Estimating treatment effects for policy evaluation

Thomas Meath

Hypothetical Situation

Intervention

OHSU implements an algorithm to flag patients with a high risk of post-discharge infection

Outcome measure

90-day readmission rates

What do we mean by treatment effects?

Two parallel universes

one where the intervention occurred

one where the intervention did not occur

Policy effect = difference between the outcomes in those universes

$$E(Y = 1|T=1) - E(Y=1|T=0)$$

Causal inference with observational data?

The Dream:

To be able to say, this intervention caused the outcome to change by X

The Reality:

There are a number of other things that may have caused changes to the outcome

Each evaluation method attempts to adjust or account for some of those alternative hypotheses

Prediction vs Inference

Prediction problems:

How accurately can we predict the outcome?

We care primarily about the accuracy of our prediction, not the individual coefficients.

We can use whatever model produces the best accuracy!

Prediction vs Inference

Inference problems:

How much does our treatment change the outcome?

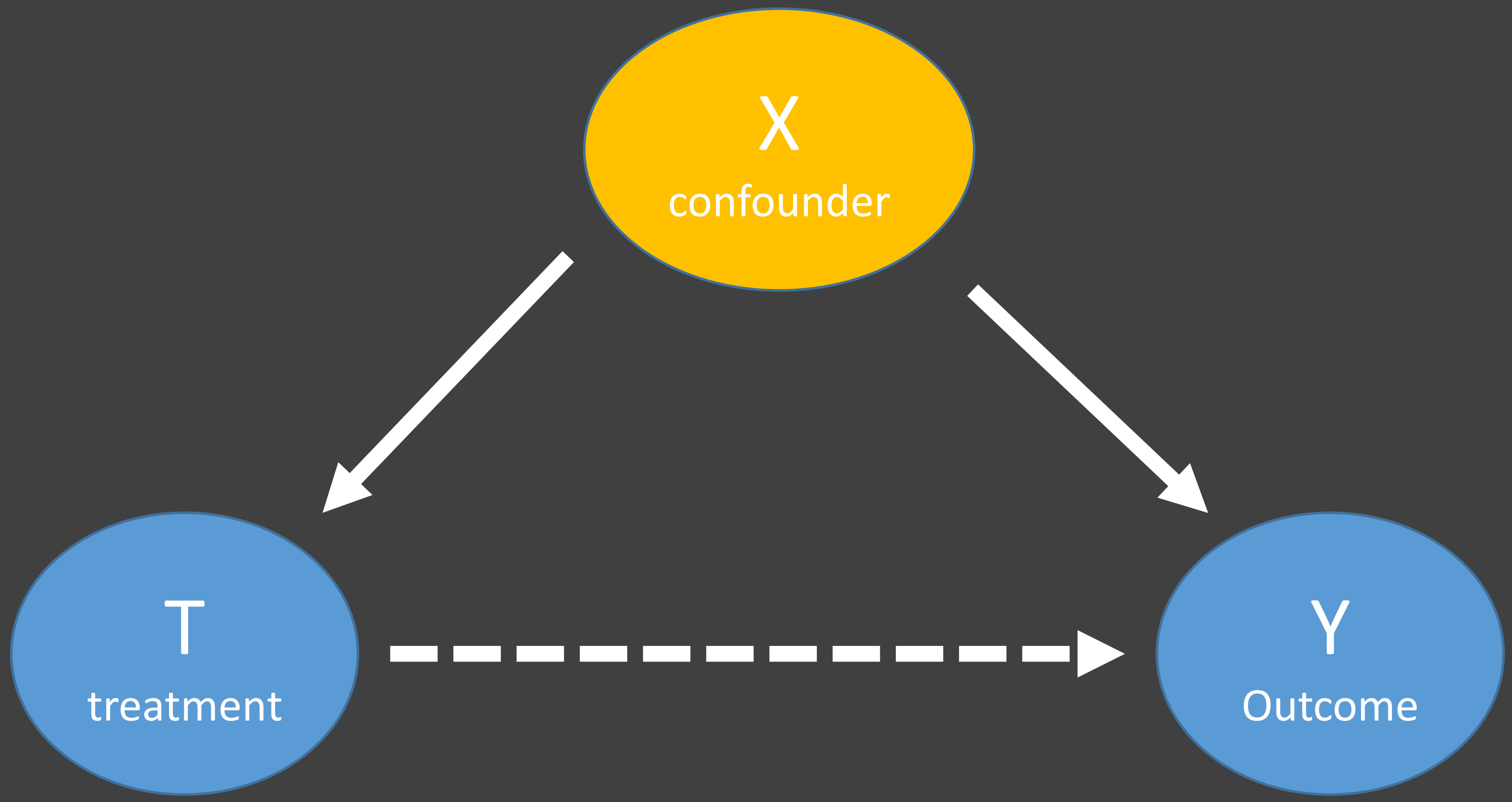
We care very much about the individual coefficients, and it is important to correctly isolate the correct change.

This means the form of the underlying model is very important.

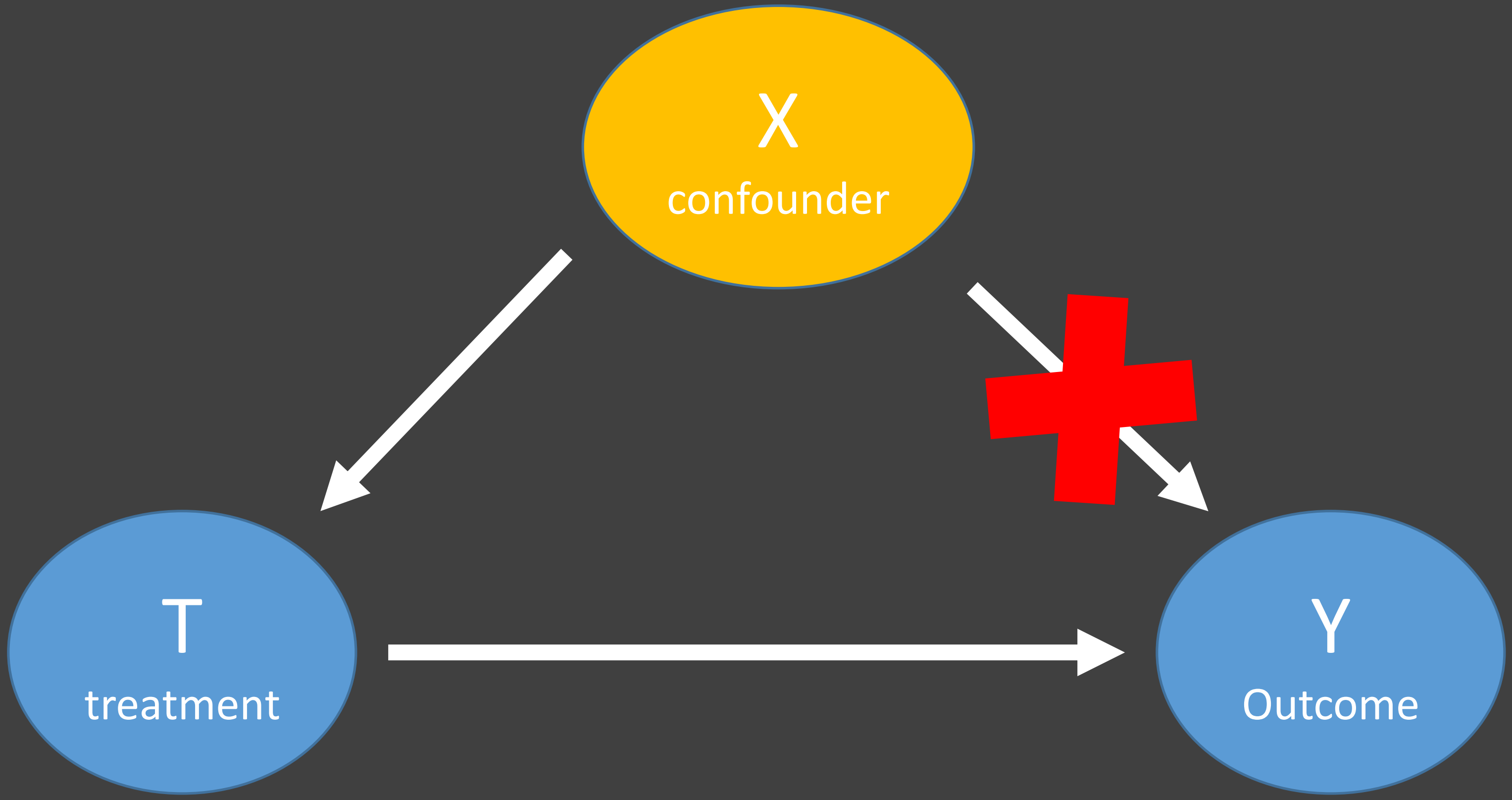
(See Berkson's Paradox)

Classic confounding

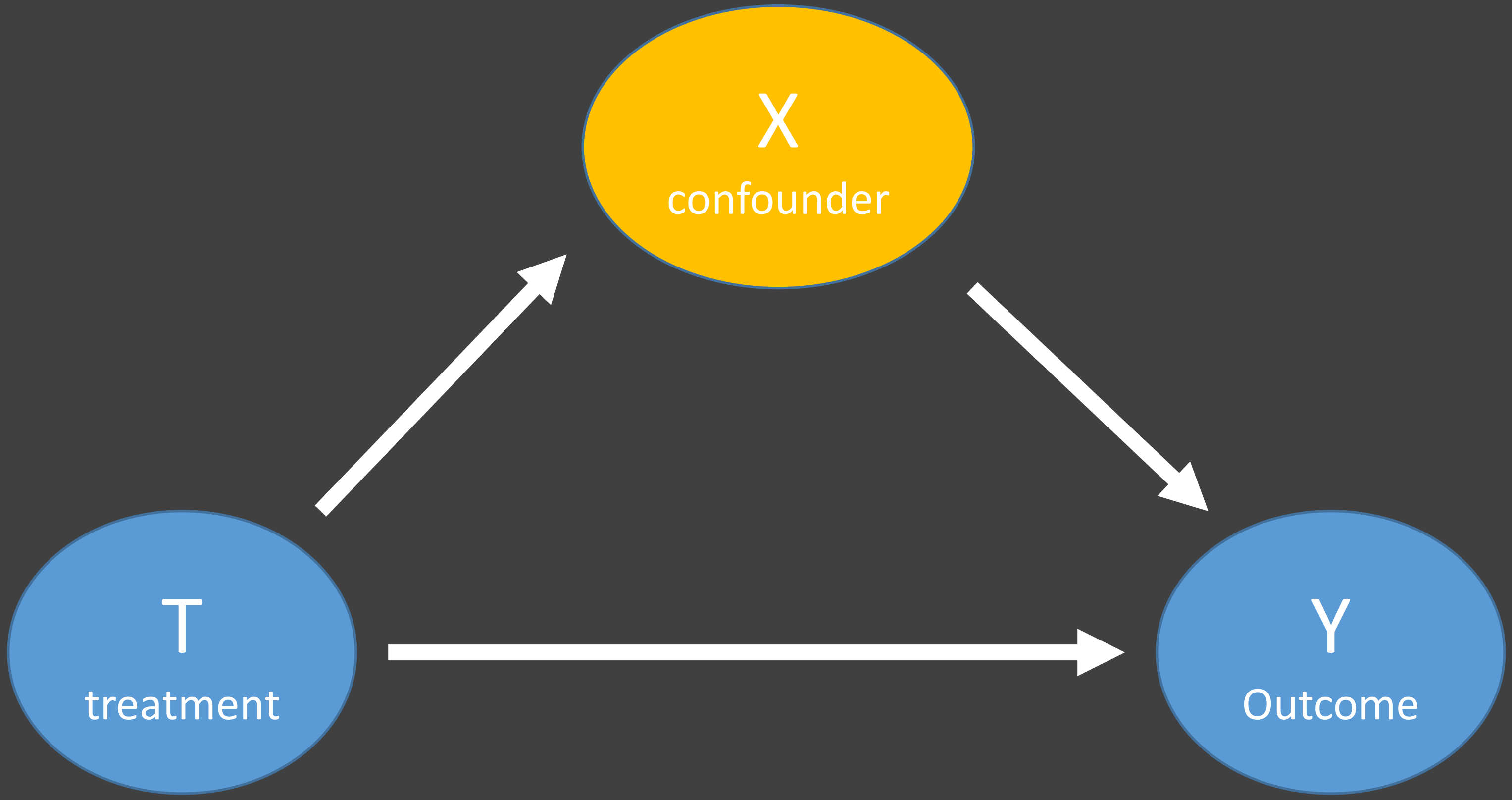
Classic confounding



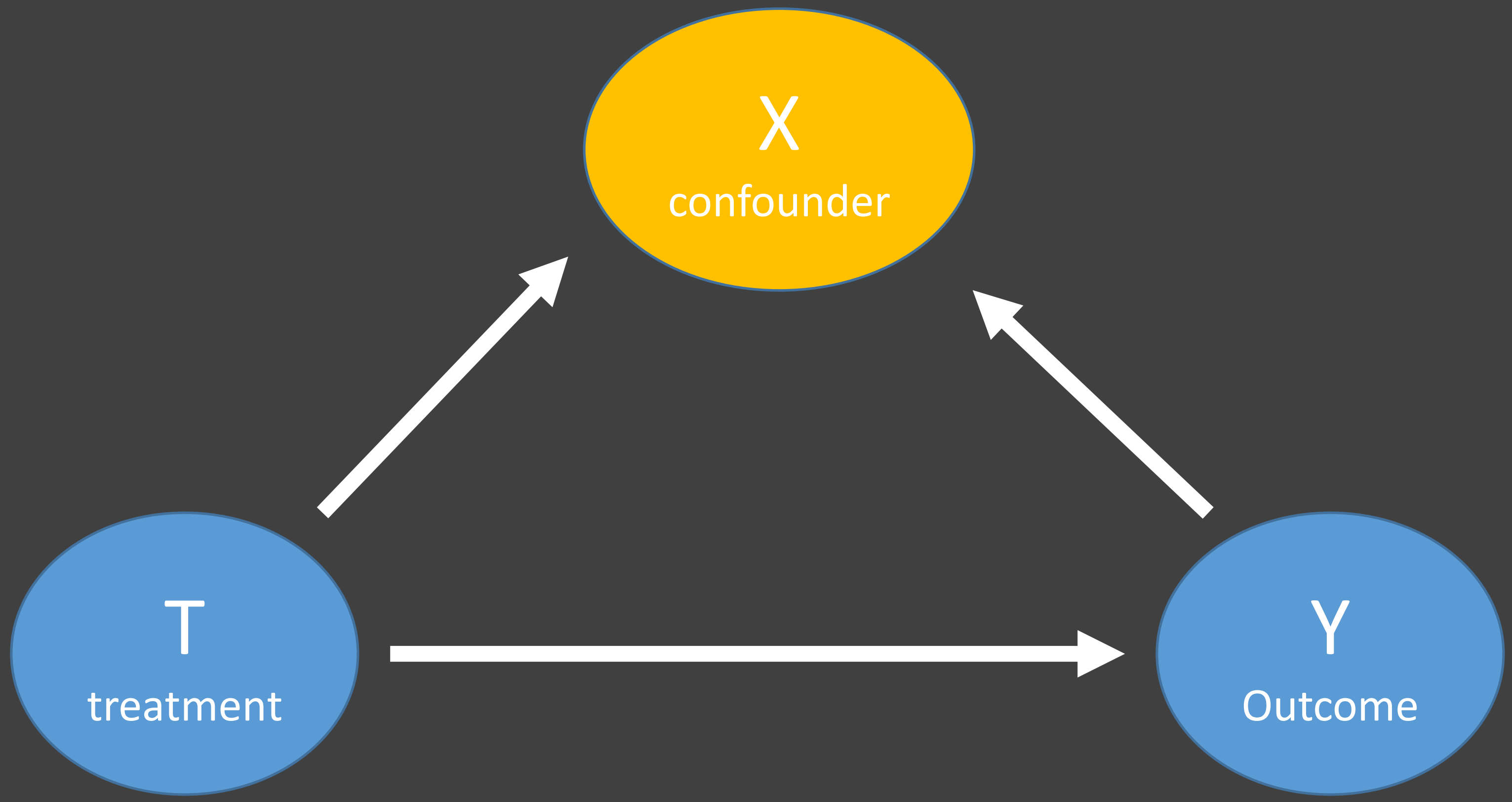
Classic confounding – adjusted out



Not confounding – in the causal pathway



Not confounding – downstream of outcome



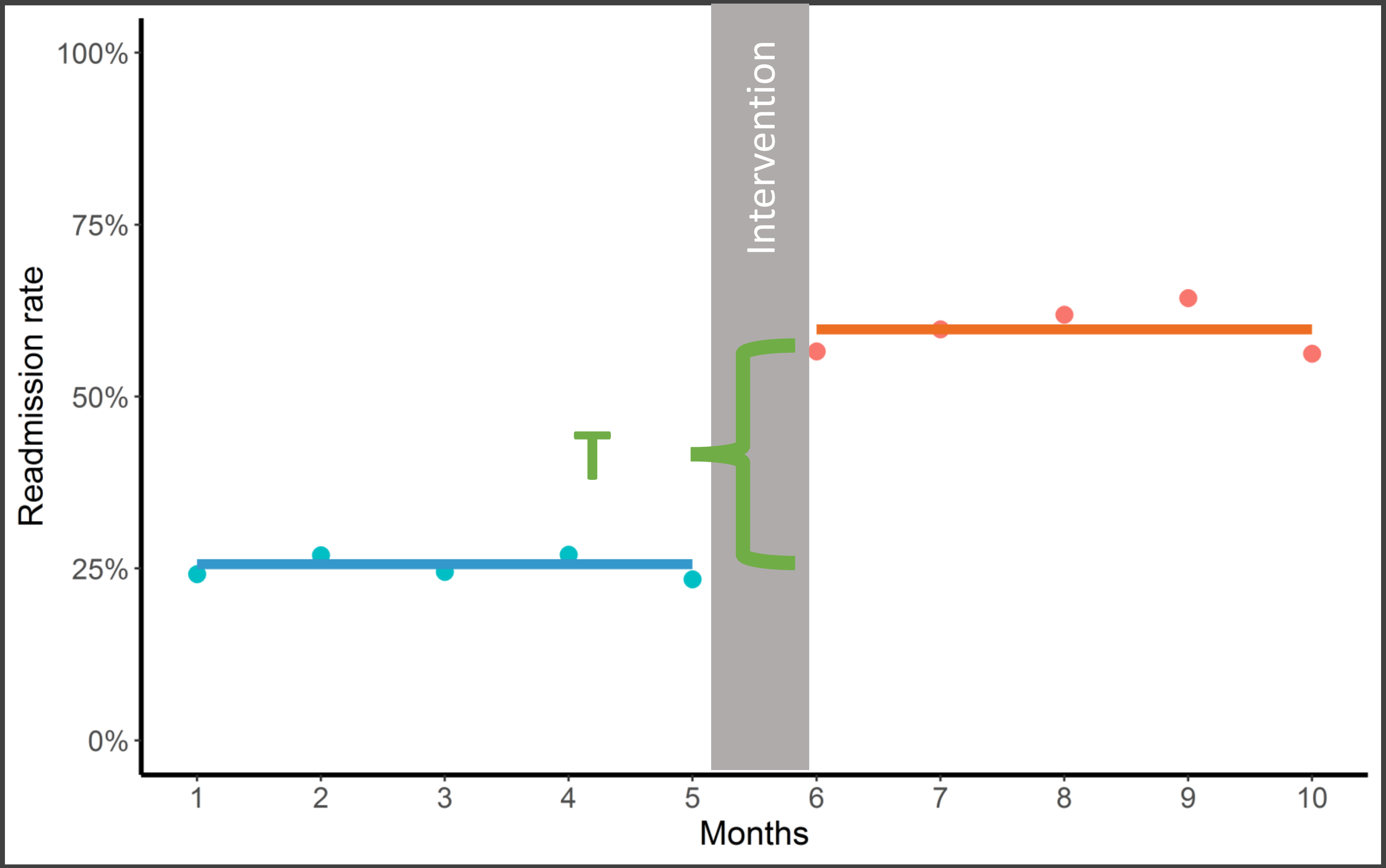
Pre-post tests

Difference between pre- and post-intervention outcomes

$$Y = \beta_0 + \boldsymbol{\beta_1 * PostPeriod} + \beta_x * X + \varepsilon$$

Assumptions:
Outcomes would stay the same over time in the absence of the intervention

Pre-post tests



Pre-post tests

Assumptions:
Outcomes would stay the same over time in the absence of the intervention

Protects against:
Baseline value for outcomes

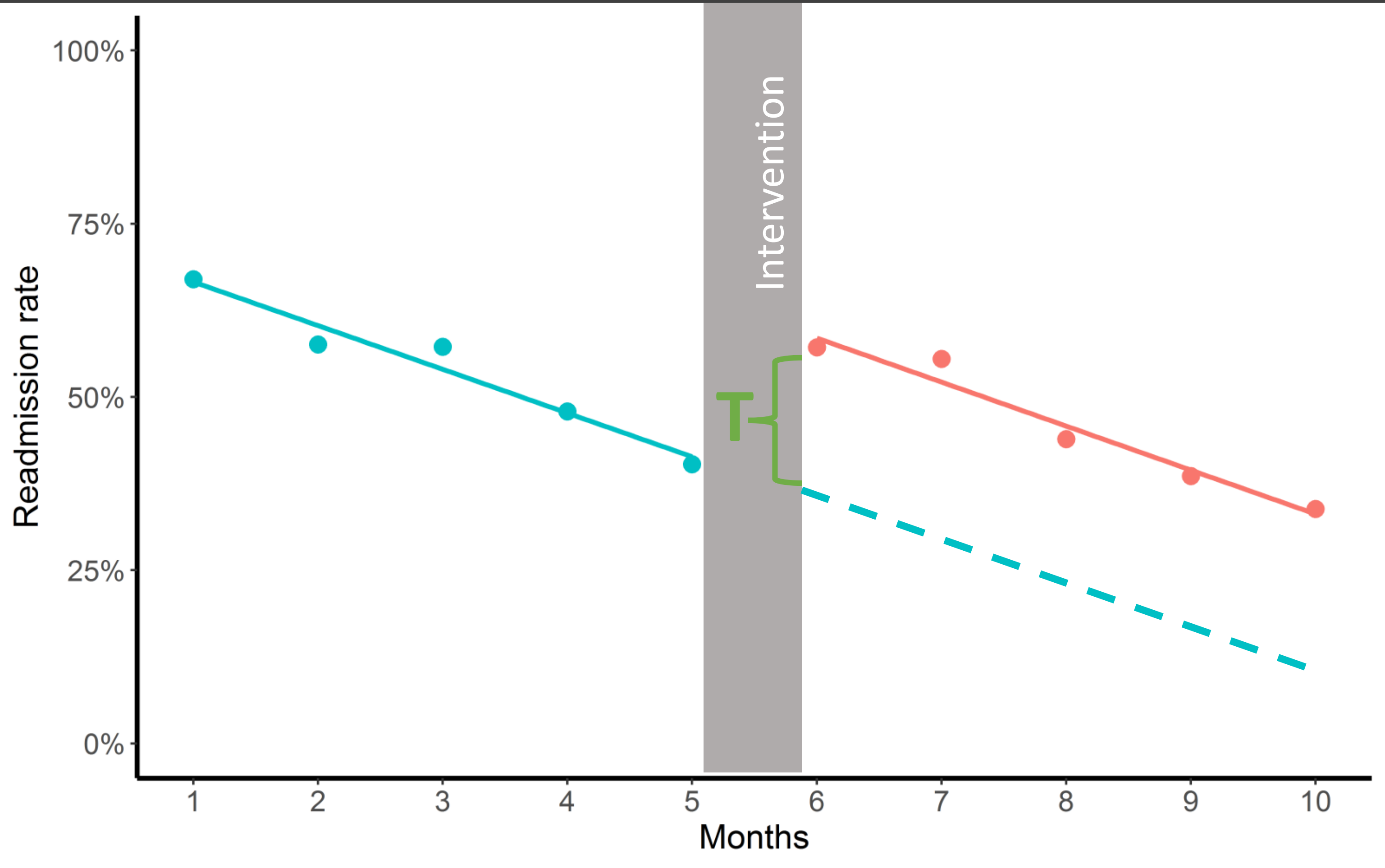
Does not protect against:
If the outcome was already getting better or worse
Anything that changed outcomes unrelated to the intervention

Interrupted Time Series (ITS)

Difference between outcomes in the post-intervention period and predicted outcomes assuming no intervention

$$Y = \beta_0 + \beta_1 * f(Time) + \boldsymbol{\beta_2 * PostPeriod} + \beta_x * X + \varepsilon$$

Interrupted Time Series (ITS)



Interrupted Time Series (ITS)

Assumptions:
We can use pre-period data to accurately predict what would happen without an intervention.

Protects against:
Baseline level of the outcome
If the outcome was already getting better or worse

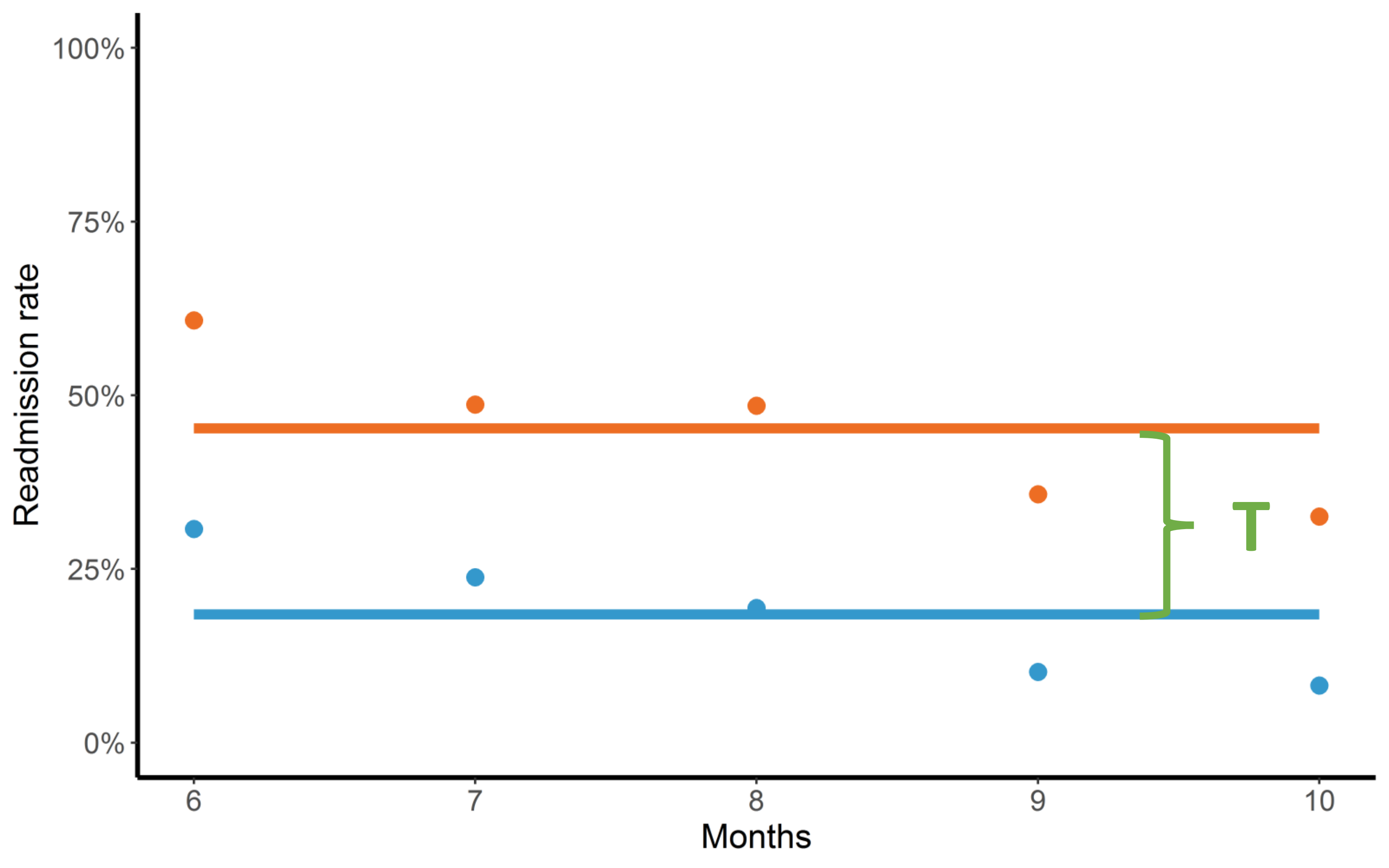
Does not protect against:
Anything that changed outcomes unrelated to the intervention in the post-period

Two group post-mean comparison

Difference in outcome between the treatment and control group in the post-intervention period

$$Y = \beta_0 + \boldsymbol{\beta_1 * Treatment} + \beta_x * X + \varepsilon$$

Two group post-mean comparison



Simple two group comparison

Assumptions:
Outcomes for the two groups would be the same if neither or both received the intervention

Protects against:
Anything unrelated to the intervention that changed outcomes equally for both groups

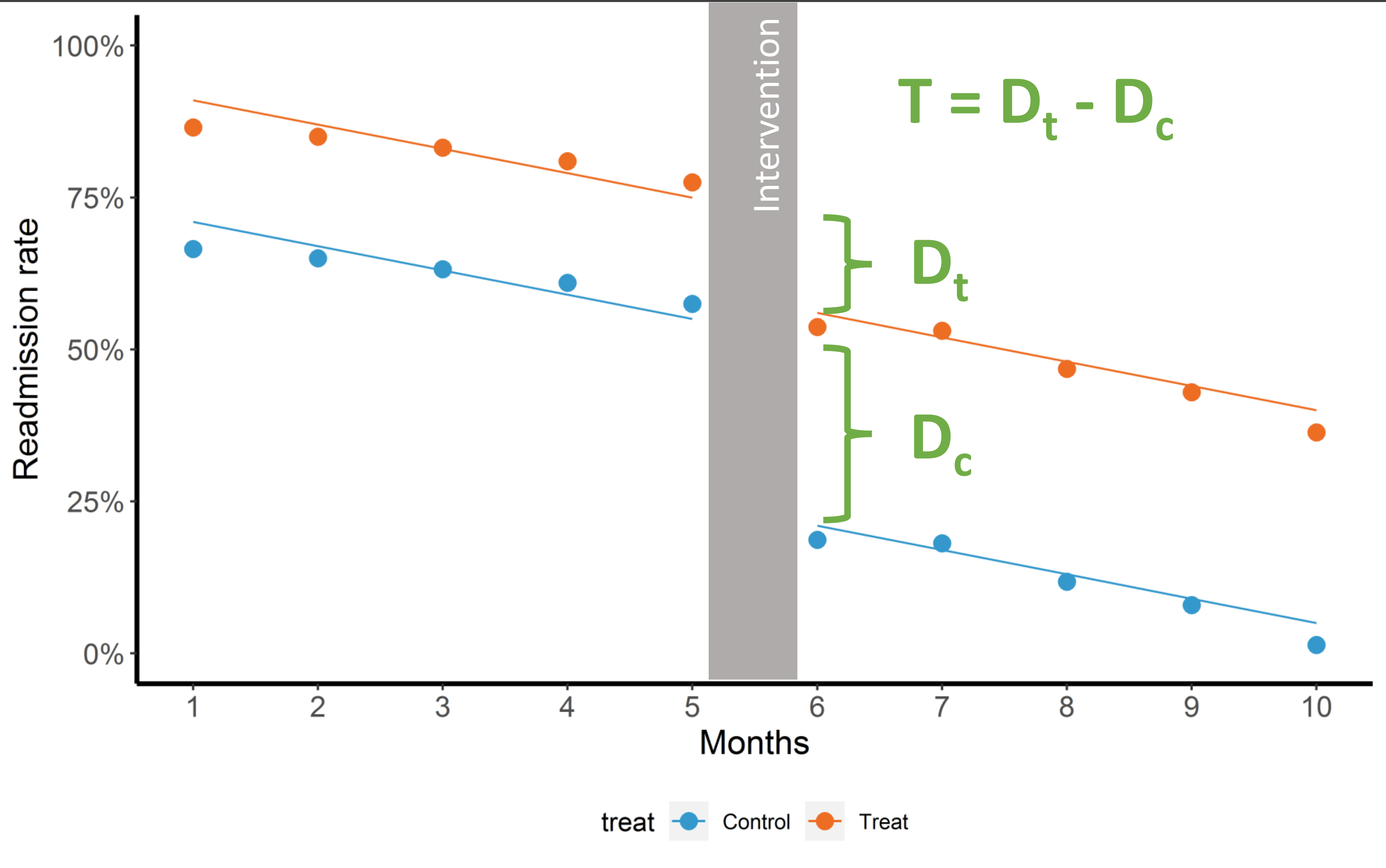
Does not protect against:
Any baseline differences in levels or slopes between the two groups
Any non-intervention changes that effected only one group

Difference-in-differences

Calculates the difference between the pre- and post-period for both treatment and control groups, then estimates the difference between those differences

$$Y = \beta_0 + \boldsymbol{\beta_1} * Treatment + \beta_2 * PostPeriod + \boldsymbol{\beta_3 * Treatment * PostPeriod} + \beta_x * X + \varepsilon$$

Difference-in-differences



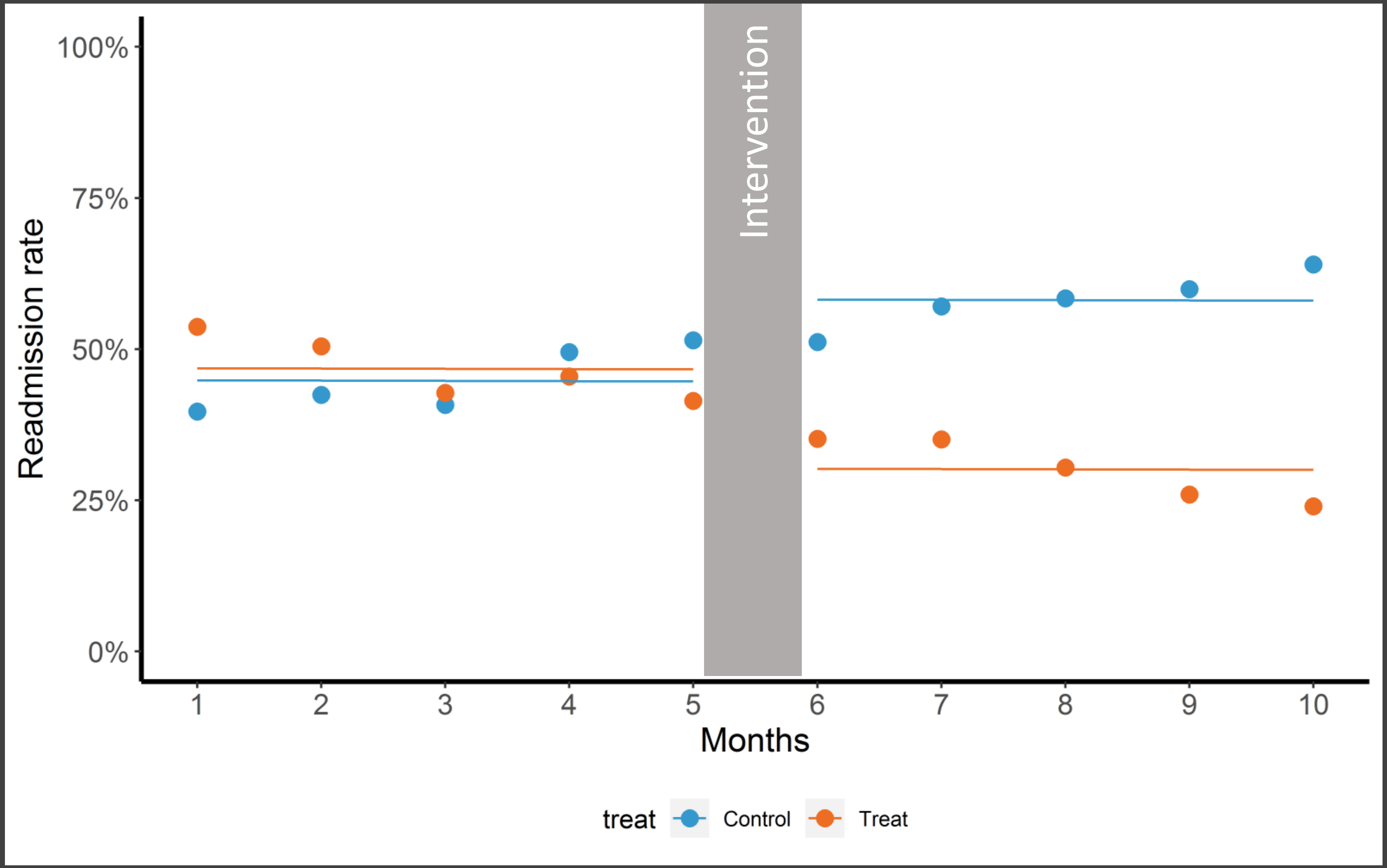
Difference-in-differences

Assumptions:
Parallel trends assumption – Difference in outcomes between groups remains constant over time

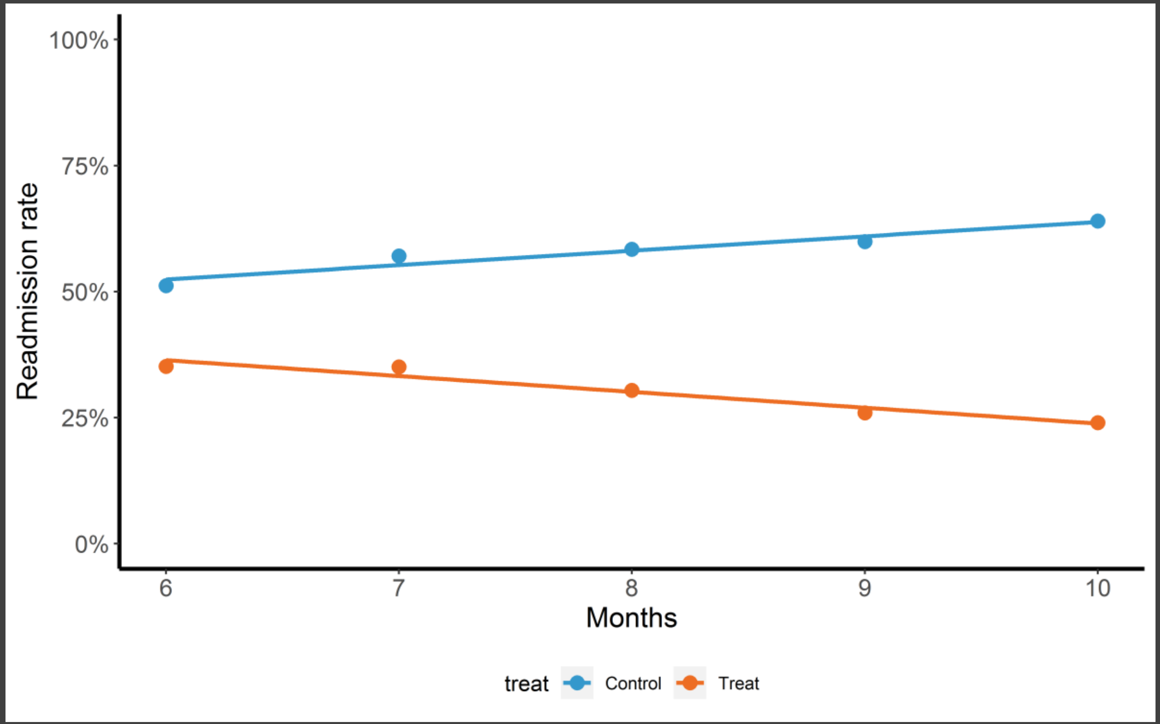
Protects against:
Baseline differences in outcomes between the two groups
Non-invention related changes that occurred in both groups

Does not protect against:
Non-intervention related changes that only occurred in the treated
Differences in baseline trajectory (slope) between the groups

Parallel pre-trend test



Parallel pre-trend test



$$Y = \beta_0 + \boldsymbol{\beta_1} * Treatment + \beta_2 * Time + \beta_2 * Time * Treatment + \beta_x * X + \varepsilon$$

Violation of parallel trends

Propensity Score Weighting / Matching

Explicitly modeling the difference between trends

Choosing a better control group

Propensity Scores

Propensity score weighting and matching is a method that attempts to remove difference between the treatment and control groups

(1) Predict allocation of treatment using observed covariates

(2) Use weighting or matching to ensure both your treatment and control group had an equal probability of receiving treatment

(3) If done correctly, the two groups should now be comparable

BUT: The details matter! (Lindner, 2018)

Explicitly modeling pre-intervention trends

The basic diff-in-diff assumes parallel pre-trends:

$$Y = \beta_0 + \boldsymbol{\beta_1} * Treatment + \boldsymbol{\beta_2} * \boldsymbol{PostPeriod} + \beta_3 * Treatment * PostPeriod + \beta_x * X + \varepsilon$$

We can add an extra term to model the difference in trends:

$$Y = \beta_0 + \boldsymbol{\beta_1} * Treatment + \beta_2 * Post + \beta_t * \boldsymbol{f(time)} * \boldsymbol{Treatment} + \beta_3 * Treatment * PostPeriod + \beta_x * X + \varepsilon$$

Choose a better control group

Violations of assumptions generally mean your two groups are not comparable

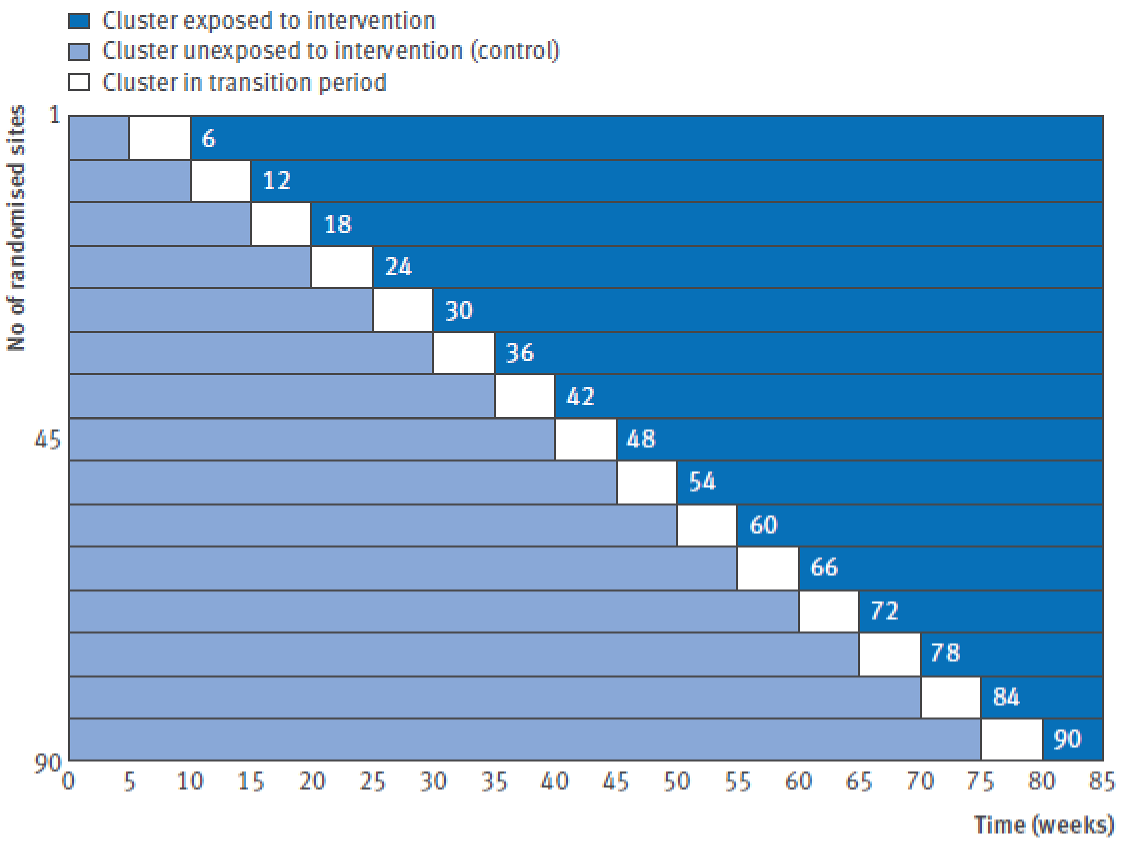
The best solution is to choose a good control group

Random treatment assignment produces the best control groups

Other methods

Step-wedge design

The intervention is implemented in waves, and we compare those with and without intervention at any point



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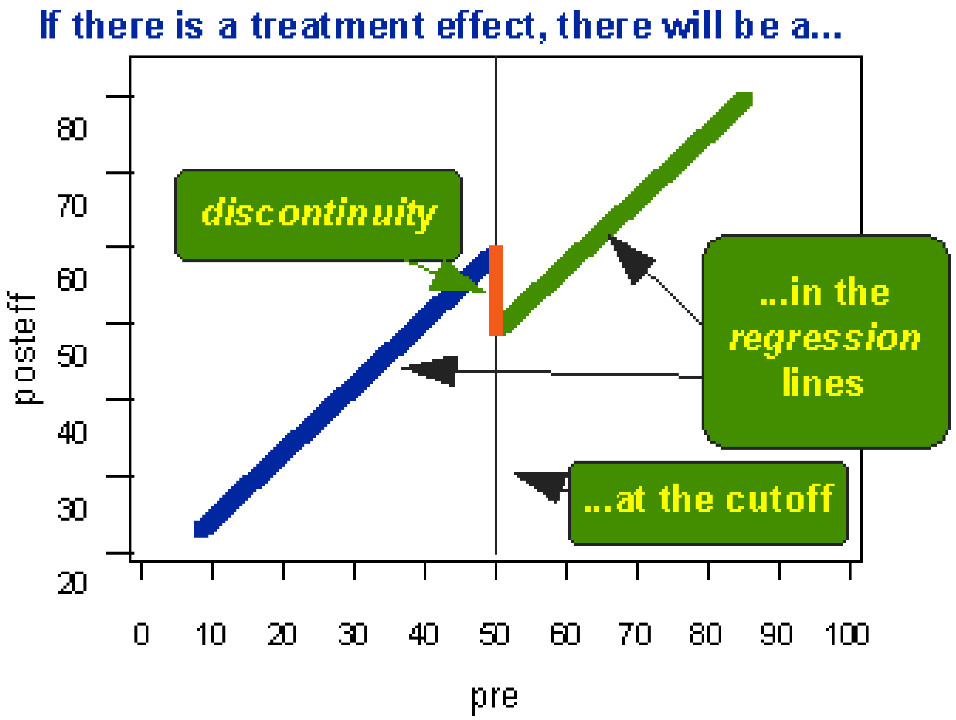
Other methods

Regression discontinuity

Treatment is assigned based on some arbitrary cutpoint of a continuous measurement.

We can compare those on slightly above the cut point to those slightly below the cut point



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Questions?