

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;

What is a causal effect?

factual

vs.

counterfactual

- Does increasing the minimum wage increase the unemployment rate?

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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 Kalla²

Existing research depicts intergroup prejudices as deeply ingrained, requiring intense intervention to lastingly reduce. Here, we show that a single approximately 10-minute conversation encouraging actively taking the perspective of others can markedly reduce prejudice for at least 3 months. We illustrate this potential with a door-to-door canvassing intervention in South Florida targeting antitransgender prejudice. Despite declines in homophobia, transphobia remains pervasive. For the intervention, 56 canvassers went door to door encouraging active perspective-taking with 501 voters at voters' doorsteps. A randomized trial found that these conversations substantially reduced transphobia, with decreases greater than Americans' average decrease in homophobia from 1998 to 2012. These effects persisted for 3 months, and both transgender and nontransgender canvassers were effective. The intervention also increased support for a nondiscrimination law, even after exposing voters to counterarguments.

- Can canvassers change minds about topics like transgender rights?

Political canvassing study



POLITICAL SCIENCE

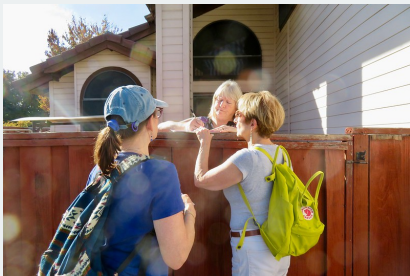
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- Experimental setting:
 - Randomly assign canvassers to have a conversation about transgender right or a conversation about recycling.
 - Trans rights conversations focused on “perspective taking”
- Outcome of interest: support for trans rights policies.

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
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Potential outcomes

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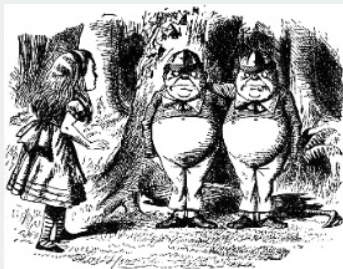
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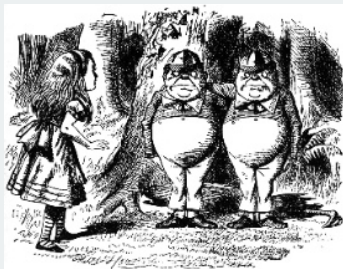
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- To infer causal effect, we need to infer the missing counterfactuals!

How can we figure out counterfactuals?



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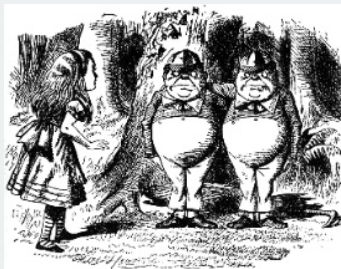
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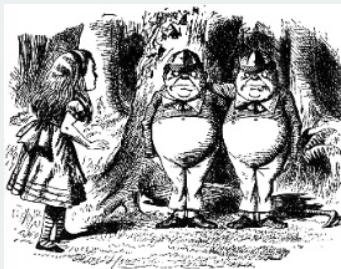
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 - \rightsquigarrow find a state similar to NJ that didn't increase minimum wage.

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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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- 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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 - \bar{X}_{control} : average value of variable for control group.

Balance checking

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

Multiple treatments

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

Multiple treatments

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 - Control condition

Multiple treatments

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 - Treatment A

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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 - Treatment C, etc
- In this case, we will look at multiple comparisons:
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 - $\bar{Y}_{\text{treated, B}} - \bar{Y}_{\text{control}}$
 - $\bar{Y}_{\text{treated, A}} - \bar{Y}_{\text{treated, B}}$
- If treatment arms are randomly assigned, these differences will be good estimators for each causal contrast.

3/ Calculating effects

Transphobia study data

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

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

```
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

```
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

```
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
```