Gov 50: 7. Observational Studies

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Roadmap

1. Calculating effects

2. Observational Studies

1/ 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_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
```

```
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
  )
```

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
```

2/ Observational Studies

Do newspaper endorsements matter?

- Can newspaper endorsements change voters' minds?
- Why not compare vote choice of readers of different papers?
  - Problem: readers choose papers based on their previous beliefs.
  - Liberals ⇝ New York Times, conservatives ⇝ Wall Street Journal.
- Study for today: British newspapers switching their endorsements.
  - Some newspapers endorsing Tories in 1992 switched to Labour in 1997.
  - **Treated group**: readers of Tory → Labour papers.
  - **Control group**: readers of papers who didn't switch.

Data

Name	Description
`to_labour`	Read a newspaper that switched endorsement to Labour between 1992 and 1997 (1=Yes, 0=No)?
`vote_lab_92`	Did respondent vote for Labour in 1992 election (1=Yes, 0=No)?
`vote_lab_97`	Did respondent vote for Labour in 1997 election (1=Yes, 0=No)?
`age`	Age of respondent
`male`	Does the respondent identify as Male (1=Yes, 0=No)?
`parent_labour`	Did the respondent's parents vote for Labour (1=Yes, 0=No)?
`work_class`	Does the respondent identify as working class (1=Yes, 0=No)?

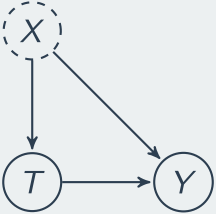
```r
library(tidyverse)
library(gov50data)
newspapers
```

```
## # A tibble: 1,593 x 7
##    to_labour vote_lab_92 vote_lab_97 age       male parent_~1 work_~2
##        <dbl>       <dbl>       <dbl> <dbl+lbl> <dbl>     <dbl>   <dbl>
##  1         0           1           1 33            0         1       1
##  2         0           1           0 51            0         1       0
##  3         0           0           0 46            0         1       1
##  4         0           1           1 45            1         1       1
##  5         0           1           1 29            0         1       1
##  6         0           1           1 47            1         1       1
##  7         0           1           1 34            1         0       1
##  8         0           1           1 31            0         1       1
##  9         0           1           1 24            1         1       1
## 10         1           1           1 48            0         1       1
## # ... with 1,583 more rows, and abbreviated variable names
## #   1: parent_labour, 2: work_class
```

Observational studies

- Example of an **observational study**:
    - We as researchers observe a naturally assigned treatment
    - Very common: often can't randomize for ethical/logistical reasons.
- **Internal validity**: are the causal assumption satisfied? Can we interpret this as a causal effect?
    - RCTs usually have higher internal validity.
    - Observational studies less so because treatment and control groups may differ in ways that are hard to measure
- **External validity**: can the conclusions/estimated effects be generalized beyond this study?
    - RCTs weaker here because often very expensive to conduct on representative samples.
    - Observational studies often have larger/more representative samples that improve external validity.

Confounding



- **Confounder**: pre-treatment variable affecting treatment & the outcome.
    - Leftists (X) more likely to read newspapers switching to Labour (T).
    - Leftists (X) also more likely to vote for Labour (Y).
- **Confounding bias** in the estimated SATE due to these differences
    - $\overline{Y}_{\text{control}}$ not a good proxy for $\frac{1}{n}\sum_{i=1}^{n} Y_i(0)$ in treated group.
    - one type: **selection bias** from self-selection into treatment

Research designs

- How can we find a good comparison group?
- Depends on the data we have available.
- Three general types of observational study **reseach designs**:
    1. **Cross-sectional design**: compare outcomes treated and control units at one point in time.
    2. **Before-and-after design**: compare outcomes before and after a unit has been treated, but need over-time data on treated group.
    3. **Difference-in-differences design**: use before/after information for the treated and control group; need over-time on treated & control group.

Cross-sectional design

- Compare treatment and control groups after treatment happens.
    - Readers of switching papers vs readers of non-switching papers in 1997.
- Treatment & control groups assumed identical on average as in RCT.
    - Sometimes called **unconfoundedness** or **as-if randomized**.
- Cross-section comparison estimate:

$$\overline{Y}^{\text{after}}_{\text{treated}} - \overline{Y}^{\text{after}}_{\text{control}}$$

- Could there be confounders?

Cross-sectional design in R

```
switched <- newspapers |>
  filter(to_labour == 1) |>
  summarize(mean(vote_lab_97))


no_change <- newspapers %>%
  filter(to_labour == 0) |>
  summarize(mean(vote_lab_97))

switched - no_change
```

```
##   mean(vote_lab_97)
## 1              0.14
```

Statistical control

- **Statistical control**: adjust for confounders using statistical procedures.
    - Can help to reduce confounding bias.
- One type of statistical control: **subclassification**
    - Compare treated and control groups within levels of a confounder.
    - Remaining effect can't be due to the confounder.
- Threat to inference: we can only control for observed variables $\rightsquigarrow$ threat of **unmeasured confounding**

Statistical control in R

```r
newspapers %>%
  group_by(parent_labour, to_labour) %>%
  summarize(avg_vote = mean(vote_lab_97)) %>%
  pivot_wider(
    names_from = to_labour,
    values_from = avg_vote
  ) %>%
  mutate(diff_by_parent = `1` - `0`)
```

```
## # A tibble: 2 x 4
## # Groups:   parent_labour [2]
##   parent_labour   `0`   `1` diff_by_parent
##           <dbl> <dbl> <dbl>          <dbl>
## 1             0 0.279 0.434          0.155
## 2             1 0.597 0.698          0.101
```

Before-and-after comparison

- Compare readers of party-switching newspapers before & after switch.
- Advantage: all person-specific features held fixed
    - comparing within a person over time.
- Before-and-after estimate:

$$\overline{Y}^{\text{after}}_{\text{treated}} - \overline{Y}^{\text{before}}_{\text{treated}}$$

- Threat to inference: **time-varying confounders**
    - Time trend: Labour just did better overall in 1997 compared to 1992.

Before and after in R

```
newspapers |>
  mutate(
    vote_change = vote_lab_97 - vote_lab_92
  ) |>
  summarize(avg_change = mean(vote_change))
```

```
## # A tibble: 1 x 1
##   avg_change
##        <dbl>
## 1      0.119
```

Differences in differences

- Key idea: use the before-and-after difference of **control group** to infer what would have happend to **treatment group** without treatment.
- DiD estimate:

$$\underbrace{\left(\overline{Y}^{\text{after}}_{\text{treated}} - \overline{Y}^{\text{before}}_{\text{treated}}\right)}_{\text{trend in treated group}} - \underbrace{\left(\overline{Y}^{\text{after}}_{\text{control}} - \overline{Y}^{\text{before}}_{\text{control}}\right)}_{\text{trend in control group}}$$

- Change in treated group above and beyond the change in control group.
- **Parallel time trend assumption**
    - Changes in vote of readers of non-switching papers roughly the same as changes that readers of switching papers would have been if they read non-switching papers.
    - Threat to inference: non-parallel trends.

Difference-in-differences in R

```r
newspapers |>
  mutate(
    vote_change = vote_lab_97 - vote_lab_92,
    to_labour = if_else(to_labour == 1, ”switched”, ”unswitched”)
  ) |>
  group_by(to_labour) |>
  summarize(avg_change = mean(vote_change)) |>
  pivot_wider(
    names_from = to_labour,
    values_from = avg_change
  ) |>
  mutate(DID = switched - unswitched)
```

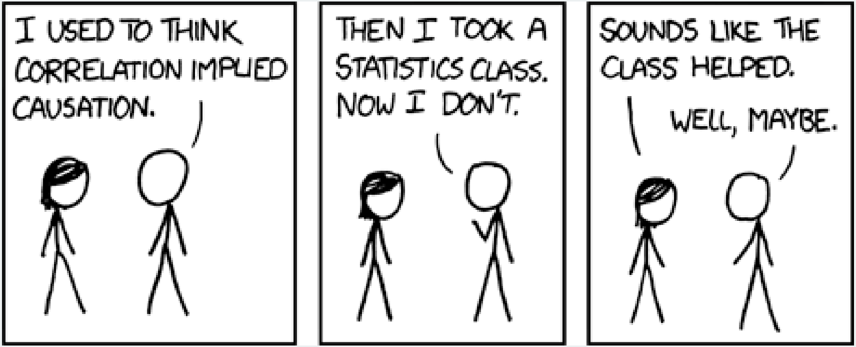
```
## # A tibble: 1 x 3
##   switched unswitched    DID
##      <dbl>      <dbl>  <dbl>
## 1    0.190      0.110 0.0796
```

Summarizing approaches

1. **Cross-sectional comparison**
    - Compare treated units with control units after treatment
    - Assumption: treated and controls units are comparable
    - Possible confounding
2. **Before-and-after comparison**
    - Compare the same units before and after treatment
    - Assumption: no time-varying confounding
3. **Differences-in-differences**
    - Assumption: parallel trends assumptions
    - Under this assumption, it accounts for unit-specific and time-varying confounding.

- All rely on assumptions that can’t be verified to handle confounding.
- RCTs handle confounding by design.

Causality understanding check


I USED TO THINK CORRELATION IMPLIED CAUSATION.
THEN I TOOK A STATISTICS CLASS. NOW I DON'T.
SOUNDS LIKE THE CLASS HELPED.
WELL, MAYBE.