Lecture 15

Difference in Difference Method (DiD Method)

Annoucements

- PS4 uploaded is due on 04/15/2020
- It can be a hard problem set do come prepared with questions for Wedneday class.

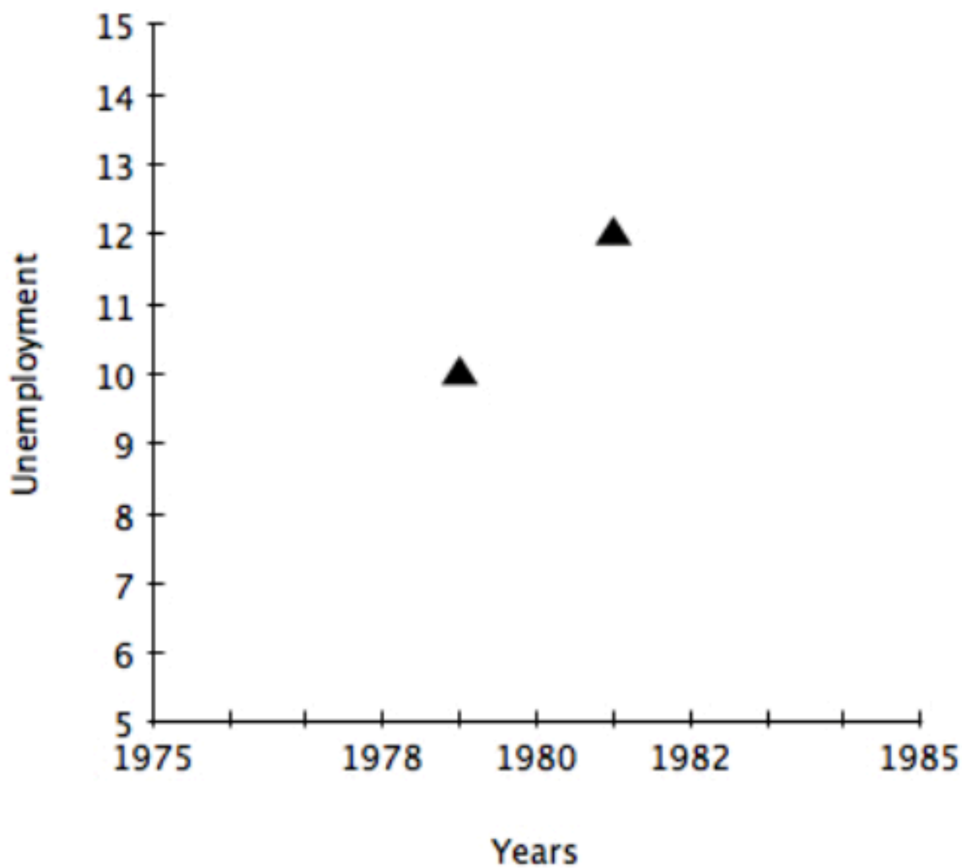
Outline

- Intro to simple DID
- DID regression and mapping parameters to the graph
- DID identification assumption test
- Causes that DID fails

Example: The Mariel boatlift

- In 1980 Castro allowed 125,000 immigrants to leave Cuba. They all went to Miami and about 1/2 stayed there
- David Card studied the impact of this immigration influx on unemployment and wages of natives
- What is the simple before/after comparison?

Simple before/after comparison

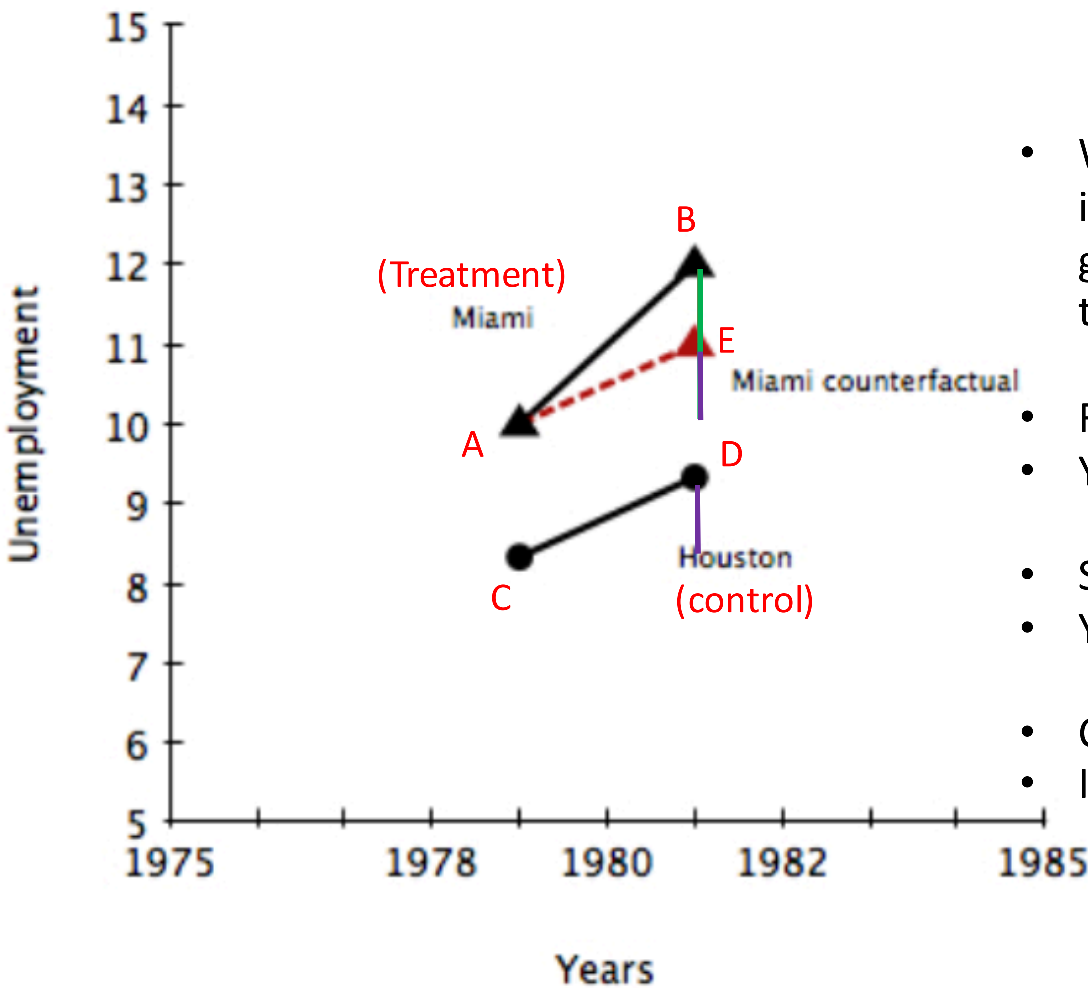


- Compare unemployment in Miami in 1979 to unemployment 1981
- Unemployment increases between 1979 and 1981. Is this the causal impact of immigrants? What can be omitted variables?

Basic idea of DID

- Differences-in-differences is a an improved version of the before/after estimator
- The DID design does a before and after comparison, but uses a control group. In his study, Card compares unemployment changes in Miami to unemployment changes in Atlanta, Los Angeles, Houston and Tampa
- The DID gets it's name because it is the difference of two differences

Basic idea of DID-graphical presentation



- We were worried about time trend as an omitted variable in simple before/after comparison. Now we add a control group and assume the control group is only affected by time trend (no treatment effect)

- First diff:Comparing A and B: before/after for treatment
- $Y_{Miami,after}$-$Y_{miami,before}$ =Y_B-Y_A= δ1

- Second diff:Comparing C and D: before/after for control
- $Y_{Houson,after}$-$Y_{houson,before}$=Y_D-Y_C= δ2

- Causal impact is a difference in differences: δ=δ1-δ2
- It's vertical distance of BE

Identification assumption: common trends

- The change in unemployment of Houston between 1981 and 1979 would have been the same in the absence of immigration in Miami
  - In other words, Miami would have experienced the same time trends with Houston if there were no immigration
  - Note, we do not assume Houston and Miami are the same. The key thing is they would have followed common trends (the change in employment will be the same)

Exercise: Minimum legal dirking age (MLDA)

- Alabama lowered its MLDA to 19 in 1975, but geographically proximate Arkansas has had an MLDA of 21. Does gaining legal access to drinking at a younger age lead to more deaths?
- The dependent variable is death rate for 19 year olds; the outcome Y_{st}- s denotes state, t denotes time. s takes on two values: AL and AR. t takes on two values: 1974, 1976
- $Y_{AL,74}$: death rate of AL, before policy change
- $Y_{AL,76}$: death rate of AL, after policy change
- $Y_{AR,74}$: death rate of AR, before policy change
- $Y_{AR,76}$: death rate of AR, after policy change

Questions:

1. Which state is the treatment and which is control?
2. What is the first difference?
3. What is the second difference?
4. What is the DID estimate?
5. Can you use a graph to illustrate all four points and the causal impact? (assume AL has a higher death rate than AR in 74, and the general trend of death rate is decreasing)
6. What is the identification assumption?

DID implementation

- We use regression to get the δs
- Suppose we only have 2 years (1979&1981) and we have 2 cities (Miami&Houston)
- $Y = \alpha + \gamma Miami + \beta 1981 + \delta 1981 * Miami + \varepsilon$
  - Miami is a dummy variable. If the city is Miami, Miami=1
  - 1981 is a dummy variable. If the year is 1981, 1981=1
- What do α, γ, β, δ each correspond to?
  - When Miami, 1981 and 1981*Miami are all zero, we are at the observation for Houston in 1979, and that is the interpretation of α. Using similar logic, we can get at all the parameters
  - $Y_{1979,\ Houston} = \alpha$
  - $Y_{1981,\ Houston} = \alpha + \beta$
  - $Y_{1979,\ Miami} = \alpha + \gamma$
  - $Y_{1981, Miami} = \alpha + \gamma + \beta + \delta$
- What is the first difference? (before/after for treatment)
  - $(\alpha+\gamma+\beta+\delta)-(\alpha+\gamma)=\beta+\delta$
- What is the second difference? (before/after for control)
  - $(\alpha+\beta)- \alpha=\beta$-time trends of the control
- What is difference-in-differences?
  - $(\beta+\delta)-\beta=\delta$

Parameters in the DID regression

- The DID estimator is simply the coefficient on the **interaction term**
- δ is the DID
- α is the unemployment rate in Houston in 1979
- γ is the difference between the unemployment rate in Miami and Houston in 1979.
- β is the difference between the unemployment rate in Houston in 1981 compared to 1979, which is the impact of general time trends (It’s the slope of the control group)

Exercise: MLDA-DID implementation

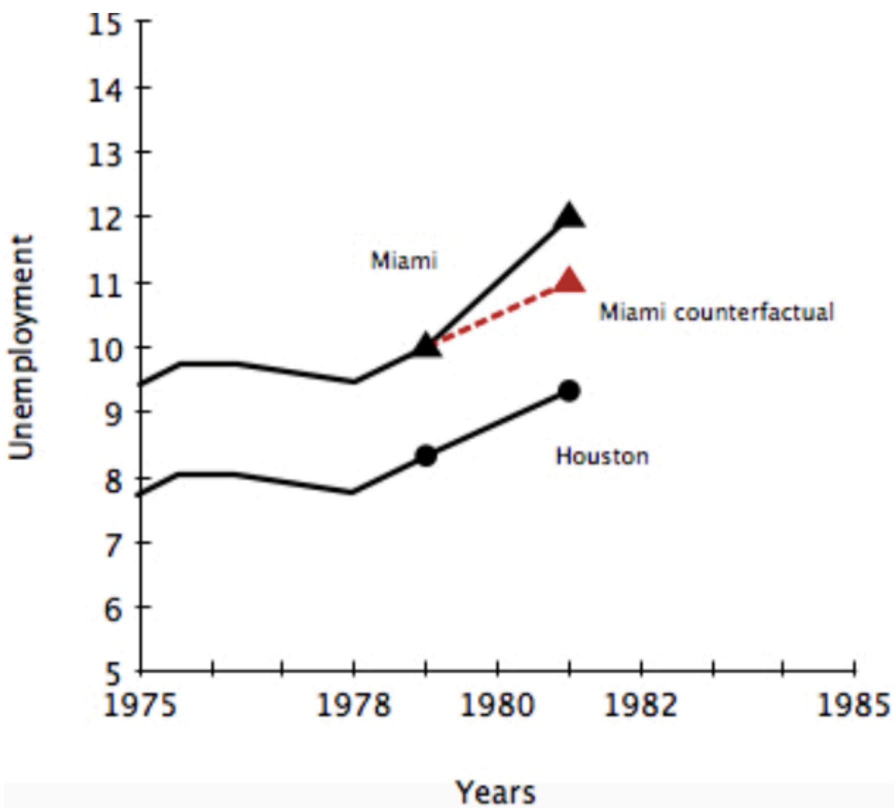
- Write out an DID regression for the MLDA exercise. Which parameter is the causal impact of gaining legal access to drinking on death rate?
- Start by answering
  - What is the outcome variable?
  - What is the post indicator?
  - What are the treatment and control group?
- Can you map each parameter to the graph? On the DID graph
  - What is α, β, γ?
  - What is first difference and second difference?
  - What is δ?

Test the identification assumption

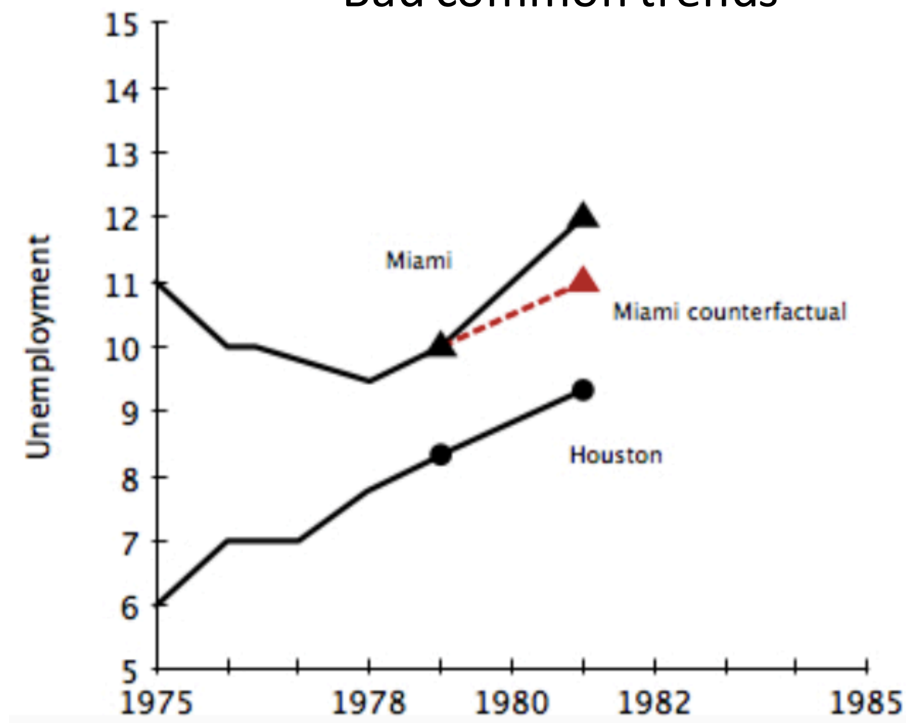
- Unlike OLS and IV, we have an explicit test for DID's identification assumption.
- What is the assumption?
  - Common trends: we assume that Miami would have followed Houston's unemployment between 1979 and 1981 if it wasn't for the immigrants
- How do we explicitly test it?
  - We should see Houston and Miami move together until 1980 and then diverge-show pre-trends graph. (pre-trends mean pre-treatment trends)
  - Note that Miami and Houston have very different unemployment rates the entire time and that's fine as long as they are parallel

Test common trends assumption using graph

Good common trends



Bad common trends



Why does common trends test work?

- Common trends assumption is about what would have happened in Miami if there were no treatment (immigrants)
- But the test is about the trend in pre-treatment years. Why does that work?
- Note this is again, an indirect test. The idea is if both states in pre-treatment years have followed parallel trends, it is very likely in the treatment years they would have followed parallel trends
- Bottom line: if you fail common trends test-invalid research design-don't use DID

Why DID fails

1. Common trend assumption fails
   - This is the most common concern and it can be tested indirectly by looking at the pretrends
2. Simultaneous treatment effect
   - If something else happens at the same time in Miami, it will bias estimates
   - The pretrend test will not detect this problem
3. Contamination
   - If Houston is impacted by Miami's labor market this will bias estimates (usually biases estimates towards zero).
   - The pretrend test will not detect this problem.

Why DID fails

- 4. Policy endogeneity
  - If the policy was implemented in response to something, this will probably bias estimates.
  - e.g. If Chicago passes a new anti-violence law, we might be concerned that the laws passage was done because Chicago anticipated that crime would rise a lot next year without the policy
  - It will downward bias the effect of the law
  - The pretrend test could detect this problem, but it could also miss it
    - If the policy is based on previous years, the pretrend test will detect it

Review for quizzes

- Know what DID is and its identification assumption
- The regression for simple DID-know what each parameter means on a graph
- the Identification test
- Why DID fail-know examples