Natural Experiments and Difference-in-Differences

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March 1, 2017

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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?
  A. I am very familiar with the concept of natural experiments
  B. I have a working understanding of what natural experiments are
  C. 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?
  A. I am very familiar with difference-in-differences
  B. I have a working knowledge of difference-in-differences
  C. 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, assumptions, example, 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 March 8

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:

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

- $\hat{\beta}_3$: 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

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

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

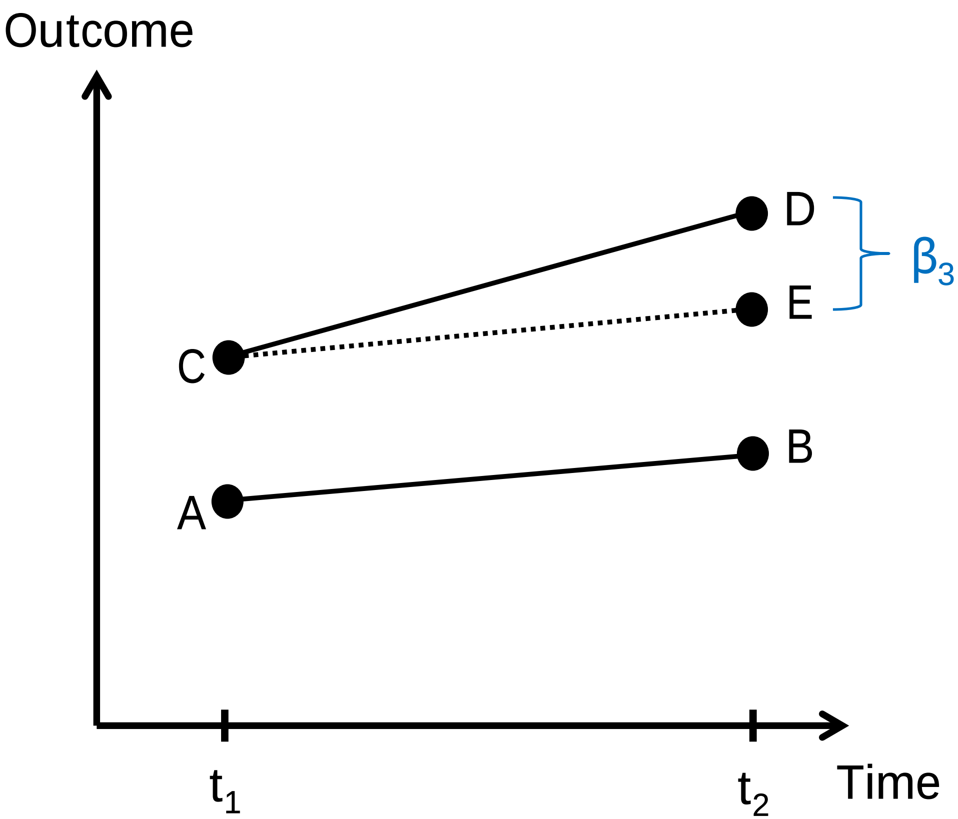
$$\left.\begin{array}{l} \blacksquare\ E(y_{it}|tx_i = 1\,, post_t = 0) = \beta_0 + \beta_1 \\ \blacksquare\ E(y_{it}|tx_i = 1\,, post_t = 1) = \beta_0 + \beta_1 + \beta_2 + \beta_3 \end{array}\right\} d_1$$

$$d_0 = \beta_2$$

$$d_1 = \beta_2 + \beta_3$$

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

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

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.

Poll: Underlying Assumptions

- Select all that apply:
  A. Tennessee and Georgia are similar
  B. There were no other changes besides the change in fee policy that affect the variables of interest in Tennessee relative to Georgia
  C. What would have happened to the variables of interest in Tennessee had the fee policy not been changed is what happened in Georgia

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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- Gruber, Jonathan, Kathleen Adams, and Joseph Newhouse. 1997. "Physician Fee Policy and Medicaid Program Costs." *Journal of Human Resources*, 32(4): 611-634.
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