Program Evaluation (Causal Inference) 2: Difference-in-differences

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Section 1

Introduction

Introduction

- Difference-in-differences (DID)
  - Exploit the panel data structure to estimate the causal effect.
- Consider that
  - Treatment and control group comparison: selection bias
  - Before v.s. After comparison: time trend
- DID combines those two comparisons to draw causal conclusion.

DID in Figure (on screen)

Plan of the Lecture

- Formal Framework
- Implementation in a regression framework
- Parallel Trend Assumption

Reference

- Angrist and Pischke "Mostly Harmless Econometrics" Chapter 5
- Marianne Bertrand, Esther Duflo, Sendhil Mullainathan, How Much Should We Trust Differences-In-Differences Estimates?, *The Quarterly Journal of Economics*, Volume 119, Issue 1, February 2004, Pages 249–275, https://doi.org/10.1162/003355304772839588
  - Discuss issues of calculating standard errors in the DID method.
- Hiro Ishise, Shuhei Kitamura, Masa Kudamatsu, Tetsuya Matsubayashi, and Takeshi Murooka (2019) "Empirical Research Design for Public Policy School Students: How to Conduct Policy Evaluations with Difference-in-differences Estimation" February 2019
  - Slide: https://slides.com/kudamatsu/did-manual/fullscreen/#
  - Paper: https://docs.google.com/viewer?a=v&pid=sites&srcid=ZGVmYXVsdGRvbWFpbnxta3VkYW1hdHN1fGd4OjM4YzkwYmVjM2ZmMz

Section 2

Framework

Framework

- Consider two periods: $t = 1, 2$. Treatment implemented at $t = 2$.
- Y_{it}: observed outcome for person i in period t
- G_i: dummy for treatment group
- D_{it}: treatment status
  - $D_{it} = 1$ if $t = 2$ and $G_i = 1$
- *potential outcomes*
  - $Y_{it}(1)$: outcome for i when she is treated
  - $Y_{it}(0)$: outcome for i when she is not treated
- With this, we can write

$$Y_{it} = D_{it} Y_{it}(1) + (1 - D_{it}) Y_{it}(0)$$

Identification

- Goal: ATT at $t = 2$

$$E[Y_{i2}(1) - Y_{i2}(0)|G_i = 1] = E[Y_{i2}(1)|G_i = 1] - E[Y_{i2}(0)|G_i = 1]$$

- What we observe

	Pre-period ($t = 1$)	Post ($t = 2$)
Treatment ($G_i = 1$)	$E[Y_{i1}(0)\|G_i = 1]$	$E[Y_{i2}(1)\|G_i = 1]$
Control ($G_i = 0$)	$E[Y_{i1}(0)\|G_i = 0]$	$E[Y_{i2}(0)\|G_i = 0]$

- Under what assumptions can we the ATT?
  - Simple comparison if $E[Y_{i2}(0)|G_i = 1] = E[Y_{i2}(0)|G_i = 0]$.
  - Before-after comparison if $E[Y_{i2}(0)|G_i = 1] = E[Y_{i1}(0)|G_i = 1]$.
  - Other (more reasonable) assumption?

Parallel Trend Assumption

- Assumption:

$$E[Y_{i2}(0) - Y_{i1}(0)|G_i = 0] = E[Y_{i2}(0) - Y_{i1}(0)|G_i = 1]$$

  - Change in the outcome *in the absence of treatment* is the same across two groups.

- Then,

$$\begin{aligned}\underbrace{E[Y_{i2}(1) - Y_{i2}(0)|G_i = 1]}_{ATT} =& E[Y_{i2}(1)|G_i = 1] - E[Y_{i2}(0)|G_i = 1] \\ =& E[Y_{i2}(1)|G_i = 1] - E[Y_{i1}(0)|G_i = 1] \\ &- \underbrace{(E[Y_{i2}(0)|G_i = 1] - E[Y_{i1}(0)|G_i = 1])}_{=E[Y_{i2}(0)-Y_{i1}(0)|G_i=0]\ (pararell\ \ trend)}\end{aligned}$$

- Thus,

$$ATT = E[Y_{i2}(1) - Y_{i1}(0)|G_i = 1] - E[Y_{i2}(0) - Y_{i1}(0)|G_i = 0]$$

which is why this is called “difference-in-differences”.

Section 3

Estimation

Estimation Approach

1. Plug-in estimator
2. Regression estimators

Plug-in Estimator

- Remember that the ATT is

$$ATT = E[Y_{i2}(1) - Y_{i1}(0)|G_i = 1] - E[Y_{i2}(0) - Y_{i1}(0)|G_i = 0]$$

- Replace them with the sample average.

$$\begin{aligned} A\hat{TT} = & \{\bar{y}(t=2, G=1) - \bar{y}(t=1, G=1)\} \\ & - \{\bar{y}(t=2, G=0) - \bar{y}(t=1, G=0)\} \end{aligned}$$

where $\bar{y}(t, G)$ is the sample average for group G in period t .

- Easy to make a 2×2 table!

Example: Card and Kruger (1994)

Variable	Stores by state PA (i)	NJ (ii)	Difference, NJ – PA (iii)
1. FTE employment before, all available observations	23.33 (1.35)	20.44 (0.51)	−2.89 (1.44)
2. FTE employment after, all available observations	21.17 (0.94)	21.03 (0.52)	−0.14 (1.07)
3. Change in mean FTE employment	−2.16 (1.25)	0.59 (0.54)	2.76 (1.36)

Figure 1: image

Regression Estimators

- Run the following regression

$$y_{it} = \alpha_0 + \alpha_1 G_i + \alpha_2 T_t + \alpha_3 D_{it} + \beta X_{it} + \epsilon_{it}$$

  - G_i: dummy for treatment group
  - T_t :dummy for treatment period
  - $D_{it} = G_i \times T_t$. α_3 captures the ATT.
- Regression framework can incorporate covariates X_{it}, which is important to control for observed confounding factors.

Regression Estimators with FEs

- With panel data

$$y_{it} = \alpha D_{it} + \beta X_{it} + \epsilon_i + \epsilon_t + \epsilon_{it}$$

where ϵ_i is individual FE and ϵ_t is time FE.

- Do not forget to use the cluster-robust standard errors!
  - See Bertrand, Duflo, and Mullainathan (2004, QJE) for the standard error issues.

Section 4

Parallel Trend

Discussions on Parallel Trend

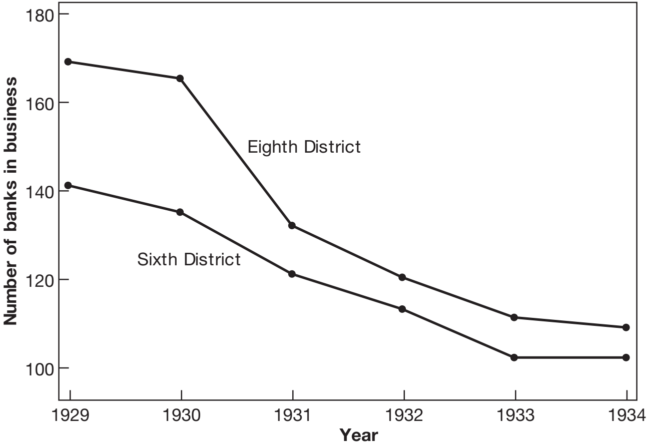
- Parallel trend assumption can be violated in various situations.
- Most critical issue: Treatment may depend on *time-varying factors*
  - DID can only deal with **time-invariant factors**.
- Self-selection: participants in worker training programs experience a decrease in earnings before they enter the program
- Targeting: policies may be targeted at units that are currently performing best (or worst).

Diagnostics for Parallel Trends: Pre-treatment trends

- Check if the trends are parallel in the pre-treatment periods
- Requires data on multiple pre-treatment periods (the more the better)
- This is very popular. You MUST do this if you have multiple pre-treatment periods.
- Note: this is only diagnostics, NEVER a direct test of the assumption!
  - You should never say "the key assumption for DID is satisfied if the pre-treatment trends are parallel.

Example (Fig 5.2 from Mastering Metrics)

FIGURE 5.2
Trends in bank failures in the Sixth and Eighth Federal Reserve Districts



Note: This figure shows the number of banks in operation in Mississippi in the Sixth and Eighth Federal Reserve Districts between 1929 and 1934.

Other Diagnostics: Placebo test

- Placebo test using other period as treatment period.

$$y_{it} = \sum_{\tau} \gamma_\tau G_i \times I_{t,\tau} + \mu_i + \nu_t + \epsilon_{it}$$

  - The estimates of γ_τ should be close to zero up to the beggining of treatment (Fig 5.2.4 of Angrist and Pischke)
- Placebo test using different dependent variable which should not be affected by the policy.

Section 5

Research Strategy

Research Strategy using DID

- Going back to Ishise et al (2019)
  1. How to find a research question
  2. What outcome dataset to look for
  3. What policy to look for (except for example 1 and 2).