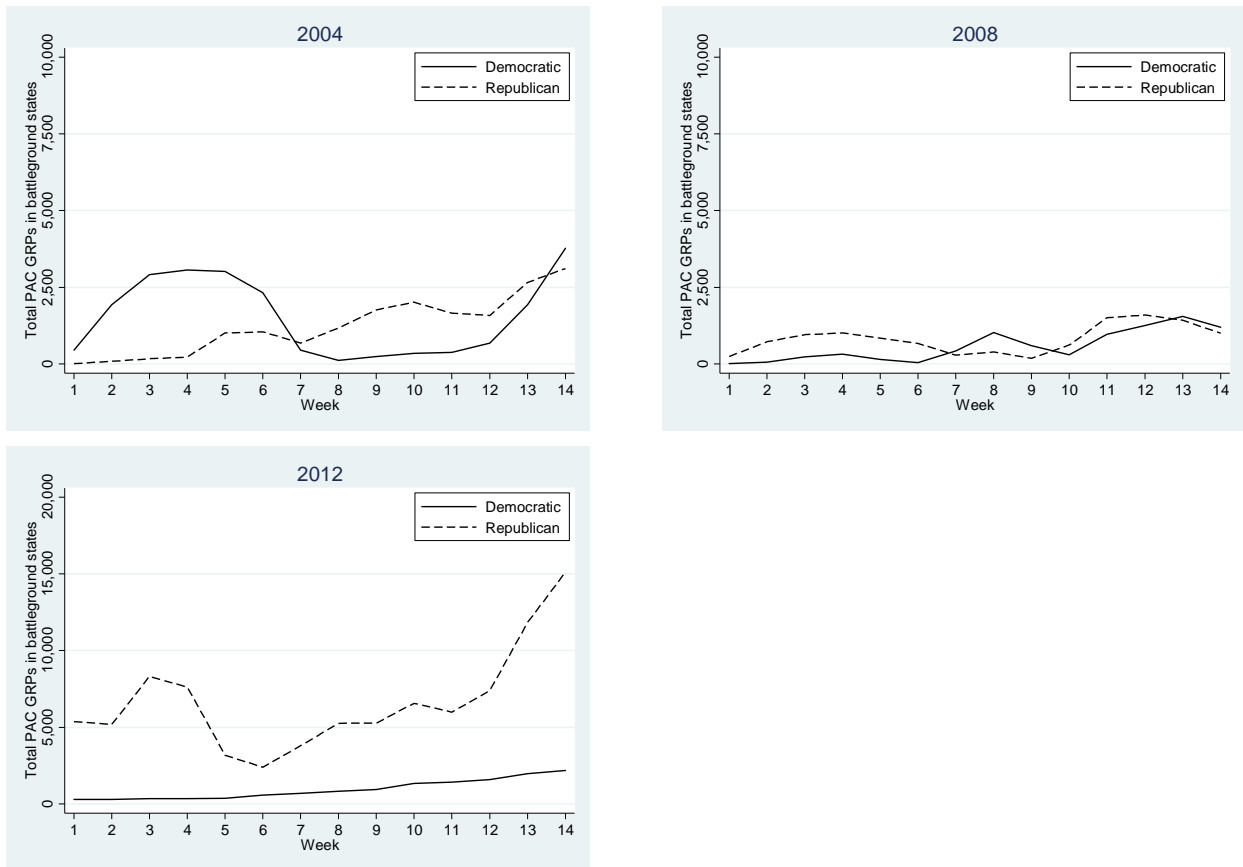
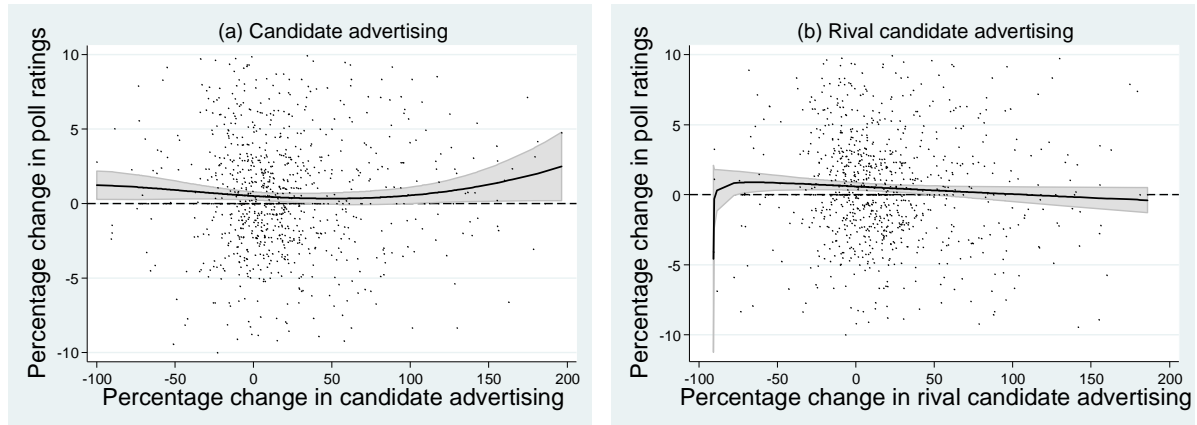
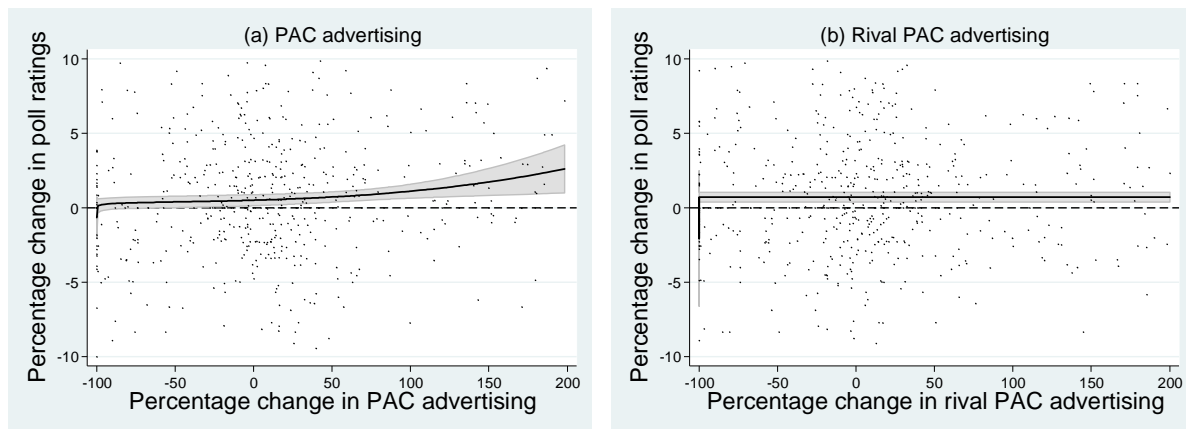


Figure 3: Changes in Voter Preferences against Changes in Candidate Advertising



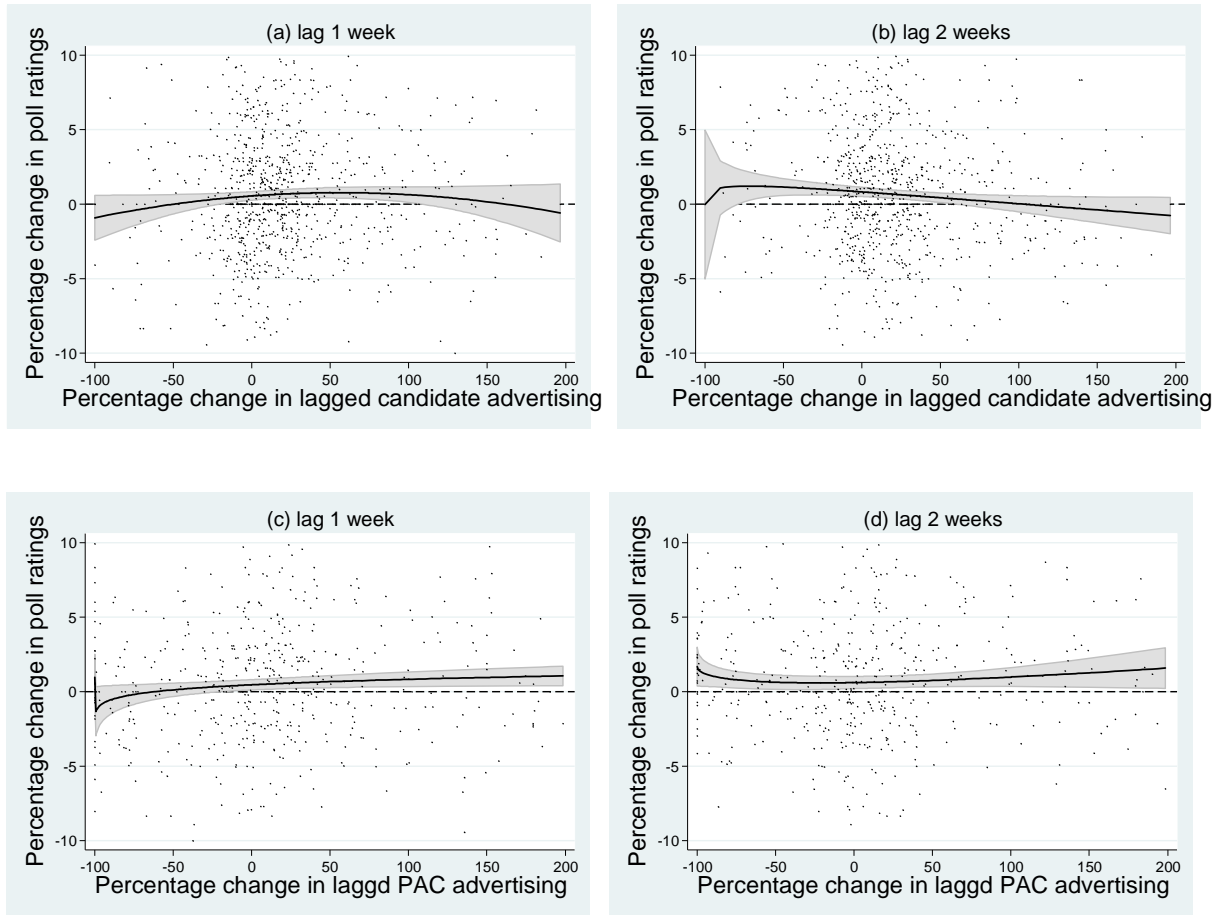
Note: The solid line represents the best-fitting non-parametric smoothed polynomial. The 95 % confidence intervals are shared in gray.

Figure 4: Changes in Voter preferences against Changes in PAC Advertising



Note: The solid line represents the best-fitting non-parametric smoothed polynomial. The 95 % confidence intervals are shared in gray.

Figure 5: Changes in Voter Preferences against Lagged Changes in Advertising



Note: The solid line represents the best-fitting non-parametric smoothed polynomial. The 95 % confidence intervals are shared in gray.