Differences in differences

PSCI 2301: Quantitative Political Science II

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March 31, 2025

Recap

Last time we met: Regression discontinuity designs

- Method for observational data with unobserved confounders
- Key assumptions
  - → Treatment status determined by cutoff in “running variable”
  - → No discontinuities in confounders/other background characteristics near the treatment cutoff
- Application: Estimating effects of candidate extremism
  - → RDD on margin in primaries b/w extremist and moderate
  - → Assumes districts where extremist *barely* wins primary not very different from those where moderate barely wins
  - → Estimate sizable advantage for moderates in general election

Today's agenda

Difference in differences (DiD):

- Another method for observational data w/ unobserved confounders
- Data requirements
  - → Observe same units over time
  - → Some units never treated, others sometimes treated
- How to estimate the causal effect of treatment?
  1. Calculate diff over time among sometimes-treated obs
  2. Calculate diff over time among never-treated obs
  3. Subtract (2) from (1)
- Relies on parallel trends assumption: if treated units had not been treated, would have had same average trend over time as untreated ones

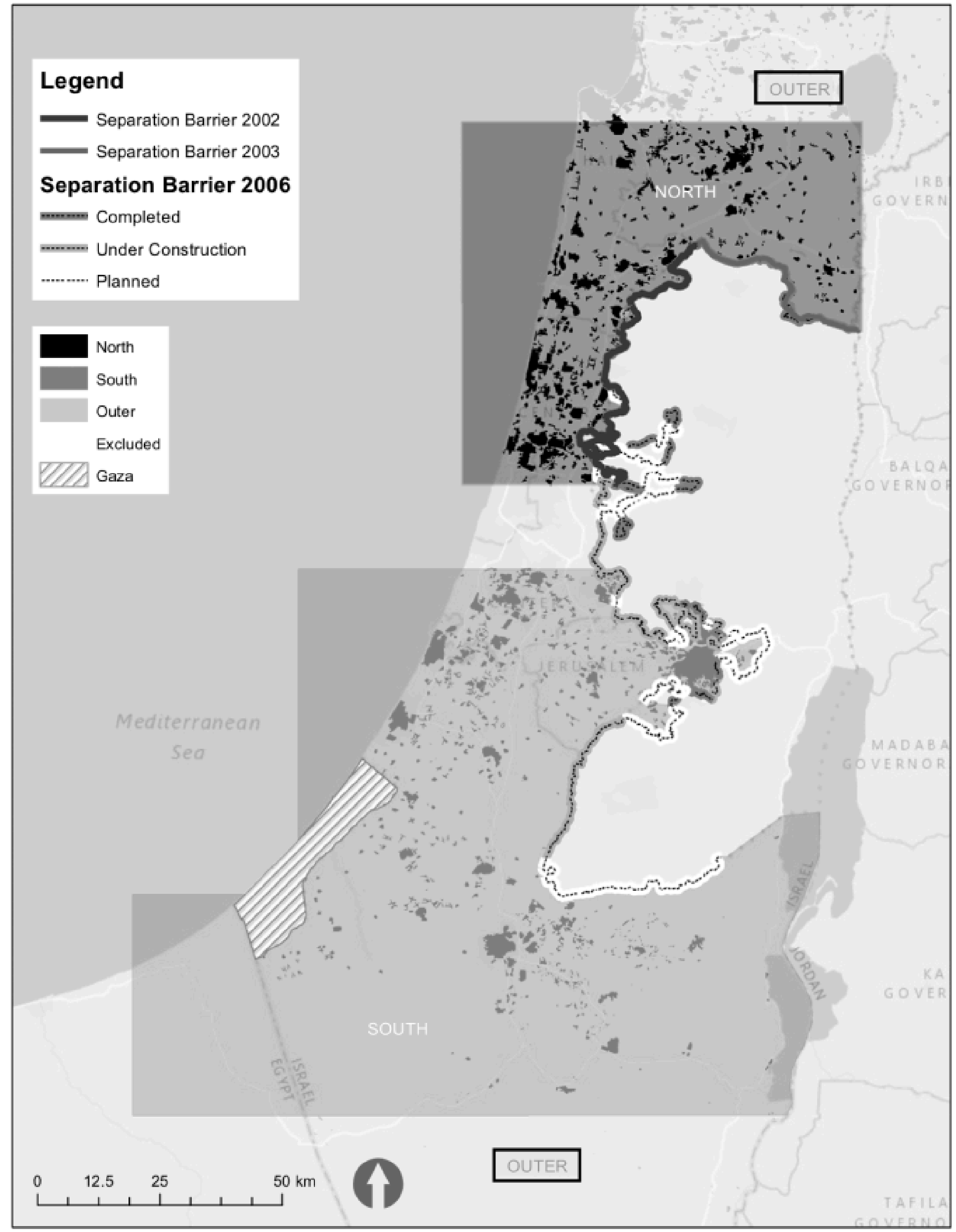
Motivating question: Border walls and crime

Causal question

What is the effect of physical barriers on smuggling across borders?

Context — early-2000s barriers b/w Israel and West Bank

- Primary motivation: deter suicide attacks
- But most car theft at time also went to West Bank
- Did wall construction reduce car theft, or just displace it?



Difficulties for causal inference

Obviously can’t randomize $\rightsquigarrow$ experimental study impossible

What about regression/matching?

- Need to control for all confounders
- Not realistic here: would need everything that affects car theft rates + proximity to border wall construction

Other strategies?

- IV: hard to think of as-if random variation in wall construction, let alone one that would satisfy exclusion restriction
- RDD: no running variable that determines treatment status

Getmansky, Grossman, Wright's approach

Three groups to compare:

- North: barrier built in early 2000s
- South: barrier not yet completed in early 2000s
- Outer: no barrier, stolen cars not going to West Bank

Observe car theft rates in each place <u>before and after</u> 2002 construction

Difference in differences:

- Calculate pre-2002 vs post-2002 difference in theft in each region
- Compare these differences to draw causal inferences

Differences in differences

Key ingredients

Standard causal model, with two changes

1. We observe each unit at two times: $t = 1$ and $t = 2$
2. Units are only treated at time $t = 2$, and only some of them

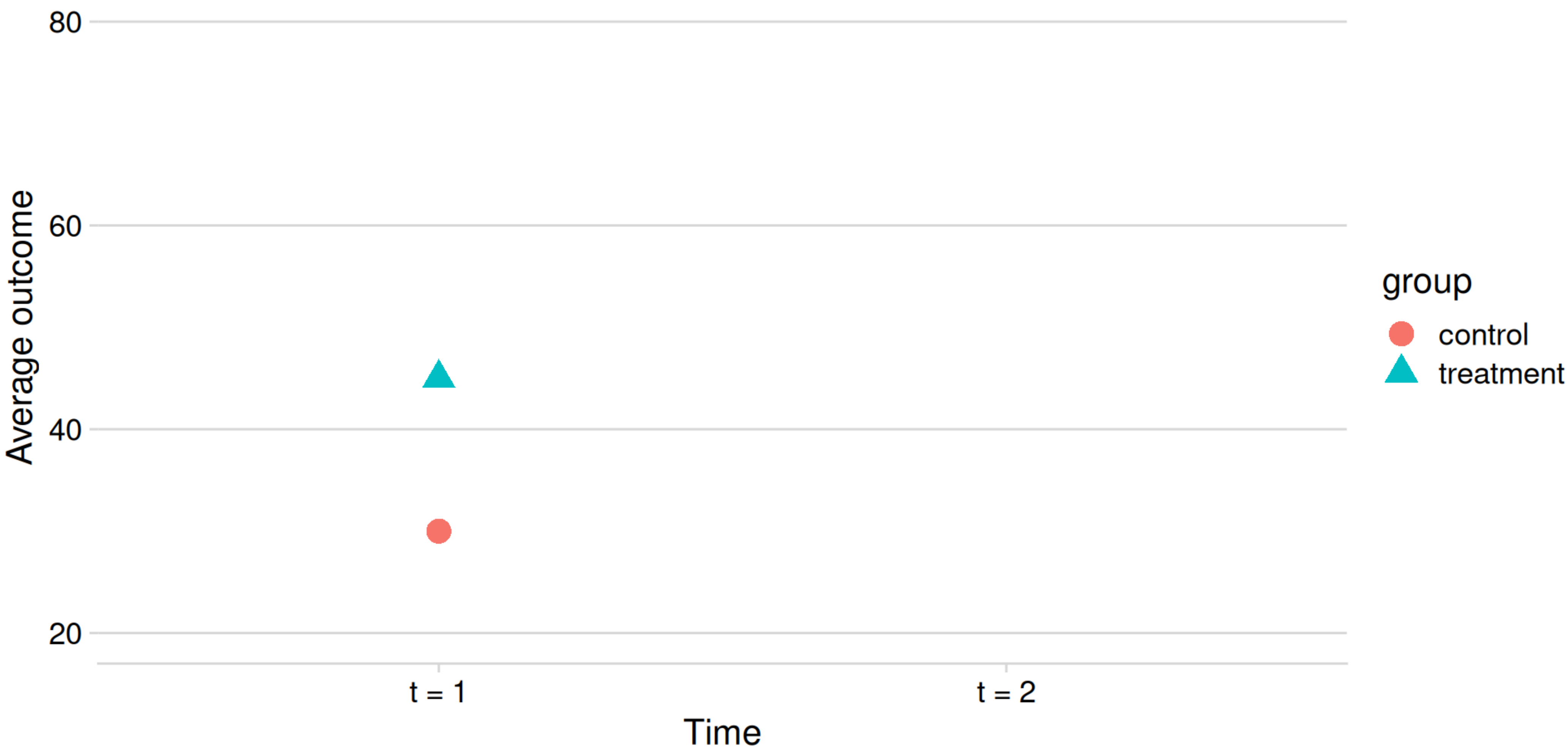
Potential outcomes in first period: Y^1_{0i}, Y^1_{1i}

Potential outcomes in second period: Y^2_{0i}, Y^2_{1i}

Treatment group indicator: $D_i \in \{0, 1\}$

- $D_i = 0 \rightsquigarrow$ control both periods
- $D_i = 1 \rightsquigarrow$ control period 1, treatment period 2

What we observe (and don’t)



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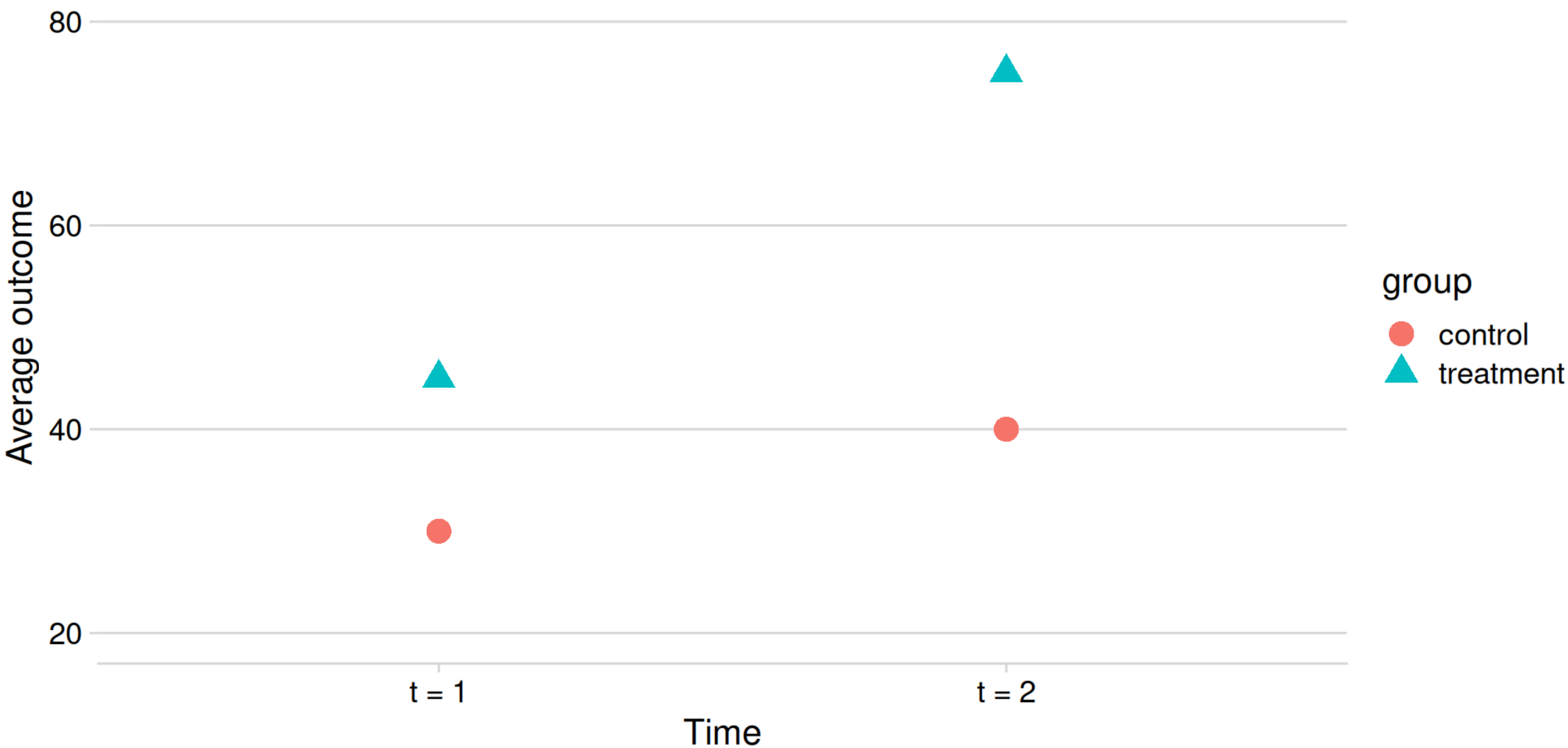

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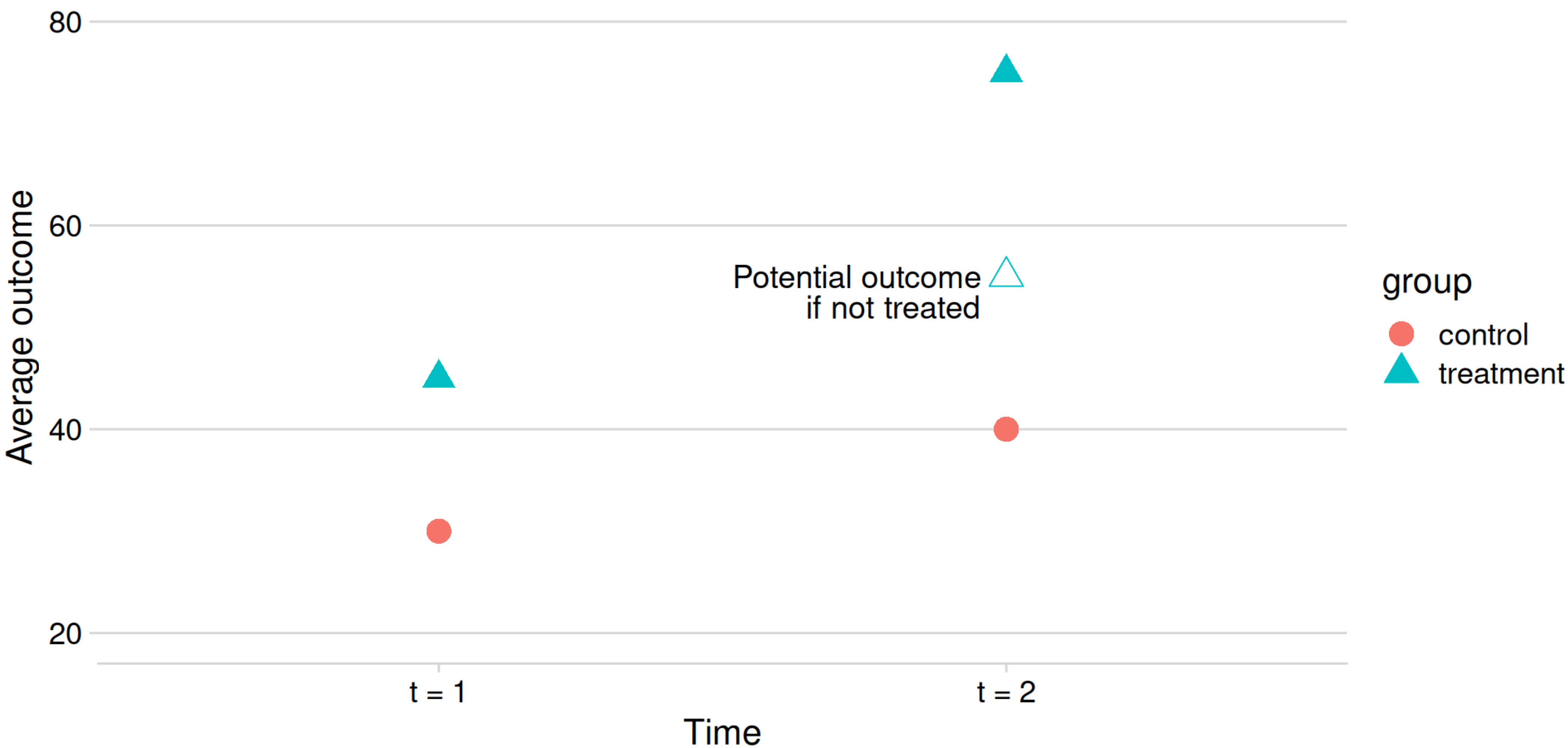

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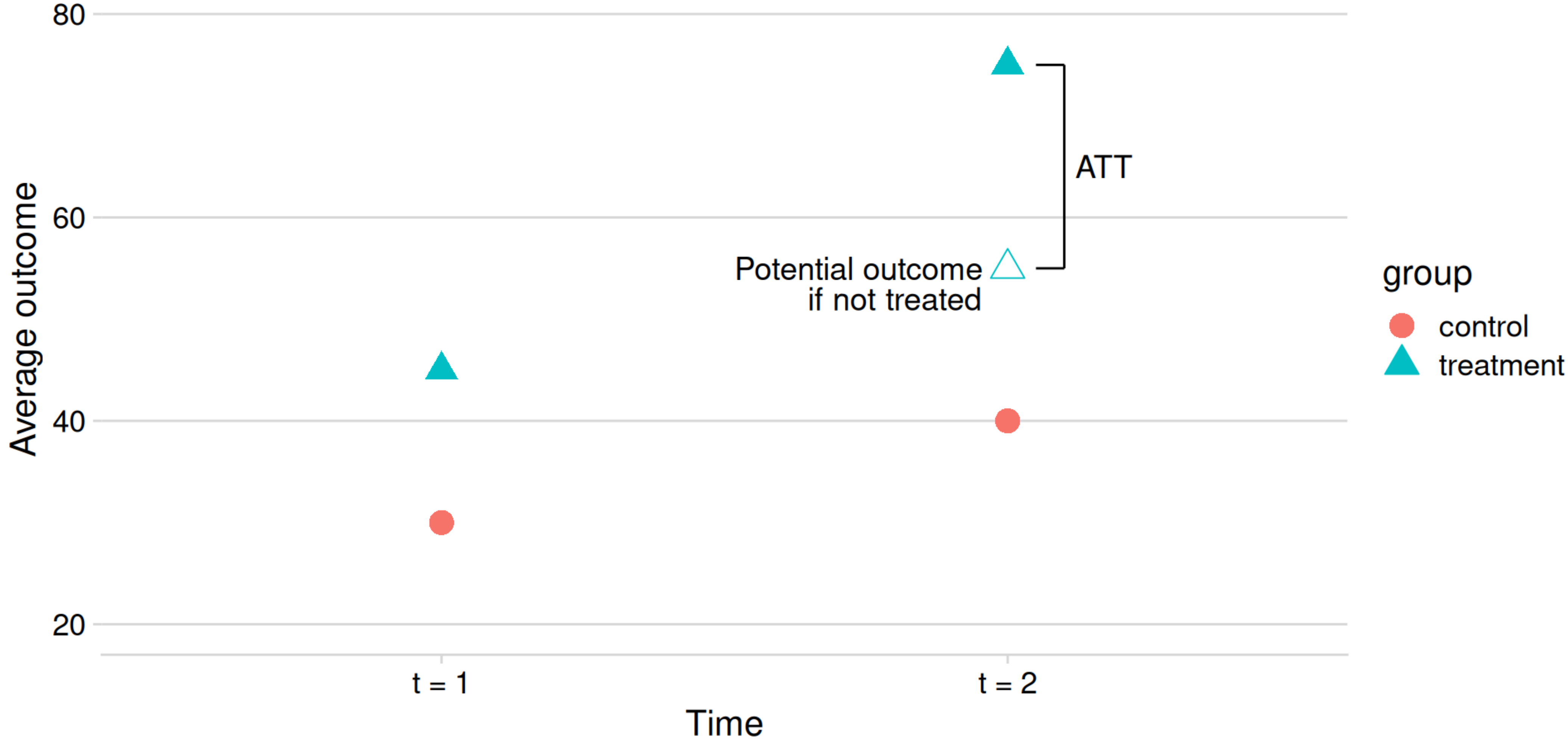


Bad option #1: Before-and-after comparison

What if we ignored control, just did before-and-after with treated?

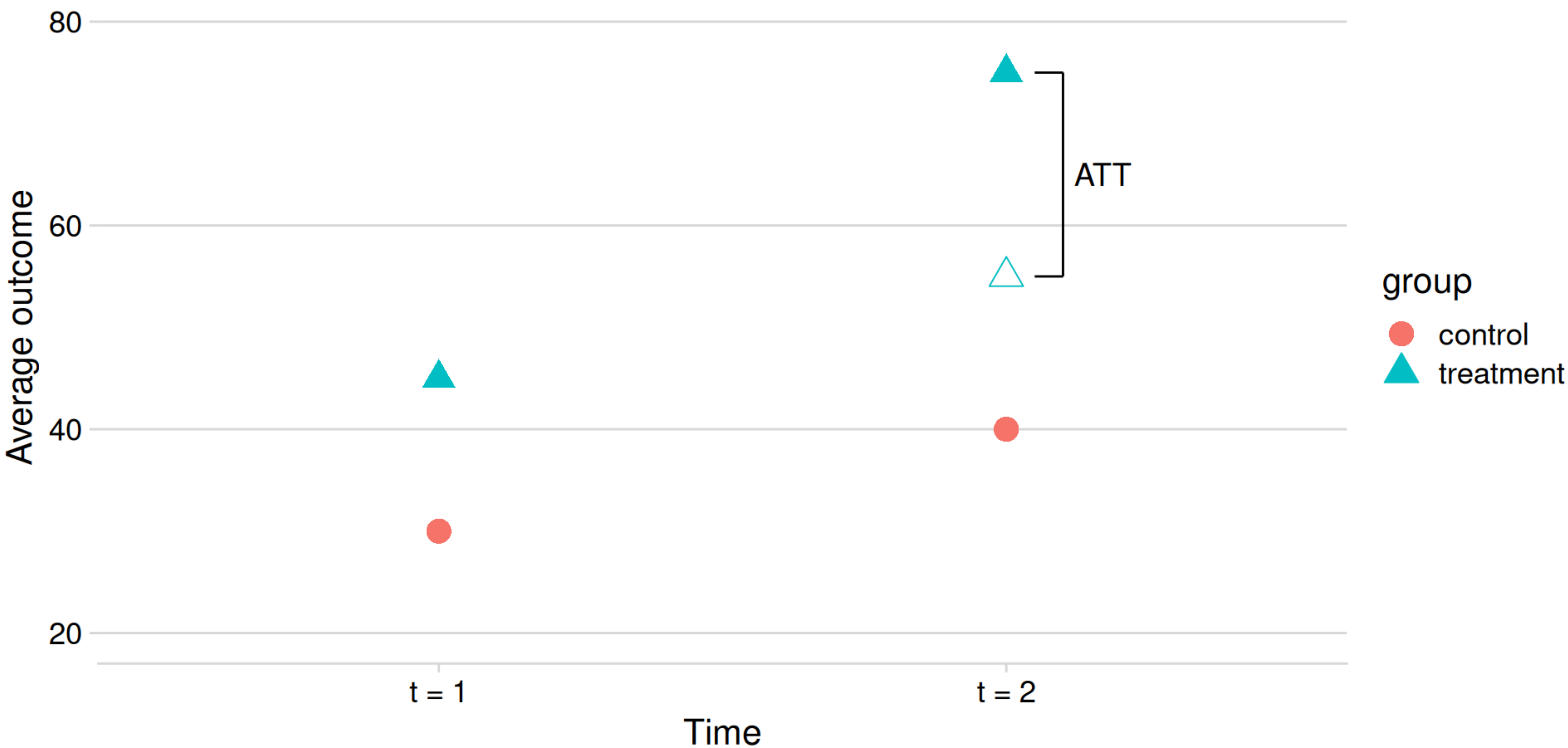
Before-and-after estimator:

$$\hat{\tau} = \mathbb{E}[Y_i^2 \mid D_i = 1] - \mathbb{E}[Y_i^1 \mid D_i = 1]$$

Problem: Must assume would have been no change if not treated

Only equals ATT if $\mathbb{E}[Y_{0i}^2 \mid D_i = 1] = \mathbb{E}[Y_{0i}^1 \mid D_i = 1]$

Bad option #1: Before-and-after comparison



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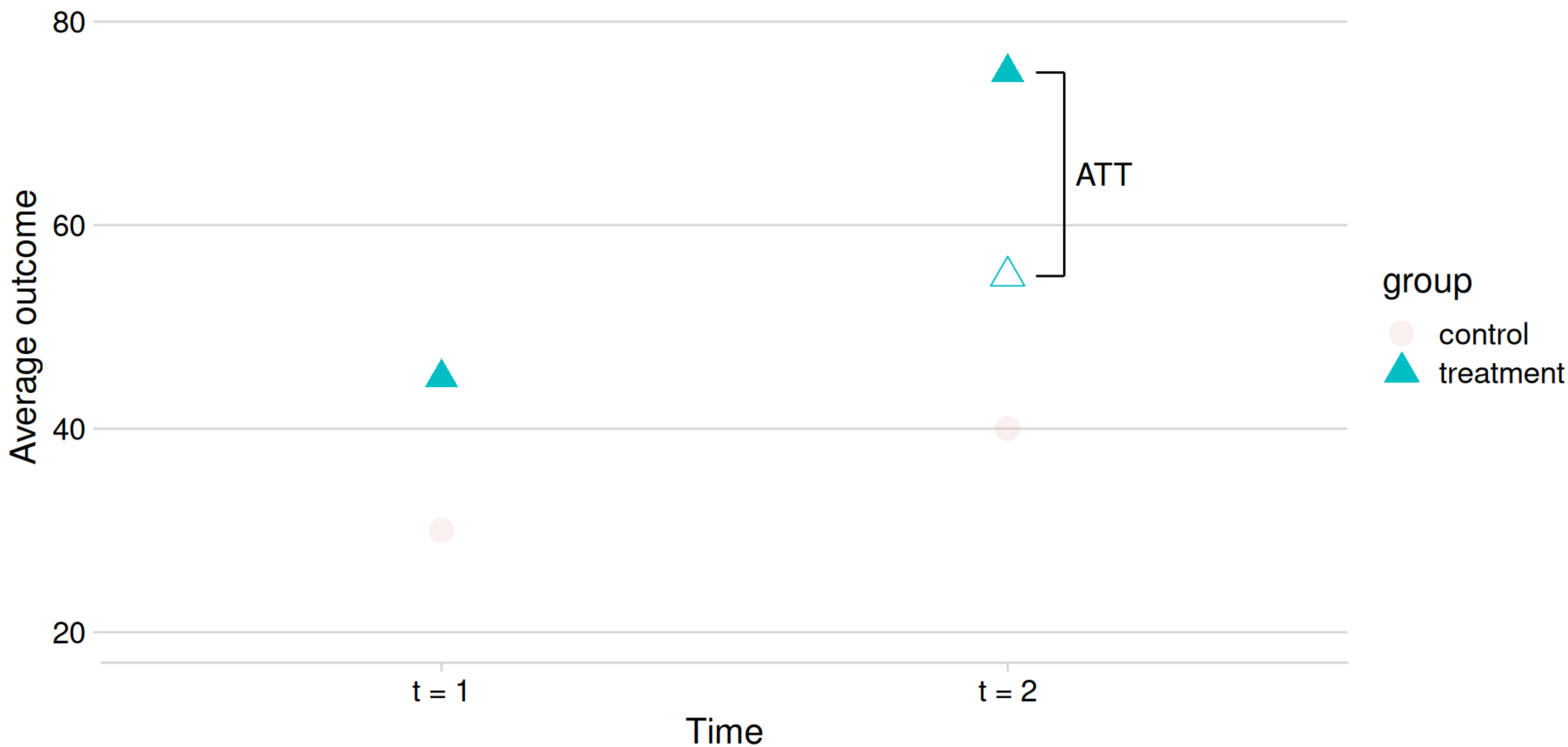

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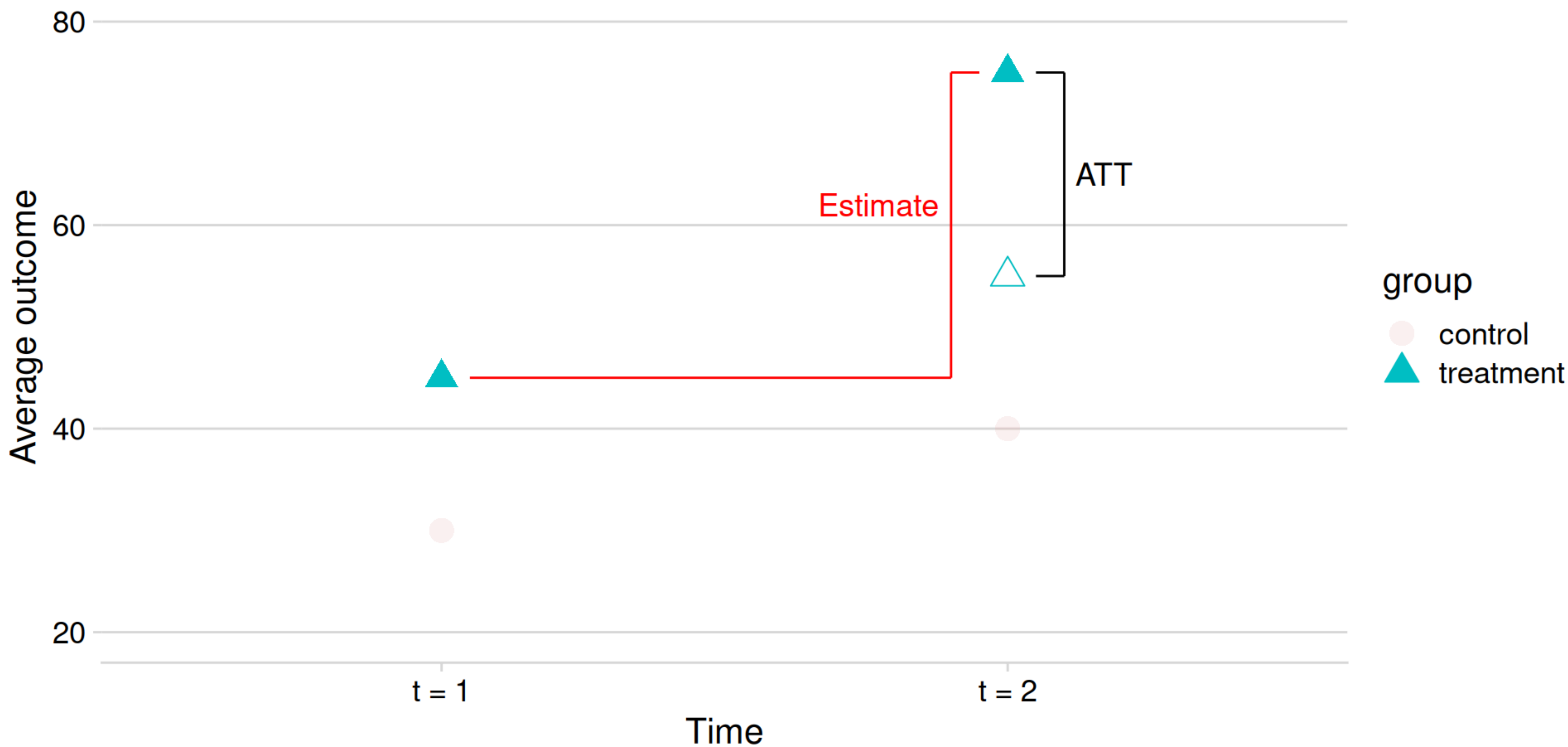


Bad option #2: Period 2 comparison

What if we ignored $t = 1$, just compared treated to control at $t = 2$?

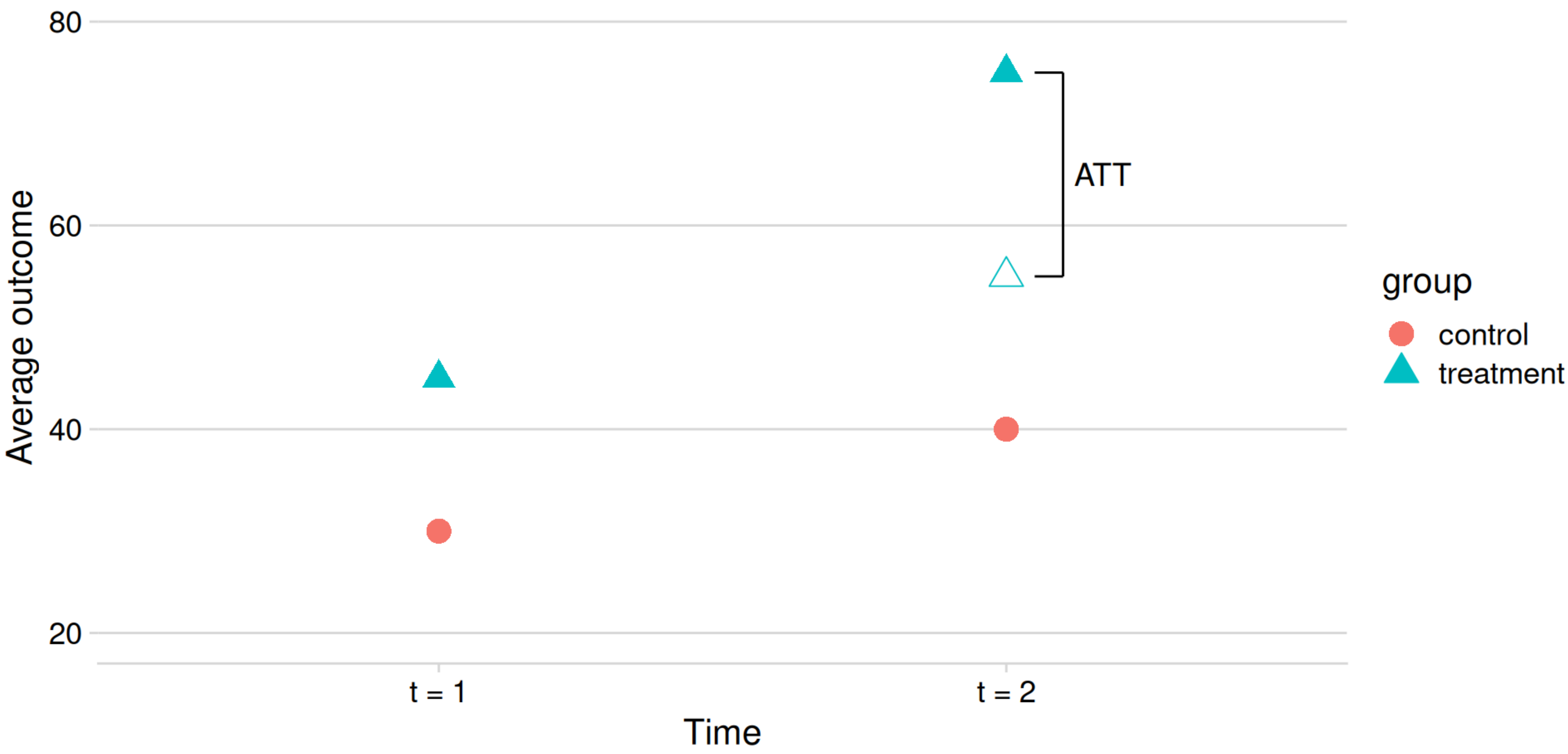
Period 2 difference of means estimator:

$$\hat{\tau} = \mathbb{E}[Y_i^2 \mid D_i = 1] - \mathbb{E}[Y_i^2 \mid D_i = 0]$$

Problem: Must assume the usual independence condition!

Only equals ATT if $\mathbb{E}[Y_{0i}^2 \mid D_i = 0] = \mathbb{E}[Y_{0i}^2 \mid D_i = 1]$

Bad option #2: Period 2 comparison



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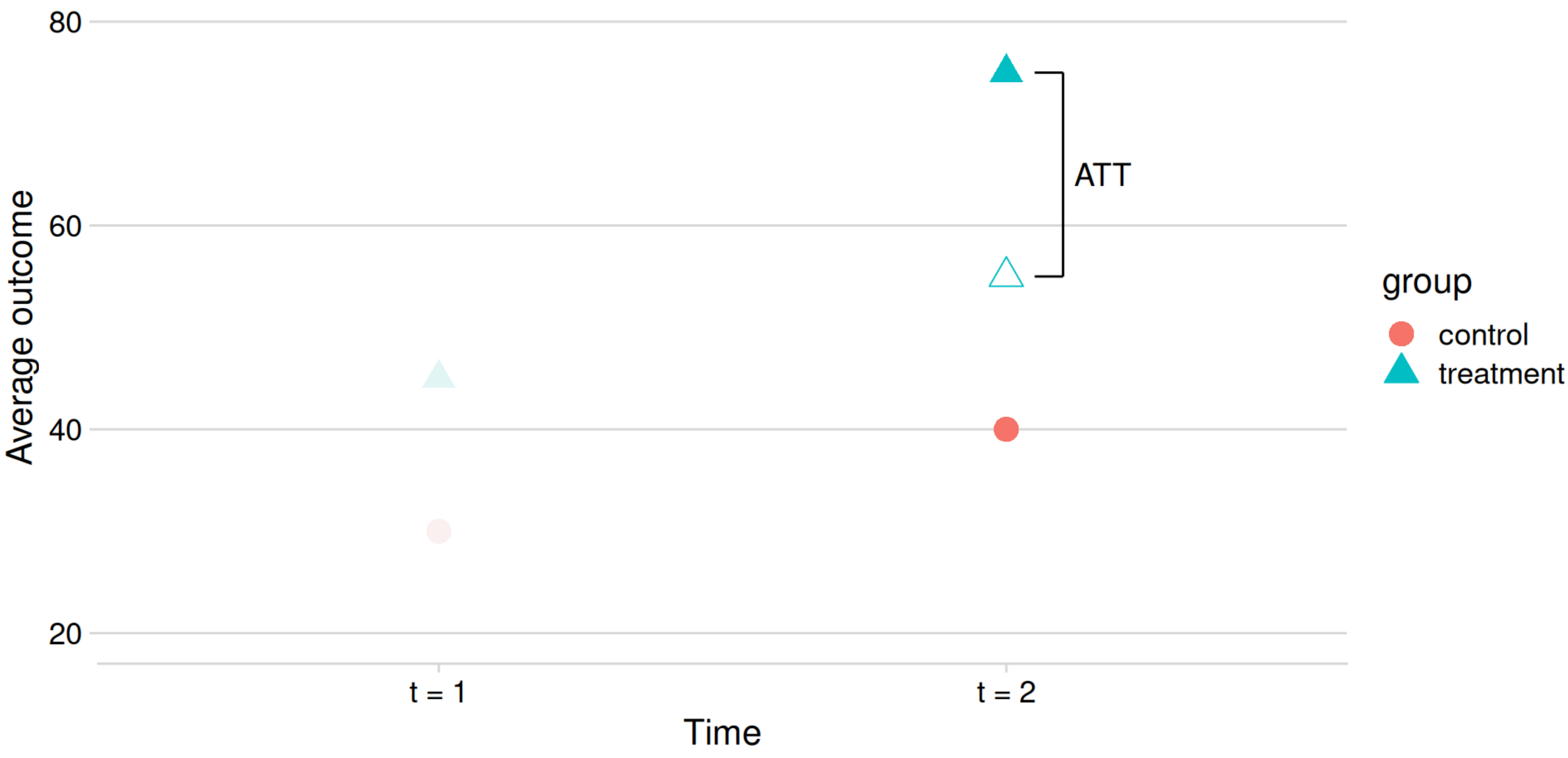

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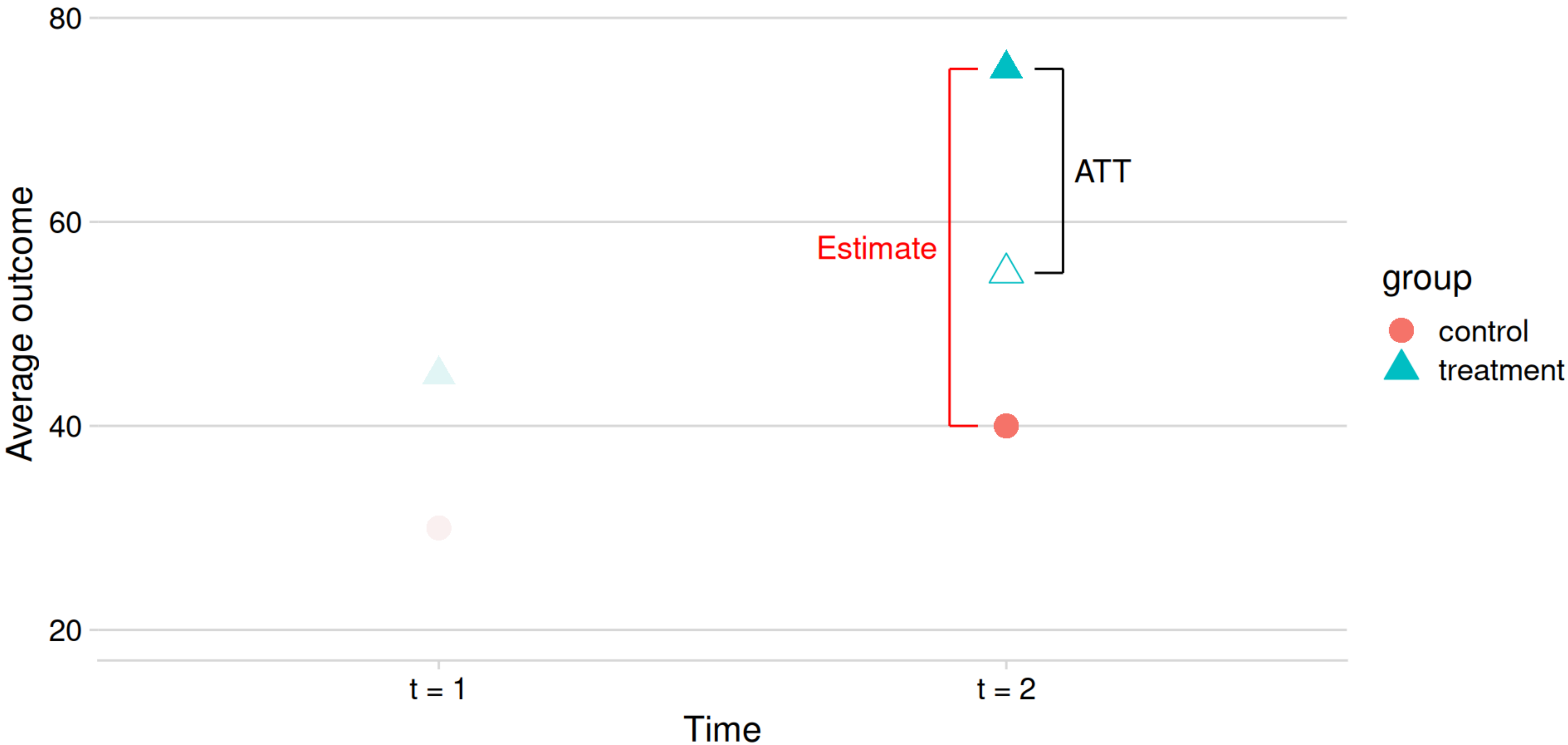


A better option: Difference in differences

We need a good guess about $\mathbb{E}[Y_{0i}^2 \mid D_i = 1]$

- Avg t = 2 outcome among treated obs if they hadn't been treated

Avg t = 1 outcome among treated obs doesn't work

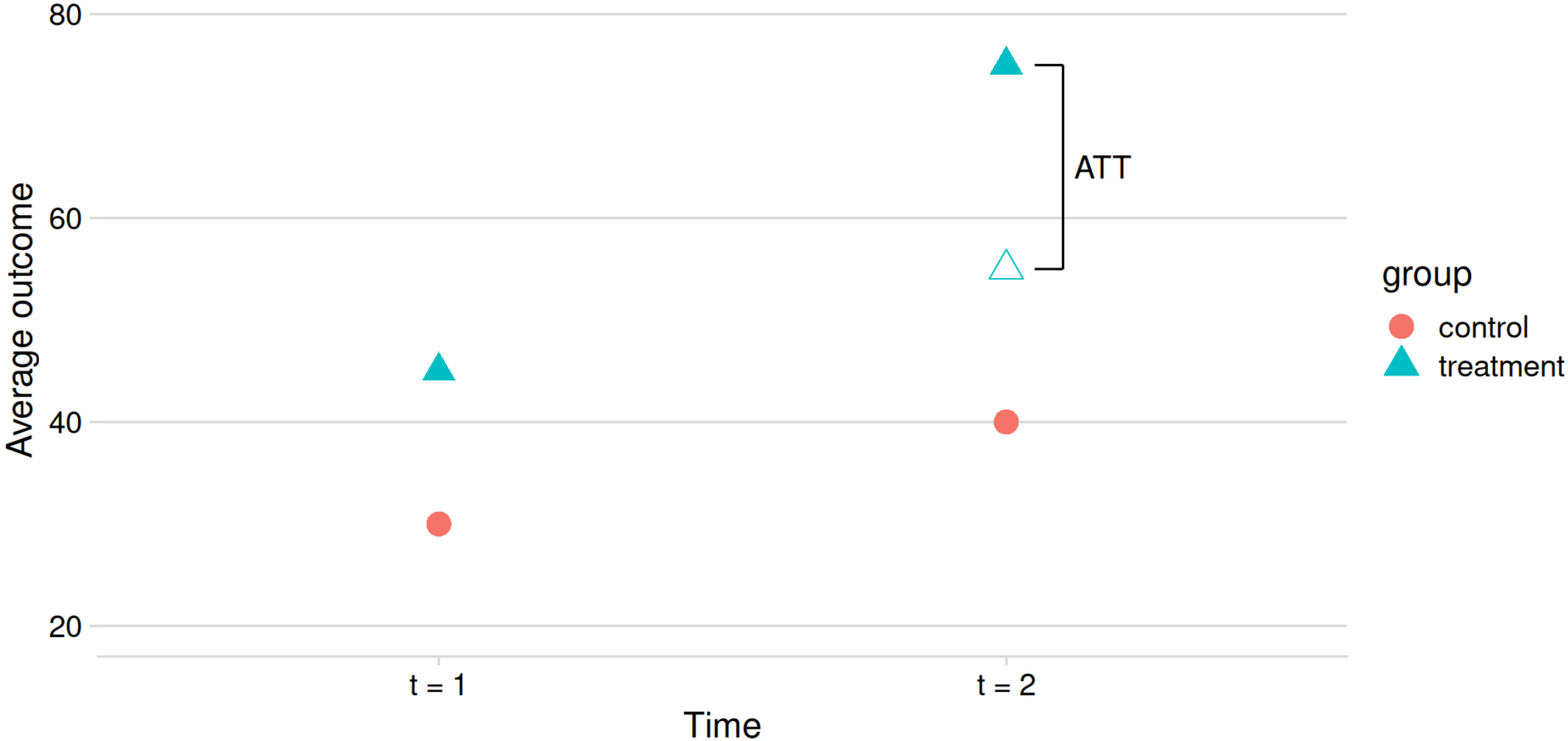
- Could have been change over time even if untreated

Avg t = 2 outcome among untreated obs doesn't work

- Could be systematic differences due to non-random assignment

But we can **combine** these to get a better guess

A better option: Difference in differences



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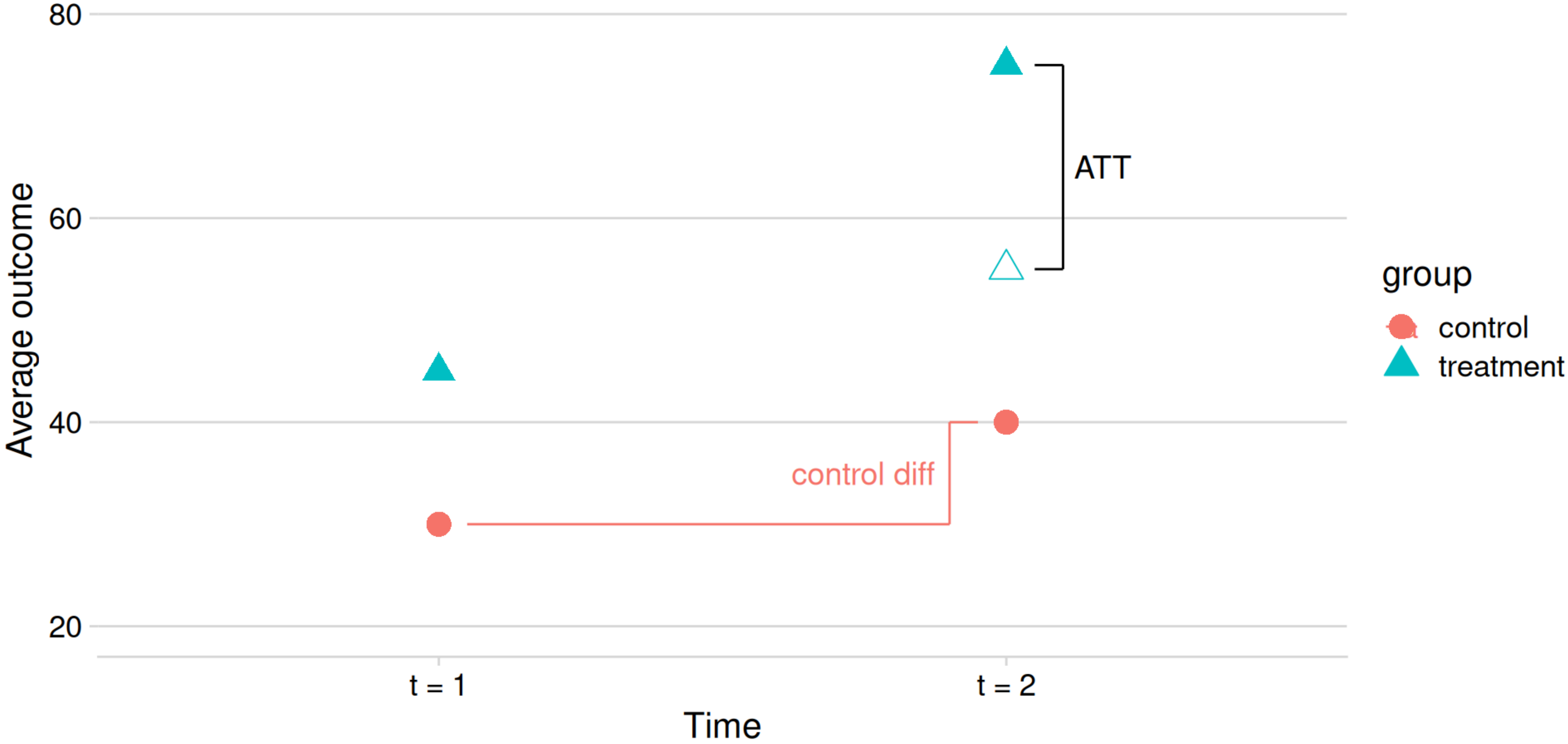

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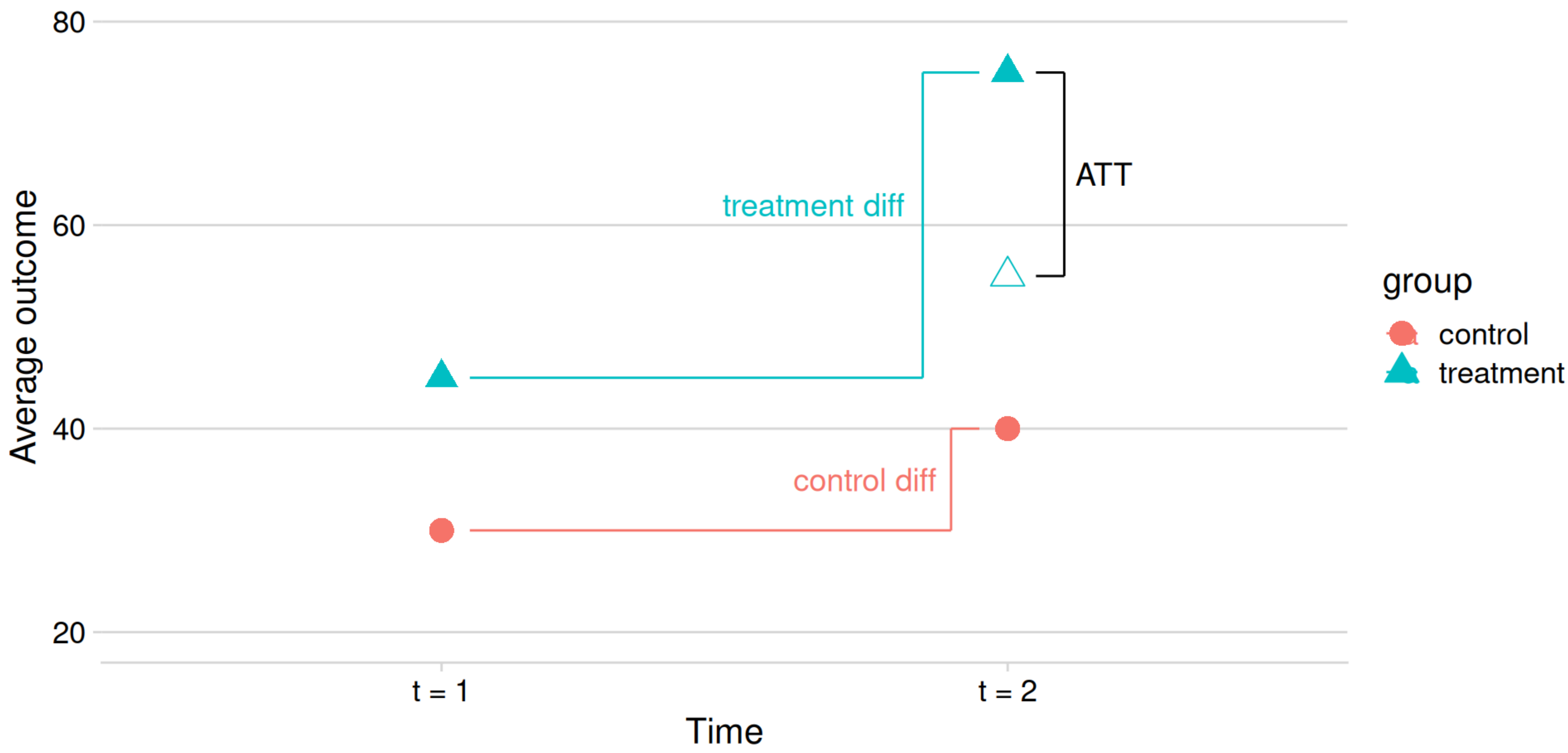

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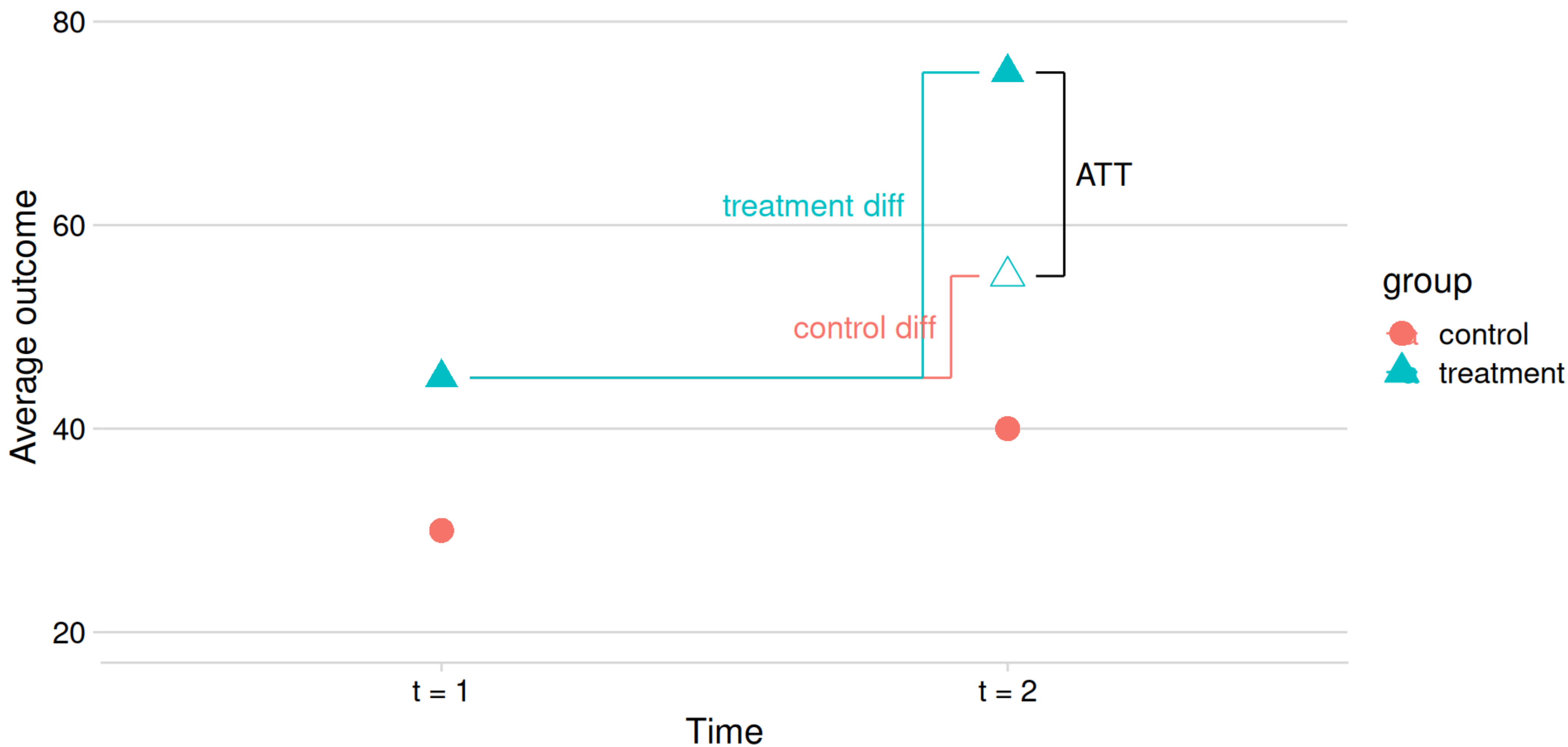

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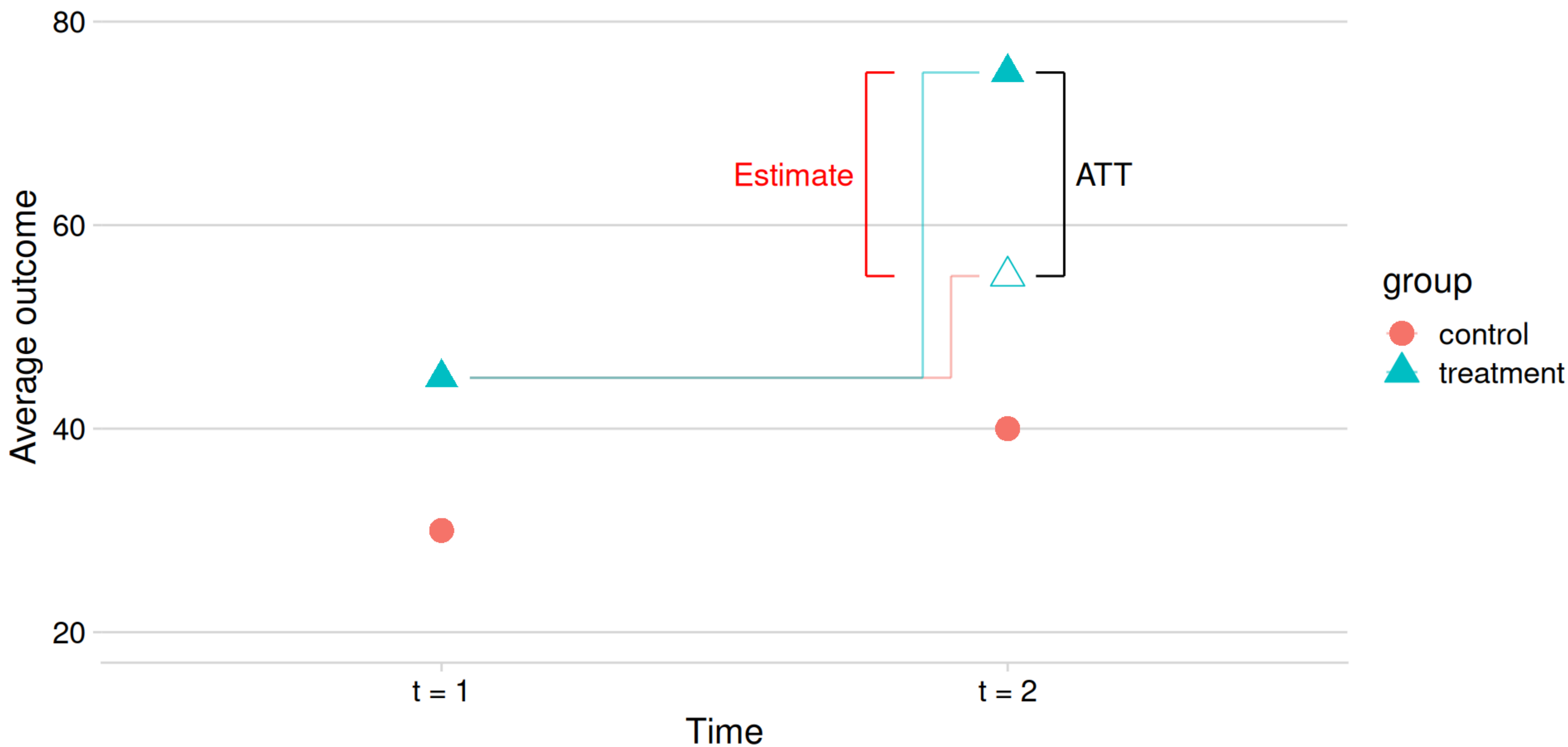


Difference in differences

The difference in differences estimate of the ATT:

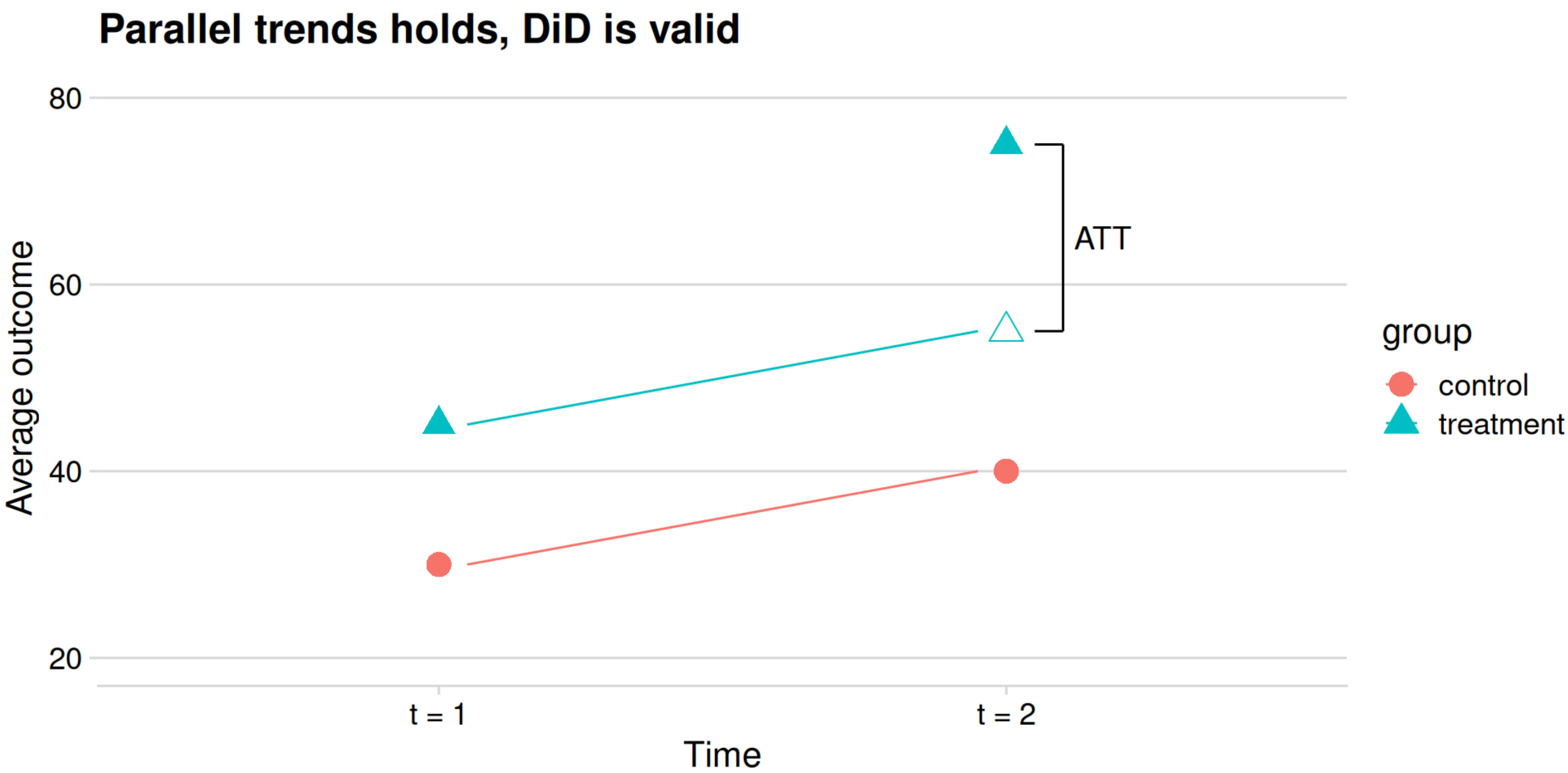
$$\hat{\tau} = \left\{\mathbb{E}[Y_i^2 \mid D_i = 1] - \mathbb{E}[Y_i^1 \mid D_i = 1]\right\} \\ - \left\{\mathbb{E}[Y_i^2 \mid D_i = 0] - \mathbb{E}[Y_i^1 \mid D_i = 0]\right\}$$

Key assumption that makes this work: parallel trends

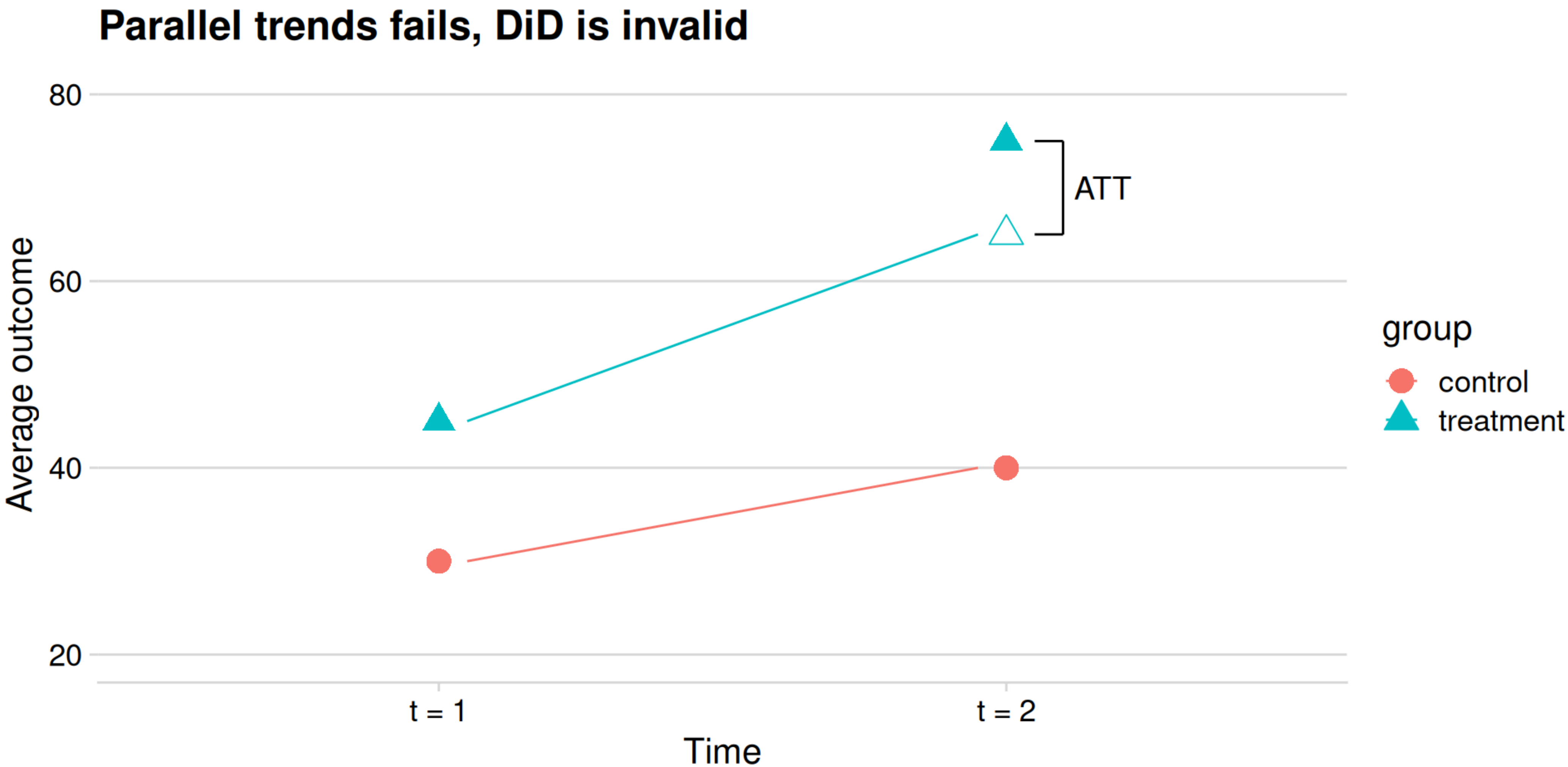
- If not treated, treatment group would have had same <u>change</u> as control
- Formal condition:

$$\mathbb{E}[Y_{0i}^2 \mid D_i = 1] - \mathbb{E}[Y_{0i}^1 \mid D_i = 1] \\ = \mathbb{E}[Y_{0i}^2 \mid D_i = 0] - \mathbb{E}[Y_{0i}^1 \mid D_i = 0]$$

The parallel trends assumption



The parallel trends assumption



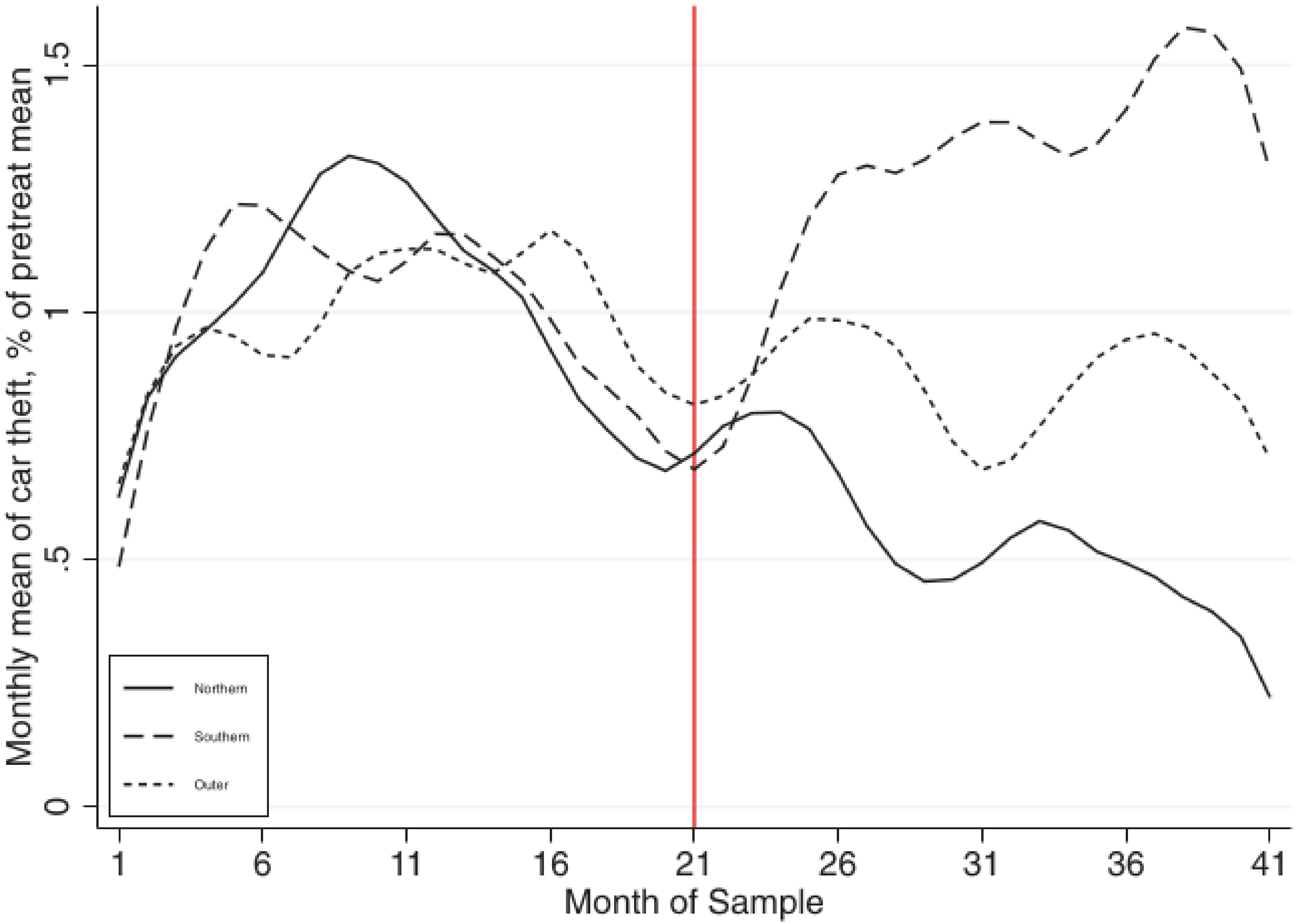
Assessing parallel trends

Not directly testable, as we can't observe $\mathbb{E}[Y_{0i}^2 \mid D_i = 1]$

How to convince yourself + others this assumption is valid?

- Know your data!
    - → Why did only some observations get the treatment?
    - → What accounts for differences b/w treatment and control at t = 1?
    - → Any other changes at same time that'd only affect treatment group?
- If data available for earlier periods, do trends look parallel?

Assessing parallel trends in GGW



Wrapping up

What we did today

The difference in differences estimator:

- Data requirements
  - → Observe same units over time
  - → Some units never treated, others sometimes treated
- Method to estimate the ATT
  1. Calculate diff over time among sometimes-treated obs
  2. Calculate diff over time among never-treated obs
  3. Subtract (2) from (1)
- Parallel trends assumption
  - → If treated units had not been treated, would have had same average trend over time as untreated ones
  - → Not directly testable (fundamental problem of causal inference)

Plan for the rest of the semester

- Weds 4/2: **No class**
- Mon 4/7: DiD in practice
- Weds 4/9: A crash course on synthetic control
- Mon 4/14: Presentations of final projects
  - → Should be 10-12 minutes each
  - → Main points to hit: your causal question, your data, how you identify a causal effect, your main findings
- Weds 4/16: Likely no class