

# Sustainability of Public Policy

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# Regression Discontinuity

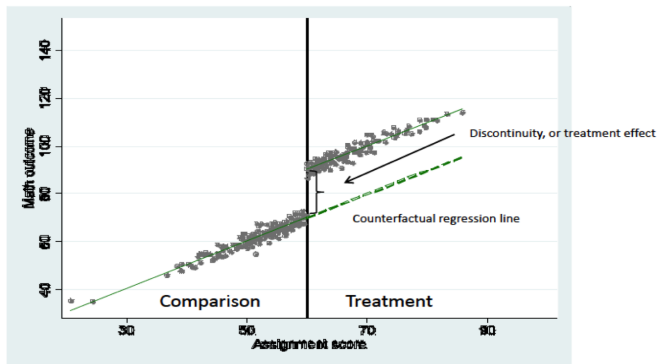
Regression Discontinuity exploits natural experiments in all such cases where a somewhat arbitrary rule determines treatment.

Possible examples are:

- ▶ Maximum class size set at 32 students
- ▶ Minimum Legal Drinking Age (MLDA) set at age 21
- ▶ 15000 population threshold to determine the type of electoral system for mayoral elections
- ▶ 16000 ISE threshold to be entitled to a studentship

# Graphical explanation

## RDD Visual Depiction



# RDD rationale

- ▶ Selection process is completely known and can be modelled through a regression line of the assignment/forcing and outcome variables
- ▶ Untreated portion of the forcing variable serves as a counterfactual
- ▶ It is like an experiment around the cutoff
- ▶ Advantage: No need to identify a functional form

# Required Assumptions for RD design

- ▶ The probability of being treated has to be discontinuous at the cutoff. More of those receiving treatment should be on the treatment side of cutoff than the other side. If all are, then “sharp” RD. Otherwise, “fuzzy” RD
- ▶ There should be no discontinuity in potential outcomes at the cutoff (the “continuity restriction”). That is, no alternative interpretation should also show a discontinuity at the cutoff.

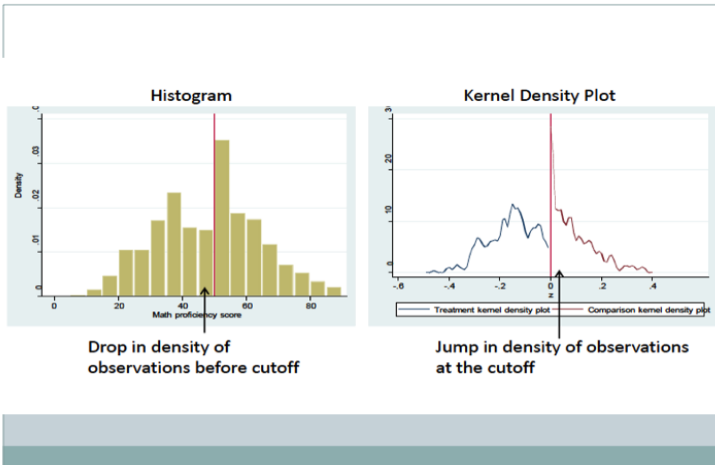
# Threats to the RD Design

- ▶ Overrides to the cutoff
  - ▶ Sharp design
  - ▶ Fuzzy design
- ▶ Manipulation of the assignment score
- ▶ Misspecification of the response function

# Manipulation of the forcing score

- ▶ Occurs when participants manipulate assignment scores to receive or avoid treatment.
- ▶ Different from “overrides to the cutoff” because researcher does not know what scores and treatment assignment participants should have received.
- ▶ No definitive test for knowing when it occurs, but graphical analysis can help detect when it does.

# Manipulation





# McCrary Test

Can perform “McCrary Test” (2008)

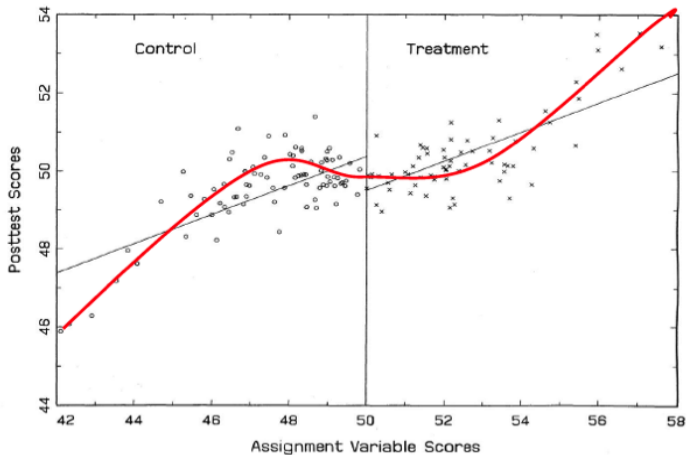
- ▶ Basically a statistical test for assessing whether there is a discontinuity in the density of observations at the cutoff.
- ▶ Test is “reassuring” for the analyst, but not sufficient for proving the validity of the design.
- ▶ Must combine consideration of the assignment process with observation of the distribution of data around the cutoff.

# Misspecification of the response function

Anything that affects the size of the discontinuity at the cutoff other than treatment is a threat.

- ▶ We assumed the relationship between assignment and outcome was linear → regressions are straight lines.
- ▶ Functional form can be nonlinear due to:
  - ▶ Nonlinear relationships between the forcing variable and the outcome
  - ▶ Interactions between the forcing variable and treatment.
- ▶ Effects are unbiased only if the functional form of the relationship between the forcing variable and the outcome is correctly specified

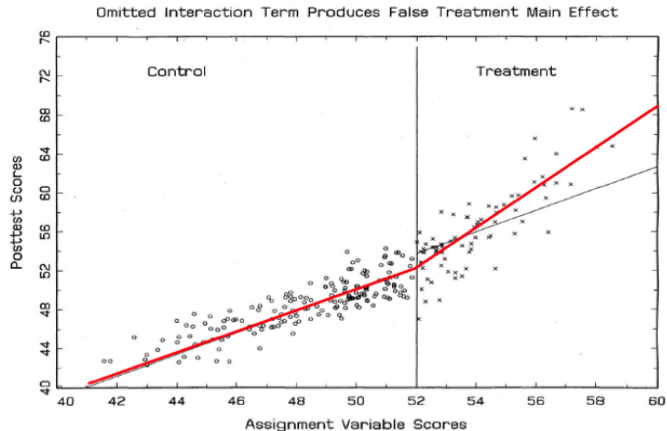
# Misspecification of the response function



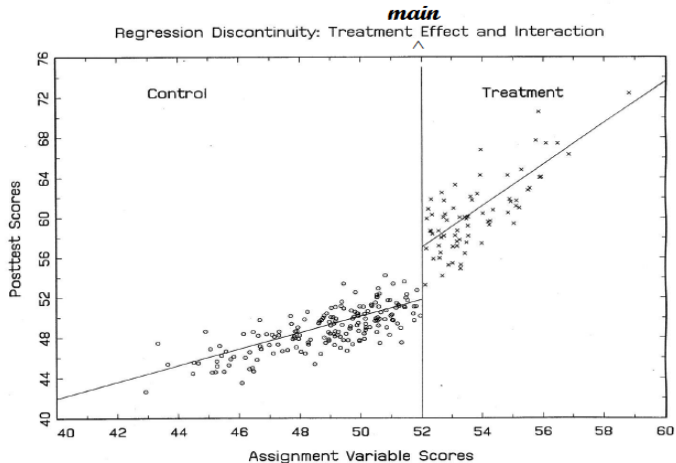
# Misspecification of the response function - Interactions

- ▶ Sometimes the treatment works better for some people than for others
- ▶ For example students from advantaged backgrounds benefit more from treatment than students from a disadvantaged one
- ▶ If this is not modelled correctly we will detect a false discontinuity

# Misspecification of the response function - Interactions



# Main effect and Interaction effect



# Detecting non-linearities

- ▶ Graphical analysis
- ▶ Computer programs
- ▶ Overfitting the model (adding polynomial terms)

# Non-linearities

We can include non-linear functions of the forcing variable ( $z$ )

$$Y_i = \beta_0 + \beta_1 d_i + \beta_2(z_i - z_c) + \beta_3(z_i - z_c)^2 + e \quad (1)$$

We can also include interactions between the treatment and the forcing variable

$$Y_i = \beta_0 + \beta_1 d_i + \beta_2(z_i - z_c) + \beta_3 d_i(z_i - z_c) + e \quad (2)$$



# Non-linearities 2

We can include both polynomials and interactions

$$Y_i = \beta_0 + \beta_1 d_i + \beta_2 (z_i - z_c) + \beta_3 (z_i - z_c)^2 + \beta_4 d_i (z_i - z_c) + \beta_5 d_i (z_i - z_c)^2 + e$$

(3)

If in doubt, add more polynomial and interaction terms than needed, and then eliminate the nonsignificant ones

# Non-parametric approach

- ▶ It is complementary to the parametric one
- ▶ More efficient with large samples
- ▶ Estimates the effect in proximity of the threshold
- ▶ Local Linear Regression
- ▶ Equivalent to the parametric approach in a close neighbourhood on the threshold

# LLR Implementation

- ▶ Check to see whether treatment effects are robust to alternative specifications of bandwidth
- ▶ State of art is to use Imbens Kalyanaraman (2010) (IK) optimal bandwidth module that takes account of boundary issues
- ▶ In Stata: `rdbwselect`
- ▶ Estimate treatment effects using bandwidths that were ? and double the size of the IK optimal bandwidth to check robustness of estimates.

# MLDA example

- ▶ Carpenter and Dobkin (2009) analyse the effect of MLDA on Mortality using RDD
- ▶ They exploits the fact that a small change in age generates big changes in access to alcohol and ultimately in deaths
- ▶ Even a day can make a big difference. When plotting days from the 21st birthday against number of deaths a spike shows up at exactly day 0
- ▶ This spike is specific the the 21st birthday and therefore does not reflect a birthday party effect
- ▶ They use a sharp RD design to evaluate whether there is a causal effect of MLDA on mortality

# MLDA example



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