EC 1152 - Using Big Data to Solve Economic and Social Problems

Review Session #3: Regression Discontinuity
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Disclaimer: multiple TFs contributed to those slides. All mistakes are mine.

Outline: Regression Discontinuity

- RDs as a tool for causal inference
- Example (Lindo, Sanders and Oreopoulos, 2010)
  - Visualization
  - Estimation
- Key Assumptions
  - Robustness Checks and Advanced Topics
- Stata Code

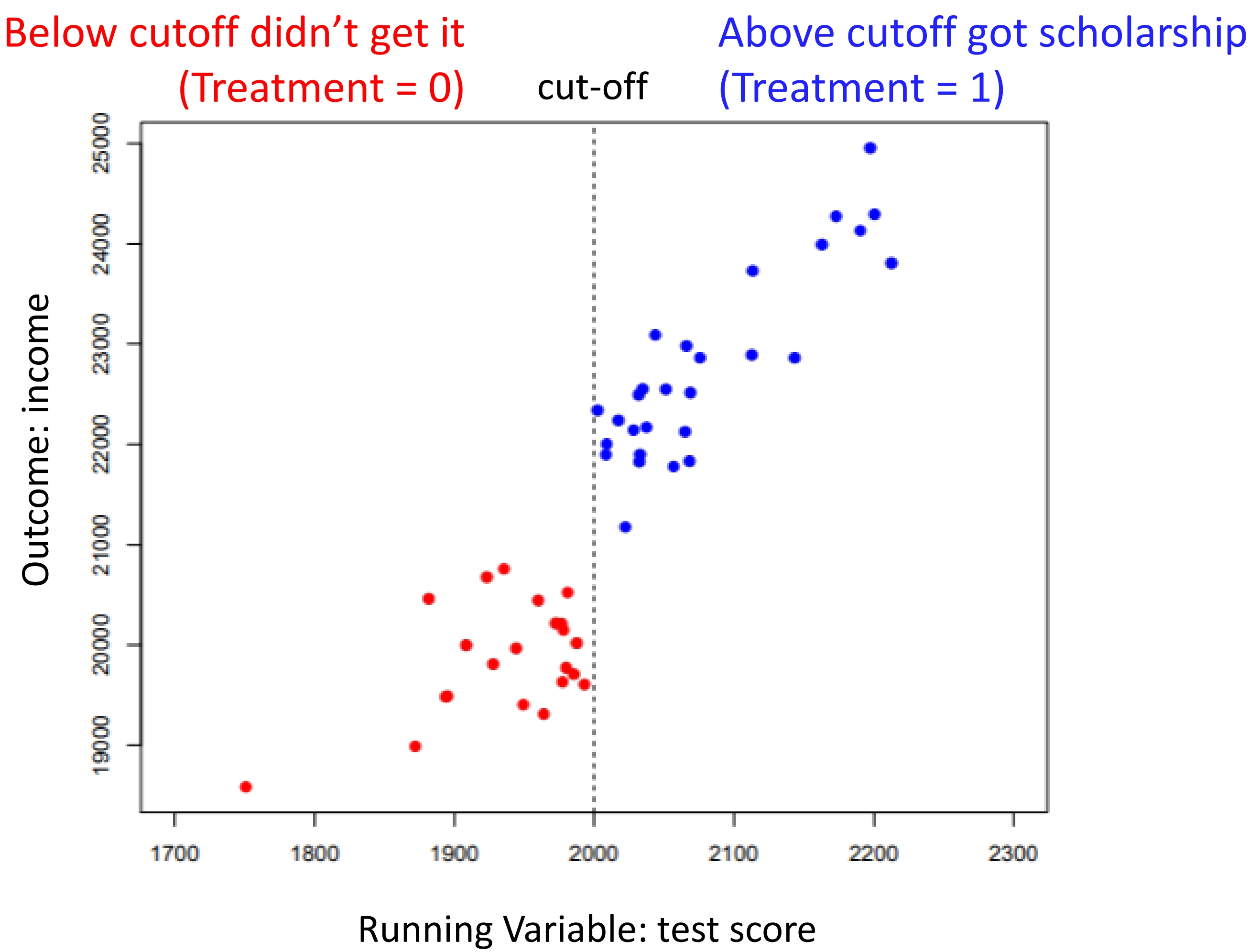
Causal Inference: Randomized is gold

METHODOLOGY	DESCRIPTION	WHO IS IN THE COMPARISON GROUP?	THE METHODOLOGY IS ONLY VALID IF...
Randomized Evaluation example: MTO	Random assignment (e.g. a coin toss or random number generator) determines who may participate in the program so that those assigned to participate in the program are, on average, the same as those who are not, in both observable and unobservable ways. Since the participants and nonparticipants are comparable, except that one group received the program, any differences in outcomes result from the causal effect of the program.	Participants who are randomly assigned to not participate in the program. This is often called the "control" group.	Randomization "worked" and the two groups are statistically identical (on observed and unobserved factors). The effects of the treatment do not spill over to the control group. Any behavioral changes are driven by the program—not by the evaluation itself, or by the fact that the participants or non-participants are being studied. If outcome data are missing, data for the same types of individuals are missing from both the control and treatment groups.

Source: https://www.povertyactionlab.org/sites/default/files/resources/2016.08.31-Impact-Evaluation-Methods.pdf

Intuition

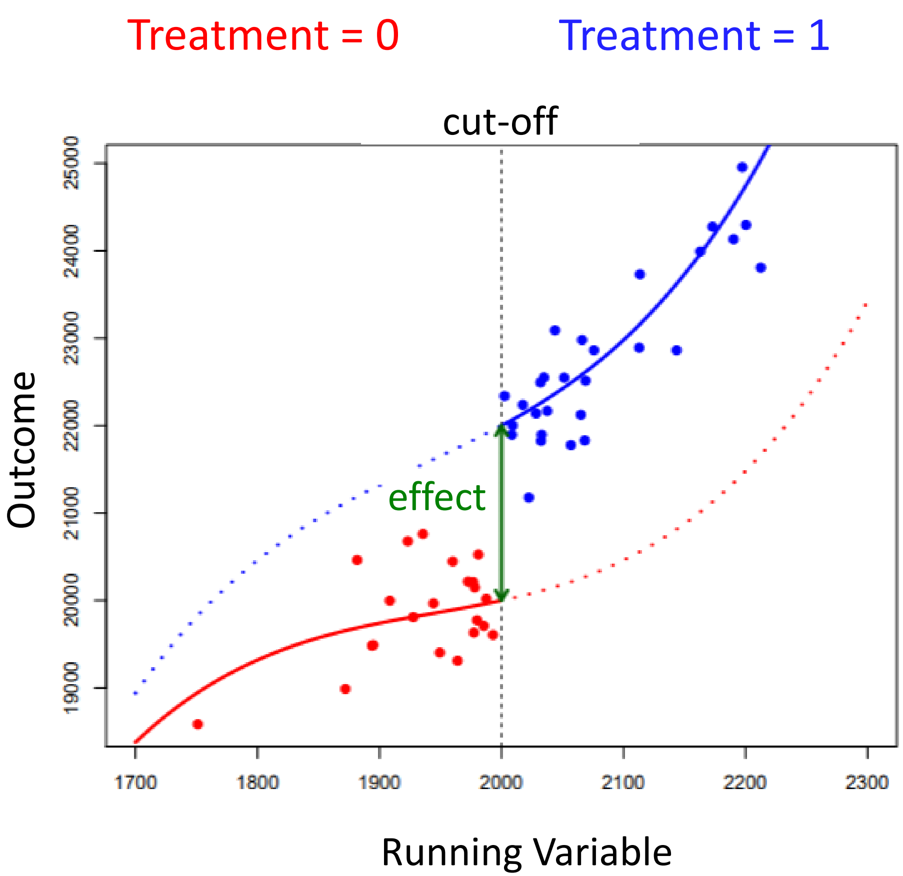
Unfortunately, people were not randomized into scholarships (treatment).. but there was a **rule to decide who got treated.** Can we claim causal effects?

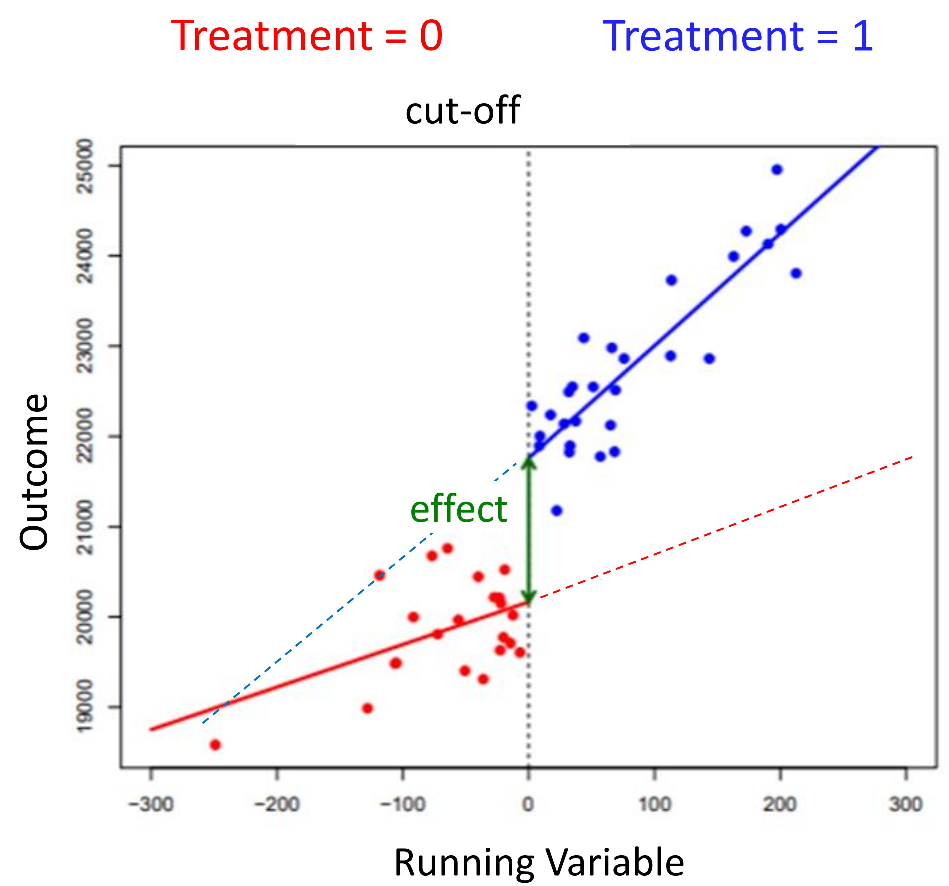


Source: Yamamoto (2016)

Intuition

Could use different *extrapolation* methods, but you're interested in the *jump*, the **discontinuity** between those who *almost* got treated and *almost* didn't





Source: Yamamoto (2016)

Causal Inference: Randomized vs RD

METHODOLOGY	DESCRIPTION	WHO IS IN THE COMPARISON GROUP?	THE METHODOLOGY IS ONLY VALID IF...
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METHODOLOGY	DESCRIPTION	WHO IS IN THE COMPARISON GROUP?	THE METHODOLOGY IS ONLY VALID IF...
Regression Discontinuity Design example: Zimmerman (2014): FIU	Individuals are ranked or assigned a score based on specific, measureable criteria. A cutoff determines whether an individual is eligible to participate in the program. Participants who are just above the cutoff are compared to non-participants who are just below the cutoff.	Individuals who are close to the cutoff, but fall on the "wrong" side of that cutoff, and therefore do not get the program.	After adjusting for the eligibility criteria (and other observed characteristics), the individuals directly below and directly above the cut-off score are statistically identical. The cutoff criteria must have been strictly adhered to. The cutoff must not have been manipulated to ensure that certain individuals qualify for the program.

Source: https://www.povertyactionlab.org/sites/default/files/resources/2016.08.31-Impact-Evaluation-Methods.pdf

Example: Lindo, Sanders and Oreopoulos 2010

To estimate returns to a college education, LSO (2010) use data from Canadian university and a **regression discontinuity design**

Compares students just above and just below GPA cutoff in their 1st year for being put in academic probation:

- Discourages some students from returning, reducing graduation rates
- Improves subsequent performance for those who remain

Next we will go over:

- How do we visualize this?
- How do we estimate the causal effect?
- What do we need to interpret a RD as causal?

Visualizing Regression Discontinuities

An arbitrary cut-off point, C, determines treatment assignment

- GPA is the **forcing variable or running variable** (often re-centered at the cutoff to facilitate visualization/interpretation of estimates)

FIGURE 1. DISTRIBUTION OF STUDENT GRADES RELATIVE TO THEIR CUTOFF

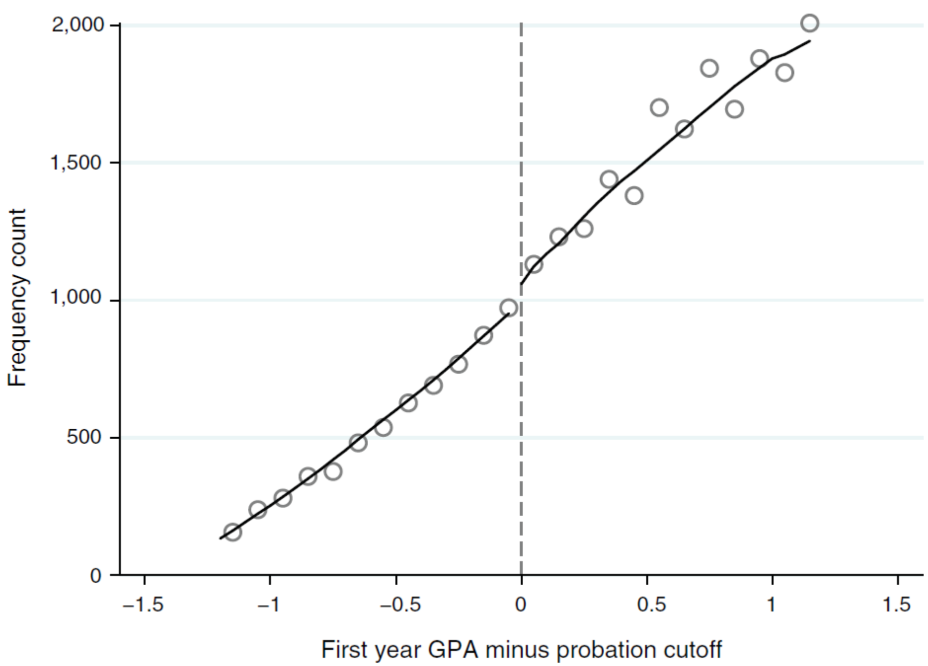
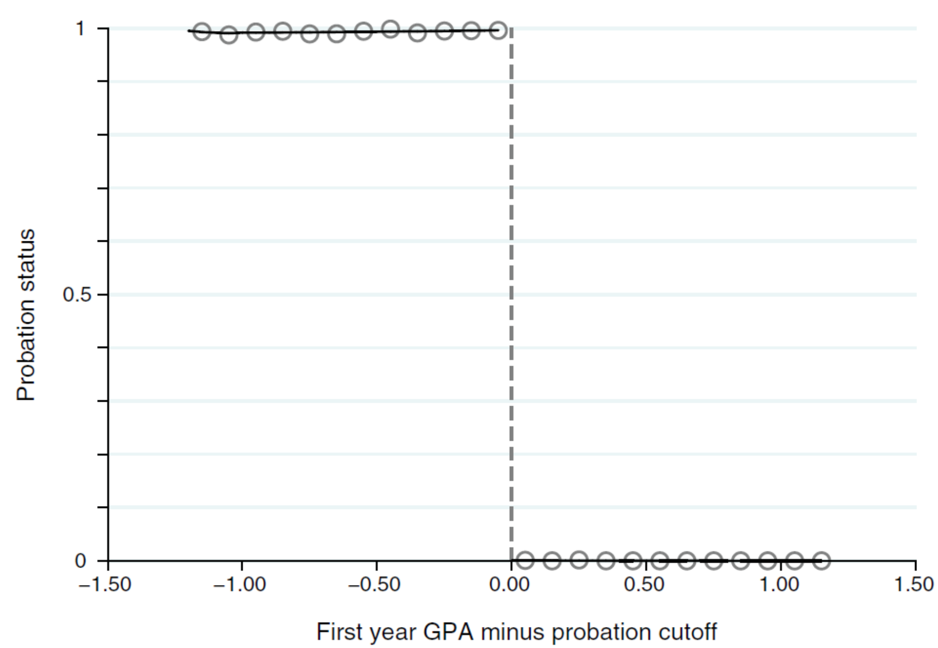


FIGURE 2. PROBATION STATUS AT THE END OF THE FIRST YEAR



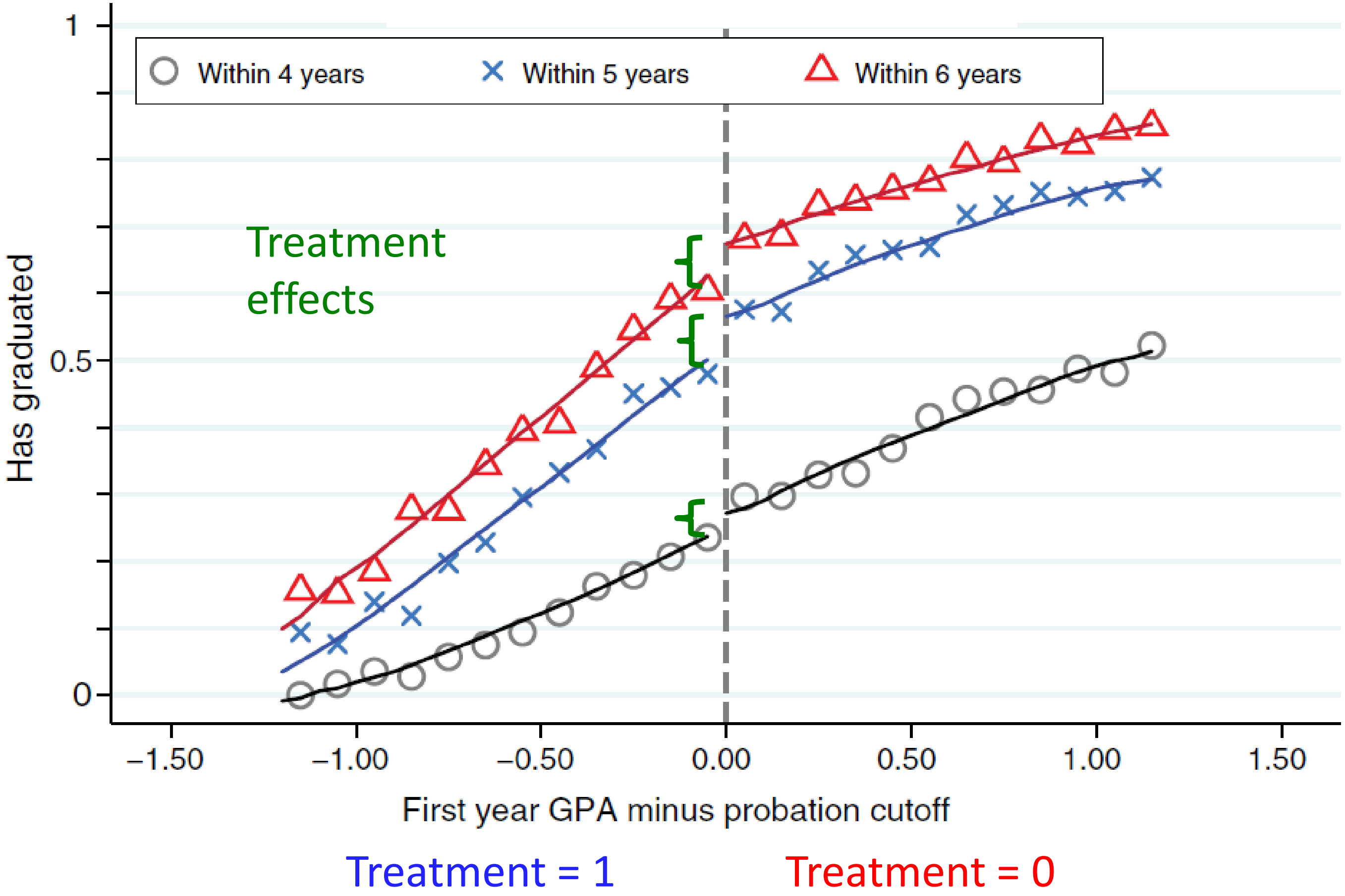
Treatment = 1 Treatment = 0 Treatment = 1 Treatment = 0

Source: Lindo, Sanders and Oreopoulos (2010)

Visualizing Regression Discontinuities

Jump at cutoff is significant => probation reduces graduation rates

FIGURE 5. GRADUATION RATES

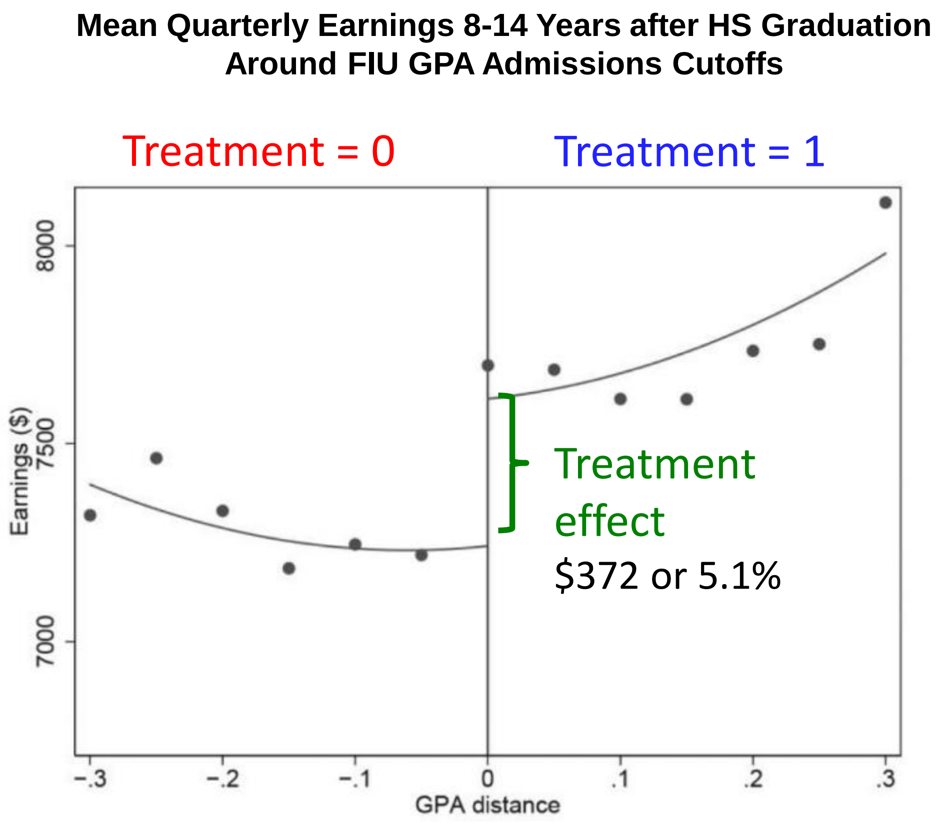


Source: Lindo, Sanders and Oreopoulos (2010)

Example: Zimmerman (2014)

To estimate returns to a college education, Zimmerman compares students just above and just below state-level GPA cutoff for admission to the Florida State University System:

- You will see this example in next Chetty's lecture!!!



Source: Zimmerman (2014)

Can you think of other RD examples?

Discuss with a partner or two!

- Close elections
- Social program eligibility cut-off
- Scholarships
- Education admissions
- Tax brackets
- Pregnancy induction
- Birth weight
- Address determining school district assignment

Regression Discontinuity Estimation

Typical steps:

- Re-center running variable: X = GPA – cutoff C
- Treatment dummy: T = 1 if GPA< cutoff (probation) and T = 0 if GPA > cutoff (no probation)
- Regress:

Outcome treatment dummy re-centered running variable

$$\text{Linear: } Y = \beta_0 + \beta_1 T + \underbrace{\beta_2 X}_{\text{Controls for slope of those without treatment}} + \underbrace{\beta_3 T \cdot X}_{\text{Controls for slope to the other side of the cutoff}} + \varepsilon$$

$$\text{Quadratic: } Y = \beta_0 + \beta_1 T + \beta_2 X + \beta_3 T \cdot X + \beta_4 X^2 + \beta_5 T^* X^2 + \varepsilon$$

In these cases, __β_1__ estimates the discontinuity of interest.

HAS causal interpretation

We estimate β_2 and β_3 separately because we don't presume the same relationship at both sides of the cutoff.

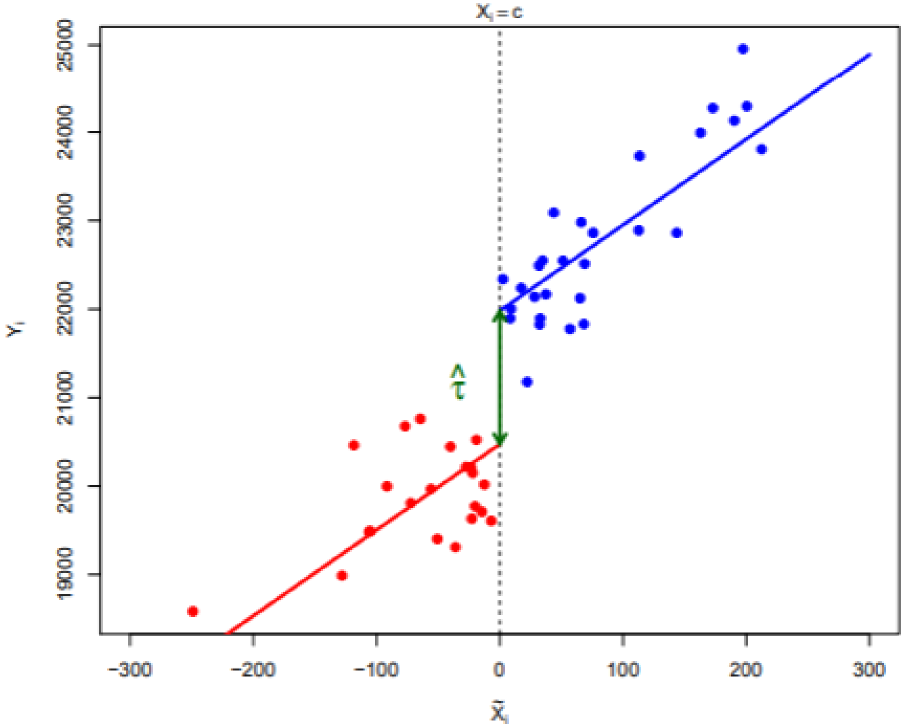
We include β_4 and β_5 to allow for a quadratic form (more terms for cubic, etc).

NO causal interpretation

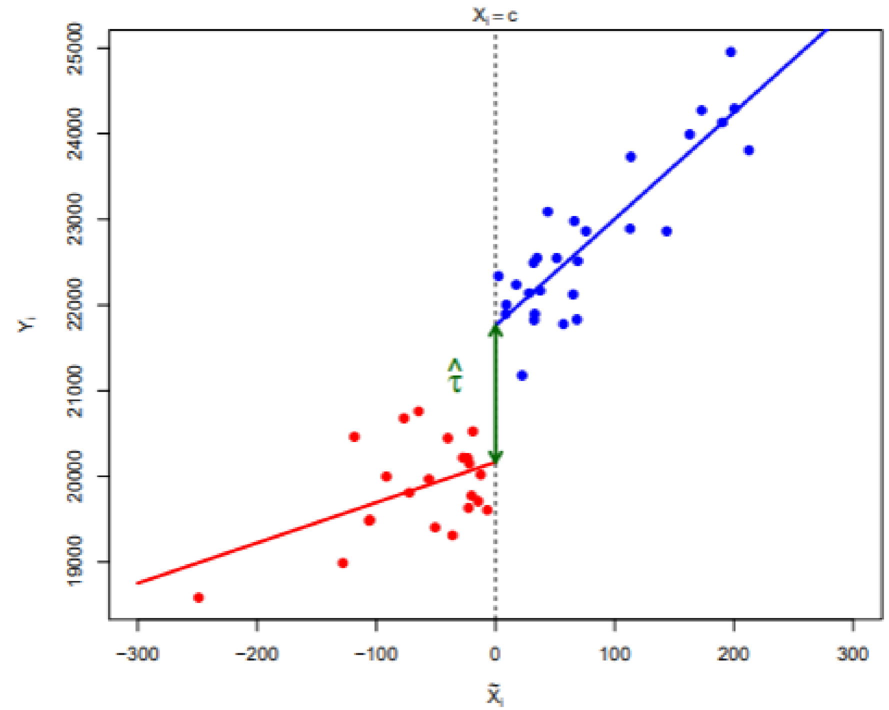
Common slope vs different slope RD

Estimated considering slope to be, around the cut-off:

Common



Different



But only the **jump** has causal interpretation!!!

Source: Yamamoto (2016)

Regression Discontinuity Estimation Continued

To what population does this estimate apply?

RD is a local estimate

- The results are based on observations right above and below C
- Local average treatment effect (LATE)

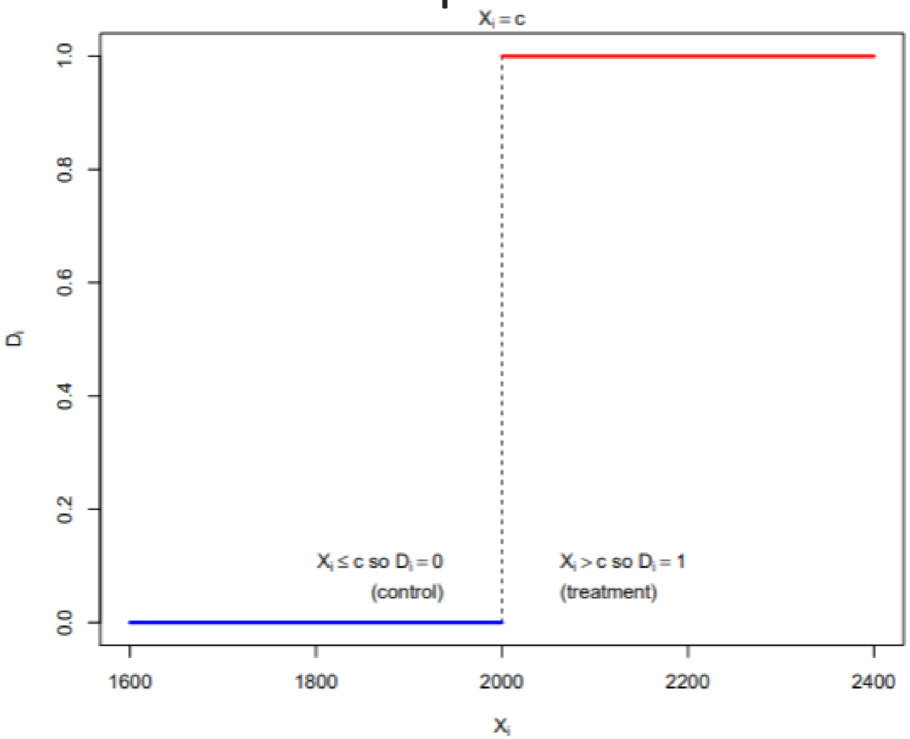
For external validity, we would need additional data to make generalizations:

- Are people farther from the cut-off different than those closer?
- Other methods that ensure identifying assumptions remain satisfied

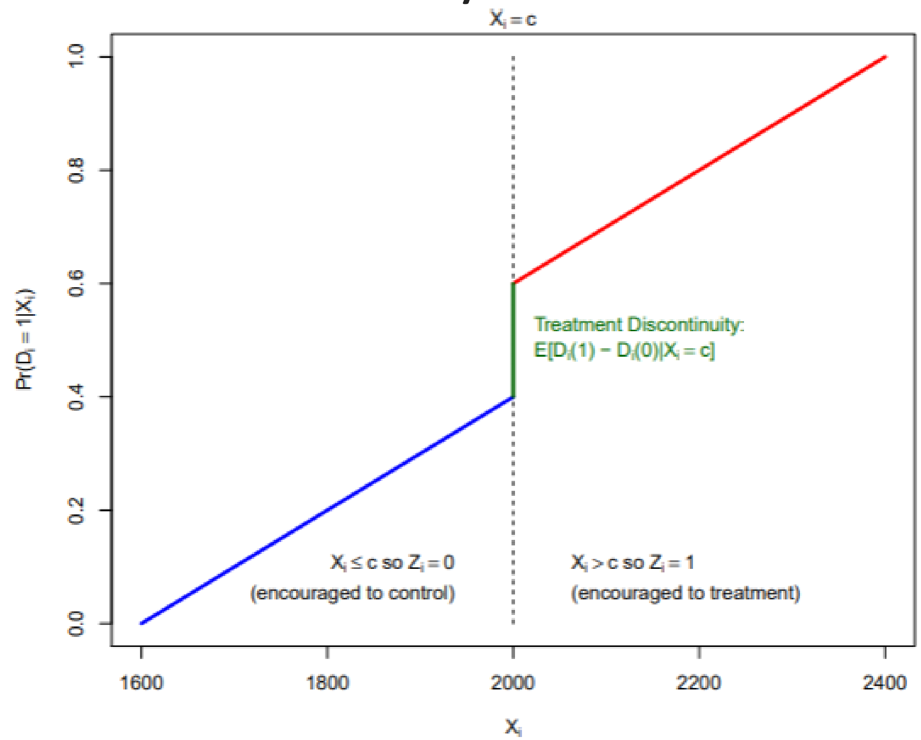
Sharp vs Fuzzy RD

Probability of Treatment in:

Sharp RDD



Fuzzy RDD



Corresponding example:
Lindo Sanders Oreopoulos 2010

Zimmerman 2014

Regression Discontinuity Assumptions

- What is necessary to interpret a RD as causal?
- Key Assumptions

1. No manipulation of the running variable
2. No other discontinuities: other determinants of the outcome (covariates) evolve smoothly across the cut-off
3. No other treatments occur at the cut-off

Assumption 1: No Manipulation

No manipulation (or imperfect control) of the running variable

- Imagine if people could control whether they get the pill or a placebo
- Manipulation introduces selection bias and differences in unobservables

How do we test if this assumption is violated?

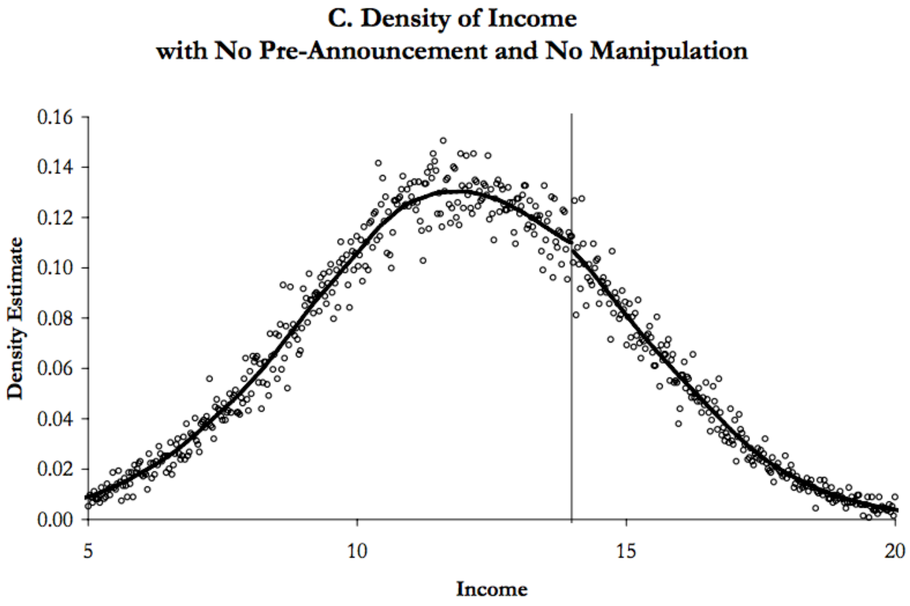
- Consider the setting & treatment: Is the cut-off published? How can individuals change their X, if at all?
- McCrary Test – Can look at Density of Observations around the cutoff
  - It was figure 1 in the Lindo Sanders Oreoupoulos 2010 example

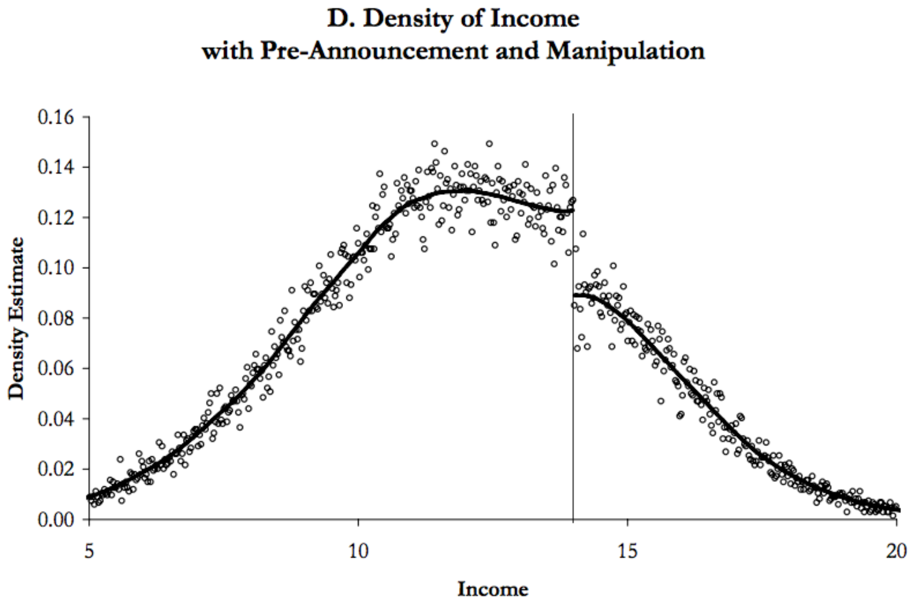
McCrary Test

McCrary Test – Look at Density of Observations around the cutoff for evidence of manipulation

No Discontinuity at X=C

Discontinuity at X=C





Source: Hypothetical Example: Gaming the System with an Income-Tested Job Training Program
https://eml.berkeley.edu/~jmccrary/mccrary2006_DCdensity.pdf

Assumption 2: No Other Discontinuities

Other determinants of treatment should evolve smoothly across the threshold

- Imagine if treatment assignment were related to age, gender, income, etc.
- Differences in observables may confound estimates
- The treatment and control groups wouldn’t look similar

How do we test if this assumption is violated?

- Visualize using binscatter
- Show covariate balance

Assumption 2: No Other Discontinuities

- Landais (2015) used binscatter plots to check this assumption this for a paper evaluating UI

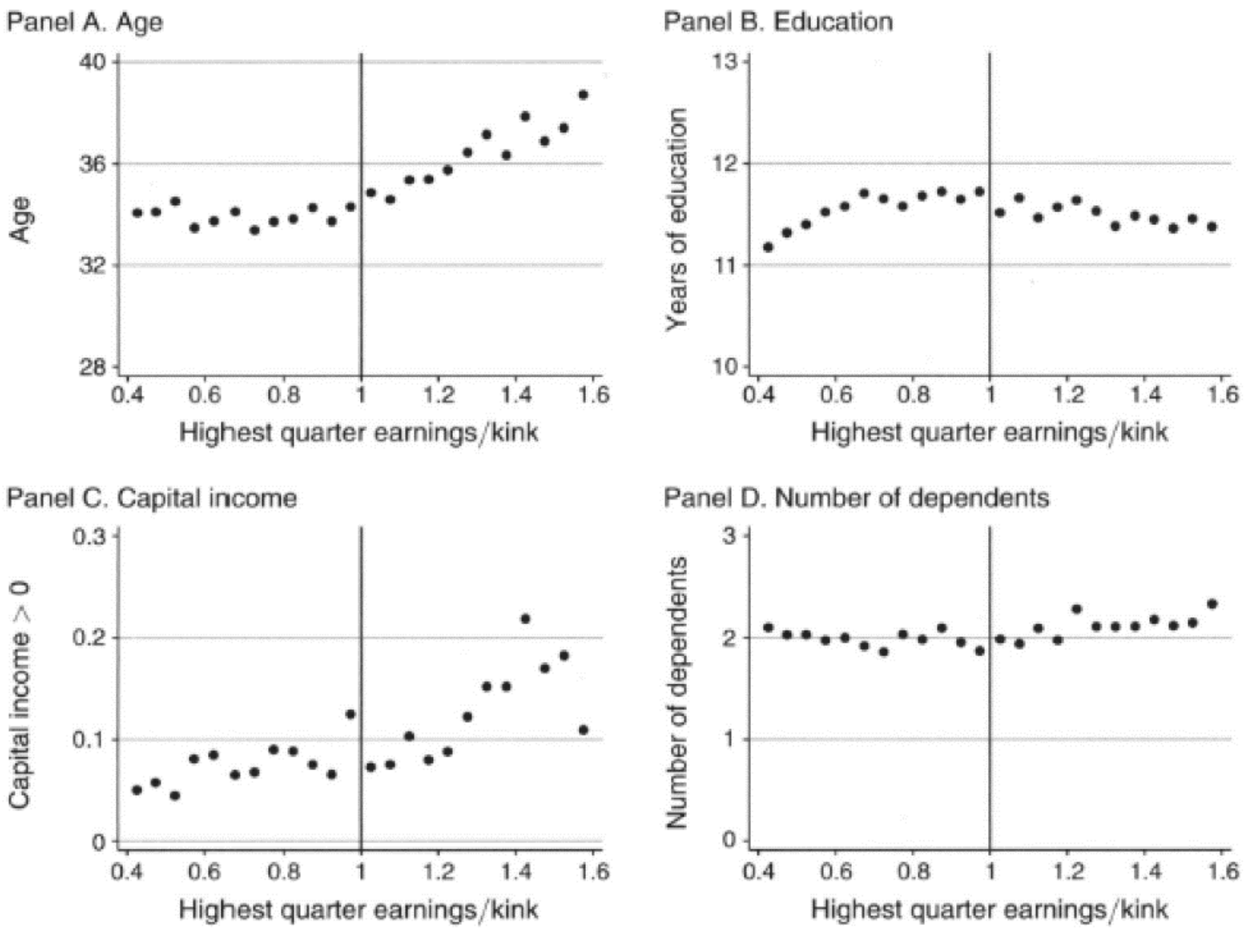


Figure 5. Distribution of Highest Quarter Earnings and Covariates, Louisiana

Assumption 2: No Other Discontinuities

- You can also show this in a table, like in Goodman & Cohodes (2014)
- Replace the outcome with the covariates in the regression equation

Measures discontinuity

$$Y = \beta_0 + \beta_1 Treat + \beta_2 Distance + \beta_3 Distance * Treat + \epsilon$$

Covariate

Controls for slope to the Left

Controls for slope to the Right

TABLE 3—COVARIATE BALANCE

	Female (1)	Black (2)	Hispanic (3)	Asian (4)	Low income (5)	Special ed. (6)	Pred math score (7)	Pred. ELA score (8)
Panel A. Classes of 2005–2006								
Adams eligible	–0.005	0.006*	–0.000	–0.005	0.003	0.003	–0.007	–0.006
	(0.010)	(0.004)	(0.004)	(0.005)	(0.006)	(0.003)	(0.005)	(0.005)
$\overline{Y}$	0.508	0.038	0.033	0.052	0.103	0.018	0.331	0.339
Observations	41,190	41,190	41,190	41,190	41,190	41,190	41,190	41,190

Assumption 3: Only one treatment at the cutoff

No other treatment is taking place at the cut-off, C

- Imagine if the program eligibility for food stamps, Medicaid, TANF, and EITC were the same
- Then, it would be difficult to distinguish whether food stamps (or another program or another combinations of programs) are driving the results

How do we test if this assumption is violated?

- Understand institutional details

Robustness and Assumption Checks

1. Manipulation of running variable (McCrary test)
    - Donut hole to exclude manipulators

2. Placebo test
    - Covariates as outcomes
    - Fake cutoffs

3. Run regressions with multiple specifications
    - Bandwidth selection (what is “close” to cutoff)
    - Try different functional forms (linear, quadratic, cubic, etc)

How to address manipulation: donut hole

- Use a donut-hole RD to exclude the manipulators (Hoxby and Bulman, 2016)
- Or focus on the subsample where people can't manipulate (Card et al, 2008)

C.M. Hoxby, G.B. Bulman / Economics of Education Review 51 (2016) 23–60

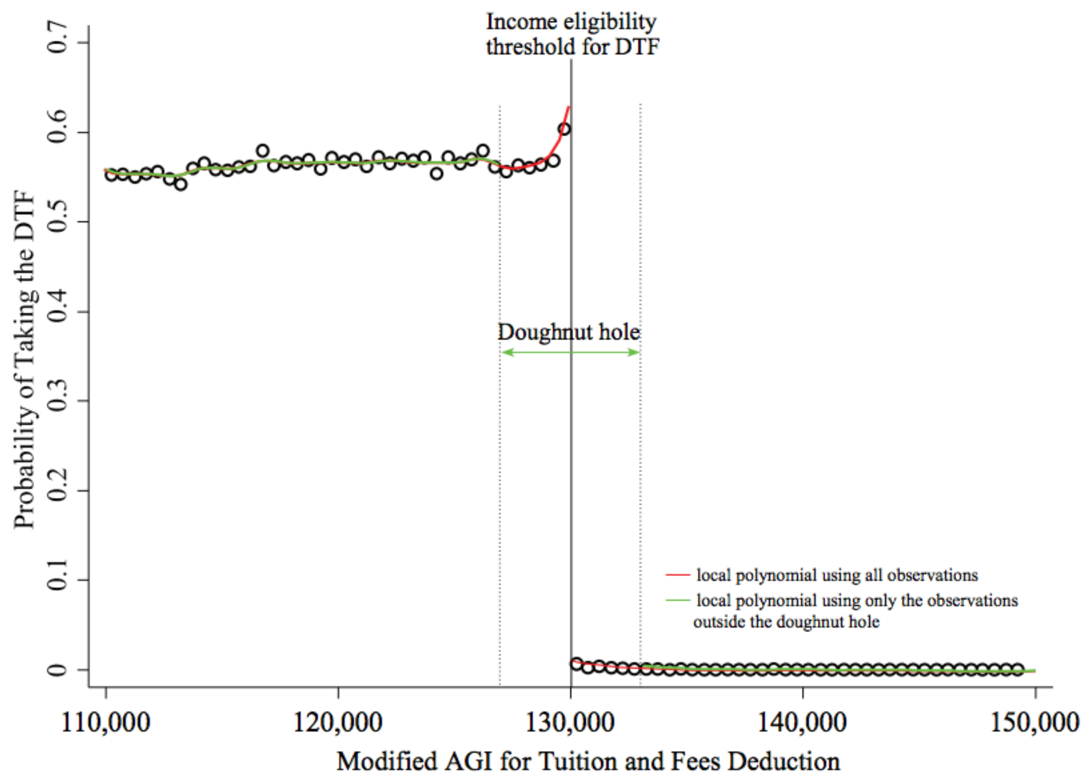
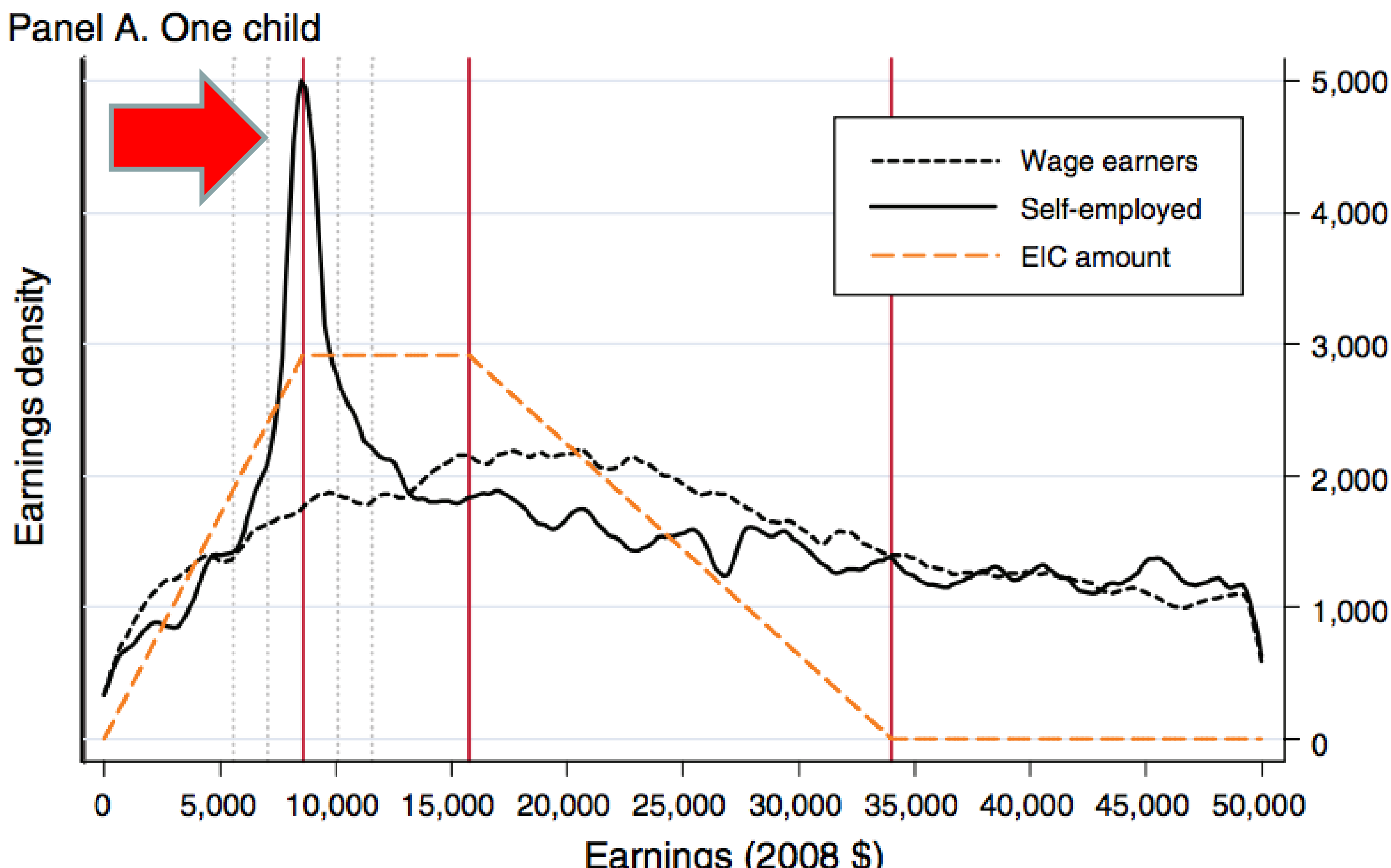


Fig. 2. Taking the DTF and modified AGI near the 2002–03 married eligibility threshold.

Evidence of Manipulation for Other Studies

- Sometimes, manipulation can be informative.
- Saez (2010): EITC bunching informs Chetty et al. use of EITC bunching as an instrument for knowledge of a program to evaluate EITC impact



Back to Zimmerman (2014): results table

Table 5
Earnings Effects 8–14 Years after High School Completion

	Main	Controls	BW=.5	BW=.15	Local Linear
Reduced-form estimates:					
Above cutoff	372*	366**	409**	479**	410**
	(141)	(130)	(154)	(198)	(147)
Instrumental variables estimates:					
FIU admission	1,593*	1,575**	1,665**	1,700**	2,001*
	(604)	(584)	(645)	(621)	(696)
Years of SUS attendance	815**	792**	833**	966***	977**
	(276)	(262)	(271)	(305)	(306)
BA degree	6,547*	6,442*	7,366*	10,769	5,958**
	(2,496)	(2,411)	(2,998)	(5,726)	(2,024)
N	6,542	6,542	9,659	3,294	6,542

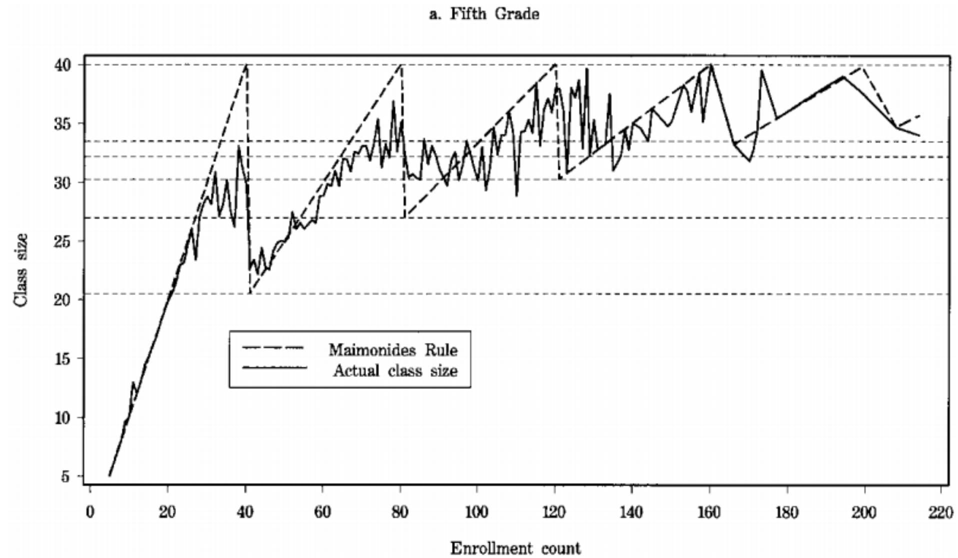
Main = 0.3 bandwidth with quadratic control function
"Controls" adds gender, race, free-lunch status, and 12th-grade cohort
"BW = 0.5" is 0.5 bandwidth with quartic control function
"BW = 0.15" is 0.15 bandwidth with linear control function

Zimmerman (2014)

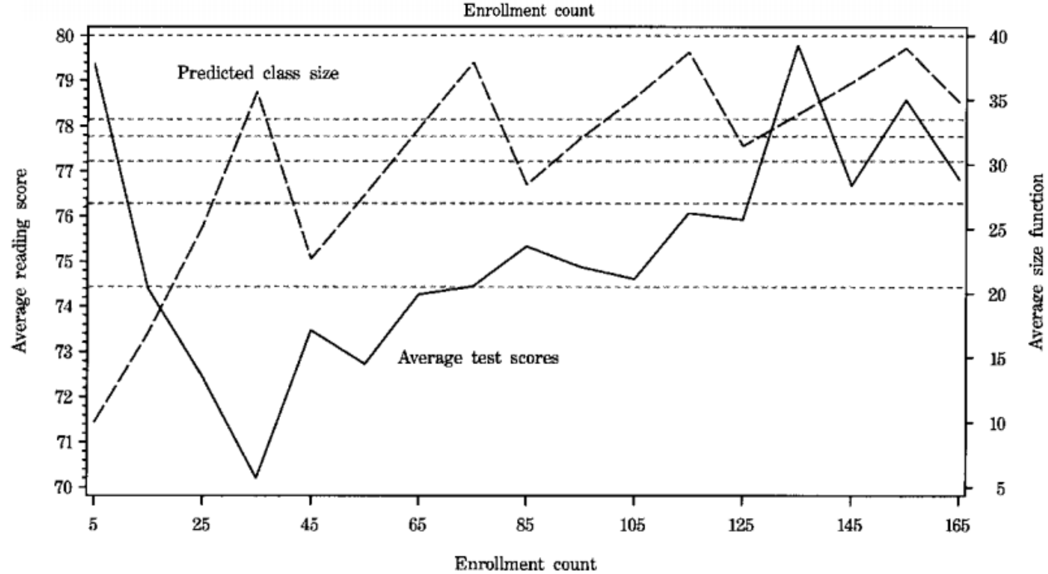
RD Basics & Another Visual with Multiple Cut-offs

- You can also have multiple cut-offs
- Angrist & Lavy (1999) study the effect of class size on test scores

Multiple cut-offs based on class size



Multiple treatment effects



Practice Code

We will go over:

- Creating the running variable
- Binscatters
- McCrary Test
- RD Regression
- Robustness Tests

STATA/R code is available on Canvas, please follow along!

[version I'm using in: **bit.ly/ec1152drive**]