# HANDOUT 16 – DIFFERENCES-IN-DIFFERENCES

## AGENDA

- Introduction
- Differences-in-differences: Comparing 4 means
- Differences-in-differences: Identifying assumption
- Differences-in-differences: Regression framework
- Takeaways
- Vocabulary

## BIBLIOGRAPHY FOR TODAY´S CLASS

- Card and Krueger (1994). Minimum Wages and Employment: A case of the Fast-Food Industry in NJ and PA. (*) (Focus on the introduction and first 3 rows/columns of Table 3).
- Stock and Watson (2007), 13.3 (**)
- Angrist and Pishke (2015), 5 (**)

## INTRODUCTION

- Consider a simple case in which we observe two groups in two time periods.
- In the first time period neither group is "treated" by a policy.
- In the second time period a policy is changed so that only one of the two groups is affected.
- We can estimate the impact of this policy using differences-in-differences estimation, an approach we already mentioned on our class on interactions.
    - Intuition from simple mean comparisons (recalls our Interactions class).
    - Regression framework using an interaction variable.
- We will illustrate this technique with a study by Card and Krueger (1994) on the impact of the minimum wage on employment.

## COMPARING FOUR MEANS

- Policy question: How does the minimum wage affect employment?
- What does basic economic theory (i.e. API-101) predict about how employment changes when the minimum wage raised?

- Why can't we estimate impact of the minimum wage by regressing state-level employment on an indicator for whether a state has high minimum wage?

- To eliminate these sources of omitted variable bias, Card and Krueger (the first of many that came later on) used a differences-in-differences approach.
- In April 1992, New Jersey's minimum hourly wage rose $4.25 to $5.05.
- The minimum wage in Pennsylvania did not change.
- Card and Krueger surveyed four-hundred fast-food restaurant in New Jersey and eastern Pennsylvania (which borders New Jersey) in:
    - February 1992 (before the minimum wage increase).
    - November 1992 (after the minimum wage increase).
- Suppose we only had data on employment in New Jersey.
- We could do a simple before-after comparison:

Average Number of Employees per Restaurant

| | Before | After | Difference |
|---|---|---|---|
| New Jersey | 17.0 | 17.5 | |

- Why is this difference not necessarily the impact of the minimum wage?

- Suppose we only had data on employment after the change.
- We could do a simple treatment-control comparison:

Average Number of Employees per Restaurant

| | After | Difference |
|---|---|---|
| New Jersey | 17.5 | |
| Pennsylvania | 17.8 | |
| Difference | | |

- Why is this differences not necessarily the impact of the minimum wage?

- Suppose we had data on employment in both states and times (Tables 3, Row 3).

Average Number of FT Employees per Restaurant

| | Before | After | Difference |
|---|---|---|---|
| New Jersey | 20.44 | 21.03 | |
| Pennsylvania | 23.33 | 21.17 | |
| Difference | | | |

- Calculate the difference between the states and the difference in employment over time. This is a **difference-in-differences estimator** (diff-in-diff, DID).
- If we think of New Jersey as "treatment and Pennsylvania as "control", DID estimates the difference in mean between the two groups in two time periods:

$$DID = \underbrace{(\bar{Y}_{T2} - \bar{Y}_{T1}) - (\bar{Y}_{C2} - \bar{Y}_{C1})}_{\text{Difference between changes within each state}} = \underbrace{(\bar{Y}_{T2} - \bar{Y}_{C2}) - (\bar{Y}_{T1} - \bar{Y}_{C1})}_{\text{Differences between states at the end minus differences at the beginning}}$$

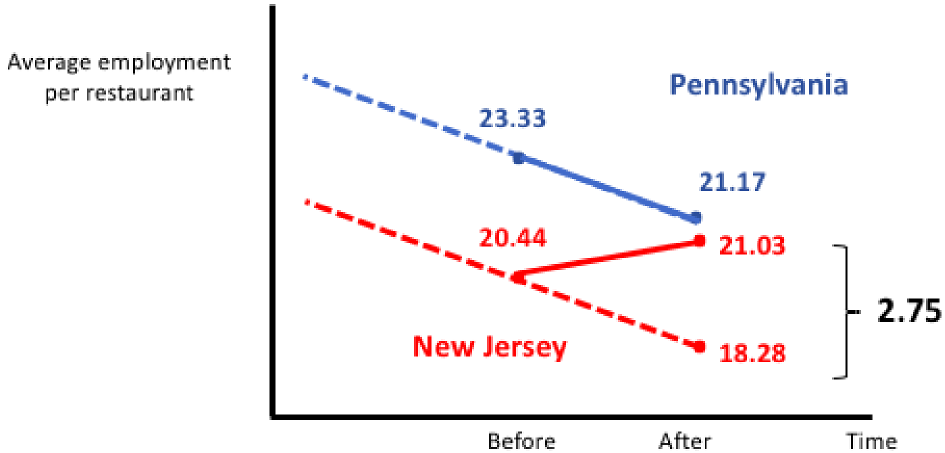
IDENTIFYING ASSUMPTION

- Does this new estimate suffer from the sources of OVB we identified in the before-after comparison of New Jersey?

- Does this new estimate suffer from the sources of OVB we identified in the treatment-control New Jersey-Pennsylvania comparison?

- What remaining factors would prevent us from interpreting the difference-in-difference estimate as the impact of the minimum wage increase?

- Key assumption DID estimator to be an unbiased measure of impact:
    - If not for the minimum wage policy change, NJ's employment change would have been the same as the employment change we observed in PA.
- This is often referred to as the "parallel trends" assumption:




- What additional data would make this assumption more plausible?

- For the difference-in-difference estimator:
    - Unobservable differences between New Jersey and Pennsylvania do not create a bias if they correspond to factors that do not change over time within states.
    - Unobservable differences between New Jersey and Pennsylvania do not create a bias if the factors underlying them change, but the difference between states remains constant (they change in parallel).
- The only source of bias can be factors that differ across the two states in a way that varies over time.

REGRESSION FRAMEWORK

- We can perform a difference-in-difference estimation in a regression framework, with two advantages over the approach described above:
    - We control for other variables that may affect employment.
    - We can test the statistical significance of the impact estimate.
- Here is how you normally would collect the data (this is how the original Card-Krueger data set looks):

| | sheet | NewJersey | empft | emppt | empft2 | emppt2 |
|---|---|---|---|---|---|---|
| 1 | 46 | 0 | 30 | 15 | 3.5 | 35 |
| 2 | 49 | 0 | 6.5 | 6.5 | 0 | 15 |
| 3 | 506 | 0 | 3 | 7 | 3 | 7 |
| 4 | 56 | 0 | 20 | 20 | 0 | 36 |
| 5 | 61 | 0 | 6 | 26 | 28 | 3 |
| 6 | 62 | 0 | 0 | 31 | . | . |
| 7 | 445 | 0 | 50 | 35 | 15 | 18 |
| 8 | 451 | 0 | 10 | 17 | 26 | 9 |
| 9 | 455 | 0 | 2 | 8 | 3 | 12 |
| 10 | 458 | 0 | 2 | 10 | 2 | 9 |

sheet = sheet number (unique store id)

NewJersey = 1 if New Jersey, 0 if Pennsylvania

empft = number of full-time employees (First interview, Feb 1992)

emppt = number of part time employees (First interview, Feb 1992)

empft2 = number of full-time employees (Second interview, Nov 1992)

emppt2 = number of part-time employees (Second interview, Nov 1992)

- Card-Krueger use full-time equivalent employees:
    - Employees = Full-time employees + 0.5 Part-time employees

| | sheet | NewJersey | emp1 | emp2 |
|---|---|---|---|---|
| 1 | 46 | 0 | 37.5 | 21 |
| 2 | 49 | 0 | 9.75 | 7.5 |
| 3 | 506 | 0 | 6.5 | 6.5 |
| 4 | 56 | 0 | 30 | 18 |
| 5 | 61 | 0 | 19 | 29.5 |
| 6 | 62 | 0 | 15.5 | . |
| 7 | 445 | 0 | 67.5 | 24 |
| 8 | 451 | 0 | 18.5 | 30.5 |
| 9 | 455 | 0 | 6 | 9 |
| 10 | 458 | 0 | 7 | 6.5 |

sheet = sheet number (unique store id)

NewJersey = 1 if New Jersey, 0 if Pennsylvania

emp = number of full-time equivalent employees (First interview, Feb 1992)

emp2 = number of full-time equivalent employees (Second interview, Nov 1992)

- This regression generates the difference-in-difference estimator:

$$Employees = \beta_0 + \beta_1 NewJersey + \beta_2 After + \beta_3 NewJersey * After + \varepsilon$$

  - *Employees* = number of people employed by restaurant
  - *NewJersey* = 1 if restaurants in NJ, 0 if in PA
  - *After* = 1 if observation is after minimum wage increase, 0 if before

- In order to perform the regression of interest we need to reorganize our database (STATA has a *reshape* command that does that):

| | sheet | NewJersey | emp | After | NewJersey_~r |
|---|---|---|---|---|---|
| 1 | 1 | 1 | 31 | 0 | 0 |
| 2 | 1 | 1 | 40 | 1 | 1 |
| 3 | 2 | 1 | 13 | 0 | 0 |
| 4 | 2 | 1 | 12.5 | 1 | 1 |
| 5 | 3 | 1 | 12.5 | 0 | 0 |
| 6 | 3 | 1 | 7.5 | 1 | 1 |
| 7 | 4 | 1 | 16 | 0 | 0 |
| 8 | 4 | 1 | 20 | 1 | 1 |
| 9 | 5 | 1 | 20 | 0 | 0 |
| 10 | 5 | 1 | 25 | 1 | 1 |
| 11 | 6 | 1 | 3 | 0 | 0 |
| 12 | 6 | 1 | 6 | 1 | 1 |
| 13 | 8 | 1 | . | 0 | 0 |
| 14 | 8 | 1 | 27.5 | 1 | 1 |
| 15 | 9 | 1 | 32 | 0 | 0 |
| 16 | 9 | 1 | 16 | 1 | 1 |
| 17 | 10 | 1 | 25 | 0 | 0 |
| 18 | 10 | 1 | 22.5 | 1 | 1 |

- Regression output:

| emp | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| NewJersey | -2.883534 | 1.403338 | -2.05 | 0.040 | -5.638209 | -.1288592 |
| After | -2.40651 | 1.594091 | -1.51 | 0.132 | -5.535623 | .7226031 |
| NewJersey_After | 2.913982 | 1.736818 | 1.68 | 0.094 | -.4952963 | 6.323261 |
| _cons | 19.94872 | 1.317281 | 15.14 | 0.000 | 17.36297 | 22.53447 |

$$\widehat{Employess} = 19.95 - 2.88 NewJersey - 2.41 After + 2.91 NewJersey * After$$

- Based on the regression output complete the following table:

Predicted Number of Employees per Restaurant

| | Before | After | Difference |
|---|---|---|---|
| New Jersey | | | |
| Pennsylvania | | | |
| Difference | | | |

- How would you interpret the "New Jersey" coefficient in column 1?

- Which of the coefficients of the regression is our difference-in-difference estimator of the causal impact?

- Notice that through the regression (2.91) we could not replicate the exact difference in means of slide 14 (2.75) (but we should have! Such is the life of the people that replicate papers…).

TAKEAWAYS

- The difference-in-difference estimator is useful when you can divide the world into two time periods and two groups (treatment and control).
- In those cases, the interaction coefficient in the following specification gives you the causal difference-in-difference estimate of interest:

$$Y = \beta_0 + \beta_1 Treated + \beta_2 After + \beta_3 Treated * After + \varepsilon$$

- The estimate is causal if the parallel trends assumption holds, so whether it holds is always the key question to ask.
- Another advantage of the difference-in-difference approach is that you can use it to estimate impacts over longer periods and more than two states, by combining difference-in-differences with fixed effects.
    - Next class we'll discuss a more complex version of the difference-in-difference approach involving multiple states and years.

VOCABULARY

- Difference in difference estimator: an estimator that arises in policy analysis with data for two time periods. One version of the estimator applies to independently pooled cross sections and another to panel data sets.
- Parallel trends assumptions: is the most critical of the assumptions to ensure internal validity of DID models and is the hardest to fulfill. It requires that in the absence of treatment, the difference. Between the "treatment" and "control" group is constant over time.