Part E: Regression Discontinuity

E2: RDD Extensions

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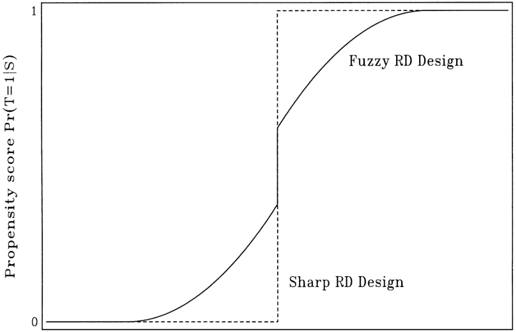
E2 Outline

1. Fuzzy RDD
2. Discrete running variables
3. Adding covariates
4. Politician characteristics RDDs
5. Multiple thresholds and cutoffs
6. Local randomization approach
7. Extrapolating RD estimates

Reading: Cattaneo, Idrobo, Titiunik ("Practical introduction: Extensions," 2023)

Fuzzy RDD

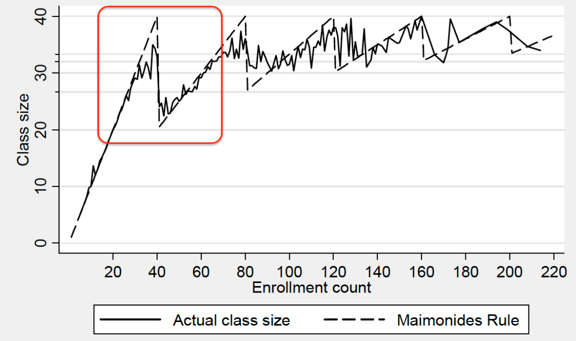
- Think of fuzzy RDD as using $Z_i = \mathbf{1}[X_i \geq c]$ as an instrument:
  - $D_i \neq Z_i$: treatment is not fully determined by X_i
  - But $\mathbb{E}[D_i \mid X_i]$ jumps at the cutoff $\implies Z_i$ is a relevant IV around $X_i = c$



(Illustration from van der Klaauw 2002, Fig. 2)

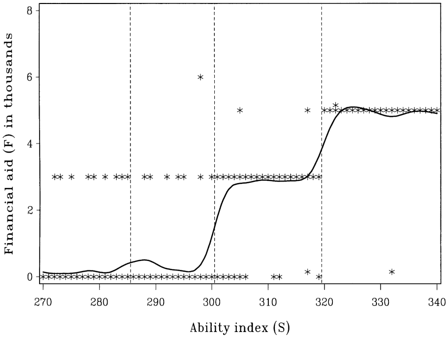
Fuzzy RDD examples

Class size "first stage"



(MHE, Fig. 6.2.1a, based on Angrist and Lavy 1999)

Financial aid "first stage"



(van der Klaauw 2002, Fig. 4)

Identification and estimation

- With binary treatment, need standard IV assumptions:
  - *Exclusion*: $Y_i(d, z) \equiv Y_i(d)$
  - *Independence*: continuity of $\mathbb{E}[D_i(z) \mid X_i = x]$ and $\mathbb{E}[Y_i(d) \mid X_i = x]$ at $x = c$
  - *Monotonicity*: $D_i(1) \geq D_i(0)$
- Then, Reduced form/First stage $\equiv \tau_Y / \tau_D$ identifies LATE:

$$\frac{\tau_Y}{\tau_D} = \mathbb{E}[Y_i(1) - Y_i(0) \mid D_i(1) > D_i(0),\ X_i = c]$$

  - Show RD plots for the first stage and reduced form (ITT)
- Report $\hat{\tau}_D$, $\hat{\tau}_Y$ and fuzzy RD estimate $\hat{\tau}_Y / \hat{\tau}_D$ from local polynomial estimation with the same bandwidth for Y and D
  - `rdrobust` chooses bandwidth to minimize MSE for the IV

Outline

Discrete running variables

- In many RDD applications X_i is discrete
  - E.g. number of kids in a cohort *(Angrist and Lavy 1999)*
- Does this matter conceptually?
  - $\lim_{x \downarrow, \uparrow c} \mathbb{E}\left[Y_i \mid X_i = x\right]$ is not well-defined $\implies$ RD identification fails
  - As $N \to \infty$, we can't shrink bandwidth $h \to 0$
- Does this matter in practice?
  - If there are many mass points of X_i around c, can probably ignore the issue
  - If X_i is sparse around c, it's more salient

An "honest" approach

- Armstrong and Kolesar (2020) and Kolesar and Rothe (2018) develop an "honest" approach to RDDs
  - Acknowledges that bias in local linear estimation is inevitable
  - With discrete X_i we cannot consistently estimate bias
- Instead, it bounds worst-case bias by assuming that $\mathbb{E}[Y_i \mid X_i]$ is sufficiently smooth on either side of c
  - Choose bound M on the curvature of $\mathbb{E}[Y_i \mid X_i] \Rightarrow$ get a partially identified set of τ
  - Reminds you of anything?
- Choosing M is annoying but ignoring discreteness does the same implicitly
  - A rule of thumb is available

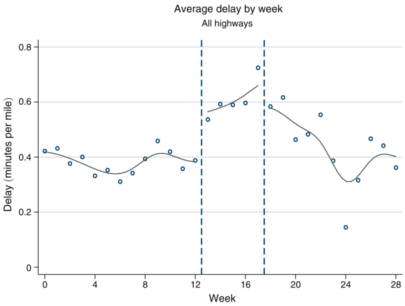
An "honest" approach (2)

- `rdhonest` produces a "bias-aware" confidence interval
  - Centered around the local linear estimator
    - For bandwidth optimized for CI length but similar to the Calonico et al. (2014) bandwidth
  - Adds worst-case bias rather than estimated bias
- Approach applies even with continuous running variable
  - And can have good finite-sample properties because doesn't rely on h being small
- See Imbens and Wager (2019) for an honest approach not based on local linear estimation
  - More complex (via numerical optimization) but more generalizable

RD in time

Related problems arise with "**RD in time**"

- X_i = period; often no cross-sectional variation at all, just a time series
- E.g. Anderson (2014): the effect of a public transit strike in LA on highway congestion



(Anderson 2014, Fig. 2)

- Similar situation: X_i = age

How to think about RD in time?

- Theoretically, time is a continuous variable
  - Could measure the outcome 1 second before and after the policy change — like event studies in finance
  - Asymptotic with data frequency growing
- In practice, outcomes are measured at discrete intervals, and collecting more data involves going further in time from c
  - As $T \to \infty$ the bandwidth can't (and doesn't) shrink
  - Understanding check #1: how come, given $h \propto T^{-1/5}$?
  - Understanding check #2: what if we also observe cross-sectional variation, $N \to \infty$? E.g. congestion separately by neighborhood
  - Understanding check #3: is the McCrary test helpful here?

Outline

Adding covariates

As usual, covariates W_i can be added to increase efficiency or to avoid OVB

- If W_i are predetermined, i.e. $\mathbb{E}[W_i \mid X_i]$ is continuous at the cutoff:
  - Include W_i in the regression implementation of local linear estimator *without* interactions:

$$Y_i = \tau D_i + \gamma_0 + \gamma_1(X_i - c) + \gamma_2(X_i - c)D_i + \delta' W_i + \text{error}$$

  - This increases efficiency without changing the estimand *(Calonico et al. 2019)*
  - See Noack, Olma, Rothe (2023) on flexible covariate adjustment
- If W_i jumps at the cutoff, the effects of D_i and W_i cannot be separated without further assumptions
  - Frölich and Huber (2019) make a selection-on-observables assumption; see also Peng and Ning (2021)

Outline

Politician characteristics RDDs

- Marshall (2022) studies RD designs where $D_i =$ some characteristic of winning politician
  - E.g. the effect of having a female politician in office
  - Sample restricted to close races between a woman and a man
- This is an unusual setup:
  - Standard RDD: effect of winning (e.g. on candidate longevity) $\implies$ observe outcomes for both winners and losers
  - Here: effect of being female *conditional on winning* $\implies$ only observe outcomes for winners (or the district)

Politician characteristics RDDs (2)

How do we interpret the estimand?

- Standard issue: being female is an attribute not a cause — a bundle of characteristics
- Additional issue in RDDs: consider a characteristic W_i uncorrelated with D_i among all candidates
  - Suppose both D_i and W_i affect vote shares
  - Then among close races, D_i and W_i will be correlated — "compensating differential"
- Is this a bias or a different interpretation/mechanism?
  - Marshall (2022) argues for bias: it's not the effect of changing D_i while holding other characteristics fixed

Outline

Multiple thresholds and cutoffs

Three scenarios:

1. Binary treatment with heterogeneous cutoffs
2. Multi-valued treatment with multiple cutoffs
3. Multi-dimensional running variable

Note: package `rdmulti` provides commands for estimation and plotting

Binary treatment with heterogeneous cutoffs

- E.g. states have different income cutoffs for a means-tested program: $D_i = \mathbf{1}[X_i \geq C_i]$ for $C_i \in \{c_1, \ldots, c_K\}$

- Obviously, we can RD by subgroup $C_i = c$:

$$\tau_c = \mathbb{E}[Y_i(1) - Y_i(0) \mid X_i = c, C_i = c]$$

- Can also pool them by using "normalized" $\tilde{X}_i = X_i - C_i$ with a cutoff of zero
  - Pooled RDD identifies a weighted average of group-specific ones:

$$\tau_{\text{pooled}} = \frac{\sum_c \omega_c \tau_c}{\sum_c \omega_c}, \qquad \omega_c = f_{X|C}(c, c)$$

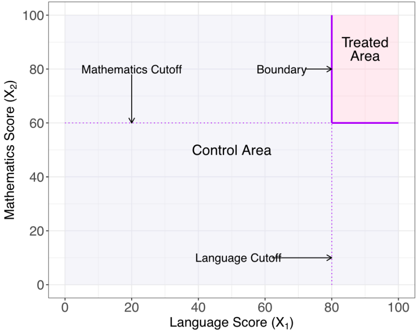
Multi-valued treatment with multiple cutoffs

- E.g. the Maimonides rule *(Angrist, Lavy 1999)* generates cutoffs at $X_i = 40, 80, \ldots$
- Or federal subsidies determined by local population, with several discontinuities
- Consider a sharp design with $D_i = \begin{cases} d_0, & \text{if } X_i < c_1 \\ d_1, & \text{if } c_1 \leq X_i < c_2 \\ \ldots & \\ d_K, & \text{if } c_K \leq X_i \end{cases}$
- RDD on subsample with $D_i \in \{d_{k-1}, d_k\}$ identifies $\mathbb{E}\left[Y_i(d_k) - Y_i(d_{k-1}) \mid X_i = c_k\right]$
- Mostly similar to the previous case
  - Same observation can be used twice (unless bandwidth is small enough)

Multi-dimensional running variable

E.g. scholarship awarded to students scoring above a cutoff in *both* math and English:

$$\boldsymbol{X}_i = (Math_i, English_i)\,, \qquad D_i = \mathbf{1}\left[Math_i \geq c_{Math}\right] \times \mathbf{1}\left[English_i \geq c_{English}\right]$$

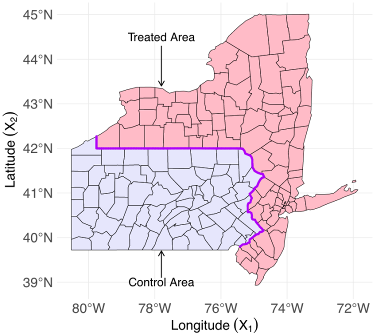


(Cattaneo and Titiunik 2023, Fig. 5.5a)

- Note that a student needn't be close to the border on *both* running variables to be near the boundary

Multi-dimensional running variable (2)

Spatial discontinuity designs are a special case: $\boldsymbol{X}_i = (Longitude_i, Latitude_i)$



(Cattaneo and Titiunik 2023, Fig. 5.5b)

- E.g. Black (1999) compares house prices across boundaries of elementary school catchment areas (within school districts and administrative areas)
  - D_i = average test score in the school

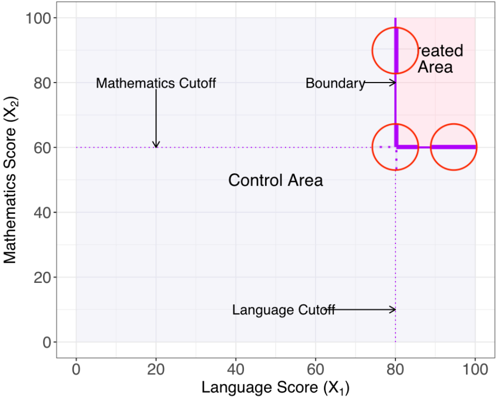
Estimand #1: Effects at a single boundary point

- Let $D_i = a(\boldsymbol{X}_i)$, $A_0 = \{x\colon a(x) = 0\}$, $A_1 = \{x\colon a(x) = 1\}$, and $B =$ boundary between A_0 and A_1
- Assume $\mathbb{E}\left[Y_i(d) \mid \boldsymbol{X}_i = x\right]$ is continuous at $x \in B$
  - Violated when multiple outcome-relevant treatments jump at the same boundary
  - Or when location $\boldsymbol{X}_i$ can be manipulated
- Average causal effect at point $b \in B$, $\tau(b)$, is identified by

$$\tau(b) = \lim_{x \to b,\ x \in A_1} \mathbb{E}\left[Y_i \mid \boldsymbol{X}_i = x\right] - \lim_{x \to b,\ x \in A_0} \mathbb{E}\left[Y_i \mid \boldsymbol{X}_i = x\right]$$

  - To implement, let $d(\boldsymbol{X}_i, b)$ denote some distance metric (e.g. Euclidean)
  - Use $\tilde{X}_i = d(\boldsymbol{X}_i, b) \cdot (2D_i - 1)$ as a scalar running variable with a cutoff of zero

Estimand #1: Effects at a single boundary point (contd.)



Estimand #2: Pooled effect

- How can we estimate the average effect pooling across boundary points, $\mathbb{E}\left[Y_i(1) - Y_i(0) \mid \mathbf{X}_i \in B\right]$?

- Naive approach: Compute distance $d_{min}(\mathbf{X}_i)$ to the *closest* boundary point

    - Use scalar $\tilde{X}_i = d_{min}(\mathbf{X}_i) \cdot (2D_i - 1)$ with a cutoff of zero

    - But in finite samples this may not be enough...

    - Observations on the two sides of the border may be geographically imbalanced

Pooled effect: better estimators

- Black (1999): use minimum distance but include FEs of boundary segments as controls to improve geographic balance

- Imbens and Zajonc (2009): manually average estimated $\hat{\tau}(b)$ over the boundary $b \in B$

- The honest approach of Imbens and Wager (2019)
  - Directly chooses the optimal estimator (via numerical optimization), accounting for worst-case bias under a bound on two-dimensional curvature of $\mathbb{E}[Y_i(d) \mid \mathbf{X}_i]$

Spillovers in spatial RDDs

- We assumed away spillovers (SUTVA violations)
  - But in some spatial RDDs they are very important
  - Comparing places just around the boundary is a terrible idea when Y_i can be affected by $D_{\text{neighbors}(i)}$
- One popular approach: "donut" estimation
  - Pick a smaller bandwidth $h' < h^*$ and drop observations within h' from the cutoff when estimating the direct effect
  - Used also in conventional RDDs when some manipulation is possible
- What do you think of this idea? How would you estimate the effect?
  - See Noack and Rothe (2023)

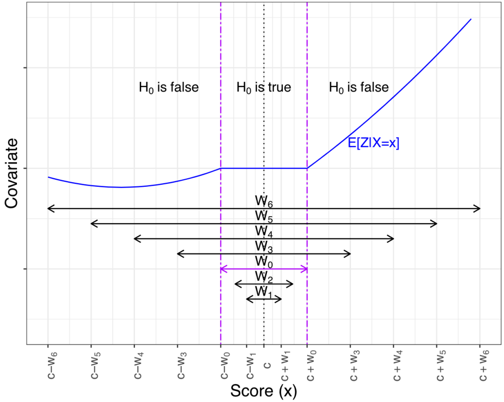
Outline

Local randomization approach to RDDs

- Lee (2008) title: *"Randomized experiments from non-random selection in U.S. House elections"*
- In the continuity approach this idea is a heuristic
  - D_i is only approximately independent from $Y_i(d) \Longrightarrow$ local polynomial adjustments, approximate permutation tests, etc.
- Local randomization approach (Cattaneo et al. 2015) takes this idea seriously
  - Assume $X_i \perp\!\!\!\perp Y_i(d) \mid X_i \in \mathcal{X}$ in a finite neighborhood $\mathcal{X} = [c-h, c+h]$
  - And that $F(X_i \mid X_i \in \mathcal{X})$ is known, e.g. uniform in $\mathcal{X}$ or across permutations
  - For no good reason!
- Under these assumptions, can use all RCT machinery
  - E.g. randomization inference that is valid in finite-samples (in contrast to Canay and Kamat 2018)

Choosing the window

Cattaneo et al. (2015) propose to start from smallest h and increase it until you reject balance of some predetermined W_i



(Cattaneo and Titiunik 2023, Figure 2.4)

Outline

Extrapolating RD estimates

A key limitation of RDDs is the local nature of $\tau = \mathbb{E}\left[Y_i(1) - Y_i(0) \mid X_i = c\right]$

- Kids who barely receive financial aid and politicians who barely win may be unusual
- When can we identify effects away from the cutoff to improve external validity?

Idea #1 (Dong and Lewbel 2015): local linear estimation also yields

$$\phi = \frac{\partial \mathbb{E}\left[Y_i(1) - Y_i(0) \mid X_i = x\right]}{\partial x}\Big|_{x=c}$$

- Difference in regression slopes on the right and left
- Thus, $\mathbb{E}\left[Y_i(1) - Y_i(0) \mid X_i = x\right] \approx \tau + \phi(x - c)$ for $x \approx c$
  - Still a local parameter but a useful measure of sensitivity of τ to shifting the cutoff

Extrapolating RD estimates (2)

Idea #2 (Angrist and Rokkanen 2015): suppose X_i is a noisy version of observable W_i

- E.g. $D_i =$ offer for selective school in Boston, $X_i =$ admission test score
  - Assume X_i is random noise conditionally on pre-application test score
- Conditional independence assumption:

$$\mathbb{E}\left[Y_i(d) \mid X_i, W_i\right] = \mathbb{E}\left[Y_i(d) \mid W_i\right] \quad \Longrightarrow \quad \mathbb{E}\left[Y_i(d) \mid D_i, W_i\right] = \mathbb{E}\left[Y_i(d) \mid W_i\right]$$

  - Given W_i, we can compare treated and untreated, as long as there is overlap
  - Can use standard CIA methods to get the ATE (on everyone — nothing local)
  - *Note*: we used that D_i is a deterministic function of X_i, but not its discontinuity

Extrapolating RD estimates (3)

Angrist and Rokkanen's CIA assumption is falsifiable:

$$\begin{aligned}\mathbb{E}\left[Y_i(d) \mid X_i, D_i, W_i\right] = \mathbb{E}\left[Y_i(d) \mid W_i\right] &\implies \mathbb{E}\left[Y_i(d) \mid X_i, D_i, W_i\right] = \mathbb{E}\left[Y_i(d) \mid D_i, W_i\right] \\ &\implies \mathbb{E}\left[Y_i \mid X_i, D_i, W_i\right] = \mathbb{E}\left[Y_i \mid D_i, W_i\right]\end{aligned}$$

- Among the treated, X_i should not predict Y_i given W_i; same for the untreated

Note: RDD with heterogeneous cutoffs, $D_i = \mathbf{1}\left[X_i \geq C_i\right]$, where C_i is **not** correlated with potential outcomes is a special case:

$$\text{For } \tilde{X}_i = X_i - C_i, \qquad \mathbb{E}\left[Y_i(d) \mid \tilde{X}_i, X_i\right] = \mathbb{E}\left[Y_i(d) \mid X_i\right]$$