Econometrics for Causal Inference

URP Part 1: Causal Inference and Difference-in-Difference

Sungkyunkwan University
- Machine Learning and Econometrics -

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Econometrics and Causal Inference

- Mastering Econometrics
- Mostly Harmless Econometrics
- Empirical Strategy for Microeconomics

Econometrics and Causal Inference

Econometrics

- Examine empirical relationship between variables

$$y = X\beta + \epsilon$$

1. $E[Y|X] = X\beta$: explain the average behavior of Y given X
   - Association between variables
   - Causal inference

2. $Y_{t+1} = E[Y|X_{t+1}]$: predict Y based on X

What is Causal Inference

- Forecasting and Causal Relationship
  : Causal Inference vs Machine Learning

- **Pattern** between variables $\longrightarrow$ predicting Y using X

$$Y = f(X)$$

Econometrics and Causal Inference

What is Causal Inference

- Forecasting and Causal Relationship
  : Causal Inference vs Machine Learning

- **Causal Association**
  - Association: variables "move together" (Correlation)
  - Ceteris Paribus: other conditions remaining the same
  - specific change (T) $\longrightarrow$ consequence (Y)
  - $E[Y|X, T=1] - E[Y|X, T=0]$

- Causality = Association + Ceteris Paribus + Direction

Causal Inference and Regression

- Regression in the perspective of causal inference

$$y = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + ... + \beta_k x_k + \epsilon$$

$$\beta_1 = \frac{\partial y}{\partial x_1}$$

- Estimation procedure
  1. $x1$ to x_2, ... $x_k \longrightarrow Residual_{x1}$
  2. y to x_2, ... $x_k \longrightarrow Residual_y$
  3. $Residual_y$ to $Residual_{x1}$

- If we perfectly make a regression model, then each coefficient can be interpreted as a causal relationship

Counterfactual

Identification of Causal Relationship

- Causal association: specific change $\longrightarrow$ consequence
  - Specific change: **Treatment**
  - Consequence: **Effect**

- Example: the causal effect of graduate school

Counterfactual

Identification of Causal Relationship

- Causal association: specific change $\longrightarrow$ consequence
  - Specific change: **Treatment**
  - Consequence: **Effect**

- Example: the causal effect of graduate school
  - Treatment: graduate school (G)
  - Effect: income, etc.... (y)

Identification of Causal Relationship

- How can we make "Ceteris Paribus"

Counterfactual!

- Example: the causal effect of graduate school
  - Graduate school person A: Y_{1A}
  - No graduate school person A: Y_{0A}
- Treatment effect $= Y_{1A} - Y_{0A}$
- Average treatment effect $= E[Y_{1i} - Y_{0i}]$

Counterfactual

Identification of Causal Relationship

- However.... actually there's not "a counterfactual"
- Real: $E[Y_{1i} - Y_{0j}] = E[Y_{1i} - Y_{0j}] + E[Y_{0i} - Y_{0j}]$
- We need to make strategies for identifying 'causal relationship'
- **Difference-in-Difference** is the one of the most important strategy for identifying 'causal relationship'

Difference-in-Difference

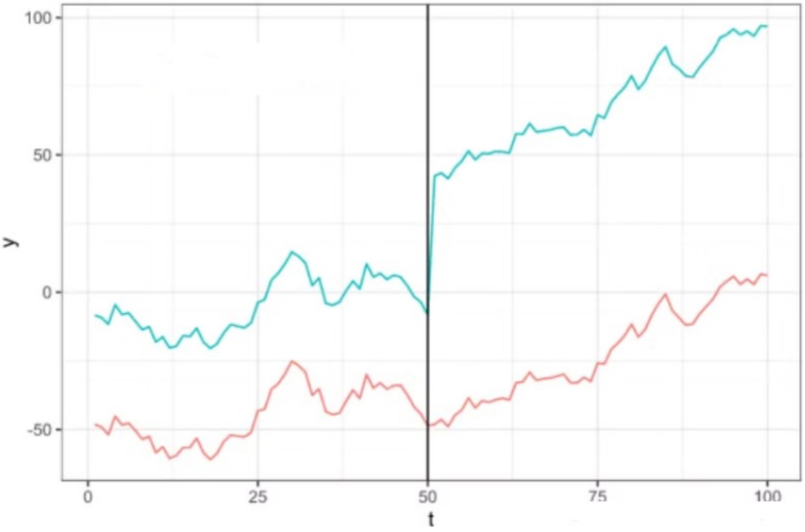

Figure: Difference-in-Difference

Difference-in-Difference

What is DiD?

- Specific treatment happens at a point
- How can we analyze the effect of treatment?
- Counterfactual: untreated group similar to treated group
- Compare groups before and after treatment

Difference-in-Difference

Identification Strategy

$$Y_{it} = \beta_0 + \beta_1 Treat_i + \beta_2 Post_t + \tau Treat_i \times Post_t + \epsilon_{it}$$

	Post=0	**Post=1**
Treat=0	β_0	$\beta_0 + \beta_2$
Treat=1	$\beta_0 + \beta_1$	$\beta_0 + \beta_1 + \beta_2 + \tau$

$$Effect = (E[Y|Treat = 1, Post = 1] - E[Y|Treat = 1, Post = 0])$$
$$-(E[Y|Treat = 0, Post = 1] - E[Y|Treat = 0, Post = 0]) = \tau$$

Difference-in-Difference

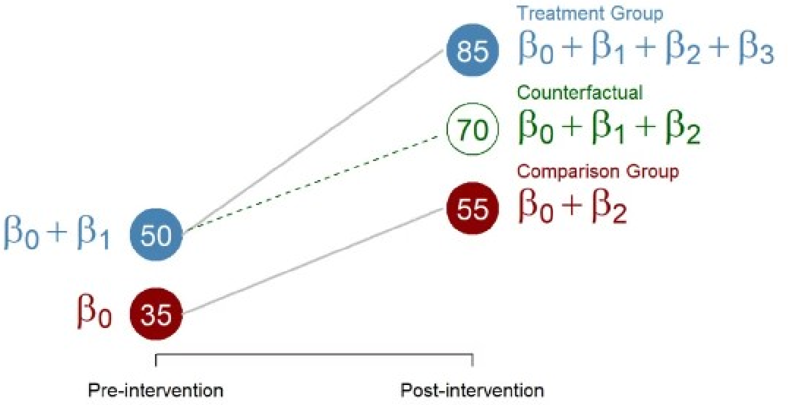

Figure: Difference-in-Difference

Richardson and Troost (2009)

Mississippi Experiment: The Great Depression

- US Federal Reserve System is organized into 12 districts.
  - St. Louis Fed - 6th Districts
  - Atlanta Fed - 8th Districts

  $\longrightarrow$ cut Mississippi state into halves

- The effect of Fed monetary policy
  - Treatment: Caldwell fails / banking crisis begins
  - St. Louis Fed(Treatment): active monetary policy
  - Atlanta Fed(Control): inactive monetary policy

Richardson and Troost (2009)

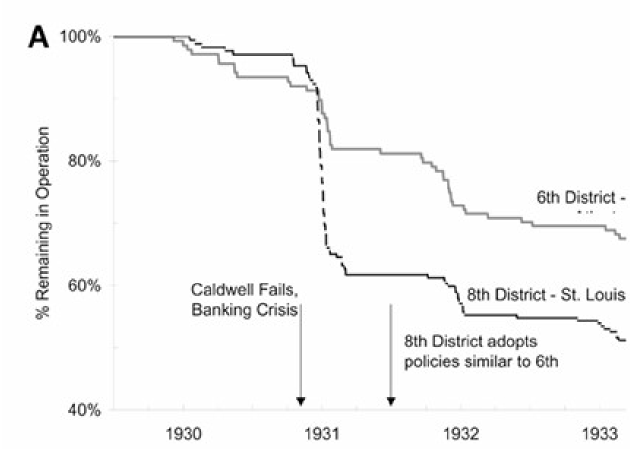

Figure: Richardson and Troost (2009)

Homework

Card and Kruger (1994)

- The effect of minimum wage using DiD
- What is the treatment in this research?
- Find the treatment group and control group
- Find main τ in this paper and replicate it in two ways
- What can be the potential problems in this research?
- Write one page report including above things

Next Time: Problems and Solution

$$E[Y_{1i} - Y_{0j}] = E[Y_{1i} - Y_{0i}] + E[Y_{0i} - Y_{0j}]$$
$$= ATE + SelectionBias$$

$$\tau^{\hat{D}D} = (Y_{i,t=1}(1) - Y_{i,t=0}(0)) - (Y_{j,t=1}(0) - Y_{j,t=0}(0))$$
$$= (Y_{i,t=1}(1) - Y_{i,t=0}(0)) - (Y_{j,t=1}(0) - Y_{j,t=0}(0))$$
$$+(Y_{i,t=1}(0) - (Y_{i,t=1}(0))$$
$$= (Y_{i,t=1}(1) - Y_{i,t=1}(0)) + [(Y_{i,t=1}(0) - Y_{i,t=0}(0)) - (Y_{j,t=1}(0) - Y_{j,t=0}(0))]$$
$$\approx E[Y_{i,t=1}(1) - Y_{i,t=1}(0) | T_i = 1] + E[Y_{i,t=1}(1) - Y_{i,t=1}(0) | T_i = 1]$$
$$-E[Y_{j,t=1}(1) - Y_{j,t=1}(0) | T_i = 0]$$
$$= \tau + CounterfactualTrend - UntreatedTrend$$