Electoral Studies xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Electoral Studies

journal homepage: www.elsevier.com/locate/electstud

When campaigns call, who answers? Using observational data to enrich our understanding of phone mobilization

Marisa Abrajano[a,*], Taylor N. Carlson[a], Lisa Garcia Bedolla[b], Stan Oklobdzija[a], Shad Turney[b]

[a] UC San Diego, United States
[b] UC Berkeley, United States

ABSTRACT

For decades, campaigns have used phone calls to move voters to the polls. Political scientists have made great strides using field experiments to study whether campaign calls effectively increase turnout. However, due in part to limited access to observational data, some of the most basic questions about this mobilization strategy have gone overlooked. In this paper, we take a step back to provide a rich descriptive analysis of a novel dataset of millions of campaign phone calls made in California during the 2016 election. We use this dataset to shed light on three important questions: Whom do campaigns call? When campaigns call, who answers? Are those who answer more likely to turn out to vote? Our analysis reveals patterns consistent with previous theories, but also sheds light on new patterns. For example, we find that about two-thirds of campaign calls are to landlines, but those who are called on a mobile phone are twice as likely to answer. We conclude by using a matching analysis to examine the relationship between answering the phone and turning out to vote. We find that those who answer the phone are 5.9–6.8 percentage points more likely to turn out to vote. The rich descriptive analysis included in this paper provides empirical validation of prior theories of campaign mobilization, and opens avenues for future field experiment research.

One of the most prominent modes of campaign contact is via the telephone. Each electoral cycle, millions of phone calls are made by campaigns in an attempt to mobilize individuals to vote (Gerber and Green, 2015). Campaigns rely on phones to reach out to voters due to their cost effective nature—especially when compared other modes of contact, such as canvassing—as well as their ability to contact large numbers of voters in a relatively short period of time. Despite the fact that mobilization by phone allows campaigns to contact millions of voters, a key question remains: *Whom* are campaigns calling? Conventional wisdom suggests that campaigns are more likely to contact high-propensity voters: those who have voted consistently in previous elections. High propensity voters tend to be disproportionately White, wealthy, and more educated, and self-reported survey data supports the notion that ethnoracial minorities and those from lower socioeconomic backgrounds are less likely to be contacted by campaigns (Rosenstone and Hansen 1993). Political scientists have made great strides in identifying the causal effect of campaign phone calls on turnout by using field experiments that remove the confound of strategic contact by campaigns (e.g. Nickerson, 2006; Nickerson et al., 2006; Gerber and Green 2000). However, by focusing so much on causal identification, we have lost sight of some of the most fundamental questions in phone mobilization: Whom do campaigns call? When campaigns call, who answers? Are those who answer more likely to turn out to vote?

In this paper, we use a novel observational dataset to answer these questions and enrich our understanding of phone mobilization. In contrast to experiments in which potential voters are randomly selected to be in the study and then randomly assigned to receive a phone call, we analyze observational data of the millions of call records from the predictive dialers used by a variety of campaigns to mobilize voters in California?s 2016 general election. The mobilization efforts in our data came on behalf of candidates, statewide ballot initiatives, unions, and non-partisan organizations. This dataset includes information on when the calls were placed, how often a voter was targeted, and whether a voter was contacted on a cell phone or landline. We then merged these data with the California voter file, which provides us with actual turnout data not only for the 2016 general election, but also for all previous elections in which the voter participated. We also obtained important demographic information about each potential voter from Political Data Inc., which allows us to analyze variation based on age, ethnorace, and partisanship. This means that we overcome all of the issues associated with self-reported behavioral data– both with regard to turnout (Shaw et al 2000) and campaign contact (Hillygus, 2005). We are also able to observe whom campaigns actually target as opposed to researchers targeting individuals at random. Moreover, our research allows us to address important questions regarding whether the mode of telephone communication (e.g. cell phone versus landline) matters not only in terms of who picks up the phone but also whether or not one votes. Finally, the substantial size of the data (more than 2.3 million

* Corresponding author.
E-mail address: mabrajano@ucsd.edu (M. Abrajano).

https://doi.org/10.1016/j.electstud.2019.03.001
Received 6 September 2018; Received in revised form 28 February 2019; Accepted 1 March 2019
0261-3794/

observations) enables us to make more precise inferences with a great degree of external validity. Between the impressive size of our data and its observational nature, we are able to provide insight into these important questions about campaign contact via phone.

Our primary goal is not to identify the causal effect of campaign phone calls on turnout. Rather, our intent is to utilize unique observational data to identify patterns in campaign contact. In so doing, we are able to show observationally, without relying on self-reported data, which groups campaigns target. Our findings reveal that the type of phone the campaigns called was important. Nearly two-thirds of campaign calls were made to landline phones, but individuals called on mobile phones were nearly *twice* as likely to answer than those called on landlines. Moreover, our analysis indicates that significant gaps exist in the rate at which campaigns target different ethnoracial voters. However, the differences in rates of *answering* the phone are relatively small across groups, meaning voters of color are not substantially less likely to answer the phone if contacted. When it comes to turnout, we find that individuals who answered the phone were about 5.9–6.8 percentage points more likely to turn out to vote than those who were called but did not answer the phone. Of course, it is important to keep in mind that such estimates are not causally identified and likely overestimate the effect these calls had on turnout (Arceneaux et al., 2006).

We hope that utilizing this novel observational dataset to more closely examine phone mobilization in the real world achieves two fundamental goals. First, we hope that it provides empirical validation to many theories in the campaign mobilization literature. For example, some classic theories suggest that one reason ethnoracial minorities are less likely to turn out to vote is because campaigns do not ask them (e.g. Rosenstone and Hansen 1993). Instead of relying on self-reported survey data on campaign contact, we can show observationally that campaigns indeed targeted African American and Asian voters at lower rates, though not disproportionately lower relative to their share of the California population. Second, we hope that this paper's descriptive analysis opens new avenues for future research, both for theory development and causal identification. For example, our finding on the target, contact, and turnout gaps between landline and mobile phone numbers could prompt innovative field experiments on landline versus mobile phone contact. In service of these two goals, this paper makes important contributions to the literature by using observational data to lay the groundwork for important future trajectories in campaign research.

1. The effectiveness of campaign contact via phone

Despite the increasing difficulty that campaigns face in being able to contact voters via phone (and especially via landlines), there is little doubt that contact via phone is a central component of campaigning (Nickerson, 2006; Nickerson et al., 2006; Michelson et al., 2009; Gerber and Green, 2015). Although arguably not as effective as face-to-face canvassing (Gerber and Green 2000, 2015), Nickerson's (2006; Nickerson et al., 2006) extensive work on campaign contact has consistently found that tactics such as phone banking increased voter turnout (see Gerber and Green, 2015 for an important critique). For instance, Nickerson's findings suggest that phone banking increases turnout by over 3 percentage points. Others have supported the direction of these findings with even stronger results, suggesting phone banking increases turnout by up to 5 percentage points (McNulty, 2005; RRamírez 2005; Ramírez, 2007; Wong, 2005). Michelson, Garcia Bedolla, and McConnell (2009) find that voters who were specifically targeted multiple times were significantly more likely to vote. Moreover, Ha and Karlan's (2009) meta-analysis indicates that the weighted average treatment-on-treated effect of campaign phone calls on turnout is about 0.008 percent. Gerber and Green's (2015) more recent meta-analysis on GOTV phone efforts finds an effect size of 2.88 percentage points for volunteer phone banks and 0.797 percentage points for commercial phone banks.[1] While the effect sizes vary across studies, there is a general consensus that mobilization phone calls can boost turnout.

Virtually all of the research on the effect of campaign phone calls relies on GOTV field experiments in which potential voters are randomly assigned to be contacted or not. This research design allows for important causal identification by removing the problem of selection into treatment or non-equivalent groups. In the real world, however, campaigns strategically target certain voters, particularly high-propensity voters and campaign supporters (Huckfeldt and Sprague, 1992). Past research has shown that campaigns emphasize specific issues or messages to mobilize different groups within the electorate (Abrajano 2010; Hassell and Visalvanich 2015) or focus campaign efforts in important geographic locales (Darr and Levendusky, 2014) or venues Lovett (2010).

Many campaigns are especially likely to target high-propensity voters, and it is easy to understand why: phone banking efforts which specifically target those who have voted in the past and/or have indicated they plan on voting in upcoming elections, can boost turnout by more than 10 percentage points (Michelson et al., 2009). Depending on how much data can be gathered beforehand, these targeting efforts can be remarkably accurate (Endres, 2016). However, as Hersh (2015) finds, campaigns often have difficulty identifying persuadable voters who are also likely to turn out to the polls on Election Day.

To date, the only way of analyzing the effect of phone calls on turnout outside of the context of an academic field experiment was to rely on self-reported contact and turnout in survey data. But, we know that individuals over-report turning out to vote (Vavreck, 2007; Silver et al., 1986). Our goal in this paper is to fill this empirical gap in the literature by providing a descriptive analysis to complement these experimental and self-reported survey-based studies. By using a rich observational dataset of actual campaign contact, validated vote history, and demographic information, we are able to avoid the problems of self-report bias. In addition, because of the volume of useful covariates, such as demographics and vote propensity, we are able to utilize matching techniques to model the two-step process of voter targeting and subsequent voter mobilization utilized by real-world political campaigns. Thus, the wealth of data utilized in this analysis provides key insights regarding which voters campaigns chose to appeal to and how successful those appeals were in getting those voters to turn out to vote.

To do this, we used matching techniques to *approximate* a causal relationship between answering a campaign phone call and turning out to vote. However, because of the limitations of using matching methods, we do not view this analysis as the central contribution of the paper. Instead, it provides findings that complement our observational analysis and are instructive in terms of avenues for future research.

2. Case: mobilization in the 2016 general election in California

Our study focuses on mobilization efforts in the 2016 general election in California. The generalizability of our study is limited in that we only were able to study campaign efforts from progressive organizations in one state, but the size of our data aids our ability to make valid statistical inferences. In this section, we provide information on the electoral context in that California election. Overall, turnout in California for that election cycle was 75.27 percent among registered voters.[2]

Aside from the presidential race, the other high-profile candidate election was for an open-seat US Senate race. The race was competitive, with Kamala Harris (then CA Attorney General) and Loretta Sanchez

[1] These effect sizes were calculated using random effects meta-analysis.

[2] http://elections.cdn.sos.ca.gov/sov/2016-general/sov/04-historical-voter-reg-participation.pdf.

(US Congresswoman from Orange County) competing against one another. Ultimately, Harris beat Sanchez, 61.6 percent versus 38.4 percent. A total of 17 statewide ballot measures were also on the ballot in this election cycle, and the issues ranged from efforts to increase taxes to fund bilingual education, prescription drug pricing, criminal justice sentencing, marijuana legalization, and the death penalty. More than $488.8 million was spent on campaigns for these ballot measures, setting a new record for spending in a statewide election.[3]

Progressive grassroots and community based organizations, many of whom are part of a statewide alliance known as the Million Voter Project, devoted the bulk of their efforts and resources to urging voters to turnout and vote, particularly in support of Proposition 55, a measure that would extend the personal income tax on incomes over $250,000. These taxes would be directed towards funding K-12 public schools, community colleges, and Medi-Cal and other health programs. Organized labor also campaigned heavily in support of Proposition 55 and raised more than $50 million in support of the measure.[4] This ballot initiative ultimately passed, with almost two thirds of voters (63.27 percent) in support of the measure.

In addition to campaigns focused on the presidential election, our data includes mobilization efforts focused on the aforementioned Senate race and highly salient ballot propositions. To protect the anonymity and confidentiality of the campaigns, we are not able to directly access the scripts used by the callers, which means that we cannot definitively determine which calls were made from which campaign. Thus, while our campaign data does not indicate the specific ballot initiatives or candidates for which they advocated, we can surmise from the information above that many of their efforts centered around Prop 55.

3. Data and empirical strategy

Our data combines campaign outreach efforts in the 2016 general election with the California voter file.[5] The campaign data consists of the calls made by progressive campaigns in California's 2016 general election. These campaigns included those on behalf of candidates, labor unions, ballot initiatives, as well as 501(c)(3)/(c)(4) organizations.[6] All of the calls were made using predictive dialers, which is a type of software that automates the process for making campaign calls. Predictive dialers are an attractive choice for campaigns because they allow callers to make an average of 30–35 calls an hour, as opposed to traditional hand dialing, which makes anywhere from 10 to 12 calls per hour.[7] This data includes every attempt that was made to contact a voter by these campaigns, which therefore means that a voter could have been called multiple times. We also have information on whether or not the voter actually responded to the call, whether the voter was contacted via landline or cellphone, as well as when the calls (date and time) were made and by which type of campaign. What the data does not include, however, are the actual scripts that were used by the callers if and when they were able to speak to someone. As such, we are limited in our ability to make any inferences about the relationship between specific campaign messages and turnout. Nonetheless, given that we know, for example, that many labor organizations focused their efforts on amassing support for Prop 55, it is highly likely that the script made mention of this statewide ballot measure.

We compiled information on calls to about 2.32 million unique individuals, of which about 279,000 were successfully contacted either on a landline or mobile phone. Of those successfully contacted, about 117,000 were successfully contacted on a mobile phone. We are then able to merge these call records with the California voter file, which provides us information on an individual's vote history (whether or not they voted in the 2016 general election as well as previous elections) along with other information based on unique identifying codes assigned to voters in the Political Data Incorporated (PDI) database. Demographic information such as the voter's age, party affiliation, and demographic information based on neighborhood statistics was available for each individual contacted by the predictive dialers. PDI also supplements the information from the voter file by providing information such as the partisan composition of the voter's household, ethnoracial background, and vote propensity.

We use a variety of empirical approaches to examine the relationship between campaign contact and turnout. First, we broadly analyze the percentage of voters who actually turned out to vote, both at the aggregate level as well as by the characteristics discussed above. This allows us to describe variation in turnout between important demographic groups by examining the raw data before introducing our empirical models.

The primary variable of interest is successful campaign contact: talking to someone from the campaign on the phone. We code a successful contact as a situation where an agent was able to successfully record answers to the questions on their script from a respondent on the other end of the line. As other research has shown, whether someone answers the phone when a campaign calls is certainly not random, as we will demonstrate descriptively.[8] Because of this, our observational data make it difficult to discern whether someone who answered the phone was more likely to turn out to vote because of (1) the conversation on the phone, or (2) some other factor(s) that make him or her both more likely to answer the phone and more likely to turn out to vote. In an effort to approximate causal identification and rule out the second explanation, we use two empirical strategies: logit regression analysis and matching. Since our data are so rich, we are able to statistically control for many observable factors that might make someone both more likely to answer the phone and more likely to turn out to vote based on previous research. Specifically, we are able to control for age, gender, socioeconomic status, and most importantly, previous vote history. Thus, in a logit regression framework, we can see if the effect of answering the phone still holds even after controlling for all of these other factors that could drive turnout.

Pushing our analysis even further, we conduct a matching analysis to prune our data to create highly similar groups on all available observed characteristics, with the only observable variation being whether the individual answered the phone. We use propensity score and coarsened exact matching procedures. This approach helps address the problem of selection into treatment. The main drawback of matching is that we are unable to match on unobservable variables that could still drive selection into treatment. However, we are able to account for a breadth of observable characteristics that could explain selection into treatment and likelihood of turning out to vote. We want to be clear in noting that we do not intend this analysis to represent a precise causal relationship between answering the phone and turning out to vote. Importantly, Arceneaux et al. (2006) find, matching methods, even when including a host of observable covariates, can overestimate turnout. As such, we include this analysis as it is the best that we can do with the data that we have, but we encourage readers to interpret the results with caution.

[3] http://www.latimes.com/politics/la-pol-ca-road-map-california-2018-campaign-spending-20170219-story.html.

[4] http://www.mercurynews.com/2016/10/08/proposition-55-should-california-extend-temporary-income-taxes-on-top-earners/.

[5] We purchased these data from Political Data, Inc. (PDI).

[6] 501(c)(4) organizations are political organizations, whereas 501(c)(3) organizations are non-partisan, only engaging in civic engagement and voter education work.

[7] Another advantage of predictive dialers is that they only connect the callers to calls that are answered by people, and not voice mail, busy signals, etc.

[8] See the appendix for our model that estimates the probability of being successfully contacted.

4. Findings

We begin by comparing some key demographics of our sample to the demographics of registered voters in California and the citizen voting age population (CVAP). Although our dataset includes several different campaigns and millions of targeted voters, it does not include the full universe of potential voters in California. Compared to California registered voters and the citizen voting age population, the campaigns in our sample targeted more ethnoracial minorities and fewer Whites. Specifically, the campaigns in our data contacted 19.2 percentage points fewer Whites than the actual percentage of White registered voters in California, and 11.8 percentage points fewer than the percentage of Whites in the citizen voting age population. While the difference is smaller, campaigns in our sample also targeted a greater percentage of women than the percentage of women registered to vote in California and in the citizen voting age population. Altogether, our results reflect a sample that over represents ethnoracial minorities and women, compared to state averages. However, understanding the impact of campaign contact on these groups is increasingly important for a majority-minority state such as California. In light of the demographic changes that are also occurring nationally, these insights will also be of great import in the years to come.

4.1. Whom do campaigns call?

To address this question, Table 1 offers several important pieces of information. The second column provides the percentage of individuals who were targeted by the campaigns, broken down by the demographic characteristics listed in each row entry in Column 1. The campaigns targeted voters who comprise their most likely supporters-registered Democrats, females, and voters of color. Just over two-thirds, or 67.7 percent, of those targeted are registered Democrats, with the remaining voters either registering with neither party (decline to state) (21.6 percent) or as Republicans (7.6 percent). Given that this dataset includes campaign phone calls made in California, a Democratic stronghold, it is not surprising that very few Republicans were contacted in our dataset. We also know that a large share of the calls made in our dataset were made on behalf of unions, which lean heavily Democratic. It seems, then, that consistent with conventional wisdom, campaigns are more likely to contact their likely supporters. This speaks to the idea of trying to mobilize the base instead of persuading others to change their mind and support your candidate.

Beyond partisanship, the demographic trends of those who were called also generally map onto Democratic supporters. We see that a significantly larger proportion of females were called, relative to males (62.3 percent vs. 37.7 percent). In fact, women were nearly twice as likely as men were to be targeted by the campaigns we analyzed in this particular election cycle. Looking at age, we observe that nearly one quarter of these campaigns' intended targets were millennials. About half of the individuals targeted by these campaigns were somewhat younger voters, being millennials or Generation X. This is a much greater percentage than many other campaign efforts that might concentrate more on older voters who are generally more likely to turn out to vote. While concentrating mobilization efforts on older voters might be more efficient, assuming that they are more likely to turn out to vote than younger voters, our results here suggest that campaigns in California in 2016 put a strong effort into calling younger voters, even if they were a less efficient, riskier group to contact. Additionally, we observe that unmarried individuals were far more likely to be targeted than were married individuals (79.67 percent versus 20.33 percent), yet the rate of contact was virtually the same for both groups.

These campaigns also devoted much of their time and energy targeting voters of color; amongst those targeted, 61.8 percent are nonwhite, with about 53.5 percent coming from the largest ethnoracial minority groups: Asian Americans, Latinos, and African Americans. As can be seen in Table 3, the percentage of ethnoracial minorities targeted in these campaigns was notably above the shares of these groups among California registered voters. For instance, African-Americans made up 7.6 percent of all voters called, a share that is 30 percent higher than the 5.8 percent share of California registered voters who are African American.[9] Latinos comprised 35.3 percent of those targeted by the groups in our dataset in this election cycle, nearly 40 percent higher than the 26 percent share of registered voters who are Latino. It is important keep in mind that while California is a majority-minority state, Whites still comprise the majority of likely voters (about 60 percent).[10] As such, understanding whether these mobilization efforts exert a positive impact on turnout is especially important.

Finally, we consider variation in campaign phone call targeting based on the mode of contact. Stepping aside from the demographic characteristics, we consider campaigns' abilities to contact individuals based on the type of phones that they have. About two-thirds of all voters were targeted using their landline, meaning that the number of voters contacted using their mobile phones was significantly smaller. This bias toward landlines might be due to practical considerations from campaigns because of restrictions making it challenging to contact individuals on a mobile phone. Regardless of the reason for the vast majority of the phone calls going out to landlines, this bias carries with it important implications for who is being targeted. The bias towards landlines means that certain populations of voters (e.g. millennials, Latinos) were not as easy to target as others were because millennials and Latinos are substantially less likely to have landline phones in the first place. As discussed previously, the campaigns in our dataset put forth strong efforts to mobilize millennial and Latino voters, despite the challenges in reaching them. However, it is important to consider how these results might vary in other states or electoral contexts in which young, nonwhite voters might not be as politically advantages to the campaigns.

On a number of other characteristics, the voters who were targeted by these campaigns varied to a greater degree when compared to the overall state trends. For instance, the median household income for those targeted in our data was 8,000 dollars lower than the median income level for California in 2015. Moreover, veterans make up 4.5 percent of the population in California, but made up only 1 percent of those targeted in our data. Table 2 shows the demographics by

Table 1
Targeting, contact and voting rates in CA's 2016 general election.

Demographic Attribute	% Targeted	% Contacted	% Contacted & Voted
Asian-Americans	10.55	6.423	79.65
Latinos	35.32	8.133	82.87
African-Americans	7.588	9.704	82.77
Whites	38.25	9.766	87.67
Renters	21.57	10.91	81.53
Veterans	0.63	14.22	89.35
Domestic Partnerships	0.18	8.301	94.49
Married	20.33	8.448	92.03
Unmarried	79.67	8.827	83.43
Men	37.73	8.75	83.36
Women	62.27	8.75	86.19
Democrats	67.74	9.309	86.57
Republicans	7.607	7.694	86.51
Decline-to-State	21.6	7.474	79.67
Mobile Phone Contacts	32.96	12.87	82.25
Landline Contacts	67.04	6.725	87.82
Millenials	24.68	7.488	76.01
Generation X	23.73	7.473	85.14
Baby Boomers	30.52	7.481	87.68
Greatest Generation	20.88	13.5	89.02

[9] The data on ethnorace and gender of California's registered voters are from Catalist. Data on CVAP is from the 2015 American Community Survey.

[10] http://www.ppic.org/publication/californias-likely-voters/.

Table 2
Comparing targeted voters to California registered voters and voting age population.

	Targeted	CA Registered Voters	CA Voting Age Population
African American	**7.6**	**5.8**	**6.9**
Women	4.3	3.3	3.5
Men	2.8	2.5	3.4
Asian	**10.5**	**10.0**	**13.5**
Women	5.4	5.2	7.2
Men	3.9	4.8	6.3
Latinx	**35.3**	**26.0**	**28.6**
Women	20.4	14.3	14.6
Men	13.7	11.7	14.1
White	**36.1**	**55.3**	**47.9**
Women	21.3	28.6	24.1
Men	13.3	26.6	23.8
Unknown/Other	**10.5**	**2.9**	**3.1**
Women	5.7	1.7	1.6
Men	4.0	1.2	1.5

Table 3
The effect of successful contact on turnout (logit model).

	Dependent variable:	
	Voted in Nov 2016 Election	
	(1)	(2)
Any Successful Contact	0.445***	
	(0.006)	
Mobile Phone Successful Contact		0.412***
		(0.015)
Male	−0.203***	−0.167***
	(0.004)	(0.012)
Age	−0.005***	−0.007***
	(0.0001)	(0.0003)
Afr. Amer.	−0.201***	−0.162***
	(0.007)	(0.023)
Asian Amer.	−0.234***	−0.299***
	(0.006)	(0.021)
Latino	0.131***	0.089***
	(0.004)	(0.014)
Homeowner	0.228***	0.207***
	(0.004)	(0.013)
Pct. w/o HS Educ. in Neighborhood	−0.005***	−0.006***
	(0.0002)	(0.001)
Median Inc. of Neighborhood	0.00000***	0.00000***
	(0.00000)	(0.00000)
Married	0.160***	0.144***
	(0.005)	(0.018)
Pct. of White-Collar Workers in Neighborhood	0.005***	0.003***
	(0.0001)	(0.0004)
Pct. of Whites in Neighborhood	0.002***	0.003***
	(0.0001)	(0.0003)
Num. Attempted Contacts	−0.044***	−0.065***
	(0.001)	(0.004)
Vote Propensity	0.934***	0.887***
	(0.002)	(0.006)
Constant	−0.200***	0.274***
	(0.011)	(0.039)
Observations	2,320,504	279,426
Log Likelihood	−1,016,976.000	−100,366.700
Akaike Inf. Crit.	2,033,982.000	200,763.400

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

ethnorace and gender for those targeted by campaigns, all California registered voters, and the California voting age population.[11] The biggest difference is that these campaigns targeted disproportionately fewer White individuals, compared to the proportion of White registered voters and the California voting age population.

Finally, we were also able to examine where these targeting efforts took place. The locations of those targeted generally conformed to the distribution of population through California counties, though slight over-targeting took place in the San Francisco Bay Area as well as the Los Angeles metro region, (see the appendix for a map of all calls made during the campaign).

4.2. When campaigns call, who answers?

Our analysis suggests that of all the voters targeted, 12 percent were successfully contacted by one of the campaigns in our dataset. This completion rate is consistent with existing studies which finds that automated dialer contact rates are about 15 percent or less (Gerber and Green, 2015, 70). These results suggest that individuals were fairly unlikely to answer the phone when campaigns called. The third column of Table 1 shows the percentage of individuals who answered the phone within each demographic group who were targeted. For example, of all Asian Americans who were called by a campaign, 6.4 percent answered the phone, thus making a successful contact.

While the results suggest that only about 1 out of 9 individuals answered campaign phone calls overall, we do see some interesting patterns of successful contact between groups. For instance, Whites and African Americans were more likely to pick up the phone, compared to Latinos and Asian Americans. Perhaps this is due to the differing levels of political socialization for immigrant-origin groups such as Latinos and Asians, who are still learning about the ins and outs of US politics and may therefore be less inclined to engage with campaigns, relative to Whites and African Americans (Abrajano and Alvarez 2010). There is virtually no difference in likelihood of answering the phone based on marital status or gender. Democrats were marginally more likely to answer the phone than were Republicans. This could have had something to do with the groups that were calling: Republicans might have screened calls coming from progressive groups.

The oldest voters (The Greatest Generation), were the most likely to pick up the phone (13.5 percent) when compared to other age groups. Younger voters, especially millennials, were the least likely to be successfully contacted. Overall, across all demographic groups, successful contact rates were remarkably low, with veterans being the most likely to answer the phone at 14.2 percent and Asian Americans being least likely to respond to these campaign calls at only 6.4 percent.

The biggest difference in successful contact that we observe, aside from age, is whether someone was called on a mobile or landline phone. Those who were targeted on a mobile phone were more than twice as likely to answer the call (12.9 percent) than individuals targeted on a landline phone (6.7 percent). These differential success rates vary across demographics. For some groups, such as the Greatest Generation, over 1 in 10 landline attempts were successful while just two percent of mobile attempts resulted in someone picking up the phone. For millennials and members of Generation X, the opposite trend held true, with a higher rate of successful contact amongst these voters via cell phone rather than landline.

4.3. Are those who answer more likely to vote?

In line with the existing experimental GOTV research on phone contact, campaign contact should be positively associated with voting, *ceteris paribus*. To test this hypothesis, we first simply examine the percentage of individuals who turned out to vote. Overall, the vast majority of individuals who were successfully contacted (e.g. answered the phone) turned out to vote in the November 2016 general election, as shown in Table 1. Turnout was highest among those in domestic partnerships and married, with 94.49 percent and 94.5 percent of those successfully contacted in each group turning out to vote. Those least

[11] The data source for the registered voters and the voting age population is from Catalist.

likely to vote after a successful campaign contact still voted at very high rates: about 76.01 percent of millennials and 79.7 percent of both Asian Americans and those who are registered as Decline-to-State who were successfully contacted turned out to vote. It is also worth noting that although far more individuals were successfully contacted on mobile phones than landline phones, once a successful contact was made, individuals with landlines were more likely to turn out to vote (87.82 percent versus 82.25 percent). Considering that the California statewide turnout rate among registered voters for this election was 75.27 percent, it appears that those who were contacted by these campaigns voted at higher rates.

While these broad patterns in turnout are highly informative at a descriptive level, there are many other factors that could be driving these results beyond the campaign phone call. For instance, individuals who are older are both more likely to vote and more likely to have landlines than are younger people. As a result, the difference in turnout between those successfully contacted via mobile phone and landline could be driven by age. In an effort to better isolate the effect of successful campaign contact on turnout, we estimated a model to control for a whole host of individual-level as well as contextual characteristics. Table 3 shows the results from two logistic regression analyses in which the dependent variable takes the value of 1 if the individual voted by absentee or at the polls in November 2016 and 0 otherwise. In Model 1, the key independent variable of interest is successful contact, which takes the value of 1 if an individual answered the phone when a campaign called, and 0 if he or she did not answer the phone. Even after controlling for demographic and socioeconomic variables that might also explain whether someone turns out to vote, the results in Model 1 of Table 3 indicate that individuals who answered the phone were significantly more likely to turn out to vote than those who did not answer the phone ($p < 0.01$).

Building on the finding that those who answered the phone were more likely to vote, we examine whether those who were contacted on a mobile phone were more likely to turn out to vote than those contacted on a landline. Model 2 of Table 3 thus restricts our sample to only those who answered the phone. The key independent variable of interest is the type of phone, which takes the value of 1 if an individual answered on a mobile phone and 0 the individual answered on a landline. The results indicate that those who answered the call on a mobile phone were significantly more likely to vote than those who answered on a landline ($p < 0.05$). This result stands in contrast to our descriptive result presented in Table 1, which shows that 87.82 percent of those contacted on a landline voted, whereas 82.25 percent of those contacted on a cell phone voted. These two different results are likely driven by age. Since older individuals are more likely to vote and are more likely to have landlines than younger individuals, the raw descriptive difference between mobile and landline phones is likely driven by age. Thus, once we control for age in Table 3, we see that those who answered on mobile phones were actually more likely to vote. As we would expect, vote propensity, which is calculated as the number of times an individual voted in the last four elections, is positively correlated with turnout.

We then calculated the predicted probabilities to assess the magnitude of the effect of contact on turnout. More specifically, we estimated the predicted probability of turning out to vote, conditional on successful contact, holding all other variables constant at their mean or mode. Fig. 1 displays the predicted probabilities of turning out to vote at various levels of Census block median household income among African Americans, Latinos, Asians, and Whites. The blue lines represent the predicted probability of voting among those who answered the phone, and the red lines represent the predicted probability of voting among those who did not answer the phone when a campaign called.

Regardless of ethnorace, individuals who lived in areas with a higher median household income had a greater predicted probability of voting than those living in lower-income areas. This is consistent with previous research that individuals of higher socioeconomic status are more likely to turn out to vote (Rosenstone and Hansen 1993). Turning to the effect of answering the phone, among all ethnoracial groups, individuals who answered the phone had a higher predicted probability of voting than those who did not answer the phone, thus supporting the results from experiments in the existing literature. Importantly, Fig. 1 demonstrates important variation in the magnitude of the effect of answering the phone between ethnoracial groups. Noting that the blue (answered the phone) and red (did not answer the phone) lines are closest together among African Americans (Fig. 1a), it appears that answering the phone has the smallest effect among African Americans. Looking at the wide gap between those who answered the phone and those who did not answer the phone in Fig. 1c, we can see that answering the phone had a very large effect on voting among Asians.

4.4. Matching analysis

Because individuals in our dataset were not randomly assigned to successful campaign contact (answering the phone), we are unable to causally identify whether successful contact leads to turnout. However, matching methods provide consistent estimates of causal effects conditional on observable characteristics that may drive selection into both ”treatment” and the outcome of interest.

For robustness, we use two separate matching methods, propensity score matching and coarsened exact matching. In the propensity score match, we first use logit regression to estimate the probability of being ”treated” (answering the phone) to calculate a propensity score. We estimate one's propensity to answer the phone as a function of gender, ethnorace, age, party registration (Democrat, decline-to-state, Republican), homeowner/renter, marital status, number of times the individual was called, and a voter turnout propensity variable based on voters' turnout history in California elections in which they were eligible to vote going back to 2004. We also match on available population characteristics of voters' Census block geographies, including median household income, the proportion of the Census block population with a high school education, some college, and a college degree, the proportion that is white, and the proportion that is classified as holding a blue collar job. We then match ”treatment” (answered the phone) and ”control” (did not answer the phone) group individuals on their propensity scores using one-to-one nearest-neighbor matching.[12] For the coarsened exact match, we use all of the same individual- and group-level covariates as in the propensity score matching analysis, manually coarsen the continuous covariates (e.g. age), and then use exact matching to generate ”treatment” and ”control” groups.[13] After matching, imbalances on the categorical covariates are reduced to zero, while those on the continuous covariates are virtually eliminated, as shown in Fig. 2.

The estimates presented in Table 4 reveal that the coefficients on campaign contact is statistically significant and positively signed, suggesting that successful campaign contact positively predicts turnout. Specifically, the effect of successful contact on the matched data was 6.8 percentage points using propensity score matching and 6.5 percentage points using coarsened exact matching. Both of these effects are close to the effect of 5.9 percentage points from the above logit analysis using the full, unmatched dataset.[14] We understand that Arceneaux, Gerber, and Green's (2006) would suggest that these estimates may be

[12] Propensity score matching was performed in R with the Matching package (Sekhon, 2011), with caliper set to 0.2, and the replace and ties options set to FALSE.

[13] Coarsened exact matching (CEM) was performed in R with the MatchIt package (Gary, Ho, Stuart, Imai, 2011).

[14] Based on simulated first-differences for a logit regression with all variables held at their mean/modal value. The simulation was done using the R package Zelig.

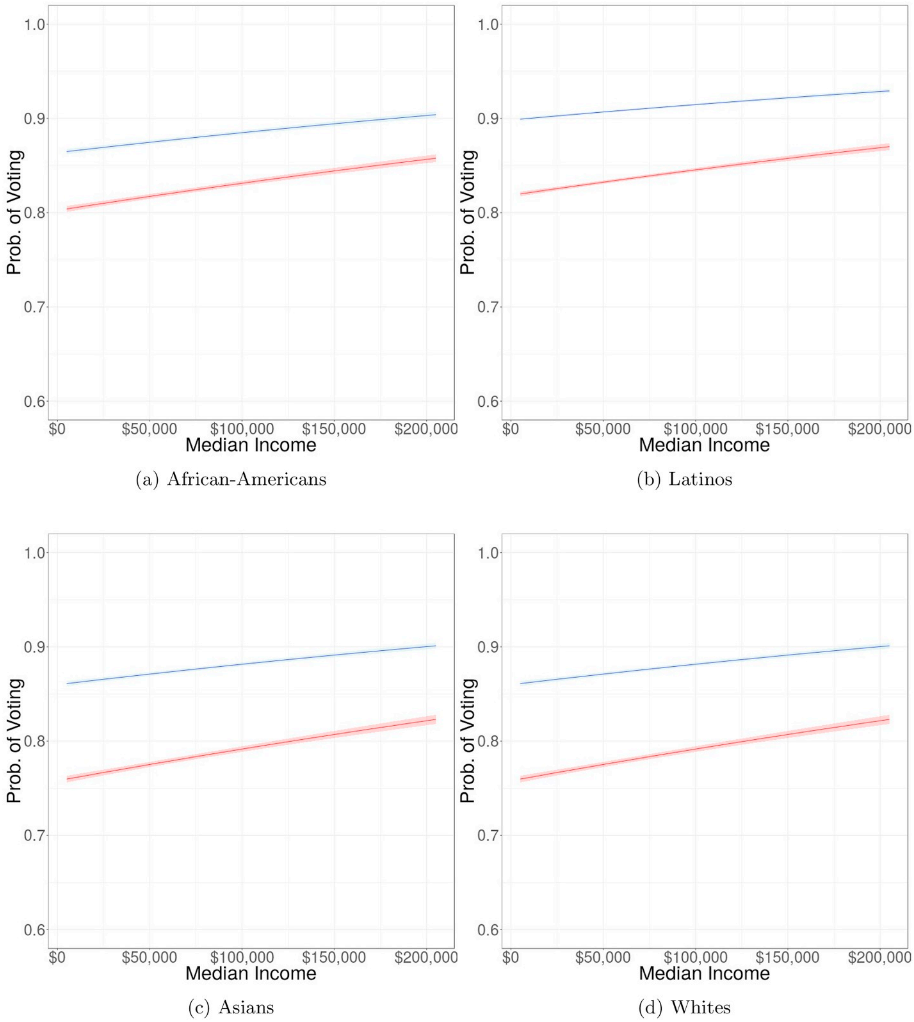

Fig. 1. Change in Predicted Probability of Voting by Neighborhood Median Income, by Ethnorace. Green lines represent those who answered the phone, and red lines represent those who did not answer the phone. The lighter shading around each line represents a 95 percent confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

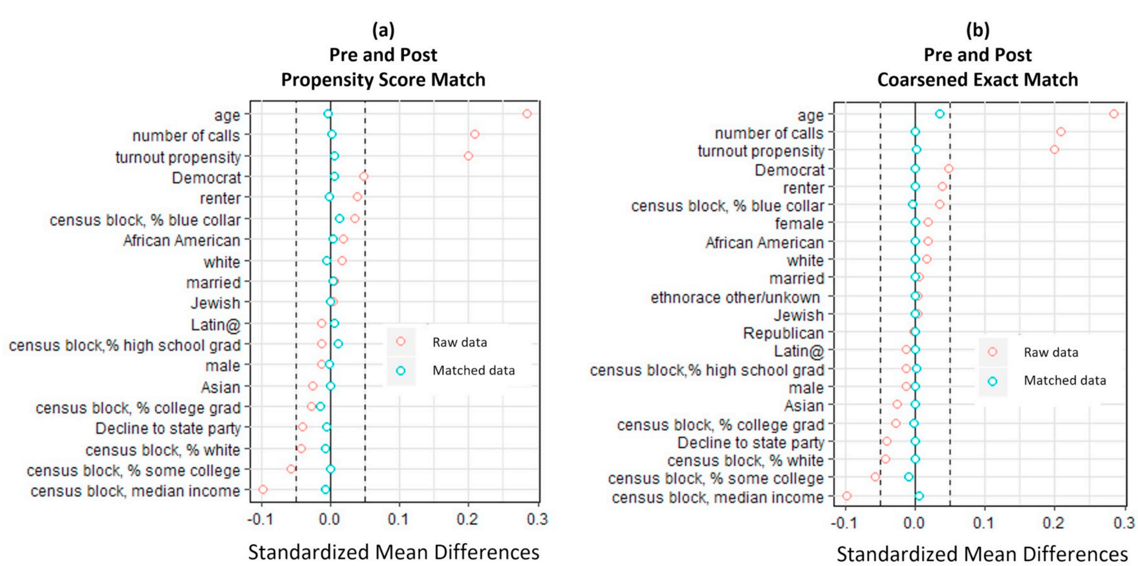

Figure 2. Balance on key covariates between the raw data and matched data. (a) shows the propensity score matched data and (b) shows the coarsened exact matched data. Red points represent the raw data and green points represent the matched data. Vertical dashed lines at ± 0.05 standardized mean differences are added for ease of visual interpretation.

Table 4
Estimated effect of successful contact using propensity and coarsened matching.

	Logit regression	Propensity Score Matching	Coarsened Exact Matching
Treatment Effect	5.9	6.8	6.5
Standard Error	(.0006)	(0.1)	(0.1)
N (treated)	279,426	275,843	123,261
N (control)	2,041,078	347,569	355,108

inflated. But our analysis suggests that these calls did have a positive, and not trivial, impact on voter turnout.

5. Conclusion

In this paper, we sought to provide a descriptive analysis that would serve to (1) empirically validate previous theories that relied on self-reported survey data, and (2) open avenues for future research on phone mobilization. As the campaign landscape in the United States. Continues to change, particularly with technological advances, it is important to carefully analyze how campaigns are actually using that technology, such as phones, in the real world. Analyzing the millions of call records from dozens of progressive campaigns in California combined with the state voter file enables us to enrich our understanding of phone mobilization in U.S. elections.

We are able to largely confirm previous findings from self-reported data that campaigns strategically target high propensity voters. However, we find some interesting patterns by examining targeting patterns across ethnoracial groups. We find that, consistent with previous research, campaigns target African American and Asian American voters at substantially lower rates than they contact White voters, but in this case, the rates of contact are comparable to the demographic composition of California. One surprising note, however, is that Latinos in this election were targeted at almost the same rate as Whites, at least among the groups included in our dataset. If future researchers are able to acquire similar datasets from other states, it will be important to consider whether the same patterns occur in states that are less ethnoracially diverse than California.

This analysis also reveals new insights about mode of contact that have gone largely underexplored. We find that those called on cell phones were about twice as likely to answer the phone than those who were called on a landline, even though about two-thirds of the calls went to landlines. If we look just at the raw descriptive data, it appears that those contacted on a landline were more likely to turn out to vote, however, our regression analysis suggests that after controlling for age, those contacted on mobile phones were more likely to turn out to vote. These findings are important because there are important demographic differences between those who rely on landlines and mobile phones that could make it even harder to reach marginalized communities if campaigns continue to target landlines. As of 2013, millennials and individuals from lower income groups were most likely to be in mobile phone only households.[15] A 2014 report from the CDC also suggests that Latinos are the ethnoracial group most likely to be in a mobile-only household.[16] Young, lower-income, and Latino individuals already participate in politics at very low rates, and the increasing challenge of contacting them might only exacerbate these turnout gaps. These findings are important for the academic literature because they suggest that future studies on campaign mode effects that largely focus on comparing phone, direct mail, and canvassing, might consider nuances between each broad mode category and across different groups of target voters. Examining heterogeneous treatment effects for campaign contact on a landline or mobile phone could be important for future researchers to consider, especially as fewer individuals have landlines altogether.

Our final set of analyses focused on examining the relationship between answering the phone and turning out to vote. Neither the regression analysis nor the matching analysis can perfectly estimate a causal relationship. In particular, these matching estimates might be biased (Arceneaux et al., 2006). We find that among those who answered the phone, their likelihood of voting increased between 5.9 and 6.8 percentage points, relative to those who did not answer the phone. While this analysis is not the core focus of our paper, we believe it is still important. Selection bias is clearly an important problem in mobilization research. In our case, it could be that those who answered the phone and were thus successfully contacted answered because of features that already make them more likely to turn out to vote. This is one of the problems that field experiments sought to address by randomizing contact. However, by doing so, researchers may be essentially conducting a forced exposure experiment, by exposing some voters to campaign mobilization who would otherwise never be contacted. By using observational data and the best proxies for causal identification available, we are able to show that those who answer campaign phone calls are more likely to turn out to vote than those who were targeted by a campaign, but did not answer the call. Future field experiment research might consider randomizing contact from a campaign's target list to more fully analyze this relationship.

While telephone communication is a rapidly changing medium, being able to successfully contact a voter can yield a positive impact on turnout. In the predicted probability calculations, being successfully contacted as opposed to not, consistently increases the likelihood of voting across different types of voters by about ten percentage points. These effect sizes are about 2.5 times larger than the effect sizes calculated from the meta-analysis of GOTV phone experiments conducted by Gerber and Green (2015), but again these effect sizes are likely inflated due to the fact that we can only match on *observable* characteristics, which may be insufficient to fully approximate random assignment (Arceneaux et al., 2006).

This research offers several important contributions to the existing literature. First, we are able to address fundamental questions about campaign strategy and behavior by using a dataset containing the actual strategies employed by campaigns in California, which is then merged with turnout data from the state voter file. By doing so, we avoid all of the issues associated with self-reported data on campaign contact and voting. In addition, the substantial size of our data enables us to empirically address important questions on campaign contact in a more precise manner than previous research efforts.

Our findings also pave the way for a host of future research endeavors. Most notably, scholars could examine whether the particular scripts used by campaigns yield differential effects on turnout. While there is some experimental GOTV research suggesting that certain messages, particularly those that tap into social pressure (Gerber and Green, 2015) are effective at increasing rates of turnout, supplementing these findings with observational data would help to confirm these results. Moreover, we hope that this paper highlights the usefulness of observational data to answer questions about voter mobilization. For instance, researchers might consider using campaigns' actual thresholds for targeting (e.g. a modeled vote propensity score over a certain value) as cutoffs in a regression discontinuity design. Taken altogether, with the greater availability of data today, campaign scholars now have the ability to dig deeper and further investigate the strategies used by campaigns to target and mobilize voters.

[15] http://www.pewresearch.org/fact-tank/2013/12/23/for-most-wireless-only-households-look-south-and-west/.

[16] https://www.cdc.gov/nchs/data/nhis/earlyrelease/wireless201506.pdf.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.electstud.2019.03.001.

Appendix

Table 5
Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Age	2,320,615	48.993	19.384	0	99
African-American	2,321,047	0.076	0.265	0	1
Renter?	2,321,047	0.216	0.411	0	1
Median Inc.	2,321,047	53,533.420	25,996.210	0	200,001
Avg. Home Value	2,321,047	401,911.700	193,073.200	0	1,500,000
Median Household Size	2,321,047	29.553	7.989	0	67
Veteran	2,321,047	0.006	0.079	0	1
Reg. Domestic Partner	2,321,047	0.002	0.043	0	1
Male	2,321,047	0.377	0.485	0	1
Asian	2,321,047	0.105	0.307	0	1
Latino	2,321,047	0.353	0.478	0	1
Mobile Phone Contact	2,321,047	0.330	0.470	0	1
Married	2,321,047	0.203	0.402	0	1
Voted	2,321,047	0.780	0.414	0	1
Pct. Whites in Neighborhood	2,321,047	55.290	22.838	0	99
Pct. White Collar Workers in Neighborhood	2,321,047	60.211	18.132	0	99
Democrat	2,321,047	0.677	0.467	0	1

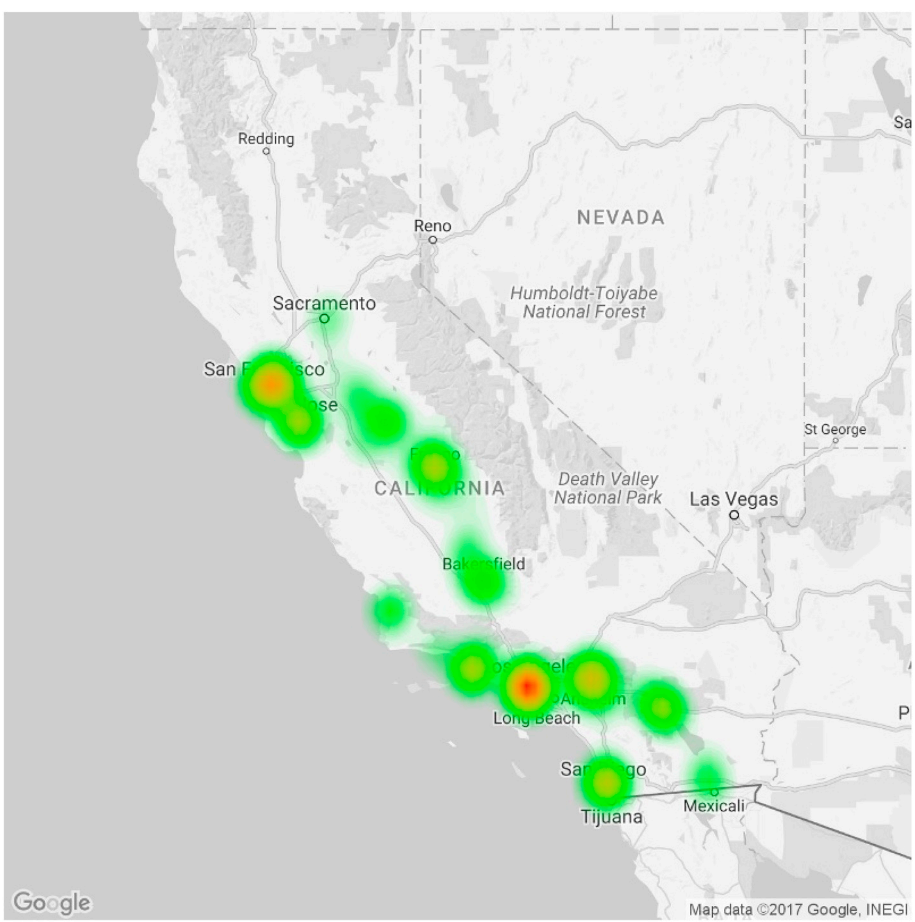

Fig. 3. Heat Map of all Calls Placed by Campaign

Table 6
The Probability of Being Contacted by a Campaign

	Dependent variable:
	Successful Contact
Male	0.0001
	(0.0004)
Age	0.002***
	(0.00001)
Afr. Amer.	−0.005***
	(0.001)
Asian Amer.	−0.022***
	(0.001)
Latino	−0.006***
	(0.0005)
Homeowner	0.003***
	(0.0004)
Pct. of HS Grads in Neighborhood	−0.001***
	(0.00003)
Median Inc. of Neighborhood	−0.00000***
	(0.000)
Married	−0.002***
	(0.0005)
Pct. of White-Collar Workers in Neighborhood	−0.00005***
	(0.00001)
Pct. of Whites in Neighborhood	0.0001***
	(0.00001)
Mobile	0.083***
	(0.0004)
Constant	0.003**
	(0.001)
Observations	2,320,504
R^2	0.024
Adjusted R^2	0.024
Residual Std. Error	0.279 (df = 2320491)
F Statistic	4,687.640*** (df = 12; 2320491)

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 7
Determinants of Voting Propensity.

	Dependent variable:
	Voting Propensity
Any Successful Contact	0.145***
	(0.002)
Male	−0.105***
	(0.002)
Age	0.027***
	(0.00004)
Afr. Amer.	0.113***
	(0.003)
Asian Amer.	−0.278***
	(0.003)
Latino	−0.153***
	(0.002)
Homeowner	0.302***
	(0.002)
Pct. w/o HS Educ. in Neighborhood	−0.005***
	(0.0001)
Median Inc. of Neighborhood	−0.00000***
	(0.00000)
Married	0.309***
	(0.002)
Pct. of White-Collar Workers in Neighborhood	0.002***
	(0.0001)
Pct. of Whites in Neighborhood	0.002***
	(0.00004)
Num. Attempted Contacts	0.033***
	(0.001)
Constant	0.125***
	(0.005)
Observations	2,320,504

(*continued on next page*)

Table 7 (*continued*)

	Dependent variable:
	Voting Propensity
R^2	0.265
Adjusted R^2	0.265
Residual Std. Error	1.119 (df = 2320490)
F Statistic	64,347.740*** (df = 13; 2320490)

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

References

Abrajano, Marisa, 2010. Are Blacks and Latinos responsible for the passage of Proposition 8? Analyzing voter attitudes on California's proposal to ban same-sex marriage in 2008. Pol. Res. Quart 63 (4), 922–932.

Abrajano, Marisa, Alvarez, R. Michael, 2010. New faces, new voices: The Hispanic electorate in America. Princeton University Press.

Arceneaux, K., Gerber, A.S., Green, D.P., 2006. Comparing experimental and matching methods using a large-scale voter mobilization experiment. Polit. Anal. 14 (1), 37–62.

Darr, Joshua P., Levendusky, Matthew S., 2014. Relying on the ground game: The placement and effect of campaign field offices. Am. Pol. Res. 42 (3), 529–548.

Endres, Kyle, 2016. The accuracy of microtargeted policy positions. PS: Political Science & Politics 49 (4), 771–774.

Gerber, A., Green, D.P., 2015. Get Out the Vote: How to Increase Voter Turnout. Brookings Institution Press, Washington, DC.

Gerber, A.S., Green, D.P., 2000. The effects of canvassing, telephone calls, and direct mail on voter turnout: A field experiment. Am. Pol. Sci. Rev. 94 (3), 653–663.

Ha, S.E., Karlan, D.S., 2009. Get-out-the-vote phone calls: does quality matter? Am. Pol. Res. 37 (2), 353–369.

Hassell, Hans JG., Visalvanich, Neil, 2015. Call to (in) action: The effects of racial priming on grassroots mobilization. Polit. Behav 37 (4), 911–932.

Hersh, Eitan D., 2015. Hacking the electorate: How campaigns perceive voters. Cambridge University Press.

Hillygus, D. Sunshine, 2005. Campaign effects and the dynamics of turnout intention in election 2000. J. Politics 67 (1), 50–68.

Huckfeldt, Robert, Sprague, John, 1992. Political parties and electoral mobilization: political structure, social structure, and the party canvass. Am. Pol. Sci. Rev. 86 (1), 70–86.

Gary, King, Ho, Daniel, Stuart, Elizabeth A., Imai, Kosuke, 2011. MatchIt: nonparametric preprocessing for parametric causal inference.

McNulty, J.E., 2005. Phone-based GOTV? What?s on the line? Field experiments with varied partisan components, 2002-2003. Ann. Am. Acad. Pol. Soc. Sci. 601 (1), 41–65.

Michelson, M.R., García Bedolla, L., McConnell, M.A., 2009. Heeding the call: the effect of targeted two-round phone banks on voter turnout. J. Politics 71 (4), 1549–1563.

Nickerson, David, 2006. Volunteer phone calls can increase turnout: evidence from eight field experiments. Am. Pol. Res. 34 (3), 271–292.

Nickerson, D.W., Friedrichs, R.D., King, D.C., 2006. Partisan mobilization campaigns in the field: results from a statewide turnout experiment in Michigan. Polit. Res. Q. 59 (1), 85–97.

Ramírez, Ricardo, 2005. Giving voice to Latino voters: a field experiment on the effectiveness of a national nonpartisan mobilization effort. Ann. Am. Acad. Pol. Soc. Sci. 601 (1), 66–84.

Ramírez, Ricardo, 2007. Segmented mobilization: Latino nonpartisan get-out-the-vote efforts in the 2000 general election. Am. Pol. Res. 35 (2), 155–175.

Rosenstone, S.J., Hansen, J.M., 1993. *(Mobilization, Participation, and Democracy in America*. By Steven J. Rosenstone and John Mark Hansen. Macmillan, New York.

Shaw, Daron, de la Garza, Rodolfo O., Jongho, Lee, 2000. Examining Latino turnout in 1996: a three-state, validated survey approach. Am. J. Pol. Sci. 44, 332–340 (April).

Sekhon, Jasjeet S., 2011. Multivariate and Propensity Score Matching Software with Automated Balance Optimization: The Matching package for R. J. Stat. Softw. 42 (7), 1–52.

Silver, B.D., Anderson, B.A., Abramson, P.R., 1986. Who overreports voting? Am. Pol. Sci. Rev. 80 (2), 613–624.

Vavreck, Lynn, 2007. The exaggerated effects of advertising on turnout: the dangers of self-reports. Q. J. Political Sci. 2, 325–343.

Wong, Janelle, 2005. Mobilizing Asian American voters: a field experiment. Ann. Am. Acad. Pol. Soc. Sci. 601 (1), 102–114.