Lawn Signs
Voter Mobilization in the 2018 Elections

PRE-ANALYSIS PLAN

December 16, 2018

Introduction

We use a randomized controlled trial (RCT) to evaluate the mobilizing effects of lawn signs that encourage voter turnout. MoveOn deployed its signs in randomly assigned precincts in three congressional districts in Colorado. Although no mobilizing effects have been found in previous RCTs involving lawn signs, the signs used in those campaigns focused solely on candidates. This plan is being filed before precinct-level results have been officially certified; the research team has not to date gathered preliminary outcome data.

Hypotheses

The principal hypothesis is that precincts in which signs are deployed will vote at higher rates than untreated precincts. In keeping with previous work, we consider a "spillover" hypothesis: untreated precincts that are adjacent to treated precincts vote at higher rates than non-adjacent control precincts.

Sample

All precincts are drawn from the three congressional districts of interest: CO-03, CO-05, and CO-06. The original set of precincts was restricted to precincts with: median partisan >= 60; ratio of registered Democrats to Republicans of 1.25 or greater; total population of 200 or more; treatable population of 125 or more individuals (subscribed MOMs + unsubscribed MOMs + textable voters). Excluded precincts primarily lie in the southern tier of state, specifically in counties of Alamosa, Costilla, Conejos, Huerfano, Saguache, La Plata, San Miguel, Ouray, and Rio Grande. These selection criteria resulted in 92 treatment precincts and 204 control precincts.

Random Assignment of Treatment

The experiment used blocked random assignment. Blocking used the following variables (using quartiles for numeric variables): (a) congressional district, (b) 2016 turnout, (c) 2014 turnout, (d) county, (e) and precinct area.

After random assignment, balance checks were conducted on the following precinct-level variables: mean_partisan median_partisan p25_partisan ratio_dem_to_rep mean_general_turnout mean_ideology mean_trump_resist mean_trump_support mean_age pct_female pct_caucasian pct_hispanic pct_married g2017_turnout g2016_turnout g2015_turnout g2014_turnout g2013_turnout g2012_turnout. The assignments are generated in the program "5_precinct_ra.R" and the results are captured in the data table "precinct_treatment_assignment.RDS." The code is listed here:

The balance check required that the chi-squared statistic from an Anova comparing a regression of treatment on the balance variables to a null model be greater than 0.7. \

```
min_p_value <- 0.7
balance_p_value <- 0
iteration_n <- 0
seed <- 222

while(balance_p_value < min_p_value) {
 seed <- seed + 1
 if(iteration_n >= 10) {
  stop("Too many iterations; check the data for this geo!")
 }
 set.seed(seed)
 print(runif(1))
 studyprecincts_final_df %<>% mutate(treatment = randomizr::block_ra(blocks = block,
                                    num_arms = 2,
                                    condition = c(0,1),
                                    prob_each = c(0.70, 0.30)))


 # Balance check by other precinct-level stats
 multi_fit <- glm(treatment ~
             mean_partisan +
             median_partisan +
             p25_partisan +
             ratio_dem_to_rep +
             mean_general_turnout +
             mean_ideology +
             mean_trump_resist +
             mean_trump_support +
             mean_age +
             pct_female +
             pct_caucasian +
             pct_hispanic +
             pct_married +
```

```
                g2017_turnout +
                g2016_turnout +
                g2015_turnout +
                g2014_turnout +
                g2013_turnout +
                g2012_turnout,
            data = studyprecincts_final_df,
            family='binomial')

  multi_null_fit <- glm(treatment~1, data = studyprecincts_final_df, family='binomial')
  anova_model <- anova(multi_null_fit,multi_fit, test='Chisq')
  balance_p_value <-anova_model$`Pr(>Chi)`[2]
  iteration_n <- iteration_n + 1
  print(iteration_n)
}
```

In light of this re-randomization procedure, we will use randomization inference to assess p-values based on the admissible set of randomizations. If simulations with re-randomization reveal that precincts have different probabilities of assignment to treatment, we will use inverse probability weights to obtain estimates of treatment effects.

Noncompliance

It became apparent in the week leading up to the election that we were unlikely to successfully treat all randomly identified treatment precincts. As of approximately Friday October 25th, the only signs that had been distributed to the Aurora area precincts were those claimed by individuals. In order to salvage the random assignment of precincts in Aurora, we randomly ordered the 47 precincts in Aurora and decided to have the volunteers plant signs in areas based on this randomized order. They were able to treat 36 of these precincts. The remaining 11 untreated precincts had received individually claimed signs but did not receive any additional volunteer planted ones. This randomization is captured in the document denver_precincts_random_order.csv. Thus, we effectively have two experimental sub-populations: Aurora (where the randomization is the ordering) and non-Aurora (where the random assignment is a binary treatment).

Intervention

Precincts assigned to the treatment group were encouraged to plant signs. The approximate number of signs that actually were planted may be found in the accompanying spreadsheet. Due to incomplete or variable implementation, we treat the number of signs planted as the endogeneous independent variable, with random assignment (priority number or binary, depending on location) as the instrumental variable.

Data and Outcome Measures

Our primary outcome measure will be precinct-level turnout, measured by the number of votes cast compared to the number of registered voters in each precinct. We expect treatment to increase voter turnout. It is doubtful that the intervention affected registration; we will test this as well. Rather than use a post-treatment variable (registrants as of election day) in the denominator of the turnout measure, we will calculate voter turnout rates in relation to fixed denominator: registration as of some pre-treatment date (no later than September 30, 2018). We will obtain this fixed registration number in a way that is consistent across treatment and control precincts within a given block.

A secondary outcome is the difference in the number of votes cast for the Republican versus Democratic candidates for US House of Representatives. We do not expect an effect here, given the nonpartisan nature of the signs.

Method for Estimating Average Treatment Effects

Since the experiment is blocked (in part) by location, with different types of random assignments, we will analyze Aurora and non-Aurora separately and pool the results using a precision-weighted average. Our initial analysis will be an intent-to-treat regression of outcomes on a treatment indicator (non-Aurora) or priority number (Aurora). We will control for blocking strata as well as all general elections' turnout since the last redistricting cycle. Randomization inference will be used to obtain exact p-values in light of the complex blocked and clustered design (which also involves a balance criterion).

Next, we will explore the possibility of spillovers by applying inverse probability weights of being in treatment, adjacent-to-treatment, or pure control. The ITT regression will use two indicator variables, one for treatment and the other for spillover. The same covariate set as above will be included.

Finally, under the assumption of constant treatment effects, we will obtain the average effect of each sign by regressing outcomes in each block on the number of signs planted, instrumenting for random assignment (indicator or priority number, depending on block) and controlling for the covariate set above. The p-value for these IV regressions will be obtained using the ITT results.

Default Procedures for Decisions Not Explicitly Specified

For any decisions not explicitly specified in this pre-analysis plan, we plan to follow the "standard operating procedure" document of Donald P. Green's research group (version 1.05, June 7, 2016), which can be found on GitHub.