

Gov 50: 7. Randomized Experiments

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Roadmap

1. Randomized experiments
2. Calculating effects

Political canvassing study



POLITICAL SCIENCE

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

David Broockman^{1*} and Joshua Kalla²

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 - Trans rights conversations focused on “perspective taking”
- Outcome of interest: support for trans rights policies.

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 - Observe $Y_i = Y_i(1)$ if $T_i = 1$ or $Y_i = Y_i(0)$ if $T_i = 0$
- To infer causal effect, we need to infer the missing counterfactuals!

1/ Randomized experiments

Match groups not individuals



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 - Similar on both observable and unobservable characteristics.

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$$\sum_{i=1}^n Y_i = Y_1 + Y_2 + Y_3 + \dots + Y_n$$

- $\sum_{i=1}^n$ means sum each value from Y_1 to Y_n

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

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

Quantity of interest

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

$$\begin{aligned}\text{Sample Average Treatment Effect (SATE)} &= \frac{1}{n} \sum_{i=1}^n \{Y_i(1) - Y_i(0)\} \\ &= \frac{1}{n} \sum_{i=1}^n Y_i(1) - \frac{1}{n} \sum_{i=1}^n Y_i(0)\end{aligned}$$

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- When will the difference-in-means is a good estimate of the SATE?

Why randomization works

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

$$\bar{Y}_{\text{treated}} - \bar{Y}_{\text{control}} \approx \frac{1}{n} \sum_{i=1}^n Y_i(1) - \frac{1}{n} \sum_{i=1}^n Y_i(0) = \frac{1}{n} \sum_{i=1}^n \{Y_i(1) - Y_i(0)\} = \text{SATE}$$

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- **Hawthorne effects:**

- Respondents act differently just knowing that they are under study.

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

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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

```
## 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

```
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

```
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
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## 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

```
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
  )
```

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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

```
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

```
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

```
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

```
trans |>
  mutate(
    treat_ind = if_else(treat_ind == 1, "Treated", "Control"),
    age_group = case_when(
      age < 25 ~ "Under 25",
      age >= 25 & age < 65 ~ "Between 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
```