Natural Experiments and Difference-in-Differences

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Objectives

- Provide a basic introduction to natural experiments and difference-in-differences methods used in observational studies
  - Not meant for those already experienced with these methods
  - No advanced topics covered
- Provide examples of these methods

Outline

- Causality and study design
- Natural Experiments
- Difference-in-differences

Poll 1

Select one option

- I’m experienced in diff-in-diff
- I know a little about diff-in-diff
- What’s diff-in-diff?

Outline

- Causality and study design
- Natural Experiments
- Difference-in-differences

Causality

- In HSR, we often study impact of implementing new program, intervention, or policy.
- Ideally, would estimate causal effect of treatment on outcomes by comparing outcomes under counterfactual
  - Treatment effect=$Y_i(1)$-$Y_i(0)$
  - Observe outcome Y when patient gets treatment, t=1 and when same patient does not get treatment, t=0
  - Compare difference in outcomes to get impact of treatment
  - In reality we don't observe same patients with and without treatment

Randomized Study Design

- Randomize who gets treatment T

R	T	O
R		O

- Compare outcome between treated and untreated groups to get impact of treatment
- Because treatment was randomized, there are no <u>systematic</u> differences between treated and untreated groups.
- Differences in outcomes can be attributed to causal effect of treatment

Estimating Treatment Effect

- Randomize Program P: 0=no, 1=yes

  $Y = \beta_0 + \beta_1 P + \varepsilon$
- β_1 is average treatment effect
- Assumption that error term (ε) is uncorrelated with program (P) assignment
  - Error term (ε) is exogenous
  - β_1 is unbiased

Causality and Observational Studies

- Randomization, e.g. randomized controlled trials (RCT), not commonly used for programs, policies, and many treatments
- Most HSR is observational
  - Causality difficult to show because of confounding (endogeneity)
  - Error term (ε) correlated with program (P) assignment and endogenous
  - Estimate of treatment effect (β_1) is biased

Poll 2

Select one option

- Randomization removes systematic differences b/t trt and control groups
- Correlation b/t error term and trt leads to unbiased estimates of trt effect
- Multivariable analysis eliminates all bias from endogeneity

Outline

- Causality and study design
- Natural Experiments
- Difference-in-differences

Natural Experiments

- Type of quasi-experimental design
- Assignment of program/treatment (often unintended) is due to exogenous variation
  - Variation across time and events
- Mimics features of a randomized study
- Need to consider context
- Generalizability can be limited

Examples of Natural Experiments

- Lottery prize winners and health outcomes (Lindahl, 2005)
- Voluntary state Medicaid expansion to higher-income individuals under ACA (Sommers, 2015)
- CA first state to pass law on minimum nurse staffing ratios in acute care hospitals in 1999 (Mark, 2013)

Comparing Outcomes in Natural Experiments

- One approach involves ignoring control group and use change in mean outcome in treatment group over time (pre-treatment/post-treatment)
- $Y = \beta_0 + \beta_1 Post + \varepsilon$
- Post=0, pre-treatment period
- Post=1, post-treatment period
- β_1 biased if change unrelated to program/policy

Comparing Outcomes in Natural Experiments

- Another approach is compare mean outcome between treatment and control groups only in the post-treatment period
- $Y = \beta_0 + \beta_1 \text{Treatment} + \varepsilon$
- Treatment=0, control group
- Treatment=1, treatment group
- β_1 biased if there are unmeasured differences between groups

Outline

- Causality and study design
- Natural Experiments
- Difference-in-differences

Difference-in-Differences

- Often applied to natural experiments
- Need data for at least two time periods for two groups-- treatment and control group
- Subtract out differences between treatment and control groups and differences over time
- Assumes similar time trend between groups
- If treatment assigned as if randomly received, then causal effect can be estimated through OLS

Diff-in-Diff Regression

$Y = \beta_0 + \beta_1 Post + \beta_2 Treatment + \beta_3 Post{*}Treatment + \varepsilon$

- Mean outcome for control group in pre-period
  $\bar{Y} = \beta_0$
- Mean outcome for control group in post-period
  $\bar{Y} = \beta_0 + \beta_1$
- Mean outcome for treatment group in pre-period
  $\bar{Y} = \beta_0 + \beta_2$
- Mean outcome for treatment group in post-period
  $\bar{Y} = \beta_0 + \beta_1 + \beta_2 + \beta_3$

Diff-in-Diff Estimator

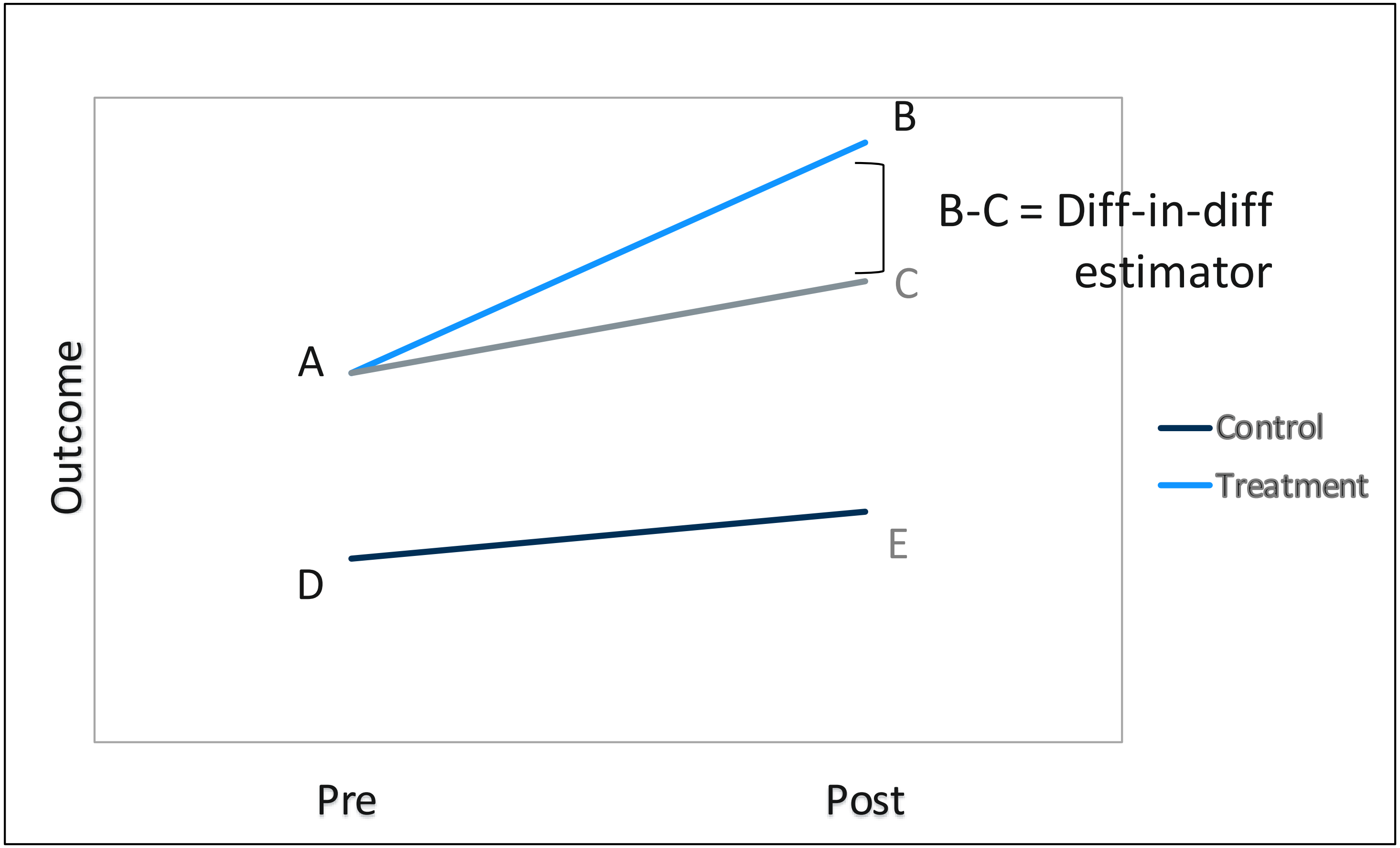
$$Y = \beta_0 + \beta_1 Post + \beta_2 Treatment + \beta_3 Post{*}Treatment + \varepsilon$$

$$(\bar{Y}^{\text{Treatment, Post}} - \bar{Y}^{\text{Treatment, Pre}}) - (\bar{Y}^{\text{Control, Post}} - \bar{Y}^{\text{Control, Pre}})$$

$$[(\beta_0+\beta_1+\beta_2+\beta_3) - (\beta_0+\beta_2)] - [(\beta_0+\beta_1) - \beta_0)] = \beta_3$$

- β_3 is the diff-in-diff estimator

Chart for Diff-in-Diff



Strengths and Weaknesses

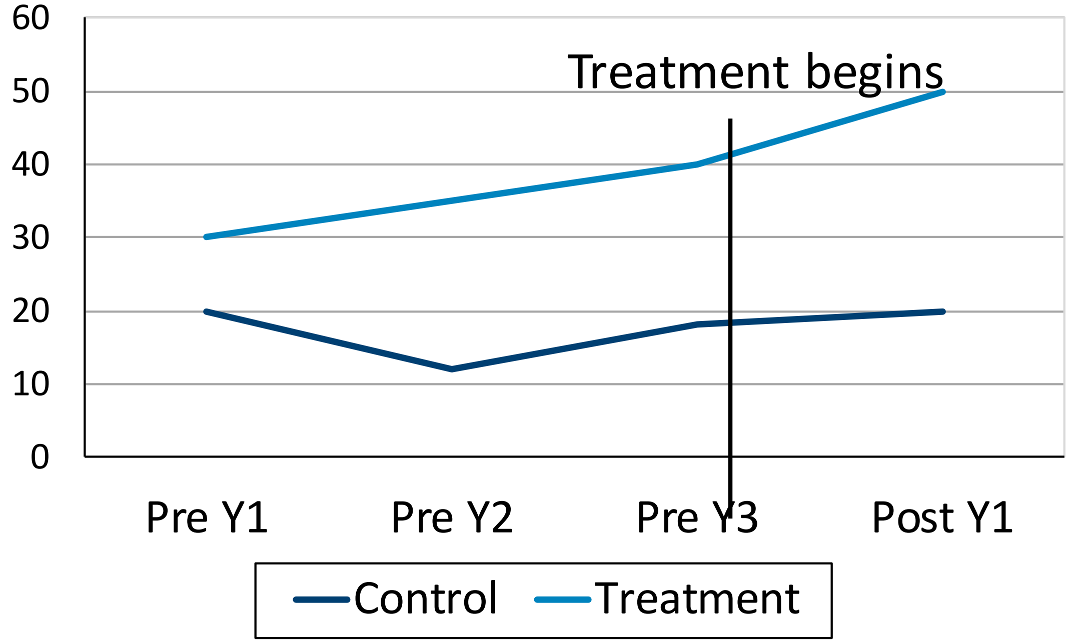
- Strengths
  - Eliminates any pre-treatment differences in outcome between groups
  - Difference out time trend in treatment group
- Weaknesses
  - If unobserved factors that change over time, can have biased estimates

Panel data and Diff-Diff

- $Y_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 Post_{it} + \gamma_i + \varepsilon_{it}$
- $Y_{i2} - Y_{i1} = \beta_1 (T_{i2} - T_{i1}) + \beta_2 + \beta_3 (T_{i2} - T_{i1}) + (\varepsilon_{i2} - \varepsilon_{i1})$
- $\Delta Y_i = \beta_1 \Delta T_i + \beta_2 + \Delta \varepsilon_i$
- Addresses omitted variables bias if unmeasured time invariant factors

Test of Natural Experiments and Diff-in-Diff: Parallel trends assumption

- Examine trends in pre-treatment period



- Control group has upward trend in pre-treatment period
- Treatment group has downward and then upward trend in pre-treatment period

❖ Violates parallel trends

Test of Natural Experiments and Diff-in-Diff: Different Outcomes

- Measure outcomes not likely to be affected by treatment
- Significant differences only for outcomes expected to be impacted by treatment
  - Suggests causal association between treatment and outcomes of interest
- Significant differences both for outcomes expected to be impacted by treatment and unrelated outcomes
  - Suggests not causal association for treatment and outcomes of interest

Threats to Validity

<u>Internal Validity</u>

- Imperfect randomization ⟶ Instrumental Variables
- Failure to follow treatment protocol/attrition
- Treatment variation is not exogenous

<u>External validity</u>

- Non-representative treatment or sample

D-D Example

- Sommers, Benjamin D., et al. "Changes in self-reported insurance coverage, access to care, and health under the Affordable Care Act." *Jama* 314.4 (2015): 366-374.
- Voluntary Medicaid expansion to higher income adults by state in 2014
- 28 states had Medicaid expansion and 22 did not by March 2015
- Measure outcomes from 2012 and 2015 in low-income adults

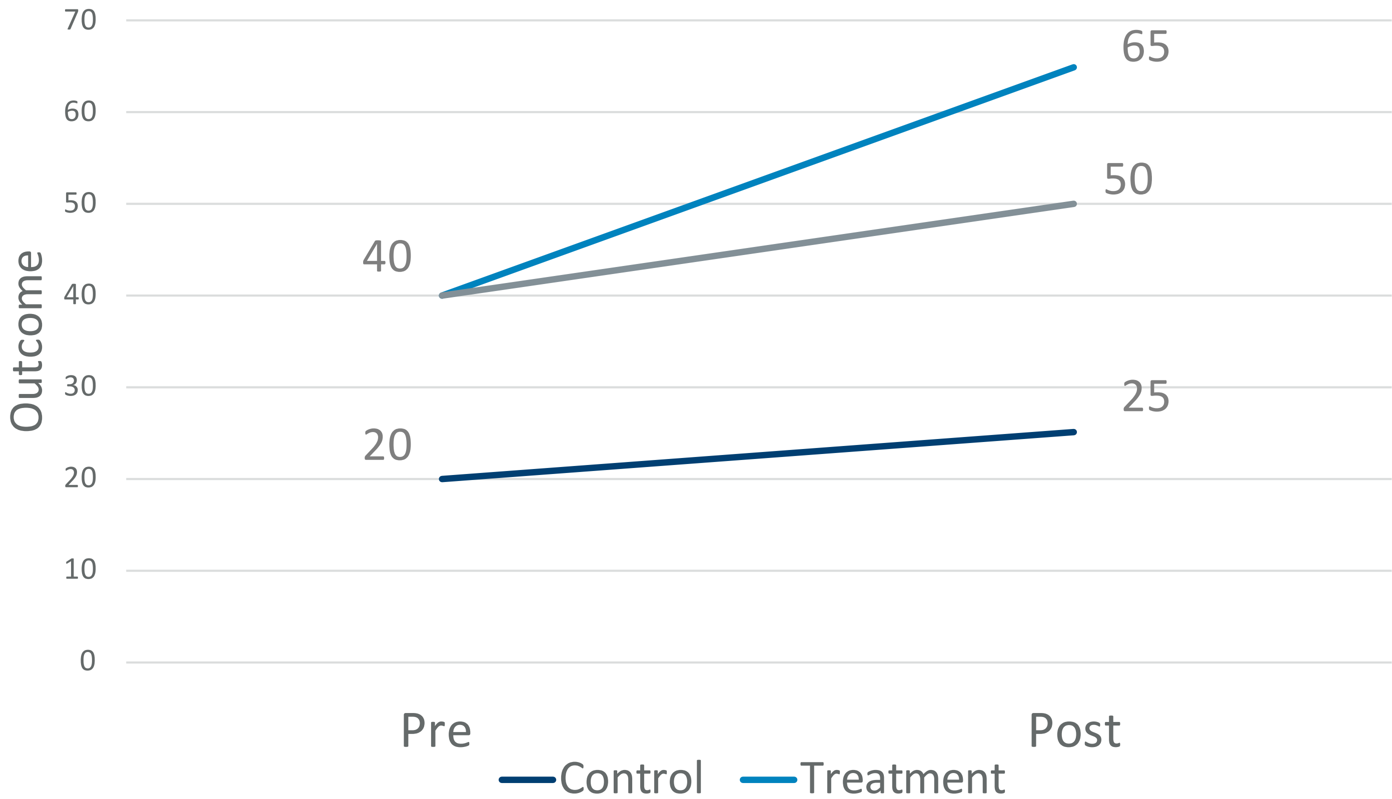
D-D Example

Table 4. Changes in Self-reported Coverage, Access to Care, and Health Among Low-Income Adults in Medicaid Expansion vs Nonexpansion States

Outcome	States, Unadjusted Mean, % (95% CI)[a] Medicaid Expansion (n = 48 905) Before ACA[b]	Medicaid Expansion (n = 48 905) After ACA[c]	Nonexpansion (n = 37 283) Before ACA[b]	Nonexpansion (n = 37 283) After ACA[c]	Differences-in-Differences Adjusted Estimate: Net Change After ACA (95% CI)	*P* Value
Uninsured	35.9 (35.3 to 36.5)	26.5 (25.8 to 27.3)	44.3 (43.5 to 45.0)	39.7 (38.9 to 40.6)	−5.2 (−7.9 to −2.6)	<.001
No personal physician	38.5 (37.8 to 39.1)	35.8 (35.0 to 36.7)	43.0 (42.3 to 43.7)	43.0 (42.0 to 44.0)	−1.8 (−3.4 to −0.3)	.02
No easy access to medicine	17.3 (16.8 to 17.8)	15.0 (14.4 to 15.7)	18.8 (18.2 to 19.4)	18.7 (17.9 to 19.5)	−2.2 (−3.8 to −0.7)	.005
Cannot afford care	35.5 (34.9 to 36.1)	33.1 (32.3 to 33.9)	40.2 (39.5 to 41.0)	39.5 (38.5 to 40.5)	−1.3 (−3.7 to 1.0)	.27
Fair/poor health	34.2 (33.6 to 34.8)	34.9 (34.0 to 35.7)	34.3 (33.6 to 35.0)	34.1 (33.2 to 35.1)	−0.1 (−1.7 to 1.4)	.84
% of Last 30 d in which activities were limited by poor health	16.4 (16.0 to 16.8)	16.6 (16.0 to 17.1)	17.4 (17.0 to 17.9)	17.2 (16.6 to 17.8)	−0.1 (−0.9 to 0.7)	.78

Sommers, Benjamin D., et al. "Changes in self-reported insurance coverage, access to care, and health under the Affordable Care Act." *Jama* 314.4 (2015): 366-374.

Poll 3
What is the Diff-in-diff estimator?



Possible responses: A. 10 B. 15 C. 25

Review

- Quasi-experimental methods can help address common sources of bias of treatment effects in observational studies.
- Natural experiments are a type of quasi-experimental design that exploit variation in implementation of treatments/ programs/ policies
- Difference-in-differences is frequently used in natural experiments since it can difference out any pre-treatment and post-treatment changes in outcomes not related to the treatment itself

D-D References

- Stock, James H., and Mark W. Watson. *Introduction to econometrics*. 2015.
- Wooldridge, J. M.: *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, Mass., 2002.
- Campbell, D. T., and Stanley, J. C. *Experimental and Quasi-experimental Designs for Research*. Chicago: Rand McNally, 1966.

More Advanced D-D References

- Daw, Jamie R., and Laura A. Hatfield. "Matching and regression to the mean in difference-in-differences analysis." *Health services research* 53.6 (2018): 4138-4156.
- Kahn-Lang, Ariella, and Kevin Lang. "The promise and pitfalls of differences-in-differences: Reflections on 16 and pregnant and other applications." *Journal of Business & Economic Statistics* 38.3 (2020): 613-620.
- Lindner, Stephan, and K. John McConnell. "Difference-in-differences and matching on outcomes: a tale of two unobservables." *Health Services and Outcomes Research Methodology* 19.2 (2019): 127-144.

References for Examples Used

Sommers, Benjamin D., et al. "Changes in self-reported insurance coverage, access to care, and health under the Affordable Care Act." *Jama* 314.4 (2015): 366-374.

Lindahl, Mikael. "Estimating the effect of income on health and mortality using lottery prizes as an exogenous source of variation in income." *Journal of Human resources* 40.1 (2005): 144-168.

Mark, Barbara A., et al. "California's minimum nurse staffing legislation: results from a natural experiment." *Health services research* 48.2pt1 (2013): 435-454.

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Regression Discontinuity

Liam Rose, Ph.D.

March 3, 2021

Instrumental Variables

Kritee Gujral, Ph.D.

March 10, 2021

Interval Regression

Libby Dismuke, Ph.D.

Questions?

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