Gov 50: 6. Causality

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Roadmap

1. What is causality?
2. Randomized experiments
3. Calculating effects

1/ What is causality?

Two roads diverged in a yellow wood,
And sorry I could not travel both
And be one traveler, long I stood
And looked down one as far as I could
To where it bent in the undergrowth;

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factual vs. counterfactual

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- **Fundamental problem of causal inference**:
  - Can never observe counterfactuals, must be inferred.

Political canvassing study

POLITICAL SCIENCE

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

David Broockman[1*] and Joshua Kalla[2]

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- Can canvassers change minds about topics like transgender rights?

Credit: Fabrice Florian via Flickr

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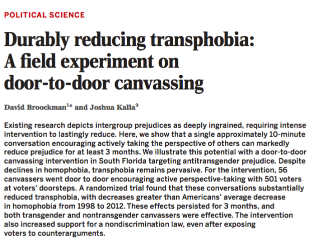

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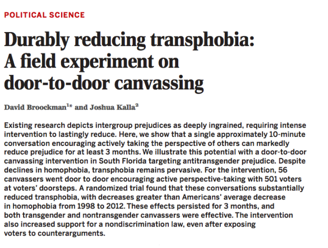

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  - Randomly assign canvassers to have a conversation about transgender right or a conversation about recycling.
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- Outcome of interest: support for trans rights policies.

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A tale of two respondents

	Conversation Script	Support for Nondiscrimination Law
Respondent 1	Recycling	No
Respondent 2	Trans rights	Yes

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Did the second respondent support the law **because** of the perspective-taking conversation?

Translating into math

Useful to have **compact** notation for referring to **treatment variable**:

$$T_i = \begin{cases} 1 & \text{if respondent } i \text{ had trans rights conversation} \\ 0 & \text{if respondent } i \text{ had recycling conversation} \end{cases}$$

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Similar notation for the **outcome variable**:

$$Y_i = \begin{cases} 1 & \text{if respondent } i \text{ supports trans nondiscrimination laws} \\ 0 & \text{if respondent } i \text{ doesn't support nondiscrimination laws} \end{cases}$$

i is a placeholder to refer to a generic unit/respondent: Y_{42} is the outcome for the 42nd unit.

A tale of two respondents (redux)

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becomes...

i	T_i	Y_i
Respondent 1	0	0
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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!

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  - $\rightsquigarrow$ find a state similar to NJ that didn't increase minimum wage.

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- How can we correct for that?

2/ Randomized experiments

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    - Similar on both observable and unobservable characteristics.

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

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

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

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:

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

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

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- Can we determine if randomization "worked"?
- If it did, we shouldn't see large differences between treatment and control group on **pretreatment variable**.
  - Pretreatment variable are those that are unaffected by treatment.
- We can check in the actual data for some pretreatment variable X
  - $\overline{X}_{\text{treated}}$: average value of variable for treated group.
  - $\overline{X}_{\text{control}}$: average value of variable for control group.
  - Under randomization, $\overline{X}_{\text{treated}} - \overline{X}_{\text{control}} \approx 0$

Multiple treatments

- Instead of 1 treatment, we might have multiple **treatment arms**:

Multiple treatments

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    - Control condition

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- Instead of 1 treatment, we might have multiple **treatment arms**:
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Multiple treatments

- Instead of 1 treatment, we might have multiple **treatment arms**:
    - Control condition
    - Treatment A
    - Treatment B

Multiple treatments

- Instead of 1 treatment, we might have multiple **treatment arms**:
  - Control condition
  - Treatment A
  - Treatment B
  - Treatment C, etc

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    - $\overline{Y}_{\text{treated, B}} - \overline{Y}_{\text{control}}$
    - $\overline{Y}_{\text{treated, A}} - \overline{Y}_{\text{treated, B}}$
- If treatment arms are randomly assigned, these differences will be good estimators for each causal contrast.

3/ 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

```
trans
```

```
## # A tibble: 565 x 9
##      age female voted_gen_14 voted_g~1 treat~2 racen~3 democ~4 nondi~5
##    <dbl>  <dbl>        <dbl>     <dbl>   <dbl> <chr>     <dbl>   <dbl>
##  1    29      0            0         1       0 Africa~       1       1
##  2    59      1            1         0       1 Africa~       1       1
##  3    35      1            1         1       1 Africa~       1       0
##  4    63      1            1         1       1 Africa~       1       0
##  5    65      0            1         1       1 Africa~       0       1
##  6    51      1            1         1       0 Caucas~       0       1
##  7    26      1            1         1       0 Africa~       1       1
##  8    62      1            1         1       1 Africa~       1       1
##  9    37      0            1         1       0 Caucas~       0       1
## 10    51      1            1         1       0 Caucas~       0       0
## # ... with 555 more rows, 1 more variable: nondiscrim_post <dbl>, and
## #   abbreviated variable names 1: voted_gen_12, 2: treat_ind,
## #   3: racename, 4: democrat, 5: nondiscrim_pre
```

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
```

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
```

```r
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

```
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
```

```
## # 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
```