# 14.32/320: RD review

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- **Basics:** You have a running variable $R_i$ (e.g. test scores) that should influence an outcome $Y_i$ *smoothly* (e.g. probability of going to college) and something that changes *discontinuously* at a certain cutoff of $R_i$ (e.g. winning a scholarship to go to college), which in turn impact $Y_i$.

- **Sharp RD vs Fuzzy RD**

  - Sharp RD: deterministic treatment, perfect function of your running variable (everyone above a certain cutoff is treated, everyone below is not)
  - Fuzzy RD: treatment is not deterministically determined by the threshold-crossing rule, but treatment intensity or treatment probability changes discontinuously at the cutoff

- **Sharp RD - Regression estimation:**

$$Y_i = \alpha + \beta Treat_i + f(x_i) + \varepsilon_i \tag{1}$$

where $Treat_i = 1(x_i >$ some cutoff $c)$ and $f(.)$ is typically a polynomial in $x_i$

- **Fuzzy RD - Regression estimation:** Implemented as 2SLS!

$$Y_i = \alpha + \beta Treat_i + f(x_i) + \varepsilon_i \quad \text{“Second stage”} \tag{2}$$
$$Treat_i = \gamma + \delta Z_i + g(x_i) + u_i \quad \text{“First stage”} \tag{3}$$

where the instrument is $Z_i = 1(x_i > c)$

- **Mechanics:**
  - **Parametric RD** $\rightarrow$ You control for the relationship between $R_i$ and $Y_i$ through linear or polynomial controls (Formally: you explicitly model $E[Y_{0i}|R_i]$ and $E[Y_{1i}|R_i]$ - the CEF of potential outcomes as a function of the running variable - and control for it); it uses all the data
  - **Nonparametric RD** $\rightarrow$ You only look within a very small interval around the cutoff (**Intuition:** around arbitrary policy cutoffs or thresholds, individuals are extremely similar to each other, but some individuals are exposed to a treatment while others are not.)
    - Note 1: you need to choose how close to the cutoff you want to be - i.e. you need to choose the **bandwidth**. (optimal bandwidth minimizes MSE - trades off variance and bias)
    - Note 2: you can choose to give more weight to observations that are closer to the cutoff (**kernel-weighting**)
  - **Nonparametric RD via Local Linear Regression** $\rightarrow$ Combines the insights from the two above

- **Main identification assumption: Continuity** of potential outcomes (observables and unobservables) at the cutoff. Since treatment (or treatment intensity) is *only* determined by the running variable crossing a predetermined cutoff, the only source of OVB can come from the running variable:
  - Parametric RD: Identification hinges on nailing the correct functional form assumption
  - Non-parametric RD: assumption is that the only thing that changes as the cutoff affecting outcome is the treatment status.

$$\lim_{x \downarrow c} E[Y_i(0)|x_i] = \lim_{x \uparrow c} E[Y_i(0)|x_i] \tag{4}$$

  Note: RD induces a local RCT! in a narrow bandwidth around $r_0$, RD treatment assignment behaves like a coin toss. [implication: pre-treatment covariates should be balanced!]

- **Threats to identification:** Identification fails if continuity fails.
  - **When will it happen?** Purposeful sorting around the cutoff will do: when agents strive to avoid or cross the threshold, $E[Y_i(0)|x_i]$ is unlikely to be continuous around $c$. (When interested parties manipulate to avoid or cross a cutoff, potential outcomes need not be similar left and right)
    * for instance, firms might artificially keep employment below 50 if crossing a 50-employee threshold subjects them to more stringent labor regulations (e.g. in France)
  - **How do I check for this?** Typically test for this by looking at:
    * **Covariate balance tests** on both sides of cutoff. Recall that the key assumption is that the jump is orthogonal to potential outcomes. This implies that anything that is pre-determined relative to treatment should *not* change around the cutoff.
    * **Density smoothness.** If the running variable distribution is not continuous, be suspicious! (Formally: McCrary test)

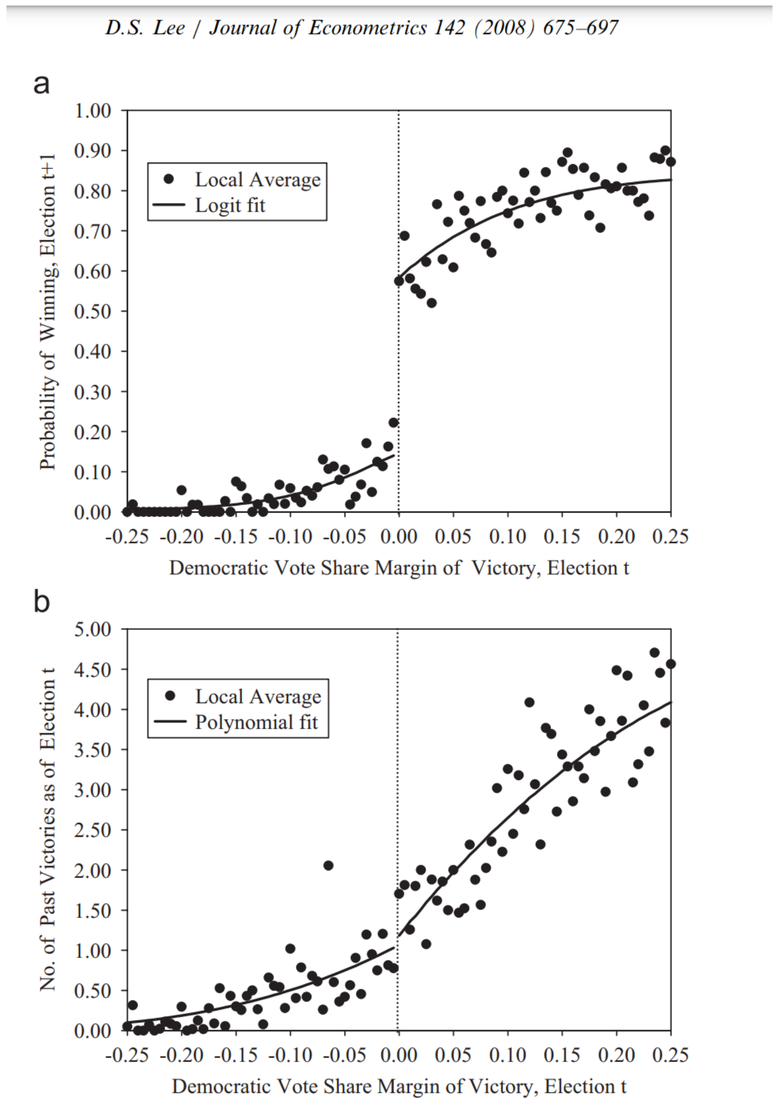


Figure 1: RD from Lee (2008)
Note: Panel (a) shows a post-treatment (incumbency) outcome, Panel (b) shows a pre-treatment outcome

## Maimonides' Rule (Angrist and Lavy, 1999)

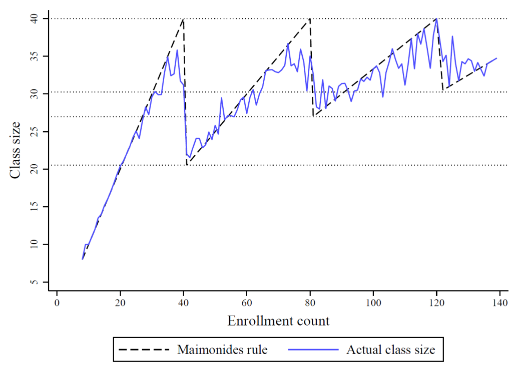


Figure 2: Fuzzy RD: enrollment count discontinuously affects class size

## Enrollment Manipulation: Breaking Maimonides Rule

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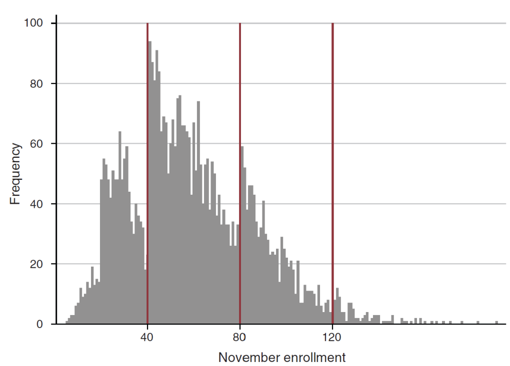


Figure 1. The Fifth-Grade Enrollment Distribution Reported in November (2002–2011)

*Notes:* This figure plots the distribution of fifth-grade enrollment as reported by school headmasters in November. Reference lines indicate Maimonides' rule cutoffs at which an additional class is added.

- From Angrist, Lavy, Leder-Luis, and Shany (2019)

Figure 3: Be careful! Evidence of manipulation