

# **PSC4375: Observational Studies**

## **Week 2: Lecture 3**

Prof. Weldzius

Villanova University

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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  $\rightarrow$  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 assumptions 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 and 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
  - $\bar{Y}_{control}$  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 **research 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 **Differences-in-differences design**: use before/after information for the treated and control group; need over-time data on treated and 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 and control groups assumed identical on average as in RCT
  - Sometimes called **unconfoundedness** or **as-if randomized**
- Cross-section comparison estimate:

$$\bar{Y}_{treated}^{after} - \bar{Y}_{control}^{after}$$

- 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 controls 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 and after switch
- Advantage: all person-specific features held fixed
  - comparing within a person over time
- Before-and-after estimate:

$$\bar{Y}_{treated}^{after} - \bar{Y}_{treated}^{before}$$

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



# Differences in differences (Diff-in-Diff)

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

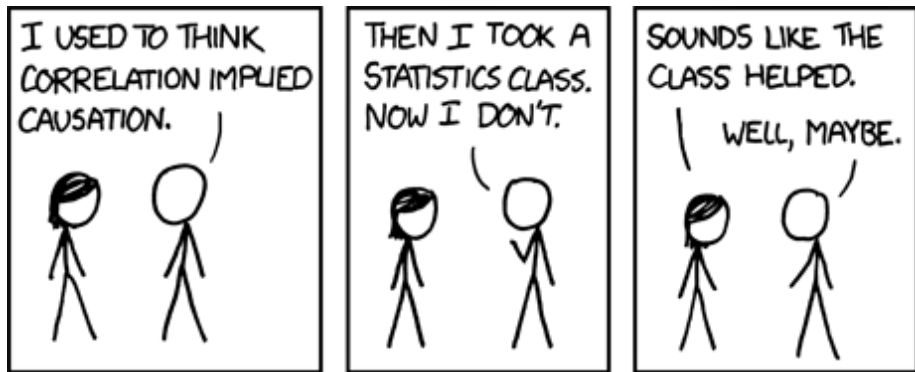
$$\left( \bar{Y}_{treated}^{after} - \bar{Y}_{treated}^{before} \right) - \left( \bar{Y}_{control}^{after} - \bar{Y}_{control}^{before} \right)$$

- 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 control 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



See also: <https://www.tylervigen.com/spurious-correlations>