FLS 6441 - Methods III: Explanation and Causation

Week 7 - Discontinuities

Jonathan Phillips

May 2019

		Independence of Treatment Assignment	Researcher Controls Treatment Assignment?
Controlled Experiments	Field Experiments	✓	✓
	Survey and Lab Experiments	√	√
Natural Experiments	Natural Experiments	√	
	Instrumental Variables	√	
	Discontinuities	√	
Observational Studies	Difference-in-Differences		
	Controlling for Confounding		
	Matching		
	Comparative Cases and Process Tracing		

Close Elections

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Close Elections

Discontinuities

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Natural Experiments

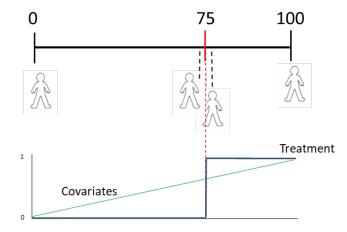
Discontinuities

- ► Natural Experiments
- ► Where the 'as-if' random treatment assignment comes from discontinuities in rules

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- Where the 'as-if' random treatment assignment comes from discontinuities in rules
 - ► Rules that treat very similar people very differently
 - ► Small differences on a **continuous** variable create big differences on a **binary treatment** variable

Discontinuities



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- ► Example thresholds:
 - Exam cutoffs
 - ► Age cutoffs
 - ► Policy eligibility rules
 - ► Close elections
 - ► Adminsitrative boundaries

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Close Flections

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 - ▶ Weather
 - ► Chance
 - Mistakes

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 - ► They are plausible counterfactuals for each other

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Comparisons in a regression discontinuity are always imperfect

Close Elections

Discontinuities

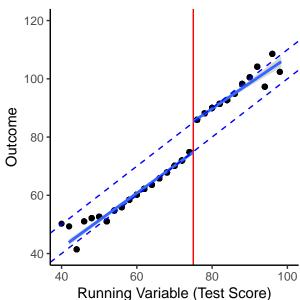
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- ► So we need more assumptions (and more N)!





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 - **Outcome** Y_i : Any subsequent outcome you have measured

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Close Elections

- 1.2 The threshold is not chosen strategically
- 2. No compound treatments
- No spillovers (SUTVA)

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 - ► The running variable is hard to manipulate precisely
 - ► The threshold is chosen before scores are known
- We need qualitative evidence to support these assumptions

Discontinuities

- ► We can check for sorting with a density test
- ► If units are bunched just above the threshold, this suggests manipulation

Close Elections

Estimating Regression Discontinuities

Estimating Discontinuities

- ➤ 3 Regression Discontinuity Methodologies:
 - 1. **Difference-in-means:** Define a small window either side of the threshold and compare average outcomes in this window
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$$Y_i = \alpha + \beta_1 Running_Variable_i + \beta_2 Treatment_i + \epsilon_i$$

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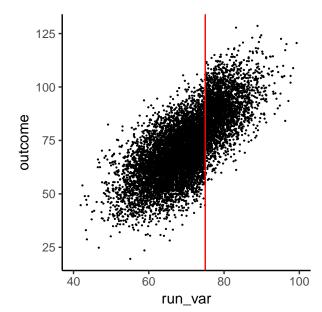
Close Flections

2. 'Full data' regression discontinuity: Uses all the data:

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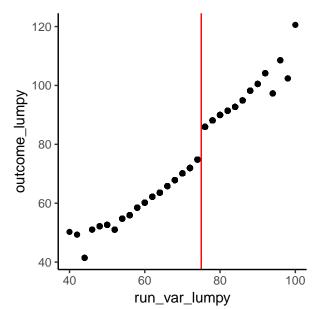
- Controls for the 'smooth' variation in the running variable
- Estimates the 'jump' impact of treatment with a binary variable (dummy)
- 3. 'Limited-bandwidth' regression discontinuity: A regression only using only data close to the threshold
 - ▶ What bandwidth around the threshold do we use?

Raw Data

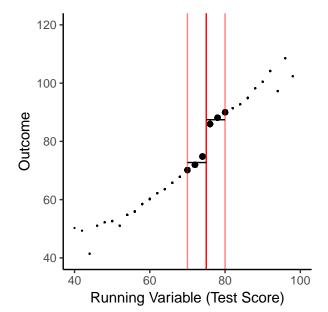


Close Elections

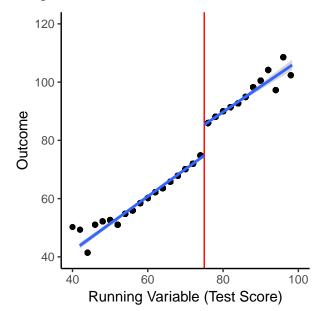
'Binned' Data



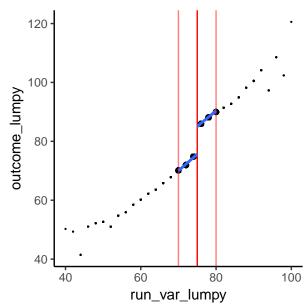
1. Difference-in-Means



2. Full Data Regression - Linear



3. Limited-bandwidth Regression - Local Linear



Close Elections

Estimating Discontinuities

► Which method?

Close Elections

Estimating Discontinuities

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Close Elections

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Close Flections

Estimating Discontinuities

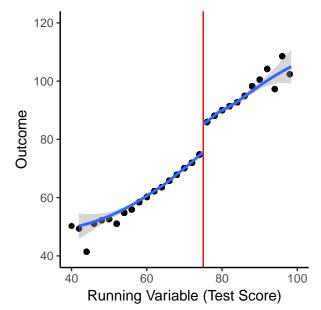
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Close Flections

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 - ► The combined approach uses less data (-precision) but is less dependent on the right model (-risk of bias)
- In practice, apply all three as robustness checks

2b. Full Data Regression - Non-linear



Discontinuities

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Close Elections

Discontinuities

- Regression Discontinuity estimates a Local Average Treatment Effect
 - Treatment assignment is only random at the threshold
 - Our estimates only apply to units close to the threshold
 - ► Units far from the threshold are very different for a reason, and causal effects are likely to be different

Limitations:

Discontinuities

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Close Elections

Limitations:

Discontinuities

- ► Lots of alternative specifications so no single simple test
- Less precise than a randomized trial, so we need more data
- Risk of sorting/manipulation

Section 3

Close Elections

► Close elections are one type of regression discontinuity in which political office is 'as-if' randomized

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- ► Useful for understanding the effects of political power

Close Elections

- ► Close elections are one type of regression discontinuity in which political office is 'as-if' randomized
- ▶ Useful for understanding the effects of political power
 - ► Running Variable: Margin of victory
 - ► **Treatment:** Winning a close election
 - ► Control: Losing a close election
 - ▶ Outcome: Anything that happens later...

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- Politicians (incumbents, the wealthy) can control whether they win, even when it's a tight race
- ► They have extremely detailed information to predict vote results
- So potential outcomes are not balanced
- ▶ But no other case (9 countries) has this problem

Discontinuities

► Boas and Hidalgo (2011): How does incumbency affect control of the media?

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Close Elections

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- Boas and Hidalgo (2011): How does incumbency affect control of the media?
 - ► Radio licencing process depends on ability to lobby the Ministry and Congress
 - ► Local radio systematically used to favour specific politicians
 - Incumbents better placed to initiate exchange between Mayors and legislators
- What is the challenge to causal inference here?

- **Population:** Brazilian councillors
- ▶ **Sample:** Brazilian councillors in close elections that made radio licence applications in 2000/2004

- ► Running Variable: Vote margin
- ► **Treatment:** Just winning close election
- **Control:** Just losing close election
- ▶ Treatment Assignment: 'As-if' random in close elections
- **Outcome:** Approved radio licence application rate

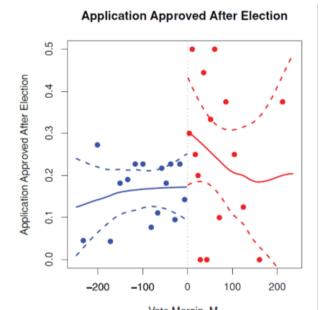
Discontinuities

- Boas and Hidalgo (2011) Methodology:
 - 1. Local Linear regression within bandwidth of 165 votes

Close Elections 00000000

2. Difference-in-Means within 10-40 vote bandwidth

- Results
 - ► Incumbent Vereadores are twice as likely (14-27 % points) to have their radio licence applications approved



Close Elections

Discontinuities

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Discontinuities

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Close Elections

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- Socioeconomic, geographic and national governance conditions are very similar at the border
- ► Families have lived in their villages for decades
- ▶ The two states were only created in 2001; before that they experienced the same relationship with government
- ▶ The border was set according to old district borders, and not politically
- Iharkhand did not experience the same governance improvements as Bihar

Methodology

► The 'running variable' is distance to the border, but in 2-dimensions:

$$+x^{2} * y^{2} + x^{3} * y^{3} + x * y^{2} + x * y^{3} + x^{2} * y + x^{3} * y + \epsilon_{i}$$
 (1)

 $y_i = \alpha + \beta Bihar_i + x_i + y_i + x^2 + y^2 + x^3 + y^3 + x^4 + y^4 + x * y$

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Close Elections

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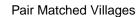
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 - ► Treatment Assignment:

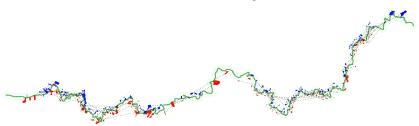
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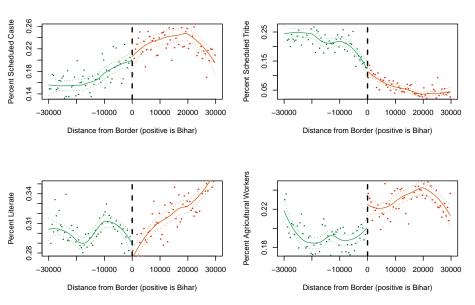
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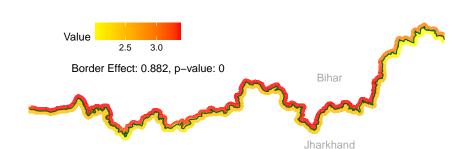
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 - ► Control: Residents on the Jharkhand side of the border
 - ► **Treatment Assignment:** State separation in 2001, Family history, and migration
 - ▶ Outcome: Political attitudes and behaviour









Predicted Value Plot of Likelihood of Incumbent Providing Public Goods if Reelected

Jharkhand

Predicted Value Plot of Likelihood of Corrupt Elite being Caught

Jharkhand

Predicted Value Plot of Gram Sabha Attendance

► Interpretation:

- Programmatic policy has changed voters' attitudes and expectations
- ▶ But some imbalance at the border...

► Interpretation:

- Programmatic policy has changed voters' attitudes and expectations
- But some imbalance at the border...
- ...And compound treatment makes interpretation difficult