Gov 50: 7. Randomized Experiments

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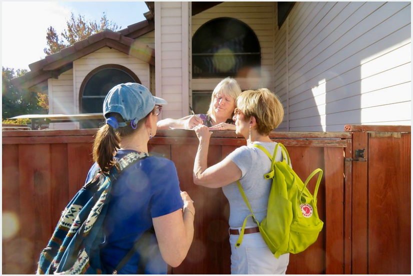
Harvard University

Roadmap

1. Randomized experiments

2. Calculating effects

Political canvassing study



POLITICAL SCIENCE

Durably reducing transphobia: A field experiment on door-to-door canvassing

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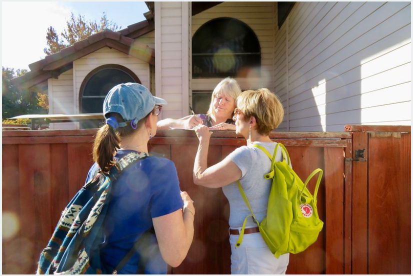

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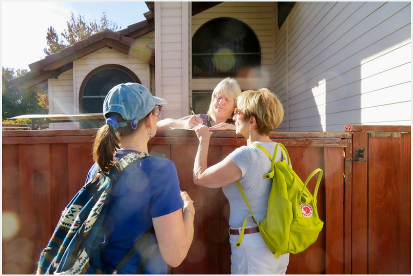

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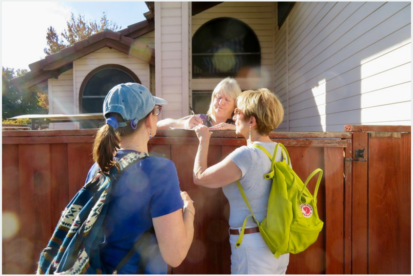

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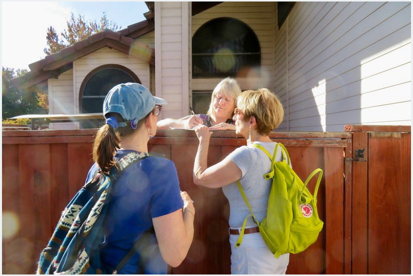

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- Outcome of interest: support for trans rights policies.

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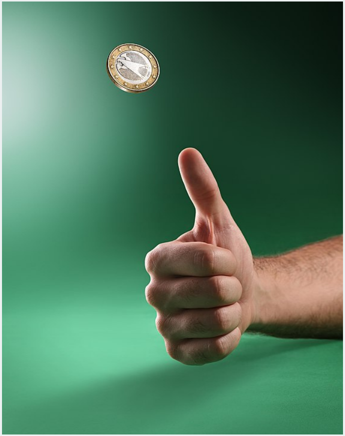
- To infer causal effect, we need to infer the missing counterfactuals!

1/ Randomized experiments

Match groups not individuals



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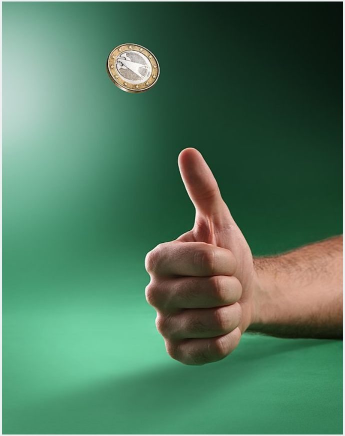

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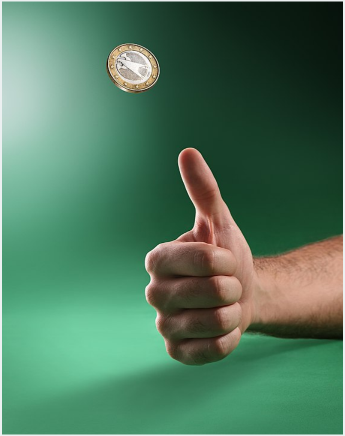

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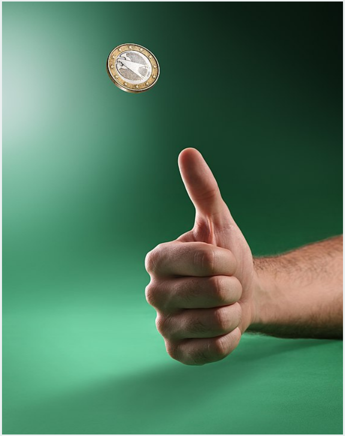

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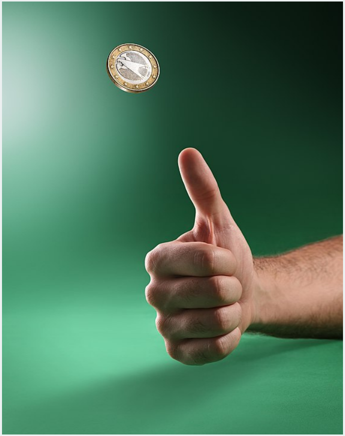

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    - Similar on both observable and unobservable characteristics.

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- Suppose we surveyed 6 people and 3 supported nondiscrim. laws:

$$\overline{Y} = \frac{1}{6}(1+1+1+0+0+0) = 0.5$$

Quantity of interest

- We want to estimate the average causal effects over all units:

$$\text{Sample Average Treatment Effect (SATE)} = \frac{1}{n}\sum_{i=1}^{n}\{Y_i(1) - Y_i(0)\}$$
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- When will the difference-in-means is a good estimate of the SATE?

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- Implies difference-in-means should be close to SATE:

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- **Placebo effects**:
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- **Hawthorne effects**:
    - Respondents act differently just knowing that they are under study.

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  - $\overline{X}_{\text{treated}}$: average value of variable for treated group.
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  - Under randomization, $\overline{X}_{\text{treated}} - \overline{X}_{\text{control}} \approx 0$

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- If treatment arms are randomly assigned, these differences will be good estimators for each causal contrast.

2/ Calculating effects

Transphobia study data

```r
## reinstall gov50data if necessary
library(gov50data)
```

Variable Name	Description
age	Age of the R in years
female	1=R marked "Female" on voter reg., 0 otherwise
voted_gen_14	1 if R voted in the 2014 general election
vote_gen_12	1 if R voted in the 2012 general election
treat_ind	1 if R assigned to trans rights script, 0 for recycling
racename	name of racial identity indicated on voter file
democrat	1 if R is a registered Democrat
nondiscrim_pre	1 if R supports nondiscrim. law at baseline
nondiscrim_post	1 if R supports nondiscrim. law after 3 months

Peak at the data

```r
trans
```

```
## # A tibble: 565 x 9
##      age female voted_gen_14 voted_gen_12 treat_ind racename
##    <dbl>  <dbl>        <dbl>        <dbl>     <dbl> <chr>
##  1    29      0            0            1         0 African~
##  2    59      1            1            0         1 African~
##  3    35      1            1            1         1 African~
##  4    63      1            1            1         1 African~
##  5    65      0            1            1         1 African~
##  6    51      1            1            1         0 Caucasi~
##  7    26      1            1            1         0 African~
##  8    62      1            1            1         1 African~
##  9    37      0            1            1         0 Caucasi~
## 10    51      1            1            1         0 Caucasi~
## # i 555 more rows
## # i 3 more variables: democrat <dbl>, nondiscrim_pre <dbl>,
## #   nondiscrim_post <dbl>
```

Calculate the average outcomes in each group

```r
treat_mean <- trans |>
  filter(treat_ind == 1) |>
  summarize(nondiscrim_mean = mean(nondiscrim_post))
treat_mean
```

```
## # A tibble: 1 x 1
##   nondiscrim_mean
##             <dbl>
## 1           0.687
```

Calculate the average outcomes in each group

```
treat_mean <- trans |>
  filter(treat_ind == 1) |>
  summarize(nondiscrim_mean = mean(nondiscrim_post))
treat_mean
```

```
## # A tibble: 1 x 1
##   nondiscrim_mean
##             <dbl>
## 1           0.687
```

```
control_mean <- trans |>
  filter(treat_ind == 0) |>
  summarize(nondiscrim_mean = mean(nondiscrim_post))
control_mean
```

```
## # A tibble: 1 x 1
##   nondiscrim_mean
##             <dbl>
## 1           0.648
```

Calculating the difference in means

```r
treat_mean - control_mean
```

```
##   nondiscrim_mean
## 1           0.039
```

We'll see more ways to do this throughout the semester.

Checking balance on numeric covariates

We can use group_by to see how the mean of covariates varies by group:

```
trans |>
  group_by(treat_ind) |>
  summarize(age_mean = mean(age))
```

```
## # A tibble: 2 x 2
##   treat_ind age_mean
##       <dbl>    <dbl>
## 1         0     48.2
## 2         1     48.3
```

Checking balance on categorical covariates

Or we can group by treatment and a categorical control:

```
trans |>
  group_by(treat_ind, racename) |>
  summarize(n = n())
```

```
## # A tibble: 9 x 3
## # Groups:   treat_ind [2]
##   treat_ind racename             n
##       <dbl> <chr>            <int>
## 1         0 African American    58
## 2         0 Asian                2
## 3         0 Caucasian           77
## 4         0 Hispanic           150
## 5         1 African American    68
## 6         1 Asian                4
## 7         1 Caucasian           75
## 8         1 Hispanic           130
## 9         1 Native American      1
```

Hard to read!

pivot_wider

`pivot_wider()` takes data from a single column and moves it into multiple columns based on a grouping variable:

```
trans |>
  group_by(treat_ind, racename) |>
  summarize(n = n()) |>
  pivot_wider(
    names_from = treat_ind,
    values_from = n
  )
```

pivot_wider

`pivot_wider()` takes data from a single column and moves it into multiple columns based on a grouping variable:

```
trans |>
  group_by(treat_ind, racename) |>
  summarize(n = n()) |>
  pivot_wider(
    names_from = treat_ind,
    values_from = n
  )
```

`names_from` tells us what variable will map onto the columns

`values_from` tell us what values should be mapped into those columns

```r
trans |>
  group_by(treat_ind, racename) |>
  summarize(n = n()) |>
  pivot_wider(
    names_from = treat_ind,
    values_from = n
  )
```

```
## # A tibble: 5 x 3
##   racename           `0`   `1`
##   <chr>            <int> <int>
## 1 African American    58    68
## 2 Asian                2     4
## 3 Caucasian           77    75
## 4 Hispanic           150   130
## 5 Native American     NA     1
```

Calculating diff-in-means by group

```r
trans |>
  mutate(
    treat_ind = if_else(treat_ind == 1, "Treated", "Control"),
    party = if_else(democrat == 1, "Democrat", "Non-Democrat")
  ) |>
  group_by(treat_ind, party) |>
  summarize(nondiscrim_mean = mean(nondiscrim_post)) |>
  pivot_wider(
    names_from = treat_ind,
    values_from = nondiscrim_mean
  ) |>
  mutate(
    diff_in_means = Treated - Control
  )
```

```
## # A tibble: 2 x 4
##   party        Control Treated diff_in_means
##   <chr>          <dbl>   <dbl>         <dbl>
## 1 Democrat       0.704   0.754        0.0498
## 2 Non-Democrat   0.605   0.628        0.0234
```

Creating more complicated groups with `case_when`

```r
trans |>
  mutate(
    age_group = case_when(
      age < 25 ~ "Under 25",
      age >=25 & age < 65 ~ "Bewteen 25 and 65",
      age >= 65 ~ "Older than 65"
    )
  ) |>
  count(age_group)
```

```
## # A tibble: 3 x 2
##   age_group             n
##   <chr>             <int>
## 1 Bewteen 25 and 65   369
## 2 Older than 65       116
## 3 Under 25             80
```

Calculating ATE by age group

```r
trans |>
  mutate(
    treat_ind = if_else(treat_ind == 1, "Treated", "Control"),
    age_group = case_when(
      age < 25 ~ "Under 25",
      age >=25 & age < 65 ~ "Bewteen 25 and 65",
      age >= 65 ~ "Older than 65"
    )
  ) |>
  group_by(treat_ind, age_group) |>
  summarize(nondiscrim_mean = mean(nondiscrim_post)) |>
  pivot_wider(
    names_from = treat_ind,
    values_from = nondiscrim_mean
  ) |>
  mutate(
    diff_in_means = Treated - Control
  )
```

```
## # A tibble: 3 x 4
##   age_group         Control Treated diff_in_means
##   <chr>               <dbl>   <dbl>         <dbl>
## 1 Bewteen 25 and 65   0.694   0.683       -0.0112
## 2 Older than 65       0.576   0.614        0.0378
## 3 Under 25            0.556   0.829        0.273
```