Advertising Effects in Presidential Elections

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Abstract

We estimate the effects of television advertising in presidential elections. Advertising shifts voters’ preferences for candidates at the county level through an aggregate discrete choice model. We instrument for the endogenous advertising levels using the prior year’s market price for advertising to avoid the possibility that political advertising affects market prices. We also use an extensive set of fixed effects at the party-market level to control for other unobservable cross-sectional factors that might be correlated with advertising, outcomes and instruments. The results indicate significant positive effects of advertising exposures for the 2000 and 2004 general elections. Advertising elasticities are smaller than are typical for branded goods, yet significant enough to shift election outcomes. For example, if advertising were set to zero and all other factors held constant, five states’ electoral votes would have changed parties in 2000, leading to a different president.

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1 Introduction

Advertising is ubiquitous. In 2008, firms spent roughly $65 billion on television advertising alone on products ranging from branded goods to political candidates.\(^1\) The prevalence of advertising suggests it must be influential. Consequently, the study of advertising often turns to understanding what it affects and why: economists and marketers debate whether advertising is informative or persuasive; marketers also assess its effects on intermediate measures such as brand recall; political scientists wonder if negative advertisements depress voter turn out.\(^2\) Nevertheless, conclusive evidence on the efficacy of advertising is still quite elusive. Most papers lack any source of exogenous variation, and those studies with experimental variation have had trouble detecting robust effects.\(^3\) We focus on the question of effectiveness in the context of presidential elections.

The potential to alter the choice of president of the United States is perhaps one of the widest-reaching decisions on which advertising focuses. Most advertising occurs at the brand level, seeking to influence individual consumers or households. At most, it affects those in contact with the consumer. An election aggregates the decisions of many into a single outcome affecting the inhabitants of that state as well as those of all other states with which it interacts. Concerns over advertising’s ability to manipulate choice are therefore substantially greater in this setting, leading to debates over fundraising and spending limits in elections. Despite this concern, the evidence on advertising effects in elections is inconclusive (Gordon

\(^1\)Source: TNS Media Intelligence.


\(^3\)Lodish et al. (1995) conduct a meta-analysis of split cable television experiments and do not find conclusive positive effects of advertising. In the context of internet advertising, the experimental variation alone in Riley and Lewis (2009) was not able to find significant positive advertising effects.
et al. 2010). Some studies suggest only a positive turn out effect (Shachar, 2009). Others suggest the effect is entirely persuasive (Huber and Arceneaux, 2007; Lovett and Peress, 2010). Some debate whether negative ads decrease turn out or not (Wattenberg and Brians, 1999; Ansolabehere et. al., 1999).

Presidential elections provide a data-rich setting that is well suited to identify the causal effects of advertising. Two challenges in estimating the effects of advertising are econometric endogeneity and disentangling the effects of past and present advertising. First, like in most empirical questions, the existence of unobservables creates an endogeneity problem in isolating the causal effect of advertising. Suitable instruments for advertising are often not obvious. Potential instruments are variables that enter the decision process of advertisers, but not that of the targets to be influenced. One potential variable is the price of advertising, which is excluded from demand just as costs are excluded when seeking instruments for price.\footnote{Dubé and Manchanda (2005) and Doganoglu and Klapper (2006) both use advertising costs as instruments.} One problem with using contemporaneous prices is that advertisers may not be price takers, or multiple advertisers may be exposed to common shocks that correlate prices and household choices. This effect was noted during the 2010 midterm elections in a number of markets.\footnote{Associated Press, “Sick of Campaign Ad Avalanche? TV Stations Aren’t,” October 30, 2010. Accessed at http://finance.yahoo.com/news/Sick-of-campaign-ad-avalanche-apf-3274707232.html.}

To address this issue, we take advantage of the fact that there are no elections during odd years, and thus use the prior year’s advertising prices as cost instruments that are net of political campaign effects. We also address the likely cross-sectional correlation between advertising costs and market characteristics and unobservables by using panel data to focus on within-market variation in advertising costs.

The second challenge is that the effects of advertising are typically spread over long horizons and many choice occasions, which may be why the few positive advertising effects causally identified have primarily been concentrated in the case of new products (e.g. Ackerberg,
2001, Lodish et al., 1995, Eastlack and Rao, 1989). Much of this literature, motivated in part by Nerlove and Arrow (1962), therefore focuses on measuring latent advertising stocks that depreciate and are reinvested over long horizons (Naik, Kalyan, and Srinivasan, 1998; Dubé, Hitsch, and Manchanda, 2005; Rutz and Bucklin, forthcoming). Fortunately, political advertising concentrates both the choices and spending into a well-defined short window of time. Choices are fully concentrated on Election Day. Spending in general elections for the US president is concentrated in the post-primary period between Labor Day and Election Day. Although advertising capital stocks may depreciate a little during the post-primary period, we can avoid specifying a stock of advertising goodwill or awareness that might depend heavily on initial conditions. Another concern might be the persistence of advertising from past elections, but the absence of advertising between elections suggests a substantial depreciation of any advertising stocks. The electoral college system also distorts advertising incentives across geographic areas such that advertising varies from zero in some markets to significant per-capita levels in battleground states.

We use advertising data from the 2000 and 2004 presidential elections to measure the effect of advertising on county-level voting decisions. Following the work of Berry, Levinsohn, and Pakes (1995, hereafter BLP), we estimate an aggregate discrete choice model in which the candidate and his advertising influence voters’ decisions. To measure the advertising effect as cleanly as possible, we include an extensive set of fixed effects at the party-market level. Focusing on within-market variation removes the worry that unobservables in the candidate choice equation might be cross-sectionally correlated with the advertising price instrument. Such a correlation could exist because major metropolitan areas have higher advertising prices and tend to lean Democrat. The fixed effect shifts inference to how within-market changes in advertising prices between two elections indirectly affect within-market changes in vote shares. Furthermore, by pooling candidate-share observations across counties and two
elections, we are able to observe over 9,500 advertising exposure and resulting vote shares.

The estimates of the advertising show robust positive effects across a number of specifications. Advertising elasticities are smaller than estimates typically found in consumer packaged goods categories. To provide a better metric for the role and importance of advertising, we consider how the absence of advertising would have affected state outcomes, and hence electoral votes. We find that some states in both the 2000 and 2004 elections shift sides, with the 2000 shift being sufficient for Gore to overtake Bush in electoral votes. The point of this exercise is merely to highlight that advertising’s causal effects are great enough to shift the election outcome and that advertising can be disproportionate between candidates. These results should not be interpreted as a strict prediction since our demand specification must hold many factors fixed, but they still serve as a useful benchmark for evaluating an election outcome’s sensitivity to advertising.

Our paper contributes in several ways to the literature on measuring the effects of political advertising. First, and most critically, our particular instrumental variables strategy allows us to address the endogeneity of advertising. The endogeneity of candidate decision variables has long been a challenge in the literature (Green and Krasno, 1988; Gerber, 1998; and Hillygus, 2005). Second, most work separately examines the effects of advertising on turn out and candidate choice, rarely considering the two decisions simultaneously.6

Other papers have taken a somewhat structural approach to analyzing political advertising, but differ in important ways. Shachar (2009) analyzes both the marketing decisions and voting, but restricts advertising effects to turn out and does not account for potential unobservable shocks. Perhaps the two papers closest to our own are Che, Iyer, and Shanmugam (2007) and Rekkas (2007). The former estimates an individual-level nested logit model using a combination of voter surveys and market-level advertising quantity data. Lacking information

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6Degan and Merlo (2009) study participation and voting in an uncertain voter model but do not consider the effects of advertising.
on exposure rates, the authors use the total number of ads aired. Rekkas (2007) studies the effects of overall campaign spending on Parliamentary elections in Canada using a BLP model. Both papers consider only a single election year, such that identifying advertising’s effects rests on cross-market variation that might be confounded with party-market unobservables. Our strategy of focusing on within-market changes alleviates such a concern about our analysis.

The remainder of the paper is structured as follows. The next section describes the advertising and election outcome data we use. Section 3 describes the aggregate discrete choice demand model. Section 4 presents the estimates and the zero-advertising analysis. Section 5 concludes.

2 Data

This section details our data sources and provides some reduced-form evidence of a relationship between advertising and voting outcomes. The data vary in the geographic unit at which they are measured. Electoral votes are measured at the state level, but candidates set advertising quantities at the media market level (DMA), which can span multiple states. We measure voting outcomes at the county level, which, in all but a few cases, only includes one media market.7

2.1 Advertising

The primary advertising data come from the Campaign Media Analysis Group (CMAG) for the 2000 and 2004 presidential elections, and were made available through the University of Wisconsin Advertising Project. CMAG monitors political advertising activity on all national television and cable networks, and assigns each advertisement to support the proper candidate. The data provide a complete record of every advertisement broadcast in each

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7Of the 1,342 counties, only five belong to multiple DMAs. We use zip-code-level population data to weight the advertising proportionally according to the share of the population in a given state.
of the country’s top designated media markets (DMAs), representing 78% of the country’s population. Television ads are the largest component of media spending for political campaigns according to AdWeek (2009). See Freedman and Goldstein (1999) for more details on the creation of the CMAG data set.

The data contain a large number of individual presidential ads: 247,643 for the 75 largest DMAs in 2000, and 807,296 for the 100 largest DMAs in 2004. Because we focus our identification on cross-election changes in outcomes, we restrict all subsequent analysis to the 75 largest DMAs. We further concentrate on all advertisements appearing after Labor Day, which marks the conclusion of the primaries and the beginning of earnest competition in the general election. For each ad, we observe all the dates and times which it aired, the length in seconds, the candidate supported (e.g., Democrat, Republican, Independent, etc.), and the sponsoring group (e.g., the candidate, the national party, independent groups, or “hybrid/coordinated”). Total spent on television advertising by all candidates was $168 million in 2000 and $564 million in 2004.

Another key variable we observe is an estimate of the ad’s cost calculated by CMAG. The standard practice in analyzing advertising effects, however, is to use Gross Rating Points (GRPs), which we do not directly observe. A GRP gives a measure of the number of exposures per capita. It fundamentally differs from the number of ads in that a single ad may be run on a channel with many viewers or few viewers. The GRP measure captures this extra dimension of the “quality” of the ad run.

We reconstruct the GRPs for an ad based on the advertisement’s cost and the price per GRP, which is commonly referred to as the Cost-Per-Point (CPP). We obtain the CPP data from SQAD, a market research firm that specializes in estimating media costs. These data provide quarterly forecasts of CPP by market, population subcategory, and time slot (daypart). We focus on the 18-and-over demographic to align with voting age, then match each
advertisement with the corresponding CPP according to the three categories just mentioned. We obtain the total GRPs by summing across ads:

\[ GRP_{tmj} = \sum_a \frac{Cost_{atdmj}}{CPP_{tdm}} \]

where \( a \) indexes an ad, \( t \) the 3rd quarter of the election year, \( d \) denotes the daypart, \( m \) the media market, and \( j \) the candidate. In other words, the equation above simply represents the total advertising expenditure by a candidate in a particular market and daypart, divided by the cost per GRP in that market and daypart. The ratio of these two quantities should roughly equal the number of GRPs a candidate purchased.

Our GRP measure contains two potential sources of measurement error. First, the CPP we observe is a forecast, so the true CPP likely differed from our data. Second, the price a particular candidate received could have been above or below even a non-forecasted measure of the CPP.\(^8\) The latter source is unlikely to be present in our data because CMAG reconstructed the cost from actual GRPs they observed and their own estimates of the CPP, which would have the same error. We therefore believe our GRP measure suffers only from forecast error in measurement. We have explored getting the GRP data directly from CMAG and Nielsen, but the cost is prohibitive.

Table 1 displays summary statistics for the major party candidates’ advertising in 2000 and 2004. Both the quantity of ads purchased as well as the total expenditures significantly increased between 2000 and 2004, which is consistent with the growing importance of advertising in political elections. Dividing the total expenditures through by the GRPs, the average price for Republicans dropped from $151 to $144 per point, and from $143 to $139 for Democrats. However, the advertising prices for the most common daypart (early news) increased by just over 5 percent. This observation indicates they may have found more

\(^8\)Even with a non-forecasted CPP, the price represents an average taken over the entire quarter. Candidates might pay a higher-than-average advertising price in the week prior to Election Day.
Table 1: Market-Level Advertising by Candidate and Election Year

economical means of exposures in 2004, perhaps by selecting cheaper dayparts. We also see the non-incumbent party advertised more.

The minimums and maximums of the advertising indicate substantial variation in the extent of advertising across the 75 DMAs. For Republicans, the number of zero-advertising observations ranges from 20 in 2000 to 32 in 2004. For Democrats, the numbers are 28 in 2000 and 25 in 2004. These data are encouraging because we estimate the effect of advertising based on variation with a wide support of advertising levels. Given that our focus will be on within-DMA variation in advertising spending, Figure 1 plots the change in GRPs from 2000 to 2004 for the Republican and Democratic candidates. As expected, we see a high correlation, indicating they tended to increase and decrease spending in the same DMAs. The incentives the electoral college creates drives much of the observed pattern of advertising, which we explore in detail in Gordon and Hartmann (2010). We also see the Democrats tended to spend more on average in 2004 than in 2000. A reasonable amount of variation also exists that will help identify the advertising effects.
2.2 Instruments

We naturally expect the advertising variation depicted in Figure 1 above to reflect some knowledge the candidates might have about where their advertising may be most effective. Interestingly, the direction of the bias is not clear. Candidates are unlikely to advertise in markets where they have little chance of winning and are also unlikely to advertise in markets where they are sure to win. Therefore, whether unobserved demand shocks will be substantially higher or lower in the presence of more advertising is unclear. Nevertheless, we
would like to avoid any possible confounds, so we consider a candidate’s decision process to find instruments. Although we do not model the candidates’ decisions here (see Gordon and Hartmann 2010), one obvious potential variable affecting advertising allocations but not likely affecting voter’s preferences is the price of advertising, CPP. The only caveat to this assertion is that political candidates’ demands for advertising in a market could alter the market price of advertising. To avoid this concern, we use the prior year’s CPP (1999 for 2000 and 2003 for 2004), when market advertising prices were free of political factors. Using lagged CPP instead of current CPP also avoids the potential problem of having the instrument enter the denominator of the variable for which it is instrumenting. We do not expect measurement error in the lagged CPP to be correlated with the error in the current CPP, because SQAD updates its CPP predictions each period to account for realized prices in the past quarters. If the measurement error were correlated SQAD would have to systematically make mistakes in the same direction, recognize that, and not correct it.

Although most of our analysis aggregates over dayparts, we use each of the eight dayparts as an instrument because different dayparts may be particularly relevant to a given candidate in a given market. Figures 2 and 3 show how each candidate spread his GRPs across dayparts in the top 10 DMAs in 2000. The Early News and Daytime slots are the most common across DMAs, yet Gore for instance bought fewer GRPs in Kansas City during the Early News than in Prime Access or Late Fringe. For Bush, we see that although 30 percent of GRPs in Spokane were in Early News, less than 15 percent in Milwaukee were in Early News. Given this mix, each of the daypart CPPs is potentially relevant for the advertising decisions in a given market, though the daypart CPPs differ in importance across DMAs. Because of these diverse daypart roles and the possibility that candidates vary in the relative importance they place on each daypart, we also add instruments interacting each of these CPP measures with an indicator for the party-election year. This interaction gives us a total of 32 instruments
varying across the 75 DMAs we observe for two years.

Table 2 provides summary statistics of the 1999 to 2003 change in each of these eight dayparts. Recall that we use the prior year/same quarter CPP as the instrument. We observe substantial variation in the changes in daypart CPPs over time. Most CPPs increased over this period, with only a few markets experiencing declines. Although not shown here, daypart CPPs are correlated—though not perfectly—with one another. For example, the minimum correlation is between Daytime and Prime Time at 0.55, whereas the maximum is between the Late Fringe and Prime Time at 0.93.

![Figure 2: Daypart Mix for Democrats in 2000: Top 10 DMAs in GRPs](image-url)
A large literature in political science explores the use of instrumental variables in estimating the effects of campaign spending or advertising, particularly in the context of congressional elections. In an early study, Green and Krasno (1988) use lagged incumbent spending to instrument for incumbent spending but assume challenger spending is exogenous. Recognizing these issues, Gerber (1998) uses a combination of instruments, including a measure of the challenger’s personal wealth and the state voting-age population. The idea behind the first variable is that a wealthier candidate should be able to spend more on advertising, although

Figure 3: Daypart Mix for Republicans in 2000: Top 10 DMAs in GRPs
Table 2: Summary Statistics of the Change in the Lag CPP IVs from 2000 to 2004

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Obs</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early Morning</td>
<td>75</td>
<td>36</td>
<td>63</td>
<td>-19</td>
<td>452</td>
</tr>
<tr>
<td>Daytime</td>
<td>75</td>
<td>9</td>
<td>33</td>
<td>-82</td>
<td>182</td>
</tr>
<tr>
<td>Early Fringe</td>
<td>75</td>
<td>24</td>
<td>50</td>
<td>-48</td>
<td>357</td>
</tr>
<tr>
<td>Early News</td>
<td>75</td>
<td>45</td>
<td>76</td>
<td>-41</td>
<td>510</td>
</tr>
<tr>
<td>Prime Access</td>
<td>75</td>
<td>85</td>
<td>133</td>
<td>-3</td>
<td>1002</td>
</tr>
<tr>
<td>Prime Time</td>
<td>75</td>
<td>120</td>
<td>189</td>
<td>-33</td>
<td>1125</td>
</tr>
<tr>
<td>Late News</td>
<td>75</td>
<td>98</td>
<td>138</td>
<td>-24</td>
<td>957</td>
</tr>
<tr>
<td>Late Fringe</td>
<td>75</td>
<td>36</td>
<td>76</td>
<td>-57</td>
<td>493</td>
</tr>
</tbody>
</table>

one concern might be that candidate wealth is correlated with an unobserved quality attribute that affects voters’ decisions. The motivation for the second variable is that a candidate can raise more funds in a more highly populated state. This instrument seems valid in a senate context but does not transfer to a presidential election setting. Ansolabehere et al. (1999) consider the effects of negative ads on voter turn out using GRPs as instruments. However, GRPs are a choice variable the candidate potentially determines in response to an econometric unobservable in the choice equation.

2.3 Votes

The county-level vote data are available from [www.polidata.org](http://www.polidata.org). For each of the 1,342 counties, we observe the number of votes cast for all possible candidates and the size of the voting-age population (VAP). The VAP estimates serve as our market-size parameters and allow us to calculate a measure of voter turn out at the county level. The voting-eligible population (VEP), a more accurate measure for calculating turn out that removes non-citizens and criminals, is only available at the state level. See the web page maintained by Michael McDonald at [http://elections.gmu.edu/voter_turnout.htm](http://elections.gmu.edu/voter_turnout.htm) for more information on measures of voter turn out.
Table 3: Summary Statistics of County-Level Voting in the 2000 and 2004 Elections

<table>
<thead>
<tr>
<th></th>
<th>Obs</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>2000 Election</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Votes Bush</td>
<td>1596</td>
<td>23,569</td>
<td>51,889</td>
<td>210</td>
<td>871,930</td>
</tr>
<tr>
<td>Votes Gore</td>
<td>1596</td>
<td>25,520</td>
<td>78,142</td>
<td>77</td>
<td>1,710,505</td>
</tr>
<tr>
<td>Share Bush</td>
<td>1596</td>
<td>0.297</td>
<td>0.086</td>
<td>0.039</td>
<td>0.630</td>
</tr>
<tr>
<td>Share Gore</td>
<td>1596</td>
<td>0.214</td>
<td>0.064</td>
<td>0.056</td>
<td>0.472</td>
</tr>
<tr>
<td><strong>2004 Election</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Votes Bush</td>
<td>1596</td>
<td>29,168</td>
<td>63,315</td>
<td>216</td>
<td>1,076,225</td>
</tr>
<tr>
<td>Votes Kerry</td>
<td>1596</td>
<td>29,698</td>
<td>89,285</td>
<td>95</td>
<td>1,907,736</td>
</tr>
<tr>
<td>Share Bush</td>
<td>1596</td>
<td>0.341</td>
<td>0.089</td>
<td>0.047</td>
<td>0.666</td>
</tr>
<tr>
<td>Share Kerry</td>
<td>1596</td>
<td>0.229</td>
<td>0.081</td>
<td>0.057</td>
<td>0.569</td>
</tr>
</tbody>
</table>

than did Republicans. On the other hand, the Republicans had higher average shares per county. Together, these voting outcomes reveal that the Democrats tend to do better in larger counties. By focusing on counties within the top 75 DMAs, our data omit a greater number of Republican votes. Whether excluding such Republican-leaning counties would bias our results in any particular way is unclear (we take the voting outcomes in these excluded counties as fixed in our zero-ad counterfactual).

In our estimation, we group all candidates not belonging to one of the two major parties into a single third-party candidate option, summing the votes and GRPs across these candidates. Estimating the model without aggregating the smaller candidates into a single option is possible. However, the majority of voters were probably unaware of these candidates. Their votes shares were very small (below 0.5 percent), and many spent little on advertising; thus we prefer to aggregate them so we can focus on measuring the effectiveness of advertising for the Republican, Democrat, and collective third-party candidates.

2.4 Other Explanatory Variables

By focusing on within-market variation, fixed effects absorb the systematic variation across geographies, such that we can estimate the advertising effect as cleanly as possible. That said, accounting for some within-market preference shifts is useful. We include three sets of
variables that attempt to absorb some of the remaining within-market variation: market-level party affiliation, the occurrence of a senate or gubernatorial election, and local weather patterns.

Some counties’ preferences may shift to the left or right depending on their match with the incumbent party or even the local political climate. We therefore use the National Annenberg Election Surveys to include a measure of the percentage of voters in a media market who identify with a political party. In each year, we merged the six national cross-sectional surveys into a single data set, resulting in 58,373 observations for 2000 and 81,422 observations for 2004. Between 2000 and 2004, the percentage of Republicans increased about 2.4 percentage points while the percentage of registered Democrats increased 1.3 points on average across all DMAs. Republican shares varied between 10 positive and negative percentage points at the extremes, whereas Democratic shares of registered voters dropped by at most 5.5 percentage points in a DMA, whereas the greatest increase was 7 points.

The party affiliation variables above are designed to capture some variation in preferences across parties, and hence candidates, within a market, but we also want to include variables that primarily affect a voter’s decision to turn out for the election. First, we include separate variables to indicate whether a senate or gubernatorial election also occurred that year. Although presidential elections are much more likely to drive turn out, a hotly contested senate seat or governor race could generate some spillover effects. Second, we include county-level estimates of rain and snowfall on Election Day from the National Climatic Data Center’s “Summary of the Day” database (obtained through EarthInfo, Inc). Gomez, Hansford, and Krause (2007) show that weather can play a significant role in affecting voter turn out in presidential elections.
3 Modeling Voter Preferences

We specify an aggregate discrete choice model of demand for political candidates. We allow for unobserved heterogeneity as in BLP. Aside from these features, the model is a simple, additively separable specification with extensive fixed effects. In fact, the model without heterogeneity corresponds to an OLS or 2SLS regression model depending on whether the instruments are included. Therefore, we do not expect the specification to be overly restrictive of the estimates, and we could easily accommodate alternative specifications for robustness checks.

3.1 Voter Utility

A voter’s utility for candidate \( j \) given advertising quantity \( A_{tcj} \) in election \( t \) is:

\[
    u_{itcj} = \beta_{itj} + \alpha_i A_{tcj} + \phi X_{ct} + \gamma_{mj} + \xi_{tcj} + \varepsilon_{itcj} ,
\]

where \( \beta_{itj} \) is a voter-specific taste for a candidate from party \( j \) in election \( t \), \( \alpha_i \) is the marginal utility of advertising, \( X_{ct} \) represents county-election specific observables that may affect voters’ decisions to turn out for the election, \( \gamma_{mj} \) represents market-party fixed effects, and \( \varepsilon_{itcj} \) captures idiosyncratic variation in utility across voters, candidates, and periods. The variables in \( X_{ct} \) are our indicators for whether a senate or gubernatorial election occurs in a year and the weather information (rain and snow). We restrict advertising by a candidate to only enter that candidate’s payoffs, allowing us to abstract away from classifications of positive versus negative advertising, which might allow one candidate to shift the preferences of the other (see Lovett and Shachar, 2010). We assume voters infer a candidate intends his advertising to raise their preference for him. \( \xi_{tcj} \) is a time-county-candidate-specific demand shock that is perfectly observable to voters when casting their votes, but is unobservable to the researcher. Candidates have beliefs about the demand shocks \( \xi_{tcj} \) that induce endogeneity
in candidates’ advertising strategies. If a voter does not turn out for the election, she selects
the outside good and receives a utility of

\[ u_{itc0} = \varepsilon_{itc0}. \tag{2} \]

As we typically only include advertising as the observed characteristic, the market-party
dummies \( \gamma_{mj} \) help fit the mean utility level for a party in a specific market. The dummies
also help address the endogeneity of advertising by capturing any omitted and unobserved
characteristics that vary by party and/or market. Thus we control for any correlation between
advertising and market-specific party preferences without the need for an instrument. We do
require an instrument to address the remaining unexplained variation, which corresponds to
time-specific deviations from the unobserved market-party mean utility.

To capture heterogeneity in voter preferences, we allow the candidate-election-specific
intercepts and the marginal utility of advertising to vary across individuals. We assume

\[
\begin{bmatrix}
\beta_{itj} \\
\alpha_i
\end{bmatrix}
\sim N\left(\begin{bmatrix}
\bar{\beta}_{tj} \\
\bar{\alpha}
\end{bmatrix}, \Sigma\right)
\tag{3}
\]

where \( \Sigma \) is the full covariance matrix of voter tastes. Allowing for off-diagonal terms in \( \Sigma \) is
important to remove the property of independence from irrelevant alternatives (IIA) common
to logit demand models. Specifically, it allows for a correlation between the intercept for
candidates \( j \) and \( k \) that might occur, for instance, when individuals who vote for either
candidate are more similar than those individuals less likely to turn out at all.

Each voter either selects the candidate who gives her the highest utility, or decides not to
vote.\(^{10}\) Assuming \( \{\varepsilon_{itcj}\}_j \) are i.i.d., we integrate over the idiosyncratic shocks to obtain the

\(^{10}\)The model assumes voters act sincerely in casting their votes.
following vote shares:

\[ s_{tej}(A_{tcj}, \xi_{tcj}; \theta) = \int dF(\beta, \alpha) \]

\[ \sum_{k \in \{0, \ldots, J\}} \frac{\exp\{\beta_{tk} + \alpha_i A_{tk} + \phi X_{ct} + \gamma_{mj} + \xi_{tk}\}}{\sum_{k \in \{0, \ldots, J\}} \exp\{\beta_{tk} + \alpha_i A_{tk} + \phi X_{ct} + \gamma_{mk} + \xi_{tk}\}} dF(\beta, \alpha). \quad (4) \]

The model of voter choice above does not consider whether a voter acts strategically based on whether she expects her vote to be pivotal in deciding the election outcome. Although voters’ expectations of being pivotal can play a role in small elections (e.g., Coate, Conlin and Moro 2008), the effect vanishes in larger elections (Feddersen and Pesendorfer 1996, 1999).

### 3.2 Identification

Identification of the voter-side parameters follows from standard arguments when estimating random coefficient models of demand using aggregate market shares data. We observe variation in vote shares and advertising levels across time and many markets. The mean voter preference for a party \( j \) in election \( t \), captured in \( \bar{\beta}_{tj} \), is identified by variation over elections in the mean vote shares for candidates and differential turnout rates across each candidate’s supporters. The party-market fixed effects, \( \gamma_{mj} \), represent the mean vote shares for a candidate within a market over elections. The coefficient on advertising is identified through the variation in advertising over time within parties in a market. The \( \xi_{tcj} \) are unobserved factors at the election-candidate-county level that are common to all voters. The covariance of voter tastes, \( \Sigma \), is identified through variation in vote outcomes for which the mean preference parameters do not already account. This remaining variation is due to county-level changes in voting shares from one election to the next.

### 3.3 Estimation

Our first step in estimation treats individuals as homogeneous, whereby the model reduces to a simple aggregate logit model we can estimate via two-stage least squares. To consider the BLP version of the model, we formulate the estimation objective function as a Mathematical
Program with Equilibrium Constraints (MPEC), following the work of Su and Judd (2008). We use the approach in Dubé, Fox, and Su (2009), who show how to estimate the aggregate demand model in BLP (1995) by formulating the GMM objective function as an MPEC problem. We extend their model to include party-market fixed effects and a full covariance matrix in taste heterogeneity.\textsuperscript{11} We briefly describe the method below and direct the reader to Dubé, Fox, and Su (2009) for more details.

The key insight to the approach is as follows. BLP (1995) use a nested optimization procedure that minimizes a GMM objective function in the outer loop while solving for the residuals $\xi_{tcj}$ in an inner loop using the inversion in Berry (1994). One reason this procedure is computationally inefficient is that many inner loop evaluations are made when the structural parameters are still far from the optimal values.

Dubé, Fox, and Su (2009) show that formulating the problem as an MPEC substantially improves the numerical accuracy and speed of the estimator, both of which are particularly important for our application given the large number of election-county observations. Rather than explicitly solving for the residuals during each evaluation, the objective function optimizes over both the demand shocks $\xi$ and the structural parameters $\theta$. Optimizing jointly over the parameters and shocks eliminates a common source of error in the structural parameter estimates induced by using loose convergence tolerances for the inner loop market share inversion.

Assuming the standard orthogonality condition $\mathbb{E}[\xi_{tcj} h(z_{tcj})] = 0$ holds for some vector-valued function $h(\cdot)$ of our instruments, the empirical analog is

$$g(\xi) = \frac{1}{TCJ} \sum_{t=1}^{T} \sum_{c=1}^{C} \sum_{j=1}^{J} \xi_{tcj} h(z_{tcj})$$

$S$ is the vector of observed market shares across all elections, counties, and candidates, and

\textsuperscript{11}We altered the Matlab code posted at http://faculty.chicagobooth.edu/jean-pierre.dube/vita/MPEC to estimate the voter model.
let \( s(\xi; \theta) \) be the corresponding vector of market shares implied by the model given particular values for the demand shocks and structural parameters. The MPEC objective function is

\[
\min_{\{\theta, \xi, \nu\}} \nu' W \nu \\
\text{subject to} \quad g(\xi) = \nu \\
\quad s(\xi; \theta) = S
\]  

(5)

where \( W \) is an appropriate weighting matrix. The second constraint above enforces the normal market share inversion found in BLP (1995). We use Halton sequences (Bhat, 2001) to reduce the computational burden of simulating the share integrals to compute \( s(\xi; \theta) \).

4 Results

This section begins by presenting parameter estimates from a variety of specifications. We also report advertising elasticities and the results of a counterfactual in which we set all advertising to zero and recompute the predicted election outcome.

4.1 Parameter Estimates

Table 4 presents the estimates of the various specifications we have used. We begin with a set of OLS regressions in which the dependent variable is the difference in the log shares, which is a homogeneous aggregate logit specification. Advertising has a strong significant positive effect, though we are not accounting for the endogeneity of advertising. We cluster standard errors in this and all other specifications at the DMA level to account for the fact that advertising and some of the instruments are homogeneous across counties within a DMA. The next specification uses 2SLS to instrument for the advertising levels using the one-year lagged prices of advertising. We see the coefficient increases. As we said previously, the sign of the bias is ambiguous because advertising occurs when candidates are close in a market, such that strong positive or negative unobservables both tend toward zero advertising.
Our next specification introduces party-DMA fixed effects. This specification accounts for the potential correlation between the instruments (ad prices) and cross-sectional variation in preferences, such as when ad prices are higher in metropolitan areas that tend to lean Democrat. The addition of the party-DMA fixed effects reduces the ad coefficient to a still-significant value of 0.051. We then introduce a series of additional covariates into the model. The senate and gubernatorial election indicators do not have a significant effect on turn out. The percentage of Republicans and Democrats in the county also have little effect, except for the significant role of the “percentage Democrat” on the Democratic candidate’s mean choice share (intercept). Finally, the estimates for the weather variables suggest rain is statistically significant and decreases turn out (consistent with Gomez, Hansford, and Krause 2007), although we find no such effect for snow. Across all specifications with fixed effects, the ad coefficients robustly remains just above 0.05.

We have also estimated a BLP version of the model with unobserved heterogeneity. Without fixed effects, we find significant heterogeneity. Yet when including party-DMA fixed effects the fixed effects absorb much of the cross-sectional variation that would otherwise help identify the unobserved heterogeneity. Implicitly, we rely on non-IIA substitution patterns within a DMA between elections to identify the heterogeneity and correlation in tastes for the candidates. This limited variation leads us to find no significant unobserved heterogeneity. All BLP models we did run found ad coefficients only slightly larger than those found in the 2SLS specifications.
Table 4: Parameter Estimates

<table>
<thead>
<tr>
<th>Specification</th>
<th>OLS</th>
<th>2SLS</th>
<th>2SLS</th>
<th>2SLS</th>
<th>SLS</th>
<th>2SLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advertising</td>
<td>0.110**</td>
<td>0.211**</td>
<td>0.051**</td>
<td>0.056**</td>
<td>0.050**</td>
<td>0.054**</td>
</tr>
<tr>
<td>Sen. Election</td>
<td>-0.028</td>
<td>-0.032</td>
<td>-0.026</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gub. Election</td>
<td>-0.052</td>
<td>-0.051</td>
<td>-0.052</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Party Identification</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Republicans</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Republicans</td>
<td>-0.392</td>
<td>-0.328</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Democrats</td>
<td>0.020</td>
<td>-0.167</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Democrats</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Republicans</td>
<td>-0.395</td>
<td>-0.332</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Democrats</td>
<td>1.297**</td>
<td>1.113**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3rd Party</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Republicans</td>
<td>-1.023</td>
<td>-0.955</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Democrats</td>
<td>1.993</td>
<td>1.823</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rain</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Snow</td>
<td>-0.066*</td>
<td>0.002</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed Effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Party-Year</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Party-DMA</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
</tbody>
</table>

Notes: Obs = 6,384. ** significance at α = 0.05 and *** significance at α = 0.01. F-statistic of excluded instruments = 9.56. Party-Year indicates the inclusion of party-year dummy variables. Party-DMA indicates fixed effects for each DMA and Party. Sen. Election indicates the inclusion of fixed effects for the existence of a Senate race, Gub. Election for the existence of a Gubernatorial race in the same state. Party Identification indicates that the percentage of Republicans and Democrats in DMA were included separately as “observed heterogeneity” variables for each candidate choice option.

4.2 Elasticity Estimates

Table 5 presents the elasticity estimates from our final specification above. The estimates are roughly 0.025 for the Republican and Democratic candidates, and much smaller for the third-party candidate. These sensitivities are actually rather small elasticities if we compare them to consumer packaged goods, where advertising elasticities are roughly 0.1, as reported in Hanssens, Parsons, and Schultz (2001, Ch. 8). In the case of new products, which, similar to elections, experience an intensive advertising campaign at launch, Ackerberg (2001) finds an elasticity of 0.15. Although we might at first suspect political ads to be of greater importance, seeing that people are more wedded to a political candidate than to a yogurt product is
unsurprising.\textsuperscript{12} Next, we illustrate the importance of the advertising by seeing its potential to shift electoral votes.

\begin{center}
\textbf{Table 5: Elasticity Estimates}
\end{center}

\begin{center}
\begin{tabular}{lrrr}
\hline
 & Republican & Democrat & 3rd Party \\
\hline
Republican & 0.0255 & -0.0091 & -0.0002 \\
Democrat & -0.0115 & 0.0275 & -0.0002 \\
3rd Party & -0.0114 & -0.0092 & 0.0028 \\
\hline
\end{tabular}
\end{center}

Notes: Table reports elasticity estimates using the full 2SLS specification. For example, a 1\% increase in Democrat advertising implies a 0.0091\% decrease in the market share of the Republican candidate.

\subsection*{4.3 Zero Advertising}

In this section, we consider the power of advertising as an influential variable in the competitive interactions between candidates. The above documents that advertising can influence choice, but candidates’ advertising might cancel each other out. To assess the potential of advertising to shift election outcomes, we therefore consider how the electoral votes would have changed if all advertising were set to zero, and everything else was held fixed. Note that we are not predicting what would have happened if advertising were banned, because many other variables might have endogenously responded. However, this exercise might give some idea of the rough preferences of voters were it not for advertising, though the earlier caveat that we hold all else fixed still applies.

Table 6 below indicates how the electoral votes would have changed under this scenario.

\textsuperscript{12}Advertising elasticities vary across studies depending both on context and the sophistication of the estimation approach. Counter the previous examples with the case of cigarettes, which now face substantial advertising restrictions. Studies from the 60s and 70s found cigarette advertising elasticities to be insignificant from zero, at 0.05, or as high as 0.6 in a study noted to have many confounds (Hamilton, 1972).
The column “Switched States” lists states that switched to the candidate listed in that row. With zero advertising in 2000, Bush would have won New Mexico (NM), Oregon (OR), and Wisconsin, whereas Gore would have picked up Florida (FL) and New Hampshire (NH). For Bush, this new scenario represents a net loss of six electoral votes to Gore, tipping the election outcome in Gore’s favor. Bush and Gore each spent roughly $7 million on advertising in 2000 in the five states that switched, an amount that represents less than 10% of each candidate’s advertising budget. In 2004, Bush would have gained two additional states, significantly increasing the margin against Kerry.

Table 6: Zero Advertising Counterfactual

<table>
<thead>
<tr>
<th>Election Year</th>
<th>Candidate</th>
<th>Electoral Votes Baseline</th>
<th>Zero Ad</th>
<th>Switched States (Electoral Votes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>Bush</td>
<td>271</td>
<td>265</td>
<td>NM(5), OR(7), WI(11)</td>
</tr>
<tr>
<td>2000</td>
<td>Gore</td>
<td>267</td>
<td>273</td>
<td>FL(25), NH(4)</td>
</tr>
<tr>
<td>2004</td>
<td>Bush</td>
<td>286</td>
<td>300</td>
<td>NH(4), WI(10)</td>
</tr>
<tr>
<td>2004</td>
<td>Kerry</td>
<td>252</td>
<td>238</td>
<td>—</td>
</tr>
</tbody>
</table>

5 Conclusions

This paper documents a robust positive effect of advertising in the case of general elections for the US president. The findings illustrate that advertising is capable of shifting the electoral votes of multiple states and consequently also the outcome of elections. Aside from the political implications, the application is well suited to estimating the effect of advertising in general. The use of advertising prices as instruments is well motivated, based on the underlying structure of the candidate’s decision process. Furthermore, the occurrence of elections in even years allows us to use lagged prices the candidates’ demands for advertising did not affect. These instruments may be useful in other advertising applications, but the
potential for those advertisers to alter market prices is a legitimate concern. Finally, analyzing advertising in elections frees the researcher from many of the dynamic concerns in which advertising is invested over long periods of time, and effects persist across multiple choice occasions. We believe this estimation strategy allows us to find robust positive effects of advertising, whereas the results for branded goods often find no effects with experimental variation.
References


