

# rdlocrand: Inference in RD Designs Under Local Randomization

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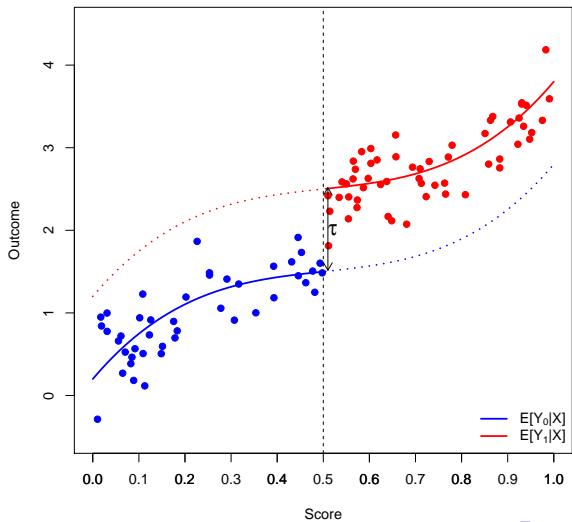
# Introduction

- Regression discontinuity designs (RDDs) are one of the most popular methods for causal inference.
- RDDs can be interpreted as a local experiment in a window around the cutoff.
- `rdlocrand` analyzes RDDs using tools from classical randomized experiments literature:
  - `rdwinselect`: window selection
  - `rdrandinf`: randomization inference
  - `rdsensitivity`: sensitivity analysis
  - `rdrbounds`: Rosenbaum bounds

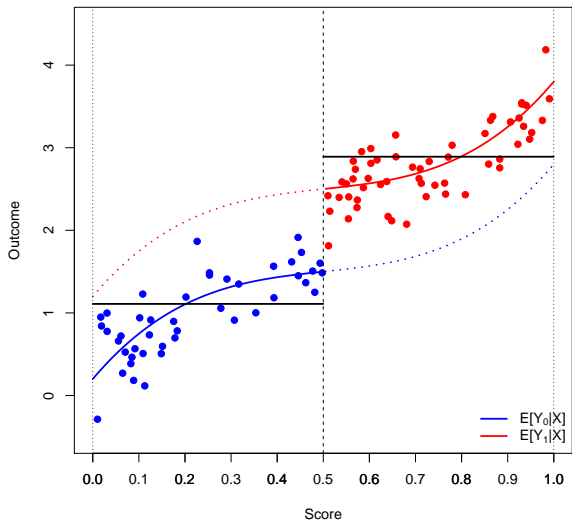
# Regression Discontinuity Designs: motivation

- Many programs or policies are assigned based on whether a score (running variable)  $X$  exceeds a threshold  $c$ :
  - Scholarship to students above a certain test score.
  - Subsidy to households above a poverty threshold.
- RDDs exploit the discontinuity in the probability of treatment assignment at the cutoff.
  - Sharp design:  $D_i = \mathbb{1}(X_i \geq c)$ .
- Intuition: in a “small” window around the cutoff, units above and below are comparable.

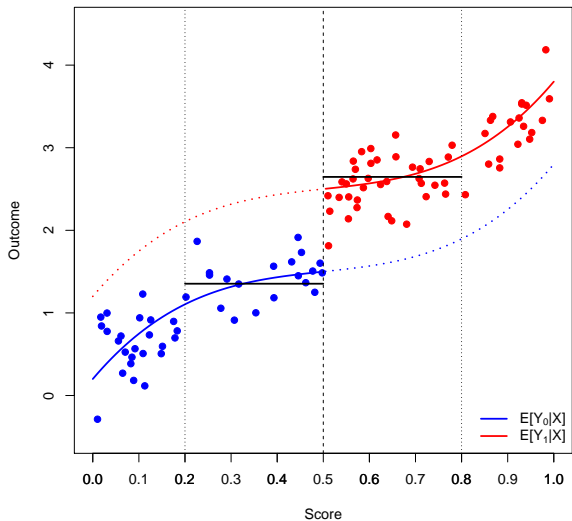
# RDD: intuition



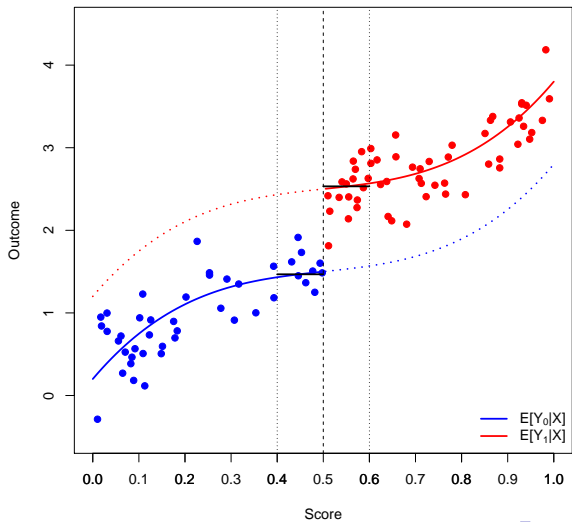
# RDD: intuition



# RDD: intuition



# RDD: intuition



# Inference in classical randomized experiments

- RDDs as randomized experiments around the cutoff.
  - Key assumption: existence of a window in which this is true.
- Inference in classical experiments:
  - Fixed (nonrandom) potential outcomes.
  - Known assignment mechanism.
- Randomization (finite sample) p-value:
  - Choose a statistic  $T$  (e.g. difference in means),
  - Calculate  $T$  for all permutations of treatment assignment,
  - Find  $\mathbb{P}(T \geq T_{obs})$ .
- In Stata:  
`permute d stat = (r(mu_1)-r(mu_2)): ttest y, by(d).`



# Randomization inference with `rdrandinf`

```
. rdrandinf demvoteshfor2 demmv, wl(-.75) wr(.75)
```

```
Selected window = [-.75 ; .75]
```

```
Running permutation test...
```

```
Permutation test complete.
```

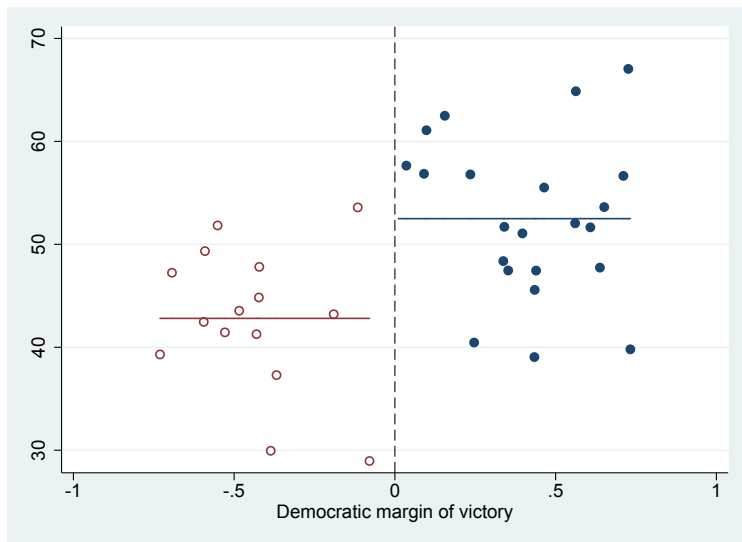
```
Inference for sharp design
```

Cutoff c = 0.00	Left of c	Right of c		
Number of obs	595	702	Number of obs =	1390
Eff. Number of obs	15	22	Order of poly =	0
Mean of outcome	42.808	52.497	Kernel type =	uniform
S.D. of outcome	7.042	7.742	Reps =	1000
Window	-0.750	0.750	Window =	set by user
			H0: tau =	0.000
			Randomization =	fixed margins

```
Outcome: demvoteshfor2. Running variable: demmv.
```

Statistic	Finite sample		Large sample	
	T	P> T	P> T	Power vs d = 3.52
Diff. in means	9.689	0.001	0.000	0.300

# Randomization inference with `rdrandinf`



# Choosing the window with rdwinselect

```
. rdwinselect demmv $covariates, wmin(.5) wstep(.125) reps(10000)
```

Window selection for RD under local randomization

Cutoff c = 0.00	Left of c	Right of c	Number of obs =	1390
Number of obs	640	750	Order of poly =	0
1th percentile	6	8	Kernel type =	uniform
5th percentile	32	38	Reps =	10000
10th percentile	64	75	Testing method =	rdrandinf
20th percentile	128	150	Balance test =	ttest

Window length /2	Bal. test p-value	Var. name (min p-value)	Bin. test p-value	Obs<c	Obs>=c
0.500	0.268	demvoteshlag2	0.230	9	16
0.625	0.435	dopen	0.377	13	19
0.750	0.268	dopen	0.200	15	24
0.875	0.150	dopen	0.211	16	25
1.000	0.069	dopen	0.135	17	28
1.125	0.037	dopen	0.119	19	31
1.250	0.062	dopen	0.105	21	34
1.375	0.141	dmidterm	0.539	30	36
1.500	0.092	dmidterm	0.640	34	39
1.625	0.113	dmidterm	0.734	37	41

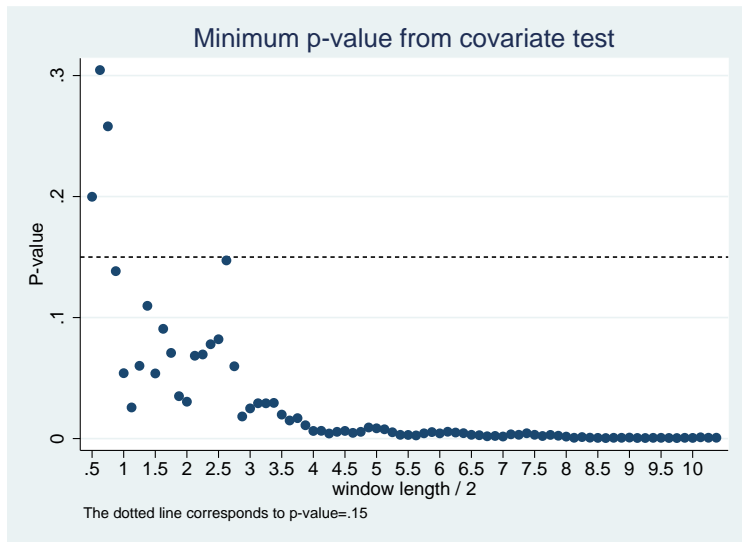
Variable used in binomial test (running variable): demmv

Covariates used in balance test: presdemvoteshlag1 population demvoteshlag1 demvoteshlag2

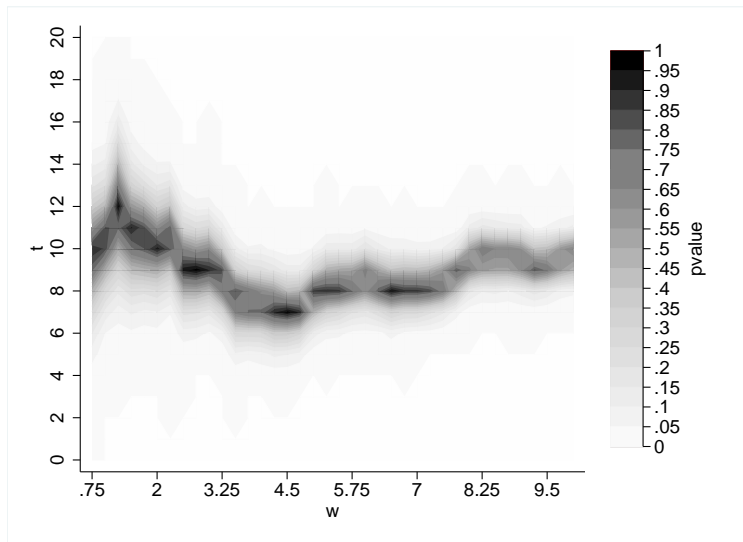
```
> demwinprv1 demwinprv2 dopen dmidterm
```

Largest recommended window is [-.75; .75] with 39 observations (15 below, 24 above).

# Choosing the window with `rdwinselect`



# Sensitivity analysis with rdsensitivity



# Rosenbaum bounds with rdrbounds

```
. rdrbounds demvoteshfor2 demmv, gammalist(.8 1 1.2) wlist(.5 .75 1) reps(1000)
```

```
Calculating randomization p-values...
```

	w =	0.500	0.750	1.000
Bernoulli p-value		0.012	0.001	0.000

```
Running sensitivity analysis...
```

gamma	exp(gamma)		w =	0.500	0.750	1.000
0.80	2.23	lower bound		0.006	0.001	0.000
		upper bound		0.068	0.015	0.002
1.00	2.72	lower bound		0.004	0.001	0.000
		upper bound		0.106	0.034	0.006
1.20	3.32	lower bound		0.003	0.001	0.000
		upper bound		0.168	0.060	0.017

## Other features of rdlocrand

- Alternative statistics: Kolmogorov-Smirnov, rank sum.
- Polynomial adjustment of potential outcomes.
- Randomization-based confidence intervals for treatment effect.
- Companion R functions with same capabilities.
- See Cattaneo, Titiunik and Vazquez-Bare (2016): Inference in Regression Discontinuity Designs under Local Randomization. *Stata Journal* 16(2): 331-367.

Thank you!



## Additional material

## Other issues: multiple testing

- `rdwinselect` performs hypothesis tests for a large set of covariates.
- Multiple testing leads to overrejection → “err on the safe side” (smaller windows).
  - Local randomization assumption only credible in a small window.
- `rdwinselect` can also test all covariates jointly using Hotelling’s  $T^2$  test.
  - Typically leads to much larger windows.

## Other issues: outcome model adjustment

- Strongest version of local randomization assumption states that potential outcomes do not depend on the score inside the window:
  - Exclusion restriction:  $Y_i(d, x) = Y_i(d)$ .
- This assumption may be too strong in some scenarios.
- `rdlocrand` allows the user to state a polynomial model for the potential outcomes to eliminate the dependence on  $X$ .
  - E.g. use a linear model to remove the slope.