Gov 51: Observational Studies

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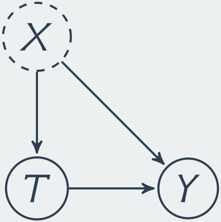
Do newspaper endorsements matter?

- 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.
- Could do a lab experiment, but there are concerns over **external validity**
- Study for today: British newspapers switching their endorsements.
    - Some newspapers endorsing Tories in 1992 switched to Labour in 1997.
    - **Treated group**: readers of Tory $\longrightarrow$ Labour papers.
    - **Control group**: readers of papers who didn't switch.

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 pre-treatment variable may differ between treatment and control groups
- **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 $Y_i(0)$ 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:

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

- Could there be confounders?

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**

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.

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.

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