

Regression Discontinuity

Jacob M. Montgomery

Quantitative Political Methodology

Regression discontinuity

Poster questions

Some thoughts on posters:

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- ▶ Correlation is not causation:
 - ▶ Panel data with fixed effects.
 - ▶ Experimental data
 - ▶ Difference in differences
 - ▶ Regression discontinuity
 - ▶ Instrumental variables

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 - ▶ Instrumental variables
- ▶ Don't forget limitations

Road map

Where we have been:

- ▶ What is causality
- ▶ Using regression for experiments
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Today:

- ▶ Regression discontinuity
- ▶ How to use RD designs to establish causality
- ▶ Some time to work with your team on your project

Causal inference

- ▶ We will use T to represent a treatment variable.
- ▶ For a categorical treatment

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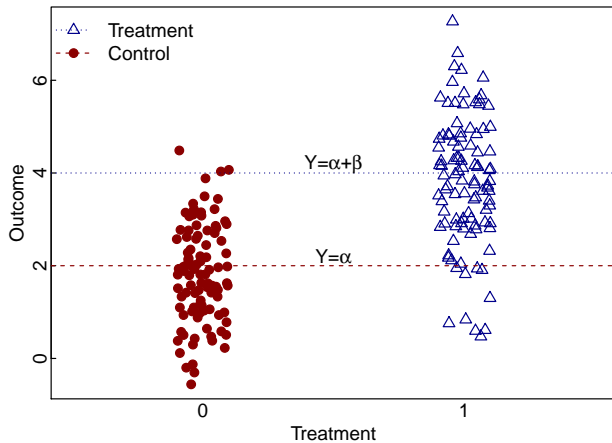
- ▶ We let y_i^1 represent the outcome of the i th unit if the treatment is given.
- ▶ We let y_i^0 represent the outcome of the i th unit if the control is given.
- ▶ One of these is observed, the other is the counterfactual – what would have been observed if the other treatment have been given?

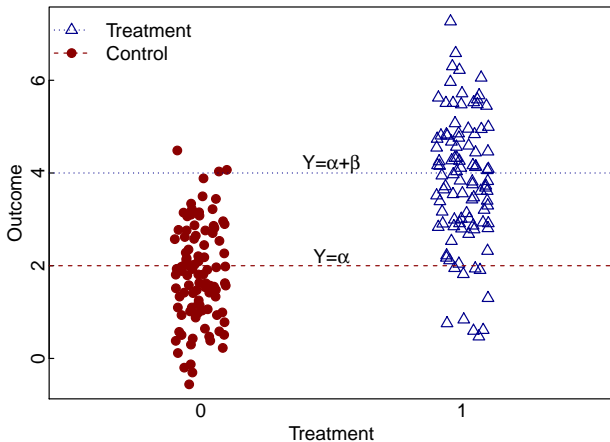
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- ▶ One of these is observed, the other is the counterfactual – what would have been observed if the other treatment have been given?
- ▶ The causal effect of T_i on observation i will then be $y_i^1 - y_i^0$





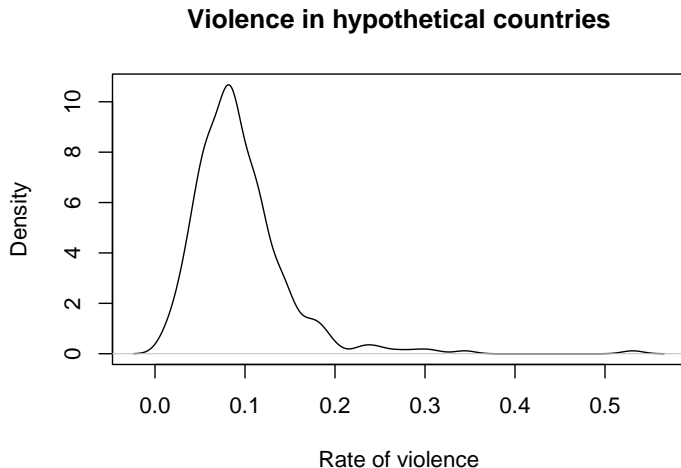
- ▶ $ATE = mean(y_i^1) - mean(y_i^0)$
- ▶ $ATE = (\alpha + \beta) - (\alpha)$
- ▶ $ATE = \beta$

A hypothetical example

Imagine we have a new and wonderful plan to end civil conflict.

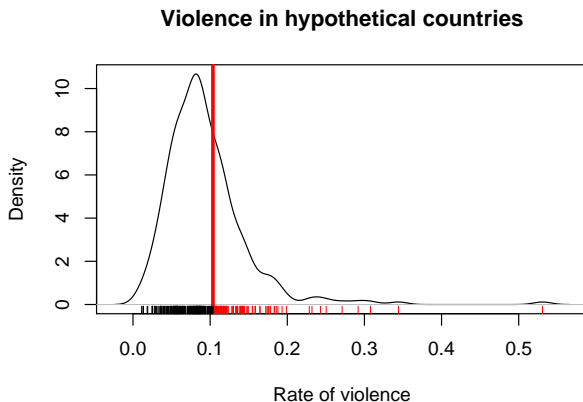
A hypothetical example

Imagine we have a new and wonderful plan to end civil conflict. Here is the distribution of the violent deaths in each (hypothetical) country.



A hypothetical example

- ▶ Our research partner does not want to do an experiment.
- ▶ Instead, they deploy their intervention in the 100 most violent countries.



Can we estimate a causal effect?

- ▶ Countries that received the intervention are obviously different than those that did not. (Confounders)
- ▶ Parallel paths assumption probably won't hold.
- ▶ But maybe countries *right near the threshold* are good counterfactuals for each other!

Can we estimate a causal effect?

- ▶ Countries that received the intervention are obviously different than those that did not. (Confounders)
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- ▶ But maybe countries *right near the threshold* are good counterfactuals for each other!
- ▶ We can use a regression discontinuity design to estimate the causal effect *right around the threshold*.

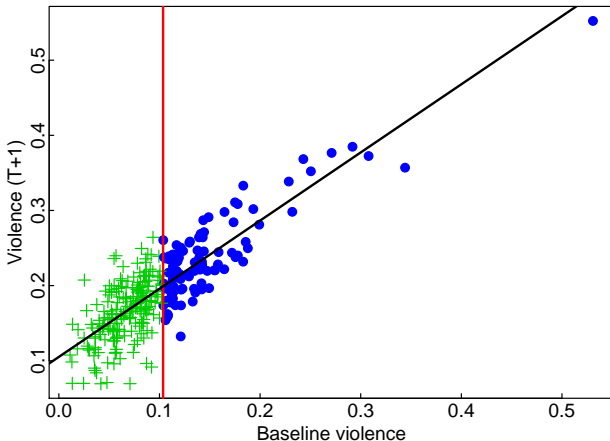
Our study design

The basic components:

- ▶ Y : An outcome variable (violence at $t + 1$)
- ▶ X : A variable that determines the cutoff (violence at t)
- ▶ D : A cutoff/threshold
- ▶ Does the relationship between Y and X “shift” right at D ?

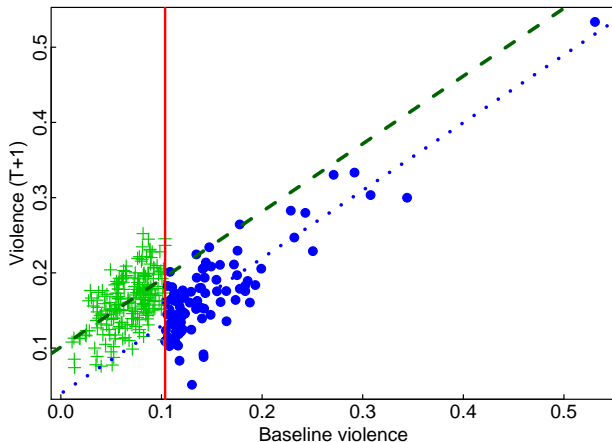
When there is no treatment effect ($\beta_2 = 0$)

$$Y = \alpha + \beta_1 X + \beta_2 I(X > D) + \epsilon$$



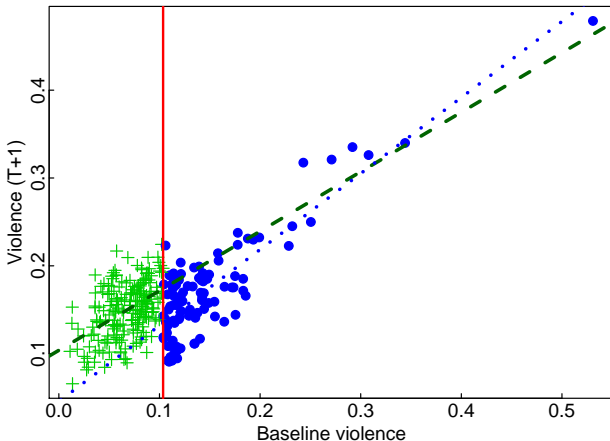
When there is a treatment effect ($\beta_2 \neq 0$)

$$Y = \alpha + \beta_1 X + \beta_2 I(X > D) + \epsilon$$



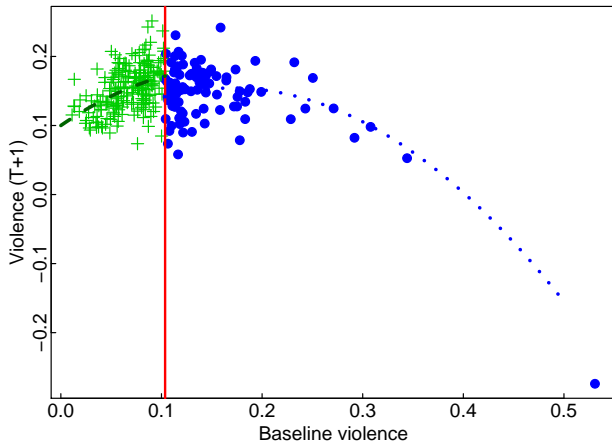
Maybe the slopes differ (still look at β_2)

$$Y = \alpha + \beta_1 X + \beta_2 I(X > D) + \beta_3 \times X \times I(X > D) + \epsilon$$



Maybe they aren't lines at all (still look at β_2)

$$Y = \alpha + \beta_1 X + \beta_2 I(X > D) + \beta_3 X^2 + \beta_3 X^3 + \epsilon$$



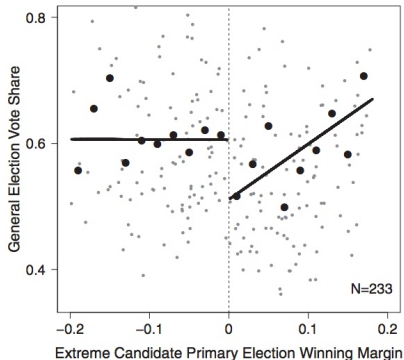
Example 1: Ideological extremity

Does nominating a more ideologically extreme candidate affect general election results?

- ▶ Y : Outcome is general election results
- ▶ X : Percent of vote the most ideologically extreme candidate won in the primary.
- ▶ D : Looking at candidates just above and below the 50% threshold for the primary.

Hall, Andrew (2015). "What Happens When Extremists Win Primaries?" *American Political Science Review*.

FIGURE 2. General-Election Vote Share After Close Primary Elections Between Moderates and Extremists: U.S. House, 1980–2010



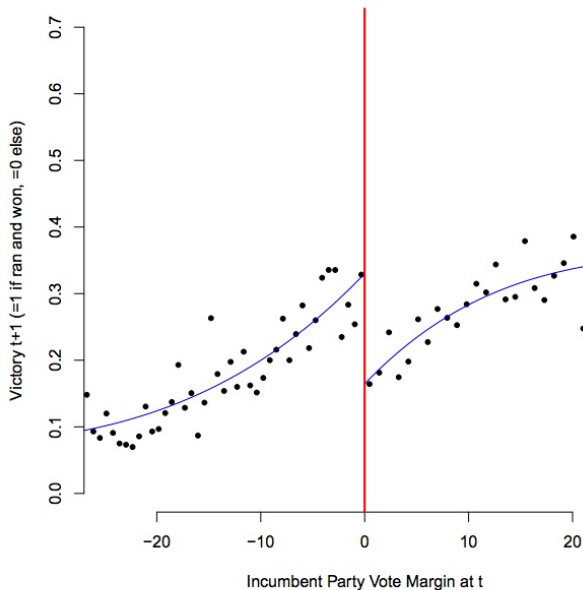
Notes: The close election of the more extreme primary candidate causes a decrease in general-election vote share for the party. Large black points are averages in 0.02 point bins of the relatively extreme candidate's winning margin; small gray points are raw data. Lines are OLS fits from raw data estimated separately on each side of threshold. Average general-election vote shares are above 0.5 on both sides of the discontinuity because contested primaries are more likely to occur in districts where the normal vote is tilted towards the party.

Example 2: Incumbency advantage in Brazilian mayoral elections

Does incumbency give parties an advantage, or is it an indicator of advantage? Looking at three sequential elections (2004, 2008, 2012), and starting with the incumbents who won in 2004.

- ▶ *Y*: Percent of incumbent-party candidates that won the in the third cycle (e.g., won in 2012)
- ▶ *X*: Percent of vote the incumbent candidate won in the previous election (e.g., how much they won in 2008).
- ▶ *D*: Looking at incumbents candidates just above and below the 50% threshold for the primary.

Marko Klasnja and Rocio Titiunik (2014). "The Incumbency Curse: Weak Parties, Term Limits, and Unfulfilled Accountability."
American Political Science Review.



Divide up into groups. Discuss this plot and explain what it means. Why does this happen? (HINT: Brazil limits mayors to two terms in office)