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# Regression Discontinuity Designs

Comparing those just above to those just below

# Introduction

## **What is a regression discontinuity design?**

- Some rule assigns treatment based on whether a running variable crosses a cutoff.
- We compare units just below and just above the cutoff.
- Argument for exogeneity: close to the threshold, nothing but the treatment should differ between the groups.

# Introduction

## **Basic ingredients**

Running variable: the variable that determines treatment.

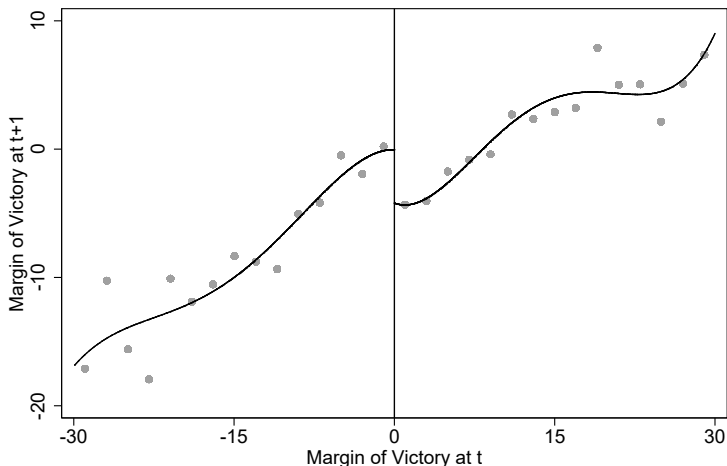
Cutoff: the threshold where treatment status changes.

Treatment: what changes at the cutoff.

Outcome: what we want to explain.

# Introduction

## RD Plot: Mayoral elections in Brazil – Klasnja and Titiunik (2017)



• Sample average within bin      — 4th order global polynomial

# Introduction

## **Basic ingredients in this example**

Running variable: margin of victory in the previous election.

Cutoff: getting more votes than the competitor.

Treatment: being the incumbent party.

Outcome: the party's margin of victory at the next election.

Result: there is a 'cost of ruling'.

# Sorting – the core assumption

## Intuitive version

- Close to the cutoff, the treatment is assigned *as if* random.
- The treatment is the only systematic difference between those just above and those just below the threshold.
- Cattaneo et al regards this as a separate framework.

## More precise

- Potential outcomes are continuous at the cutoff.
- All determinants of the outcome other than treatment change smoothly at the cutoff, so any discontinuous jump in the outcome can be attributed to the treatment.

# Sorting – the core assumption

## Sorting

- The main challenge to the core assumption is that subjects (or someone affecting their running variable) may be able to affect which side of the threshold they are on, also very close to the threshold.
- This is commonly referred to as sorting or manipulation around the threshold.

# Sorting – the core assumption

## Examples of sorting

- A teacher taking the threshold into account when grading.
- Coordinated voting (someone controls the exact vote count).
- A runner rushing to finish before her competitor.
- A municipality manipulating the population count.

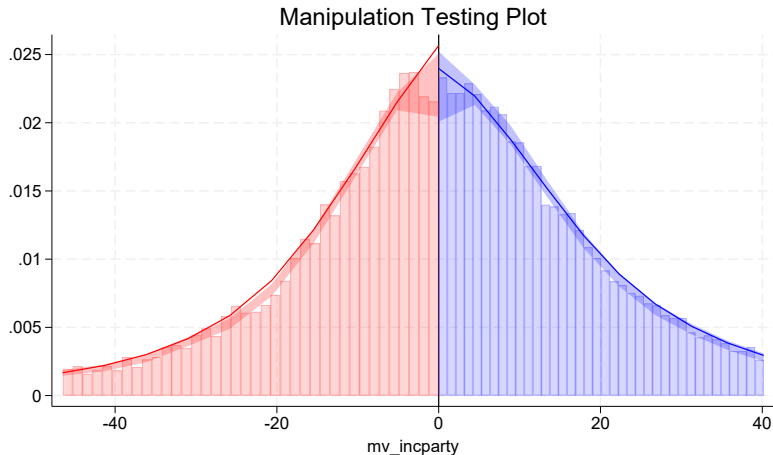
# Sorting – the core assumption

## Evaluating sorting

- Theory, intuition and previous research.
- Density around the threshold.
- Balance and placebo tests.

# Sorting – the core assumption

## Density as indication of sorting



# Sorting – the core assumption

## Density as indication of sorting

- Worrying if the density of observations differs around the threshold.
- Small levels of sorting can be problematic even if they are difficult to discern.
- Not all sorting causes asymmetric density. In the Brazilian example there is an almost mechanical symmetry, as every winner is paired with a mirrored loser.

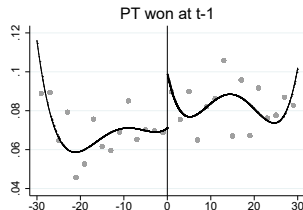
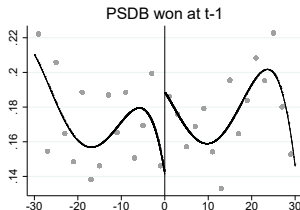
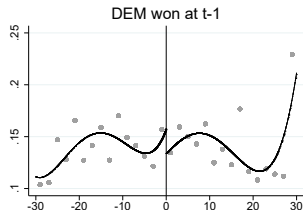
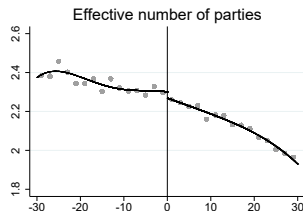
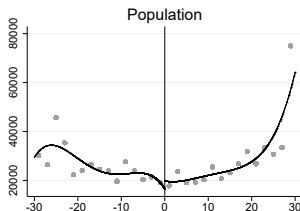
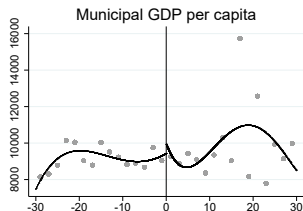
# Sorting – the core assumption

## Balance test

- Other covariates unaffected by the treatment should not change at the threshold.
- Typically estimated with the same specification as the main effect, but can also be shown as RD plots.

# Sorting – the core assumption

## Balance tests in the form of RD plots



# Group discussion

## Geographic RD: COVID mask mandates

- Example: Hansen and Mano, “Mask mandates save lives”.
- Question: did mask mandates help against COVID-19?
- Units of analysis: counties / county-weeks.
- Running: distance to state border where policy changes.
- Cutoff: crossing from a state without a statewide mask mandate to a state with one.
- Treatment: being subject to a statewide mask mandate.
- Outcome: weekly COVID-19 cases, hospital admissions, and deaths per 100,000 inhabitants.

# Group discussion

## What is the problem?

- All geographic RDs: sorting and multiple treatments
  - People have state-preferences and choose where to live.
  - States with mask mandate differ in other regards – politics, health, Covid policies – that may affect the outcome. Mandates may also be a response to level of infections.
  - Very large bandwidth – but less important for borders.
- Interference:
  - Virus may travel across border, reducing differences.
  - People may shop and socialize in the state whose policy they prefer. Bias may go either way.
  - Hospital admissions may come from the neighbouring state.

# Estimation

## Basic setup

- Outcome  $Y_i$  is regressed on the treatment indicator  $D_i$  as well as a function of the running variable  $f(x_i)$ :

$$Y_i = a + bD_i + f(x_i) + e_i$$

- Two key choices:
  - The bandwidth is the distance allowed to the threshold.
  - The function of the running variable.

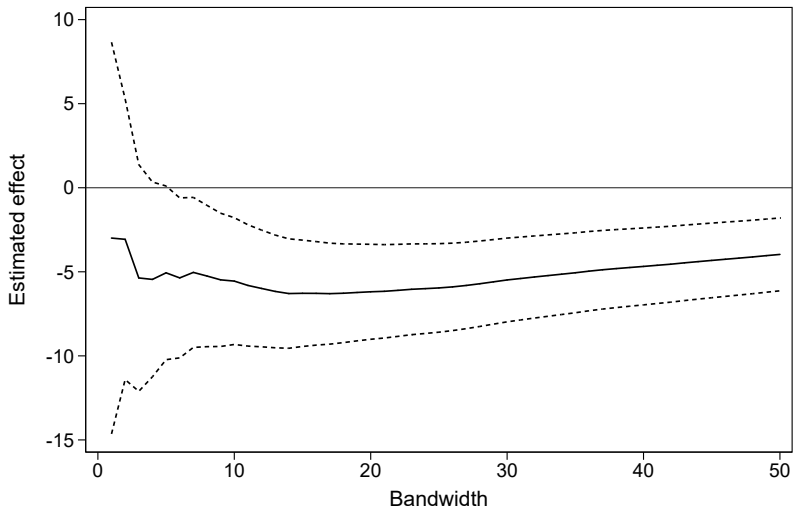
# Estimation

## Bandwidth choices

- Option 1: Pick arbitrary, even numbers.
- Option 2: Use an optimal bandwidth algorithm.
- Kernel-weighting gives more weight to observations close to the cutoff.

Always a trade-off between bias and precision (a large bandwidth could make treatment status predictable and functional form misleading). A bandwidth graph provides full transparency.

# Estimation



# Estimation

## The function of the running variable

- You can control for the running variable with a linear model or a polynomial (or splines, which we do not cover).
- Typically separate slopes on each side.
- Larger bandwidths permit higher-grade polynomials.
- Current 'best practice' favors local linear.

# Estimation

## These are the regression results for the incumbency curse

**TABLE 2. RD Effect of Winning at  $t$  on Victory at  $t + 1$  (Unconditional on Running) for Various Parties—Brazil Mayoral Elections, 1996–2012**

| Outcome: Unconditional Victory $t + 1$ |          |                   |       |       |          |          |
|----------------------------------------|----------|-------------------|-------|-------|----------|----------|
| Party                                  | Estimate | 95% CI            | p-val | $h$   | $n_{tx}$ | $n_{co}$ |
| INCUMBENT                              | −0.15    | [ −0.213, −0.101] | 0.000 | 13.55 | 2,755    | 2,547    |
| PMDB                                   | −0.11    | [ −0.180, −0.066] | 0.000 | 14.63 | 2,878    | 3,102    |
| PSDB                                   | −0.03    | [ −0.102, 0.018]  | 0.173 | 18.77 | 2,357    | 2,397    |
| DEM                                    | −0.09    | [ −0.171, −0.033] | 0.004 | 12.16 | 1,700    | 1,843    |
| PP                                     | −0.16    | [ −0.259, −0.091] | 0.000 | 12.43 | 1,333    | 1,315    |

*Note:* Running variable is party's margin of victory at  $t$ , outcome is dummy =1 if party wins the following election at  $t + 1$ , =0 otherwise. Estimate is average treatment effect at cutoff estimated with local linear regression with triangular kernel and MSE-optimal bandwidth. Columns 3–7 report, respectively, 95% robust confidence intervals, robust  $p$ -value, main optimal bandwidth, treated observations within bandwidth, and control observations within bandwidth.

# Estimation

## Visual evidence is key

- RD analyses should include a RD plot.
- You want to see the jump in the bins. Is it clear or open for interpretation?
- Don't be fooled by the fitted curves. Polynomials can behave strangely near the end-points.

# Other things

## General limitations of RD

- We can only use it in specific situations.
- RD estimates a local treatment effect at the cutoff.
  - It tells us what happens for units close to the threshold, but that may differ from effects far away from the threshold.
- It tends to eat power, because units close to the cutoff are often only a small subset of the available data.

# Other things

## **Additional limitations of election-RD in a Swedish context**

- Just-elected is a weak and bundled treatment.
  - Substitute members still play an active role and often enter the council during the term.
  - A politician may be 'randomly' elected, but their characteristics are correlated with other variables.
- An extra seat is a weak treatment and a weird quantity.
- Majority RDs are harder than you may think.
  - (Marginal) parliamentary majority is a weak instrument for the governing coalition in Swedish municipalities.
  - Distance is complicated to solve analytically so you may need to simulate the running variable.
  - Simply controlling for the vote share may be a pragmatic solution for a master thesis but not sufficient for research.

# Fuzzy RD

- So far we have assumed sharp RDs, which means that treatment status changes deterministically at the cutoff.
- In a fuzzy RD, crossing the cutoff changes the *probability* of treatment.
- Same as non-compliance: some units below the cutoff receive treatment and/or some above the cutoff do not.
- The cutoff can then be used as an instrument for treatment.

# Fuzzy RD

- How much does crossing the cutoff increase the treatment intensity/probability? This is the first stage in a IV framework and similar to compliance in an experiment.
- How much does crossing the cutoff affect the outcome? This is the reduced form in an IV framework and similar to ITT in an experiment.
- Fuzzy RD estimate: reduced form divided by first stage. This is the IV estimator and similar to ITT/compliance.
- A local treatment effect for compliers at the cutoff.

Key assumption: crossing the cutoff only affects the outcome through the treatment (excludability / exclusion restriction).

# Group discussion

## What is the problem in this study?

- A (strong) master thesis uses RD to test veto player theory in Swedish municipalities.
- Instrument: whether the largest party barely fails to win a council majority.
- Treatment: ideological dispersion among governing parties.
- Outcome: absolute change in the municipal tax rate.
- Result: Ideological dispersion leads to *more* tax changes.

Why should we be skeptical? Discuss in groups!

# Group discussion

## What is the problem in this study?

- The treatment (increased ideological dispersion) is associated with multiple government characteristics:
  - An increase in the number of parties.
  - A right-wing rather than Soc Dem government?
- The instrument may affect the outcome without affecting the treatment:
  - Whether the largest party controls the parliament is a big deal even if it does not affect the government.
  - We are comparing majority to minority governments.
  - The exclusion restriction is violated.

# RD-topics not on the course

## Things you should have heard about

- Donut RD.
- Discrete running variables.
- Regression kink designs.
- Multiple cutoffs.

## RD-topics not on the course

### Donut RD

- Sometimes observations close to the cutoff are problematic.
- A donut RD excludes observations in a small window around the cutoff.
- This can be useful when there is manipulation or rounding errors close to the threshold, or uncertainty around the exact implementation of the threshold.
- You lose the “best” observations: lower precision and more reliance on extrapolating back to the cutoff.

# RD-topics not on the course

## Discrete running variables

- In some RD designs, the running variable takes only a limited number of values.
- Examples *may* include test scores, grades, and days.
- Problem 1: The comparison may not be very local.
- Problem 2: The control function may be misleading (i.e., wrong shape or hiding weekday effects).
- Standard RD methods may then give too much confidence.
- Discreteness is gradual: the more distinct values near the cutoff, the less severe the problem.

# RD-topics not on the course

## Regression kink design

- In a standard RD, we look for a jump in the *level* of the outcome at the cutoff. In a regression kink design, we instead look for a change in the *slope*.
- This can be useful when the cutoff changes how the running variable affects treatment intensity.
- Example: the marginal incentives generated by taxes or benefits may change at a threshold, such as a ceiling in unemployment insurance.
- The design is usually less credible, because changes in slopes are harder to estimate reliably than jumps.

# RD-topics not on the course

## Multiple cutoffs

- Some RD designs have several cutoffs rather than one.
- Example: cutoffs may differ between regions or years.
- It is possible to calculate an average effect by pooling the data. Consider the following:
  - Center the running variable around each cutoff.
  - You may want to let slopes differ across cutoffs or groups.
  - More weight is given to cutoffs with many observations close to the threshold.
  - Such averages are more meaningful when the treatments and populations are similar.

# Wrapping up

## Key take-aways

- RD assumes continuity of potential outcomes at the cutoff.
  - Is there a risk that units can foresee their treatment status and act on that, 'sorting' also close to the threshold?
  - Are there imbalances around the cutoff?
- Estimation.
  - The RD-plot is key. Can you see a jump in the data?
  - The local linear is best practice. Does it fit the data?
- Is there a clean and isolated treatment?
  - Sometimes there are multiple treatments.
  - Sometimes those below the cutoff gets a similar treatment.

No Stata required for assignment. Workshop focused on RD.