Gov 50: 8. Observational Studies

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Roadmap

1. Observational Studies

1/ 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 $\rightsquigarrow$ New York Times, conservatives $\rightsquigarrow$ 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 $\rightarrow$ 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)?

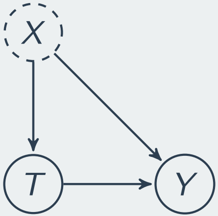
```r
library(tidyverse)
library(gov50data)
newspapers
```

```
## # A tibble: 1,593 x 7
##    to_labour vote_lab_92 vote_lab_97        age  male
##        <dbl>       <dbl>       <dbl> <hvn_lbll> <dbl>
##  1         0           1           1         33     0
##  2         0           1           0         51     0
##  3         0           0           0         46     0
##  4         0           1           1         45     1
##  5         0           1           1         29     0
##  6         0           1           1         47     1
##  7         0           1           1         34     1
##  8         0           1           1         31     0
##  9         0           1           1         24     1
## 10         1           1           1         48     0
## # i 1,583 more rows
## # i 2 more variables: parent_labour <dbl>, work_class <dbl>
```

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



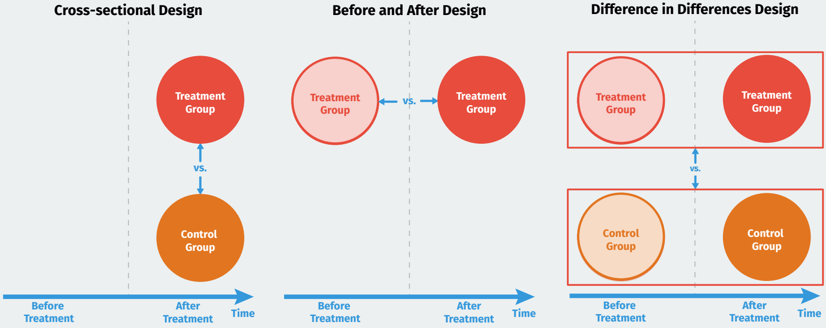
- **Confounder**: pre-treatment variable affecting treatment & the outcome.
  - Leftists (X) more likely to read newspapers switching to Labour (T).
  - Leftists (X) also more likely to vote for Labour (Y).
- **Confounding bias** in the estimated SATE due to these differences
  - $\overline{Y}_{\text{control}}$ 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

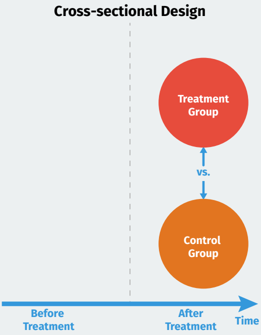
- How can we find a good comparison group?
- Depends on the data we have available.
- Three general types of observational study **reseach designs**:

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.

Research designs



Cross-sectional design



- Compare treated/control groups after treatment happens.
  - Switching readers vs non-switching readers in 1997.
- **Assumption**: groups identical on average (like RCTs)
  - Sometimes called **unconfoundedness** or **as-if randomized**.
- Cross-section estimate:

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

- Could there be confounders?

Cross-sectional design in R

```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

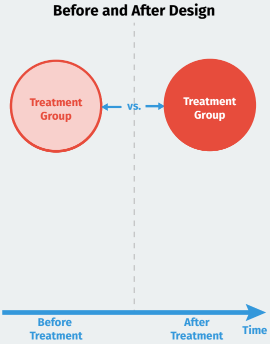
- **Statistical control**: adjust for confounders using statistical procedures.
    - Can help to reduce confounding bias.
- One type of statistical control: **subclassification**
    - Compare treated and control groups within levels of a confounder.
    - Remaining effect can't be due to the confounder.
- 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:

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

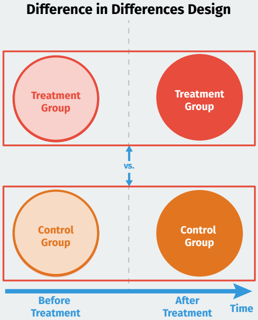
- **Assumption**: no time-varying confounders
  - Time trend: Labour just did better overall in 1997 compared to 1992.

Before and after in R

```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



- Use the before/after difference of **control group** to infer what would have happened to **treatment group** without treatment.
- DiD estimate:

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

- Change in treated group above and beyond the change in control group.
- **Assumption**: parallel trends
  - 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