Ballot measures, political advertising and contribution caps

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Abstract

Following the 2010 Citizens United Supreme Court decision, unlimited campaign spending has been permitted for all election types. As a result, there has been a notable increase in campaign contributions for ballot measures, which are a unique form of direct democracy. In this paper, we estimate the causal effect of TV political campaigns on ballot measure outcomes. Using variation in exposure to TV advertising across media markets, our reduced form estimates suggest that a 1 standard deviation increase in the net number of ads of one campaign is associated with an increase of 2.13 to 2.46 p.p. in its net vote share. We define the main features of a structural model that incorporates equilibrium effects and strategic behavior of campaigns. Further work will focus in estimating this structural model to explore counterfactual scenarios with different contribution caps, and other related questions.

1 Introduction

Ballot measures are a unique form of direct democracy: they enable voters to have a more direct say in shaping public policy and can serve as a powerful tool for citizens to express their opinions and preferences. In the United States, following the 2010 Citizens United Supreme Court decision, unlimited campaign spending has been permitted for all election types. As a result, there has been a significant rise in campaign contributions, particularly noticeable for ballot measures. Given this change, it is crucial to understand the potential impact of unlimited campaign spending on ballot measure outcomes.

While previous literature has extensively studied the influence of campaign spending in regular elections, less attention has been given to its role in ballot measures. Furthermore, the existing evidence has focused on studying the relationship between campaign spending and ballot measures prior to the 2010 legislative change. Using detailed data on campaign advertising, we fill this gap by examining whether ad exposure affects ballot measure outcomes in the current context of unlimited spending.

The case of ballot measures in the United States provides an outstanding laboratory to study the effects of electoral campaigns: the structure of TV media markets provides variation in exposure to TV advertising between counties in the same state. Moreover, ballot measures present some advantages for identification with respect to regular elections. This is important since it allows to estimate more confidently structural parameters, reducing concerns on reverse causality, omitted variables bias and within-candidate equilibrium effects.

We study this question using data from 50 ballot measures spanning the period from 2010 to 2020. We focus on the 50 elections that registered the highest number of total TV advertisements. For each of these elections, we obtain results at the county level and combine them with data on the number of aired ads in the respective media market. This means that our estimates measure the effect of exposure to campaign TV advertising on voting outcomes.

Identifying the causal effects of political advertising on ballot measure outcomes is a daunting task. First, variations in TV political advertising across counties are not necessarily exogenous. For instance, campaigns might target ad airings at territories that may provide higher political returns, due to ideological biases. Thus, a simple regression connecting exposure to TV ads to electoral outcomes has to be interpreted with caution. Second, equilibrium effects across campaigns make it difficult to precisely estimate causal effects through reduced-form estimates.

We try to overcome such challenges through two different strategies. First, in our reduced-form estimates, we follow a large literature that leverages Nielsen's DMA classification of TV markets (Shapiro, 2018; Spenkuch and Toniatti, 2018; Sides et al., 2022). This approach exploits the exogenous variation in exposure to political ads that arises from the assignment of bordering counties to different DMAs, which leads many counties to be assigned to DMAs that overlap primarily with a different state. We rely on the fact that such discontinuities are usually related to market-level factors rather than political considerations, which reduces concerns on reverse causality. Second, we go beyond this exercise and define a structural model that will estimate more precisely the causal effects of TV advertising on ballot measure outcomes. By doing so, we will also be able to estimate counterfactuals in which campaign spending is capped, and find out whether such budget constraint would have changed election results.

Our preliminary findings based on reduced form estimates indicate a substantial influence of TV political campaigns on ballot election outcomes. Results derived from the full sample show that a 1,000 additional net ads exposure (i.e., ads in favor versus ads against the measure, or vice versa) is associated to a 0.77 p.p. increase in the net vote share (i.e., % vote YES - % vote NO, or vice versa). Similarly, results from the restricted sample consisting solely of bordering counties suggest a similar but slightly larger effect of 1.07 p.p. These estimates remain robust even after accounting for variation in ideological composition across counties.

Contribution. We communicate with three main strands of the literature. First, we relate to the literature examining the effects of electoral advertising and campaign spending on ballot measure outcomes (Stratmann, 2006b; de Figueiredo et al., 2011). Most recent examples have tested the effects of political advertising through the use of natural experiments (Kalla and Broockman, 2018). We contribute to this literature by studying the effect of political advertising with actual data on campaign actions and electoral results, being the first to examine this question in the context of the recent spike of campaign spending given by the 2010 legislative change. Second, we contribute to the broader literature studying the persuasive effects of political advertising in electoral outcomes (Spenkuch and Toniatti, 2018; Sides et al., 2022). We leverage identification advantages with respect to candidate elections to define a novel structural model that accounts for equilibrium effects across campaigns within a ballot measure and strategic behavior of electoral campaigns. Finally, we aim to expand the literature on the effects of contribution limits on election outcomes (Gordon and Hartmann, 2013, 2016; Stratmann, 2006a). We do so by using our structural model to generate counterfactual estimates for ballot measure outcomes if different limits to campaign contributions had been in place. By doing so, we can explore whether the existence of budget constraints would have changed recent electoral results.

Understanding the factors that influence ballot measures in the US is crucial because they represent fundamental measures of direct democracy. These measures allow citizens to directly participate in decision-making on important policy issues, impacting the socio-economic landscape. If campaign spending by interests groups and corporations can effectively shape the result of such measures, their original purposes could be distorted and results in inefficient outcomes. Thus, analyzing these factors can enhance the understanding of direct democracy mechanisms and provide valuable insights to policymakers to foster their correct functioning.

The structure of the paper is as follows. Section 2 describes the background of ballot measures and TV media markets in the US. Section 3 describes the data. Section 4 presents reduced-form methodology and results. Section 5 introduces our structural model. Finally, section 6 concludes and lists next steps.

2 Background

2.1 Ballot measures

Ballot measures in the US. In the United States, ballot measures, also known as initiatives or referendums, constitute a vital component of the democratic process at the state and local levels. They are direct voting mechanisms that enable citizens to propose, approve, or reject specific legislative actions or constitutional amendments. Typically, ballot measures bypass the traditional lawmaking process undertaken by elected officials, allowing citizens to directly shape public policy on issues of substantial importance. By providing an avenue for direct participation, ballot measures grant ordinary citizens an influential role in the decision-making process and offer an alternative means of shaping public policy outside of the conventional representative system.

Ballot measures are widely employed across the United States and are particularly prevalent in the 24 states that have established provisions for citizen-initiated measures. These states permit citizens, often in collaboration with advocacy groups, to collect signatures from a predetermined percentage of registered voters, which, when achieved, places the proposed measure on the ballot for popular vote.

There are two primary types of ballot measures: initiatives and referendums. Initiatives are proposals put forth by citizens to introduce new laws or constitutional amendments, while referendums allow voters to approve or reject legislation or amendments previously passed by the state legislature. Overall, the prominence of ballot measures in the US political landscape underscores their pivotal role in empowering citizens and ensuring their voices are heard in matters of public concern.

Campaign contributions. Following the 2010 Citizens United Supreme Court decision, unlimited campaign spending has been permitted for all election types. As a result, the landscape of campaign finance for ballot measures has seen a fundamental transformation, as there has been a significant increase in campaign contributions (see Figure 1). The magnitude of this change calls for analysis to better understand the role of money in shaping the outcomes of ballot measures and its impact on the democratic process.

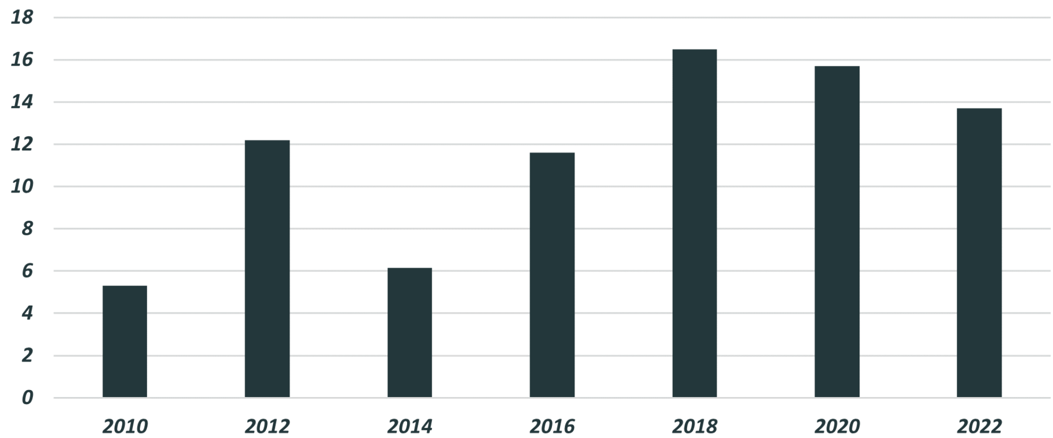

Figure 1: Contributions raised by ballot measure committees, in billion dollars.
Source: Open Secrets

2.2 Media markets

Media markets and TV advertisement. In the United States, television station offerings are segmented into designated market areas (DMA), also known as media markets. These media markets, that determine the available channels for cable and satellite subscribers, usually consist of groups of counties[1] that are not necessarily part of the same state.

As a result, counties that belong to the same state are exposed to different advertisements, due to differences in media market assignment. Such divisions are generally driven by market-level factors rather than political considerations. We exploit such variation to explore the effects of TV advertisement campaigns on ballot measure outcomes.

Media markets composition. Figure 2 provides an illustration of media market composition for the case of California. In the left side of the figure, we observe a portion of California counties, and in the right side, a portion of Nevada counties. It can be seen that Californian counties are divided in different media markets. Some of these media markets are entirely made up only by Californian counties, whereas some others belong to a media market mostly formed by Nevadan counties: Lassen, El Dorado East[2], Alpine and Mono. All these 4 counties belong to the *Reno* media market, which is formed by 4 Californian counties and 11 Nevadan counties.

This case exemplifies the two main types of media market we can find, according to their composition. Firstly, media markets in which all counties belong to the same state. Secondly, media markets formed by counties from 2 or more different states. In this second case, there is a state that predominates in the media market (the state with a higher proportion of counties in the DMA, which, in our previous example, would be Nevada), and some other counties that are a minority in the market (also in the previous example, the 4 counties in California).

[1] In very few exceptions, a county is split in different media markets.

[2] El Dorado is one of the few US counties split in 2 media markets: the East part belongs to the *Reno* media market and the West part belongs to the *Sacramento-Stockton-Modesto* media market.

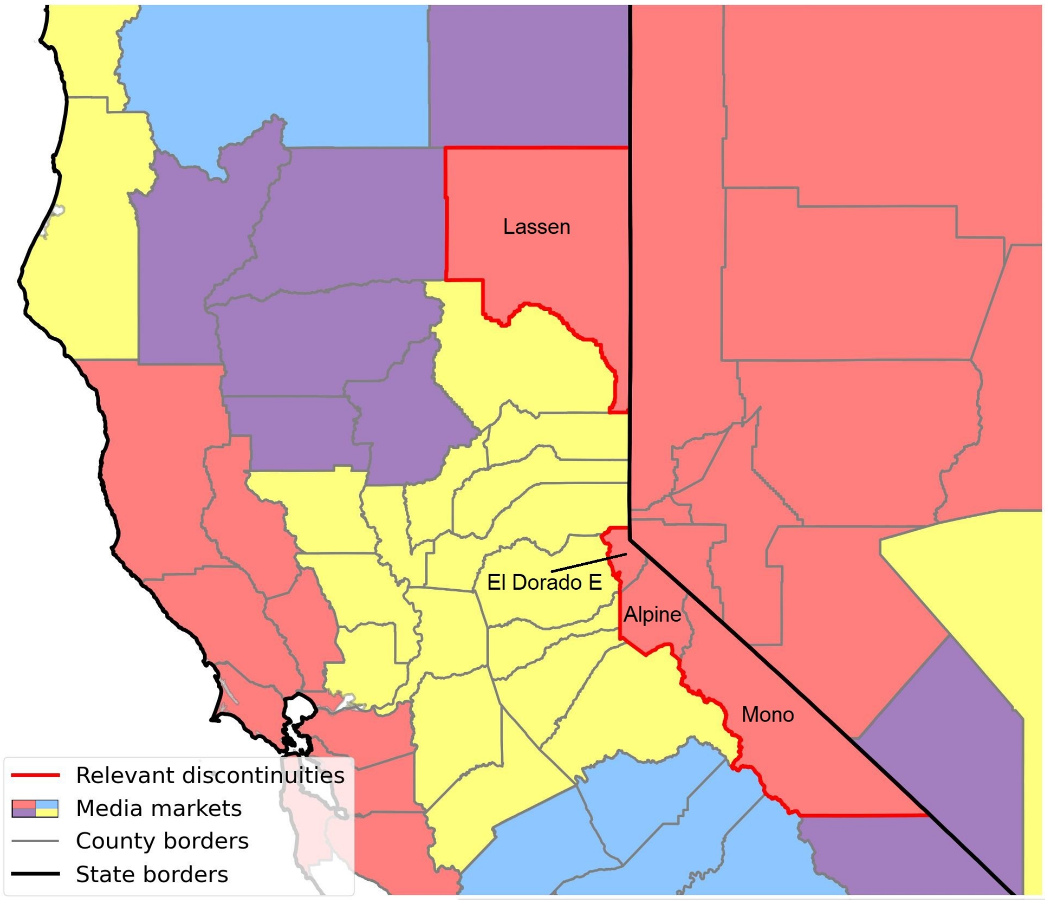

Figure 2: County and media market borders between California and Nevada.

All in all, we observe that neighboring counties within a state can be assigned to different DMAs, and many counties are assigned to DMAs that overlap primarily with a different state. Such divisions are generally driven by market-level factors rather than political considerations.

Since advertisements for ballot elections are purchased at the DMA level, this generates quasi-random variation in exposure to political advertising across bordering counties assigned to different DMA's. On one hand, ad airings for a ballot measure are usually higher in media markets formed entirely by counties within the state that votes for that measure. On the other hand, counties that belong to a media market that overlaps primarily with a different state are usually exposed to a lower number of ads. Clearly, these differences in ad exposure are mostly driven by differences in the number of population that will see the ad and its cost, but not to political factors.

3 Data

Electoral results. We use electoral results at the county level for the 50 ballot measures that had the highest TV advertisement exposure during the even-numbered years from 2010 to 2020. The data has been retrieved from the corresponding Secretaries of State. Table A1 lists the 50 ballot measures in our sample. For every ballot measure, we use the vote share in each county in the state the measure was voted.

TV advertisements. We retrieve data on all TV advertisements aired on national TV or cable networks from the Wesleyan Media Project, which provides access to Campaign Media Analysis Group (CMAG) data. For every airing, this data provides information on the time and day it was issued, the sponsor, the side of the ballot it supported, and the estimated cost of the airing.

Control variables. To account for ideological differences across counties within the same state, we use the results of the most recent presidential election prior to each ballot measure. We retrieve such data from the MIT Election Data Science Lab.

4 Reduced form analysis

4.1 Identification Strategy

Baseline specification. In our first empirical exercise, we examine the effect of TV advertising on ballot election results using two alternative regressions. First, we estimate:

$$\begin{aligned} \%\ \textit{Vote Yes}_{c,b} = \beta_1\ \textit{Ads Yes Campaign}_{m(c),b} + \beta_2\ \textit{Ads No Campaign}_{m(c),b} \\ + \alpha_b + \gamma_b\ \textit{Presid Elect}_{c,t(b)} + \varepsilon_{c,b} \end{aligned} \tag{1}$$

where c denotes a county in media market $m(c)$, and b a statewide ballot measure. $\%\ \textit{Vote Yes}_{c,b}$ is the vote share obtained by the *Yes* campaign.[3] $\textit{Ads Yes Campaign}_{m(c),b}$ and $\textit{Ads No Campaign}_{m(c),b}$ are the number of ads by the *Yes* and *No* campaigns, respectively. α_b is a set of ballot fixed effects, to capture popularity of each ballot mea-

[3] In Equation 1, we use only the vote share of the *Yes* campaign for each combination of ballot and county. Including the vote share of the *No* campaign as an additional observation wouldn't add any extra variation to the model, because we already account separately for the number of ads in the Yes and *No* campaigns as regressors.

sure across counties. Finally, $Presid\ Elect_{c,t(b)}$ is the difference in the vote share for the Democratic party and the Republican party in the previous presidential election. This accounts for ideological differences across counties that may affect each ballot measure outcome in distinct ways, given the heterogeneity across measure topics[4].

In equation 1, we assume that ads from both campaigns are going to affect ballot measure outcomes linearly and separately; this is, every additional ad from each campaign will affect the vote share, and the sum of the effects from the two campaigns determines the total effect of TV advertising.

Second, we estimate the following alternative regression:

$$Net\ vote\ share_{c,b} = \beta\ Net\ Ads_{m(c),b} + \alpha_b + \gamma_b\ Presid\ Elect_{c,t(b)} + \varepsilon_{c,b} \tag{2}$$

where $Net\ vote\ share_{c,b}$ is the difference in the vote share ($\%\ Vote\ Yes_{c,b} - \%\ Vote\ No_{c,b}$) and $Net\ Ads_{m(c),b}$ is the difference in the number of ads between the two campaigns ($Ads\ Yes\ Campaign_{m(c),b} - Ads\ No\ Campaign_{m(c),b}$). The rest of the specification remains unchanged.

In equation 2, we assume that the effect in ballot measure outcomes of TV advertising comes from the difference in the volume of ads between the two campaigns; this is, if the *Yes* and *No* campaigns exhibit the same number of ads, TV advertising should not affect the outcome of the election.

Endogeneity concerns. In our reduced-form strategy, we use variation across DMA's to study the effect of TV ads exposure on ballot measure outcomes. Still, even though counties within a state that belong to different DMA's are exposed to a different number of ads, such differences might be driven by different factors. For instance, campaigns might target ad airings at territories that may provide higher political returns, due to ideological biases. If that is the case, our estimates could not be interpreted causally anymore, as they would suffer from reverse causality.

To overcome this limitation, we follow a large literature that leverages Nielsen's DMA classification of TV markets. This approach exploits only the exogenous variation in exposure to political ads that arises from the assignment of bordering counties to different DMAs, which makes that some of them are assigned to markets in which a different state is predominant. Previous studies have used this to estimate a structural

[4] Notice the coefficient γ_b is specific for each ballot measure, because ideological biases across counties may affect each ballot measure in different ways, depending on the question voted.

model of demand spillovers from pharmaceutical advertising (Shapiro, 2018) or to explore the effects of political advertising on a range of elections, including presidential elections (Spenkuch and Toniatti, 2018) and other candidate down-ballot elections (Sides et al., 2022).

In this case, we estimate our specification in a restricted sample formed only by counties that belong to media markets dominated by a different state, and compare them to their neighboring counties in the same state. By doing so, we only use quasi-exogenous variation in exposure to political advertising that is less likely to suffer from endogeneity concerns, and more likely to be generated simply by scale factors (this is, counties receiving more/less ads only because a higher/lower share of the population in the media market to which they are assigned belongs to the state in which the election takes place).

4.2 Results

Full sample. Table 1 shows OLS estimates of Equation 1 (Columns 1 to 3) and Equation 2 (Columns 4 to 6), in the full sample. Columns (1) and (4) include only the number of ads as regressors. Columns (2) and (5) incorporate ballot fixed effects. Finally, Columns (3) and (6) also include the interaction of the difference in the vote share for the Democratic party and the Republican party in the previous presidential election with ballot dummies.

Results from Columns (1) to (3) suggest that the number of ads supporting (opposing) a ballot measure is associated with a higher (lower) vote share in favor of the measure. According to our complete specification, the effect of supporting ads and opposing ads is similar: an increase of 1 standard deviation in the number of ads (either supporting or opposing ads) is associated with an increase of 0.82 to 0.89 p.p. in the vote share.

Results from Columns (4) to (6) provide a similar picture: airing a higher number of ads than the opposing campaign is associated with better electoral outcomes. An increase of 1 standard deviation in the net number of ads (Support - opposition ads, ÷100) is associated with an increase of 2.13 p.p. in the net vote share.

Table 1: OLS results in the full sample - effect of ad exposure in the vote share

	% vote YES (p.p.)			% vote YES - % vote NO (p.p)		
	(1)	(2)	(3)	(4)	(5)	(6)
Support ads (÷100)	0.147***	0.078**	0.039***			
	(0.044)	(0.038)	(0.014)			
Opposition ads (÷100)	−0.226***	−0.000	−0.038			
	(0.073)	(0.036)	(0.023)			
Support - opposition ads (÷100)				0.387***	0.076	0.077**
				(0.107)	(0.057)	(0.035)
Ballot FE	No	Yes	Yes	No	Yes	Yes
Presid. elections control	No	No	Yes	No	No	Yes
Treatment sd	21.13/ 24.19	21.13/ 24.19	21.13/ 24.19	27.76	27.76	27.76
Observations	2,640	2,640	2,640	2,640	2,640	2,640
R^2	0.13	0.73	0.92	0.13	0.73	0.92

Border counties sample. Table 2 replicates Table 1 using the subsample of border counties, as described in Section 4.1. By restricting the sample, we reduce endogeneity concerns, since we use only the variation in exposure to ads that arises between counties that belong to media markets formed mostly by counties from other states and their neighboring same-state counties.

Results in Table 2 confirm the results previously obtained for the full sample: an increase in the number of TV ads by one campaign is related to an increase in its vote share, whether we use our specification in Equation 1 (Columns 1 to 3) or the one in Equation 2 (Columnes 4 to 6). In Column (3), an increase of 1 standard deviation in the number of ads (either supporting or opposing ads) is associated with an increase of 0.64 to 1.52 p.p. in the vote share. In Column (6), an increase of 1 standard deviation in the net number of ads (Support - opposition ads, ÷100) is associated with an increase of 2.46 p.p. in the net vote share. All in all, point estimates are very similar across the two different samples.

Table 2: OLS results in the subsample of border counties - effect of ad exposure in the vote share

	% vote YES (p.p.)			% vote YES - % vote NO (p.p)		
	(1)	(2)	(3)	(4)	(5)	(6)
Support ads (÷100)	0.199***	0.079***	0.035*			
	(0.048)	(0.029)	(0.018)			
Opposition ads (÷100)	−0.321***	−0.112***	−0.072***			
	(0.069)	(0.036)	(0.022)			
Support - opposition ads (÷100)				0.549***	0.197***	0.114**
				(0.115)	(0.062)	(0.043)
Ballot FE	No	Yes	Yes	No	Yes	Yes
Presid. elections control	No	No	Yes	No	No	Yes
Treatment sd	18.29/ 21.15	18.29/ 21.15	18.29/ 21.15	21.60	21.60	21.60
Observations	727	727	727	727	727	727
R^2	0.19	0.79	0.92	0.17	0.79	0.92

Reduced form limitations. Despite our efforts to address endogeneity concerns, reduced form estimates are still subject to several limitations. Firstly, while focusing on a carefully selected subsample of counties helps to address some issues, potential problems related to reverse causality may persist. Additionally, if bordering counties fail to represent the whole adequately, estimates derived from this subsample might lack full external validity. Secondly, the exclusion of equilibrium effects across campaigns within a ballot measure and the strategic behavior of campaigns is a notable limitation. Thirdly, our previous results require us to take non-negligible assumptions, such as assuming constant and linear returns to TV advertisements, or limiting potential interactions between the two campaigns' ads – whether they offset each other or exert independent effects. Finally, one major drawback of reduced form estimates is their inability to reliably construct counterfactual estimates for alternative scenarios with budget caps.

5 Structural model

To overcome the limitations associated to our reduced form estimates, we define a structural model that captures the basic features of the electoral competition between two sides in a ballot initiative that run TV ads to lure constituents into their camp. The basic characteristics of the model are:

- Dynamic model, finite horizon: at every period $t = 1, 2, ...T - 1$ both sides in the ballot choose how many TV ads to broadcast. At period $t = T$ the election is held and results are realised.
- Two sided game: There are two competing campaigns, the YES and the NO.
- Continuous choice: Each camp decides how many ads to broadcast at show s and time t

5.1 Value functions

This section introduces the value functions of the campaigners. There will be a value function expression for the election night T, and another expression for the campaigning period $t \leq T$.

Value function at $t = T$. At election night T, campaigns have nothing left to do: they just wait and see the results. Value functions are:

$$V_T^{yes} = \pi^{yes} \cdot \mathbb{1}\left(\frac{\sum v_{cT}^{yes}}{\sum v_{cT}^{yes} + \sum v_{cT}^{no}} > 0.5\right)$$
$$V_T^{no} = \pi^{no} \cdot \mathbb{1}\left(\frac{\sum v_{cT}^{yes}}{\sum v_{cT}^{yes} + \sum v_{cT}^{no}} < 0.5\right)$$

Where v_{cT}^{yes} is the number of votes in favor of the ballot measure. Each campaign has a private return $\pi^{\{yes,no\}}$ of winning the ballot initiative. This return is unobserved by the econometrician.

The expression of vote margin is normalized to be centered at 0.5

$$\frac{\sum v_{cT}^{yes}}{\sum v_{cT}^{yes} + \sum v_{cT}^{no}} \in [0, 1]$$

Value function at $t = T - 1$. In the last day of the campaign ($t = T - 1$), the per-period value function will instead be the following:

$$V_{T-1}^{yes} = \max_{\{a_{s,T-1}^{yes}\}} = -\sum_S p_s \cdot a_{s,T-1}^{yes} + E\left[V_T^{yes}\right]$$

Where p_s is the price of running an ad at show s, $a^{yes}_{s,T-1}$ is how many ads camp *yes* decides to broadcast at show s and time $T-1$. Both of these components are observed.

Each campaign has to choose now many ads $a_{s,T-1}$ to put in each show $s = 1, 2, ...S$ at period $t < T$, creating to a vector of optimal choices.

$$\underset{S\times 1}{\{a^{yes}_{s,T-1}\}^*}$$

The expression $E\left[V^{yes}_T\right]$ represents the expected results of the yes campaign in the day before the election.

Value function at t $<$ T $-$ 1. During the campaign ($t < T-1$), the per-period value function will instead be the following:

$$V^{yes}_t = \max_{\{a^{yes}_{st}\}} = -\sum_S p_s \cdot a^{yes}_{st} + E\left[V^{yes}_{t+1}\right]$$

Where p_s is the price of running an ad at show s, a^{yes}_{st} is how many ads camp *yes* decides to broadcast at show s and time t. Both of these components are observed.

Each campaign has to choose how many ads a_{st} to put in each show $s = 1, 2, ...S$ at period $t < T$, creating to a vector of optimal choices.

$$\underset{S\times 1}{\{a^{yes}_{st}\}^*}$$

5.2 Aggregate state

Every county c at period t is characterised by a stock of ads:

$$\Omega_{ct} = \left(A^{yes}_{c,t}, A^{no}_{c,t}\right)$$

Where $A^{yes}_{c,t}$ is the stock of *yes* ads watched in county c at time t. We assume there is a stock depreciation $\beta \leq 1$ over time:

$$A^{yes}_{ct} = \beta \cdot A^{yes}_{c,t-1} + \left(a^{yes}_{ct}\right)^{\alpha}$$

The advertisement depreciation rate β, and the decreasing returns to scale $\alpha < 1$ parameters are unobserved by the econometrician and should be estimated.

As it is standard in the literature, the aggregate state follows a VAR-1 type of process.

5.3 Audience function

The audience function $d_{cs} = d_s(X_c)$ maps, for each TV show s, the county covariates X_c (age, race, gender, income) and show audience d_{cs}.

We plan to run one regression for each show s, giving raise to S regressions $\underset{S\times 1}{d_{cs}}$. Each regression will be run at DMA level using US national data (NIELSEN), then audiences imputed to more granular, county level $\hat{d}_{cs}$.

Ultimately, we will be able to compute a measure of ad intensity at period-county level.

$$a_{ct}^{yes} = \hat{d}_{cs} \cdot a_{st}^{yes}$$

5.4 Estimation procedure

Reduced-form Estimation. Prior to solving the numerical model, we obtain reduced-form estimates for:

- The audience function $d_s(X_c)$
- Per-period audience impacts $a_{ct}^{yes}, a_{ct}^{no}$

Solving the Numerical Model. We iterate using the following steps:

1. Take candidate structural parameters:

$$\theta = \left(\pi_{yes}, \pi_{no}, \alpha, \beta\right)$$

2. For the candidate parameters (α, β), one can compute the stock of ads at time

$T, T-1, ..., t, ..., 0$:

$$A^{yes}_{cT} = \beta \cdot \left(a^{yes}_{c,T-1}\right)^{\alpha} + \beta^2 \cdot \left(a^{yes}_{c,T-2}\right)^{\alpha} + ...$$
$$A^{yes}_{c,T-t} = \left(a^{yes}_{c,T-t}\right)^{\alpha} + \beta \cdot \left(a^{yes}_{c,T-t-1}\right)^{\alpha} + \beta^2 \cdot \left(a^{yes}_{c,T-t-2}\right)^{\alpha} + ...$$

3. The previous backwards induction exercise will give raise to two matrixes of ad stocks:

$$\underset{C\times T}{A^{yes}} \qquad \underset{C\times T}{A^{no}}$$

4. Next, as we do observe voting outcomes at each county, $\{v^{yes}_{ct}, v^{no}_{ct}\}$, we can run a regression of votes on ad stock and county covariates X_c:

$$v^{yes}_{cT} = f(A^{yes}_{cT}, A^{no}_{cT}, \mathrm{X}_c)$$
$$v^{no}_{cT} = f(A^{yes}_{cT}, A^{no}_{cT}, \mathrm{X}_c)$$

Note that in the regressions above we are regressing voting outcomes against ad stocks in the last period T only.

5. Discretize the aggregate state space Ω into $g = 1, 2, ...G$ bins. If we discretize the stock of ad variable in 10 bins and there are about 50 counties (58 in California, for instance),

$$G \approx 10 \times 10 \times 50 = 5000$$

6. Use $\underset{C\times T}{A^{yes}}, \underset{C\times T}{A^{no}}$ to compute the discrete transition probability matrix T_{Ω}.

$$\underset{G\times G}{T_{\Omega}}$$

7. Use the estimated equations...

$$\hat{v}^{yes}_{cT} = \hat{f}(A^{yes}_{cT}, A^{no}_{cT}, \mathrm{X}_c)$$
$$\hat{v}^{no}_{cT} = \hat{f}(A^{yes}_{cT}, A^{no}_{cT}, \mathrm{X}_c)$$

... to find out which camp would have won at each grid point and, hence, their value functions at T:

$$\underset{G\times 1}{V_T^{yes}} = \pi^{yes} \cdot \mathbb{1}\left(\frac{\sum_c \hat{v}_{cT}^{yes}}{\sum_c \hat{v}_{cT}^{yes} + \sum_c \hat{v}_{cT}^{no}} > 0.5\right)$$

$$\underset{G\times 1}{V_T^{no}} = \pi^{no} \cdot \mathbb{1}\left(\frac{\sum_c \hat{v}_{cT}^{yes}}{\sum_c \hat{v}_{cT}^{yes} + \sum_c \hat{v}_{cT}^{no}} < 0.5\right)$$

8. Now for the maximization problem at $T-1$.

   (a) Compute the expected return:

   $$\underset{G\times 1}{E[V_t]} = T_\Omega \times V_T^{yes}$$

   The expression above is the expected return of locating at each of the grid points g at $T-1$.

   (b) Take the ad stock for each county c at $T-1$:

   $$A_{c,T-1}^{yes} \quad A_{c,T-1}^{no}$$

   (c) Drop the infeasible gripdoints. This is, those in which it is impossible to be located at $T-1$ because the realised ad stock at at least one county $A_{c,T-1}^{yes}$ or $A_{c,T-1}^{no}$ is aready above the one of the grid point g;
   if, for some county c, $A_{c,T-1}^{yes} > A_{c,g}^{yes}$, then gridpoint g is dropped.
   Where $A_{c,g}^{yes}$ is the ad stock bundle of county c at gridpoint g.

   (d) After dropping such subset, the size of the grid shrinks from G to G'.

   (e) We need to compute, for each of the surviving grid points g, which is the most cost-effective ad location that will take us there:

   $$\underset{G'\times S}{a_{sg}^{yes}*}$$

   (f) Ultimately, we can compute V_{T-1}^{yes} candidates:

   $$a_{sg}^{yes} * \times p_s + T_\Omega \times V_T^{yes}$$

   And choose the argument that returns the maximum V_{T-1}^{yes} feasible:

   $$\underset{S\times 1}{\{a_{s,T-1}^{yes}\}}$$

9. Repeat the previous process for $T-2$.

10. For $T-3$ etc.

11. Ultimately, we will get, for each period, ballot camp and tv show, a vector of optimal ad choices. Such vector will be of size:

$$S \times T \times 2$$

Matching the Model to Data. In order to evaluate the accuracy of the estimated model:

1. As a_{st}^{yes} is observed in the data, we can set up a log likelihood function that evaluates, for each a_{st}^{yes}, how well the model performs.

2. The discrepancy of the log-likelihood will direct us to new candidate parameters:θ'.

3. The process is restarted until log likelihood convergence is achieved.

6 Conclusion and next steps

In this paper, we aim to estimate the causal effect of TV political campaigns on ballot measure outcomes. Following the 2010 Citizens United Supreme Court decision, unlimited campaign spending was effectively legalized, which induced a substantial increase in campaign spending and advertising. To study its potential effects, we exploit variation of TV advertising across media markets.

Preliminary results from reduced form estimates show that TV political campaigns exert an important influence in ballot measure outcomes. A 1 standard deviation in exposure to the net number of ads (support - opposition ads, or vice versa) is associated with an increase of 2.13 to 2.46 p.p. in the net vote share (% vote YES - % vote NO, or vice versa). We also provide the basic features of a structural model of electoral competition, that incorporates the role played by equilibrium effects across campaigns within a ballot measure and the strategic behavior of campaigns, and will overcome the limitations of the reduced form.

The evidence presented here serves as the initial stepping stone for a deeper forthcoming analysis. Our primary focus entails the effort to collect electoral data for all

441 statewide ballot measures that occurred between 2010 and 2020 (those are the measures that featured some level of TV advertising). Secondly, we intend to code information related to the topic, path to the ballot, and supplementary details for each election. Thirdly, once this complete data is assembled, we will proceed with the details and estimation of the structural model, and explore various counterfactual scenarios. Finally, we acknowledge the importance of exploring additional inquiries, such as non-linearities, competing effects, distinctions between voter mobilization and switching, other factors influencing the passage or failure of ballot measures, and other related questions.

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Appendices

Table A1: List of 50 ballot measures used in our preliminary analysis

State	Year	Ballot name	TV total ads	State	Year	Ballot name	TV total ads
CA	2020	Proposition 22	83,938	CA	2014	Proposition 46	20,991
OH	2017	Issue 1 (nov)	68,889	CA	2012	Proposition 30	20,704
CA	2020	Proposition 21	65,322	WA	2018	Initiative 1631	19,059
CA	2020	Proposition 23	63,846	CA	2012	Proposition 37	18,301
CA	2018	Proposition 8	60,032	CA	2018	Proposition 6	17,180
CA	2018	Proposition 10	58,305	WA	2013	Initiative 522	17,041
IL	2020	Graduated Income Tax Amendment	50,919	ID	2018	Proposition 1	15,494
CA	2020	Proposition 15	50,333	AZ	2018	Proposition 127	15,343
CA	2016	Proposition 61	49,685	CA	2012	Proposition 38	15,215
CA	2016	Proposition 52	45,070	CA	2010	Proposition 23	15,072
MT	2018	Initiative 185	42,769	OH	2015	Issue 3	15,053
OH	2011	Issue 2	39,746	MA	2016	Question 2	15,045
CA	2016	Proposition 56	39,509	AZ	2020	Proposition 208	14,810
NV	2018	Question 3	34,423	CO	2014	Amendment 68	13,986
MI	2012	Proposition 2	34,205	FL	2018	Amendment 6	13,486
OR	2016	Measure 97	33,254	MA	2018	Question 1	13,114
CA	2012	Proposition 29	31,182	MI	2012	Proposition 6	12,917
CA	2012	Proposition 32	31,009	OR	2014	Measure 92	12,645
MI	2012	Proposition 3	30,686	MI	2018	Proposition 2	12,604
MA	2020	Question 1	29,285	OH	2018	Issue 1	12,591
FL	2018	Amendment 3	29,094	CA	2016	Proposition 53	12,564
CA	2010	Proposition 16	27,612	CA	2016	Proposition 55	11,962
MD	2012	Question 7	26,984	CA	2014	Proposition 2	11,820
CA	2014	Proposition 45	23,287	CA	2014	Proposition 2	11,820
WA	2011	Initiative 1183	22,258	CA	2020	Proposition 19	11,503