Lecture 2: Causal Inference Using Observational Data

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Using Observational Data

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- Policy design can sometimes provide plausibly exogenous variation
- Observational data that can be combined with institutional details for evaluation
- Applications may also lend themselves to natural experiments
- Observational data can also be used in such contexts

Benefits of Using Observational Data

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- Externally valid inference (depending on the data and design)
- Less fraught with behavioral concerns

Limitations of Using Observational Data

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- Data restrictions

Working with Observational Data- Methods

- Difference-in-Difference (DID)

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- Regression Discontinuity Design (RDD)

Difference-in-Difference

- Most popular method used in empirical analysis

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- Emulate an experiment with treatment and comparison groups

Difference-in-Difference

- Most popular method used in empirical analysis
- Emulate an experiment with treatment and comparison groups
- Uses panel data and is a two way fixed effects model

DID- Basic Idea

- With panel data on the treated group, can compare pre and post intervention or policy change

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- With panel data on the treated group, can compare pre and post intervention or policy change
- But any discerned effect can arise due to secular changes
- Panel data on comparison group can provide the counterfactual
- What would happen to treated group over time in absence of treatment

DID- Implementation

- Isolate the design using tabular or graphic representation

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- Isolate the design using tabular or graphic representation
- Formalize using regression analysis

Tabular Representation

DID

	Before	After	Difference
Treatment			
Control			
Difference			

Tabular Representation

DID

	Before	After	Difference
Treatment	Y_{T1}	Y_{T2}	
Control			
Difference			

Tabular Representation

DID

	Before	After	Difference
Treatment	Y_{T1}	Y_{T2}	
Control	Y_{C1}	Y_{C2}	
Difference			

Tabular Representation

DID

	Before	After	Difference
Treatment	Y_{T1}	Y_{T2}	$\Delta Y_T = Y_{T2} - Y_{T1}$
Control	Y_{C1}	Y_{C2}	
Difference			

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Difference			

Tabular Representation

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Difference			$\Delta Y_T - \Delta Y_C$

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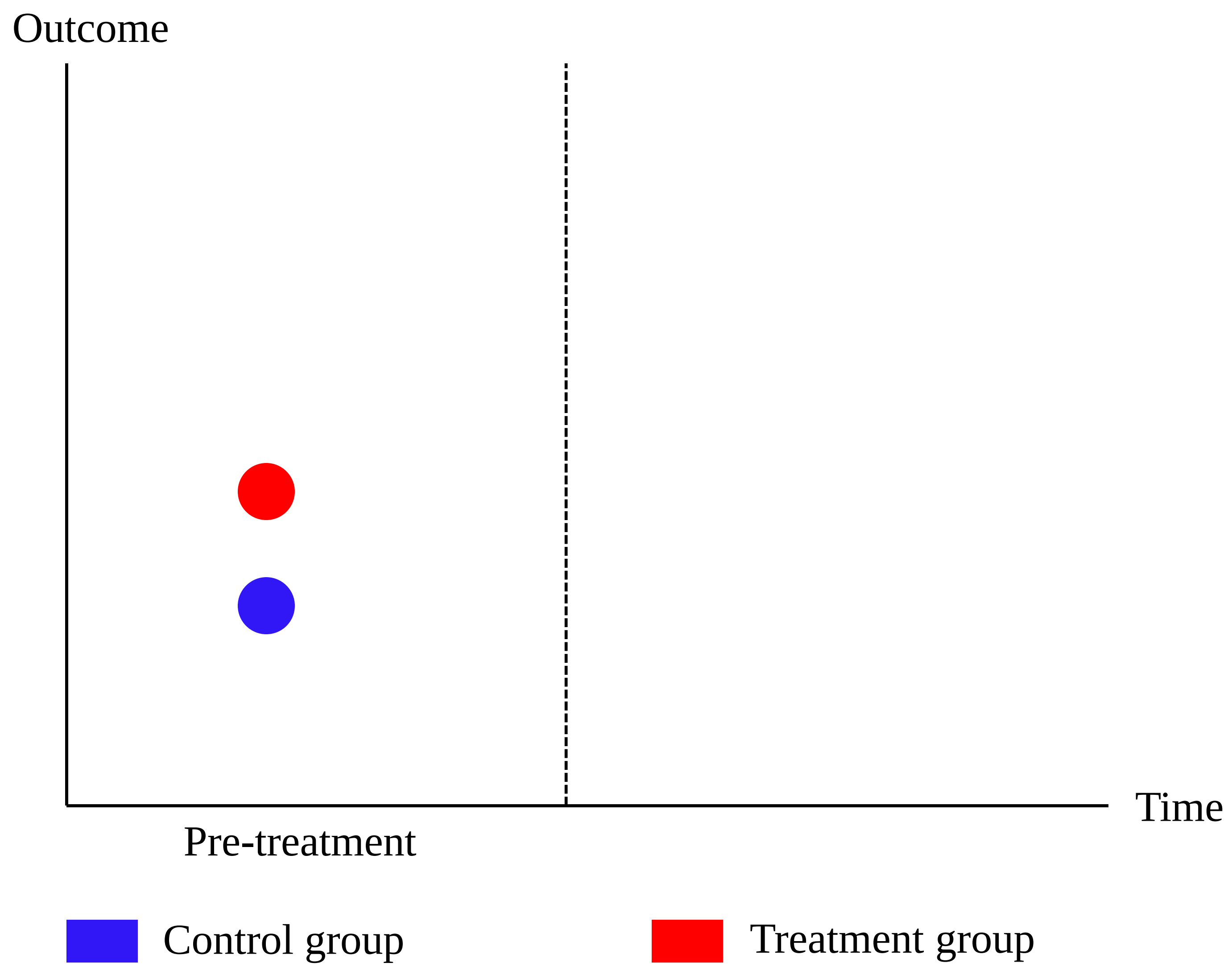
- If different time trends, effect over or under stated
- Identifying assumption- No differential pre-trends

Difference in Difference



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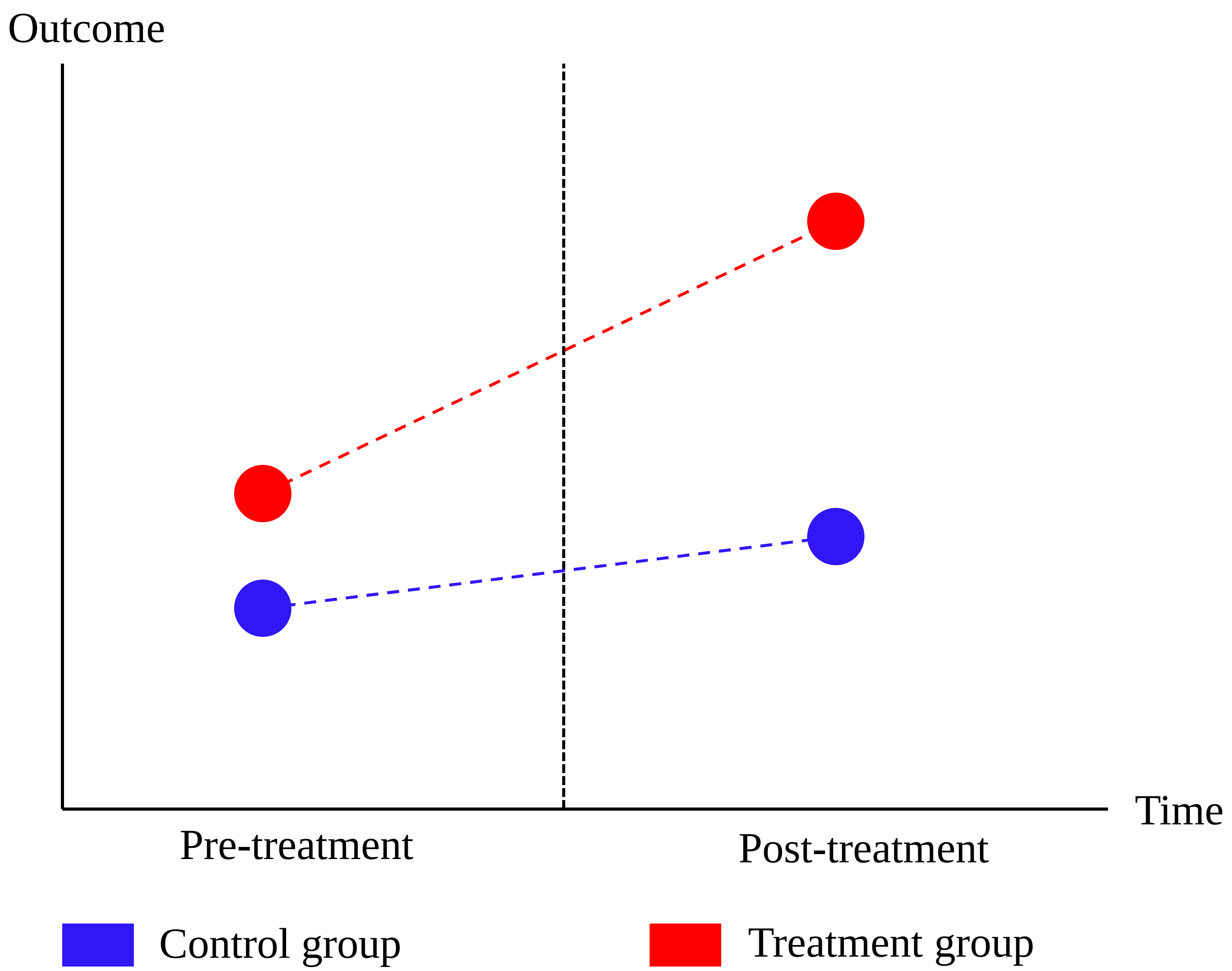

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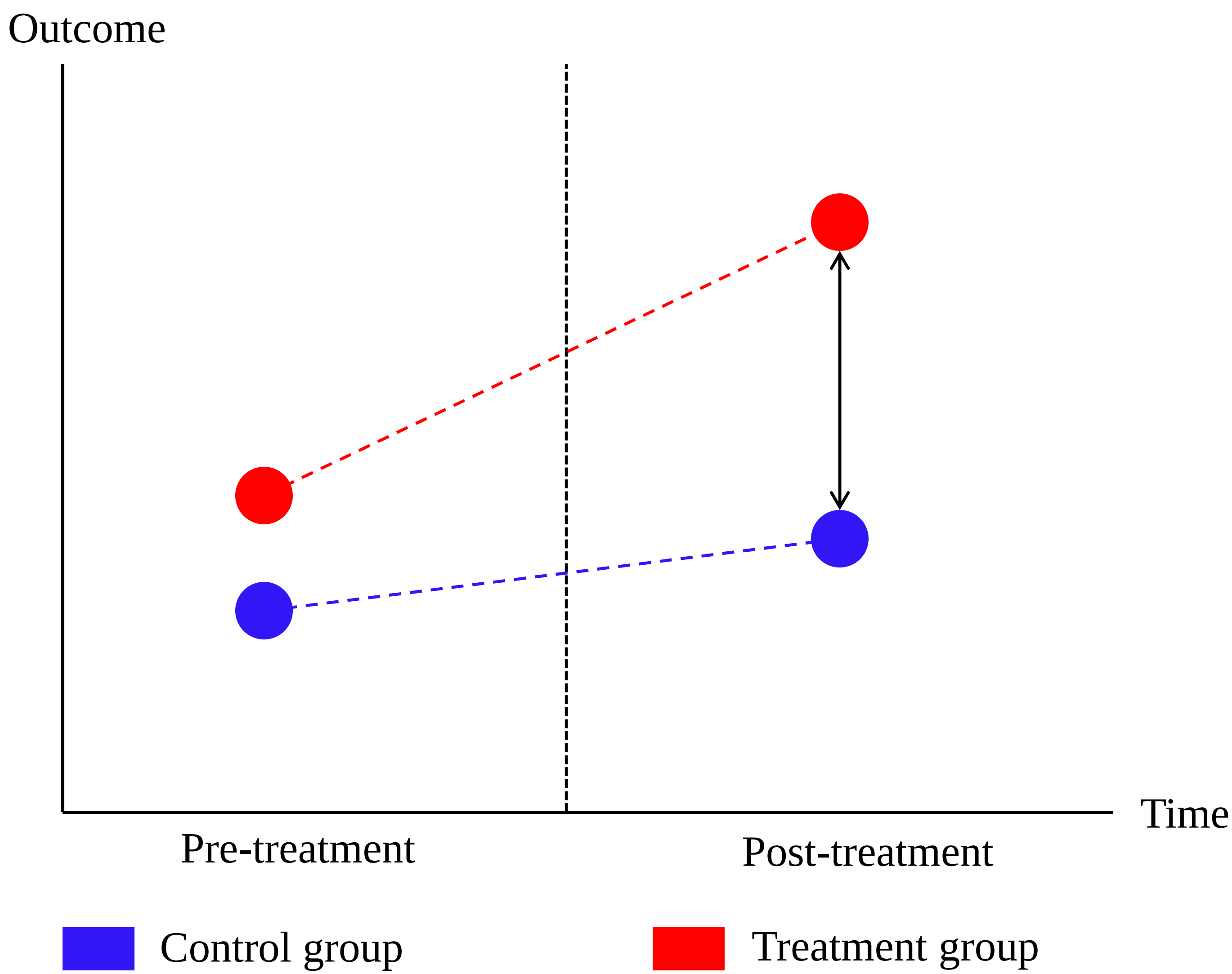

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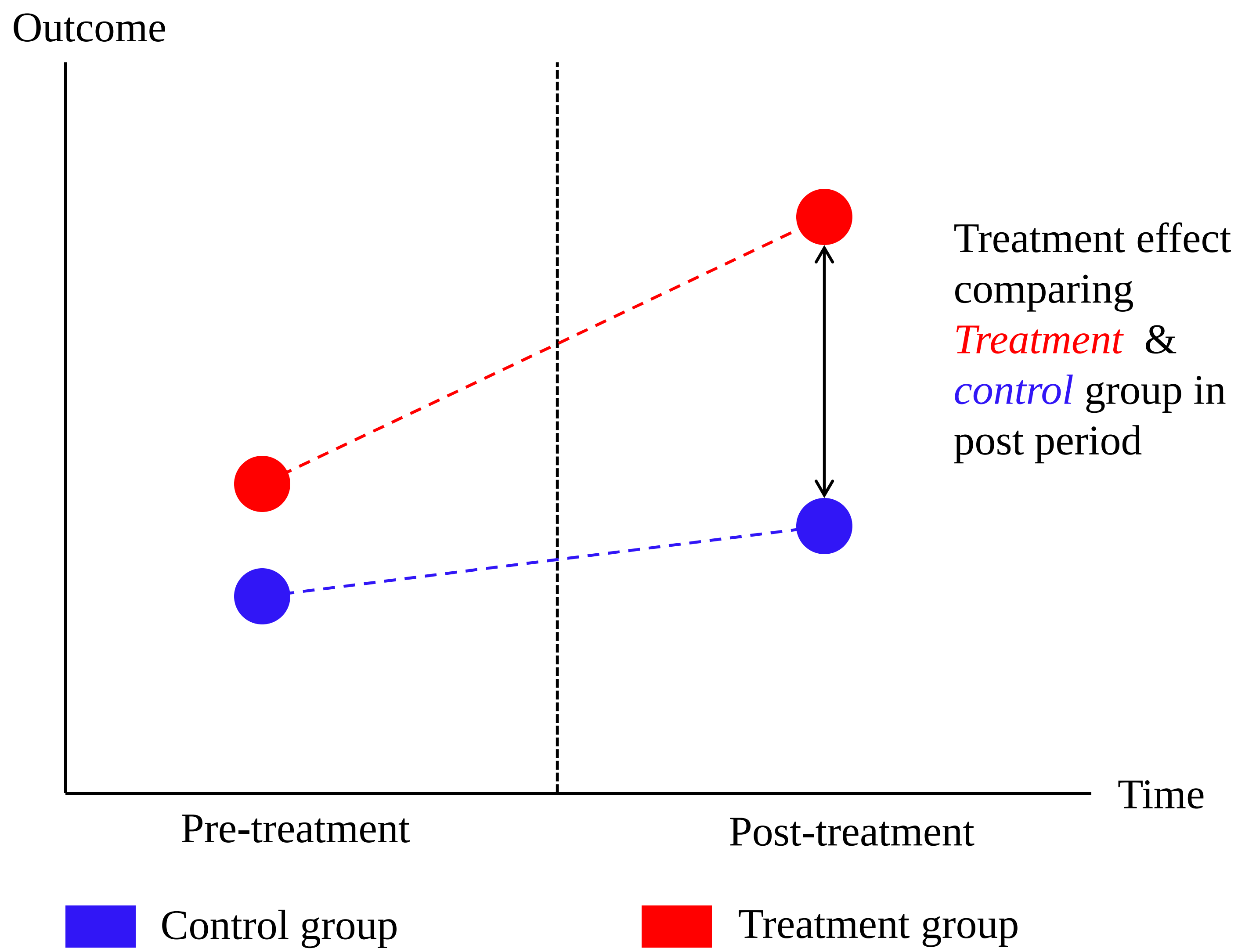

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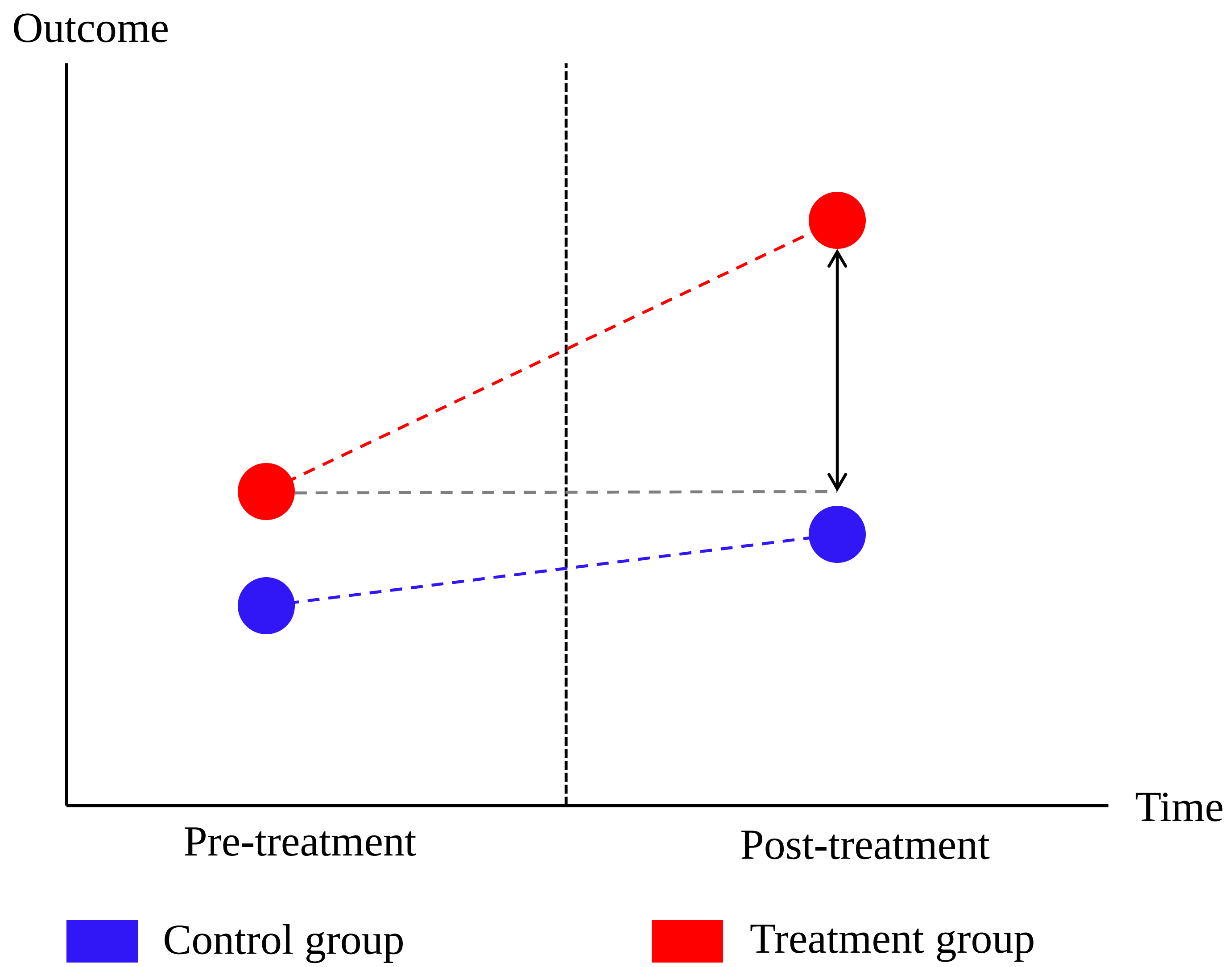

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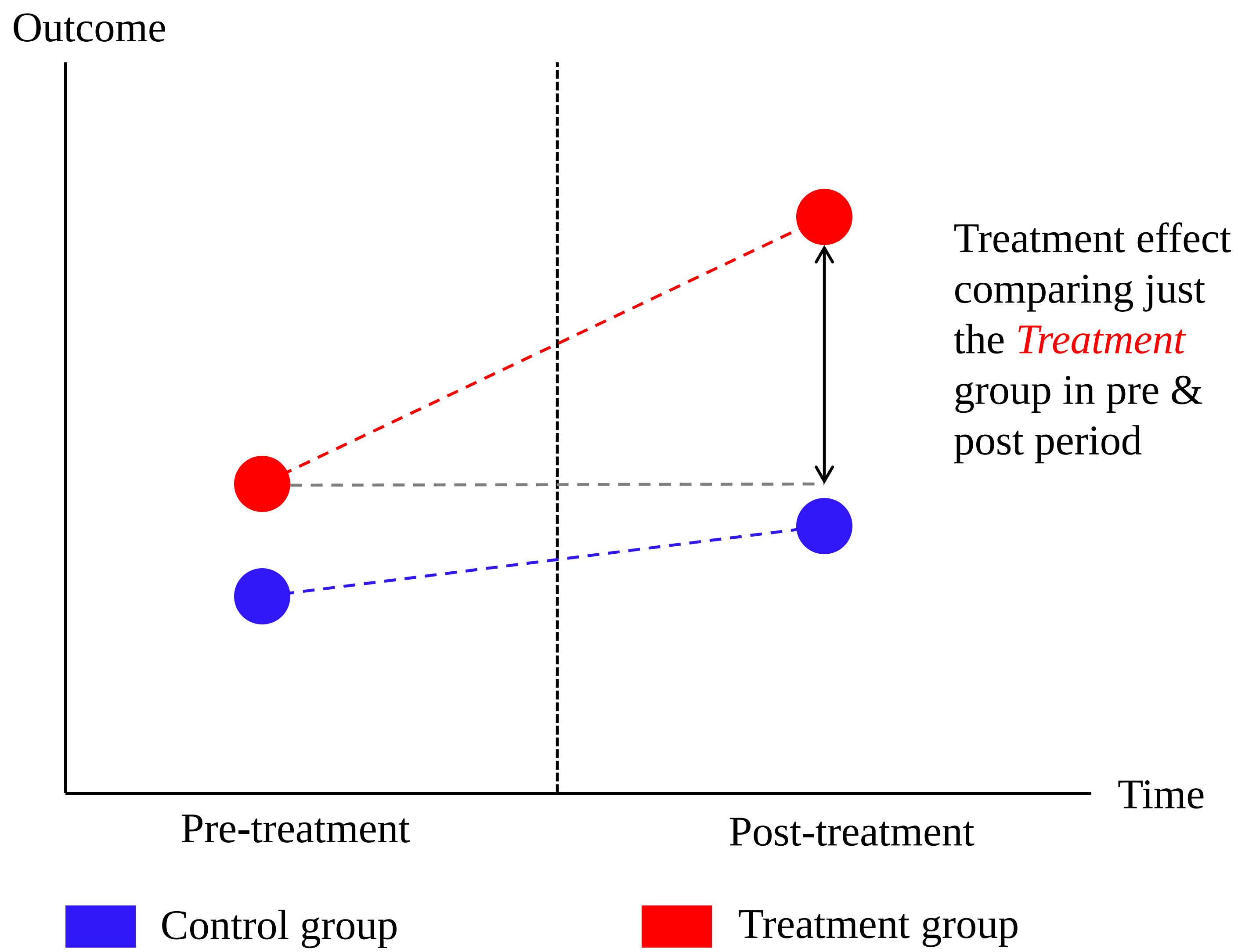

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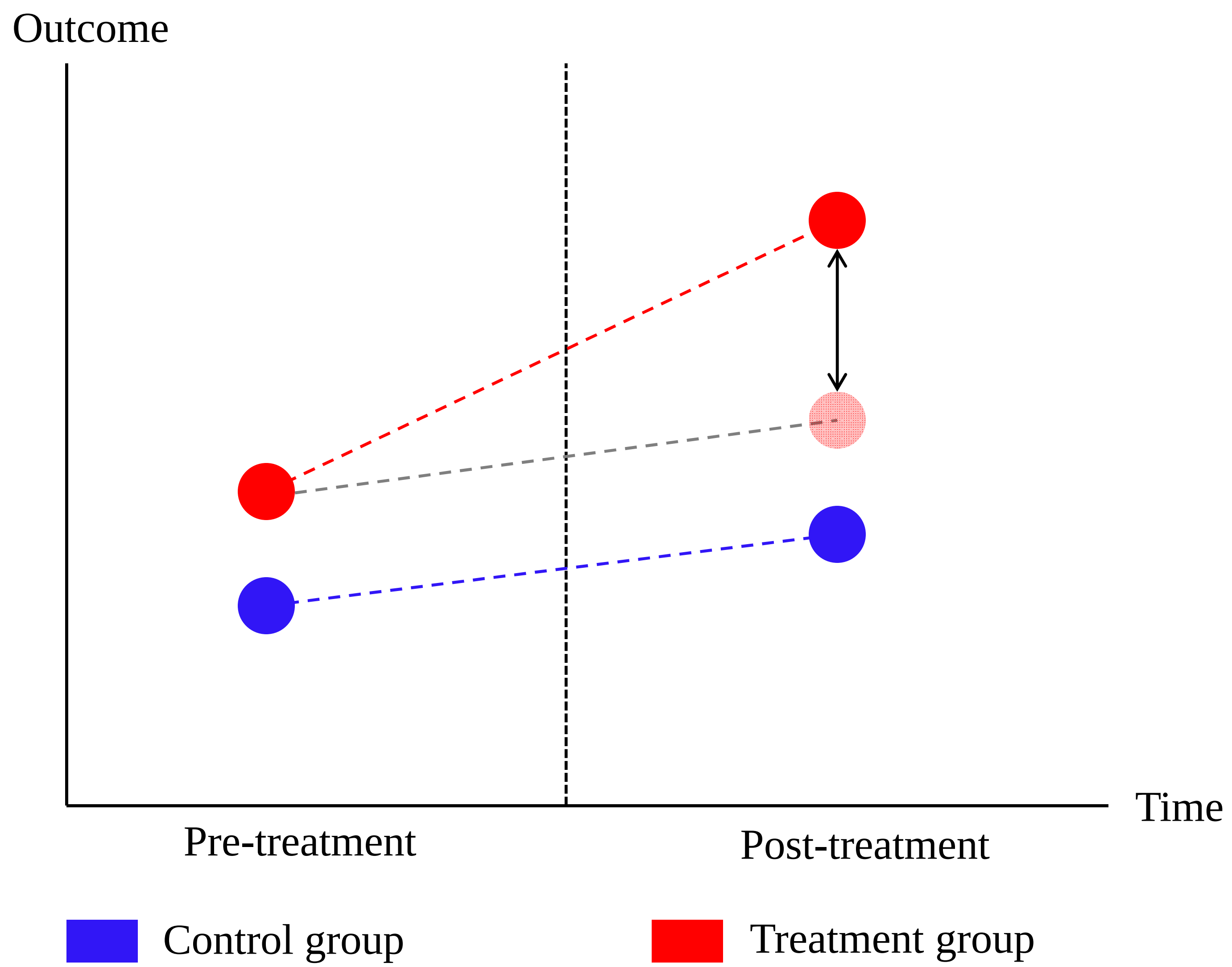

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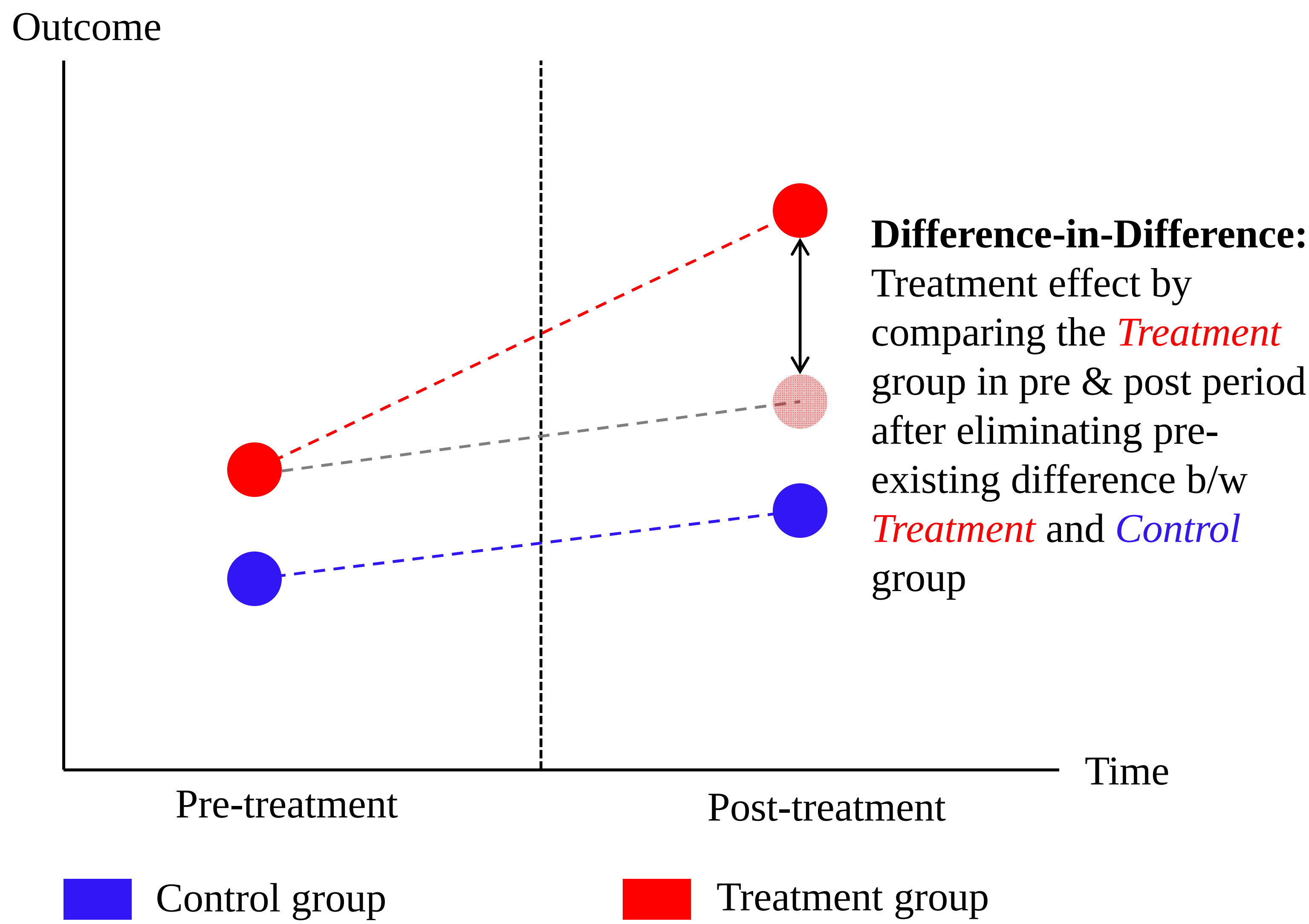
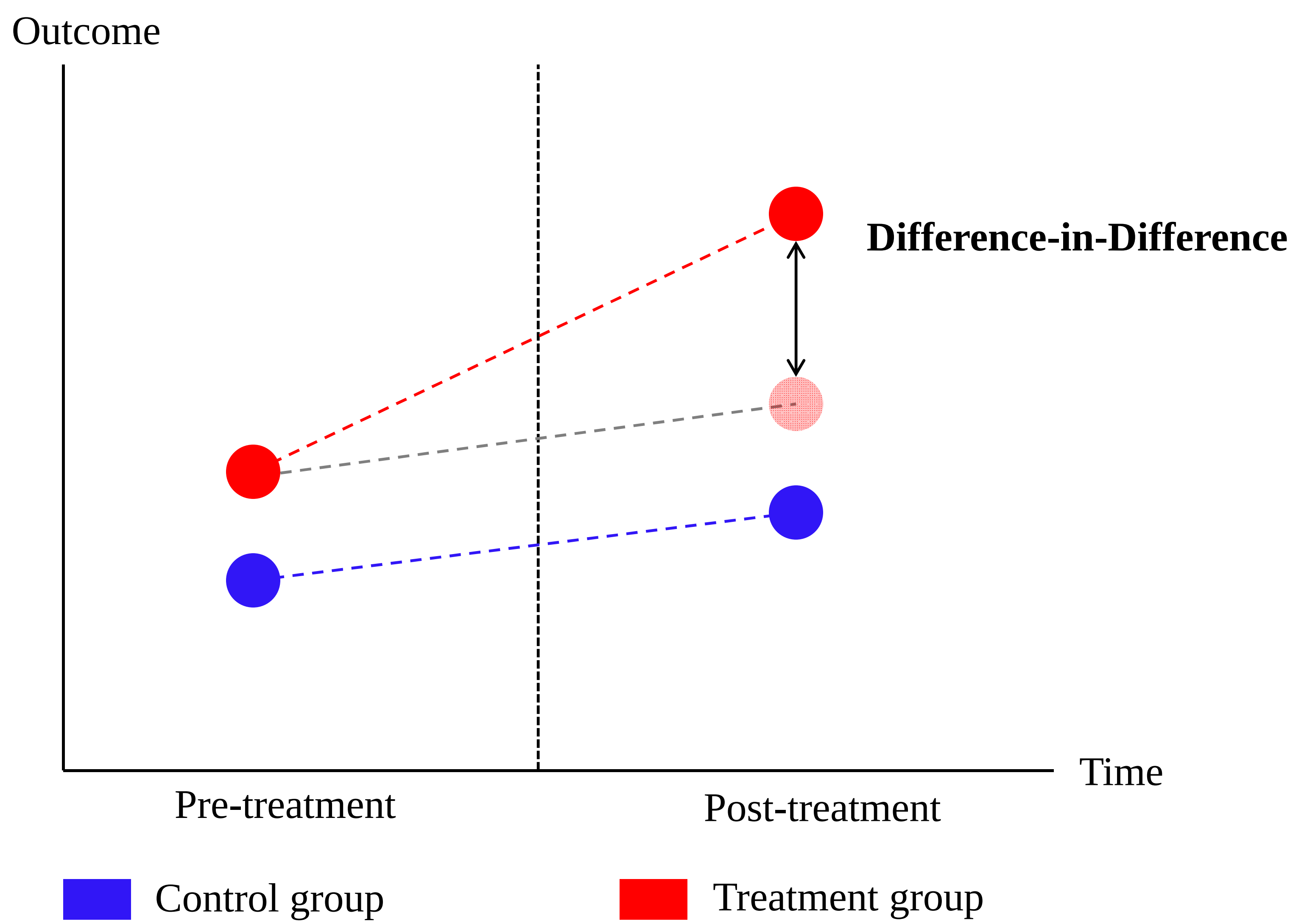


Difference in Difference: Parallel Trend Assumption



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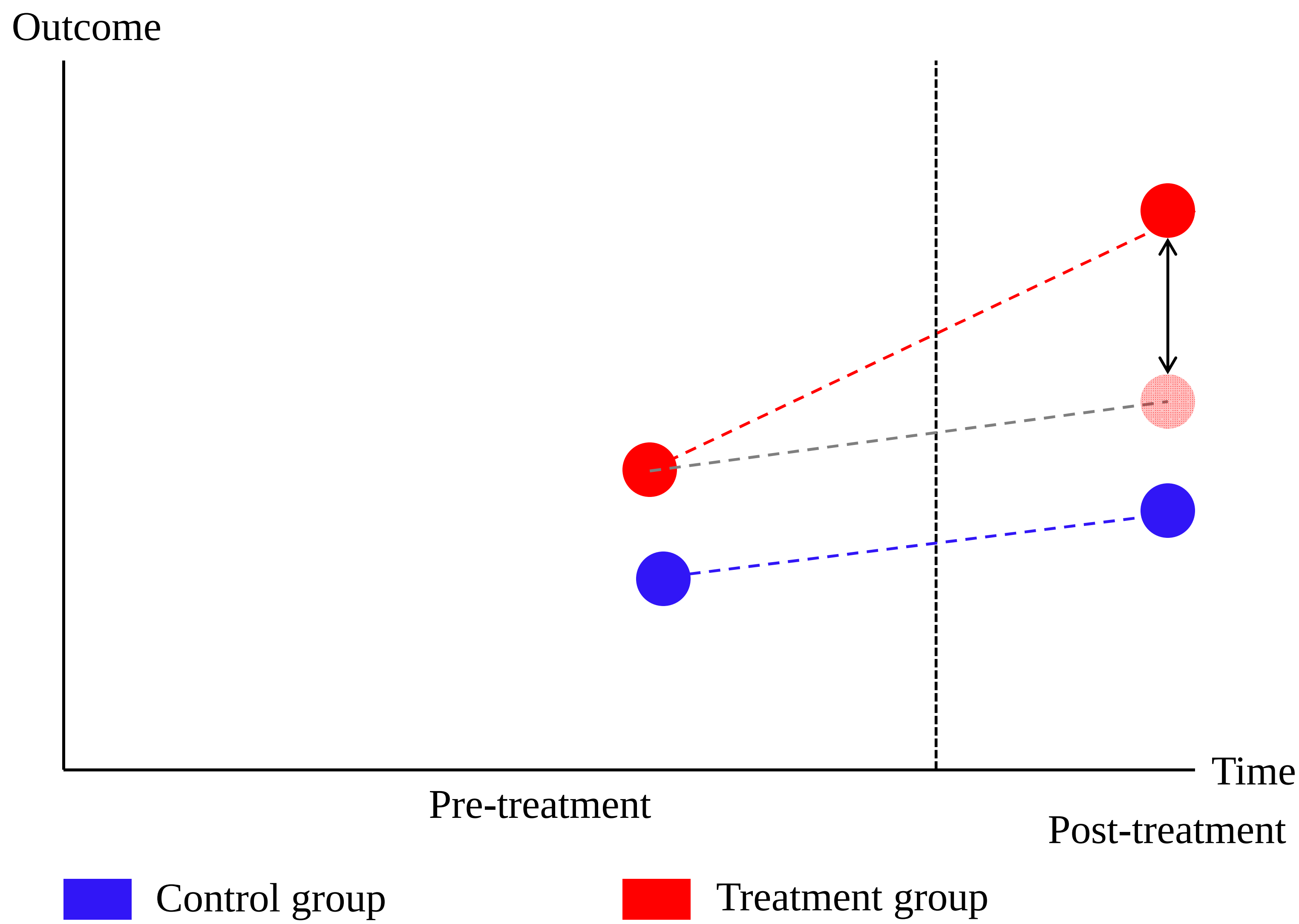

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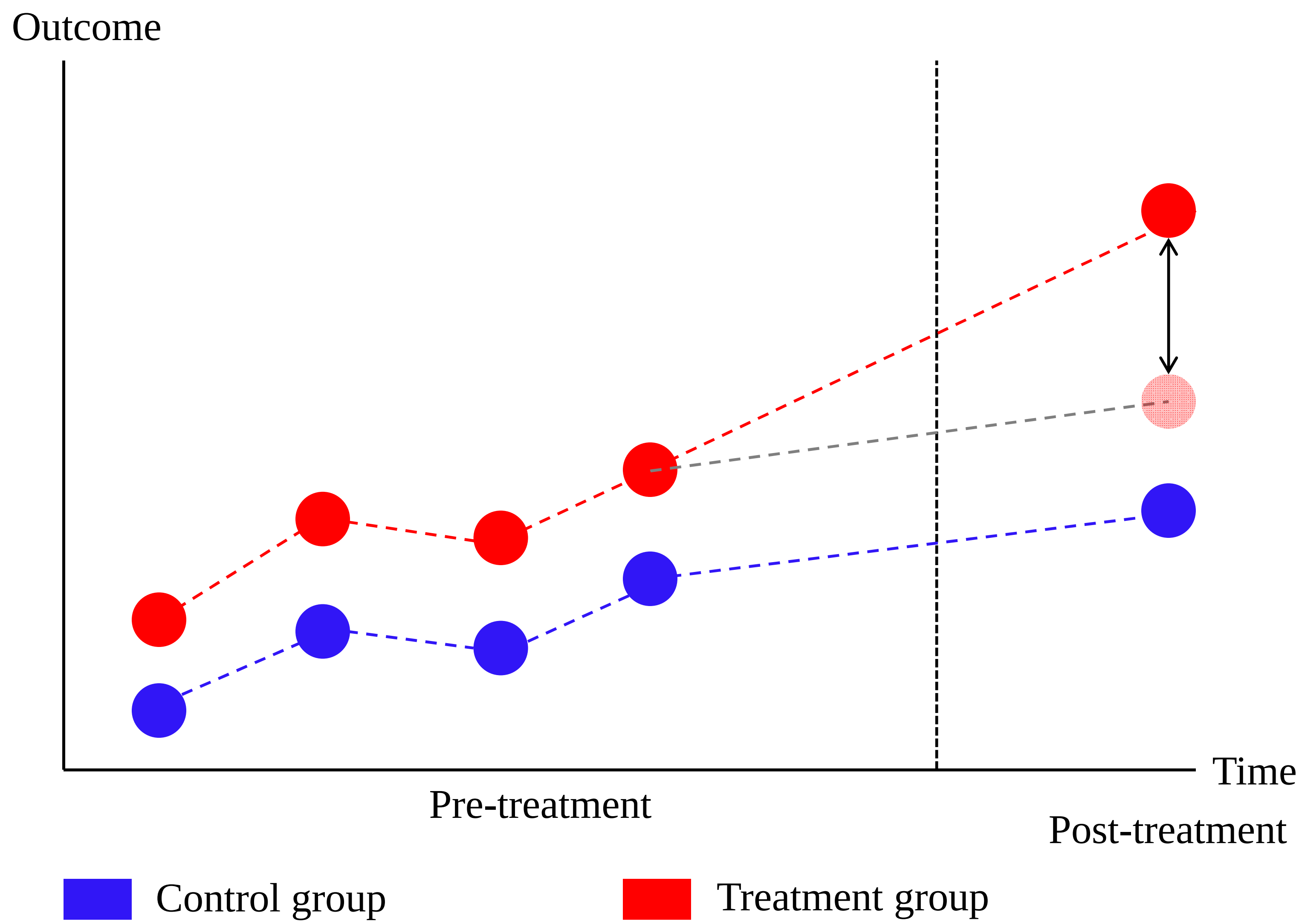
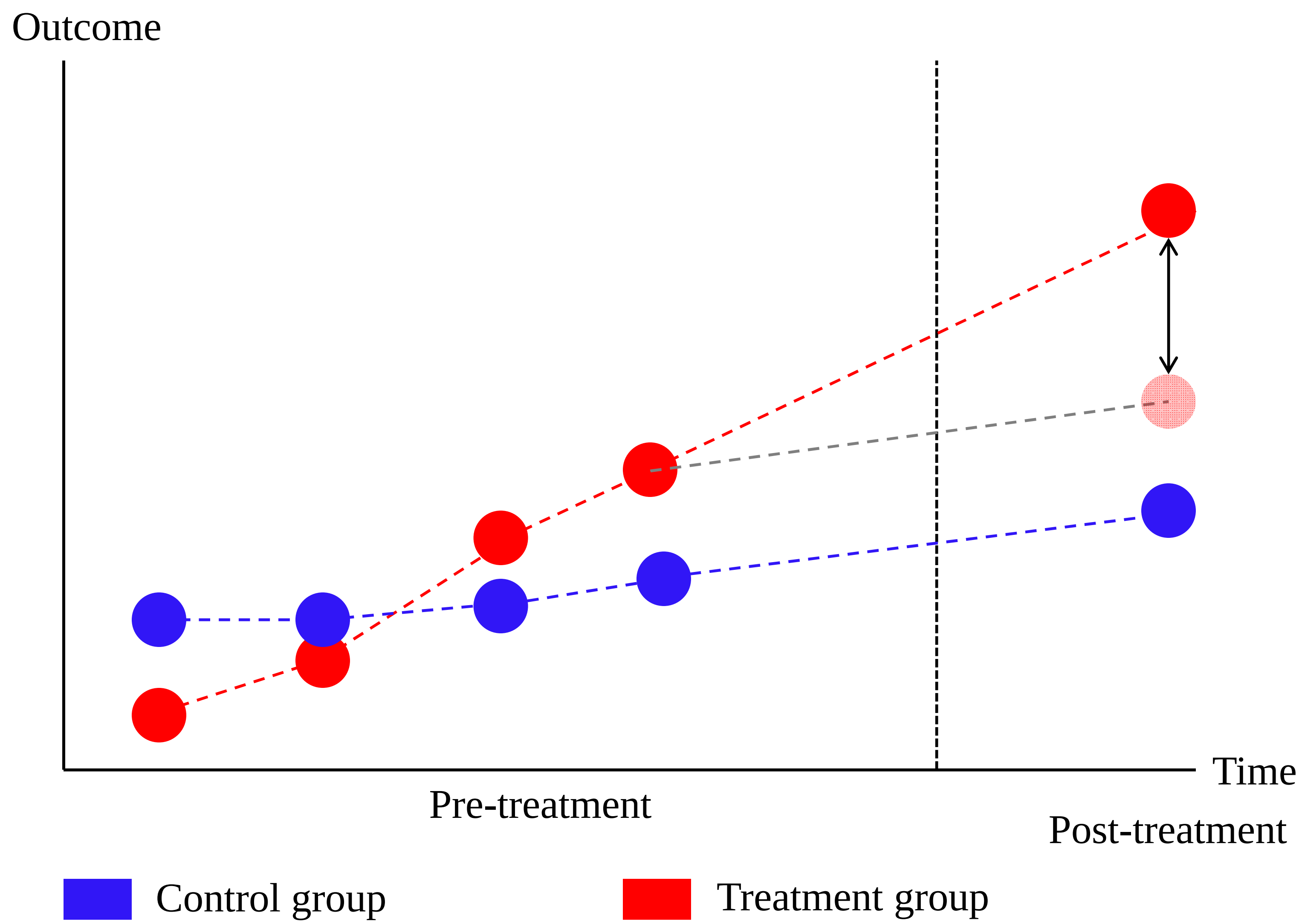


Difference in Difference: Parallel Trend Assumption Violated



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- Balance across treatment and control- selection model to show determinants of treatment not time varying

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- Allow for intervention to occur in years with different outcome variable

Regression Discontinuity Design- RDD

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- Powerful way of addressing selection
- Observable characteristics in T and C can be different
- Common support not needed

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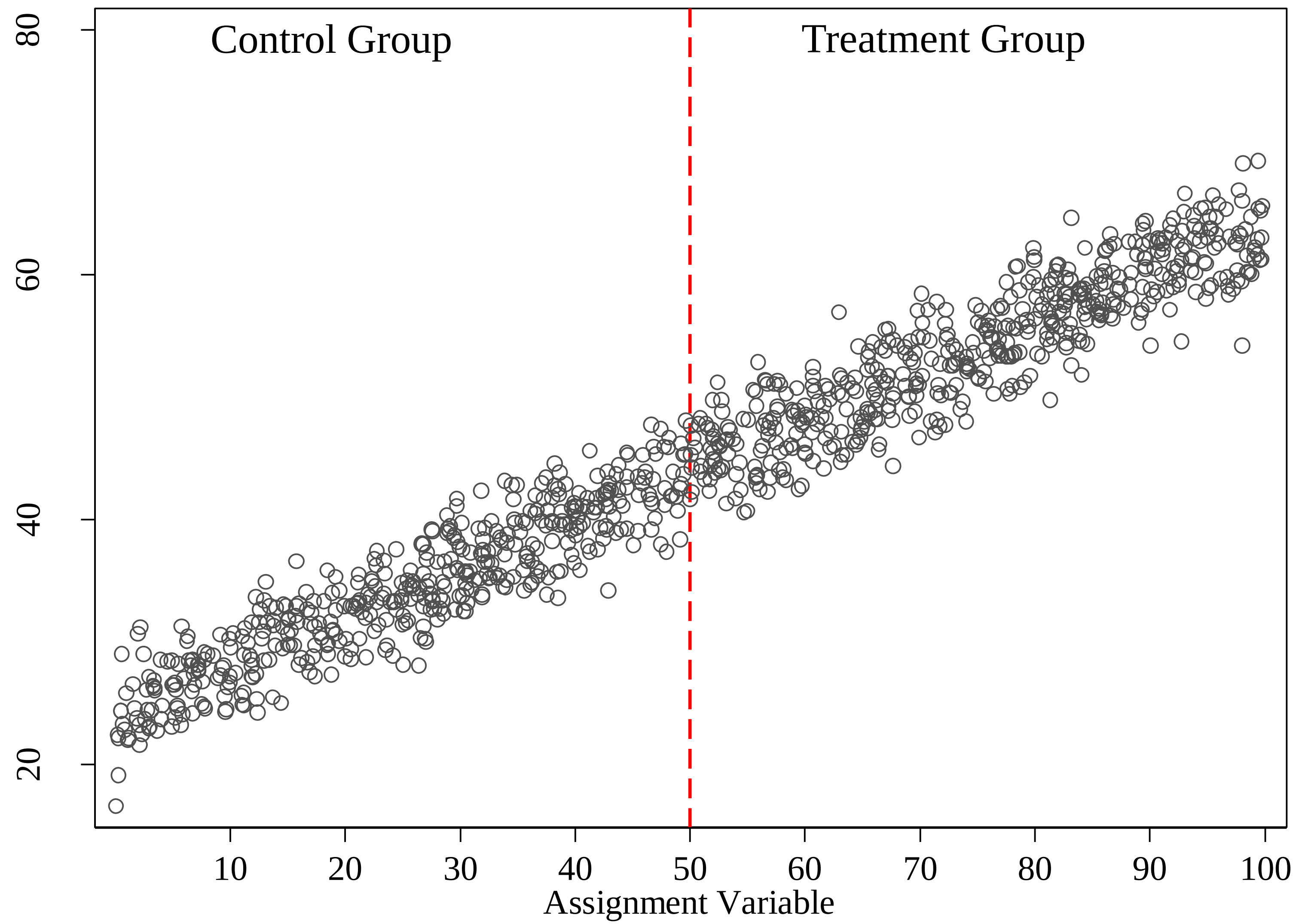
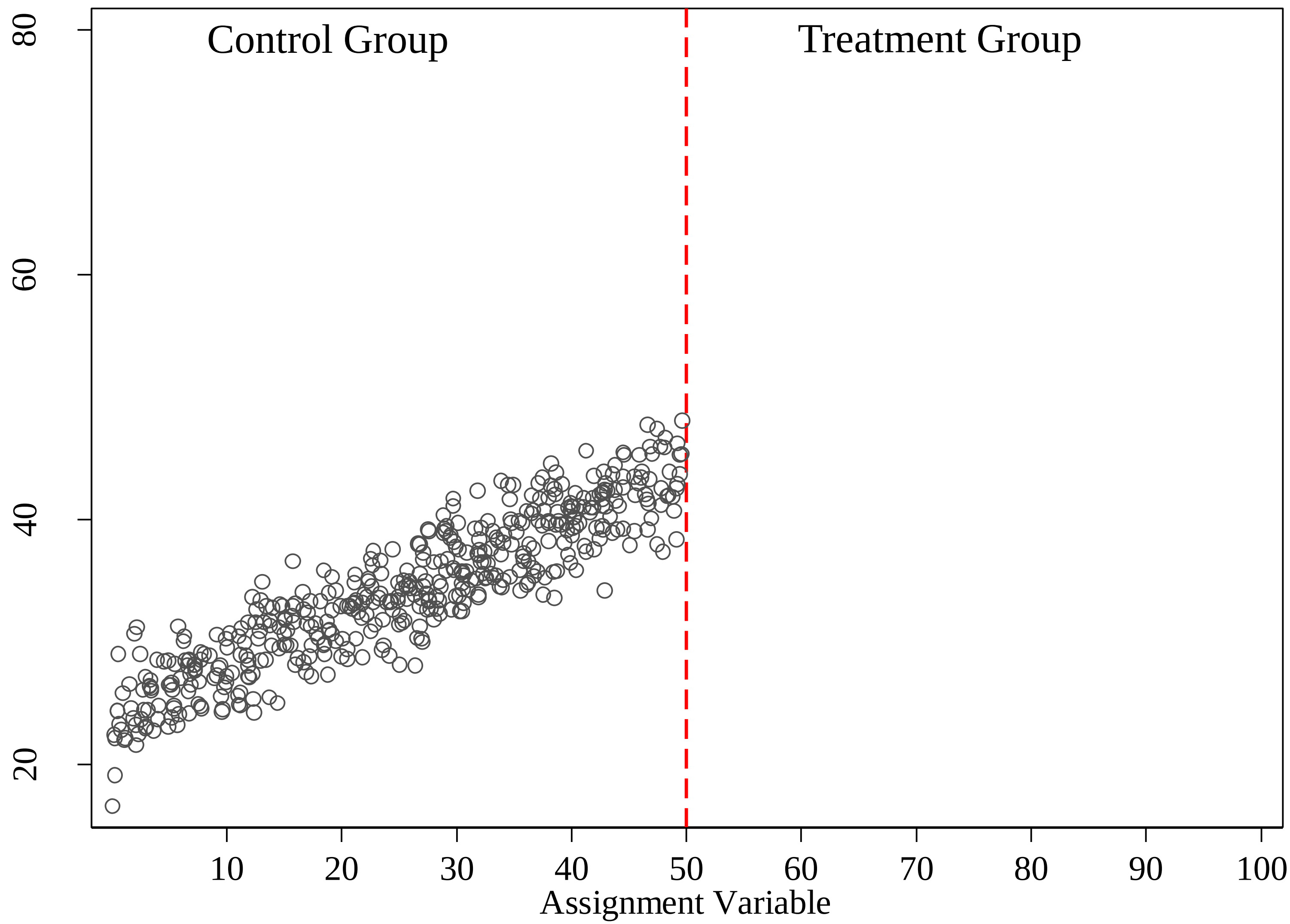
- Selection process completely known and can be modeled
- Regression function between assignment and outcome variable determined

Regression Discontinuity: No Effect



Regression Discontinuity: Significant Effect



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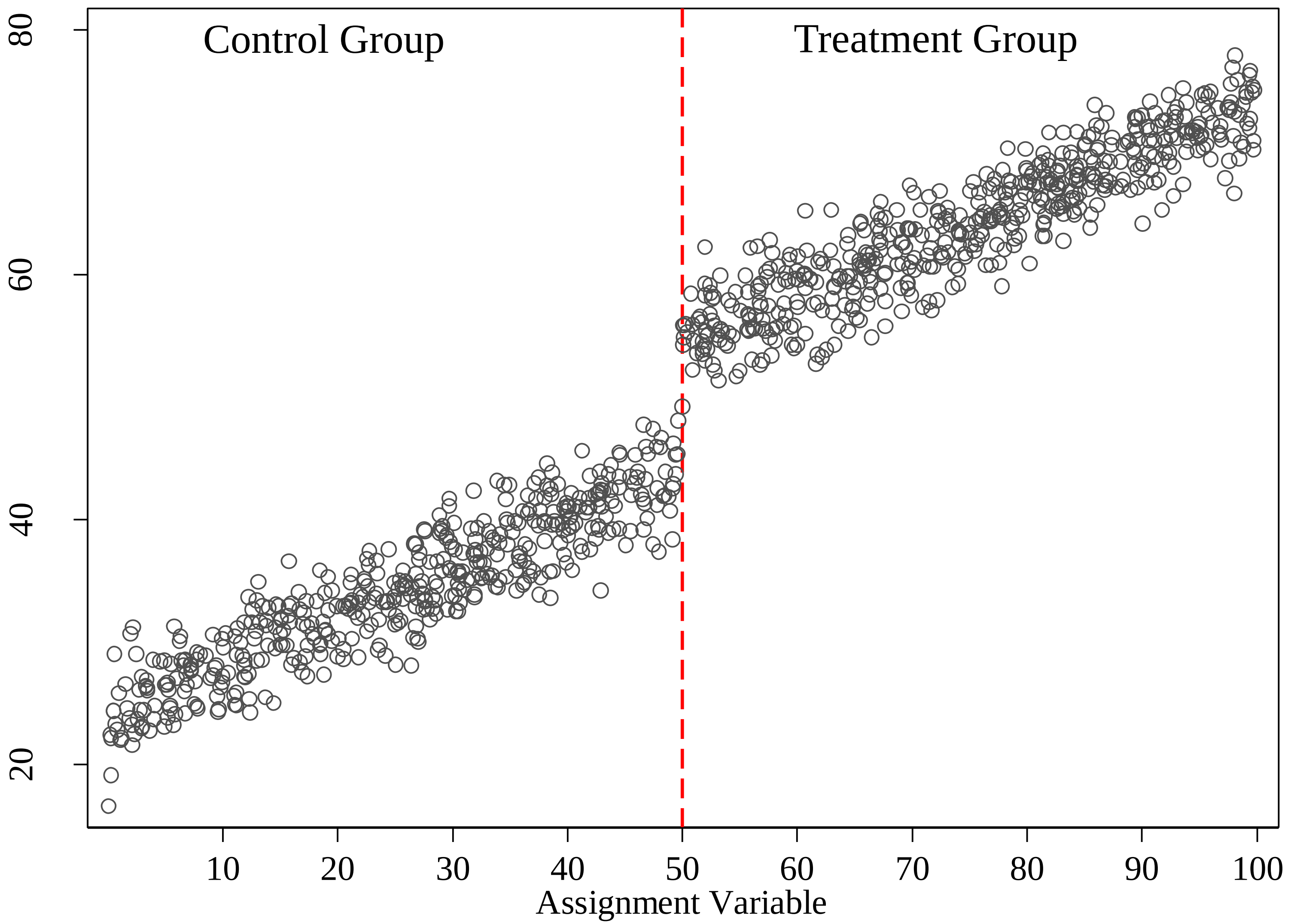

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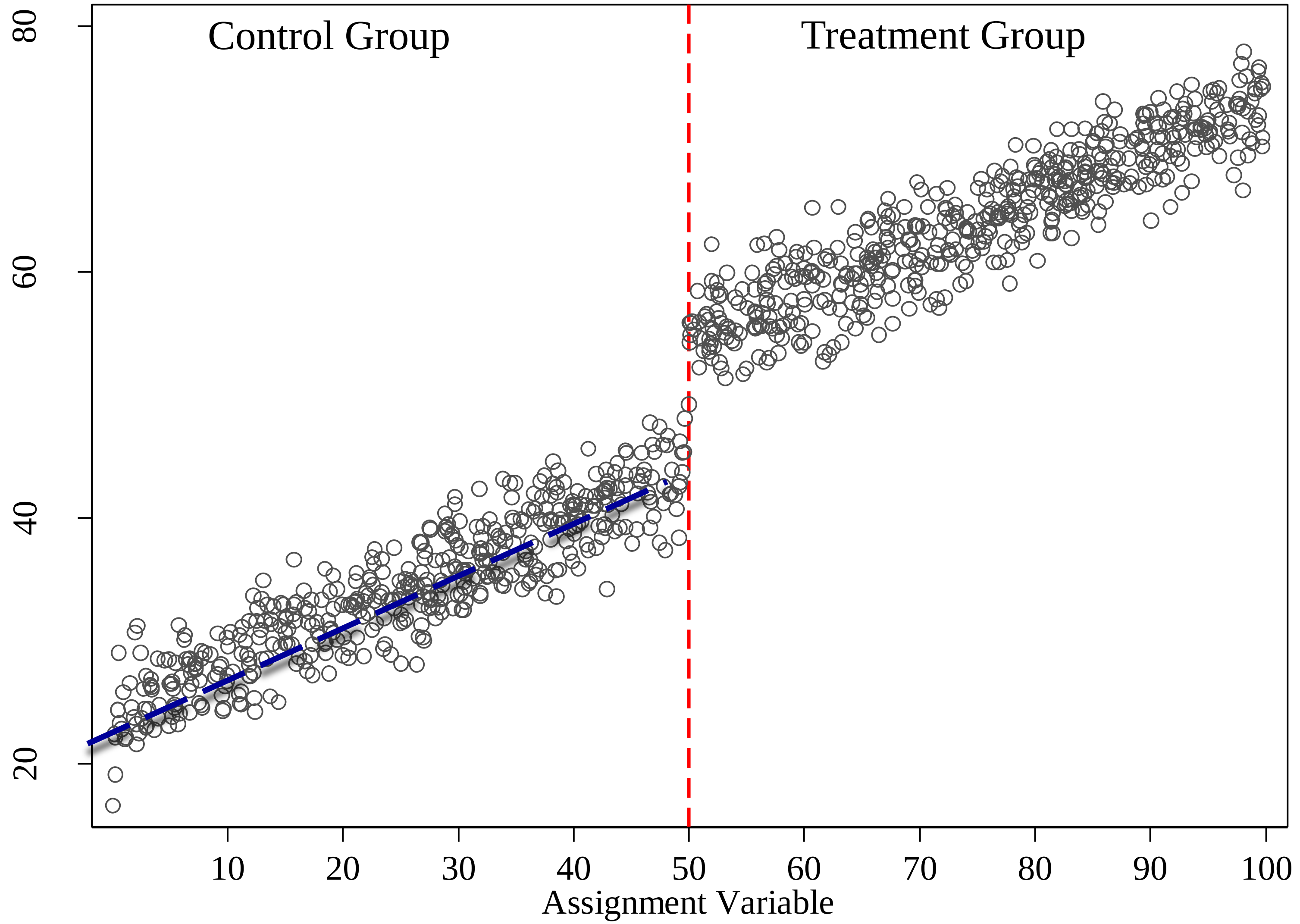

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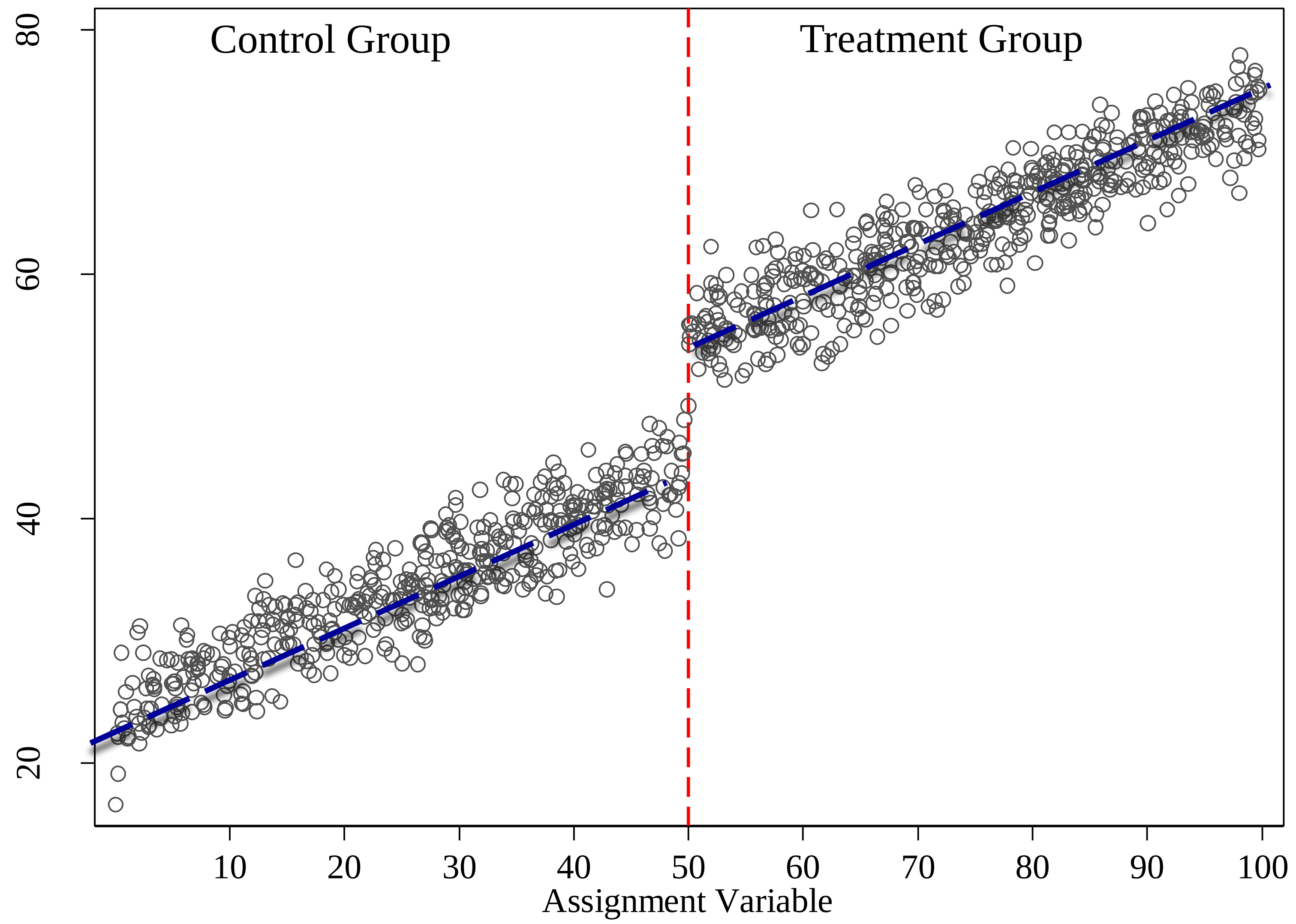

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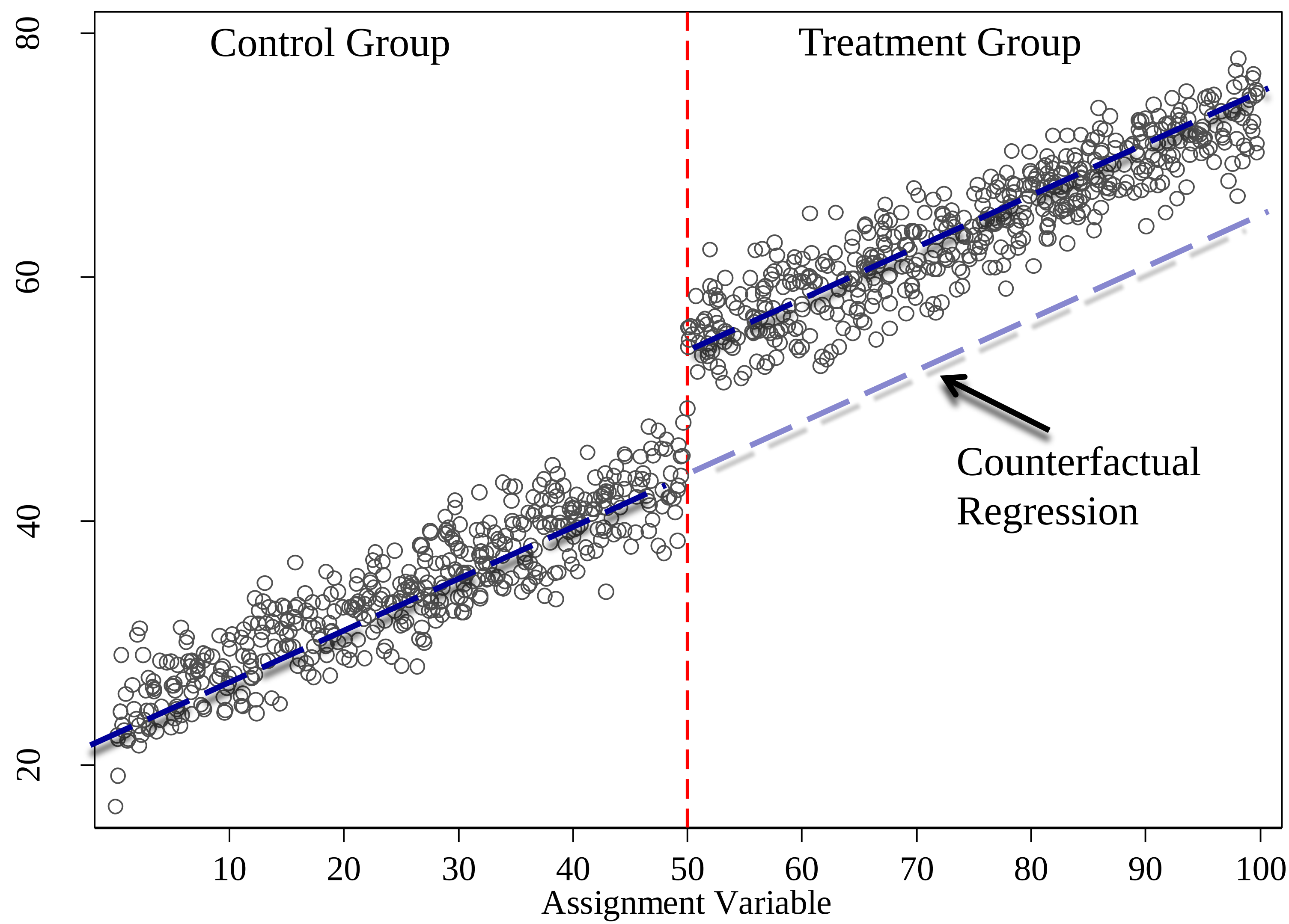

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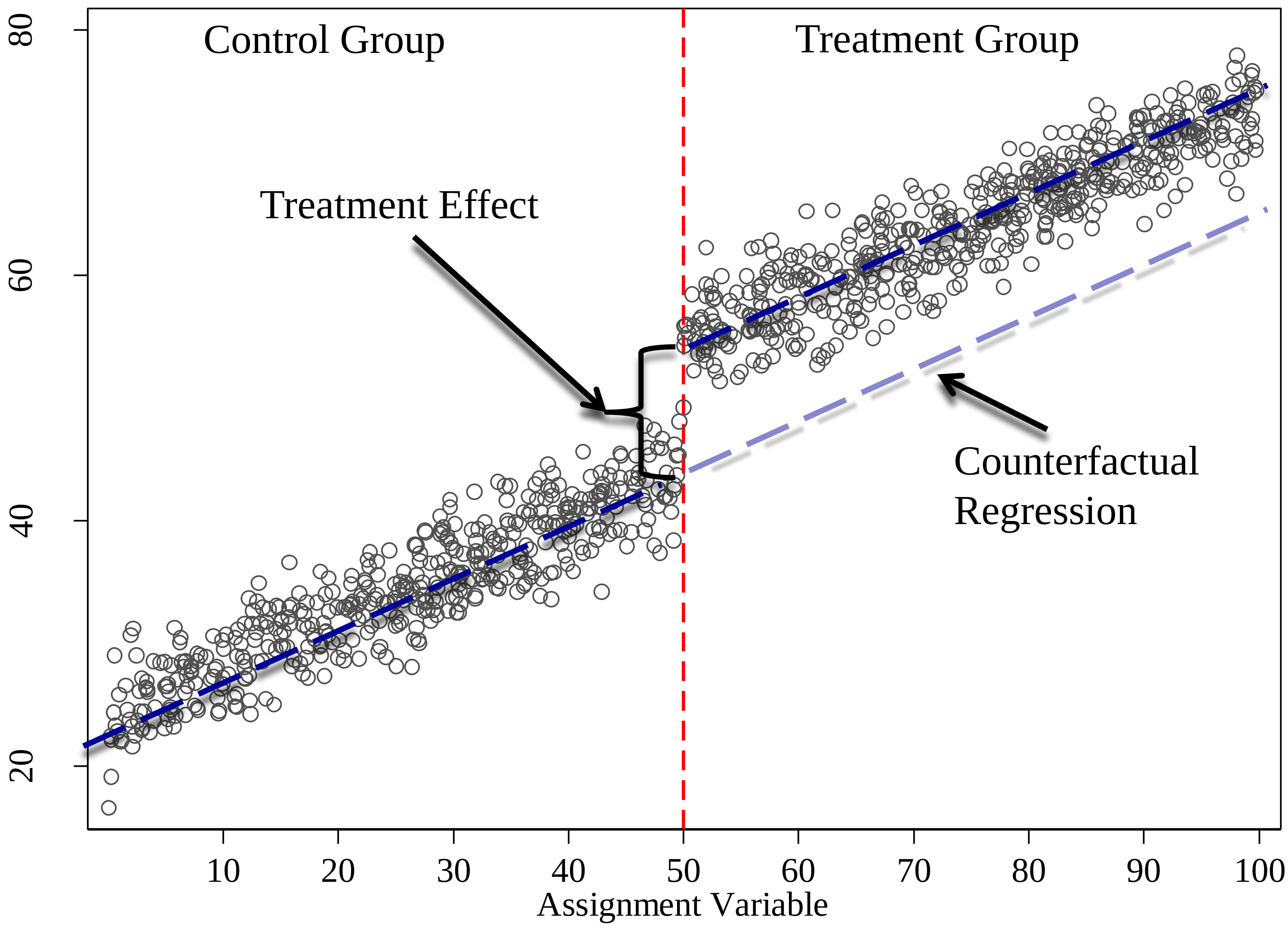

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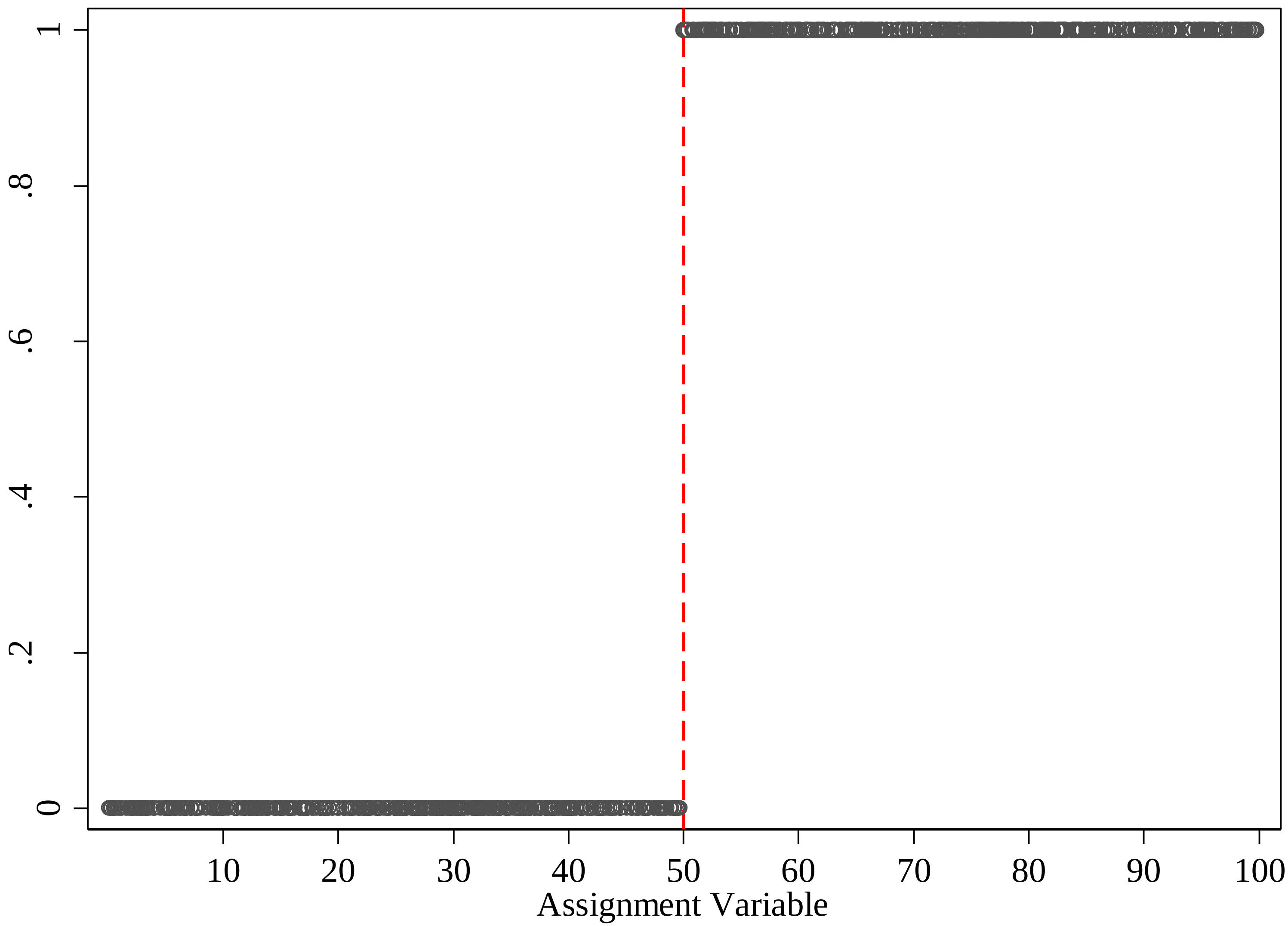
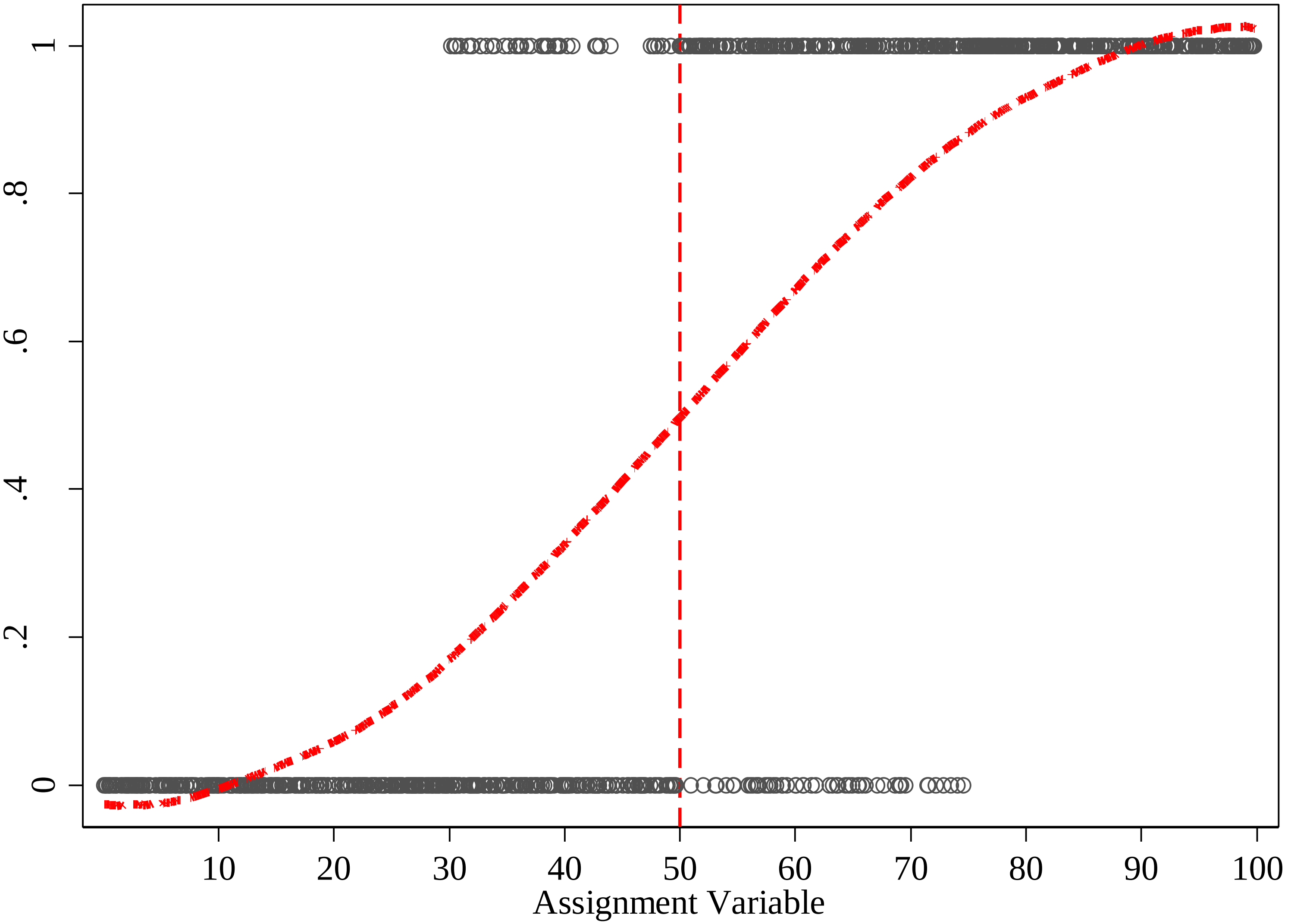
- Probability of treatment should be discontinuous at the cutoff- T sample on one side
- Those offered T should take it up and control groups should not be able to get treated
- Sharp versus fuzzy design require different approaches
- The pr of T changes from 0 to 1 at the cutoff in sharp design
- If the pr does not change very sharply or the over rides are high, use assignment as IV for treatment

Regression Discontinuity: Sharp Design



Regression Discontinuity: Fuzzy Design



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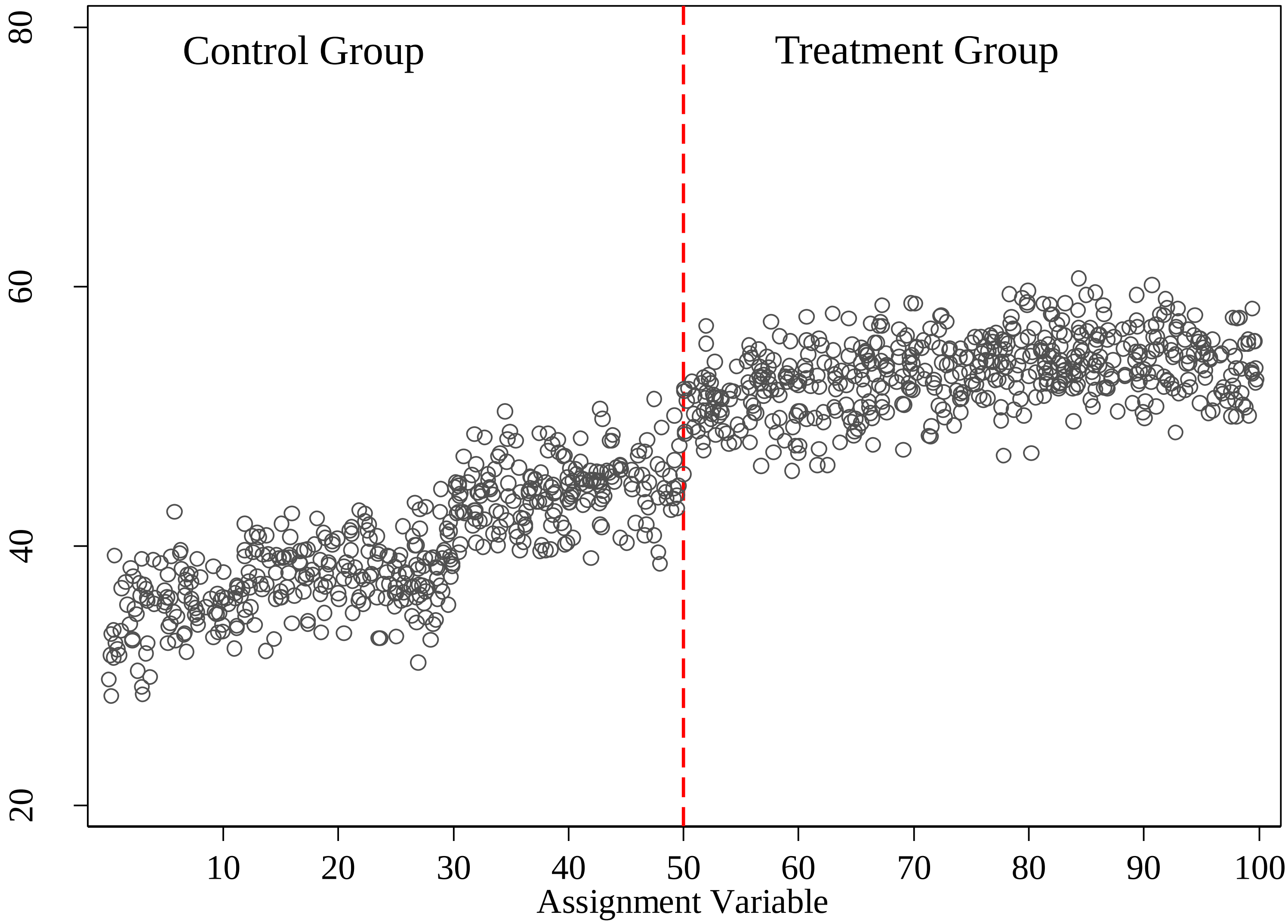
- Discontinuity in regression functions at the cutoff is the treatment effect
- Functional forms can generate spurious effects or biased effects
- Non linear functional forms estimated as linear regression functions is an example

Threats to RD: Nonlinear Functional Form



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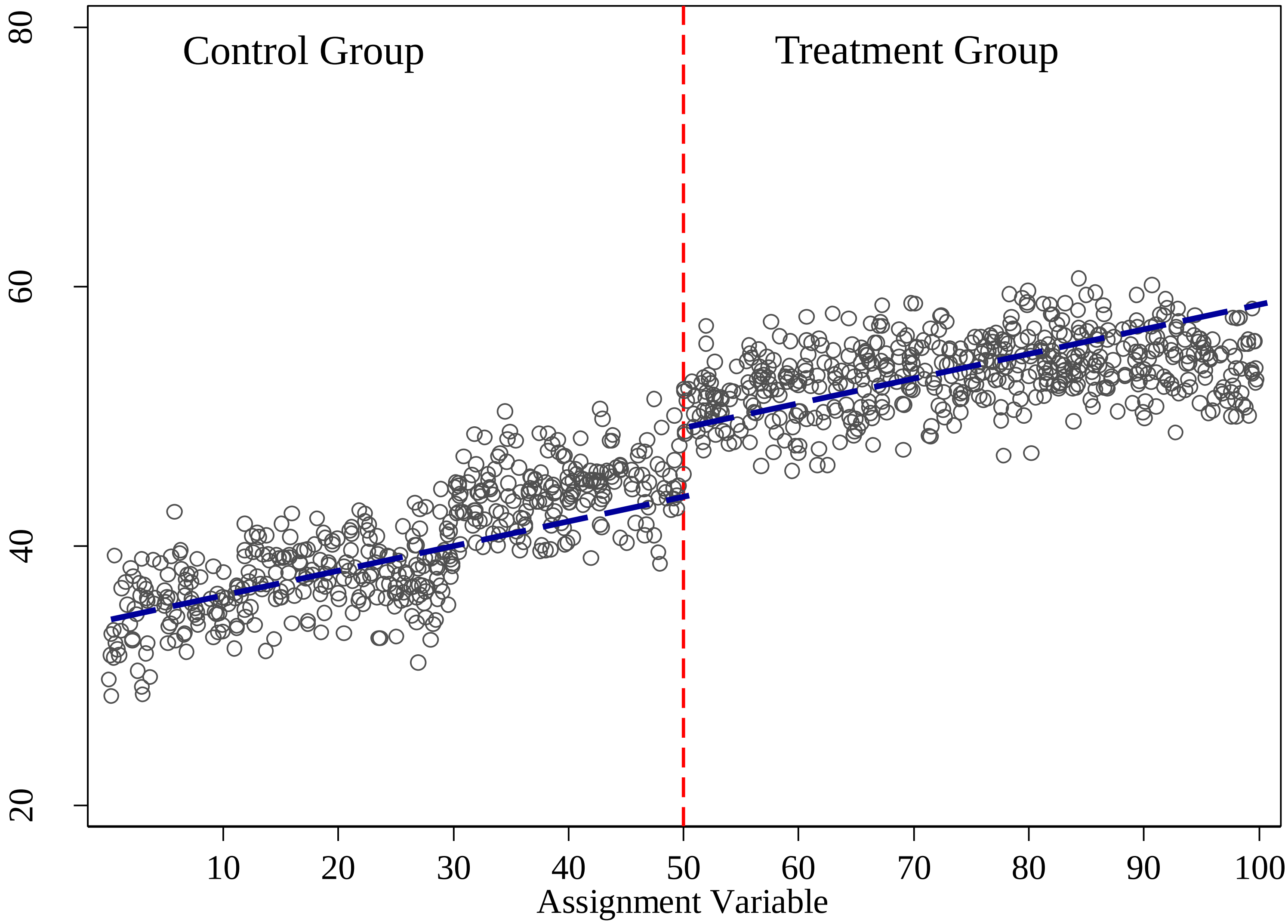

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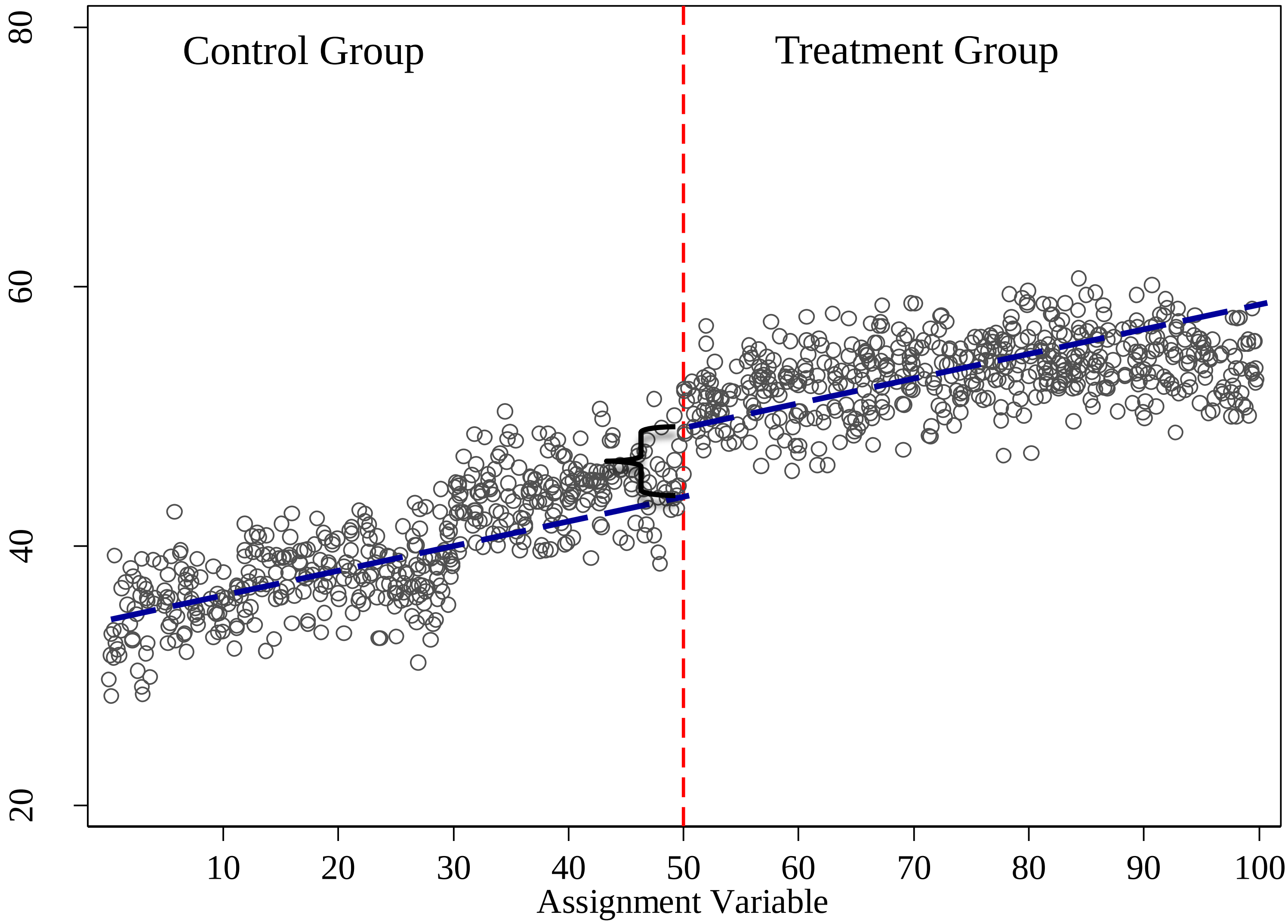

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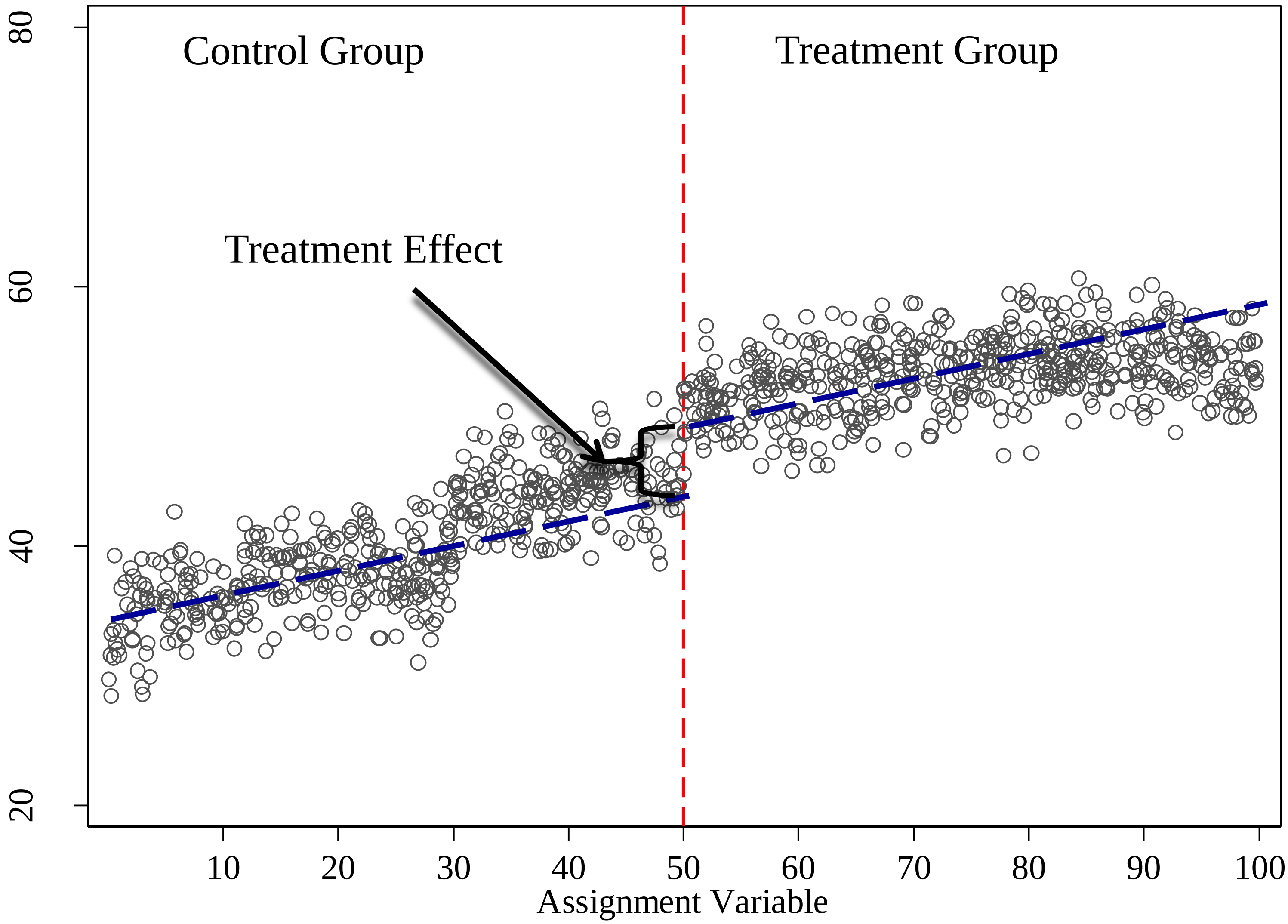

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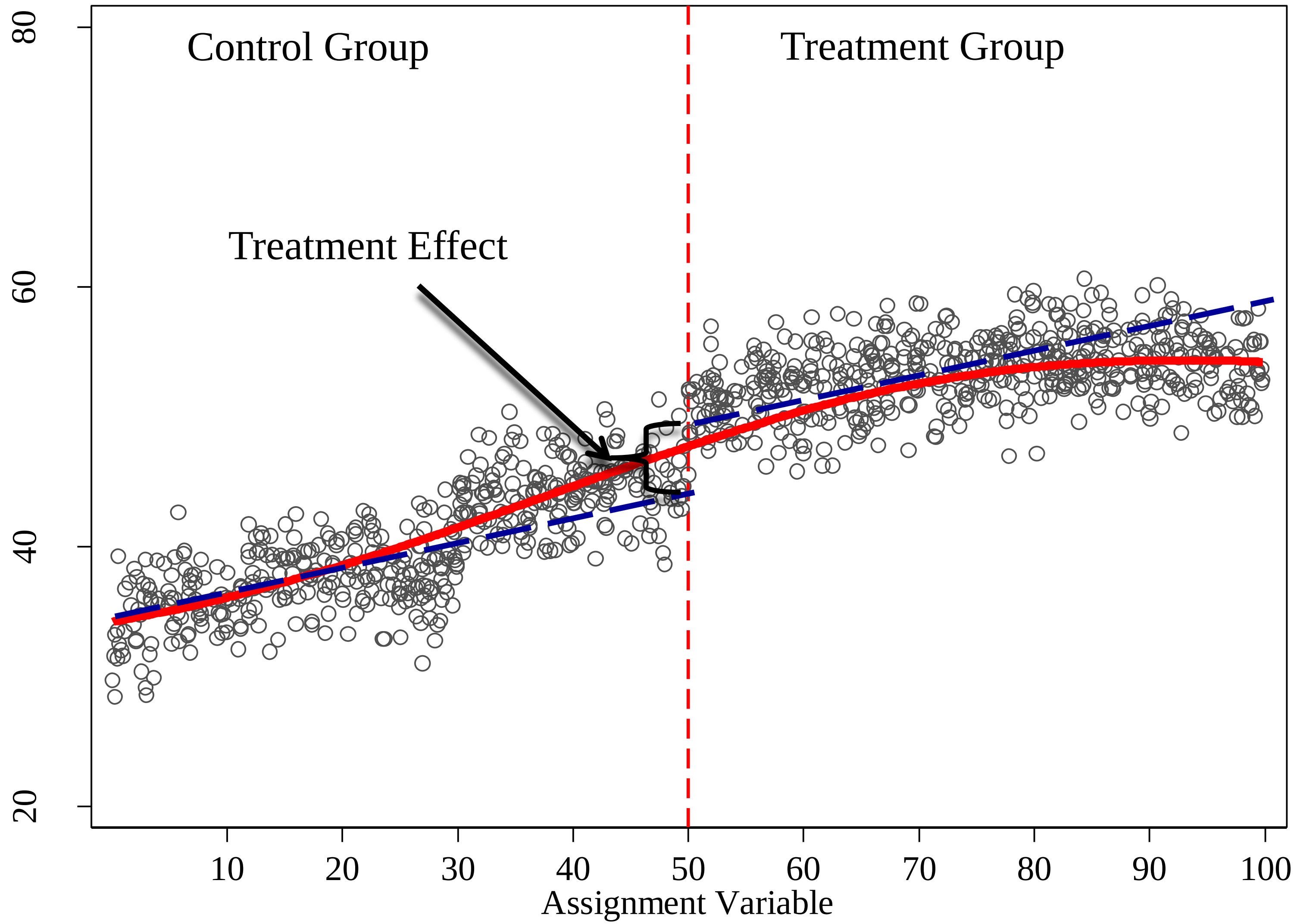

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- Over fitting the model allowing for interaction terms as well
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- Sensitivity analysis to different functional forms

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- Non parametric approaches - local linear regressions

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- Sensitivity to bandwidth and kernel choice

RDD- Functional Form

- Non parametric approaches - local linear regressions
- Sensitivity to bandwidth and kernel choice
- In semi parametric approaches, smooth function estimated with splines and covariates can be controlled

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- Cutoffs should not be manipulated
- Testing for manipulation, can perform Mcrary's test
- Other potential outcomes should be continuous to avoid alternative confounding interpretations
- Test for continuity of several available control variables

Threats to RD: Manipulation of the Assignment Variable

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McCrary Test (2008)

- Statistical test for testing discontinuity of the assignment variable at the cutoff point

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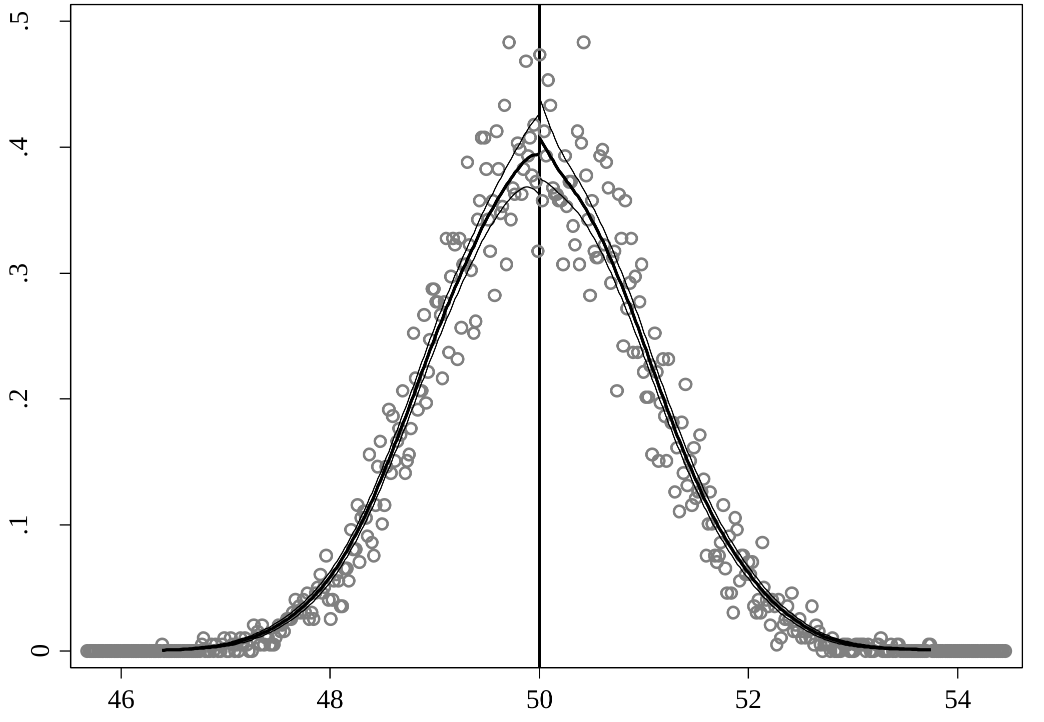
McCrary Test (2008)

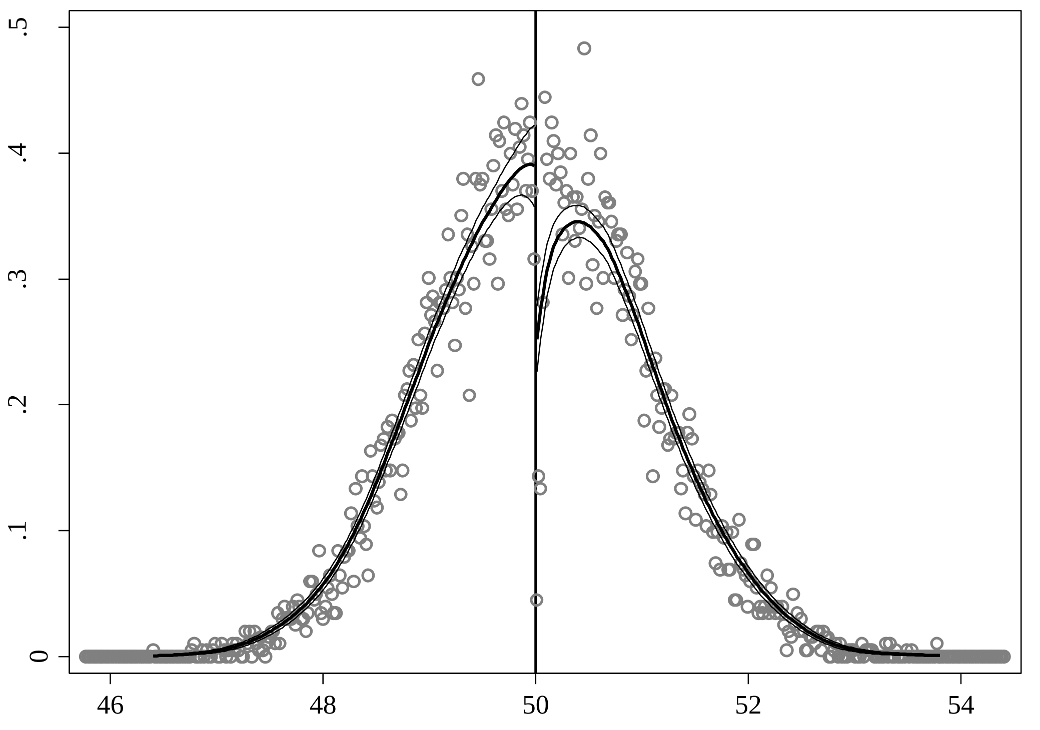
- Statistical test for testing discontinuity of the assignment variable at the cutoff point
- Assignment variable satisfying “McCrary” Test



Threats to RD: Manipulation of the Assignment Variable

McCrary Test (2008)

- Statistical test for testing discontinuity of the assignment variable at the cutoff point
- Assignment variable violating "McCrary" Test



RDD- LATE Estimator

- The limitation of RDD - effect isolated at cutoff
- Cutoff may not be policy relevant or results may not be externally valid
- RD frontier can arise if cutoff varies by years or sites
- Can pool different cutoff to get a more general estimate for the range over which cutoff varies

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- Can pool different cutoff to get a more general estimate for the range over which cutoff varies
- More generalizable but masks heterogeneity