REGRESSION DISCONTINUITY

(RD)

Technical Track Session V

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The World Bank

Introduction

- Many times random assignment is not possible
  - Universal take-up
  - Non-excludable intervention
  - Treatment already assigned

- When randomization is not feasible, how can we exploit implementation features of the program to measure its impact?

- Answer: Quasi-experiments
- Example: Regression Discontinuity Design.

Regression Discontinuity Design (RDD)

- RDD closer to randomized experiments than other quasi-experimental methods
- Relies on knowledge of the selection process
  - Need to know quantifiable selection criteria – a continuous "score" or index
  - Assignment to "treatment" depends discontinuously on this "score" at a threshold or cutoff
- Intuition
  - The potential beneficiaries (units) just above the cut-off point are very similar to the potential beneficiaries just below the cut-off.
  - Within narrow bandwidth around cut-off, treatment assignment approximates randomization
  - Comparing final outcomes of those just above cutoff to those just below can approximate treatment effect

Indexes are common in targeting of social programs

Anti-poverty programs	targeted to households below a given poverty index.
Pension programs	targeted to population above a certain age.
Scholarships	targeted to students with highest scores on standardized test—or with lowest score of poverty index.
"Community Driven Development" programs	awarded to NGOs that achieve highest scores.

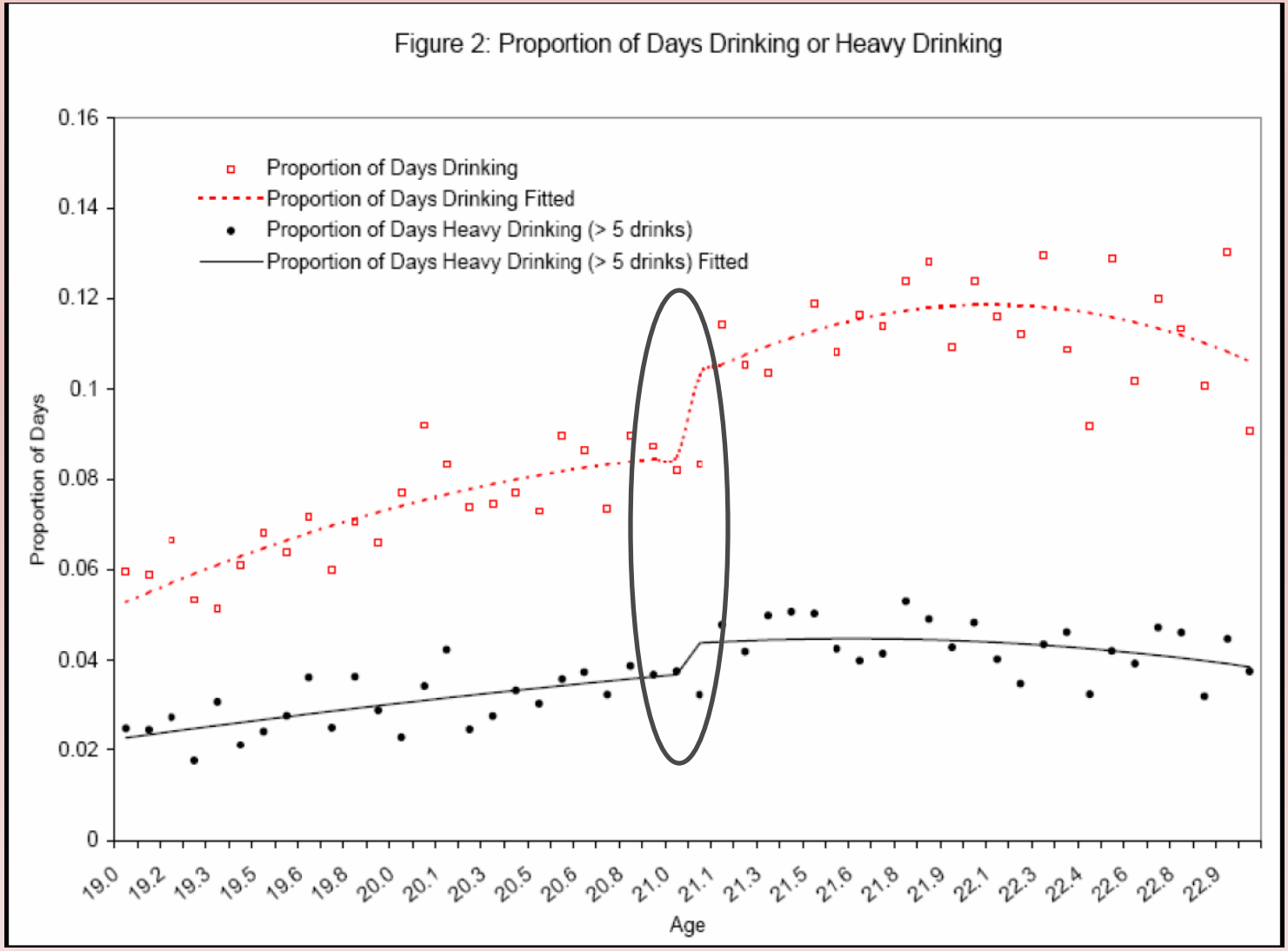
An example

- US minimum legal age for drinking alcohol is 21
  - → illegal for people younger than 21
- Consider two groups
  - People aged 20 years, 11 months and 29 days
  - 21 year olds
- Two groups treated differently under policy because of arbitrary age cut off
- But not inherently different (likelihood to go to parties, obedience, propensity to engage in risky behavior, etc)

Effect of alcohol on mortality

- Policy rule assigns people to "treatment" and "comparison" groups
  - Treatment group: People between ages 20 years and 11 months and 20 years 11 months and 29 days
  - Comparison group: individuals who just turned 21 and can now legally drink alcohol.
  - Groups should be similar in terms of observable and unobservable characteristics that affect outcomes (mortality rates) but dissimilar on legality of their alcohol consumption
- Possible to estimate impact of *legality* of alcohol consumption on mortality rates
- Also possible to isolate the causal impact of *actual* alcohol consumption on mortality rates

Graphical depiction



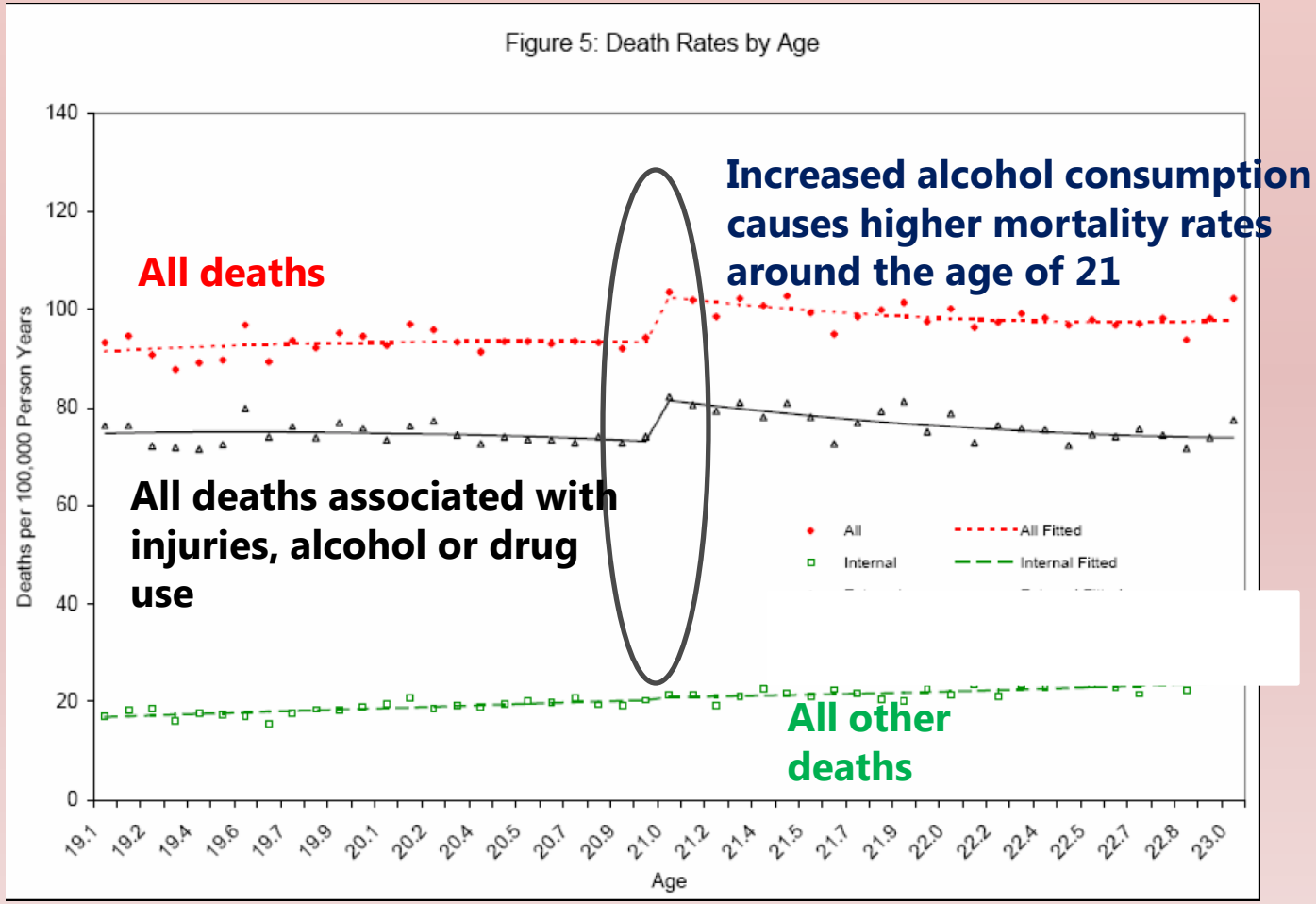


Figure 5: Death Rates by Age
Deaths per 100,000 Person Years
140
120
100
80
60
40
20
0
19.1
19.2
19.4
19.6
19.7
19.9
20.1
20.2
20.4
20.5
20.7
20.9
21.0
21.2
21.4
21.5
21.7
21.9
22.0
22.2
22.4
22.5
22.7
22.8
23.0
Age
All
All Fitted
Internal
Internal Fitted
All deaths
All deaths associated with injuries, alcohol or drug use
Increased alcohol consumption causes higher mortality rates around the age of 21
All other deaths

Sharp and fuzzy discontinuities

- Sharp discontinuity
  - Discontinuity precisely determines treatment status
  - All people 21 and older drink alcohol and no one else does

- Fuzzy discontinuity
  - Percentage of participants changes discontinuously at cut-off, but not from 0% to 100% (or from 100% to 0%)
  - Some people younger than 21 end up consuming alcohol and/or some older than 21 don’t consume at all
  - Need to use score as an instrumental variable for consumption

Example: Effect of cash transfer on consumption

Goal

Target transfer to poorest households

Method

- Construct poverty index from 1 to 100 with pre-intervention characteristics
- Households with a score ≤ 50 are poor
- Households with a score >50 are non-poor

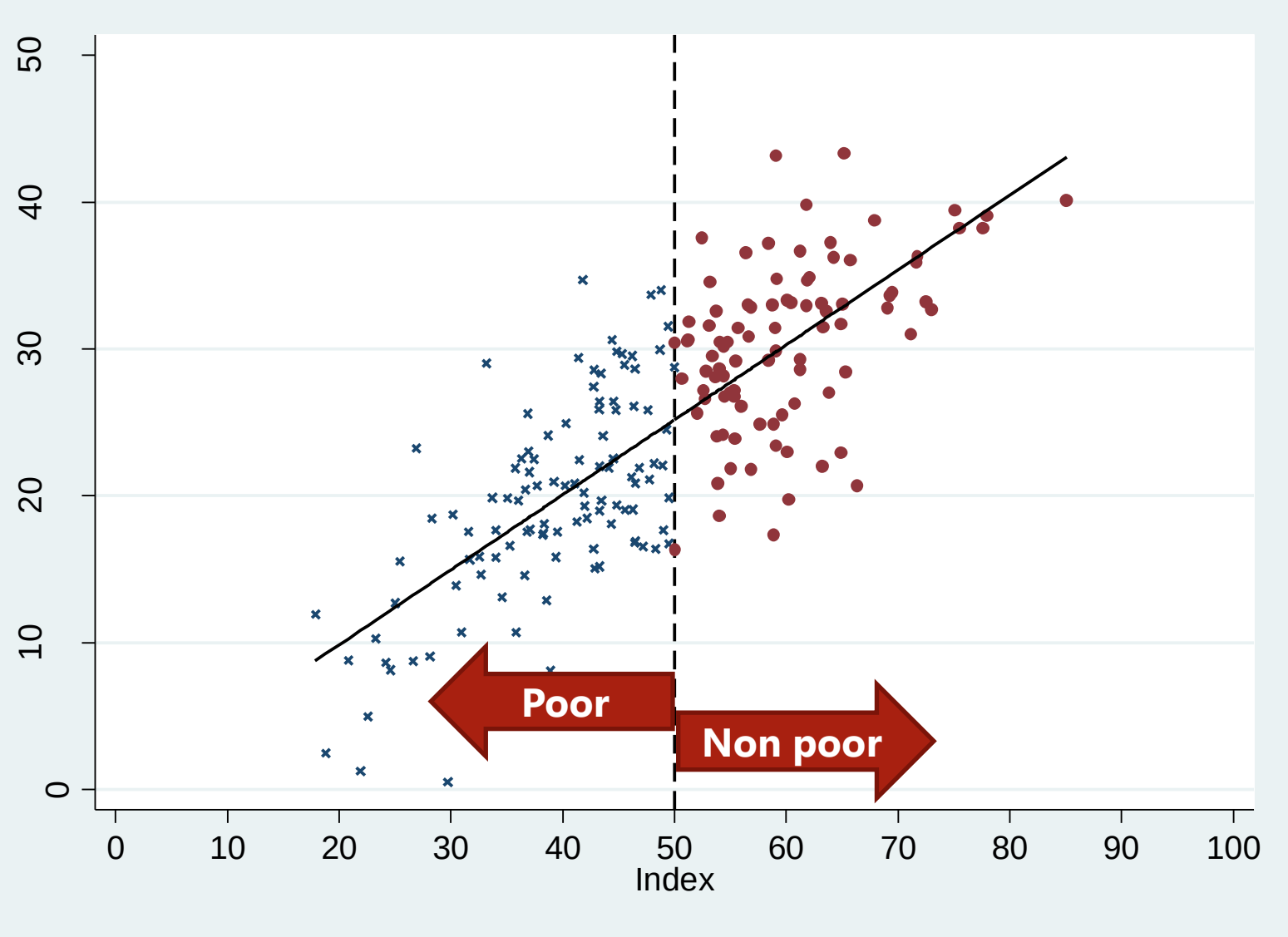
Implementation

Cash transfer to poor households

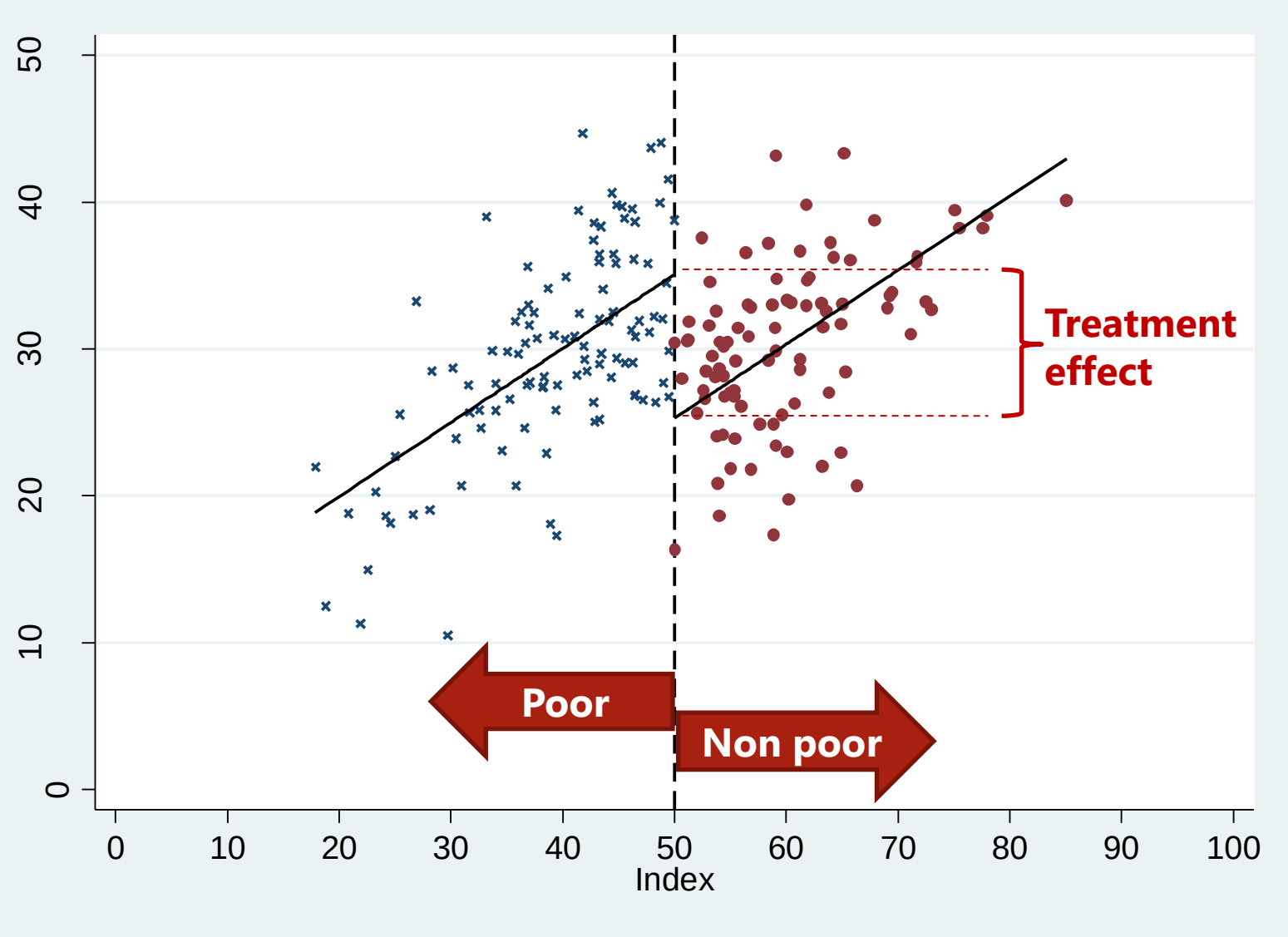
Evaluation

Measure outcomes (i.e. consumption, school attendance rates) before and after transfer, comparing households just above and below the cut-off point.

Regression Discontinuity Design-*Baseline*



Regression Discontinuity Design-*Follow-up*



Identification for sharp discontinuity

$$y_i = \beta_0 + \beta_1 D_i + \delta(score_i) + \varepsilon_i$$

$$D_i = \begin{cases} 1 & \text{If household } i \text{ receives transfer} \\ 0 & \text{If household } i \textit{ does not} \text{ receive transfer} \end{cases}$$

$\delta(score_i)$ = Function that is continuous around the cut-off point

- Assignment rule under sharp discontinuity:

$D_i = 1 \longleftrightarrow score_i \leq 50$

$D_i = 0 \longleftrightarrow score_i > 50$

Identification for fuzzy discontinuity

$$y_i = \beta_0 + \beta_1 D_i + \delta(score_i) + \varepsilon_i$$

$$D_i = \begin{cases} 1 & \text{If household receives transfer} \\ 0 & \text{If household } \textit{does not} \text{ receive transfer} \end{cases}$$

- But
  Treatment depends on whether $score_i$ > or < 50
- And
  Endogenous factors

Estimation for fuzzy discontinuity

$$y_i = \beta_0 + \beta_1 D_i + \delta(score_i) + \varepsilon_i$$

IV estimation

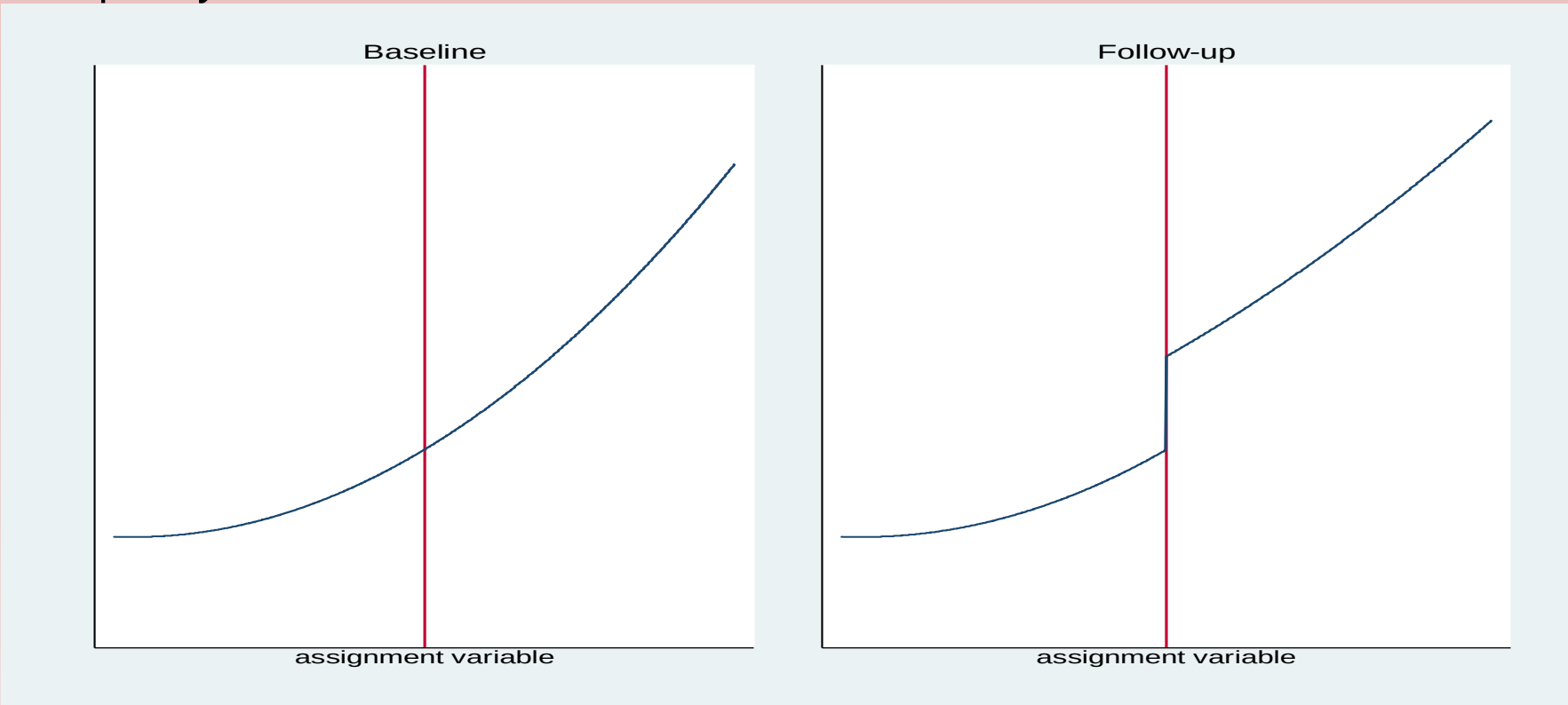
- First stage: $$D_i = \gamma_0 + \gamma_1 \underbrace{I(score_i > 50)}_{\text{Dummy variable}} + \eta_i$$

- Second stage: $$y_i = \beta_0 + \beta_1 \hat{D}_i + \underbrace{\delta(score_i)}_{\text{Continuous function}} + \varepsilon_i$$

Internal validity

- If cut-off is arbitrary, individuals to the immediate left and right of the cut-off should be very similar pre-intervention

- Post-intervention: Differences in outcomes can be attributed to the policy.



Internal Validity

- Major assumption
  - *Nothing else is happening*: in absence of policy, we would not observe a *discontinuity* in the outcomes around this particular cut off.
  - Might not be the case if cutoff meaningful for other policies
    - Bike-helmet policy stops also stops applying at age 21.

- Major data requirement
  - Requires many observations around cut-off
  - All observations away from the cut-off have less weight

Internal Validity

- Crucial that participants do not know much about formula for determining cut-offs
- Otherwise, they can adjust their behavior in ways that undermine validity
- Example 1: Pupil teacher ratios and student achievement in Chile
  - Enrollment cutoff (X) determined required number of classrooms
  - School with X students and school with X+1 students would have different number of classrooms
    - Very little difference in enrollment
    - Big difference in Pupil/Teacher Ratio
  - Once enrollment reached a trigger point, some schools began to increase fees to decrease enrollment and avoid requirement for new classroom
    - Schools with X and X+1 students, where X is the cut-off, could be very different

Internal Validity

- Crucial that participants do not know much about formula for determining cut-offs
- Otherwise, they can adjust their behavior in ways that undermine validity
- Example 2: SISBEN index in Colombia
  - Poverty index used to determine eligibility in many public programs
  - Evidence of **clumping** at index-thresholds over time

External validity

- Would the results generalize past the two groups you are comparing?

- Counterfactual group in RDD
  - Individuals marginally excluded from benefits
  - Example: people less than 21 but older than 20 years and 10 months

- Causal conclusions are limited to individuals, households, villages, near the cut-off
  - The estimated impact for units marginally or just eligible for benefits
  - Extrapolation beyond this point needs additional, often unwarranted, assumptions (or multiple cut-offs)

Advantages of RD for evaluation

- RD yields an unbiased estimate of treatment effect at the discontinuity
- Can take advantage of a known rule for assigning the benefit
  - This is common in the design of social interventions
  - No need to “exclude” a group of eligible households/ individuals from treatment

Potential disadvantages of RD

- Local average treatment effects:
  - We estimate the effect of the program around the cut-off point
  - This is not always generalizable
- Power:

  The effect is estimated at the discontinuity, so we generally have fewer observations than in a randomized experiment with the same sample size.
- Specification can be sensitive to functional form:

  Make sure the relationship between the assignment variable and the outcome variable is correctly modeled, including: (1) Nonlinear Relationships and (2) Interactions.

References

- Christopher Carpenter and Carlos Dobkin (2009), "The Effect of Alcohol Access on Consumption and Mortality: Regression Discontinuity Evidence from the Minimum Drinking Age," *American Economic Journal: Applied Economics,* Vol. 1, Issue 1, pp. 164-82

- Miguel Urquiola and Eric Verhoogen (2009), "Class-Size Caps, Sorting, and the Regression Discontinuity Design," *American Economic Review*, v. 99 no. 1, pp. 179-215, March 2009.

- Adriana Camacho and Emily Conover (2009), "Manipulation of Social Program Eligibility: Detection, Explanations and Consequences for Empirical Research," UNIVERSIDAD DE LOS ANDES-CEDE Discussion Paper 006211

Thank You

Q & A