

The Local Randomization Approach

Northwestern Causal Inference Workshop

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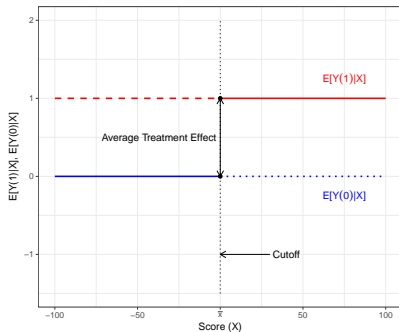
Overview: RD as a randomized experiment

- Informally, RDDs are interpreted as local experiments
- Idea: close enough to the cutoff, some units were “lucky”
 - ▶ Units slightly above and below the cutoff are comparable
- Our framework so far does not formalize this interpretation
 - ▶ Based on continuity of regression functions only
- When can we interpret an RD as a local experiment?

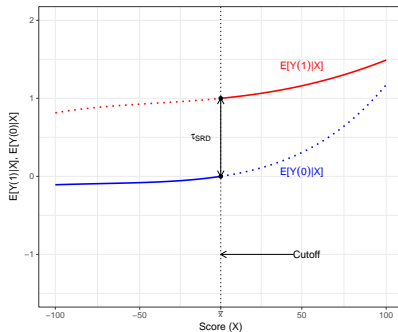
Overview: RD as a randomized experiment

- Any experiment can be thought of as an RD where:
 - ▶ The score is a uniform random variable
 - ▶ The cutoff is chosen to ensure a given probability of treatment
- Example:
 - ▶ Each unit is assigned a score $X_i \sim U[0, 1]$
 - ▶ $D_i = \mathbb{1}(X_i \geq c) \implies \mathbb{P}[D_i = 1] = 1 - c$
- Key issue: score unrelated to potential outcomes **by construction**

Experiments versus RD designs

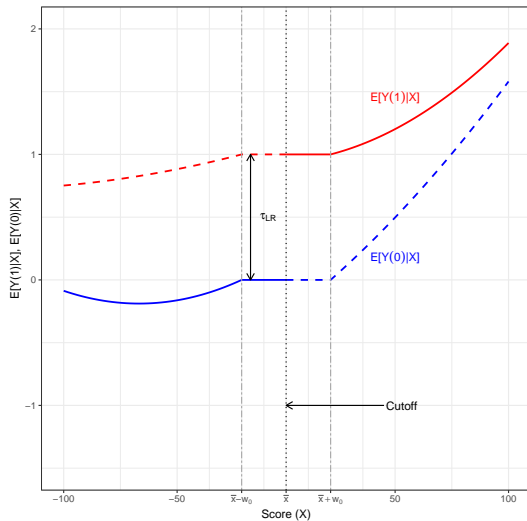


(a) Randomized Experiment



(b) RD Design

Local randomization RD



Local randomization approach to RD

- There is a window $W_0 = [c - w, c + w]$ in which:

- ▶ Probability distribution of X_i is unrelated to individual characteristics

$$\mathbb{P}[X_i \leq x | X_i \in W_0] = F_0(x), \quad \forall i$$

- ▶ Potential outcomes not affected by value of the score:

$$Y_i(d, x) = Y_i(d)$$

- Note: stronger assumption than continuity

- ▶ Potential outcomes are a constant function of the score

Window selection

- Under random assignment, covariates should be balanced:

$$\mathbb{P}[Z_i \leq z | D_i = 1] = \mathbb{P}[Z_i \leq z | D_i = 0]$$

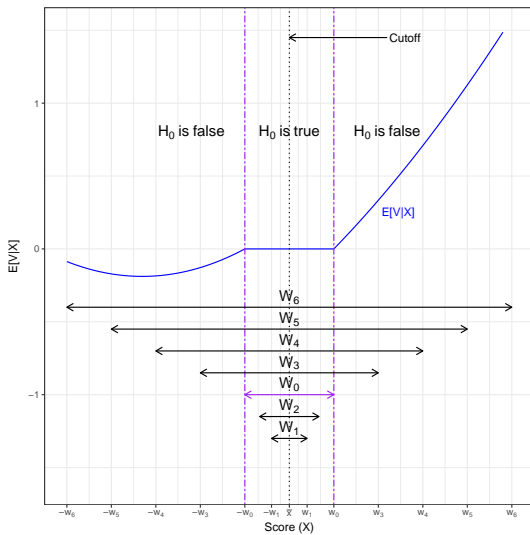
- Can use this idea as a window selection criterion:

- ▶ Find window in which all covariates are balanced

- Iterative procedure:

1. Choose a test statistic (diff. means, Kolmogorov-Smirnov,...)
2. Choose an initial “small” window $W_0^{(1)} = [c - w_{(1)}, c + w_{(1)}]$
3. Test null that covariates are balanced above and below c
4. Repeat until null hypothesis is rejected

Window selection procedure



Estimation and inference

- Once W_0 is found, proceed as in a randomized experiment

$$\hat{\tau} = \bar{Y}_1 - \bar{Y}_0$$

- Covariate-balance criterion may yield windows with few obs
- Inference based on large-sample approximations may not be reliable
- Alternative approach: Fisherian randomization inference
 - ▶ Local randomization approach

Fisher's approach to inference

- Alternative approach to inference in randomized experiments
- Finite-sample exact
 - ▶ Valid for any sample size
 - ▶ No distributional assumptions or approximations
- Conditional on a particular sample
 - ▶ Potential outcomes are fixed
 - ▶ All randomness due to treatment assignment
- Tests a specific type of hypotheses: *sharp null*
 - ▶ E.g. no treatment effect on any unit

The Lady Tasting Tea

The Design of Experiments (Sir Ronald A. Fisher, 1935)

- *“A lady declares that by tasting a cup of tea made with milk she can discriminate whether the milk or the tea infusion was first added to the cup.”*
- *“We will consider the problem of designing an experiment by means of which this assertion can be tested.”*
- *“Our experiment consists in mixing eight cups of tea, four in one way and four in the other, and presenting them to the subject in a random order.”*
- *“Her task is to divide the 8 cups into two sets of 4, agreeing, if possible, with the treatments received.”*

The Lady Tasting Tea

- There are $\binom{8}{4} = 70$ ways to arrange the cups
- H_0 : the lady is guessing at random
- Statistic: number of correct guesses
- Suppose she guesses all cups correctly
 - ▶ Probability of all guesses correct under H_0 : $\frac{1}{70} \approx 0.014$
 - ▶ 0.014 is a finite-sample exact p-value
 - ▶ No distributional assumptions or approximations

Randomization inference

- Consider a randomly assigned treatment D_i , $\mathbb{P}[D_i = 1] = 1/2$
- Suppose potential outcomes are non-random
 - ▶ Inference conditional on the observed sample
- All randomness comes through the assignment mechanism:

$$Y_i = Y_i(1)D_i + Y_i(0)(1 - D_i)$$

- Sharp null hypothesis of no treatment effect:

$$H_0 : Y_i(1) = Y_i(0), \quad \forall i = 1, \dots, n$$

Randomization inference

$$H_0 : Y_i(1) = Y_i(0), \quad \forall i = 1, \dots, n$$

- Under H_0 we can impute all the missing potential outcomes
- For any test statistic, T , under H_0

$$T(\mathbf{Y}, \mathbf{D}) = T(\mathbf{Y}_0, \mathbf{D})$$

- The distribution of T is given by the **known** distribution of \mathbf{D}

Randomization inference

$$H_0 : Y_i(1) = Y_i(0), \quad \forall i = 1, \dots, n$$

- Inference procedure:

- ▶ Calculate the observed value of the statistic, T_{obs}
- ▶ Calculate T for all possible permutations of $\mathbf{D} = (D_1, \dots, D_n)$
- ▶ Randomization inference p-value:

$$p = \mathbb{P}[T(\mathbf{Y}_0, \mathbf{D}) \geq T_{\text{obs}}]$$

- If the number of permutations is too large, use a random sample

Empirical illustration: incumbency advantage

- Cattaneo, Frandsen and Titiunik (2015, JCI)
 - ▶ Incumbency advantage in U.S. Senate
- Data:
 - ▶ Y_i = election outcome at $t + 1$ (= 1 if party wins)
 - ▶ D_i = election outcome at t (= 1 if party wins)
 - ▶ X_i = margin of victory at t ($c = 0$)
 - ▶ Additional covariates

Software implementation

- Cattaneo, Titiunik and Vazquez-Bare (2016, Stata Journal)
- rdlocrand package:
 - ▶ rdwinselect: window selection
 - ▶ rdrandinf: randomization inference
 - ▶ rdsensitivity: sensitivity analysis
 - ▶ rdrbounds: Rosenbaum bounds

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	
			Order of poly	= 0	
Number of obs	640	750	Kernel type	= uniform	
1th percentile	6	8	Reps	= 10000	
5th percentile	32	38	Testing method	= rdrandinf	
10th percentile	64	75	Balance test	= ttest	
20th percentile	128	150			
Window length /2	Bal. test p-value	Var. name (min p-value)	Bin. test p-value	Obs<c	Obs>=c
0.500	0.268	demvoteslag2	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: presdemvoteslag1 population demvoteslag1 demvoteslag2

```
> demwinprv1 demwinprv2 dopen dmidterm
```

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

Randomization inference with rdrandinf

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

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

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

```
Permutation test complete.
```

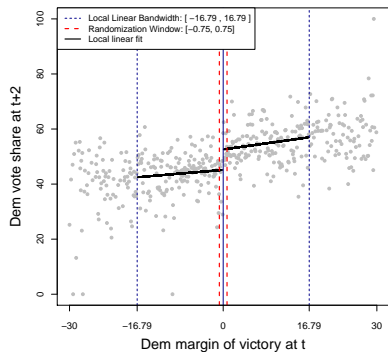
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Inference for sharp design
```

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

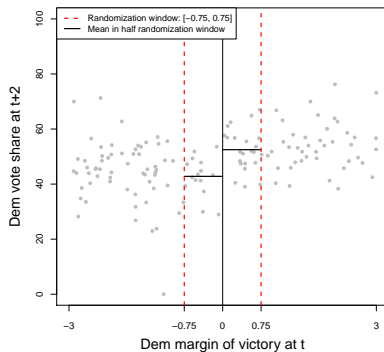
```
Outcome: demvoteshfor2. Running variable: demmv.
```

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

Continuity-based vs local randomization analysis

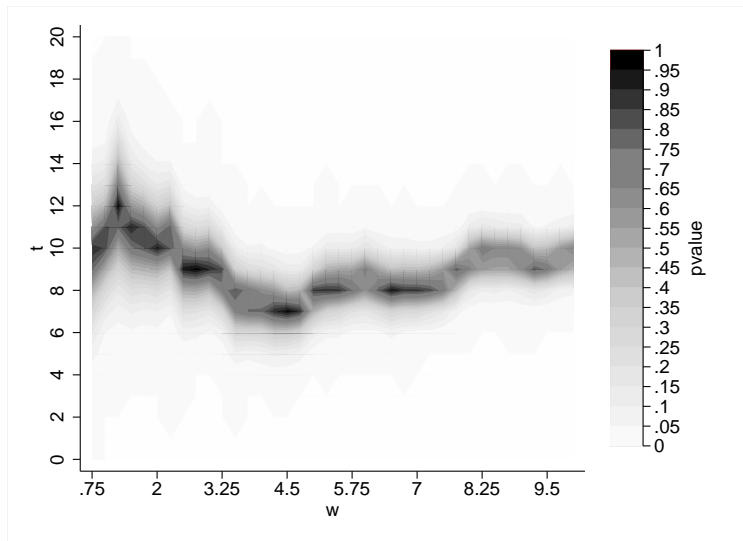


(a) Continuity-based analysis



(b) Local randomization analysis

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