Regression Discontinuity Designs in Economics

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Outline

- Overview of RDD
- Meaning and validity of RDD
- Several examples from the literature
- Estimation (where most decisions are made)
- Discussion of a paper
  - Stata code and data will be provided
- Conclusions

But when you start exercising those rules, all sorts of processes start to happen and you start to find out all sorts of stuff about people…. It's just a way of thinking about a problem, which let's the shape of the problem begin to emerge. The more rules, the more arbitrary they are, the better.

Douglas Adams, *Mostly Harmless*

(Cited in Angrist and Pischke 2009)

Introduction

- RDD is developed to estimate causal treatment effects in non-experimental settings
- It exploits precise knowledge of the rules determining treatment
- Identification is based on the idea that some rules are arbitrary and provide good quasi experiments
- Treatment effects are local (LATE)
- RD research designs provide very good internal validity
  - Most assumptions can be empirically verified
- External validity is limited
- Like RCT relatively easy to estimate

Sharp and Fuzzy Discontinuity

- Sharp discontinuity
  - The discontinuity precisely determines treatment
  - Equivalent to random assignment in a neighborhood
  - E.g. Social security payment depends directly and immediately on a person's age
- Fuzzy discontinuity
  - Discontinuity is highly correlated with treatment
  - E.g. Rules determine eligibility but there is a margin of administrative error
  - Use the assignment as an IV for program participation

Sharp RD

- Sharp RD is used when treatment status is deterministic and discontinuous function of covariate, x_i
- Suppose

$$D_i = \begin{cases} 1 & if\ x_i \geq x_0 \\ 0 & if\ x_i < x_0 \end{cases}$$

where x_0 is known threshold or cutoff and the assignment mechanism is deterministic function of x_i because once we know x_i we know D_i. Treatment is discontinuous function of x_i and no matter how close x_i gets to x_0, treatment is unchanged until x_i=x_0.

Discontinuity example

- National Merit Scholarship awards in USA
  - National Merit Scholarship Corporation (NMSC) uses PSAT/NMSQT scores as the initial screen of over 1.5 million program entrants
  - NMSC determines a national Selection Index qualifying score (critical reading + math + writing skills scores) for "Commended" recognition
  - Qualifying score is calculated each year to yield students at about the 96th percentile (top 50,000 highest scorers
  - Basically the top test-takers get a scholarship
  - A small difference in test score means a discontinuous jump in scholarship amount

Identification for sharp discontinuity

$$y_i = \beta_0 + \beta_1 D_i + \beta_2 x_i + \varepsilon_i$$

$$D_i = \begin{cases} 1 & \text{If } x_i \geq x_0 \\ 0 & \text{If } x_i < x_0 \end{cases}$$

x_i is continuous around the cut-off point and it is called a forcing or running variable

Assignment rule under sharp discontinuity:

$D_i = 1 \quad \longleftrightarrow \quad x_i \geq 50$

$D_i = 0 \quad \longleftrightarrow \quad x_i < 50$

Identification for sharp discontinuity (cont.)

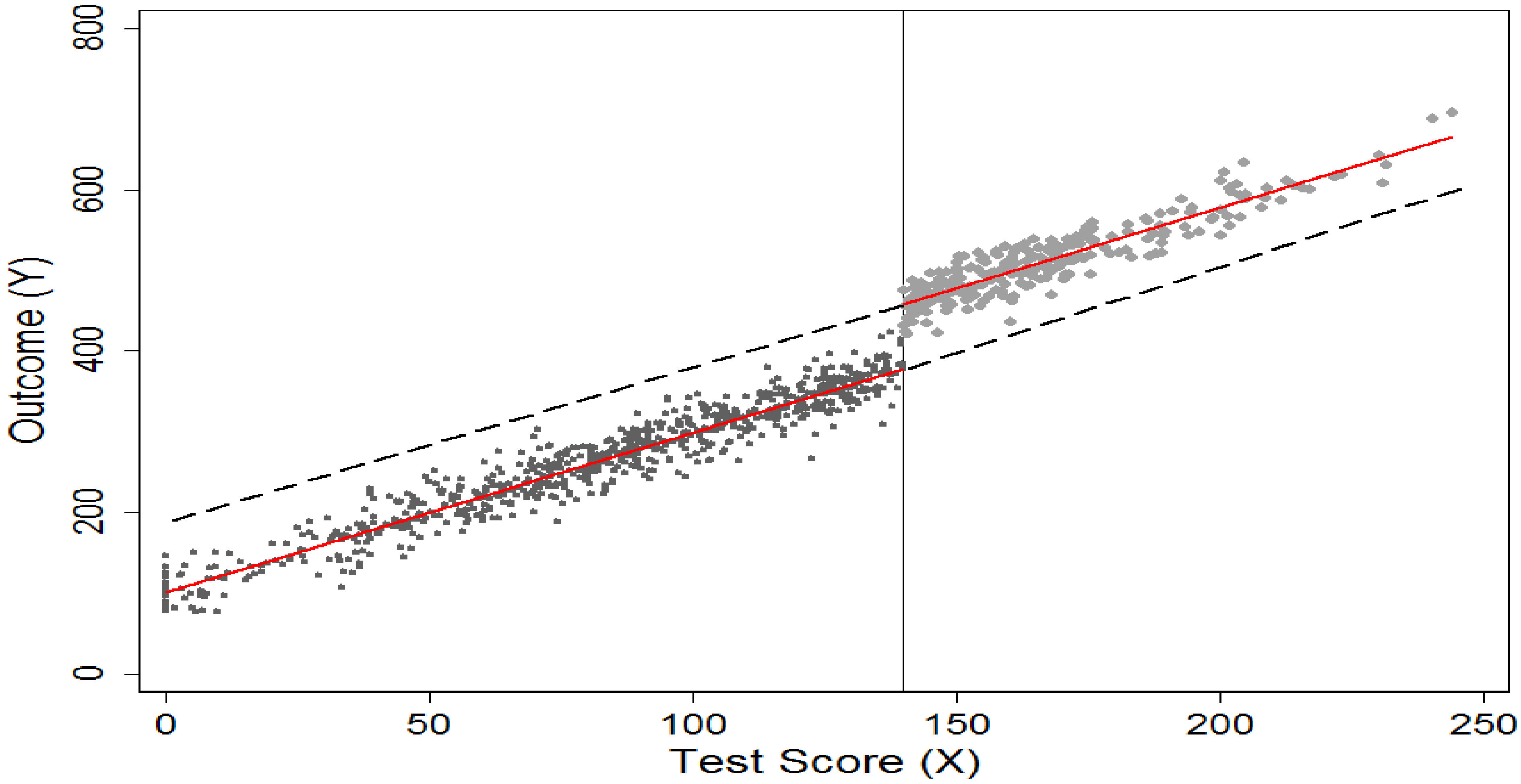
- Treatment effect is given by β_1 (causal effect of interest)

  E[Y/D = 1, X = x_0] = $\beta_0 + \beta_1$ and E[Y/D = 0, X = x_0] = β_0

  E[Y/D = 1, X = x_0]- E[Y/D = 0, X = x_0]= β_1

- Note that the estimation of treatment effect in RDD depends on extrapolation
- To the left of cutoff point only non-treated observations
- To the right of cutoff point only treated observations

Extrapolation (dashed lines)



Counterfactuals

- The extrapolation is a counterfactual or potential outcome
- Each household has two potential outcomes
- $Y_i(1)$ denotes the outcome of household i if in the treated group
- $Y_i(0)$ denotes the outcome of household i if in the non-treated group
- Causal effect of treatment for household i is

$$Y_i(1) - Y_i(0)$$

- Average treatment effect is

$$E[Y_i(1) - Y_i(0)]$$

- Only one potential outcome is observed. In randomized experiments, one group provides the counterfactual for the other because they are comparable (exchangeable)

Counterfactuals (cont.)

- In RDD the counterfactuals are conditional on x_i as in RCT
- We are interested in the treatment effect at x_i = x_0

$$E[Y_i(1) - Y_i(0)|x_i = x_0]$$

- Treatment effect is

$$lim_{x \rightarrow x_0} E[Y_i|x_i = x] - lim_{x \leftarrow x_0} E[Y_i|x_i = x]$$

- Estimation is possible because of the continuity of

$$E[Y_i(1)|x_i] \text{ and } E[\, Y_i(0)|x_i]$$

- The estimation of the treatment effect is based on extrapolation because of lack of overlap
- Therefore, the functional relationship between Y and x must be correctly specified

When to use RD design

- The beneficiaries/non-beneficiaries can be ordered along a quantifiable dimension
- This dimension can be used to compute a well-defined index or parameter
- The index/parameter has a cut-off point for eligibility
- The index value is what drives the assignment of a potential beneficiary to the treatment or to non-treatment groups

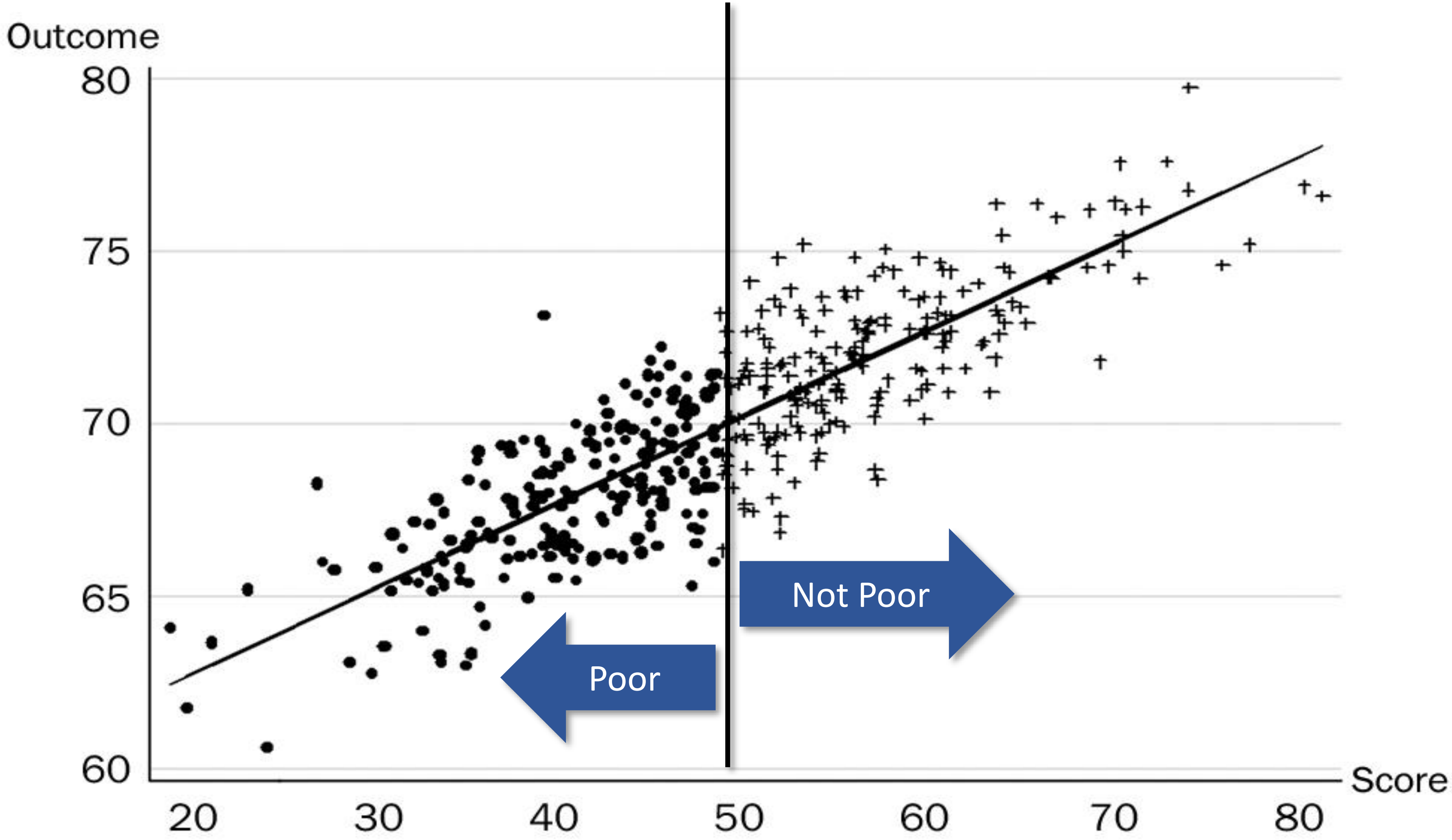
Indexes are common in targeting of welfare programs

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 high scores on standardized test
CDD programs	awarded to NGOs that achieve highest scores

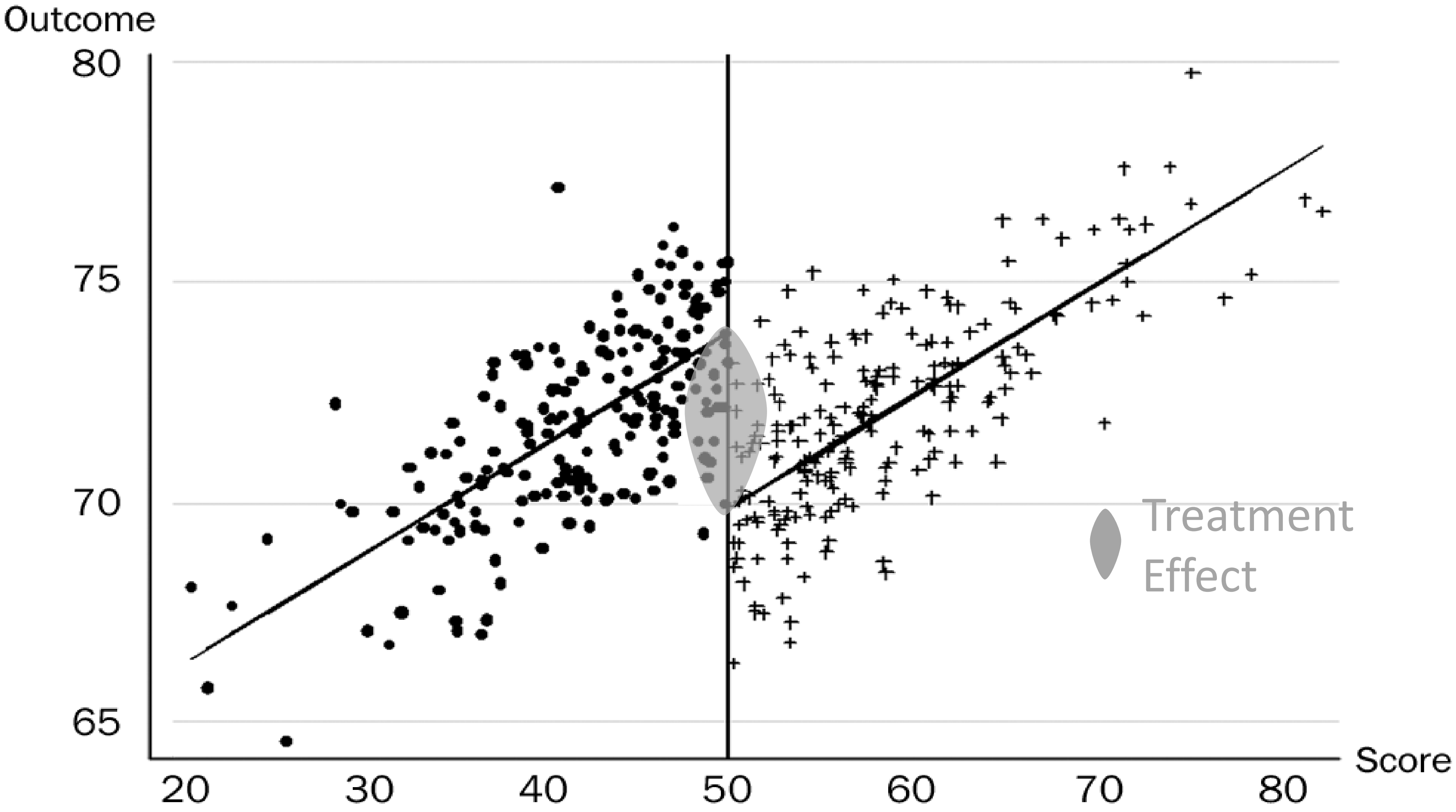
Example: Effect of cash transfers on consumption

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

Regression Discontinuity Design-Baseline



Regression Discontinuity Design-Post Intervention



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

Identification for fuzzy discontinuity (cont.)

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

IV estimation

- First stage:

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

- Second stage:

$$y_i = \beta_0 + \beta_1 D_i + \underbrace{f(score_i)}_{\text{Continuous function}} + \varepsilon_i$$

RDD examples from literature: Thistlethwaite and Campbell (1960)

- This was a first application of RD design
- They studied the impact of merit awards on future academic outcomes
- Awards are allocated based on test scores
- If a person had a score greater than c, the cutoff point, then she or he received the award
- Simple approach to the analysis: compare those who received the award to those who didn't
- Why is this the wrong approach?
  - Factors that influence the test score are also related to future academic outcomes (income, parents' education, motivation, etc.)
- Thistlethwaite and Campbell realized they could compare individuals just above and below the cutoff point

Thistlethwaite and Campbell (1960): Validity

- Simple idea: assignment mechanism is known
- We know that the probability of treatment jumps to 1 if test score > c
- Assumption is that individuals cannot manipulate with precision their assignment variable (think about standardized tests: SAT, GRE, GMAT)
- Key word: precision
- Consequence: comparable individuals near cutoff point
- If treated and untreated individuals are similar near the cutoff point then data can be analyzed as if it were a (conditionally) randomized experiment

Thistlethwaite and Campbell (1960): Validity (cont.)

- If this is true, then background characteristics should be similar near c, the cutoff point (can be checked empirically)
- The estimated treatment effect applies to those near the cutoff point, which limits the external validity
- Validity hinges on assignment mechanism being known and free of manipulation with precision or cutoff point in some way related to outcome of interest
- Manipulation and validity
  - Some manipulation is fine (you can always study harder, for example)
- Precision and lack of relation of the cutoff point to outcome is the key to identify causal effects

RDD examples from literature (Almond et al. QJE, 2010)

- Policy question: whether the benefits of additional medical expenditures exceed their costs
- RDD allows to compare health outcomes and medical treatment provision for newborns on either side of the very low birth weight threshold at 1,500 grams
- Study finds that newborns with birth weights just below 1,500 grams have *lower* one-year mortality rates than do newborns with birth weights just above this cutoff, even though mortality risk tends to decrease with birth weight
- One-year mortality falls by approximately one percentage point as birth weight crosses 1,500 grams from above
- Infants with birth weight < 1,500 grams receive more medical treatment and their hospital costs higher by $4,000 relative to mean hospital costs of $40,000 for infants with birth weight just above 1,500 grams
- Assuming observed medical spending fully captures the impact of the “very low birth weight” designation on mortality, the study estimates suggest that the cost of saving a statistical life of a newborn with birth weight near 1,500 grams is on the order of $550,000 in 2006 dollars

RD examples from literature (DiNardo & Lee, QJE 2004)

- Economic impacts of unionization on employers are difficult to estimate because of selection bias
- Unions could organize at highly profitable enterprises that are more likely to grow and pay higher wages
- Union elections
  - If employers want to unionize, board holds election
  - 50% means the employer doesn’t have to recognize the union, and
  - 50% + 1 means the employer is required to “bargain in good faith” with the union
- Multiple establishment-level datasets that represent establishments that faced organizing drives in the United States during 1984-1999

DiNardo & Lee, QJE 2004 (cont.)

- The paper applies RD design to estimate the impact of unionization on business survival, employment, output, productivity, and wages
- Paper essentially compares outcomes for employers where unions barely won the election with those where the unions barely lost
- The analysis finds small impacts on all outcomes
- The results suggest that-at least in the study period-the legal mandate that requires the employer to bargain with a certified union has had little economic impact on employers

RDD examples from literature (Angrist & Levy, QJE 1999)

- Fuzzy RD design to estimate the effects of class size on children's test scores
- School class size- Maimonides' rule
  - No more than 40 kids in a class in Israel
  - 40 kids in school means 40 kids per class
  - 41 kids means two classes with 20 and 21 kids
- Multiple discontinuities: causal variable of interest, class size, takes on many values
- First stage exploits jumps in average class size
- Finding: smaller class size increases test scores

RD examples from literature (cont.)

- Anderson and Magruder (2012) and Lucas (2012)
  - Yelp.com ratings have an underlying continuous score
  - Distribution determines cutoff points for 1 to 5 stars
  - Effect of an extra star on future reservations and revenue
- Anderson et al. (2012)
  - Young adults lose their health insurance as they age (older than 18 and in college but different after ACA)
  - Age changes the probability of having health insurance (fuzzy design)

Paper by Raffaello Bronzini and Eleonora Iachini (AEJ: Economic Policy, 2014)

- The paper uses sharp RDD to evaluate a unique R&D subsidy program implemented in northern Italy
- Firms were invited to submit proposals for new projects and only those which scored above a certain threshold received the subsidy.
- It compares the investment spending of subsidized firms with that of unsubsidized firms

Main questions in empirical research

- What is the policy question?
- What is the causal relationship of interest?
- What is the dependent variable and how is it measured?
- What is (are) the key independent variable(s)?
- What is the data source?
- What is the identification strategy?
- What is the mode of statistical inference?
- What are the main findings?

Policy question

- Governments spend substantial financial resources to support private R&D activities
  - Direct government funding of private R&D in OCED countries amounts about 0.1% of GDP, excluding tax incentives
- Economic rationale
  - Market failure
  - Liquidity constraints
- Inframarginal versus marginal projects
- Do R&D investment subsidies actually work, i.e., increase private firms' R&D activity (expenditures)?
- Do benefits of additional government expenditures on investment subsidies exceed their costs?

Program and causal relationship of interest

- Relationship between government R&D subsidies and private R&D activity (expenditures)
- “Regional Program for Industrial Research, Innovation and Technological Transfer” implemented in Emilia-Romagna (Italy)
- The regional government subsidizes the R&D expenditure of eligible firms through grants, the grant may cover up to
  - 50% of the costs of industrial research projects
  - 25% for precompetitive development projects; the 25% limit is extended by an additional 10% if applicants are SMEs
- The maximum grant per project is €250,000
- Duration of the investment is from 12 to 24 months

Dependent and key independent variables

- Dependent variable
  - Natural candidate would be R&D investment, but not available
  - Net investment calculated from the balance-sheet data as annual differences in tangible or intangible assets net of amortization
- Independent variable
  - Binary treatment variable for an R&D subsidy
  - Score
    - technological and scientific (max. 45 points)
    - financial and economic (max. 20 points)
    - managerial (max. 20 points);
    - regional impact (max. 15 points)
    - Only projects deemed sufficient in each category and which obtain a total score of at least 75 points receive the grants

Identification strategy

- Goal is to evaluate whether subsidized firms would not have made the same amount of R&D outlays without the grants
- Subsidized and nonsubsidized firms can differ in terms of unobserved characteristics correlated with the outcome
- Therefore, the variable identifying recipient firms in the econometric models can be endogenous
- To deal with the endogeneity issue, paper exploit the funds' assignment mechanism
- Only those receiving a score equal to or above a given threshold (75 out of 100) were awarded grants

Identification strategy (cont.)

- The paper applies a sharp RDD comparing the performance of subsidized and nonsubsidized firms with scores close to the threshold
- By letting the outcome variable be a function of the score, the average treatment effect of the program is assessed through the estimated value of the discontinuity at the threshold

Empirical specification

$$Y_i = \alpha + \beta T_i + (1 - T_i) \sum_{p=1}^{3} \gamma_p (S_i)^p + T_i \sum_{p=1}^{3} \gamma_p' (S_i)^p + \varepsilon_i$$

where

Y_i is the outcome variable;

T_i = 1 if firm i is subsidized (all firms with score $\geq$ 75) and T_i = 0 otherwise;

S_i = $Score_i - 75$;

γ_p and γ_p' are the parameters of the score function and allowed to be different on the opposite side of the cutoff to allow for heterogeneity of the function across the threshold;

ε_i is the random error.

Estimation

- First, a third order polynomial model was estimated on the full sample
- Second, equation was estimated through local regressions around the cutoff point using two different sample windows
  - Firms with scores between 52 and 80 (50% of the baseline sample)
  - Firms with scores between 66 and 78 (35% of the baseline sample)
- Third, paper estimated the discontinuity using other nonparametric techniques, namely the kernel regressions using two bandwidths, 30 and 15 points of the score

Estimation (cont.)

- The OLS estimates of the parameter β measures the value of the discontinuity of function $Y(S_i)$ at the cutoff point, corresponding to the unbiased estimate of the causal effect of the program
- A coefficient β equal to zero would signal complete crowding-out of private investment by public grants
  - This would mean that firms reduced private expenditure by the amount of the subsidies received and the investment turned out to be unaffected by the program
- A positive coefficient would show that overall treated firms invested more than untreated firms, plausibly thanks to the program, and that total crowding-out did not occur

Main findings

- Overall, no significant increase in investment
- Substantial heterogeneity in the program’s impact
- Small enterprises increased their investments—by approximately the amount of the subsidy they received—whereas larger firms did not

Data and Stata codes

- Data and Stata codes are in the folder