Conceptual Causality: DiD

Section 1

Sima Biondi

Spring 2025

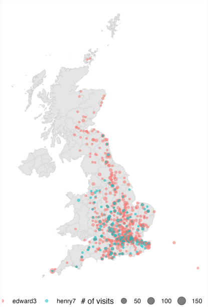
Gov 51: Data Analysis and Politics

Overview

Overview

- 3rd year PhD
- From San Francisco, CA
- State building and political development in 19th-century Egypt and Iran using statistical and computational methods
- Excited to teach Gov 51!

→



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Turn to your partner, and say hello! Learn their:

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- School year
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Share with the class!

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- Reinforce a solid foundation to engage with causal inference methodologies
- Develop a familiarity with machine learning in social science
- Understand methodological approaches in leading social science journals
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Bottom line: Gov 51 builds on material from Gov 50:

↪ Check out the course "prefresher" for more information (`tinyurl.com/GOV51prefresher`)

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  - Ben Heilbronn: Tues/Thurs 7:30pm-9:30pm @ Eliot Dining Hall; by appointment

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- Alternative section attendance is fine - just email me AND Pranav BEFORE both sections start

Last logistics

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- Questions?

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⇒ the fundamental problem of causal inference

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- But before that, let's introduce some notation to ground us

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  - For example, the $E[X]$, where X is age, could be 20 for this class

Dataset visualization

Voters	Age	Gender	Canvassed	Turnout		Causal Effect
i	X_1	X_2	T_i	$Y_i(1)$	$Y_i(0)$	$Y_i(1) - Y_i(0)$
1	19	M	1	0	???	???
2	56	F	0	???	1	???
3	89	F	0	???	0	???

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- These are just to start - there will be many more assumptions for other measures of causal effects

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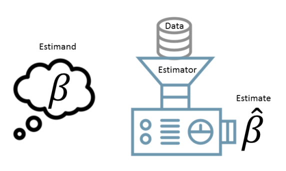
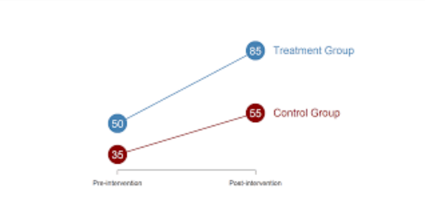


Overview

Review

- As in lecture, difference-in-difference allows us to "infer what would have happened to the treatment group without treatment"
- What assumptions are necessary for identification?



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- Difference-in-difference is a powerful tool in causal inference - they refer to a broad class of estimators that are hotly contested right now
    - Refinements include: DiDiD, moving treatments, controls in semi-parametric estimation, etc.

DiD notation

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Now: $\hookrightarrow Y_{it}(1)$

Quick review

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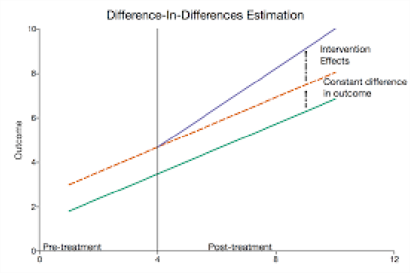
- $Y_{i1}(0)|T_i = 1$: Potential outcome in period after treatment under control given the units are treated. Never observed!

DiD estimation

What is the estimand?

- ATT (average treatment effect on the treated units), not the ATE (average treatment effect)

$$\Delta_{DiD} = E[Y_{i1}(1) - Y_{i0}(0) \mid T_i = 1]$$



DiD estimation

What is the estimand? $\Delta_{DiD} = E[Y_{i1}(1) - Y_{i0}(0) \mid T_i = 1]$

Problem? $\rightarrow$ Can't observe $Y_{i1}(0) \mid T_i = 1$

Solution $\rightarrow$ Parallel trends assumption

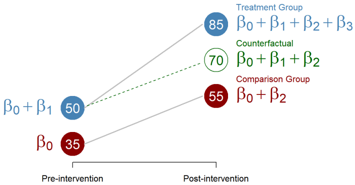
- Use the control group's trend as a stand-in for $Y_{i1}(0)$ in the control group
- Means that we assume treatment and control group share the same trend

DiD estimation

Estimand: $\Delta_{DiD} = E[Y_{i1}(1) - Y_{i0}(0) \mid T_i = 1]$

Solution $\rightarrow$ Assume parallel trends to formulate our estimator to estimate our estimand

$$\Delta_{DiD} = (E[Y_{i1}(1) - Y_{i0}(1) \mid T_i = 1]) - (E[Y_{i1}(0) - Y_{i0}(0) \mid T_i = 0])$$



See the proof we went over in class!

Next week

- Instrumental variables
- More coding!
- In the background: start brainstorming