A brief intro to

Causal inference & (Quasi) Experiments

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Overview

1. What's (and why) causal inference?
   - Quasi-experiments

2. Examples of quasi-experiments:
   - Regression Discontinuity (RD) and difference-in-differences (DiD) designs.

3. Code examples in Rstudio.

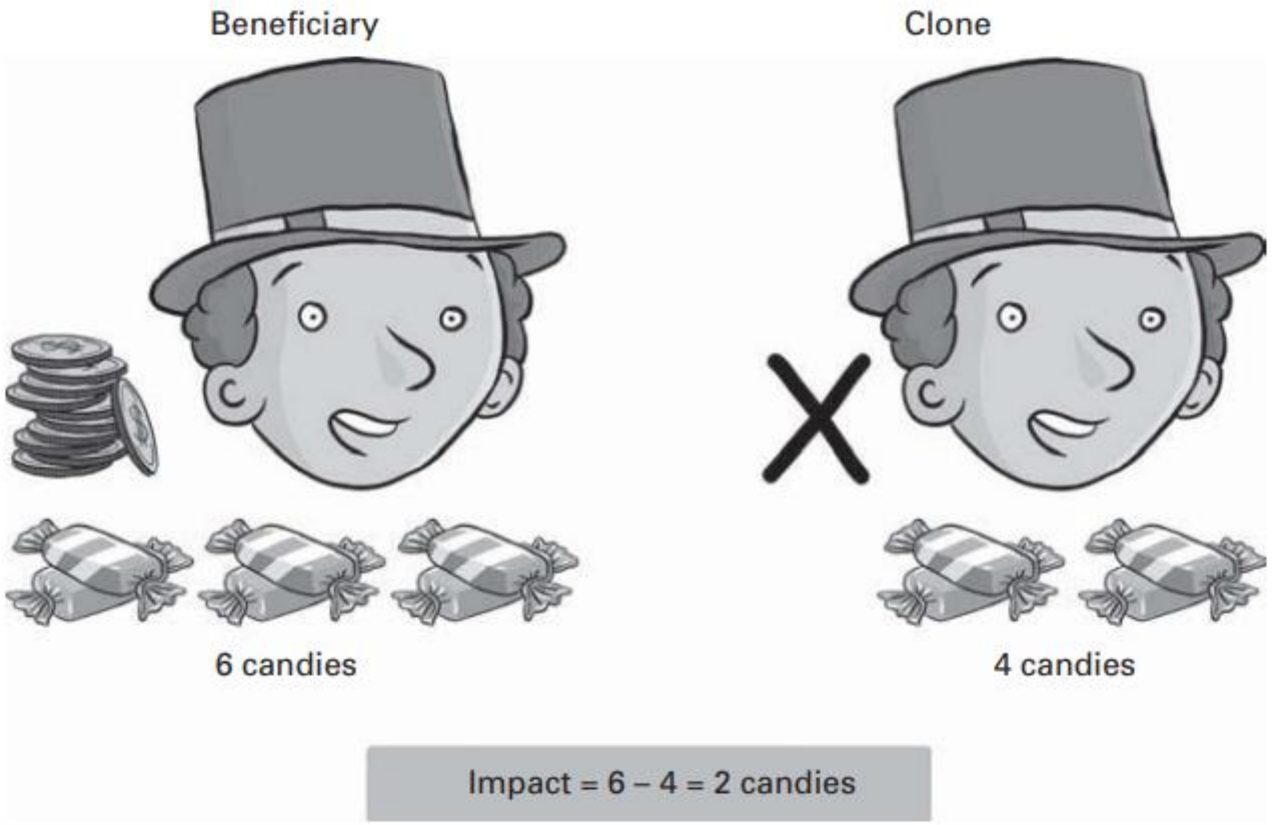
Causal Inference

- Many political and policy questions involve cause-and-effect relationships:
  - Does social media increases polarization?
  - Do systems lead to more diverse legislatures?
  - Do United Nations mediate and prevent international conflicts?

- Although cause-and-effect questions are common, answering them **accurately** can be challenging.
  - Correlation is not Causation.

- Impact evaluations (i.e., quasi-experiments) seek to answer such cause-and-effect questions precisely.
  - Empirically establishing to what extent, a particular "X"—and that IV alone— contributed to explain a "Y" or DV.

Gold Standard of Evidence: Experiments



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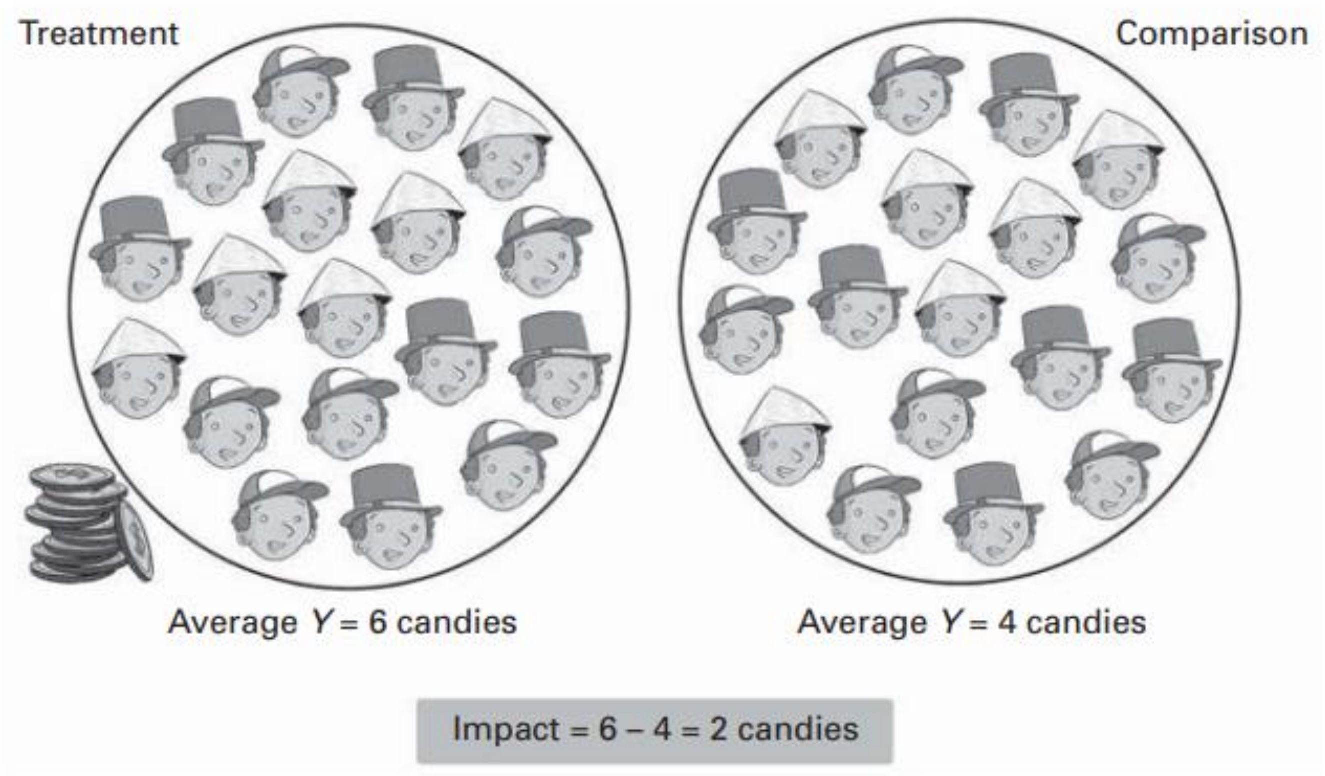

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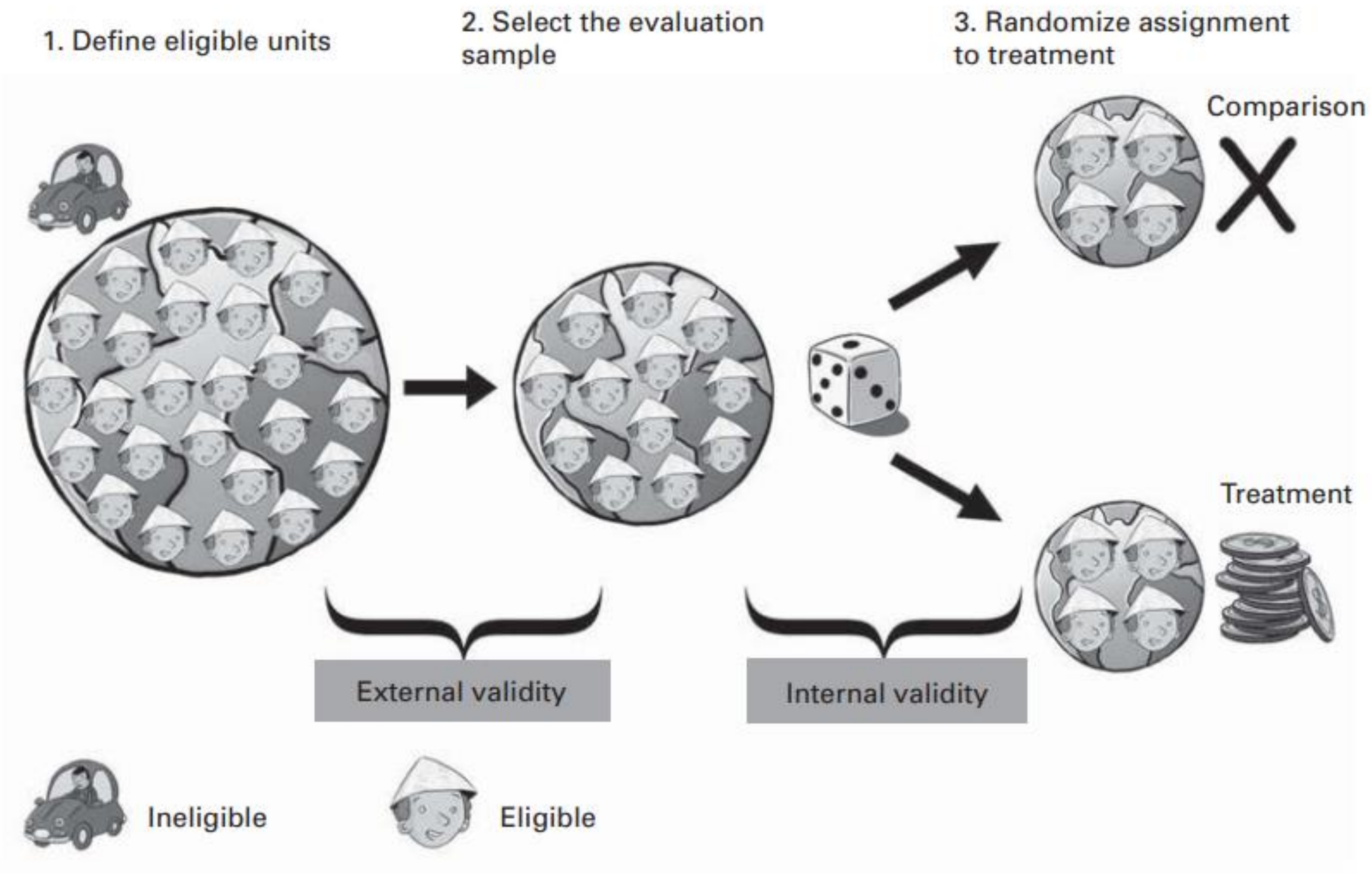

Quasi-experiments

Randomized experiments are hard to implement.

Quasi-experiments are a good approach when experiments (randomized controlled trials) are not feasible or ethical.

Some characteristics:

- Lack of random assignment.
- Pre-existing groups.
- Limited control.

Examples of Quasi-experiments

- Regression Discontinuity Design (RDD)
- Difference-in-Differences (Diff-in-diff)
- Matching (Propensity score matching - PSM)
- Instrumental Variables (IV)

- Many more!

Examples of Quasi-experiments

- **Regression Discontinuity Design (RDD)**
- **Difference-in-Differences (Diff-in-diff)**
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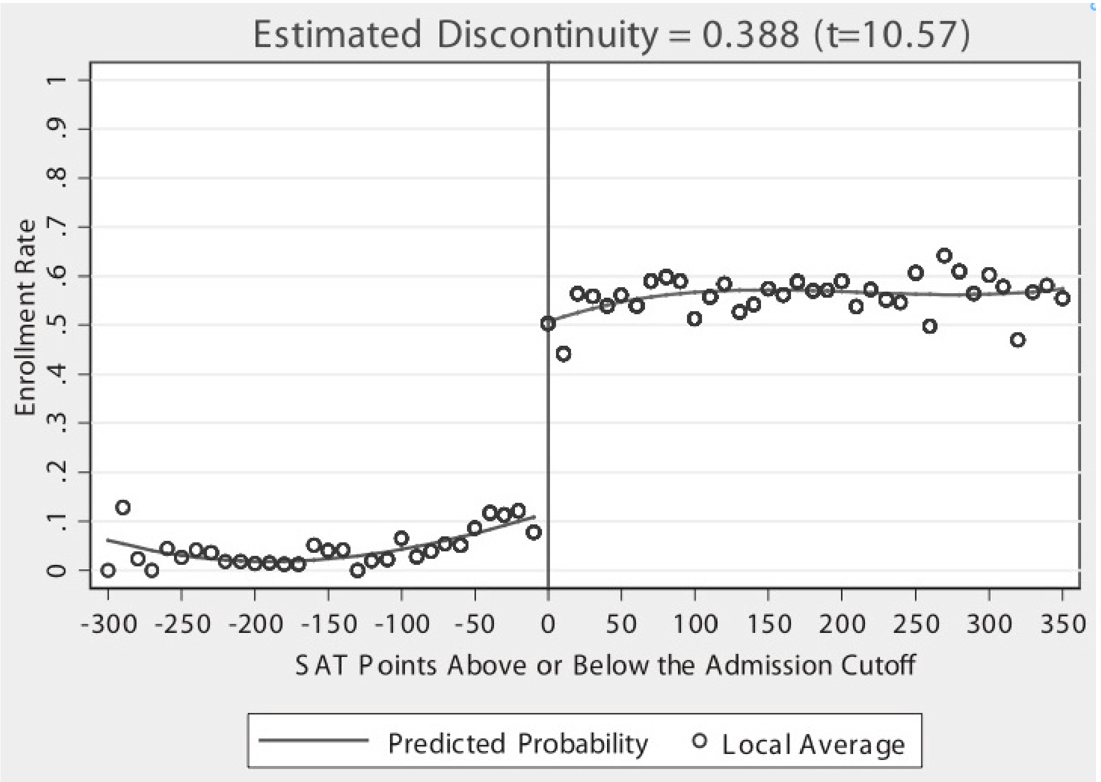
Regression Discontinuity (RDD)

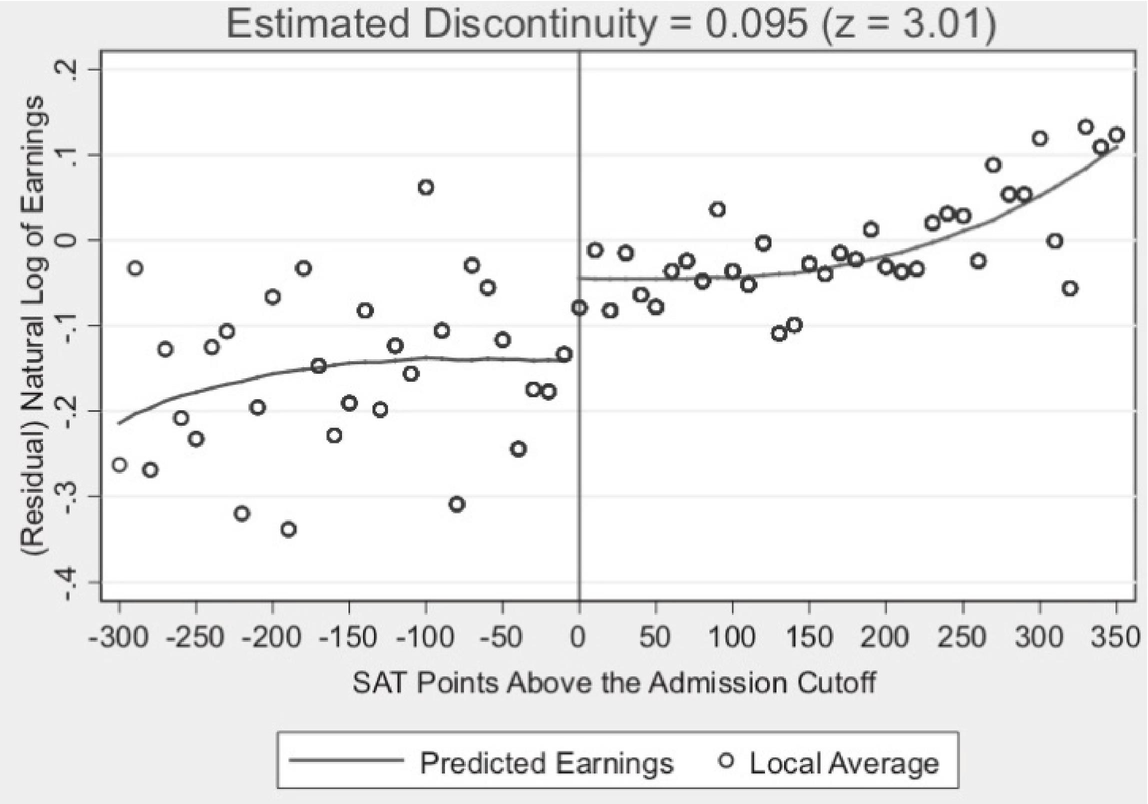
- RDD method uses a continuous **eligibility index**, to determine who is eligible and who is not.
  - A cutoff, threshold or an eligibility index.

- In politics, there are several thresholds to decide who is eligible to be part of something and who is not.
  - Elections: Margin of victory
  - Territorial boundaries: countries, states, cities, neighborhoods, etc.
  - Index in general: SAT, poverty scores.

Regression Discontinuity (RDD)

- “A picture is worth a thousand words”





Conditions of RDD

1. The index must **rank people or units** in a continuous or "smooth" way

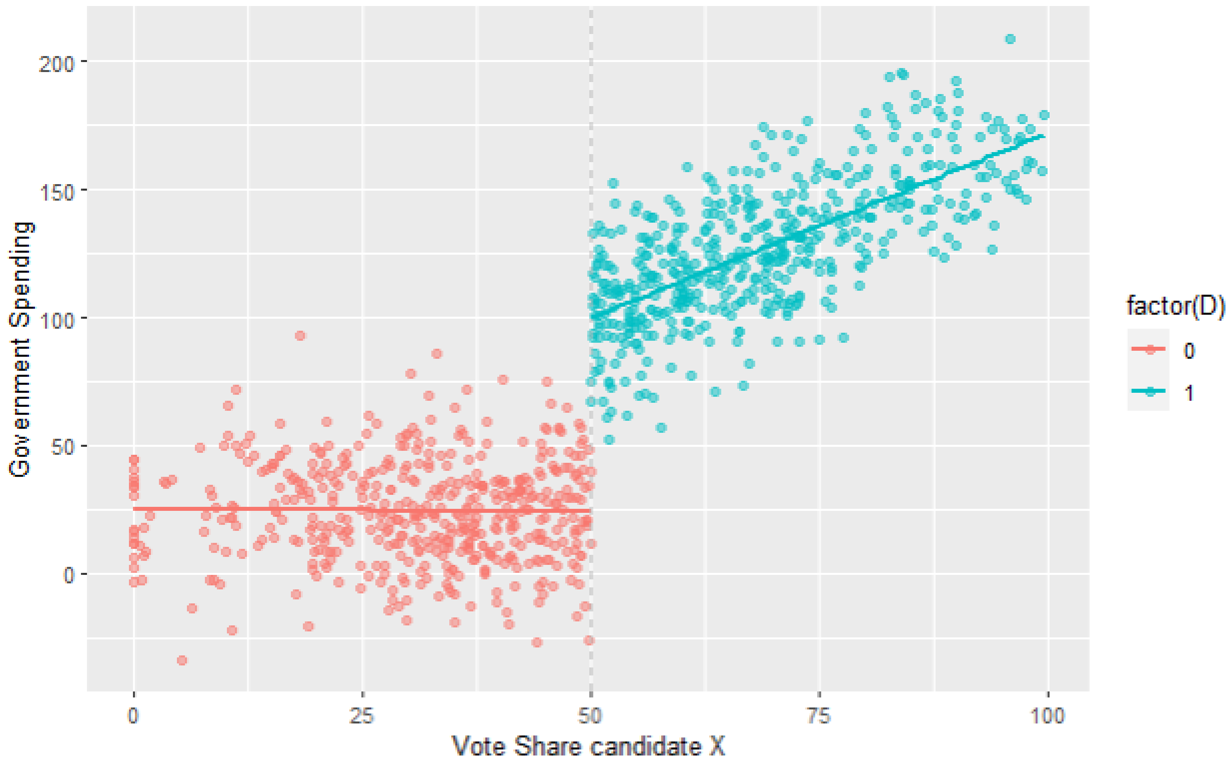
2. The index must have a clearly **defined cutoff score**.

3. For a sharp RDD: The score of a particular individual or unit **can not be manipulated** by enumerators, potential beneficiaries, program administrators, or politicians.

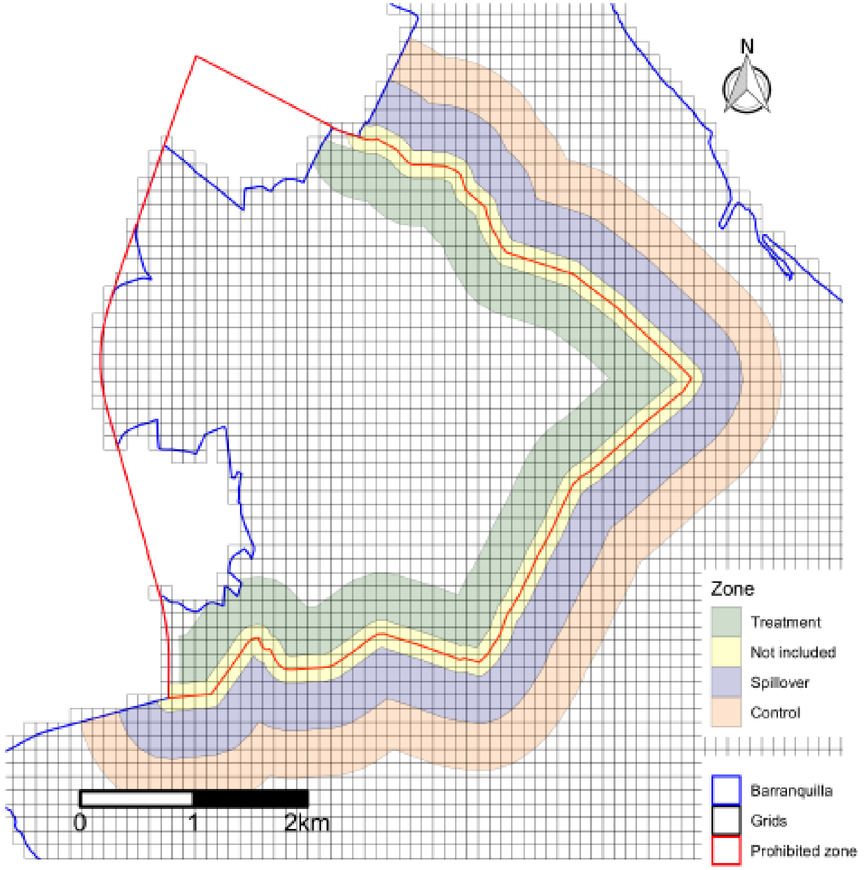
The RDD estimates impact around the cutoff based on a bandwidth around it.

RDD Visualization

Vote share: Do vote share for incumbent i affects government spending?



RDD using geographical boundaries



Source: Martínez, et al (2019)

Simulated data*

RDD Caveats

- RDD has good internal validity but weak external validity.
- RDD can be fuzzy.
- Statistical power – play with the *bandwidth* around the cutoff.
- Several functional forms: not juts positive relationships.

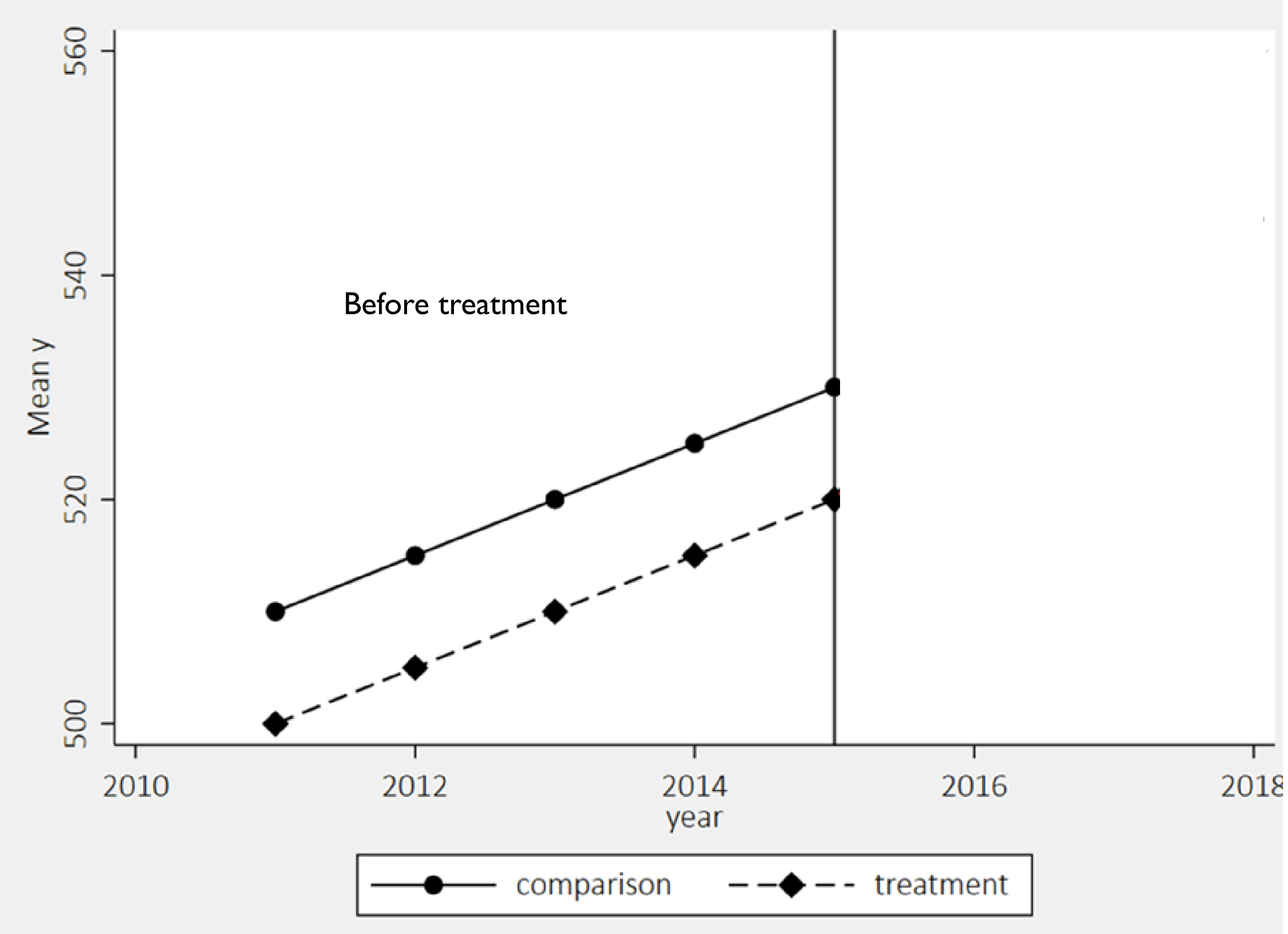
Difference-in-differences (DiD)

- DiD compares the changes in outcomes **over time** between a treatment group and its counterfactual.

- Two steps:
  - 1st difference (Within-Group Difference): The change in outcomes over time within each group, both the treatment group and the control group.
  - 2nd difference (Time-varying factors): Measure the before-and-after change in outcomes for a group that did not enroll in the program but was exposed to the same set of environmental conditions

We are estimating here is the counterfactual for the change in outcomes for the treatment group.

Difference-in-differences (DiD)



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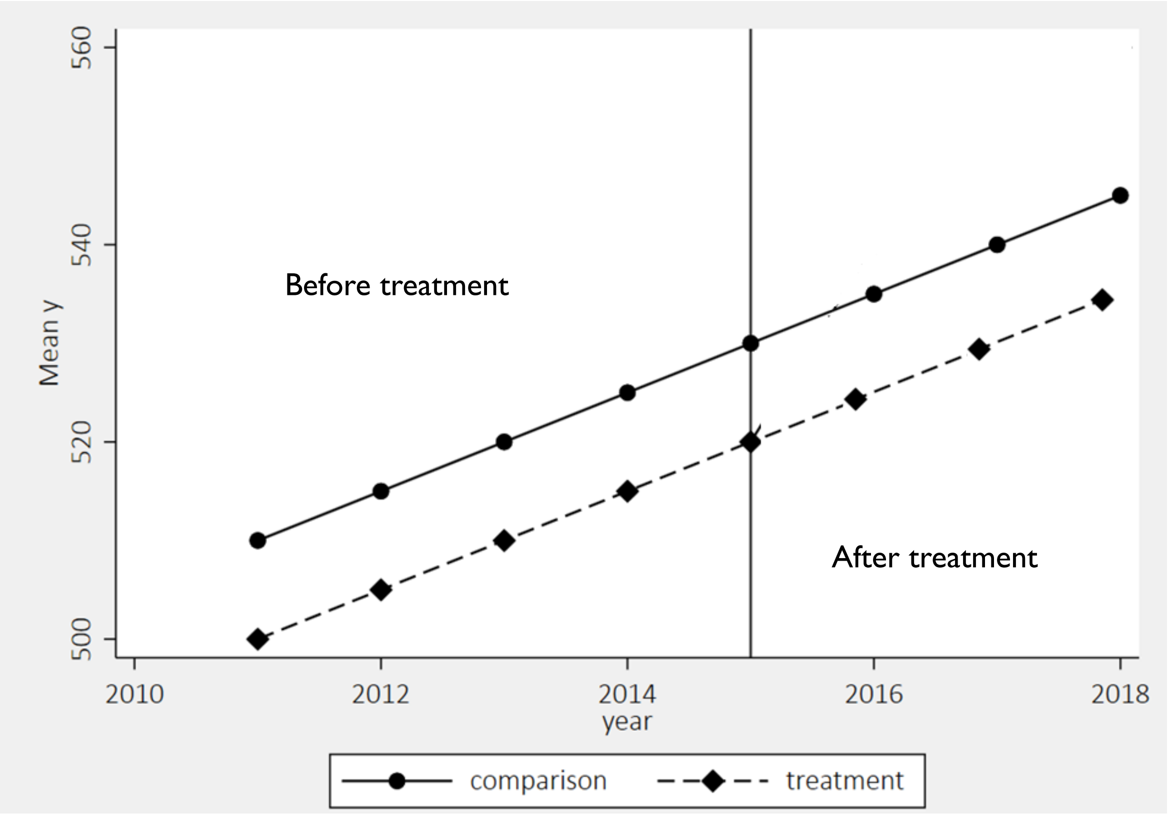
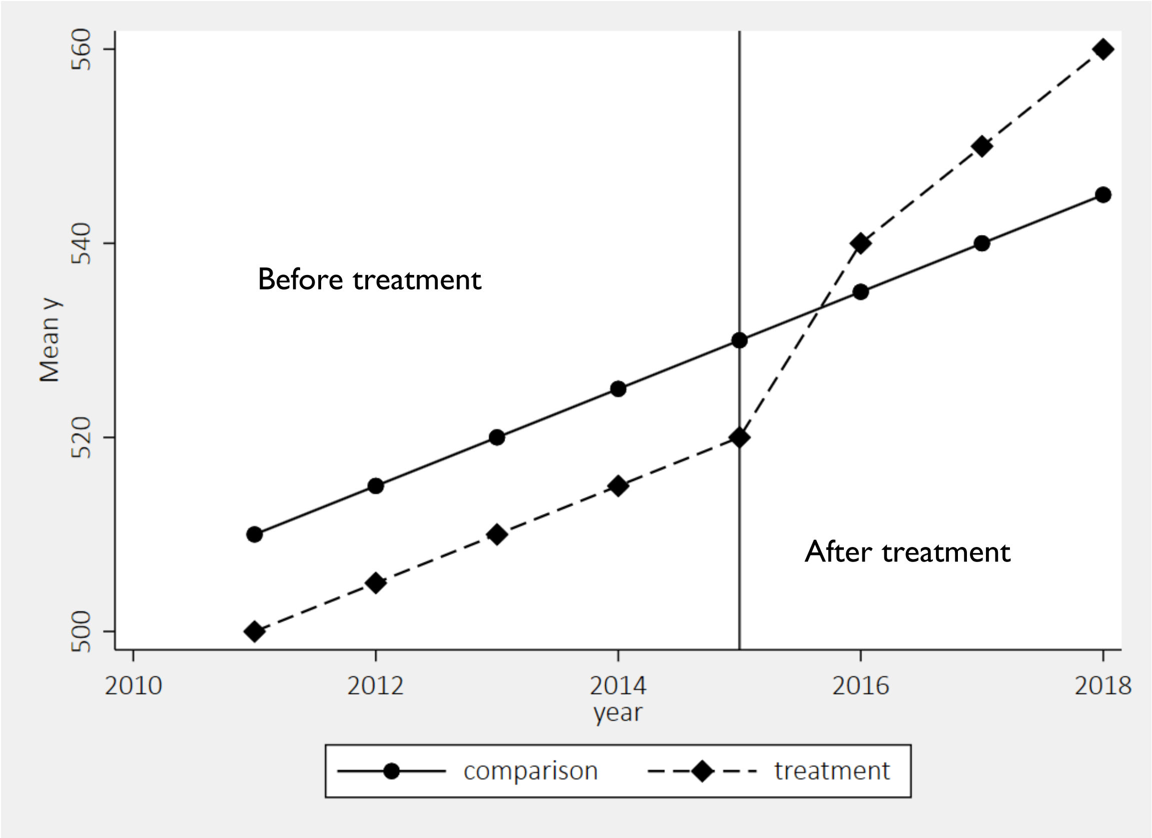


No effect – same trend

Difference-in-differences (DiD)



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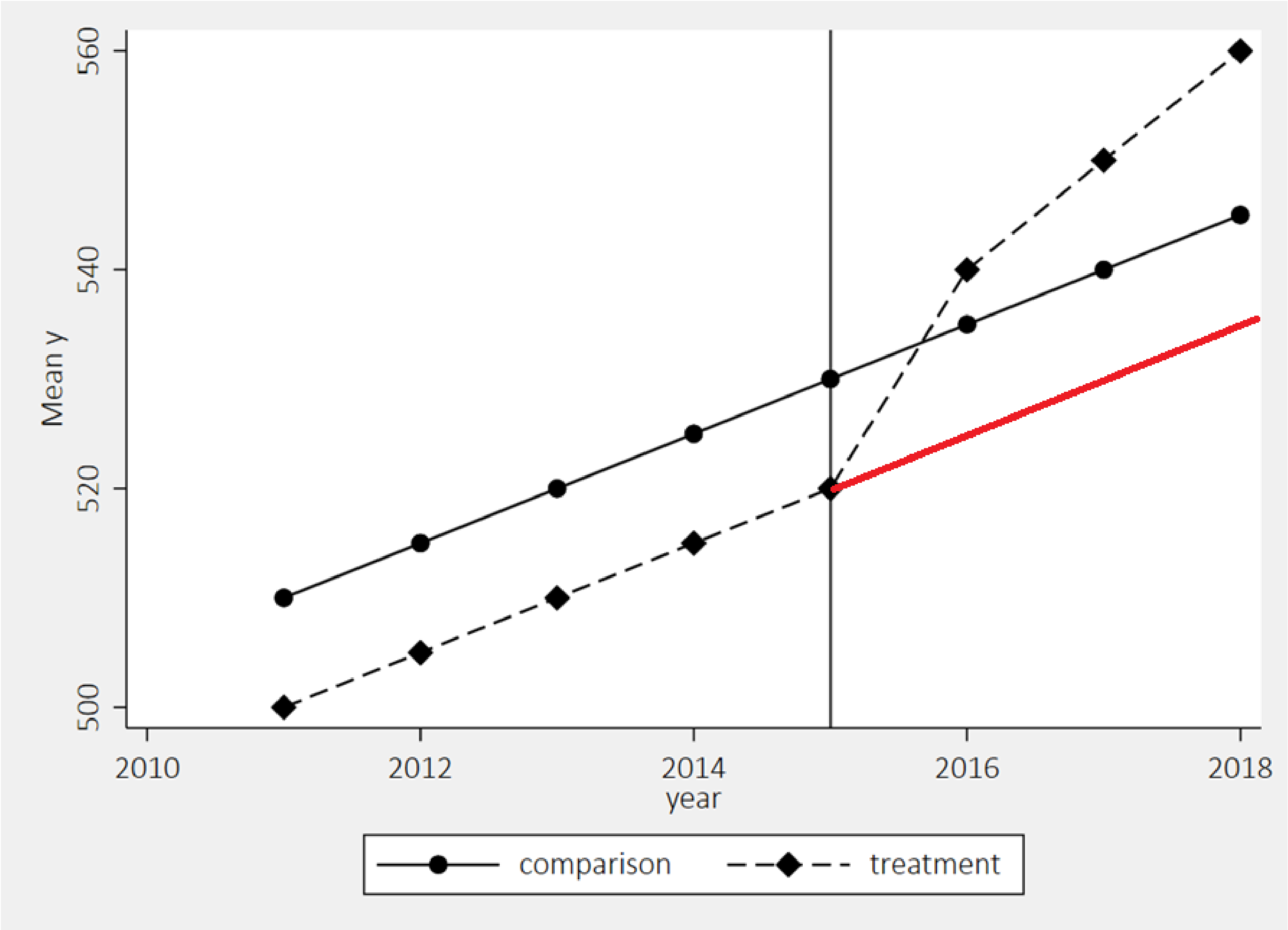

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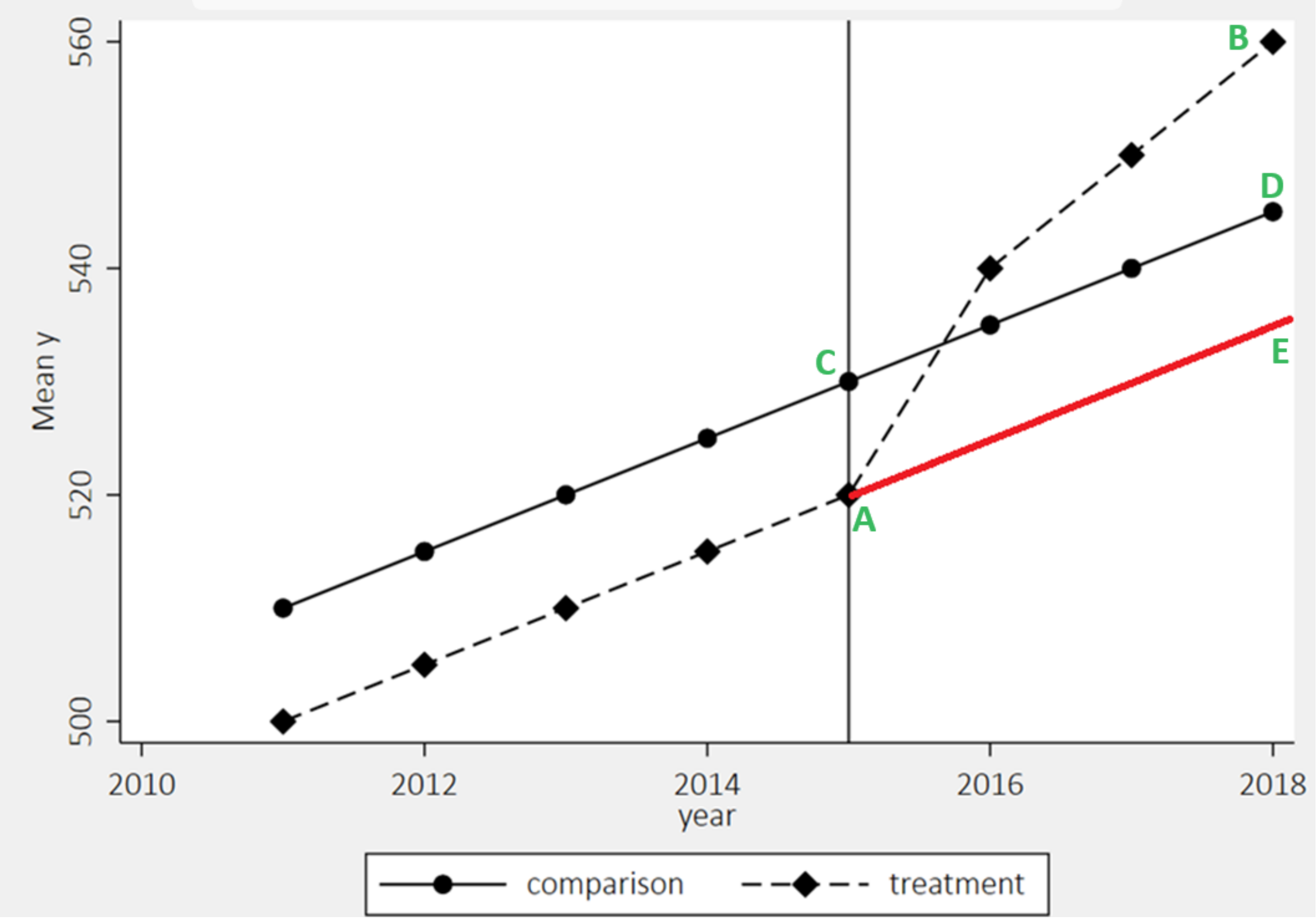


DiD computes the impact estimate as follows:

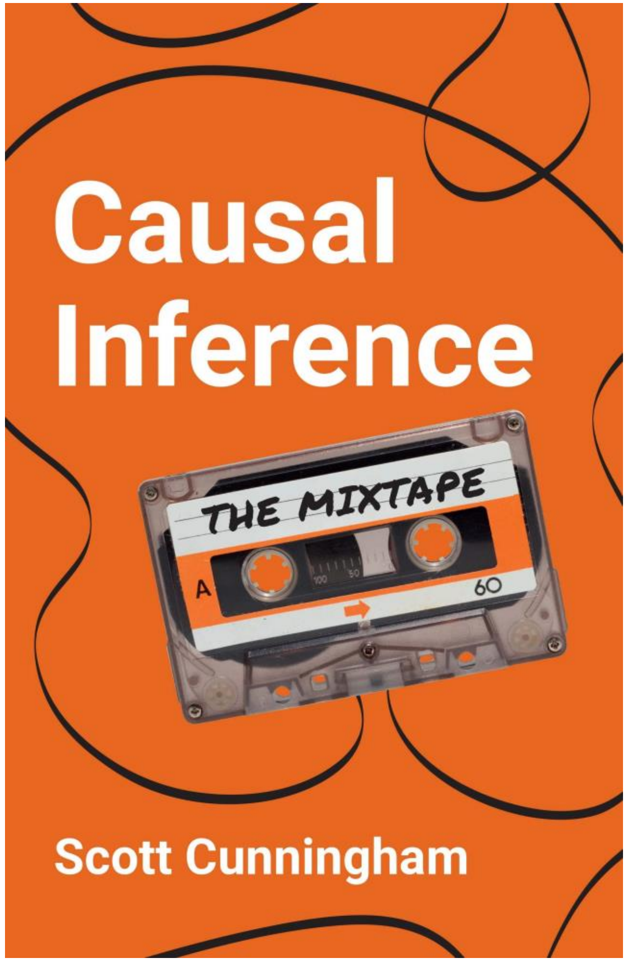
1. Calculate the difference in the outcome (Y) between the before and after situations for the treatment group
   - (B − A).
2. We calculate the difference in the outcome (Y) between the before and after situations for the comparison group
   - (D − C).
3. Finally, calculate the difference between the difference in outcomes for the treatment group (B − A) and the difference for the comparison group (D − C)
   - (B − A) − (D − C).

Assumptions of DiD

- Parallel Trends: The two groups followed parallel trends over time.
  - It's possible to test it!
- No Spillover Effects
- Time-Invariance Assumption
  - New DiD approaches have flexibility this assumption

Read Roth., et al. (2023), "What's trending in difference-in-differences? A synthesis of the recent econometrics literature", for more.

Want to know more about quasi-experiments?



Thank you!