Quasi-Experiments

POLSCI 4SS3

Winter 2024

Announcements

- Decide if you will sign up for final project by April 4
- Instructor traveling April 3-7

What did you learn this semester?

Where to go from here?

Go back to foundations

- Probability and statistics
- Philosophy of science
- Research design
- R programming

Where to go from here?

Further learning

- Programming in Python, Julia
- Survey design
- Program evaluation
- Science of science

Where to go from here?

Careers & fields

- Data science, computer science, statistics
- Computational/quantitative social science
- Econometrics
- Evidence-informed policy
- Public administration
- Business, marketing

Quasi-experiments

Data strategies

	Data strategy	
Inquiry	**Observational**	**Experimental**
Descriptive	Sample survey	List experiment
Causal		Survey/field experiment

Data strategies

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Inquiry	**Observational**	**Experimental**
Descriptive	Sample survey	List experiment
Causal	**Quasi-experiment**	Survey/field experiment

Challenges to causal interpretations

1. Reverse causation

- Instead of Z causing Y, Y causes Z
- **Simultaneity:** Z causes Y and vice versa

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> **Example**
>
> Students who are likely to participate enroll in Political Science courses more often

Challenges to causal interpretations

2. Omitted variable bias

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- There is an unobserved factor X that explains the relationship between Z and Y

Challenges to causal interpretations

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- There is an unobserved factor X that explains the relationship between Z and Y

Example

- We believe that more education increases income
- But having smart parents increases both education and income

Challenges to causal interpretations

3. Selection bias

- Individuals *sort* into condition Z in a manner that predicts outcome Y
- Treatment and control are not comparable

Challenges to causal interpretations

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Example

- Always-takers are more likely to participate in the TUP program

Challenges to causal interpretations

1. Reverse causation

2. Omitted variable bias

3. Selection bias

- Random assignment avoids this *in expectation*
- Hard to overcome with *observational causal* data strategies
- Need to pretend that we can analyze data as if it was an experiment

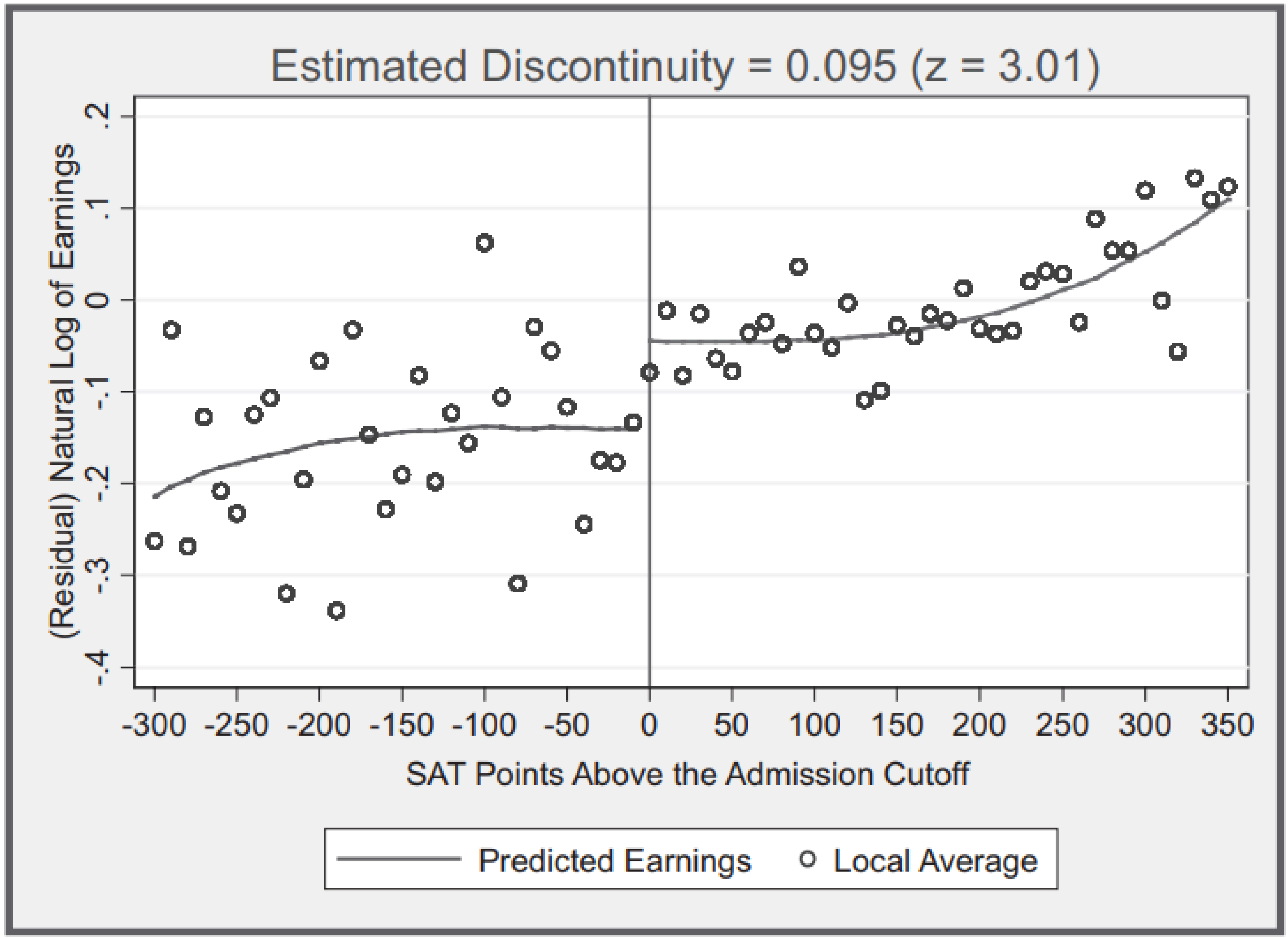
Quasi-experiments

- Answer strategies that produce data as-if they were drawn from an experiment
- **Natural experiment:** Random assignment outside of the researcher control
- **Example:** Choosing municipalities at random for auditing
- **Quasi-experiment:** Conditions are assigned in a manner that is **sufficiently orthogonal** to potential outcomes

Regression Discontinuity

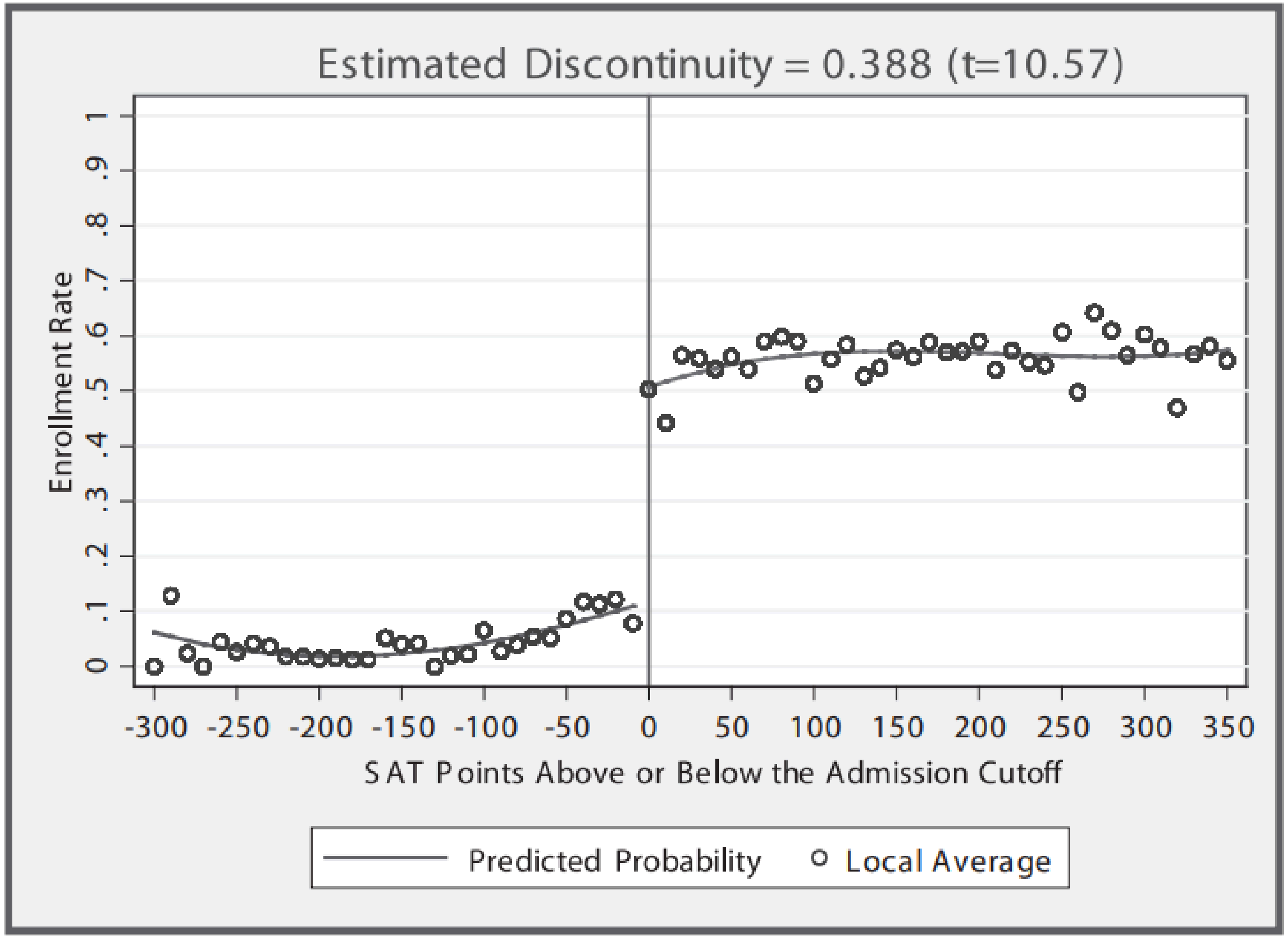
Hoekstra (2019)

Figure 2.—Natural Log of Annual Earnings for White Men Ten to Fifteen Years after High School Graduation (Fit with a Cubic Polynomial of Adjusted SAT Score)



Treatment take-up

Figure 1.—Fraction Enrolled at the Flagship State University

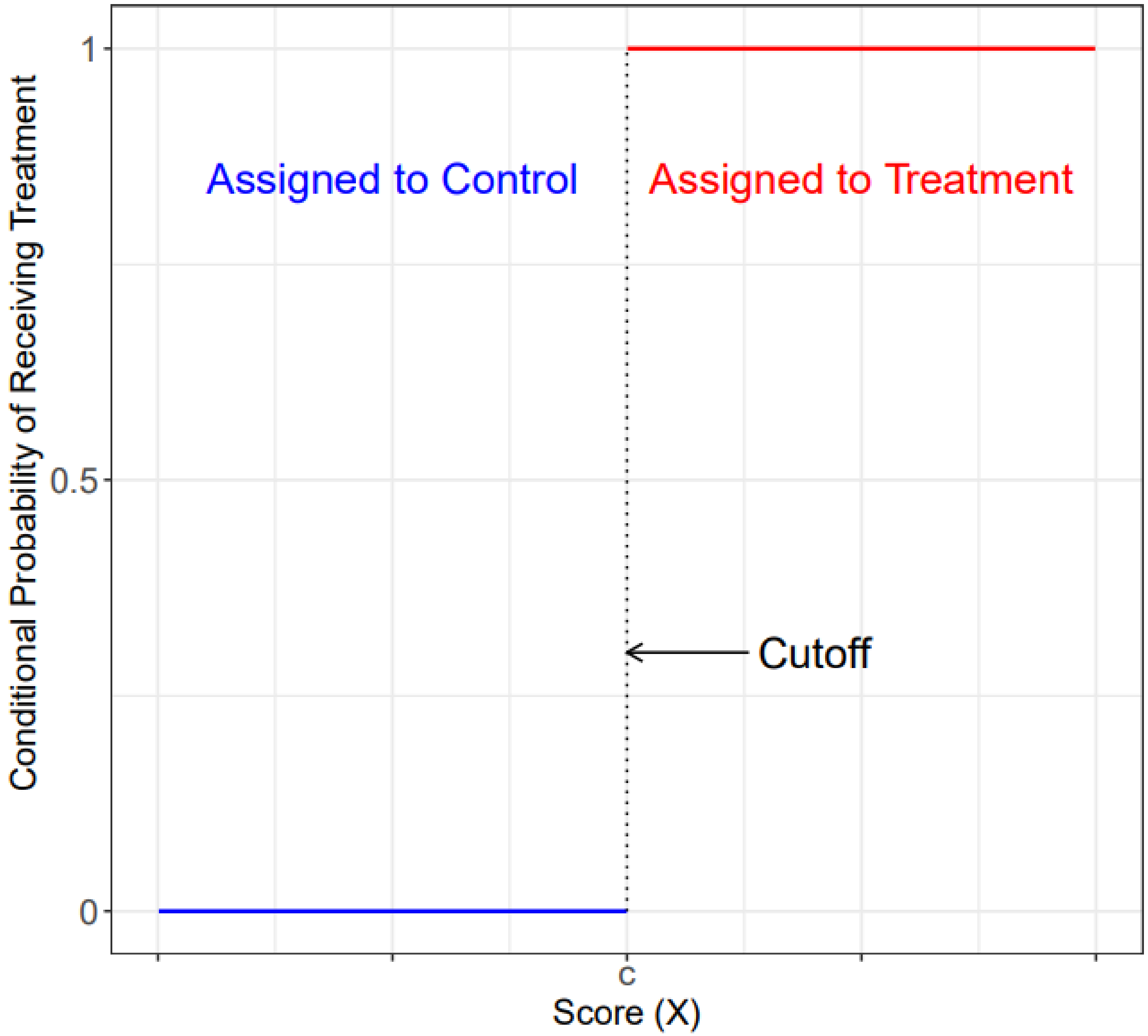


Regression discontinuity designs

- Three ingredients:

1. Score `(running variable)`
2. Cutoff `(threshold)`
3. Treatment `(at least two conditions)`

Visual representation



How do you get an estimate?

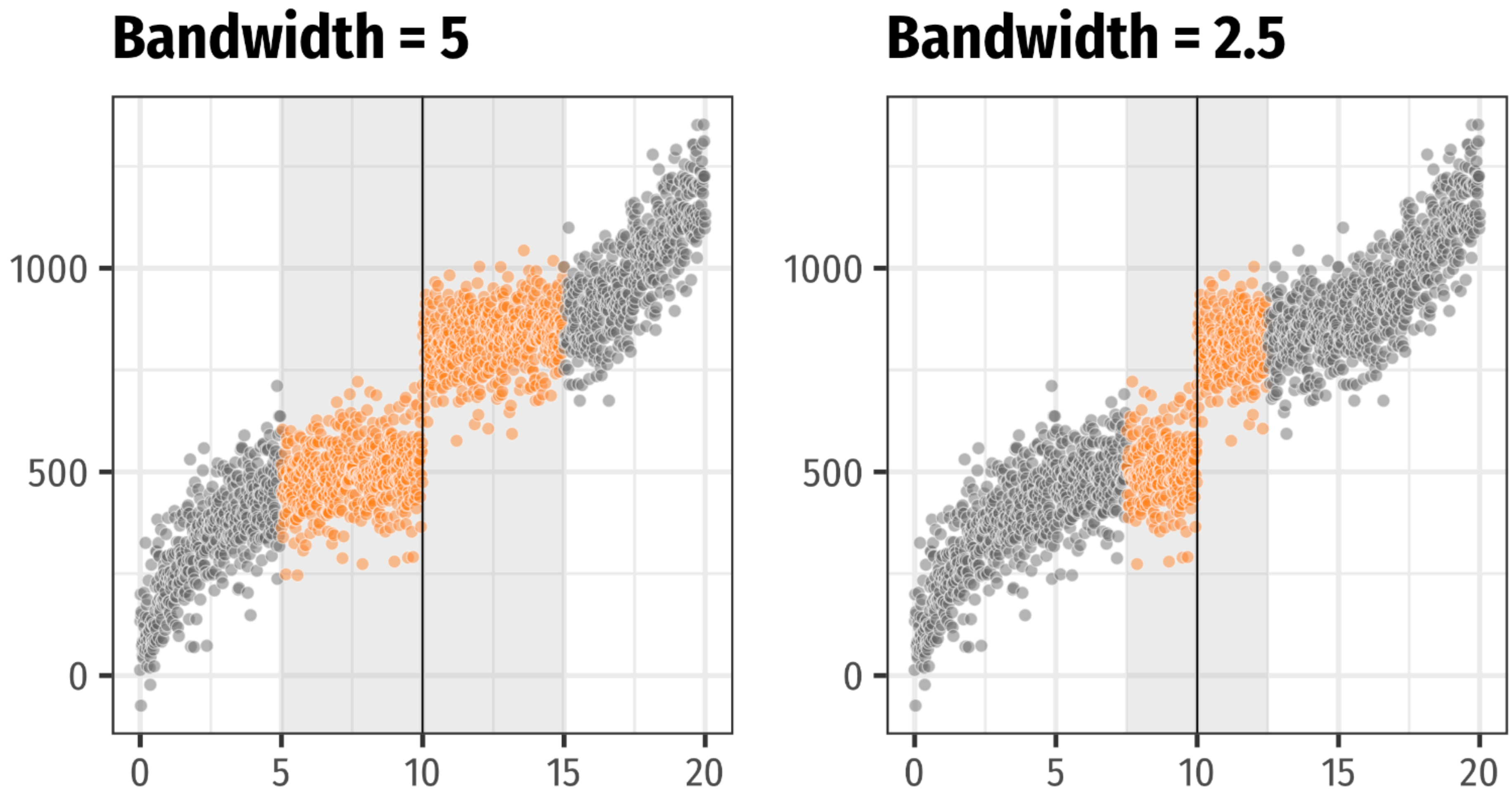
- Two approaches to RDD data:

1. Local randomization
2. Continuity-based

Local randomization

- Potential outcomes are not random because they depend on the score `(and other things)`
- However, around the cutoff, treatment assignment is as good as random
- **Example:** Barely winning an election
- So we can pretend we have an experiment within a **bandwidth** around the cutoff

Bandwidth tradeoff

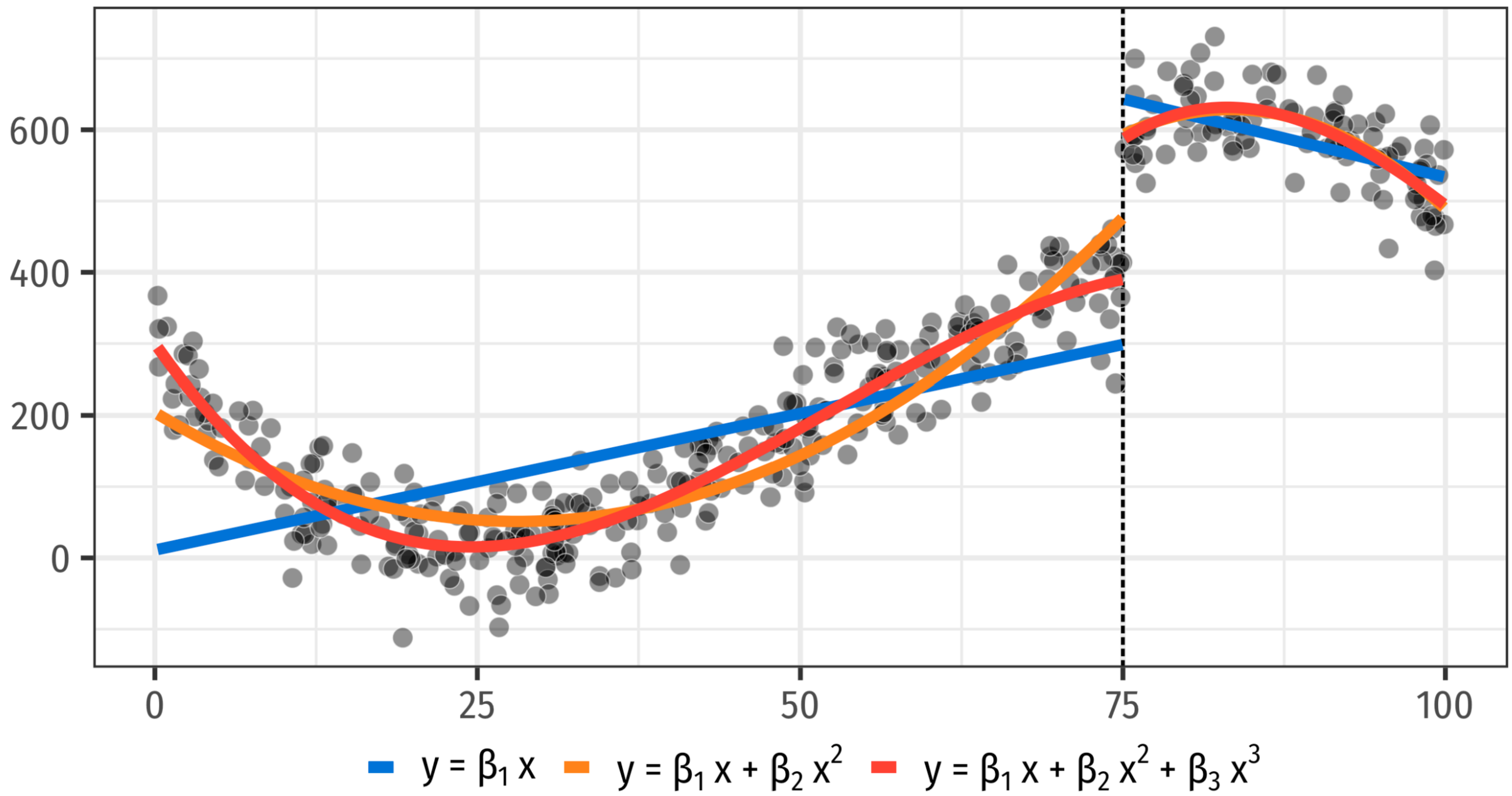


A small bandwidth has low bias but high variance. A larger bandwidth has lower variance

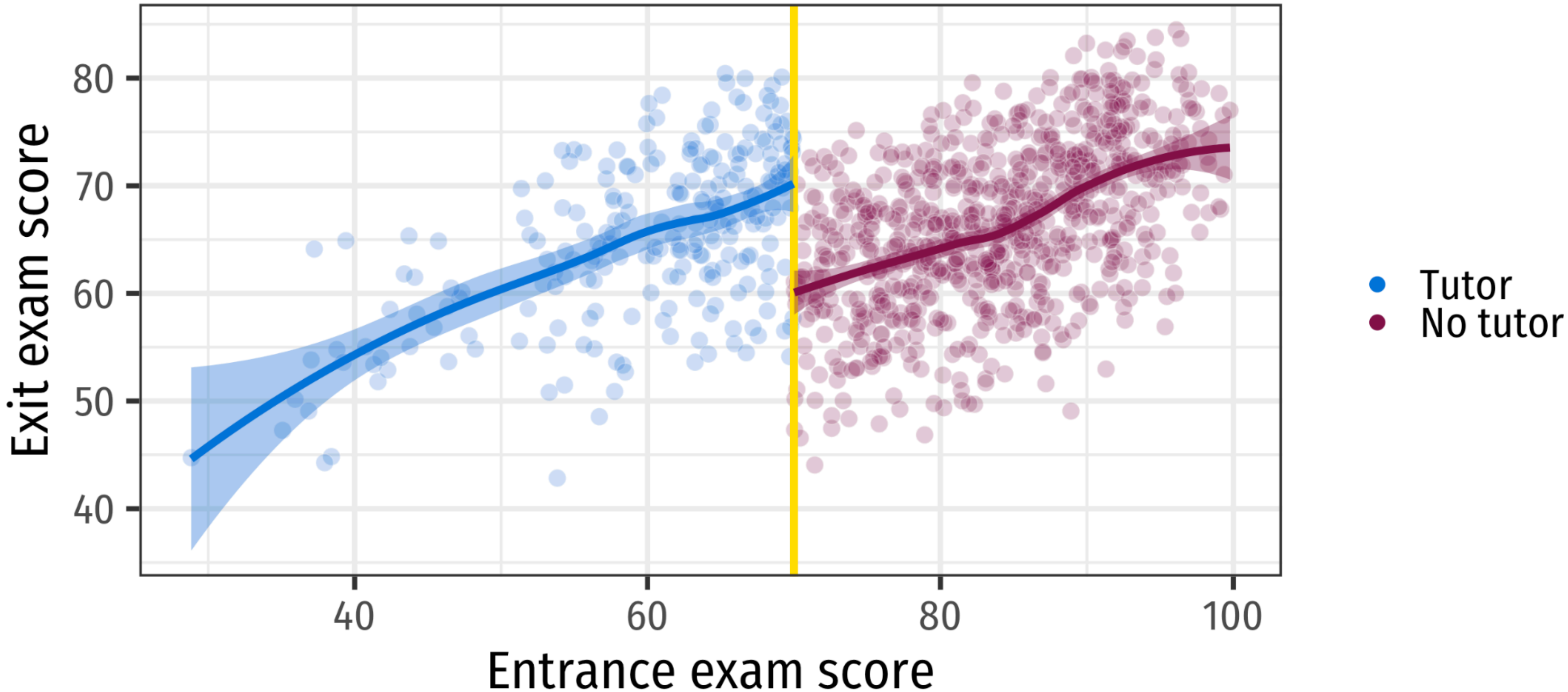
Continuity-based approach

- Treatment assignment is **deterministic at** the cutoff
- **Example:** Financial aid if income below a threshold
- But usually too few or no units at the cutoff
- **Task:** Approximate the *gap* at the cutoff as best as possible
- This becomes a **line drawing** problem

Line drawing: Parametric

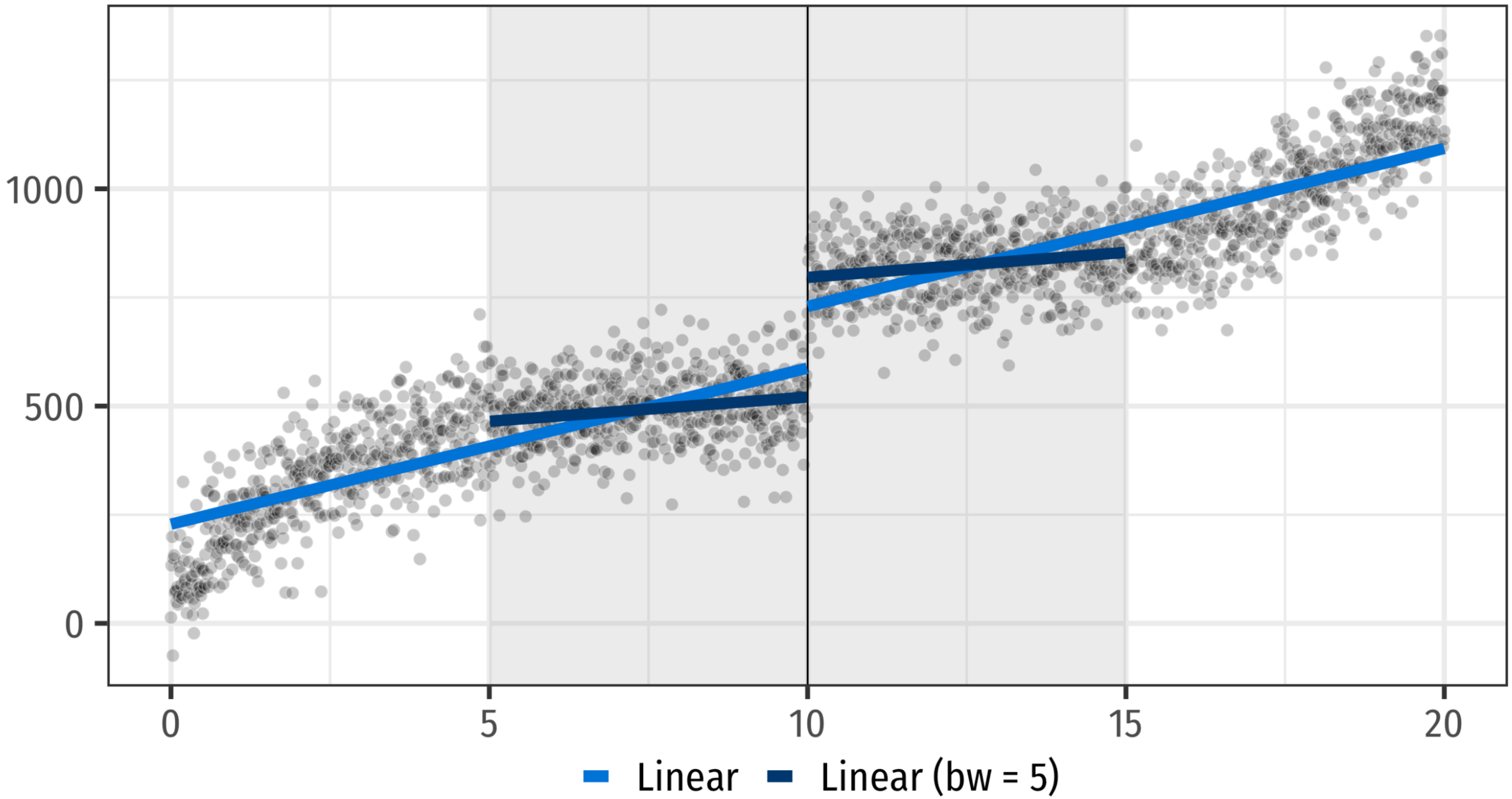


Line drawing: Nonparametric



These lines are made by an algorithm that calculates the local average at many windows

Line drawing: Bandwidth



Difference-in-differences

Leininger et al (2023)

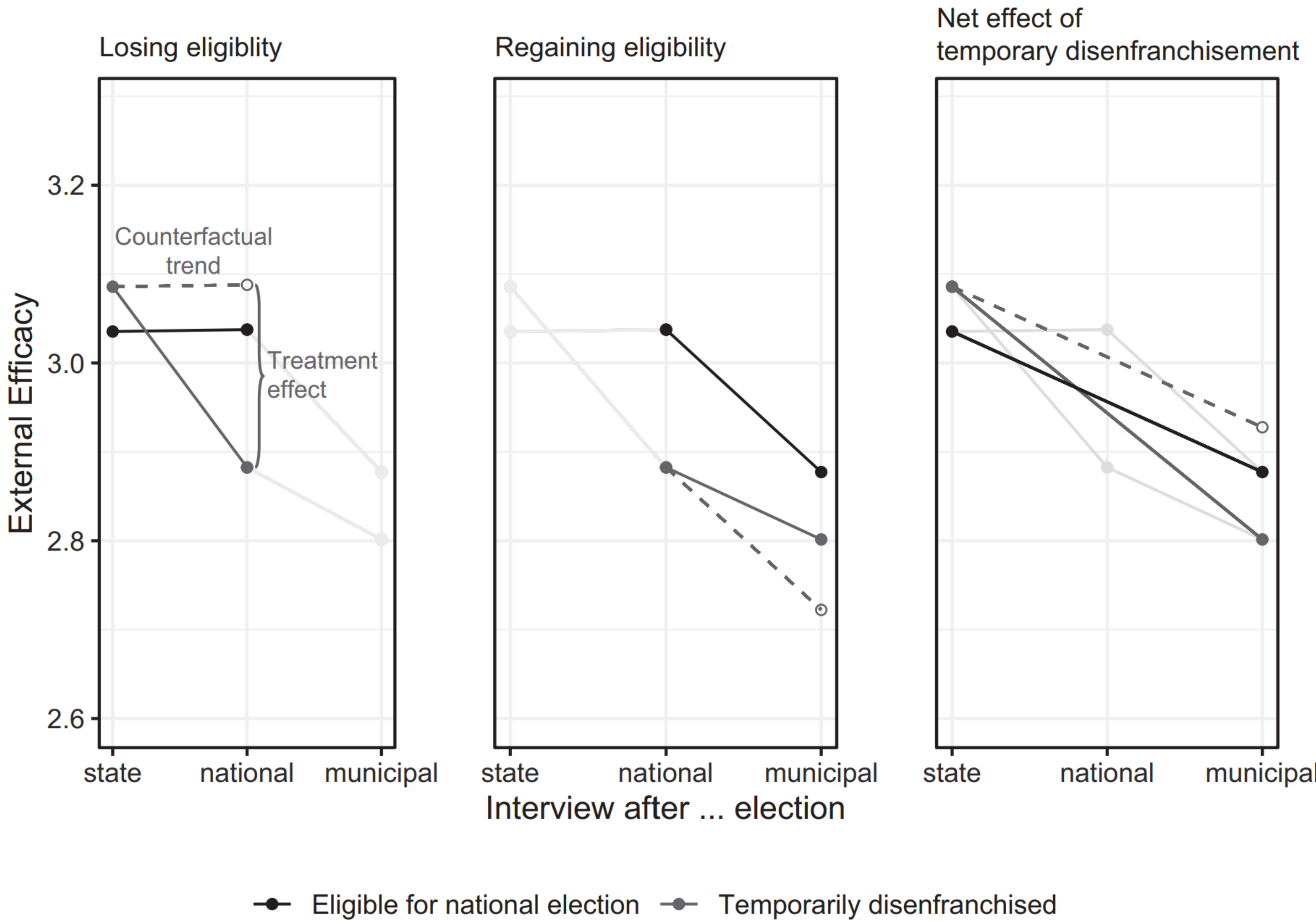
TABLE 1. Study Design

Group	Age	**State election** May 7, 2017	**National election** September 24, 2017	**Municipal elections** May 6, 2018	*N*
1 Control	18	Eligible	Eligible	Eligible	581
2 Treatment	16–17	Eligible	*Ineligible*	Eligible	916

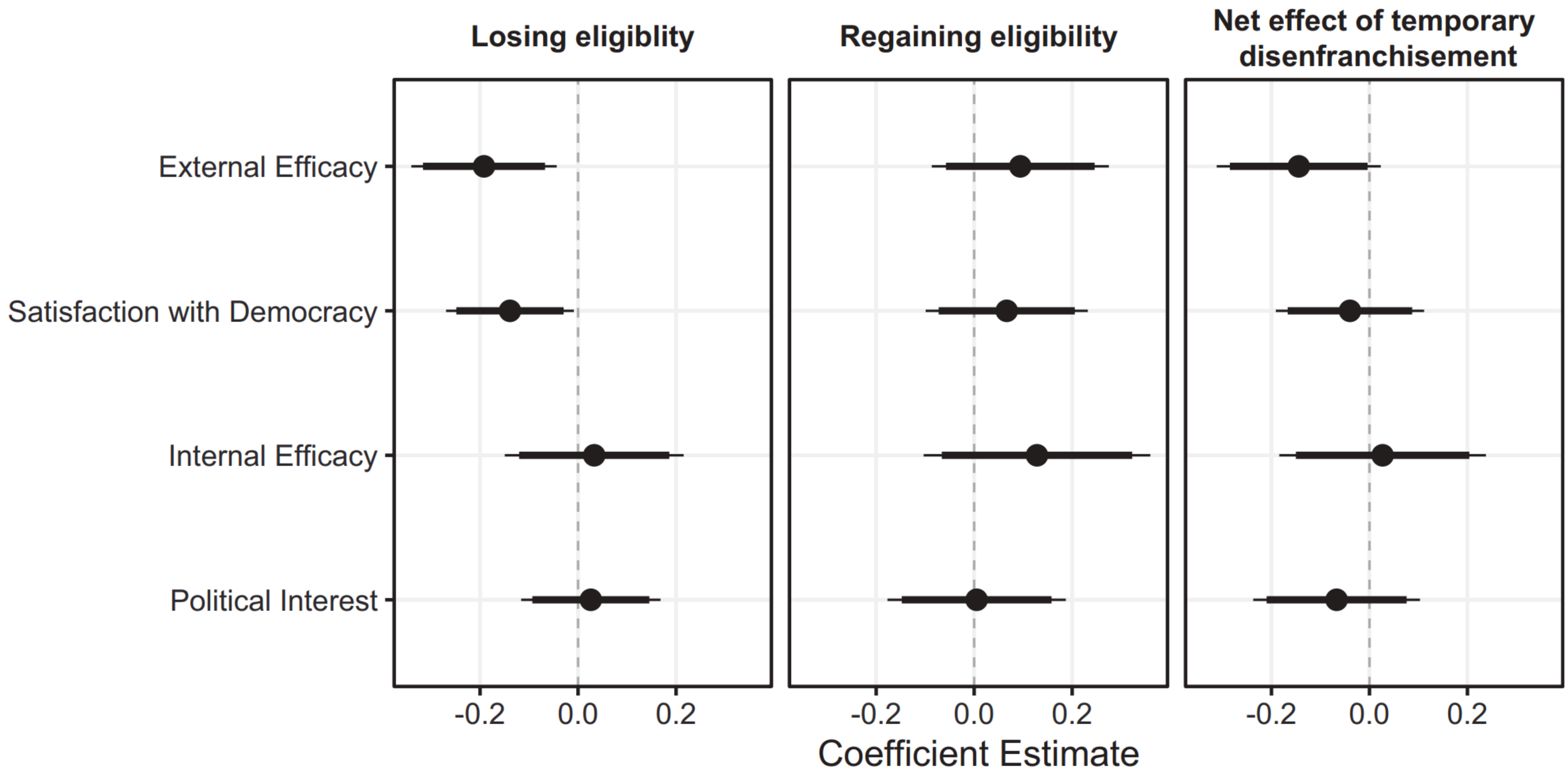
Note: The control group (1) comprises persons entitled to vote in the national election and all following elections because they were 18 on the day of the national election, and the treatment group (2) comprises persons entitled to vote in the state and municipal elections only because they were aged 16 or 17 on the day of the national election. *N* = respondents who participated in both waves 1 and 2.

- **Temporary disenfranchisement** may push voters away from democracy
- **Outcomes:** Survey questions about internal/external efficacy, satisfaction with democracy, political interest

Comparisons



Results



Losing eligiblity
Regaining eligibility
Net effect of temporary disenfranchisement
External Efficacy
Satisfaction with Democracy
Internal Efficacy
Political Interest
-0.2
0.0
0.2
Coefficient Estimate

Difference-in-differences design

- *At least* two groups or conditions `(treatment,control)`
- *At least* two time periods `(pre- and post-treatment)`
- Once treated, units **stay on**
- We accept that selection bias is unavoidable
- But comparing before-after changes between groups allows us to calculate treatment effect

Diff-in-diffs estimator

	Timing	
Group	**Before**	**After**
Treatment	A	B
Control	C	D

$$\widehat{ATE} = [\text{Mean}(B) - \text{Mean}(A)] - [\text{Mean}(D) - \text{Mean}(C)]$$

Diff-in-diffs estimator

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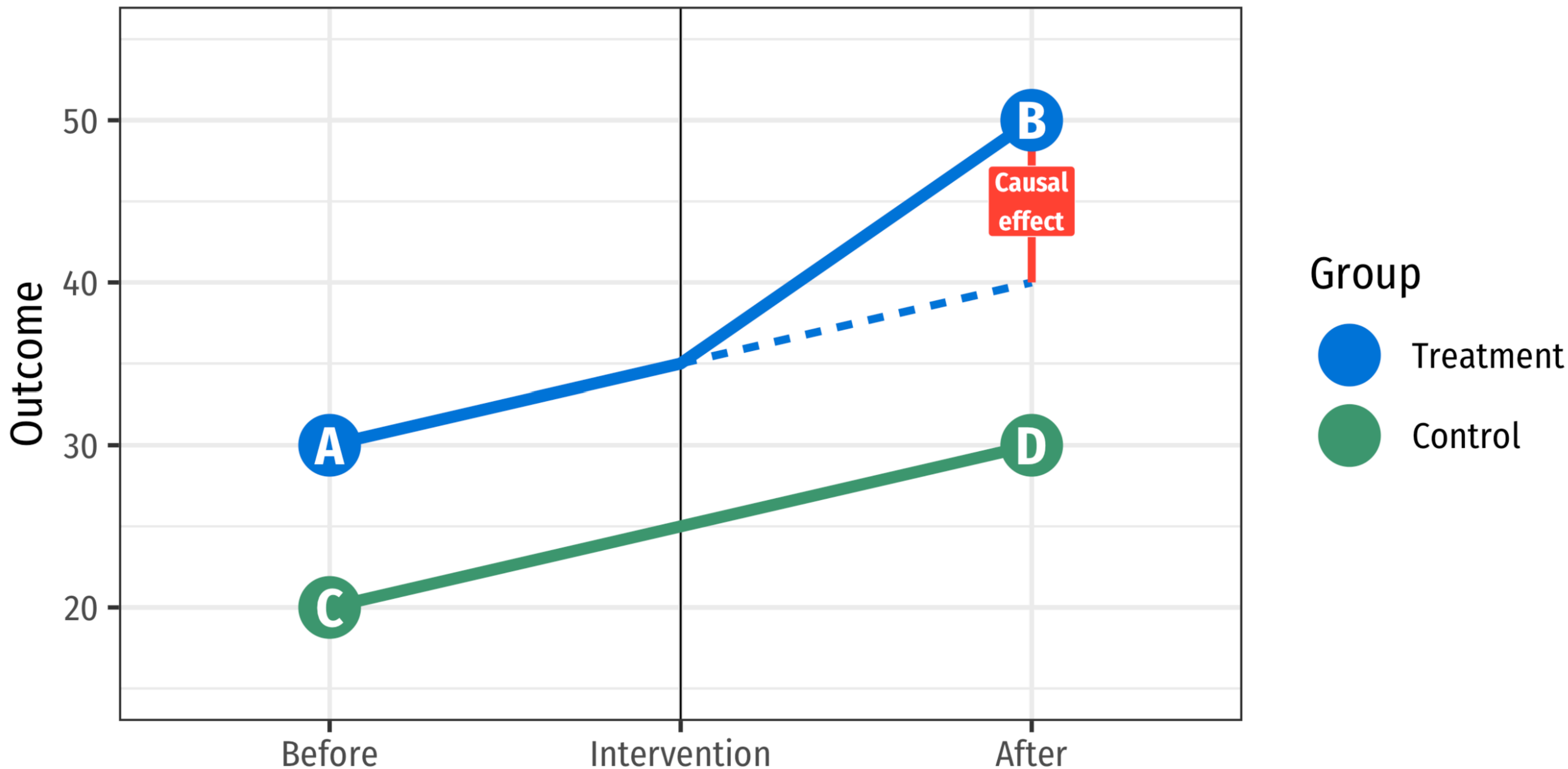
Assumption: Parallel trends



Assuming the treatment group follows the dotted line absent treatment, the difference in

What happens if we break parallel trends?

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