Difference-in-Differences

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Motivation

- You want to uncover the effect of flexible work hours on employee retention:
  - whether by giving employees more freedom to choose their work hours makes them more likely to stay with their employer.
- You can use observational data on firms from two years, and some firms introduced flexible work hours between those two years.
- How can you use this data to estimate the effect you are after?
- You work for a competition authority, and you are tasked with evaluating the effect of a merger between two companies that took place a few years ago on the prices their customers face.
- You have transaction-level data from a few years both before and after the merger took place.
- You can define several markets from this data, and you find that the two companies were present in some of those markets but weren't present in others.
- How can you use this data to estimate the effect of the merger on prices?
- In particular, could you use data aggregated to market level and compare prices before and after the merger?
- And, can you use the data to assess whether such a comparison leads to a good estimate of the average effect of the merger?

Learning Outcomes

- After working through this chapter, you should be able to:
  - identify situations in which difference-in-differences analysis may be applied to uncover the average effect of an intervention;
  - carry out difference-in-differences analysis using panel data within the framework of linear regression and interpret its results;
  - understand when difference-in-differences analysis can give a good estimate of an effect, and what kind of evidence can help assess whether those conditions hold;
  - carry out difference-in-differences analysis using pooled cross-sections, interpret its results, and understand the potential role of selection.

Basic Difference-in-Differences Analysis: Comparing Average Changes

- The effect of a binary causal variable $x = 0 \; or \; 1$ on outcome variable y.

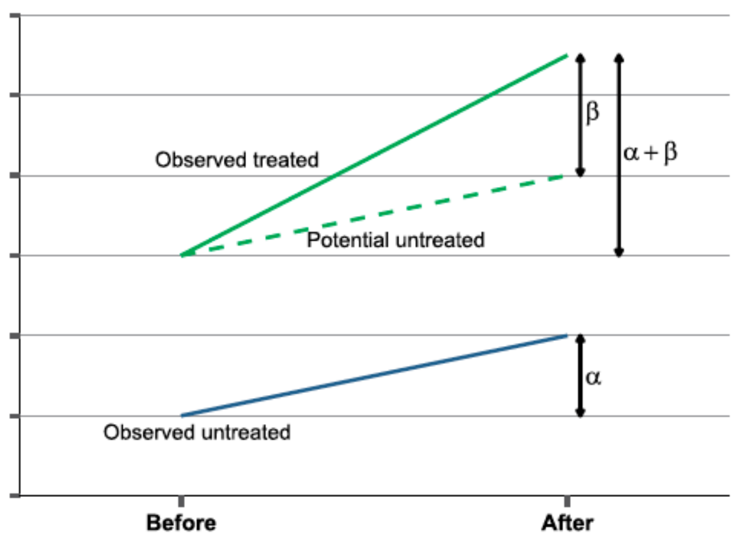
$$\Delta y_i = y_{i,after} - y_{i,before}$$
$$\hat{\beta}_{diff-in-diffs} = \Delta\bar{y}_{treated} - \Delta\bar{y}_{untreated}$$

Table 22.1 The difference-in-differences setup

	Untreated	Treated	Diff: Treated–Untreated
Before	$\bar{y}_{untreated,before}$	$\bar{y}_{treated,before}$	$\bar{y}_{treated,before} - \bar{y}_{untreated,before}$
After	$\bar{y}_{untreated,after}$	$\bar{y}_{treated,after}$	$\bar{y}_{treated,after} - \bar{y}_{untreated,after}$
Diff: After – Before	$\Delta\,\bar{y}_{untreated}$	$\Delta\bar{y}_{treated}$	$\Delta\bar{y}_{treated} - \Delta\bar{y}_{untreated}$

Basic Difference-in-Differences Analysis: Comparing Average Changes

$$\Delta y^E = \alpha + \beta_{treated}$$



Difference-in-differences: illustration of average outcomes and their changes

Basic Difference-in-Differences Analysis: Comparing Average Changes

- Basic difference-in-differences analysis estimates the average effect of an intervention on outcome y:
  - by comparing the average change in y;
  - from a time period before the intervention to a time period after the intervention;
  - between subjects that are affected by the intervention and subjects that are not affected.
- The data needs to have observations of the outcome for each subject from both time periods.

Parallel Trends Assumption

- The parallel trends assumption: without the intervention, outcomes would have changed the same way, on average, in the treatment group and the non-treatment group.
- If the assumption is true, diff-in-diffs gives a good estimate of ATET.
- If, in addition, the average of outcomes in the non-treatment group would have changed the same way, had they been treated, as it changed in the treatment group, diff-in-diffs gives a good of ATE, too.
- The parallel trends assumption cannot be verified or falsified directly.
- We can get indirect evidence on parallel trends by examining pre-intervention trends.

Conditioning on Additional Confounders in Diff-in-Diffs Regressions

- In a diff-in-diffs regression using panel data with two time periods, we should condition on the baseline values of potential confounders or their change, depending on our assumptions about how the confounders affect, or are related to, the treatment variable.
- Conditioning on the baseline value:

$$\Delta y^E = \alpha + \beta_{treated} + \gamma z_{baseline}$$

- Conditioning on the change:

$$\Delta y^E = \alpha + \beta_{treated} + \gamma \Delta z$$

Quantitative Causal Variable

- With a quantitative causal variable x measured at baseline, the diff-in-diffs regression is
$$\Delta y^E = \alpha + \beta_{baseline}$$
- Here β shows the expected difference in how y changes for subjects with a unit larger level of x at baseline.
- With a quantitative causal variable Δx, which is the change in x, the diff-in-diffs regression is
$$\Delta y^E = \alpha + \beta \Delta x$$
- Here β shows the expected difference in how y changes for subjects with a unit larger change in x.

Difference-in-Differences with Pooled Cross-Sections

- Difference-in-differences with pooled cross-sections can be computed by measuring average outcomes in the two groups in the two time periods. The formula is the same as with basic diff-in-diffs:

  $$\beta_{diff-in-diffs} = (\bar{y}_{treatment,after} - \bar{y}_{treatment,before}) - (\bar{y}_{non-treatment,after} - \bar{y}_{non-treatment,before})$$

- However, with pooled cross-sections the averages are computed using different observations in the before and the after time period.
- The regression equivalent includes observations from both before and after, and they need not be a balanced panel:

  $$y^E = \alpha + \beta treatment + \gamma\ after + \delta\ treatment \times after$$

- where δ is the difference-in-differences estimator.
- Confounder variables are best included in this regression as their baseline values, also interacted with the *after* dummy.
- In addition to the usual concerns, here we also need to pay attention to selection into measurement (what kinds of subjects are observed before vs. after).

Main Takeaways

- Difference-in-differences (diff-in-diffs) estimates the effect of an intervention by comparing how the outcome variable changes among treated subjects versus untreated subjects.
- Diff-in-diffs uses observational panel data and has a better chance to estimate the effect of an intervention than using cross-sectional data, because it conditions on pre-intervention outcomes.
- Diff-in-diffs gives a good estimate of the effect if the parallel trends assumption holds.
- We can't test the parallel trends assumption directly, but examining pre-intervention trends can give indirect evidence.

CASE STUDIES

- How Does a Merger between Airlines Affect Prices?
  - Pre-intervention trends
  - Conditioning on potentially endogenous sources of variation
  - Quantitative causal variable
  - Using the entire unbalanced panel and diff-in-diffs with pooled cross-sections