

ISEA Week 13 – Causal Inference: Difference-in-Differences

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Agenda

1. Difference-in-Differences (DiD): The Basics
2. Potential Outcomes in a DiD framework
3. Example of DiD usage in education policy
4. Application: Using DiD approach to assess user learning in an A/B test environment
 - How should we think about causality?
5. Coding

Difference-in-Differences (Graphical Approach)

> Let's draw!

Difference-in-Differences (DiD) Regression Model

$$Y_i = \alpha + \beta T_i + \gamma G_i + \tau(G_i \times T_i) + \varepsilon_i$$

$$E[Y_i | G_i = 1, T_i = 1] =$$

$$E[Y_i | G_i = 1, T_i = 0] =$$

$$E[Y_i | G_i = 0, T_i = 1] =$$

$$E[Y_i | G_i = 0, T_i = 0] =$$

Defining the Difference-in-Difference (DiD) Treatment Effect

$$\tau^{\text{DiD}} = \left[E[Y_i \mid G_i = 1, T_i = 1] - E[Y_i \mid G_i = 1, T_i = 0] \right] \\ - \left[E[Y_i \mid G_i = 0, T_i = 1] - E[Y_i \mid G_i = 0, T_i = 0] \right]$$

Potential Outcomes Revisited: Estimating the Average Treatment Effect (ATE)

Potential Outcomes Framework: (Holland, 1986)

$$Y_i = Y_i(0) + T_i(Y_i(1) - Y_i(0))$$

$$\text{if } T_i = 1: Y_i = Y_i(1)$$

$$T_i = 0: Y_i = Y_i(0)$$

Assuming constant treatment effect:

$$Y_i(1) = Y_i(0) + \tau$$

Average Treatment Effect (ATE):

$$E[Y_i(1) - Y_i(0)] = \tau$$

Use difference in averages to estimate the ATE?

$$\begin{aligned} & E[Y_i|T_i = 1] - E[Y_i|T_i = 0] \\ &= E[Y_i(1)|T_i = 1] - E[Y_i(0)|T_i = 0] \\ &= E[Y_i(0) + \tau|T_i = 1] - E[Y_i(0)|T_i = 0] \\ &= \tau + E[Y_i(0)|T_i = 1] - E[Y_i(0)|T_i = 0] \end{aligned}$$



ATE

Selection Bias!

Potential Outcomes in DiD Framework (I)

Potential Outcomes Framework in DiD: (Athey & Imbens, 2006)

$$Y_i = Y_i(0) + I_i(Y_i(1) - Y_i(0))$$

Let:

$$I_i = G_i \times T_i, \quad G_i \in \{0,1\}, \quad T_i \in \{0,1\}$$

If:

$$I_i = 1 : Y_i = Y_i(1)$$

$$I_i = 0 : Y_i = Y_i(0)$$

We need expressions
for $Y_i(1)$ and $Y_i(0)$!

Also, let's assume a constant treatment effect:

$$Y_i(1) = Y_i(0) + \tau$$

Potential Outcomes in DiD Framework (II):

Define: $Y_i(0) = \alpha + \beta T_i + \gamma G_i + \varepsilon_i$

$Y_i(1) = Y_i(0) + \tau$ Because we assume a constant treatment effect

Observed Outcome:

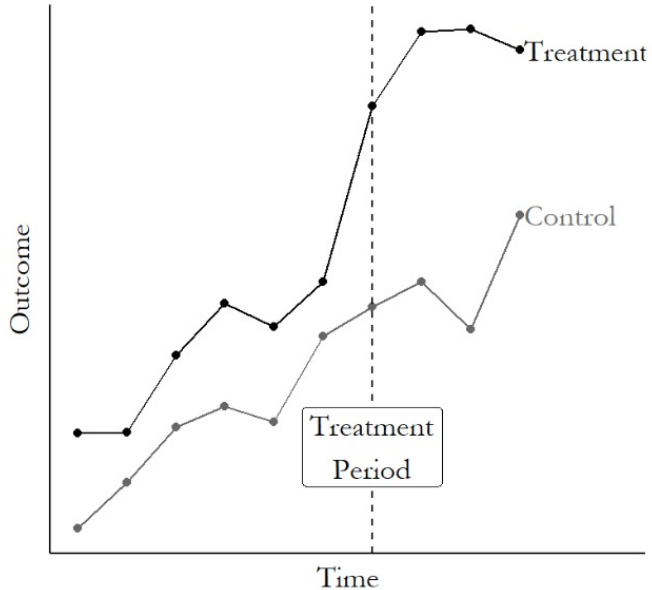
$Y_i = \alpha + \beta T_i + \gamma G_i + \tau I_i + \varepsilon_i$ where $I_i = G_i \times T_i$

Interpreting τ as Average Treatment on the Treated (ATT):

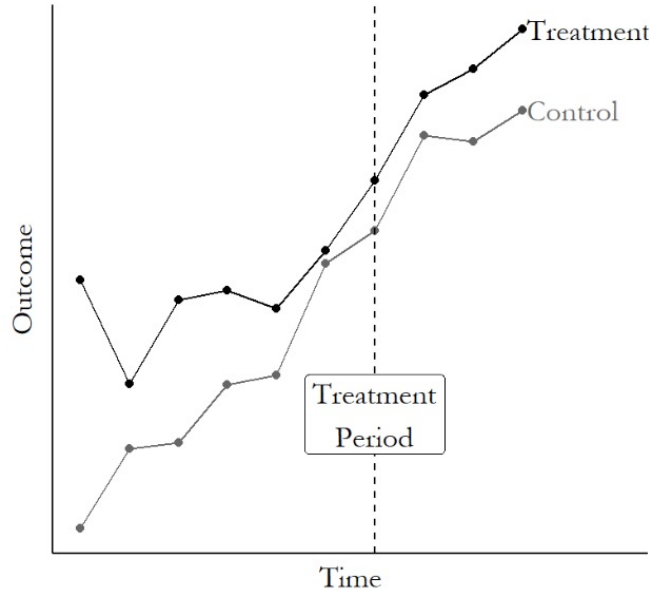
$$\begin{aligned} E[Y_i(1) - Y_i(0) | G_i = 1, T_i = 1] &= E[Y_i(1) | G = 1, T = 1] - E[Y_i(0) | G_i = 1, T_i = 1] \\ &= \tau^{\text{DiD}} \end{aligned}$$

Key Assumption: Parallel Trends

(a) Parallel Prior Trends



(b) Converging Prior Trends



Source: Huntington-Klein (2023), Chapter 18

Key Assumption: Parallel Trends

1. Parallel pre-trends (testable):

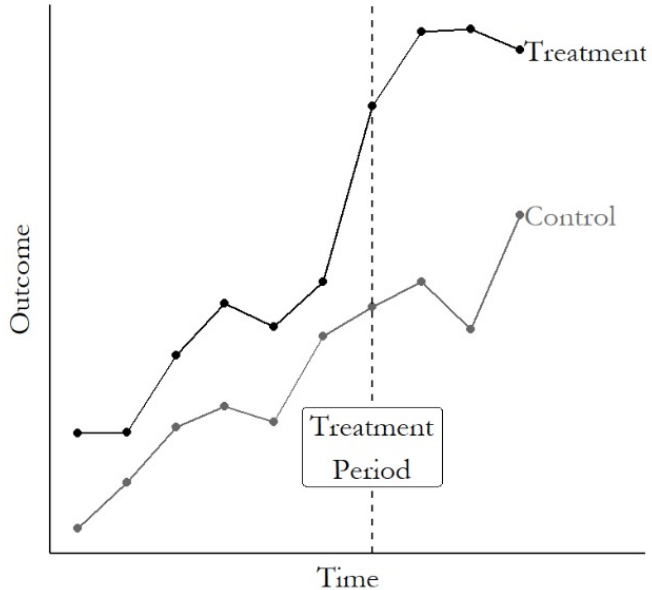
Before the treatment or intervention is introduced, the outcomes of the treatment group and the control group follow similar trends over time.

2. Common Trends/Shocks (Identifying assumption/untestable):

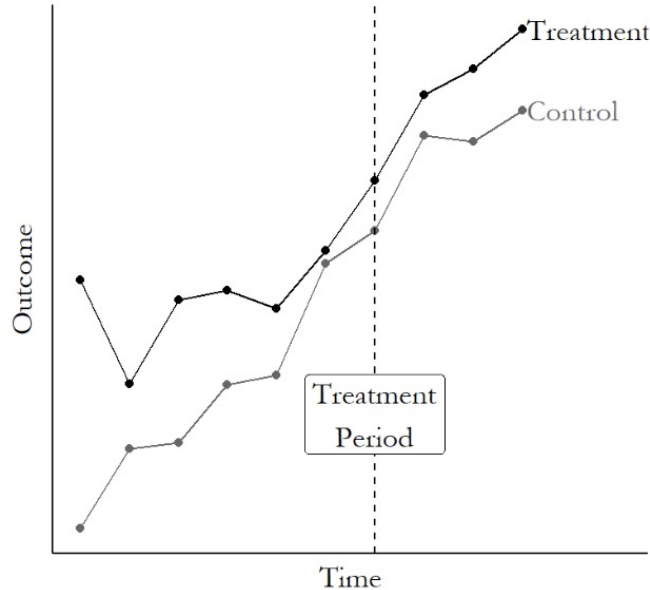
Any differences observed in the outcomes between the treatment and control groups before the treatment are due to factors other than the treatment itself, and these differences would have persisted in the absence of treatment.

Key Assumption: Parallel Trends

(a) Parallel Prior Trends

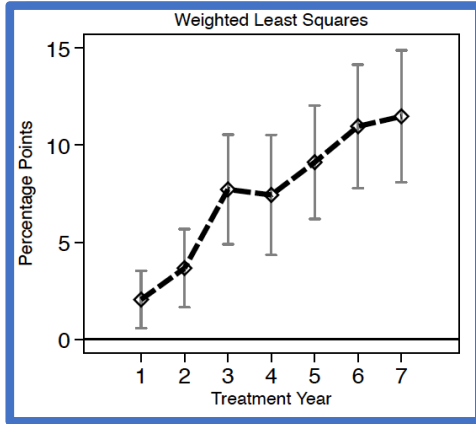


(b) Converging Prior Trends

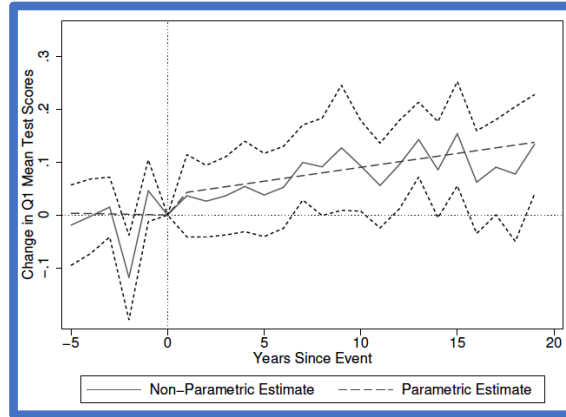


Source: Huntington-Klein (2023), Chapter 18

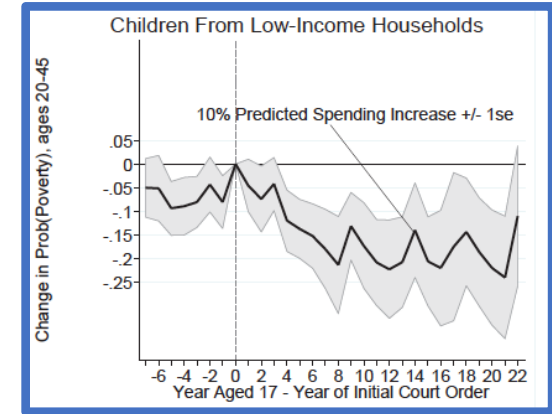
DiD in School Finance Reform Studies: Money Matters for Educational Outcomes



Graduation Rates in High-Poverty Districts ↑
(Candelaria & Shores, 2019)



Test scores for low-SES children ↑
(Lafortune et al., 2018)



Incidence of Poverty ↓
(Jackson et al., 2016)

➤ Across studies: “On average, a \$1000 increase in per-pupil public school spending (for four years) increases test scores by 0.044 standard deviations, high-school graduation by 2.1 percentage points, and college-going by 3.9 percentage points.” (Jackson & Mackevicius, 2021)

Candelaria & Shores (2019): Funding Effect Example

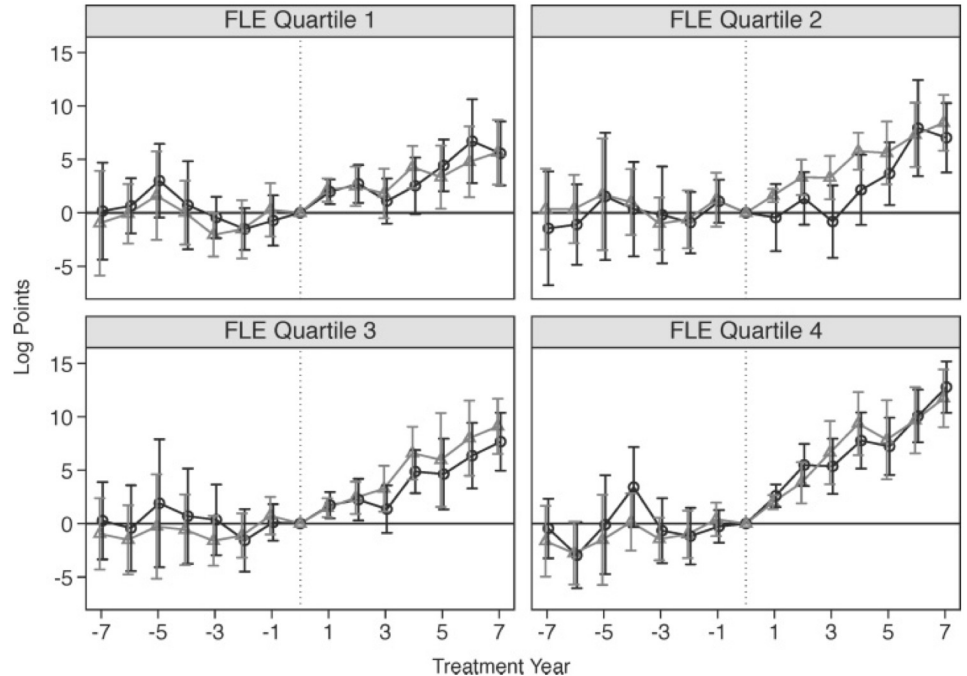
Let's assess the parallel trends assumption using an event study design:

$$Y_{sqdt} = \theta_d + \delta_{qt}$$

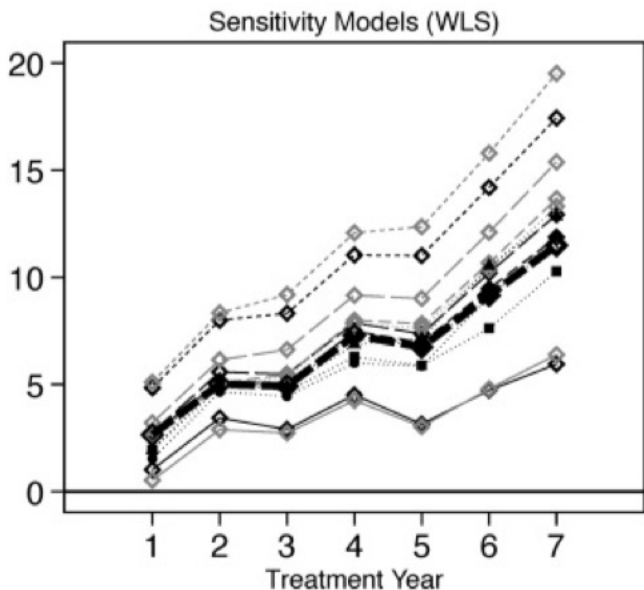
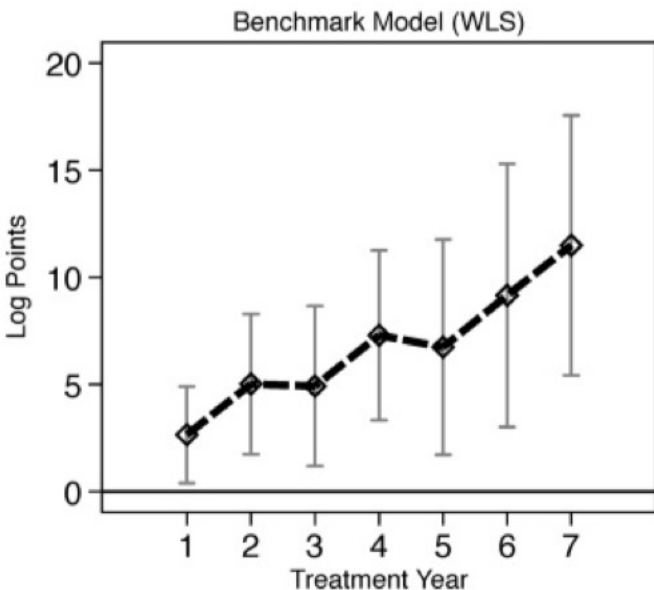
$$+ \sum_{n=1}^{16} \gamma_{(q,-n)} [1(Q_{sd} = q) \times 1(t - t_s^* = -n) \times D_s]$$

$$+ \sum_{n=1}^{19} \gamma_{(q,+n)} [1(Q_{sd} = q) \times 1(t - t_s^* = n) \times D_s] + \varepsilon_{sqdt}$$

Event Study of Log(Per-Pupil Revenues)

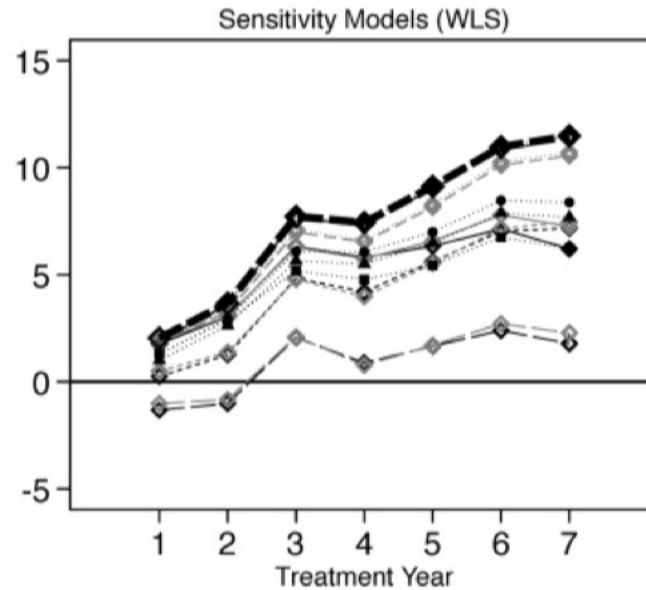
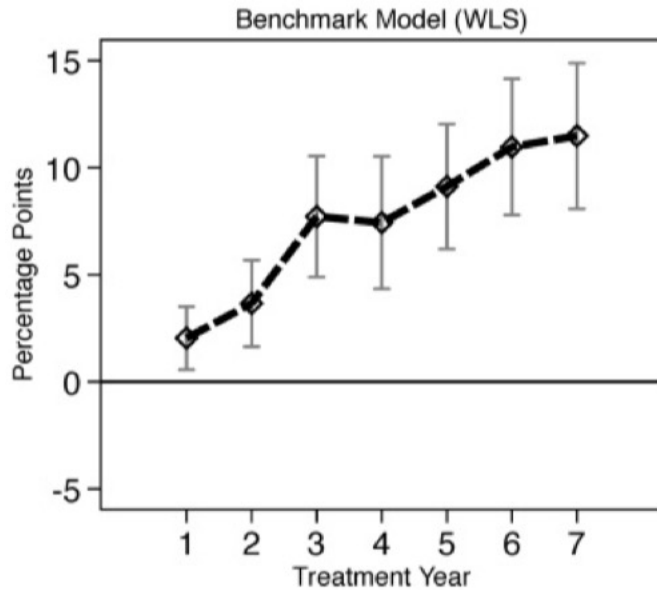


School Finance Reforms (SFRs) Increase Funding Among Lower-Income Districts



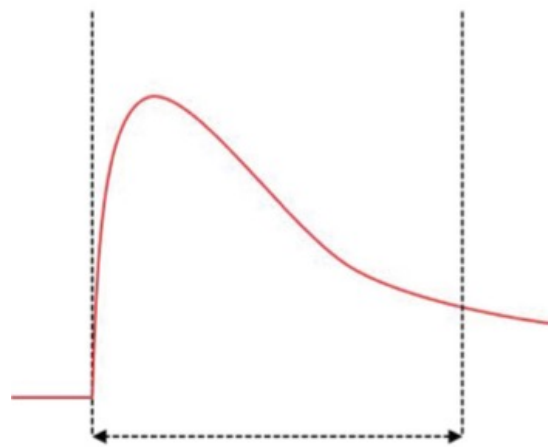
Revenues increased by 11.5% in lower-income districts 7 years after reform

SFRs Increase Graduation Rates Among Lower-Income Districts



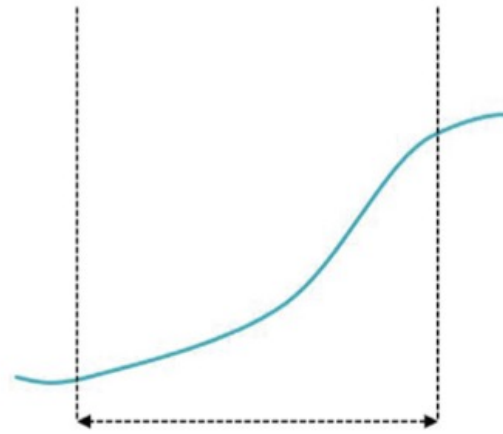
Graduation Rates increased by by 12 percentage points in lower-income districts 7 years after reform

Transition: Using a DiD approach in A/B Testing to Assess User Learning



Experiment Duration

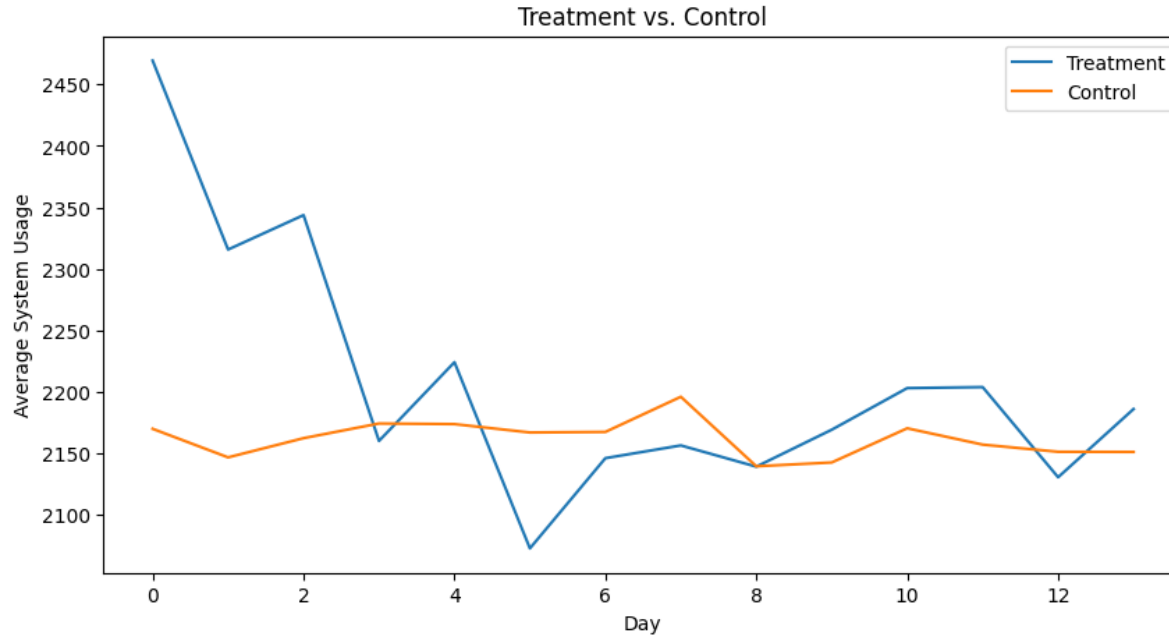
(a) Novelty effect



Experiment Duration

(b) Primacy effect

Given A/B test, how should we assess user learning?



Time to code!

- > Access the Google Colab site for our coding session