Lecture 16

Regression Discontinuity Design (RDD)

Announcements

- PS4 is due on 04/15/2020

Outline

- DID (recap)
- Intro to Regression Discontinuity (RD)
  - What is RD?
  - RD's identifying variation
  - An example of Sharp RD

Recall: Problems with OLS

Recall: Why don’t we just randomly assign people to control and treatment group?

- What are the advantages of running a randomized control trial?
- What are possible drawbacks of running a RCT?

Basic idea of DID

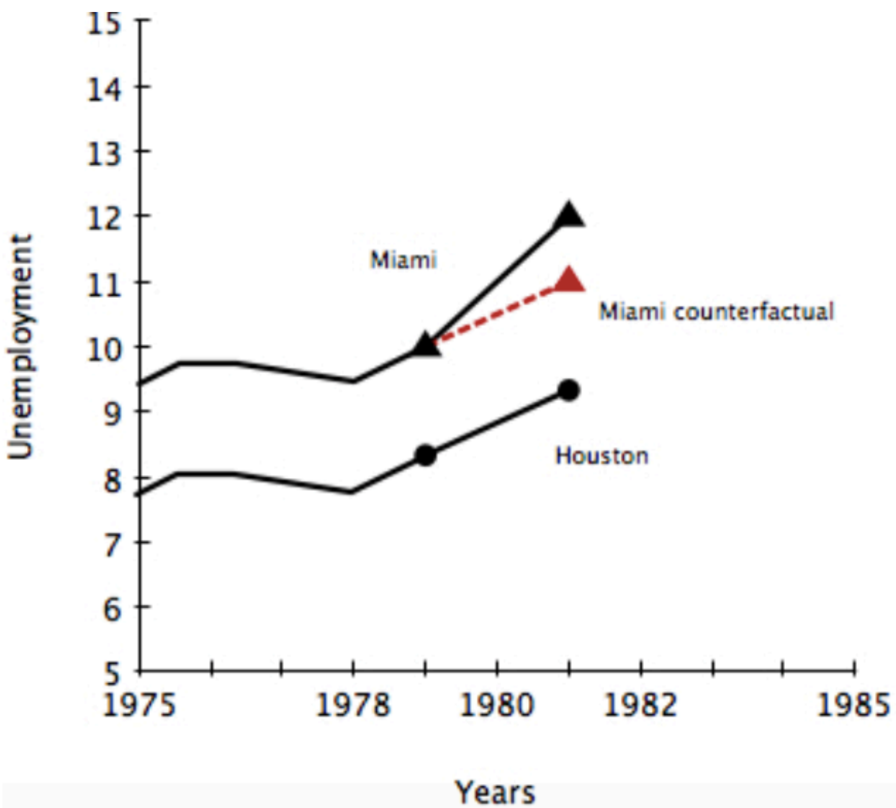
- Differences-in-differences is an improved version of the before/after estimator
- The DID design does a before and after comparison but uses a control group. In his study, Card compares unemployment changes in Miami to unemployment changes in Atlanta, Los Angeles, Houston and Tampa
- The DID gets its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

Test the identification assumption

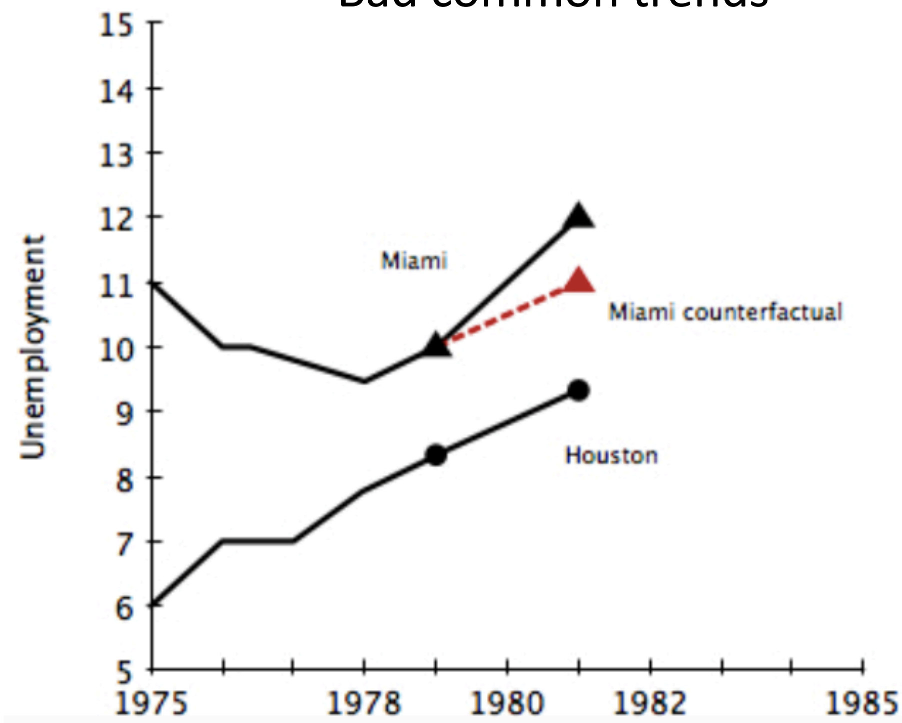
- Unlike OLS and IV, we have an explicit test for DID's identification assumption.
- What is the assumption?
  - Common trends: we assume that Miami would have followed Houston's unemployment between 1979 and 1981 if it wasn't for the immigrants
- How do we explicitly test it?
  - We should see Houston 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 might fail

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 might fail

- 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.
- the Identification test
- Why DID can fail-know examples

Intro to Regression Discontinuity

Example

- Research Question: How does getting an A in the course of econometrics affect your wage?
- Naïve comparison (simple OLS) doesn’t render causal effect because of omitted variable problem, such as motivation.
- Use RD strategy: compare average wage of students who get 90 vs. those who get 89. (89 gets a B, and 90 gets an A).
- Now are we comparing apple to apple?
  - Most likely, since in the narrow neighborhood of 90, students probably randomly receive 89 or 90.
  - Students who get 89 and those get 90 are similar in observables and unobservables

What is regression discontinuity design?

- The main problem in establishing causality is that D=0 and D=1 are not comparable
- The RD design focuses on cases in which D status is determined by an arbitrary cutoff
- We compare the individuals just right of the cutoff to those just left of the cutoff
- When done well, RD is one of the most convincing empirical methods in terms of causal effect
- The idea is that some laws or rules leading to discontinuous changes in outcome, but subjects are similar in other aspects around the discontinuity
  - e.g. Course grades — 89 gets B, 90 gets A-see next slide

RD terminology

- Running variable (also called forcing variable): this is the continuous variable which determines treatment
- Cutoff: The level of the running variable at which the treatment status changes
- What are the running variables and cutoffs?
  - Course grades — 89 gets B, 90 gets A
    - Grade is running variable. Cutoff is 90

RD identification assumption

- The purpose of using RD is to mimic randomization
- The identification assumption is that around the cutoff, treatment is randomly assigned
- In other words, around the cutoff, we assume treatment is not tainted by omitted variables; individuals just to the left and right are like "apples to apples"

Sharp vs. fuzzy RD

Two types of RD:

- Sharp RD:
  - We know the exact relationship between running variable and treatment status-treatment status is completely determined by the running variable
- Fuzzy RD:
  - There is not an exact relationship- treatment status is partially determined by the running variable
  - The discontinuity strongly influences treatment status, but there is “slippage” or “non-compliance”
  - In this case, we use the discontinuity as an **instrument** for treatment status

Example: Austrian unemployment benefit- Lalive 2008

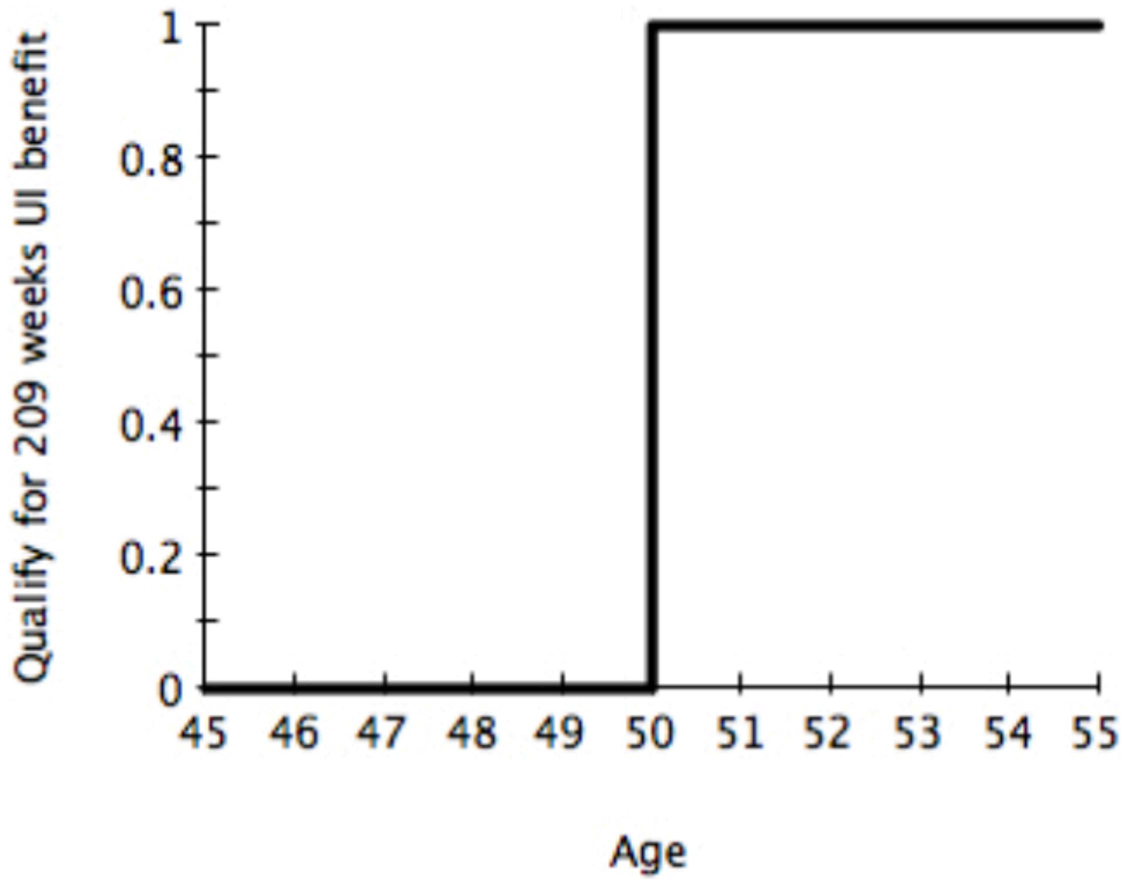
- Austrian government in 1988 extended unemployment insurance (UI) benefits for people over 50 living in certain regions of Austria from 30 weeks to 209 weeks.
- Causal question: Does the availability of 209 weeks of benefits increase unemployment duration?
- Question: Can you just compare people over 50 before and after the policy change?
- What can be some omitted variables?

Sharp RD

- Workers who are 49 only qualify for 30 weeks of unemployment insurance. Workers who are 50 qualify for 209 weeks unemployment insurance
- What is the running variable and cutoff?
- What is the mean comparison?
- Access identification assumption:
  - Are 49 years old and 50 years old different in any observed or unobserved way?
  - What are some stories that can violate the identification assumption?
- Since age perfectly predicts the maximum number of weeks unemployment, this is a sharp RD
- The sharpness can be seen in a picture

Sharp RD -“first stage”

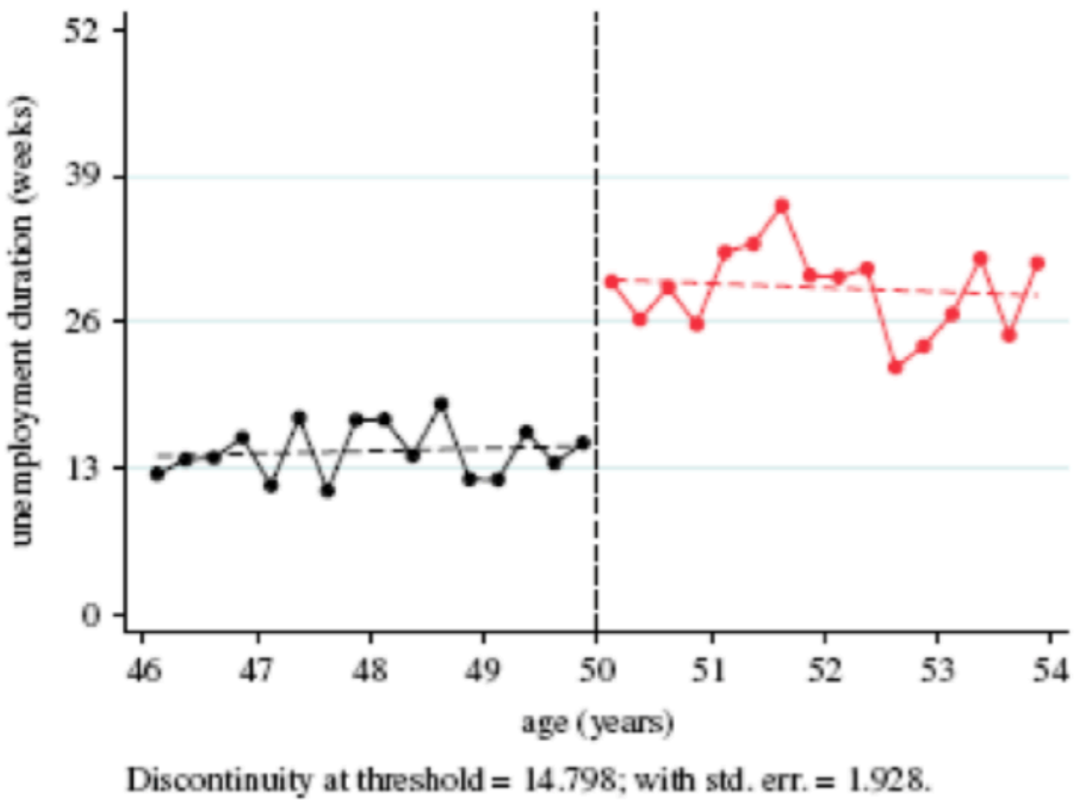
In Sharp RD, “first stage” usually is not shown



Sharp RD-”reduced form”

- Comparing unemployment duration for people aged 49 vs 50 tells us the impact on duration when age switched from 49 to 50
- It is also the impact of unemployment benefits on duration-our causal question.
- This is because we have “perfect compliance”
- All we need to assume is that 49 and 50 year olds are otherwise similar-will discuss how to explicitly test this identification assumption in the next lecture
- Results: average duration for 49 year olds was 13 weeks. For 50 year olds, average duration was 27 weeks.
- To make this even more convincing, we can show a picture

Sharp RD-”reduced form”



- Compelling evidence that the policy impacted people's unemployment duration
- The RD estimate is the vertical distance between the outcomes right at the cutoff

Exercise

- Research Question: Measure the causal impact of being the current incumbent party on the probability of winning the next election. (incumbency advantage)
- What is the naïve comparison? (identify Y and D)
- Why is the naïve comparison not causal? (identify omitted variables)

A RD research design:

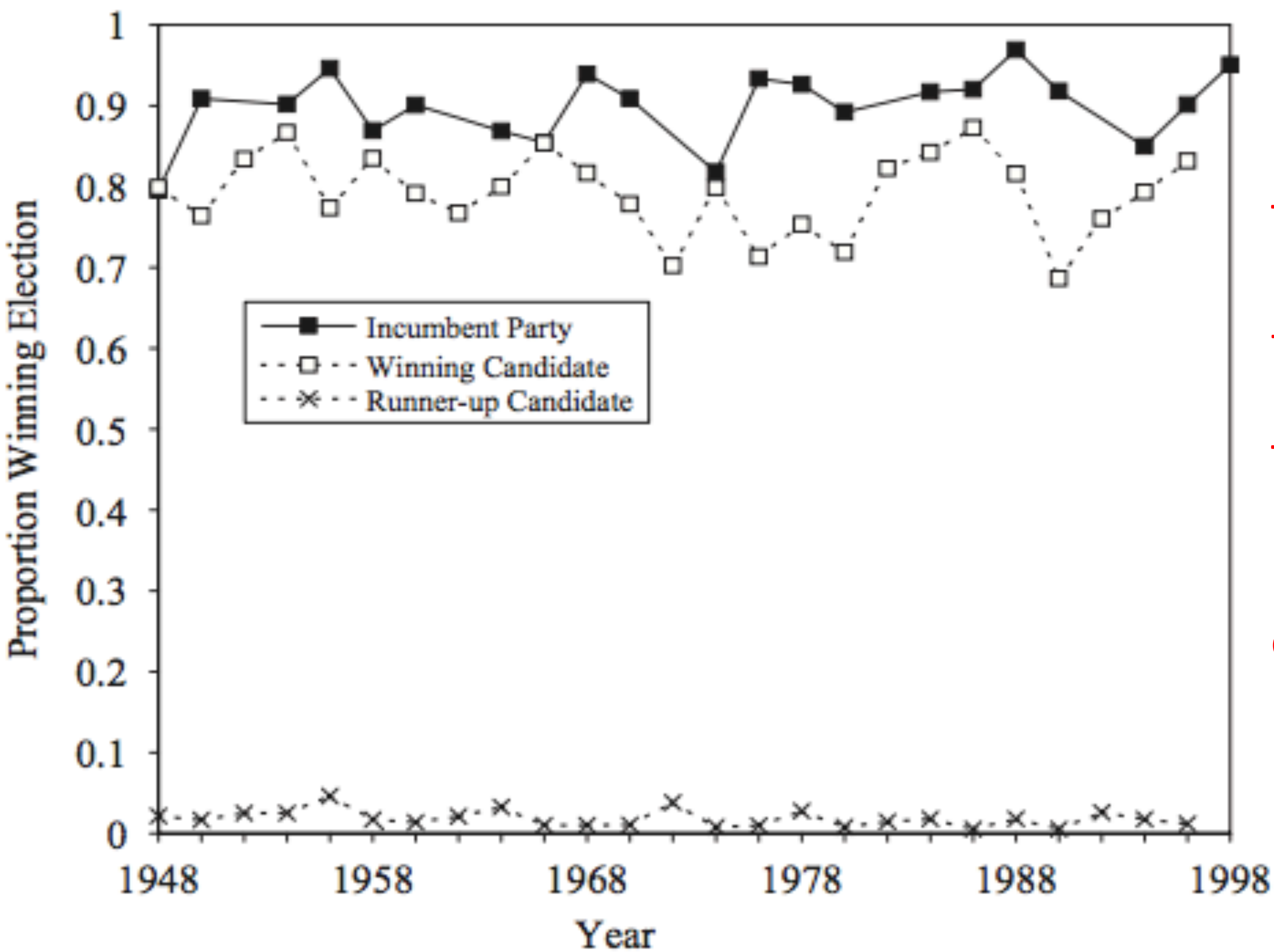
The idea: Whether or not a party is the incumbent party is a deterministic function of their vote share in the prior election.

Running variable: vote share (50.1% leads to winning, 49.9% leads to losing) in the pervious election

- Question: What is the cutoff value?
- What is the apple to apple comparison? Do you think it is reasonable?

Actual Research by David Lee

D.S. Lee / Journal of Econometrics 142 (2008) 675–697

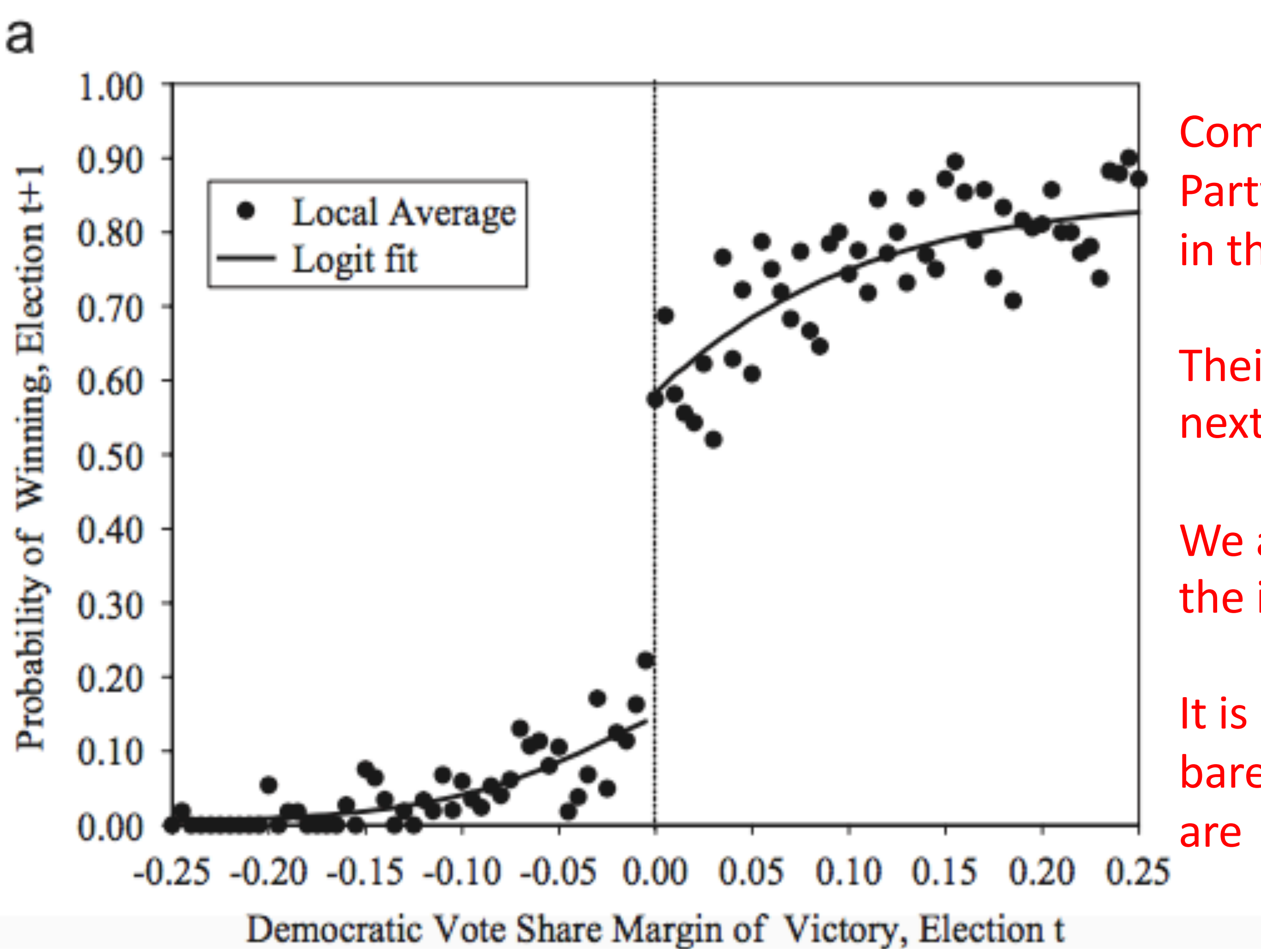


This graph shows that if a party is incumbent, it is much more likely to win the next election.

The questions is “is this because of incumbency advantage or is this because the party is in fact more capable? “

Results (note: this is a fuzzy RD)

D.S. Lee / Journal of Econometrics 142 (2008) 675–697



Compare cases when Democratic Party barely lost vs. barely won in the previous election.

Their probability of wining the next election is very different.

We attribute this difference to the incumbency advantage

It is causal because parties that barely won and those barely lost are like "apple to apple"

Review for quizzes

- Understand what RD is, why we need RD, and the identification assumption of RD
- Understand two types of RD
- Be able to recognize the running variable and cutoff value