Natural Experiments and Difference-in-Differences

Christine Pal Chee, PhD

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Health Economics Resource Center

HSR&D
HEALTH SERVICES RESEARCH & DEVELOPMENT

Overview

- Causal effects and randomized controlled trials
- Natural experiments
- Difference-in-differences estimator

Poll: Natural Experiments

- Which of the following best describes your familiarity with natural experiments?
  - I am very familiar with the concept of natural experiments.
  - I have a working understanding of what natural experiments are.
  - I am new to the concept of natural experiments.

Poll: Difference-in-Differences

- Which of the following best describes your familiarity with difference-in-differences?
  - I am very familiar with difference-in-differences.
  - I have a working knowledge of difference-in-differences.
  - I am new to difference-in-differences.

Objectives

- Provide an overview of natural experiments
  - Motivation, definition, examples
- Provide an overview of the difference-in-differences estimator
  - Motivation, definition, example, assumptions, limitations

Causal Effects

- Many questions in health services research aim to estimate causal effects
  - Does the adoption of electronic medical records reduce health care costs or improve quality of care?
  - Did the transition to Patient Aligned Care Teams (PACT) improve quality of care and health outcomes?
  - What effect will the Affordable Care Act (ACA) have on the demand for VHA services?
- Ideally studied through randomized controlled trials (RCTs)

RCTs: Estimating Causal Effects

- What is the effect of treatment on outcomes?

$$outcome_i = \beta_0 + \beta_1 treatment_i + e_i$$

  - e_i includes other factors that affect the outcome (e.g., age, gender, pre-existing conditions, income, education, etc.)
- In a RCT, treatment is randomly assigned:
  - Treatment is exogenous
    - $E(e_i | treatment_i) = 0$
    - e and treatment are uncorrelated
  - $\hat{\beta}_1$= average effect of treatment

Idealized Experiment

- To estimate the causal effect of treatment, randomly assign treatment
  - Not always feasible, ethical, or practical
  - Useful as a conceptual benchmark for observational studies

Natural Experiments

- External circumstances produce what appears to be randomization
  - Legal institutions, geography, timing of policies or programs, natural randomness in weather, birthdates, or other factors that are unrelated to the casual effect of interest
- Variation in individual circumstances make it appear ***as if*** treatment is randomly assigned
  - Exogenous variation in treatment

Example (1)

- What are the returns to physician human capital?
  - Doyle, Ewer, and Wagner (2010)
  - Setting:
    - VA hospital with affiliations with two medical schools
    - Residency programs vary substantially in terms of their rankings
    - Clinical teams from the two programs operate independently
    - Patients are assigned to clinical teams based on the last digit of their SSN (odd/even)
  - “As if” randomization of patients to clinical teams

Example (2)

- Does increasing Medicaid payments for primary care increase primary care visits and reduce hospital and emergency department use?
  - Gruber, Adams, and Newhouse (1997)
  - Setting:
    - In 1986, Tennessee increased its payments for primary care services
    - The neighboring state Georgia had a similar Medicaid reimbursement system and there were no other changes in the structure of payment incentives in either state during the study period
  - Exogenous increase in Medicaid payments for primary care

Example (3)

- Does more intensive treatment of acute myocardial infarction (AMI) in the elderly reduce mortality?
  - McClellan, McNeil, and Newhouse (1994)
  - Setting:
    - Patients who live closer to hospitals that have the capacity to perform more intensive treatments are more likely receive those treatments
    - The distance a patient lives from a given hospital should be independent of his health status
  - Distance affects the probability of intensive treatment of AMI

"As if" Randomization

- If the "as if" randomization fails to produce random assignment of treatment, then the OLS estimator, $\hat{\beta}_1$, is biased
- Evaluating the validity of the "as if" randomization assumption:
  - Check for differences between the treatment and control groups
    - Finding no observable differences is not sufficient
  - Use contextual knowledge and judgement to assess whether "as if" randomization assumption is reasonable

Types of Natural Experiments

- Two types of natural experiments:
  - Variation in individual circumstances cause treatment to be as if randomly assigned
    - Examples 1 and 2
    - Can use OLS to estimate the causal effect
  - Variation in individual circumstances only partially determines treatment
    - Example 3
    - Use instrumental variables regression to estimate the causal effect
      - More on this in the Instrumental Variables Regression lecture on April 22

Estimating Causal Effects

- One option is to compare pre- and post-treatment outcomes in the treatment group:

$$outcome_{it} = \beta_0 + \beta_1 post_t + e_i$$

$$post_t = \begin{cases} 1, & t \geq treatment\ date \\ 0, & t < treatment\ date \end{cases}$$

  – Issue: if other factors that affect the outcome or treatment changed during the study period, our estimate of the treatment effect, $\hat{\beta}_1$, will be biased

Estimating Causal Effects (2)

- Another option is to compare the post-treatment outcomes between treatment and control groups:

$$outcome_i = \beta_0 + \beta_1 treatment_i + e_i$$

$$treatment_i = \begin{cases} 1, & i\ in\ treatment\ group \\ 0, & i\ not\ in\ treatment\ group \end{cases}$$

  – Issue: if there are differences between the two groups, our estimate of the treatment effect, $\hat{\beta}_1$, will be biased

Difference-in-Differences Estimator

- Compare the change in the pre- and post-treatment outcomes across treatment and control groups:

$$
\begin{aligned}
outcome_{it} &\\
&= \beta_0 + \beta_1 treatment_i + \beta_2 post_t \\
&+ \beta_3 treatment_i \times post_t + e_{it}
\end{aligned}
$$

- $\hat{\beta}_3$: average change in outcome for those in the treatment group, minus the average change in outcome for those in the control group
  - Average treatment effect in the population studied

Difference-in-Differences

$$y_{it} = \beta_0 + \beta_1 tx_i + \beta_2 post_t + \beta_3 tx_i \cdot post_t + e_{it}$$

$$\left.\begin{aligned} &\blacksquare\ E(y_{it}|tx_i = 0\,, post_t = 0) = \beta_0 \\ &\blacksquare\ E(y_{it}|tx_i = 0\,, post_t = 1) = \beta_0 + \beta_2 \end{aligned}\right\} d_0$$

$$\left.\begin{aligned} &\blacksquare\ E(y_{it}|tx_i = 1\,, post_t = 0) = \beta_0 + \beta_1 \\ &\blacksquare\ E(y_{it}|tx_i = 1\,, post_t = 1) = \beta_0 + \beta_1 + \beta_2 + \beta_3 \end{aligned}\right\} d_1$$

$$d_0 = \beta_2$$

$$d_1 = \beta_2 + \beta_3$$

$$dd = d_1 - d_0 = (\beta_2 + \beta_3) - \beta_2 = \beta_3$$

D-D Example

- Does increasing Medicaid payments for primary care increase primary care visits and reduce hospital and emergency department use?
  – Gruber, Adams, and Newhouse (1997)

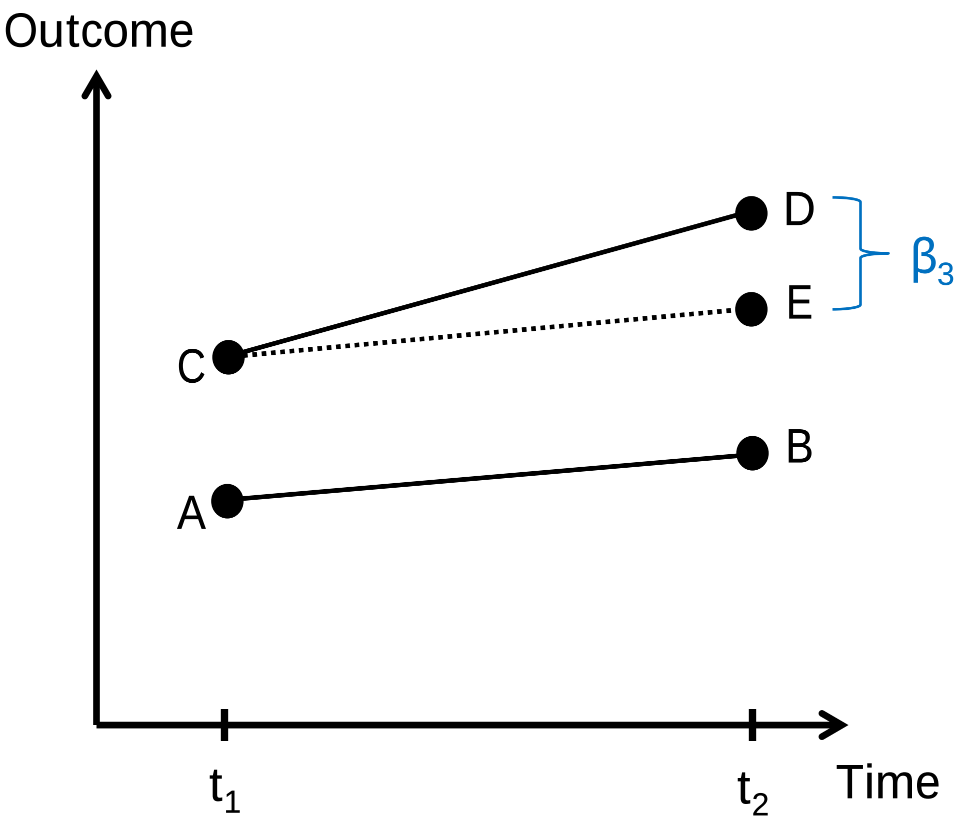
D-D Example (2)

Table 1
Dominant Site of Care

	Tennessee			Georgia			
	Before	After	Diff	Before	After	Diff	Diff-in-Diff
Physician's office	0.259	0.294	0.035	0.355	0.335	−0.020	0.055
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
	{34.1%}	{38.5%}		{47.9%}	{45.7%}		[21.2%]
Clinic	0.197	0.165	−0.032	0.084	0.092	0.008	−0.041
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
	{26.0%}	{21.6%}		{11.3%}	{12.5%}		[−20.8%]
Hospital outpatient department	0.187	0.221	0.035	0.181	0.217	0.036	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
	{24.6%}	{29.0%}		{24.4%}	{29.6%}		[0.53%]
Emergency room	0.117	0.083	−0.034	0.122	0.089	−0.032	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	{15.4%}	{10.8%}		{16.4%}	{12.2%}		[−1.71%]

Notes: Figures are the share of enrollees for whom each site is their dominant site of care for the year. Standard errors in parentheses; site effects as a share of all sites in brackets {}; DD estimates as a percentage of baseline (1985) values for Tennessee in square brackets []. "Before" is 1985; "After" is 1987 and 1988; "Diff" is after minus before; "Diff-in-diff" is diff for Tennessee minus diff for Georgia. N = 179,159 for Tennessee and 259,323 for Georgia.

Difference-in-Differences



Average outcome for:

- A: control group, pre
- B: control group, post
- C: tx group, pre
- D: tx group, post
- E: tx group, post (absent treatment)

Assumption: Common trends in the absence of treatment

Common Trends

- Assumption: Trends in the outcome would be the same in both treatment and control groups in the absence of treatment
  - Difference-in-differences estimates the deviation (due to treatment) from the common trend
- Check pre-treatment trends
  - Data and contextual knowledge

Limitations

- Limitations of estimating causal effects in natural experiments:
  - Generalizability of results to contexts other than the one studied may be limited
  - Mechanism for the treatment effect is often unknown

Additional Considerations

- When using repeated cross-sectional or panel data, estimated standard errors must account for serial correlation
  - For more details, see: Bertrand, Duflo, and Mullainathan (2004)

Summary

- Natural experiments are situations where external circumstances produce what appears to be randomization
  - ***As if*** treatment is randomly assigned
- Difference-in-differences is one method of estimating the causal treatment effect in natural experiments
  - In order to estimate the causal effect of treatment need:
    - Exogenous (as if random) variation in treatment
    - Common underlying trends
  - Difference-in-differences estimates the average treatment effect

References and Resources

- Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. 2004. "How Much Should We Trust Differences-in-Differences Estimates?" *Quarterly Journal of Economics*, 119(1): 249-275.
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- Stock, James H. and Mark W. Watson, 2011. Introduction to Econometrics (Third Edition). Boston, MA: Addison-Wesley. (Chapter 13: Experiments and Quasi-Experiments)