Class 18 Regression Discontinuity Design

Dr Wei Miao

UCL School of Management

November 29, 2023

Section 1

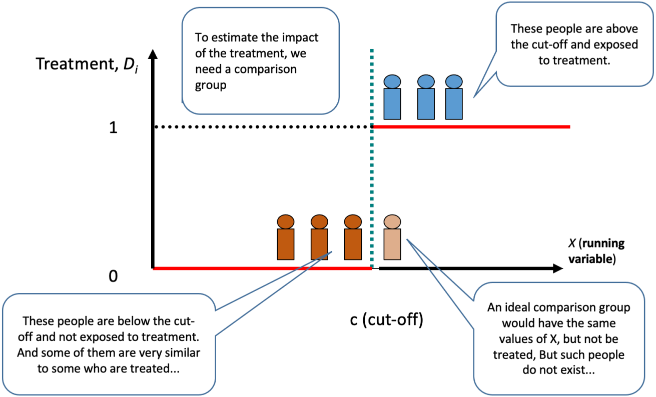
Regression Discontinuity Design

What is an RDD

- A **regression discontinuity design (RDD)** is a quasi-experimental design that aims to determine the causal effects of interventions by assigning a **cutoff** or **threshold** above or below which an intervention is assigned.
- It was invented by educational psychology[1] and generalized by economists to economics and business fields.

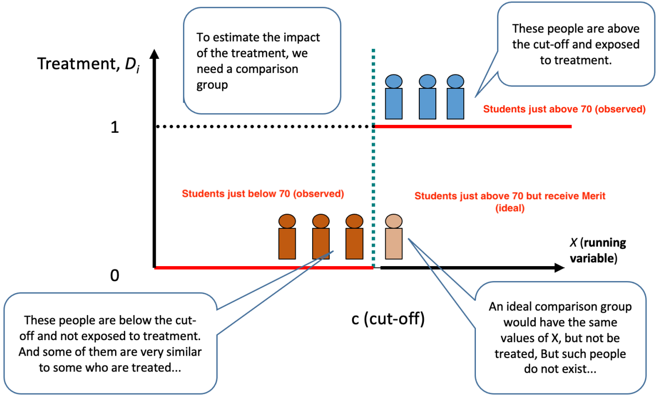
[1] Thistlethwaite, Donald L., and Donald T. Campbell. 1960. "Regression-Discontinuity Analysis: An Alternative to the Ex Post Facto Experiment." Journal of Educational Psychology 51 (6): 309.

Visual Illustration of RDD



Visual Illustration of RDD: An Example of Distinction on Salary

Question: What is the causal effect of a Distinction honor on a student's future salary?



When to Use an RDD

- An RDD arises when treatment is assigned based on whether an underlying **continuous score variable** crosses a cutoff.
  - The characteristic is often referred to as the **running variable**.
- **AND** the characteristic cannot be perfectly manipulated by individuals
  - We should only focus on individuals in the neighborhood of the cutoff point.
  - We can only estimate the **local** treatment effects from an RDD study.

Why RDD Gives Causal Effects?

- Because the "running variable" **cannot be perfectly controlled** by the individuals **around the cutoff point**, it's as if the treatment was randomly assigned in the neighborhood of cutoff.
- At the same time, individuals on either side of the cut-off should be very similar to each other, such that there should be no systematic differences across the treatment and control group other than the treatment.
- With the **treatment** being the **only discontinuity** at this threshold, a discontinuous jump in the outcome of interest at the threshold is the treatment effect.

Section 2

Steps of RDD Analyses

Step 1: Select Sample of Analysis

1. Determine the cutoff-point and select the subset of individuals near the cut-off point
   - e.g., filter out students with average scores between 69 and 70

- There is no econometric requirement on the “near”; however, we face a trade-off between external validity and internal validity:
  - **External validity**: If we have a narrower subset of individuals, we have a smaller subset of subjects which may not be representative of remaining individuals.
  - **Internal validity**: If we have a broader subset of individuals, it is more likely the control group and treatment group are less likely to be “as-if randomized”.
- In practice, we may need to run a set of different neighborhood bands as **robustness checks**.

Step 2: Examine Continuity of Observed Characteristics

2. Examine if the observed characteristics of the treatment group and control group are continuous at the cut-off point.
    - The idea is similar to “randomization check” in the Step 5 of an RCT.

Step 3: Analysis

3. Regress the outcome variable on the treatment indicator to obtain the statistical significance.
   - In R, there is also a package `rddtools` which can help us estimate an RDD model.

Section 3

RDD in R

Causal Impact of Distinction on Salaries

- It is important to understand the causal impact of degree honors on students' future salaries and other outcomes.
- Can we get causal inference from simple linear regression?[2]

$$Salary_i = \beta_0 + \beta_1 Distinction_i + X\beta + \epsilon_i$$

[2] Refer to html version for answers.

RCT, IV or DID?

- Since **omitted variable bias** prevents us from obtaining causal inference, we need to find another causal inference tool to overcome the challenge.
- How about
  - RCT
  - Instrumental Variable
  - Difference-in-Differences
- Fortunately, we can use **regression discontinuity design.**

Dataset for RDD

- To run RDD, we need to select students with very similar scores due to the tradeoff between internal validity and external validity.
  - In the selected dataset, scores range from 69.07 to 72.93

```
pacman::p_load(dplyr)
data_rdd <- read.csv('https://www.dropbox.com/s/4f0zaqqkzo0at5o/data_rd
head(data_rdd,5)
```

student_id	salary	score	experience
1	46.41270	69.06849	3.872425
2	47.55037	69.15068	3.236511
3	46.07215	69.23288	3.202071
4	44.21388	69.31507	3.280689
5	44.35247	69.39726	3.548198

Data Wrangling

- To use RDD, we need to generate the treatment variable $treated$, which equals 1 if a student receives the treatment and 0 otherwise.
    - The treatment in an RDD is in spirit similar to that of an RCT, only that the treatment is assigned by nature (hence the name "natural experiment")

```
data_rdd <- data_rdd %>%
  mutate(treated = ifelse(score>=70,1,0))
```

RDD Analysis Using R

```r
pacman::p_load(modelsummary,fixest)
rdd_result <- feols(
  fml = salary ~ treated,
  data = data_rdd
)
modelsummary(rdd_result,stars = TRUE)
```

	(1)
(Intercept)	46.143***
	(0.479)
treated	2.257***
	(0.553)
Num.Obs.	48
R2	0.266
R2 Adj.	0.250
AIC	186.8
BIC	190.5
RMSE	1.62
Std.Errors	IID

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Variant 1: Regression Discontinuity in Time

- An event or treatment occurred at a point in time. Meanwhile, the treatment affected all individuals.
  - Because all individuals were affected, there were no control group and we could not do DiD analyses.
- However, if we can justify, **seasonality** is not strong within certain time window before and after the event, then we can do a **regression discontinuity in time** design (RDiT), as follows:

$$Outcome_{i,t} = \alpha + \beta_1 Post_i + X\beta + \mu_{i,t}$$

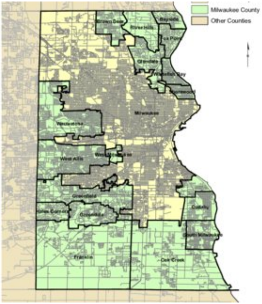
- As we learned in DiD lecture, β_1 includes both (1) the treatment effect, and (2) seasonality
  - If the time window is short, say a few weeks before and after, it is likely seasonality effect is null, and we can claim β_1 measures the causal effect of the event.

Variant 2: Spatial Regression Discontinuity

- Some new policies/events may be **region specific**. For instance, In the US, each state has their independent laws and regulations, so a state's new policy only affects that state but not other states.
- Residents near the same border should be similar in their characteristics, but only one side of the border receives the treatment.
  - As-if a randomized controlled trial

Variant 2: Spatial Regression Discontinuity

- Then we can compare the outcome of the treated residents and control residents near the border. Hence, spatial regression discontinuity is sometimes called **border strategy**.
  - Refer to this paper for a comprehensive description of the topic.



After-class Reading

- (recommended) Quasi-experiment (Econometrics with R)