Natural Experiments and Difference-in-Differences

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Health Economics Resource Center

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Health Services Research & Development Service

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 between treatment and control groups
- Correlation between error term and treatment leads to unbiased estimates of treatment 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

- VA increase in medication copayments in 2002 and lipid-lowering medication adherence (Doshi 2009)
- Patients treated in ED by low-intensity versus high intensity opioid prescribers and long-term opioid use (Barnett 2017)
- COVID-19 rates and state mandates for face masks in public during COVID-19 pandemic (Lyu 2020)

Question for Attendees

- What are other examples of natural experiments?
  - Type response in chat window

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: parallel trends assumption
- 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

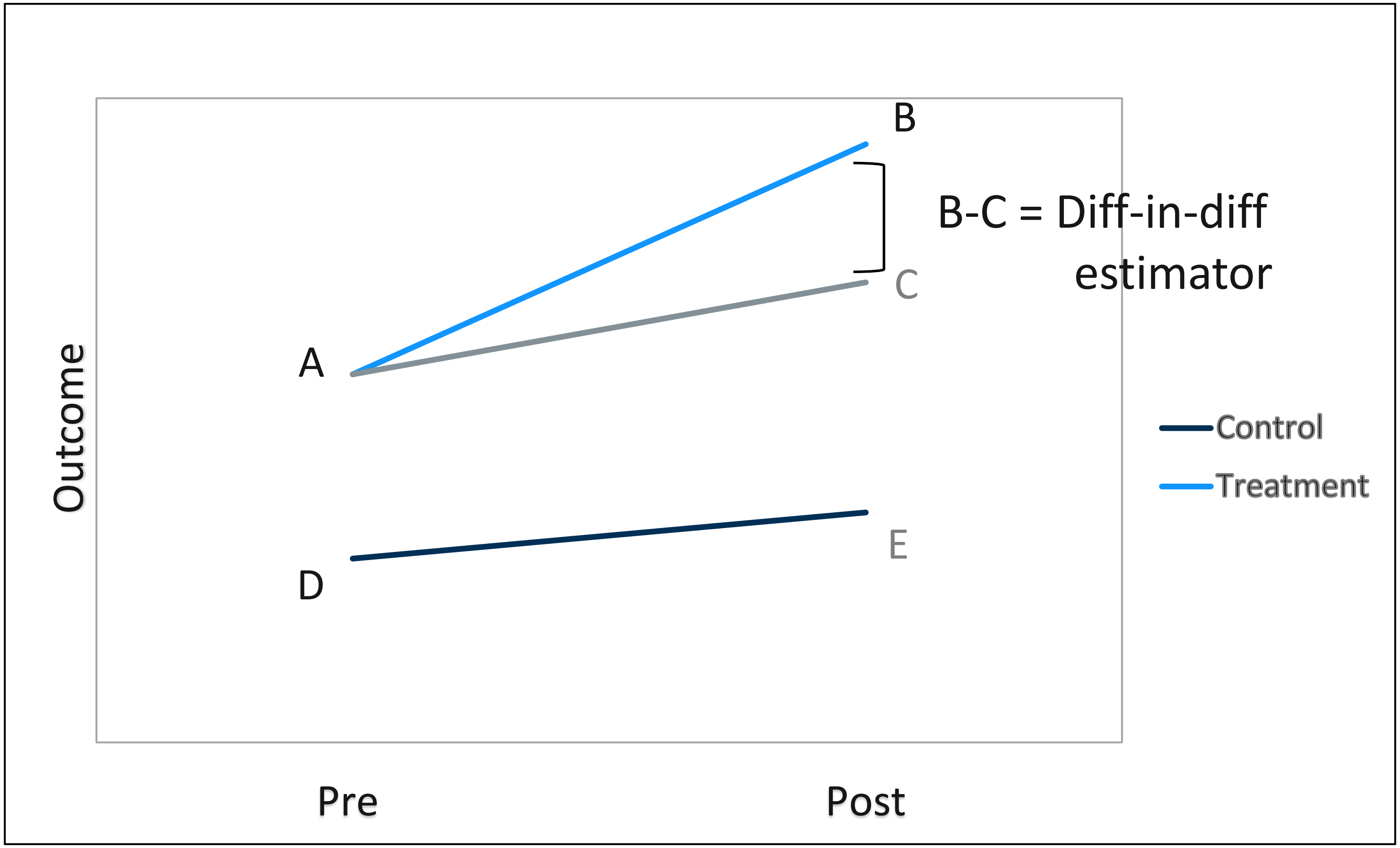
$$Y = \beta_0 + \beta_1 Post + \beta_2 Treatment + \beta_3 Post{*}Treatment + \varepsilon$$

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

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

- β_3 is the diff-in-diff estimator

Chart for Diff-in-Diff

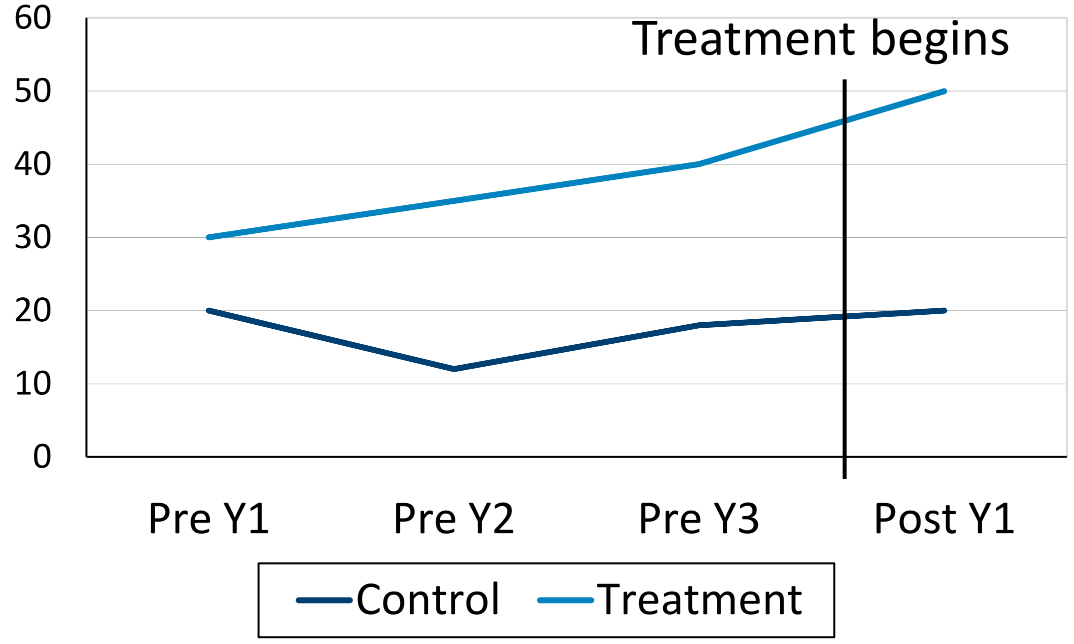


Strengths and Weaknesses

- 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

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

- Examine trends in pre-treatment period– need more than 1 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

Internal Validity

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

External validity

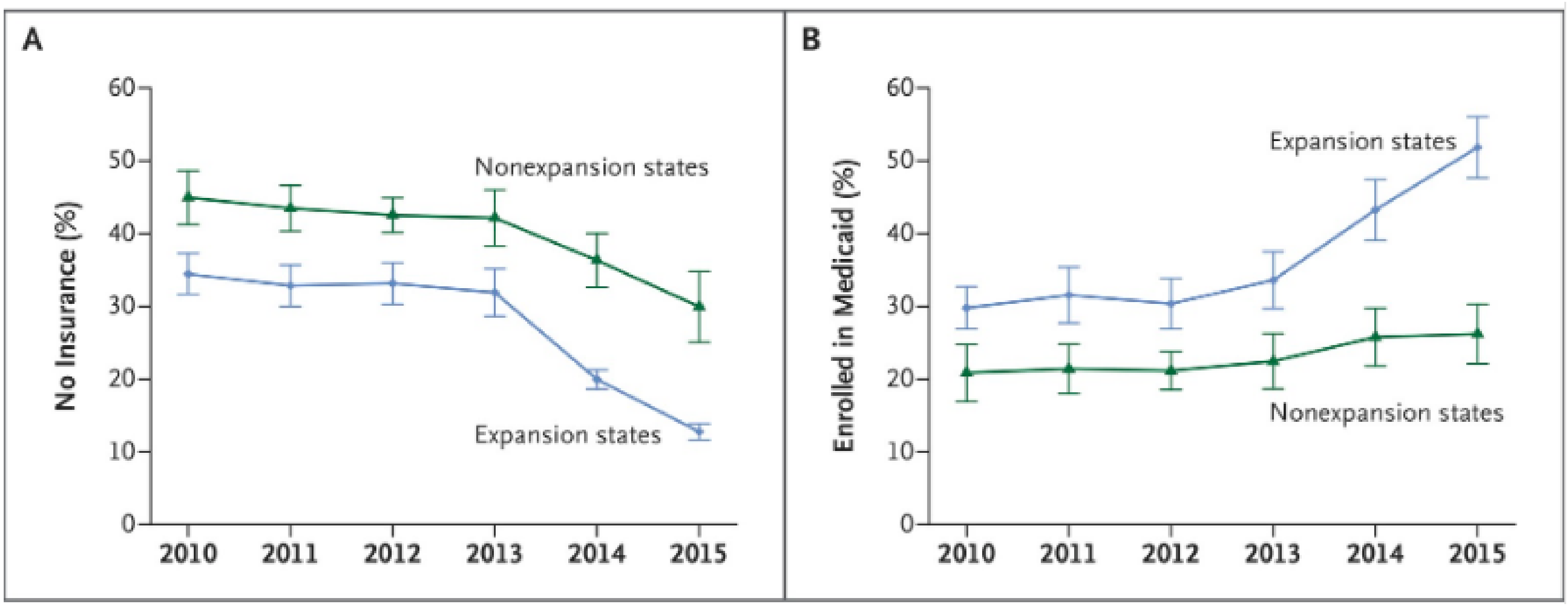
- Non-representative treatment or sample

D-D Example

- Miller, S. and Wherry, L.R., 2017. Health and access to care during the first 2 years of the ACA Medicaid expansions. *New England Journal of Medicine*, *376*(10), pp.947-956.
- Voluntary Medicaid expansion to higher income adults in some states in 2014
- 29 states had Medicaid expansion and 21 did not by March 2015
- Compared outcomes for insurance coverage, access to and use of medical care in the past 12 months, health status using survey data 4 years before and 2 years after Medicaid expansion

D-D Example:

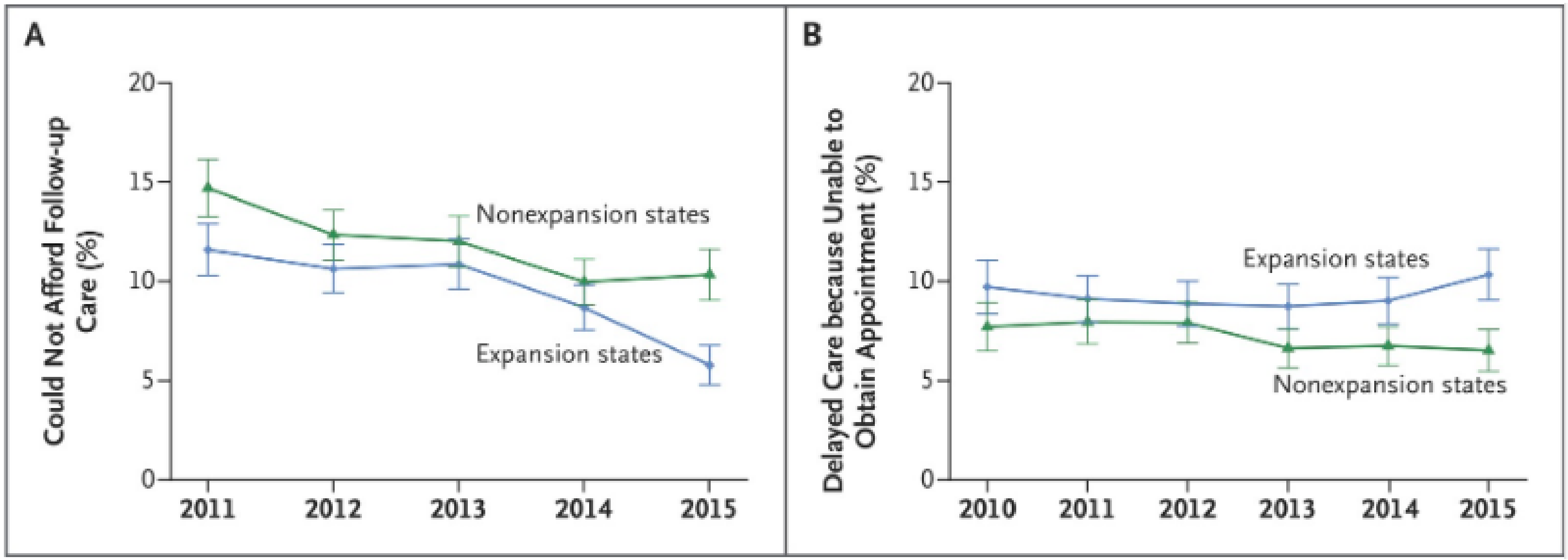
Unadjusted Trends in Insurance Coverage



Miller, S. and Wherry, L.R., 2017. Health and access to care during the first 2 years of the ACA Medicaid expansions. *New England Journal of Medicine*, *376*(10), pp.947-956.

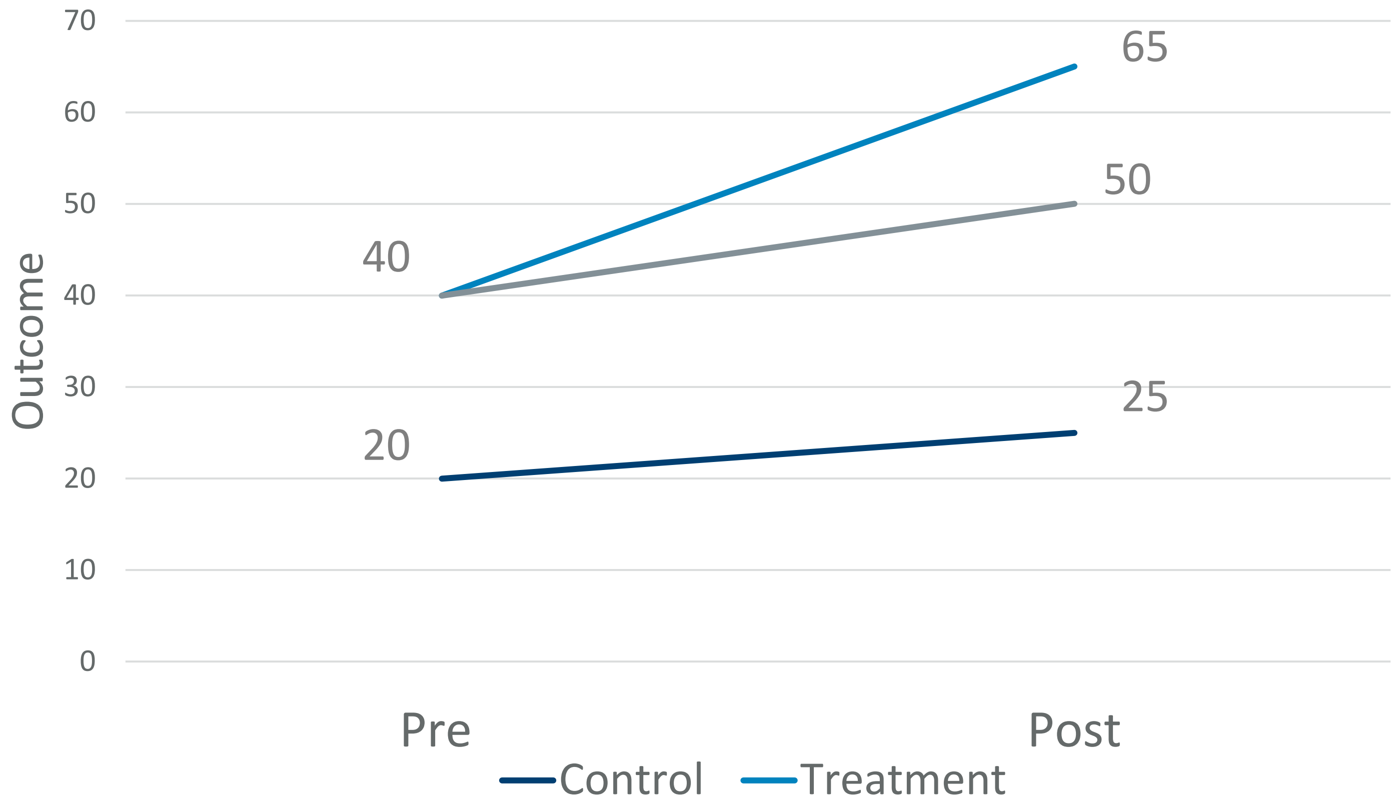
D-D Example:

Unadjusted Trends in Access to Care and Appointment Availability



Miller, S. and Wherry, L.R., 2017. Health and access to care during the first 2 years of the ACA Medicaid expansions. *New England Journal of Medicine*, *376*(10), pp.947-956.

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



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

Matching in D-D

- 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.
- Many studies used matched samples of treatment and control groups in order to obtain comparable samples
- DID does not require treatment and control groups have similar pre-intervention level of outcomes, yet studies often match on this
- When differences in pre-treatment levels of outcome are large between groups, more bias in DID effect due to regression to the mean
- Matching groups on time-varying covariates also leads to bias in DID effect

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 differences out pre- 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

- Zeldow, B. and Hatfield, L.A., 2021. Confounding and regression adjustment in difference-in-differences studies. *Health services research*, *56*(5), pp.932-941.
- Ryan, A.M., Kontopantelis, E., Linden, A. and Burgess Jr, J.F., 2019. Now trending: Coping with non-parallel trends in difference-in-differences analysis. *Statistical methods in medical research*, *28*(12), pp.3697-3711.
- 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

Miller, S. and Wherry, L.R., 2017. Health and access to care during the first 2 years of the ACA Medicaid expansions. *New England Journal of Medicine*, *376*(10), pp.947-956.

Doshi, J.A., Zhu, J., Lee, B.Y., Kimmel, S.E. and Volpp, K.G., 2009. Impact of a prescription copayment increase on lipid-lowering medication adherence in veterans. *Circulation*, *119*(3), pp.390-397.

Barnett, M.L., Olenski, A.R. and Jena, A.B., 2017. Opioid-prescribing patterns of emergency physicians and risk of long-term use. *New England Journal of Medicine*, *376*(7), pp.663-673.

Lyu, W. and Wehby, G.L., 2020. Community Use Of Face Masks And COVID-19: Evidence From A Natural Experiment Of State Mandates In The US: Study examines impact on COVID-19 growth rates associated with state government mandates requiring face mask use in public. *Health affairs*, *39*(8), pp.1419-1425.

Next HERC Lectures

3/1/2023	Interval regression	Clara Dismuke-Greer, Ph.D.
3/8/2023	Quantile regression	Diem Tran, Ph.D., M.P.P.
3/15/2023	Multipart models of continuous outcomes	Peter Veazie, PhD

Questions?

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