Advertising Effects in Presidential Elections*

Brett R. Gordon†
Columbia University

Wesley R. Hartmann‡
Stanford University

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Abstract

We estimate advertising effects in the context of presidential elections. This setting not only provides an important empirical context to study advertising's effects, but it also helps overcome two common challenges in previous advertising studies. First, the gap between elections depreciates past advertising stocks such that large advertising investments are concentrated within relatively short periods. Second, the lack of political advertising between elections allows lagged advertising prices to serve as instruments that are safely independent of candidates' current advertising choices. We analyze data from the 2000 and 2004 general elections using an aggregate discrete choice approach with extensive fixed effects at the party-market level to control for unobservable cross-sectional factors that might be correlated with advertising, outcomes, and instruments. The results indicate significant positive effects of advertising exposures. 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, three states' electoral votes would have changed parties in 2000, leading to a different president.

Keywords: advertising, politics, instrumental variables, presidential elections.

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†Associate Professor of Business, Columbia Business School. Email: brgordon@columbia.edu.

‡Associate Professor of Marketing, Stanford GSB. Email: hartmann_wes@gsb.stanford.edu.

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 turnout.[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 wide-reaching decisions on which advertising focuses. Most advertising occurs at the brand level, seeking to influence individual consumers or households. An election aggregates the decisions of many into a single outcome affecting the inhabitants of that country and countless others. Concerns over advertising's ability to affect choice are therefore substantially greater in this setting, leading to debates about whether to impose fundraising and spending limits in elections. Despite these concerns, the evidence on advertising effects in elections is inconclusive (Gordon et al., forthcoming). Some studies suggest only a positive turnout effect (Shachar, 2009). Others suggest the effect is entirely persuasive (Huber and Arceneaux, 2007; Lovett and Peress, 2010). Some debate whether negative ads decrease turnout or not (Wattenberg and Brians, 1999; Ansolabehere et al., 1999).

[1] Source: TNS Media Intelligence.

[2] For work analyzing whether advertising is informative versus persuasive, see, for example, Nelson (1974), Anand and Shachar (2000), Ackerberg (2001), Narayanan and Manchanda (2009), Clark, Doraszelski, and Draganska (2009). Draganska and Klapper (2010) incorporate the effects of brand recall through advertising on demand, and Kanetkar, Weinberg, and Weiss (1992) and Mela, Gupta, and Lehmann (1997) measure the effects of advertising on price sensitivity. Ansolabehere et al., (1999), Wattenberg and Brians (1999), and Freedman and Goldstein (1999) investigate the effects of negative advertisements on voter turnout.

[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 Lewis and Reiley (2011) was unable to find significant positive advertising effects.

Presidential elections provide a data-rich setting 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, as with most empirical questions, a correlation between unobservables and advertising creates an endogeneity problem in isolating the causal effect. Potential instruments are variables that enter the decision process of advertisers, but not that of the targets to be influenced. One potential instrument is the price of advertising, which is excluded from demand just as costs are excluded when seeking instruments for price.[4] One problem with using contemporaneous advertising prices is that advertisers may not be price takers; large advertisers (e.g., presidential candidates) could influence the market-clearing price of advertising, violating the exogeneity requirement for an instrument. The impact of demand for political advertising on advertising prices was noted during the 2010 midterm elections in a number of markets.[5] 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.

The second challenge is that advertising effects are typically spread over long horizons and multiple choice occasions. This fact may help explain why the few studies that have causally identified positive advertising effects have primarily examined 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), incorporating latent advertising stock variables that depreciate and are reinvested over long horizons (Naik, Kalyan, and Srinivasan, 1998; Dubé, Hitsch, and Manchanda, 2005; Rutz and Bucklin, 2011). Fortunately, political advertising concentrates both the choices and spending into a well-defined short window of time. Choices are fully concentrated on Election Day, and spending in presidential general elections 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.[6]

[4]Dubé and Manchanda (2005) and Doganoglu and Klapper (2006) both use advertising costs as instruments.

[5]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`.

[6]To examine whether campaign advertising depreciation might affect our model's inference, we estimated

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.

We use advertising data from the 2000 and 2004 presidential elections to measure the effect of advertising on county-level voting decisions. The electoral college system distorts advertising incentives across geographic areas such that advertising varies from zero in some markets (e.g., New York and Texas) to significant per-capita levels in battleground states (e.g., Ohio and Florida), providing us with rich variation to estimate advertising's efficacy. 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 market-party 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 advertisng levels and vote shares. Furthermore, by pooling candidate-share observations across counties and two elections, we are able to observe over 9,500 advertising exposures and resulting vote shares.

The estimates show a robust positive advertising effect across a number of specifications. Advertising elasticities are around 0.03, 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

a number of robustness checks. We were unable to find evidence that recent ads had a greater impact on voters' decisions.

evaluating an election outcome's sensitivity to advertising.

Our paper contributes in two 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, which has long been recognized as a challenge in the political science literature (Green and Krasno, 1988; Gerber, 1998; and Hillygus, 2005). Due to the difficulty of identifying reasonable instruments, more recent work in political science employs field or natural experiments to estimate advertising's causal effect (Gerber et al., 2011). Second, our model combines a voter's decision to turn out to vote, and if so, for which candidate to vote, whereas most prior work considers these decisions separately (Ashworth and Clinton 2006; Huber and Arceneaux 2007).

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 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 Berry, Levinsohn, and Pakes (1995, hereafter BLP) style 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 market-party unobservables. Our strategy of focusing on within-market changes alleviates such a concern about our analysis. Shachar (2009) also analyzes whether candidate marketing mix variables affect voting outcomes, but restricts advertising to affect turnout and not candidate choice and does not account for potential unobservable shocks.

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

2 Data

This section details our data sources and approach to constructing our instruments. 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 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. Since our identification strategy focuses on cross-election changes in outcomes, we restrict all subsequent analysis to the 75 largest DMAs. 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"). We use the candidate supported to assign it to the appropriate candidate and include all ads regardless of the sponsoring group. We further concentrate on those ads airing after Labor Day, which marks the beginning of earnest competition in the

[7]Of the 1,596 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 DMA.

general election. Total spent on television advertising by all candidates was $168 million in 2000 and $564 million in 2004.

Our key advertising variable is expressed in gross rating points (GRPs) since it provides a measure of the number of exposures per capita. One alternative measure is the number of ads aired (in seconds) in a market. However, the number of ads airs does not reflect cross-market variation in the number of viewers exposed to an ad (such as due to differences in population size and density). The GRP measure therefore captures the actual "quantity" relevant for impact.

Although we do not directly observe GRPs in our data, we reconstruct the GRPs based on the advertisement's cost and the price per GRP, which is commonly referred to as the Cost-Per-Point (CPP). The CMAG data provides us with an advertisement's estimated cost and 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 third-quarter CPP to align the timing of ad purchases and the 18-and-over demographic to align with voting age. We then atch each advertisement with the corresponding CPP according to the market, population subcategory, and daypart. Aggregating over the ads a and dayparts d, we obtain the total GRPs at the election-market-party level:

$$GRP_{tmj} = \sum_{d} \frac{\sum_{a} Expenditure_{atdmj}}{CPP_{tdm}}$$

where t is the election year, m the media market, and j the candidate. The equation above first calculates the GRP estimate within each daypart by dividing expenditures by CPP, then aggregates over dayparts to get the aggregate GRPs for the candidate in the given market and election year. We use this measure of GRPs as our advertising variable in our analysis.

Our GRP measure contains two potential sources of measurement error. First, the actual price a candidate paid could differ from our CPP data due to quantity discounts for purchases of large advertising blocks or unobserved variation in advertising prices within the quarter. This concern may not be an issue because CMAG reconstructs their advertising cost estimates

from actual GRPs and CMAG's own estimates of the CPP, so the costs we observe do not include such candidate specific CPPs. Second, the CPP we observe is a forecast made by SQAD. Although the true CPP probably differs from our data, this particular measurement error is purely random and will be absorbed into the unobservable shocks we include in the model. Measurement error may cause an attenuation bias, but the instrumental variables we describe below remove any such bias because it will only focus on the variation in our GRP measure that is attributable to variation in the instruments.

Table 2 displays summary statistics for the major party candidates' advertising in 2000 and 2004. Two important points are worth noting. First, we observe significant variation in advertising across markets within a given election. The support of the advertising distribution ranges from zero to about six million dollars in 2000 and about nine million dollars in 2004. The Republicans chose not to advertise in 20 markets in 2000 and 32 markets in 2004. For Democrats, the numbers are 28 in 2000 and 25 in 2004.[8]

Second, given that our estimation strategy focuses on within-DMA variation, we are fortunate to observe rich variation in total advertising expenditures and GRPs between 2000 and 2004. Table 2 shows that both total ad quantities and total ad expenditures significantly increased from 2000 to 2004, consistent with the growing importance of advertising in political elections. Dividing the total expenditures by the GRPs, the average price for Republicans dropped from \$151 to \$144 per point in 2004, and from \$143 to \$139 for Democrats. However, the advertising prices for the most common daypart (early news) increased by about five percent. Figure 1 plots the change in GRPs from 2000 to 2004 for the Republican and Democratic candidates. As expected, the changes in GRPs across candidates are highly correlated, indicating the candidates tended to increase and decrease spending in the same DMAs. The figure also exhibits significant variation both between elections and across DMAs.

[8]The structure of the electoral college creates particular incentives that drive much of the observed pattern of advertising. In particular, so-called battleground states receive a disproportionate share of a candidate's advertising due to the expected narrow margin of victory. Conversely, non-battleground states, where a given party expects to win by a handsome margin, receive little to no advertising from either candidate because any such intervention would not be expected to alter the state's election outcome. We explore candidates' advertising allocation decisions in detail in Gordon and Hartmann (2011).

2.2 Instruments

A central issue in our empirical application is to address the endogeneity of candidate advertising. We naturally expect the advertising variation depicted in Figure 1 to reflect some knowledge the candidates observe but that we do not. In standard differentiated product choice contexts (e.g., BLP), ignoring price endogeneity leads the researcher to underestimate price sensitivity because the unobservables are positively correlated with prices. However, in the context of political candidate choice, the direction of the bias is ambiguous. Candidates are both unlikely to advertise in markets where they have little chance of winning and are unlikely to advertise in markets where they strongly expect to win. Therefore, whether unobserved demand shocks are substantially higher or lower in the presence of more advertising is unclear, making it hard to sign the direction of the endogeneity bias.

We consider a candidate's decision process to find suitable instruments. Although we do not model the candidates' decisions here, one obvious variable that affects advertising allocations but is unlikely to affect voters' preferences is the price of advertising. Two potential concerns arise from such an instrument choice. First, it is possible that candidates purchase enough advertising in a market to effect the equilibrium price of advertising in that market, such that candidates would no longer act as price-takers. This issue would invalidate the instrument since the price would not be exogenous to candidates' advertising decisions. To avoid this concern, we use the prior year's advertising price (1999 for 2000 and 2003 for 2004), when market advertising prices were free of political factors.

Second, measurement errors in the lagged CPP estimates due to SQAD's methodology could be systematically related to current CPP estimates. We do not expect such a bias to exist because SQAD updates its advertising price predictions each quarter to account for realized prices in the past quarters. If the measurement errors were correlated, then SQAD would be making a systematic mistake in the same direction, which seems unlikely given the nature of the firm's business.

To convert the instrument to a per-capita basis, we use the cost per thousand impressions (CPM) instead of per point. Our motivation for using CPM is similar to our decision to

use GRPs as our endogenous advertising variable since CPMs more accurately account for exposures per capita. As with the CPP, the CPM in a market varies over the dayparts because the cost of reaching a thousand viewers varies over the day. We use the CPM in each of the eight dayparts as our primary lagged advertising price instruments.

We observe significant variation across candidates in when they choose to advertise during the day and in the price of advertising across elections. Figures 2 and 3 show how each candidate spread his GRPs across dayparts in ten 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. Although 30 percent of Bush's GRPs in Spokane were in Early News, less than 15 percent in Milwaukee were in Early News. Given this mix, each daypart CPM is potentially relevant for advertising decisions, and the importance of each daypart CPM varies across DMAs.

Table 3 provides summary statistics of the change in the CPM between 1999 and 2003 in each daypart, and demonstrates substantial variation in the daypart CPMs over time. Most CPMs increased over this period, with only a few markets experiencing declines. Daypart CPMs 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 4 illustrates how the Early News CPM varied within DMAs between 2000 and 2004.

It is important to consider why advertising prices varied within markets over time and to be sure that the source of this variation is not be correlated with preferences for political candidates. One source of within-market variation in ad prices is from local demand shocks for major advertisers. Another could be changes in local economic conditions or demographics, both of which could relate to changes in political preferences. We therefore detail in section 2.4 a set of economic and demographic variables that we include in the analysis to address this concern.

Given the motivation for our particular instrumental variables, we now compare our approach to the extant literature. Work in political science uses both instrumental variables

and field/natural experiments to deal with the endogeneity of candidate choice variables. First, instrumental variable techniques gained early traction in work that sought to measure the effects of aggregate candidate campaign spending on voting outcomes (Jacobson 1978). Most of this analysis examines congressional races to take advantage of more independent observations, although campaign spending levels are much lower than in a presidential campaign. Green and Krasno (1988) use lagged incumbent spending in Senate elections to instrument for current incumbent spending, but must assume challenger spending is exogenous. Recognizing this issue, Gerber (1998) uses a combination of instruments, including a measure of the challenger's personal wealth and the state voting-age population. A wealthier candidate should be able to spend more on advertising, although one concern might be that candidate wealth cannot be excluded from the voters' decisions. Local population is motivated by a candidate having more citizens from which to raise funds in more populous places. Yet more voters will need to be reached in more populous places, so such an argument may only work with respect to large fixed costs of advertising as opposed to affect advertising levels at the margin. The argument in general also does not transfer to a presidential election setting because funds can be raised nationwide. Ansolabehere et al. (1999) consider the effects of negative ads on voter turnout using GRPs as instruments, but the GRPs are a choice variable the candidate potentially determines in response to an econometric unobservable in the choice equation.[9]

A second approach is to exploit natural experiments or to conduct field experiments to generate exogenous sources of variation. Huber and Arceneaux (2007) take advantage of the fact that some media markets overlap battleground and non-battleground states, exposing voters in the non-battleground state to higher advertising levels than the candidate intended. They link the advertising data to data from the National Annenberg Election Surveys (NAES) on individuals' campaign interest and voting intentions, and find evidence that advertising influences voters' candidate choice but not whether to turn out to vote. Gerber et al. (2011)

[9]Levitt (1994) addresses candidate unobservables by examining congressional races in which the same two candidates faced one another in multiple elections. Differencing eliminates any fixed candidate or local influences, and the results suggest that congressional campaign spending has little effect on voting outcomes.

use a field experiment in the 2006 gubernatorial election in Texas to examine the effect of advertising on voters' stated attitudes and intentions (collected via telephone surveys), and find that televised ads have strong but short-lived effects on voting preferences.

2.3 Votes

The county-level vote data are available from `www.polidata.org`. For each of the 1,596 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 turnout at the county level. The voting-eligible population (VEP), a more accurate measure for calculating turnout that removes non-citizens and criminals, is only available at the state level.[10]

Table 1 summarizes the total votes and vote shares of each candidate by county and election year. The Democrats had a higher number of average votes per county in both years 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 parameter estimates is unclear. In computing our counterfactual in which we set advertising to zero, we take the voting outcomes in these excluded counties as fixed.

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 many of these candidates.[11] With the exception of Ralph Nader in the 2000 election, the other non-major

[10] See the web page maintained by Michael McDonald at `http://elections.gmu.edu/voter_turnout.htm` for more information on measures of voter turnout.

[11] The only third party candidate to run in both elections who had any significant public visibility was Ralph Nader, who ran on the Green Party ticket in 2000 and as an independent in 2004. In 2000, Nader received 2.74 percent of the popular vote, but only 0.38 percent in 2004, and both times did not win any electoral votes. In 2000, some of the other candidates included Harry Browne (Libertarian Party), Howard Phillips (Constitution Party), and John Hagelin (Natural Law Party). In 2004, the other candidates were Michael Badnarik (Libertarian Party), Michael Peroutka (Constitution Party), and David Cobb (Green Party).

party candidates' vote 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 Additional Control 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. Nevertheless, accounting for some within-market changes is useful. We include four categories of variables that attempt to absorb some of the remaining within-market variation: (1) variables that measure local political preferences (market-level party affiliation), (2) variables that affect voter turnout but not candidate choice (the occurrence of a senate or gubernatorial election and local weather patterns), (3) demographic and economic variables (population age demographics, local unemployment and wages), and (4) candidate-specific local variables (distance to the candidate's home state, whether there was a same party incumbent governor, and several candidate-intercept interactions).

Some county's 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. 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 turnout, 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 turnout in presidential elections.

We want to include some demographic type variables which exhibit some variation between the two elections. We use Census data on the percentage of the county's population between the ages of 25 and 44, 45 and 64, and older than 65. Due to the lingering effects of the baby boom and migration patterns, these percentages change even within the four-year time span. To capture variation in the local economic conditions, we obtain percentage unemployment data at the county level from the Bureau of Labor Statistics (BLS). To account for variation in economic conditions among employed persons not controlled for by unemployment, we calculated the average salary using the total annual wages paid by firms divided by the total number of employees in a county from the County Business Patterns.

Finally, we include some variables that differ across candidates within the local markets where we conduct our analysis. We use whether the candidate has a same-party incumbent governor in the state, the distance (in miles) between a given DMA and the candidate's home state, and interactions between the major party candidate intercepts and the demographic and economic variables. These interactions, in particular, allow for changes in these local conditions to exert asymmetric effects on voters' preferences for a given candidate.

3 Modeling Voter Preferences

We specify an aggregate discrete choice model of demand for political candidates. A voter chooses the candidate who yields the highest utility for the voter or opts not to vote at all. Exposure to advertising by candidate j increases the utility a voter receives from choosing candidate j. We allow for unobserved heterogeneity in voter preferences and include a rich

set of fixed effects and other control variables to explain the variation in county-level voting patterns.

Our model reflects voter utility for the candidate and is relatively agnostic about the precise mechanism through which advertising affects candidate choice. Our model also abstracts from several aspects of voter choice found in more formal models of political economy. Voters do not act strategically based on their expectations of being the pivotal voter to decide 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).[12] We further assume that voters sincerely choose the candidate for who they derive the highest utility (e.g., voters choose the candidate they favor ideologically). Degan and Merlo (2009) show that identifying the "sincerity" of voters' decisions is possible with individual-level voting data across multiple elections. Their results suggest that only three percent of observed voting outcomes in their panel are consistent with insincere voting.

3.1 Voter Utility

A voter's utility for candidate j in election t is:

$$u_{itcj} = \beta_{itj} + \alpha_i' A_{tmj} + \phi' \mathbf{X}_{tc} + \gamma_{mj} + \xi_{tcj} + \varepsilon_{itcj} \ , \tag{1}$$

where β_{itj} is a voter-specific taste for a candidate from party j in election t, A_{tmj} is advertising by the candidate,[13] α_i captures the marginal utility of advertising, γ_{mj} represents market-party fixed effects, and ε_{itcj} captures idiosyncratic variation in utility across voters, candidates, and periods. ξ_{tcj} is a time-county-candidate demand shock that is perfectly observable to voters when casting their votes, but is unobservable to the researcher. $\mathbf{X}_{tc}$ is a vector of observables (at either the county or market level) that can affect voters' decisions to turnout for the election (e.g., county-level Senate and Gubernatorial election dummies, county-level rain and

[12] Kawai and Watanabe (2010) present an estimation approach to infer strategic voting behavior using aggregate outcomes from a large number of simultaneous elections in Japan.

[13] As a robustness check in estimation, we allow opponent advertising to enter the utility for the candidate as well. We do not find the opponent's advertising to be significant.

snow) or their decision to vote for a particular candidate (market-level interactions between candidate intercepts and party identification variables). Candidates have beliefs about the demand shocks ξ_{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 (normalized) utility of $u_{itc0} = \varepsilon_{itc0}$.

The market-party fixed effects γ_{mj} help fit the mean utility level for a party in a specific market. The fixed effects control for the endogeneity of advertising due to fixed unobserved characteristics at the market-party level, removing any concern of a correlation between advertising and market-specific party preferences without relying on an instrument. We do require an instrument to address the remaining unexplained variation, corresponding to time-specific deviations from the unobserved market-party mean utility.

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

$$\begin{bmatrix} \beta_{itj} \\ \alpha_i \end{bmatrix} \sim N(\begin{bmatrix} \bar{\beta}_{tj} \\ \bar{\alpha} \end{bmatrix}, \Sigma), \tag{2}$$

where Σ is the full covariance matrix of voter tastes. Variation across individuals in their preference parameters removes the property of independence from irrelevant alternatives (IIA) common to logit aggregate demand models. While a variance in the distribution of α alone can break the IIA, we also allow for off-diagonal terms in Σ. This permits a correlation between the intercept for candidates j and k which might occur, for instance, when individuals who vote for either candidate are more similar than those individuals less likely to turn out at all. We also considered relaxing IIA using a nested-logit specification, but found the nesting parameter was insignificant.

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

following vote share:

$$s_{tcj}(\mathbf{A}_{tc}, \mathbf{X}_{tc}, \xi_{tc}; \theta) = \int_{\beta,\alpha} \frac{\exp\{\beta_{itj} + \alpha_i' \mathbf{A}_{tc} + \phi' \mathbf{X}_{tc} + \gamma_{mj} + \xi_{tcj}\}}{\sum_{k \in \{0,\ldots,J\}} \exp\{\beta_{itk} + \alpha_i' \mathbf{A}_{tc} + \phi' \mathbf{X}_{tc} + \gamma_{mk} + \xi_{tck}\}} \, dF(\beta, \alpha) \,. \quad (3)$$

3.2 Identification

We observe variation in vote shares, advertising levels, demand-side covariates and instruments across time and many markets. Identification of the parameters follows from standard arguments when estimating random-coefficient models of demand using aggregate market shares data. The specification in equation (1) involves a single endogenous variable (advertising) and the exclusion of the price of advertising from utility forms the basis for lagged advertising prices to serve as the excluded exogenous variable. There are three distinct factors to discuss about our identification strategy.

First, while most aggregate demand models use cross-market variation for identification, we use market-party fixed effects which narrow the identification to explaining within-market variation in a party's performance based on within market variation in explanatory variables and instruments. This accounts for unobserved market-specific factors which may be correlated with both candidate shares and instruments.

Second, some temporal variation in unobservable factors, not captured by our fixed effects γ_{mj}, could influence instruments and voting outcomes. Although we observe variation over time in advertising costs, some of this variation could be due to unobserved changes in demographics or economic conditions. Changes in these local conditions could also influence voter preferences if, for example, unemployment is more relevant in the locale. We address these unobservables through the observed temporal variation in our demographic and economic variables (contained in $\mathbf{X}_{tc}$), and we use interactions between these variables and candidate intercepts to allow changes in these variables to affect voter choice.

Third, we use one-year lagged advertising prices as our instrument based on its logical exclusion from utility for the candidate and its likely correlation with candidates' current advertising decisions. The advantage of the one-year lag is that it removes any current

political factors that might affect the price of advertising.

In our estimation, we consider an additional specification that allows an opposing candidate k's advertising to enter the utility for candidate j in equation (1). This introduces an additional endogenous variable, so we require an additional instrument. We obtain additional instruments by interacting the excluded advertising price with the candidate dummies and covariates, $\mathbf{X}_{tc}$, which includes variables that are either common or specific to the candidate. Such interactions must be excluded from utility because they include the price of advertising which itself is excluded. While we later test for the importance of these interactions as instruments, we briefly discuss why we expect them to shift candidates' advertising incentives. Gordon and Hartmann (2011) specify an objective function in election t where a candidate chooses advertising levels to maximize the expected probability of winning the election less the total cost of advertising:

$$\pi_{tj}(\mathbf{A}_{tj}, \mathbf{A}_{t-j}, \mathbf{X_t}, \boldsymbol{\xi}_t; \theta) = R_{tj}\mathbb{E}_\xi \left[d_{tj}(\mathbf{A}_{tj}, \mathbf{A}_{t-j}, \mathbf{X_t}, \boldsymbol{\xi}_t; \theta)\right] - \sum_{m=1}^{M} \omega_{tm} A_{tmj}\,, \tag{4}$$

where the shocks ξ_t are random from the perspective of the candidate, $\mathbf{A}_{tj} = (A_{t1j}, A_{t2j}, \ldots, A_{tMj})'$ is a vector of advertising choices across the M markets, $d_{tj}(\cdot)$ indicates whether the candidate wins the election, and ω_{tm} is the observed cost of advertising. The parameter R_{tj} converts the probability of winning the election into monetary terms. The first-order condition (FOC) with respect to advertising A_{tmj} at a solution is

$$\text{FOC:} \quad R_{tj}\frac{\partial \mathbb{E}_\xi \left[d_{tj}(\mathbf{A}_{tj}, \mathbf{A}_{t-j}, \mathbf{X_t}, \boldsymbol{\xi}_t; \theta)\right]}{\partial A_{tmj}} = \omega_{tm}\,. \tag{5}$$

A solution for advertising will therefore always involve a multiplicative relationship of X_{tm} with ω_{tm}, unless X_{tm} and A_{tmj} are additively separable in the derivative of the probability of winning the election with respect to advertising (i.e., ${}^{\partial \mathbb{E}_\xi [d_{tj}(\cdot)]}/_{\partial A_{tmj}}$). The probability of advertising, $\mathbb{E}_\xi \left[d_{tj}(\cdot)\right]$, is a cumulative distribution function. If the unobservable(s) in this cdf, ξ_t, have support on the entire real line, $\mathbb{E}_\xi \left[d_{tj}(\cdot)\right]$ must be a nonlinear function. We are unaware of such a function that would allow advertising to be additively separable from X_{tm}.

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 (2010). 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 market-party fixed effects and a full covariance matrix in taste heterogeneity.[14] We refer the reader to Dubé, Fox, and Su (2009) for more details.

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

$$g(\xi) = \frac{1}{TCJ} \sum_{t=1}^{T} \sum_{c=1}^{C} \sum_{j=1}^{J} \xi_{tcj} \cdot h(z_{tcj}) \,. \tag{6}$$

Let S be a vector of observed market shares across all elections, counties, and candidates and $s(\xi;\theta)$ be the corresponding market shares derived from the model given values for the demand shocks ξ and structural parameters θ. The MPEC objective function is

$$\begin{aligned} \min_{\{\theta,\xi,\nu\}} \quad & \nu' W \nu \\ \text{subject to} \quad & s(\xi;\theta) = S \\ & g(\xi) = \nu \end{aligned} \tag{7}$$

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

[14] We altered the Matlab coded posted at `http://faculty.chicagobooth.edu/jean-pierre.dube/vita/MPEC` to estimate the voter model.

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 from seven specifications. We cluster standard errors at the DMA level to account for the fact that advertising and some of the instruments are the same across counties within a DMA. The first two specifications include party and party-year fixed effects, and the remaining specifications add DMA-party fixed effects. For columns (1) to (6), our instruments include the lagged advertising prices and interactions between these prices and election dummies, and political party dummies. The F-statistic in the first-stage regression of our excluded instruments is 105.43, which is highly significant. In column (7), we include interactions between the lagged advertising price variables and the demographic and economic variables, as discussed in Section 3.2.[15]

We begin with an OLS regression in column (1) in which the dependent variable is the difference in the log shares of a candidate and the outside no-vote option, which is equivalent to a homogeneous aggregate logit specification. The advertising coefficient is 0.101 and significant at the one-percent level, although this estimate does not account for the endogeneity of advertising. The next specification in column (2) uses 2SLS to instrument for the advertising levels using the one-year lagged CPMs and interactions with party and year dummies. Although the advertising coefficient increases to 0.148, the larger standard error implies the coefficient is now only significant at the five-percent level.

The remaining columns in Table 4 introduce DMA-party fixed effects. These fixed effects account for potential correlation between the advertising instruments and cross-sectional

[15]We also calculated the F-statistic in the first-stage IV regression to test whether omitting all of the $X\omega$ interactions has a significant effect (while still including the primary cost instruments and interactions between them and year and party dummies). The resulting F-statistic is 30.94, which is highly significant with a p-value < 0.001.

variation in voter preferences. To illustrate, column (3) estimates an OLS regression including the DMA-party fixed effects to facilitate comparison with column (1). The additional fixed effects reduce the advertising coefficient to 0.050 but it remains highly significant at the one-percent level. When we introduce the instruments using 2SLS in column (4), the advertising coefficient increases to 0.056 and remains significant at the one-percent level. As we previously indicated, the sign of the endogeneity 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. Thus, controlling for cross-sectional unobservables with the DMA-party fixed effects seems to reduce the advertising coefficient.

Next we introduce a series of additional covariates that we explained in Section 2.4. Column (5) starts by including the percentage of the population who identify as Republicans or Democrats interacted with the three candidate-specific intercepts and control variables for senate elections, gubernatorial elections, same-party incumbent governors, rain and snowfall, and the distance to the candidate's home state. The party-partyID interactions allow for local political preferences to exert an asymmetric influence on each candidate's vote share, whereas the other control variables help shift voters' preference between turning out for the election or not voting at all. Two of the party-partyID variables are significant (omitted for brevity), yet the advertising coefficient barely changes.

Column (6) introduces the demographic and economic control variables and interactions between these variables and the two major party candidate intercepts. Four of the five base variables are highly significant and six of the (omitted) interactions are significant, suggesting these variable influence voters' decisions differently for each political party. Consistent with Gomez, Hansford, and Krause (2007), we find that rain deters voter turnout. Higher unemployment leads to lower voter turnout, whereas higher average salaries are associated with higher turnout. The inclusion of these key variables causes the advertising coefficient to increase to 0.068 and to remain significant at the five-percent level.

Our last specification in column (7) presents a robustness check which allows an opposing candidates' advertising to enter the utility for a particular candidate (restricted to the

Democrats and Republicans). Since this introduces an additional endogenous variable, we now include the covariate interactions with the lagged advertising price to provide a sufficient number of exogenous variables for identification. The estimated coefficient on the opposing candidate's advertising is, however, insignificant. The estimated own-candidate advertising coefficient increases to 0.074 and remains significant at the five-percent level.[16]

The important point to note is that across all of the specifications, the own-candidate advertising coefficient robustly remains positive and above 0.05, despite including numerous control variables, fixed effects, and correcting for the endogeneity of advertising.

We also estimated a BLP version of the model that allows for continuous unobserved parameter heterogeneity. Without the fixed effects, we find significant parameter heterogeneity. With the fixed effects, the estimated advertising coefficients were generally the same as those found in the 2SLS specifications, and the heterogeneity parameters were insignificant. The reason is that the DMA-party fixed effects absorb the cross-sectional variation that otherwise helps identify the unobserved heterogeneity.

4.2 Elasticity Estimates

Table 5 presents the elasticity estimates from the specification in column (6). The estimated elasticities are roughly 0.032 for Republicans and 0.035 for Democrats, and an order of magnitude smaller for the third-party candidate.

These sensitivities are small if we compare them to consumer packaged goods, where advertising elasticities are about 0.1, as reported in Hanssens, Parsons, and Schultz (2001, Ch. 8). However, the effectiveness of advertising is likely to vary significantly depending on the product category. For instance, Kadiyali, Vilcassim, and Chintagunta (1999) estimate an advertising elasticity of about 0.03 using GRP data for a personal care product. Anand and Shachar (2011) find significant effects of advertising in the context of new television shows. In the case of new products, which, similar to elections, experience an intense advertising

[16]We also estimated a version of the BLP model using a nested logit with only the own candidate's advertising. The nested structure first allows a voter to choose whether to vote or not, and then conditional on voting, for which candidate to vote. The estimated nesting parameter was not significantly different from zero, so a nested model does not appear helpful.

campaign at launch, Ackerberg (2001) finds an elasticity of 0.15. Although we might at first suspect political ads to be of greater influence, seeing that people are more wedded to a political candidate than to a yogurt product is unsurprising.

Comparing our estimates of advertising elasticity to previous work in the political science literature is difficult. Few studies report advertising elasticities, and many use stated preference and intentions data as dependent variables instead of actual voting outcomes. Gerber (2004) compares the estimated effects of campaign spending (as opposed to specifically television advertising) across several prominent studies and shows their predictions vary by more than an order of magnitude depending on the estimation technique.

The studies by Huber and Arceneaux (2007) and Gerber et al. (2011) permit some comparison because both use GRPs of television advertising and focus on recent large elections. Restricting attention to non-battleground states, Huber and Arceneaux (2007) use cross-sectional survey data to show that increasing Bush's advertising by 1,000 GRPs increases the probability a voter supports Bush by 1.72 percent, whereas increasing Gore's advertising by the same amount increases his support by 3.76 percent. Using a regression and actual voting data, the authors estimate that 1,000 GRPs increases Bush's proportion of the two-party vote by 4 percent.[17] Gerber et al. (2011) coupled a television field experiment with telephone surveys to gather information on candidate preferences and voting intentions, finding that 1,000 GRPs increase respondents' intentions to vote for a candidate by about 5 percent.

To help make our elasticity estimates comparable with these results, we calculate the percentage change in votes for a candidate given an increase of 1,000 GRPs. We exclude from this calculation those counties that received zero GRPs. An increase of 1,000 GRPs yields on average 1.4 percent more votes for the Republican candidate and 1.6 percent more votes for the Democrat candidate. An extra 1,000 GRPs represents a non-trivial amount of advertising dollars (for example, about $300,000 for a prime daypart in Dallas), but the predicted response could potentially have a significant effect in a state's voting outcome.

[17]For details, please refer to pages 969 and 975 of Huber and Arceneaux (2007).

Thus, our estimates are roughly consistent with—although distinctly lower than— the two other studies that exploit (quasi-) experimental variation to isolate the causal effects of advertising. This comparison comes with several caveats because our study differs from the other two, especially in our use of instrumental variables to measure advertising efficacy with actual voting data. It is also unclear whether the effectiveness of advertising will be the same across elections for different offices.

4.3 Zero Advertising Counterfactual

In this section, we consider the power of advertising as an influential variable in the competitive interactions between candidates. 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, holding all other factors fixed. Note that we do not consider this exercise to be an actual prediction of the election outcome if advertising were banned because many other variables would endogenously respond. For example, without television advertising, candidates might use other means to communicate with voters about their stances on policy issues, or perhaps candidates would even be forced to change some of their policy stances. Although the counterfactual is unable to address these issues, the exercise still gives us some idea of the rough preferences of voters were it not for the influence of advertising and of the sensitivity of the election outcome.

Table 6 indicates how the electoral votes would have changed under this scenario. The column "Switched States" lists states that switched to the candidate listed in that row. Removing advertising does not change the outcome in the 2004 election when Bush won with a margin of 36 electoral votes. However, under zero advertising in 2000, Bush would have won Oregon but lost Florida and New Hampshire to Gore. The net loss of 22 electoral votes is enough to tip the election in Gore's favor. In 2000, Bush spent about $2.5 million and and Gore spent about $1.7 million on advertising in Florida, representing only 3% of each candidate's advertising budget. In the elections, removing advertising results in a decrease in voter turnout by about 2.8 percent and 2.5 percent, respectively, or about 4.5 million fewer

voters. The variation attributable to advertising is not, however, large in comparison to the 6.4 percentage point change in turnout between the 2000 and 2004 elections. Overall, we view our counterfactuals as consistent with the findings in Lovett and Peress (2010) in that the most notable effect is on the candidate chosen.

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 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 only in even years allows lagged advertising prices to serve as instruments since they are independent of any political election influence. 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 where advertising 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.

Our analysis comes with several caveats that might be interesting to pursue as future research. First, we aggregate all of a candidate's advertising into a single variable and do not separately consider the effects of positive or negative advertisements. We made this choice because numerous papers in political science specifically examine positive versus negative advertising (e.g., Ansolabehere et al., 1999), and to analyze them from a causal perspective requires an instrument that shifts the relative balance of positive and negative advertisements across DMAs. Second, our model takes the policy positions of candidates fixed and does not consider any interaction between the advertising content and their positions. This is beyond the scope of available data because one would need to observe a sample with substantial variation in such positions. Third, we do not model voters' expectations about the potential

outcome of the election, and how this might alter their decision to vote for a given candidate. Expectations data have well-known challenges and would require additional structure that we felt would impose too stringent parametric restrictions while trying to focus on the causal relationship in the data. Fourth, we assume the effectiveness of advertising is fixed over time. If the effectiveness of advertising could vary over time and be observed, candidates could use this as a basis for scheduling advertising during the campaign, generating an additional source of endogeneity.

We hope our illustration of the value of fixed effects and instruments motivated by advertiser objective functions influences future empirical studies of these political applications as well as other questions in advertising more broadly.

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Table 1: Summary Statistics of County-Level Voting by Candidate and Election Year

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

Table 2: Market-Level Advertising by Candidate and Election Year

	Obs	Mean	Std Dev	Min	Max
2000 Election					
GRPs Bush	75	5,823	5,593	0	15,890
GRPs Gore	75	4,782	5,675	0	17,940
GRPs Other	75	75	116	0	423
Expenditures Bush	75	879,842	1,218,726	0	6,185,445
Expenditures Gore	75	681,526	1,072,944	0	5,941,607
Expenditures Other	75	20,009	44,678	0	322,879
2004 Election					
GRPs Bush	75	7,809	10,439	0	35,979
GRPs Kerry	75	9,726	12,807	0	46,221
GRPs Other	75	3	3	0	12
Expenditures Bush	75	1,123,755	1,863,433	0	8,386,410
Expenditures Kerry	75	1,349,324	2,207,179	0	9,856,520
Expenditures Other	75	1,285	2,268	0	14,165

Table 3: Summary Statistics of the change in the Lag CPMs from 1999 to 2003

Daypart	Obs	Mean Change	Std Dev	Min	Max
Early Morning	75	1.21	1.30	-1.24	4.85
Daytime	75	0.02	0.88	-2.05	2.38
Early Fringe	75	0.65	1.18	-1.98	2.74
Early News	75	1.50	1.56	-2.26	5.40
Prime Access	75	3.10	1.88	-1.11	10.06
Prime Time	75	3.82	2.80	-2.48	11.75
Late News	75	3.72	2.07	-1.75	9.06
Late Fringe	75	1.04	1.98	-3.47	6.21

Table 4: Parameter Estimates

	(1) **OLS**	(2) **2SLS**	(3) **OLS**	(4) **2SLS**	(5) **2SLS**	(6) **2SLS**	(7) **2SLS**
Candidate's Ads	0.101***	0.148**	0.050***	0.056***	0.053***	0.068**	0.074**
	(0.021)	(0.066)	(0.008)	(0.013)	(0.014)	(0.027)	(0.037)
Opponent's Ads							-0.005
							(0.040)
Senate Election					0.002	0.000	0.000
					(0.004)	(0.004)	(0.004)
Gubernatorial Election					-0.028	-0.032	-0.032
					(0.046)	(0.044)	(0.045)
Gov. Incumbent Same Party					-0.064	-0.045	-0.045
					(0.053)	(0.053)	(0.053)
Rain (inches)					-0.052	-0.105**	-0.105**
					(0.041)	(0.045)	(0.045)
Snow (inches)					-0.003	-0.001	0.000
					(0.012)	(0.013)	(0.017)
Distance*100 (miles)					0.002	-0.035	-0.035
					(0.034)	(0.142)	(0.142)
% $25 \leq$ Age < 44						2.996***	2.996***
						(0.634)	(0.637)
% $45 \leq$ Age < 64						5.455***	5.455***
						(0.910)	(0.923)
% $65 \leq$ Age						-1.009	-1.009
						(1.209)	(1.221)
% Unemployment						-0.120***	-0.120***
						(0.016)	(0.016)
Average Salary						0.010***	0.010***
						(0.003)	(0.003)
Fixed Effects							
Party	Y	Y	Y	Y	Y	Y	Y
Year-Party	Y	Y	Y	Y	Y	Y	Y
DMA-Party			Y	Y	Y	Y	Y
Interactions							
Party-PartyID					Y	Y	Y
Year/Candidate-**X**						Y	Y

Notes: Obs $= 9,576$. F-stat of excluded instruments in (6) is 105.43 (p-val < 0.001). Robust standard errors clustered by DMA are in parentheses. '*' significance at $\alpha = 0.1$ '**' significance at $\alpha = 0.05$ and '***' significance at $\alpha = 0.01$. "Senate Election" indicates a fixed effect for the existence of a Senate race, "Gubernatorial Election" for the existence of a Gubernatorial race in the same state. "Gov. Incumbent Same Party" indicates whether the incumbent governor and the candidate are in the same party. Fixed Effects: Party indicates dummies for Republicans, Democrats, and 3rd-Party Composite; Party-Year indicates party-election year dummy variables; DMA-Party indicates DMA and party dummy variables. Interactions: Party-PartyID is a set of six interactions between the Republican and Democrat intercepts and the percentage of voters who self-identify as Republican, Democrat, or Independent in a market; Year/Candidate-**X** indicates interactions between election year and Republican/Democrat choice-intercepts with the three age demographic variables and the two economic variables (the last five variables in the table). Some estimates are omitted due to space considerations.

Table 5: Elasticity Estimates

	Republican	Democrat	3rd Party
Republican	0.0318	-0.0145	-0.0145
Democrat	-0.0114	0.0347	-0.0114
3rd Party	-0.0001	-0.0001	0.0043

Notes: All estimates are significant at the $\alpha = 0.01$ level. Results use estimates in Column (6) of Table 4. For example, a 1% increase in Democrat advertising implies a 0.0114% decrease in the market share of the Republican candidate.

Table 6: Zero Advertising Counterfactual

Election		Electoral Votes		Switched States
Year	Candidate	Observed	Zero Ad	(Electoral Votes)
2000	Bush	271	249	OR(7)
2000	Gore	267	289	FL(25), NH(4)
2004	Bush	286	296	WI(10)
2004	Kerry	252	242	—

Turnout	% of Pop	
Year	Observed	Zero Ad
2000	0.6436	0.6254
2004	0.7069	0.6892

Notes: Electoral college results from setting advertising to zero in both elections, using estimates from Column (6) of Table 4. The "Observed" column presents the actual number of electoral votes received by each candidate, and the "Zero Ad" column presents the predicted number after setting advertising to zero everywhere. The right-most column indicates which states switched hands. For example, in the 2000 election, Bush loses Florida and New Hampshire to Gore but gains Oregon. Bottom panel provides the change in the percentage of voters who turnout for the election.

Figure 1: 2000 to 2004 within-DMA Changes in GRPs

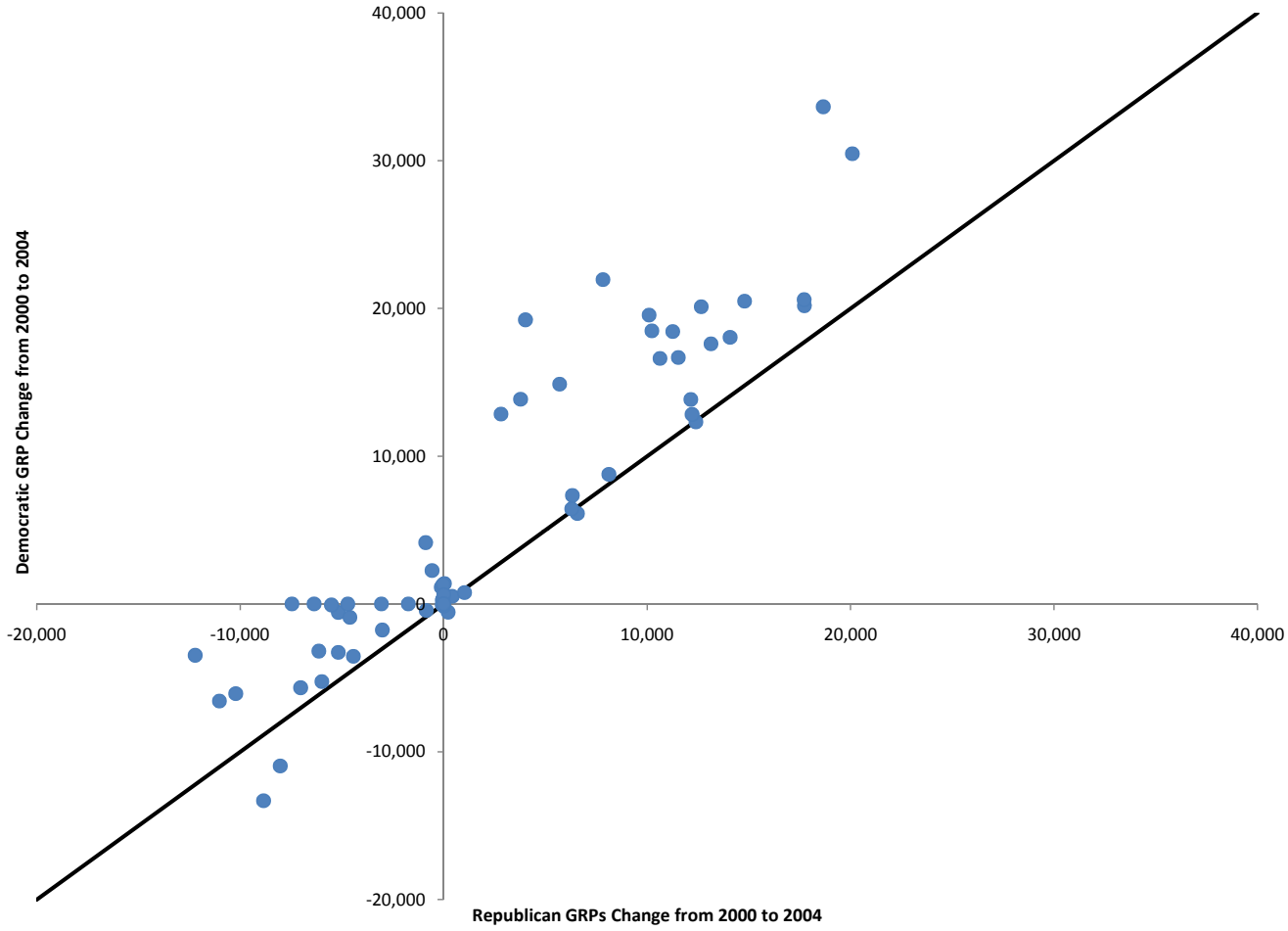

Figure 2: Daypart Mix for Democrats in 2000: Top 10 DMAs in GRPs

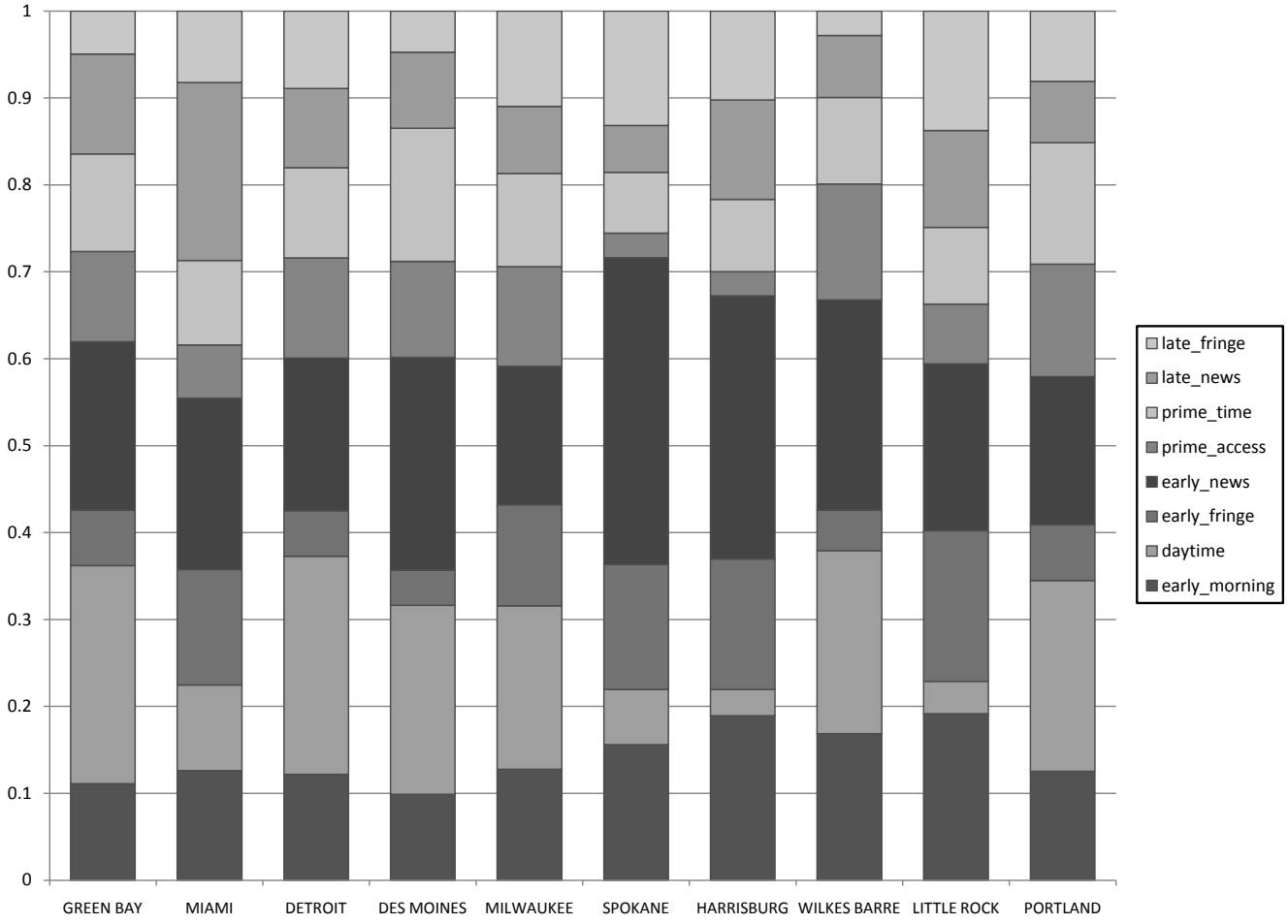

Figure 3: Daypart Mix for Republicans in 2000: Top 10 DMAs in GRPs

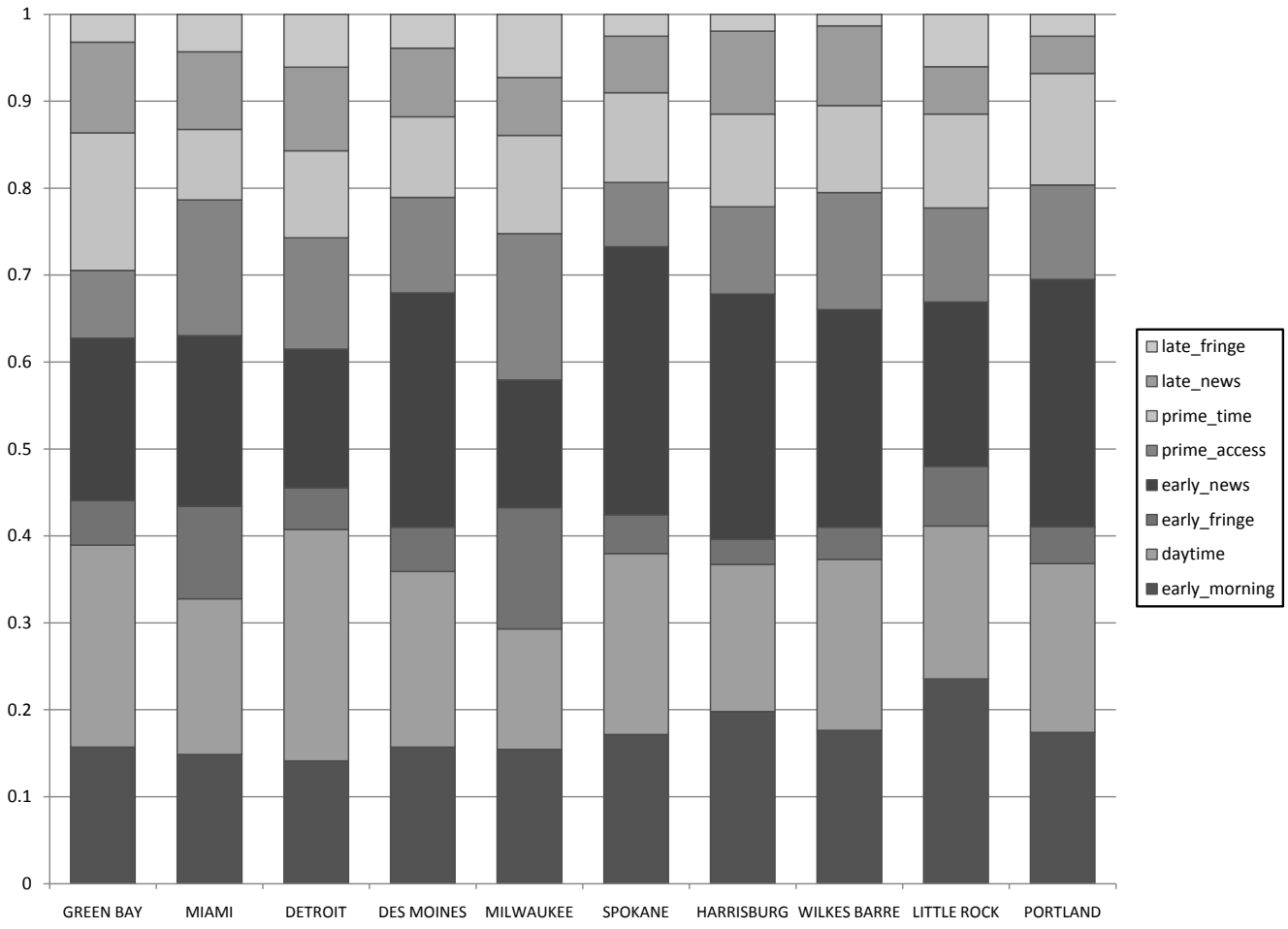

Figure 4: Early News CPM by DMA: 2000 vs. 2004