FLS 6441 - Methods III: Explanation and Causation

Week 7 - Discontinuities

Jonathan Phillips

May 2019

Classification of Research Designs

		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		

Discontinuities

- Natural Experiments

Discontinuities

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

Discontinuities

- Natural Experiments
- Where the ’as-if’ random treatment assignment comes from *discontinuities* in rules
    - Rules that **treat similar people differently**

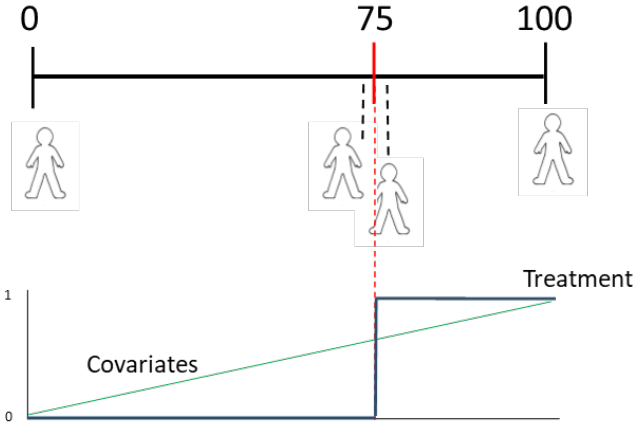
Discontinuities

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

Discontinuities

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

Discontinuities



Discontinuities

- Why do discontinuities assign treatment ’as-if’ random?

Discontinuities

- Why do discontinuities assign treatment ’as-if’ random?
- Maybe they don’t!

Discontinuities

- Why do discontinuities assign treatment 'as-if' random?
- Maybe they don't! It depends on how much **control** people have over their 'scores'

Discontinuities

- Why do discontinuities assign treatment ’as-if’ random?
- Maybe they don’t! It depends on how much **control** people have over their ’scores’
  - Could you get a score of exactly 10 in naming the Brazilian states?

Discontinuities

- Why do discontinuities assign treatment ’as-if’ random?
- Maybe they don’t! It depends on how much **control** people have over their ’scores’
  - Could you get a score of exactly 10 in naming the Brazilian states?
  - Could you get a score of exactly 150 on the GRE?

Discontinuities

- Why do discontinuities assign treatment 'as-if' random?
- Maybe they don't! It depends on how much **control** people have over their 'scores'
  - Could you get a score of exactly 10 in naming the Brazilian states?
  - Could you get a score of exactly 150 on the GRE?
- We need qualitative evidence that people cannot 'choose' their score perfectly

Discontinuities

- Why do discontinuities assign treatment 'as-if' random?
- Maybe they don't! It depends on how much **control** people have over their 'scores'
  - Could you get a score of exactly 10 in naming the Brazilian states?
  - Could you get a score of exactly 150 on the GRE?
- We need qualitative evidence that people cannot 'choose' their score perfectly
- Then the factors that influence *small* changes in score should be independent of potential outcomes
  - Weather
  - Chance
  - Mistakes

Discontinuities

- Regression Discontinuity
  - Treatment assignment is ’as-if’ random only **really close to the threshold**

Discontinuities

- Regression Discontinuity
  - Treatment assignment is ’as-if’ random only **really close to the threshold**

$$D_i = \begin{cases} 1 & \text{if } x_i \geq \bar{x} \\ 0 & \text{if } x_i < \bar{x} \end{cases}$$

Discontinuities

- Regression Discontinuity
  - Treatment assignment is 'as-if' random only **really close to the threshold**

$$D_i = \begin{cases} 1 & \text{if } x_i \geq \bar{x} \\ 0 & \text{if } x_i < \bar{x} \end{cases}$$

  - For units just above and below the threshold:
    - Their covariates are almost the same
    - Their potential outcomes are (on average) almost the same
    - They are plausible counterfactuals for each other

Discontinuities

- Regression Discontinuity
  - Treatment assignment is 'as-if' random only **really close to the threshold**

$$D_i = \begin{cases} 1 & \text{if } x_i \geq \bar{x} \\ 0 & \text{if } x_i < \bar{x} \end{cases}$$

  - For units just above and below the threshold:
    - Their covariates are almost the same
    - Their potential outcomes are (on average) almost the same
    - They are plausible counterfactuals for each other
  - So we can compare them directly

Discontinuities

- Regresssion Discontinuity Variables:
  - **Running Variable x_i:** The *continuous* variable to which the threshold/cutoff is applied, eg. exam score

Discontinuities

- Regresssion Discontinuity Variables:
  - **Running Variable x_i:** The *continuous* variable to which the threshold/cutoff is applied, eg. exam score
  - **Treatment D_i:** Binary 0/1 depending on whether the running variable is above or below the threshold ($x_i >= \bar{x}$)

Discontinuities

- Regresssion Discontinuity Variables:
  - **Running Variable x_i:** The *continuous* variable to which the threshold/cutoff is applied, eg. exam score
  - **Treatment D_i:** Binary 0/1 depending on whether the running variable is above or below the threshold ($x_i >= \bar{x}$)
  - **Outcome Y_i:** Any subsequent outcome you have measured

Discontinuities

- Regression Discontinuity Assumptions:
    1. Potential outcomes vary continuously (are independent of treatment) at the threshold

Discontinuities

- Regression Discontinuity Assumptions:
  1. Potential outcomes vary continuously (are independent of treatment) at the threshold
  2. Units cannot precisely control their score and sort either side of the threshold

Discontinuities

- Regression Discontinuity Assumptions:
  1. Potential outcomes vary continuously (are independent of treatment) at the threshold
  2. Units cannot precisely control their score and sort either side of the threshold
  3. The threshold is not chosen strategically

Discontinuities

- Regression Discontinuity Assumptions:
  1. Potential outcomes vary continuously (are independent of treatment) at the threshold
  2. Units cannot precisely control their score and sort either side of the threshold
  3. The threshold is not chosen strategically
  4. No compound treatments

Discontinuities

- Regression Discontinuity Assumptions:
  1. Potential outcomes vary continuously (are independent of treatment) at the threshold
  2. Units cannot precisely control their score and sort either side of the threshold
  3. The threshold is not chosen strategically
  4. No compound treatments
  5. No spillovers (SUTVA)

Discontinuities

- Thresholds more likely to be ’exogenous’ if:

Discontinuities

- Thresholds more likely to be ’exogenous’ if:
  - Units are not aware of the threshold

Discontinuities

- Thresholds more likely to be 'exogenous' if:
  - Units are not aware of the threshold
  - The threshold is decided after units make choices

Discontinuities

- Thresholds more likely to be 'exogenous' if:
  - Units are not aware of the threshold
  - The threshold is decided after units make choices
  - The running variable is hard to manipulate precisely

Discontinuities

- Thresholds more likely to be ’exogenous’ if:
  - Units are not aware of the threshold
  - The threshold is decided after units make choices
  - The running variable is hard to manipulate precisely
- We need qualitative evidence to support these assumptions

Discontinuities

- Comparisons in a regression discontinuity are always *imperfect*

Discontinuities

- Comparisons in a regression discontinuity are always *imperfect*
- With a field experiment, for every value of a potential confounder X we have both treated and control values

Discontinuities

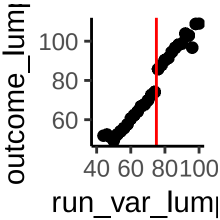
- Comparisons in a regression discontinuity are always *imperfect*
- With a field experiment, for every value of a potential confounder X we have both treated and control values
- With a discontinuity we explicitly **cannot** have treated and control values with the same value of the running variable x

Discontinuities

- Comparisons in a regression discontinuity are always *imperfect*
- With a field experiment, for every value of a potential confounder X we have both treated and control values
- With a discontinuity we explicitly **cannot** have treated and control values with the same value of the running variable x
- So to make comparisons we have to **extrapolate** to guess what the potential outcomes would be if unit i was treated instead of control

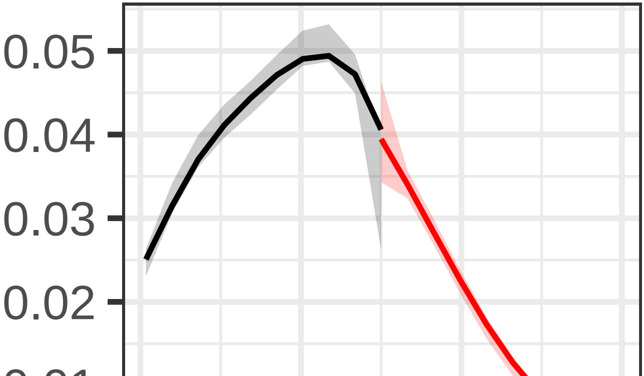
Discontinuities

- Comparisons in a regression discontinuity are always *imperfect*
- With a field experiment, for every value of a potential confounder X we have both treated and control values
- With a discontinuity we explicitly **cannot** have treated and control values with the same value of the running variable x
- So to make comparisons we have to **extrapolate** to guess what the potential outcomes would be if unit i was treated instead of control
- So we need more assumptions!



Discontinuities

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



Estimating Discontinuities

- Three Regression Discontinuity Methodologies:
  1. **Difference-in-means:** Define a small window either side of the threshold and compare average outcomes in this window
     - But can be biased since we're ignoring the confounding effect of the running variable on the outcome

Estimating Discontinuities

- Three Regression Discontinuity Methodologies:
  1. **Difference-in-means:** Define a small window either side of the threshold and compare average outcomes in this window
     - But can be biased since we're ignoring the confounding effect of the running variable on the outcome
  2. **'Full data' regression discontinuity:** Uses all the data and estimates:

$$Y_i = \alpha + \beta_1 Running\_Variable_i + \beta_2 Treatment_i + \epsilon_i$$

     - We just control for the 'smooth' variation in the running variable and estimate the 'jump' impact of treatment with a binary variable (dummy)
     - We may need to make the running variable non-linear

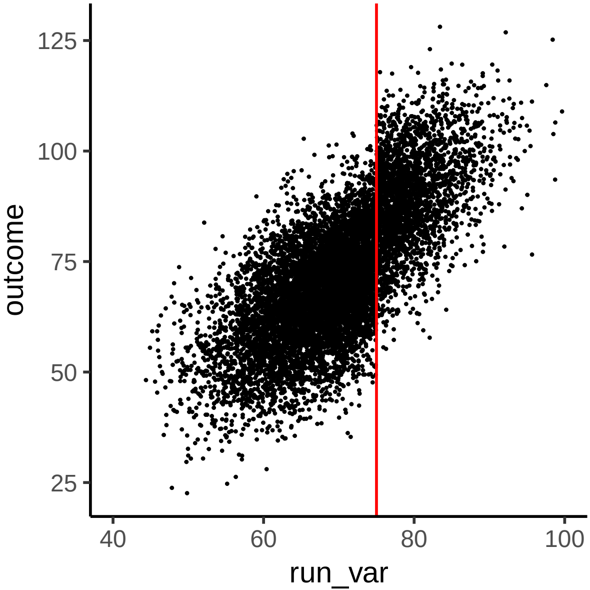
Estimating Discontinuities

- Three Regression Discontinuity Methodologies:
  1. **Difference-in-means:** Define a small window either side of the threshold and compare average outcomes in this window
     - But can be biased since we're ignoring the confounding effect of the running variable on the outcome
  2. **'Full data' regression discontinuity:** Uses all the data and estimates:

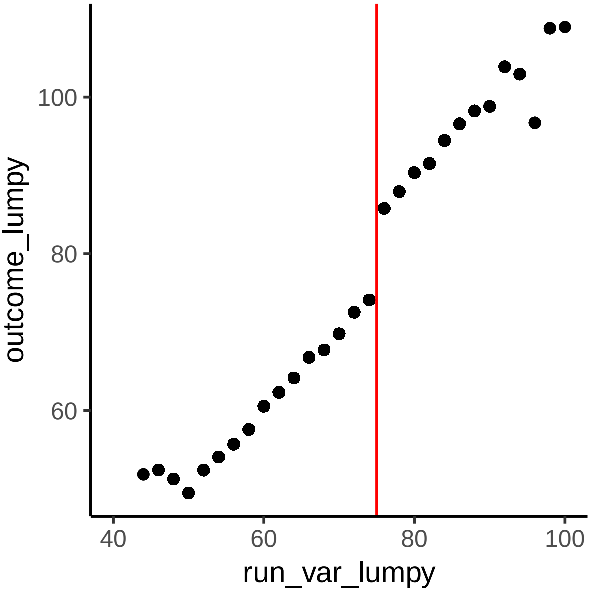
$$Y_i = \alpha + \beta_1 Running\_Variable_i + \beta_2 Treatment_i + \epsilon_i$$

     - We just control for the 'smooth' variation in the running variable and estimate the 'jump' impact of treatment with a binary variable (dummy)
     - We may need to make the running variable non-linear
  3. **'Limited-bandwidth' regression discontinuity:** Focus on values close to the threshold, but use a regression
     - What bandwidth around the threshold do we use?

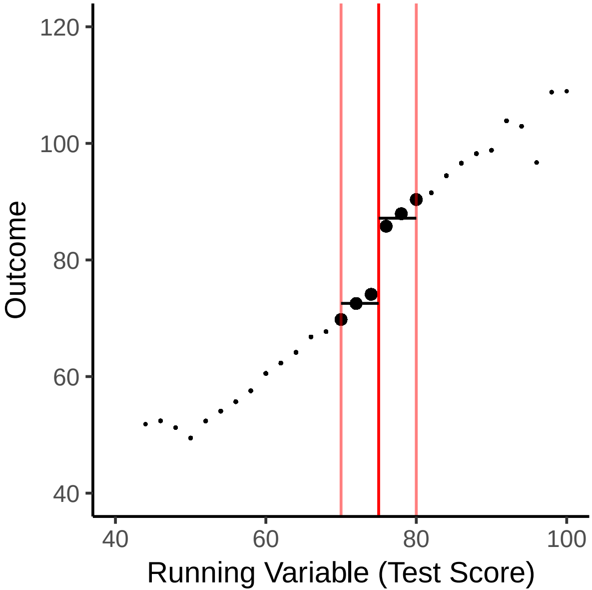
Raw Data



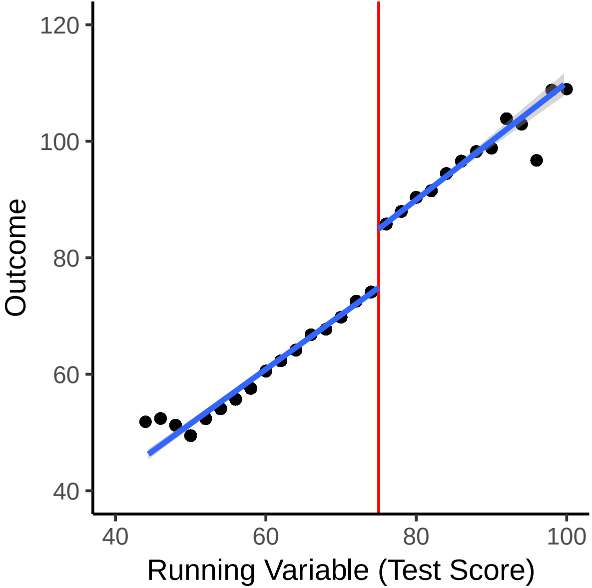
'Binned' Data



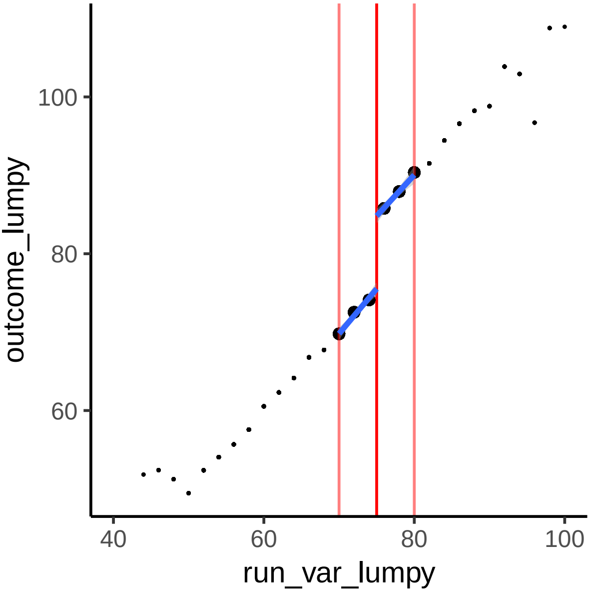
1. Difference-in-Means



2. Full Data Regression - Linear



3. Limited-bandwidth Regression - Local Linear



Estimating Discontinuities

- Which method?

Estimating Discontinuities

- Which method?
  - Difference-in-means is probably biased, and we can easily do better

Estimating Discontinuities

- Which method?
  - Difference-in-means is probably biased, and we can easily do better
  - The parametric approach uses more data (+precision) but depends on the right model: linear, quadratic, etc. (+risk of bias)

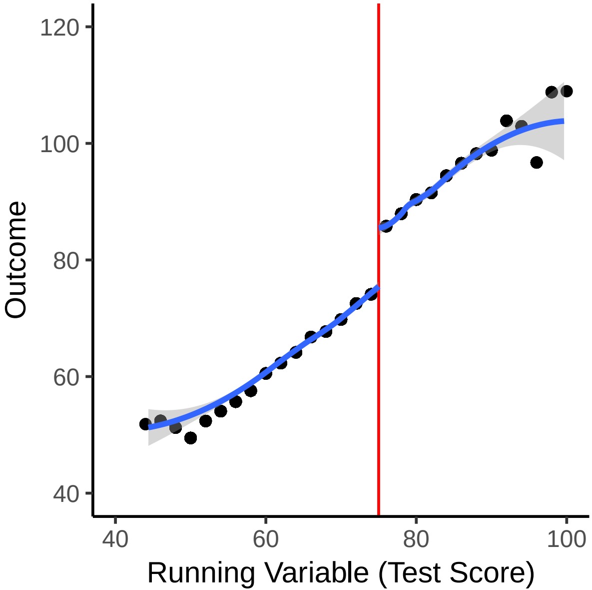
Estimating Discontinuities

- Which method?
  - Difference-in-means is probably biased, and we can easily do better
  - The parametric approach uses more data (+precision) but depends on the right model: linear, quadratic, etc. (+risk of bias)
  - The combined approach uses less data (-precision) but is less dependent on the right model (-risk of bias)

Estimating Discontinuities

- Which method?
  - Difference-in-means is probably biased, and we can easily do better
  - The parametric approach uses more data (+precision) but depends on the right model: linear, quadratic, etc. (+risk of bias)
  - 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



Estimating Discontinuities

- Why does RD estimate a **Local** Average Treatment Effect?

Estimating Discontinuities

- Why does RD estimate a **Local** Average Treatment Effect?
  - Treatment assignment is only random at the threshold

Estimating Discontinuities

- Why does RD estimate a **Local** Average Treatment Effect?
  - Treatment assignment is only random at the threshold
  - Our estimates only apply to units close to the threshold

Estimating Discontinuities

- Why does RD estimate 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

Estimating Discontinuities

- Limitations:
  - Lots of alternative specifications so no single simple test

Estimating Discontinuities

- Limitations:
  - Lots of alternative specifications so no single simple test
  - Less precise than a randomized trial, so we need more data

Estimating Discontinuities

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

Close Elections

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

Close Elections

- Close elections are one type of regression discontinuity in which political office is ’as-if’ randomized
- Particularly 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
- Particularly 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...

Close Elections

- How much faith should we have in 'close election' regression discontinuities?

Close Elections

- How much faith should we have in ’close election’ regression discontinuities?
- Eggers et al (2013):

Close Elections

- How much faith should we have in ’close election’ regression discontinuities?
- Eggers et al (2013):
  - US House of Representatives elections show sorting in very close elections (<1%)

Close Elections

- How much faith should we have in ’close election’ regression discontinuities?
- Eggers et al (2013):
  - US House of Representatives elections show sorting in very close elections (<1%)
  - Politicians (incumbents, the wealthy) can control whether they win, even when it’s a tight race

Close Elections

- How much faith should we have in 'close election' regression discontinuities?
- Eggers et al (2013):
  - US House of Representatives elections show sorting in very close elections (<1%)
  - 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

Close Elections

- How much faith should we have in ’close election’ regression discontinuities?
- Eggers et al (2013):
  - US House of Representatives elections show sorting in very close elections (<1%)
  - 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

Close Elections

- How much faith should we have in 'close election' regression discontinuities?
- Eggers et al (2013):
  - US House of Representatives elections show sorting in very close elections (<1%)
  - 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

Close Elections

- Boas and Hidalgo (2011)

Close Elections

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

Close Elections

- Boas and Hidalgo (2011)
- How does incumbency affect control of the media?
  - Radio licencing process depends on ability to lobby the Ministry and Congress

Close Elections

- 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

Close Elections

- 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

Close Elections

- 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?

Close Elections

- Boas and Hidalgo (2011)

Close Elections

- Boas and Hidalgo (2011)
- **Population:**

Close Elections

- Boas and Hidalgo (2011)
- **Population:** Brazilian councillors
- **Sample:**

Close Elections

- Boas and Hidalgo (2011)
- **Population:** Brazilian councillors
- **Sample:** Brazilian councillors in close elections that made radio licence applications in 2000/2004
- **Running Variable:**

Close Elections

- Boas and Hidalgo (2011)
- **Population:** Brazilian councillors
- **Sample:** Brazilian councillors in close elections that made radio licence applications in 2000/2004
- **Running Variable:** Vote margin
- **Treatment:**

Close Elections

- Boas and Hidalgo (2011)
- **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:**

Close Elections

- Boas and Hidalgo (2011)
- **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:**

Close Elections

- Boas and Hidalgo (2011)
- **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:**

Close Elections

- Boas and Hidalgo (2011)
- **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

Close Elections

- Boas and Hidalgo (2011) Methodology:

Close Elections

- Boas and Hidalgo (2011) Methodology:
- Local Linear regression within bandwidth of 165 votes
- Difference-in-Means within 10-40 vote bandwidth

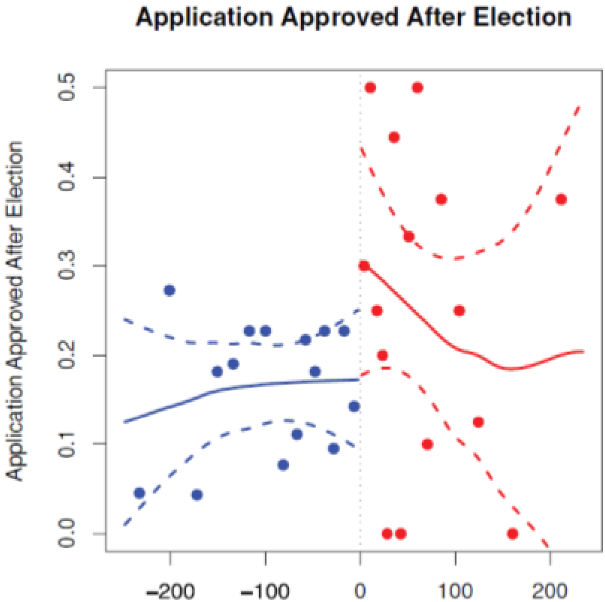
Close Elections

- Boas and Hidalgo (2011)
- Results

Close Elections

- Boas and Hidalgo (2011)
- Results
  - Incumbent Vereadores are twice as likely (14-27 % points) to have their radio licence applications approved

Close Elections



Close Elections

- Boas and Hidalgo (2011)
- Critique:

Close Elections

- Boas and Hidalgo (2011)
- Critique:
  - Municipalities that are competitive are unusual, so we learn nothing about media control in dominated places

Close Elections

- Boas and Hidalgo (2011)
- Critique:
  - Municipalities that are competitive are unusual, so we learn nothing about media control in dominated places
  - No real discussion of whether they're correctly modelling the relationship between vote margin and the outcome

Close Elections

- Boas and Hidalgo (2011)
- Critique:
  - Municipalities that are competitive are unusual, so we learn nothing about media control in dominated places
  - No real discussion of whether they're correctly modelling the relationship between vote margin and the outcome
  - Is it necessarily wrong that incumbents are more likely to get approval? Perhaps they learn valuable information or professionalism as soon as they come to office

Geographic Discontinuities

- Phillips (2017)

Geographic Discontinuities

- Phillips (2017)
  - Bihar is one of the poorest places on the planet and one of the worst goverened

Geographic Discontinuities

- Phillips (2017)
  - Bihar is one of the poorest places on the planet and one of the worst goverened
  - ’Jungle raj’: Clientelism, violence, corruption, caste bias

Geographic Discontinuities

- Phillips (2017)
  - Bihar is one of the poorest places on the planet and one of the worst goverened
  - 'Jungle raj': Clientelism, violence, corruption, caste bias
  - Bihar is a programmatic reform success case since 2005 under Nitish Kumar

Geographic Discontinuities

- Phillips (2017)
  - Bihar is one of the poorest places on the planet and one of the worst goverened
  - 'Jungle raj': Clientelism, violence, corruption, caste bias
  - Bihar is a programmatic reform success case since 2005 under Nitish Kumar
  - But has top-down reform changed how politics works?

Geographic Discontinuities

- Phillips (2017)
  - Bihar is one of the poorest places on the planet and one of the worst goverened
  - 'Jungle raj': Clientelism, violence, corruption, caste bias
  - Bihar is a programmatic reform success case since 2005 under Nitish Kumar
  - But has top-down reform changed how politics works?
  - Are voters exposed to reform more likely to avoid clientelism, trust the state and vote for reformers?

Geographic Discontinuities

- Phillips (2017)
  - Bihar is one of the poorest places on the planet and one of the worst goverened
  - 'Jungle raj': Clientelism, violence, corruption, caste bias
  - Bihar is a programmatic reform success case since 2005 under Nitish Kumar
  - But has top-down reform changed how politics works?
  - Are voters exposed to reform more likely to avoid clientelism, trust the state and vote for reformers?
- What is the challenge to causal inference?

Geographic Discontinuities

Geographic Discontinuities

- People in Jharkhand are plausible counterfactuals to people in Bihar because:

Geographic Discontinuities

- People in Jharkhand are plausible counterfactuals to people in Bihar because:
  - Socioeconomic, geographic and national governance conditions are very similar at the border

Geographic Discontinuities

- People in Jharkhand are plausible counterfactuals to people in Bihar because:
  - Socioeconomic, geographic and national governance conditions are very similar at the border
  - Families have lived in their villages for decades

Geographic Discontinuities

- People in Jharkhand are plausible counterfactuals to people in Bihar because:
  - 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

Geographic Discontinuities

- People in Jharkhand are plausible counterfactuals to people in Bihar because:
  - 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

Geographic Discontinuities

- People in Jharkhand are plausible counterfactuals to people in Bihar because:
  - 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
  - Jharkhand did not experience the same governance improvements as Bihar

Geographic Discontinuities

- Geographic Regression Discontinuity Design
  - Exactly the same as a normal regression discontinuity, but in two dimensions (longitude and latitude)

Geographic Discontinuities

- Geographic Regression Discontinuity Design
  - Exactly the same as a normal regression discontinuity, but in two dimensions (longitude and latitude)
  - **Population:**

Geographic Discontinuities

- Geographic Regression Discontinuity Design
    - Exactly the same as a normal regression discontinuity, but in two dimensions (longitude and latitude)
    - **Population:** Bihari citizens

Geographic Discontinuities

- Geographic Regression Discontinuity Design
  - Exactly the same as a normal regression discontinuity, but in two dimensions (longitude and latitude)
  - **Population:** Bihari citizens
  - **Sample:**

Geographic Discontinuities

- Geographic Regression Discontinuity Design
  - Exactly the same as a normal regression discontinuity, but in two dimensions (longitude and latitude)
  - **Population:** Bihari citizens
  - **Sample:** Bihari and Jharkhand citizens within 4km of the border

Geographic Discontinuities

- Geographic Regression Discontinuity Design
  - Exactly the same as a normal regression discontinuity, but in two dimensions (longitude and latitude)
  - **Population:** Bihari citizens
  - **Sample:** Bihari and Jharkhand citizens within 4km of the border
  - **The Running Variable:**

Geographic Discontinuities

- Geographic Regression Discontinuity Design
  - Exactly the same as a normal regression discontinuity, but in two dimensions (longitude and latitude)
  - **Population:** Bihari citizens
  - **Sample:** Bihari and Jharkhand citizens within 4km of the border
  - **The Running Variable:** Longitude and latitude

Geographic Discontinuities

- Geographic Regression Discontinuity Design
  - Exactly the same as a normal regression discontinuity, but in two dimensions (longitude and latitude)
  - **Population:** Bihari citizens
  - **Sample:** Bihari and Jharkhand citizens within 4km of the border
  - **The Running Variable:** Longitude and latitude
  - **Treatment:**

Geographic Discontinuities

- Geographic Regression Discontinuity Design
  - Exactly the same as a normal regression discontinuity, but in two dimensions (longitude and latitude)
  - **Population:** Bihari citizens
  - **Sample:** Bihari and Jharkhand citizens within 4km of the border
  - **The Running Variable:** Longitude and latitude
  - **Treatment:** Residents on the Bihar side of the border

Geographic Discontinuities

- Geographic Regression Discontinuity Design
  - Exactly the same as a normal regression discontinuity, but in two dimensions (longitude and latitude)
  - **Population:** Bihari citizens
  - **Sample:** Bihari and Jharkhand citizens within 4km of the border
  - **The Running Variable:** Longitude and latitude
  - **Treatment:** Residents on the Bihar side of the border
  - **Control:**

Geographic Discontinuities

- Geographic Regression Discontinuity Design
  - Exactly the same as a normal regression discontinuity, but in two dimensions (longitude and latitude)
  - **Population:** Bihari citizens
  - **Sample:** Bihari and Jharkhand citizens within 4km of the border
  - **The Running Variable:** Longitude and latitude
  - **Treatment:** Residents on the Bihar side of the border
  - **Control:** Residents on the Jharkhand side of the border

Geographic Discontinuities

- Geographic Regression Discontinuity Design
  - Exactly the same as a normal regression discontinuity, but in two dimensions (longitude and latitude)
  - **Population:** Bihari citizens
  - **Sample:** Bihari and Jharkhand citizens within 4km of the border
  - **The Running Variable:** Longitude and latitude
  - **Treatment:** Residents on the Bihar side of the border
  - **Control:** Residents on the Jharkhand side of the border
  - **Treatment Assignment:**

Geographic Discontinuities

- Geographic Regression Discontinuity Design
  - Exactly the same as a normal regression discontinuity, but in two dimensions (longitude and latitude)
  - **Population:** Bihari citizens
  - **Sample:** Bihari and Jharkhand citizens within 4km of the border
  - **The Running Variable:** Longitude and latitude
  - **Treatment:** Residents on the Bihar side of the border
  - **Control:** Residents on the Jharkhand side of the border
  - **Treatment Assignment:** Family history, state separation in 2001, and migration

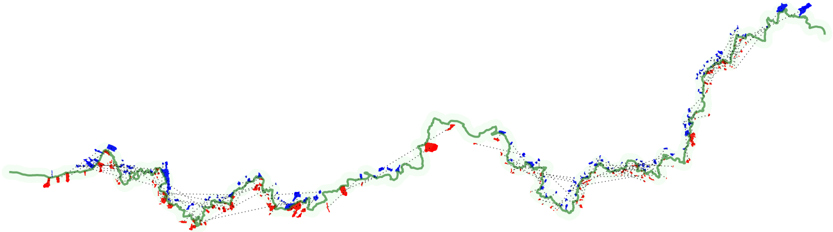
Geographic Discontinuities

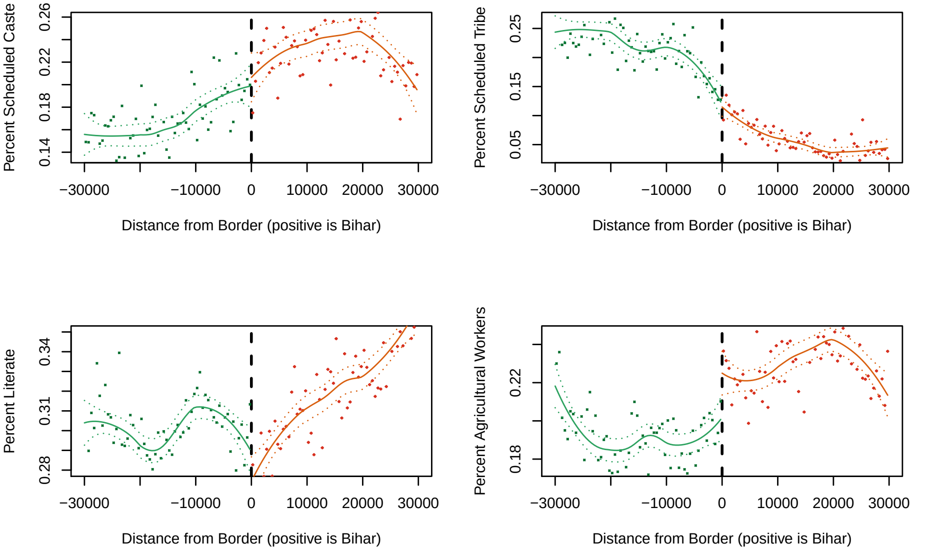
- Geographic Regression Discontinuity Design
  - Exactly the same as a normal regression discontinuity, but in two dimensions (longitude and latitude)
  - **Population:** Bihari citizens
  - **Sample:** Bihari and Jharkhand citizens within 4km of the border
  - **The Running Variable:** Longitude and latitude
  - **Treatment:** Residents on the Bihar side of the border
  - **Control:** Residents on the Jharkhand side of the border
  - **Treatment Assignment:** Family history, state separation in 2001, and migration
  - **Outcome:**

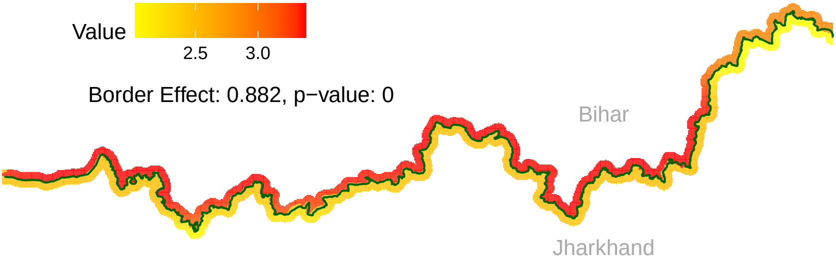
Geographic Discontinuities

- Geographic Regression Discontinuity Design
  - Exactly the same as a normal regression discontinuity, but in two dimensions (longitude and latitude)
  - **Population:** Bihari citizens
  - **Sample:** Bihari and Jharkhand citizens within 4km of the border
  - **The Running Variable:** Longitude and latitude
  - **Treatment:** Residents on the Bihar side of the border
  - **Control:** Residents on the Jharkhand side of the border
  - **Treatment Assignment:** Family history, state separation in 2001, and migration
  - **Outcome:** Political attitudes and behaviour

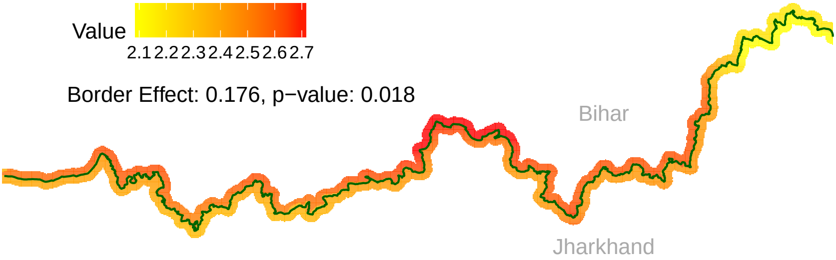
Pair Matched Villages



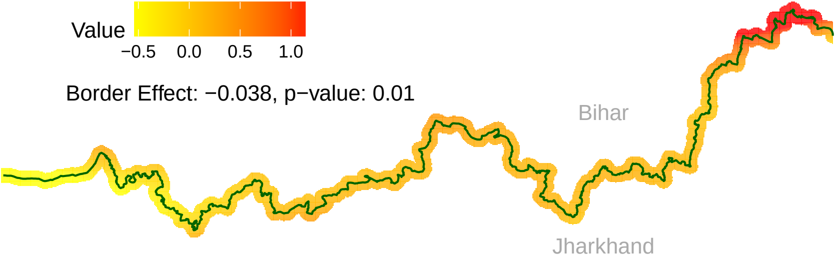

Percent Scheduled Caste
0.14
0.18
0.22
0.26
−30000
−10000
0
10000
20000
30000
Distance from Border (positive is Bihar)
Percent Scheduled Tribe
0.05
0.15
0.25
−30000
−10000
0
10000
20000
30000
Distance from Border (positive is Bihar)
Percent Literate
0.28
0.31
0.34
−30000
−10000
0
10000
20000
30000
Distance from Border (positive is Bihar)
Percent Agricultural Workers
0.18
0.22
−30000
−10000
0
10000
20000
30000
Distance from Border (positive is Bihar)



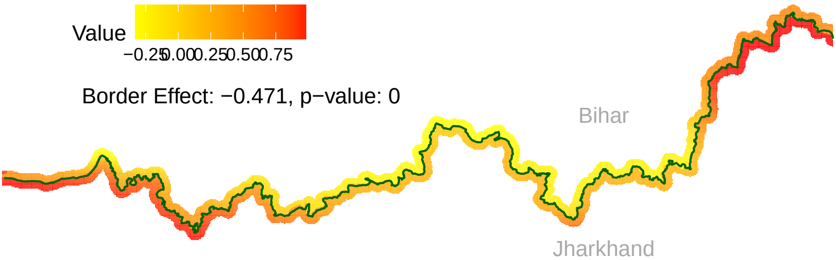
Predicted Value Plot of Likelihood of Incumbent Providing Public Goods if Reelected



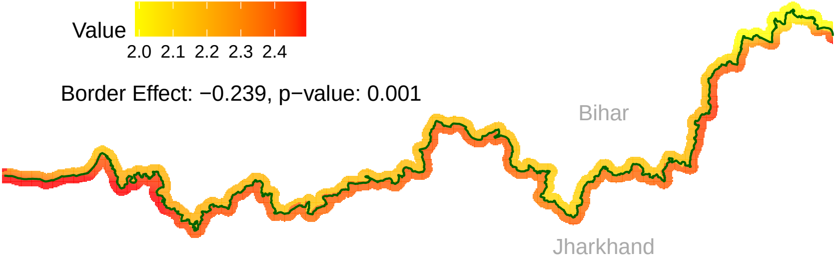
Predicted Value Plot of Likelihood of Corrupt Elite being Caught



Predicted Value Plot of Estimated Government Contacts Network Size



Predicted Value Plot of Gram Sabha Attendance



Predicted Value Plot for Trust in the Civil Service

Geographic Discontinuities

- Interpretation:
  - Programmatic policy has changed voters’ attitudes and expectations

Geographic Discontinuities

- Interpretation:
  - Programmatic policy has changed voters' attitudes and expectations
  - Incumbents' policy has **political feedback effects**

Geographic Discontinuities

- Interpretation:
  - Programmatic policy has changed voters' attitudes and expectations
  - Incumbents' policy has **political feedback effects**
  - Coordination among voters has helped re-elect the reformer twice

Geographic Discontinuities

- Interpretation:
  - Programmatic policy has changed voters' attitudes and expectations
  - Incumbents' policy has **political feedback effects**
  - Coordination among voters has helped re-elect the reformer twice
  - But no fundamental change in vulnerability or aversion to clientelism

Geographic Discontinuities

- Interpretation:
  - Programmatic policy has changed voters' attitudes and expectations
  - Incumbents' policy has **political feedback effects**
  - Coordination among voters has helped re-elect the reformer twice
  - But no fundamental change in vulnerability or aversion to clientelism
  - A reduction in clientelism may also have reduced political participation/trust