STA 235 - Causal Inference: Differences-in-Differences (Cont.)

Spring 2021

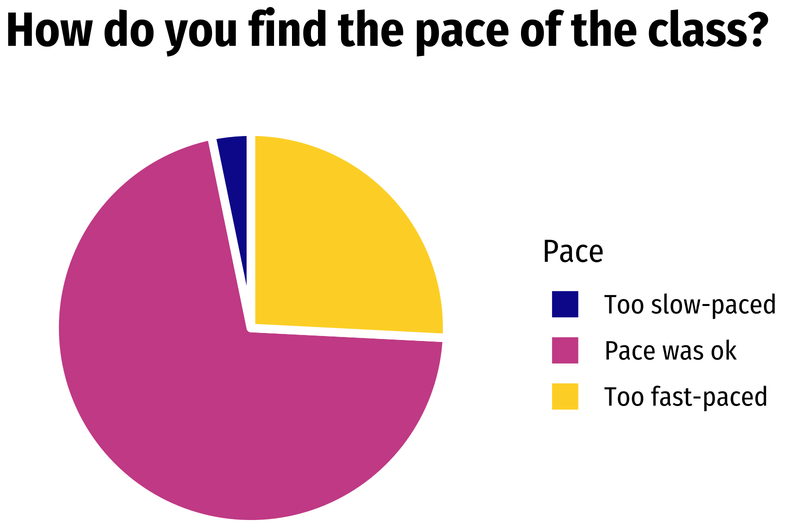
McCombs School of Business, UT Austin

Reminders

In-class midterm March 29th

- You need a **webcam**
- You will be required to **code**

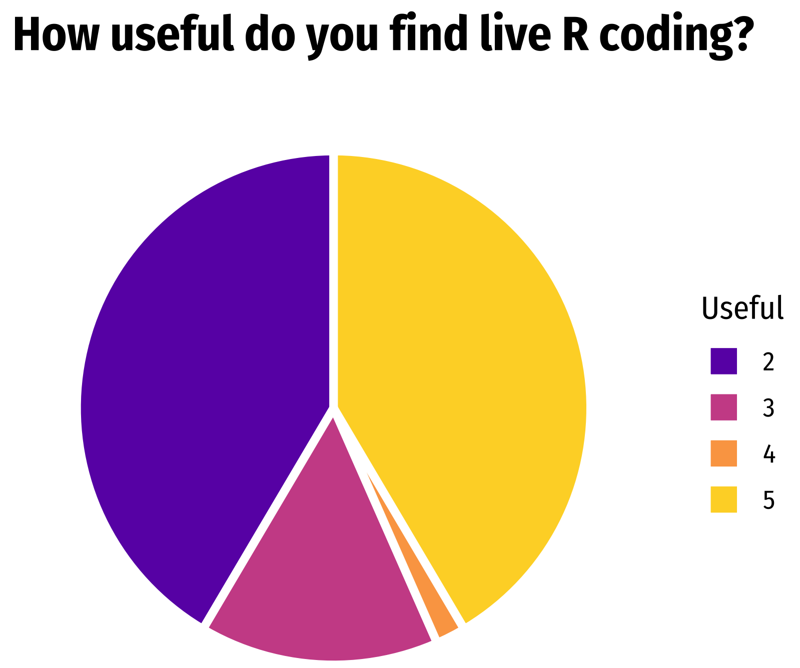
Some results from the JITTs



- Most of you think the **pace of the class is ok**
- Still, it's important that not a small portion thinks it might be **too fast-paced**
  - You can manage the pace by asking questions!
- Regarding slides and notes:
  - Slides are a **support** for the presenter.
  - Take note of **what's not in the slides**

Some results from the JITTs (cont.)

- Some of you find live R coding **useful**, but some of you **not so much**
  - Shorten live R code
  - **You will code now**.



Last Class

- **Diff-in-Diff** as an identification strategy:
    - Applies for two groups that have *different levels* but *the same trend*.
    - Don't need covariates to be the same.
    - **Time-invariant confounders**.

Today

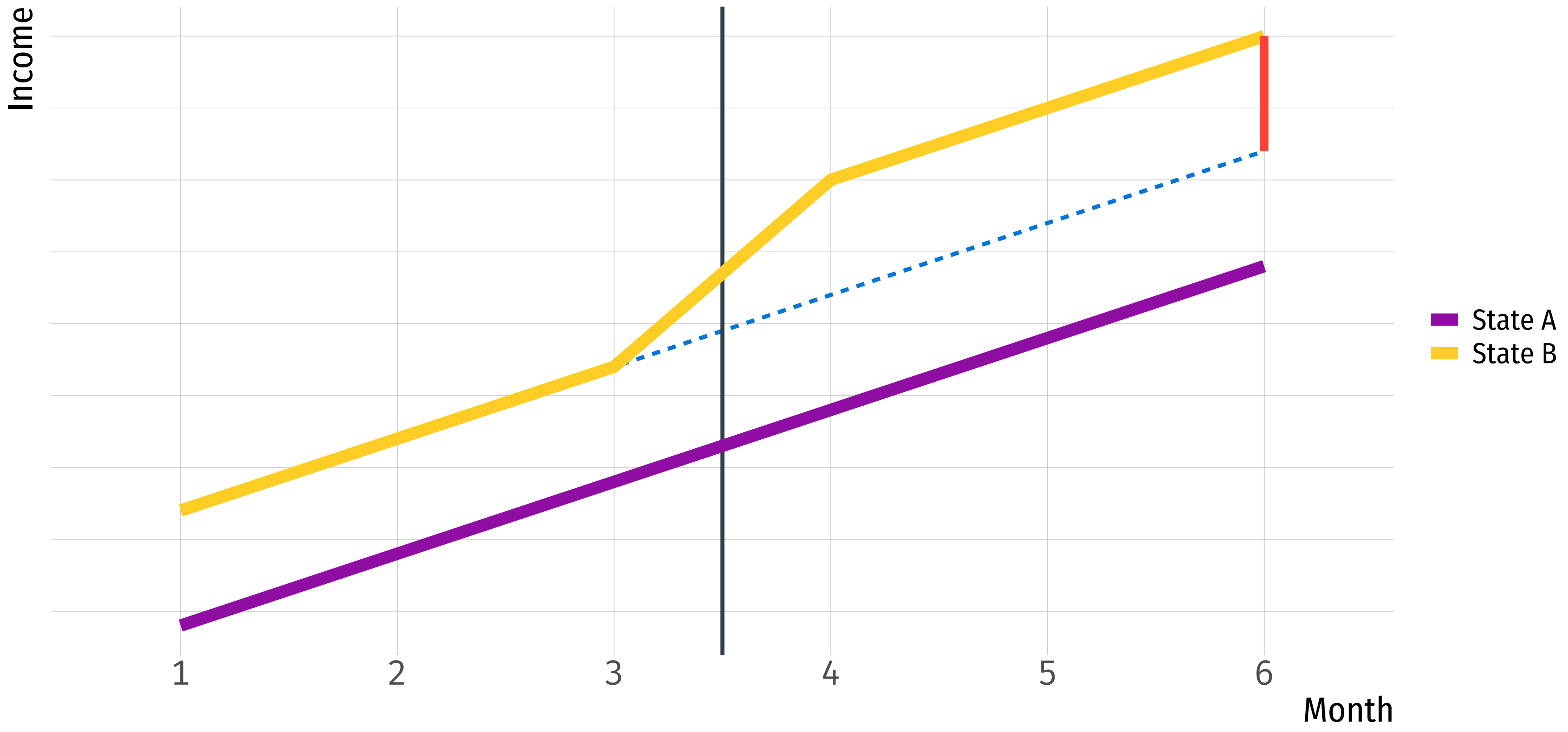
- Finish with **diff-in-diff**:
  - Assumptions.
- **Regression Discontinuity Designs**:
  - Finding natural "jumps" in assignment.
  - Use that variation in treatment assignment for causal inference.

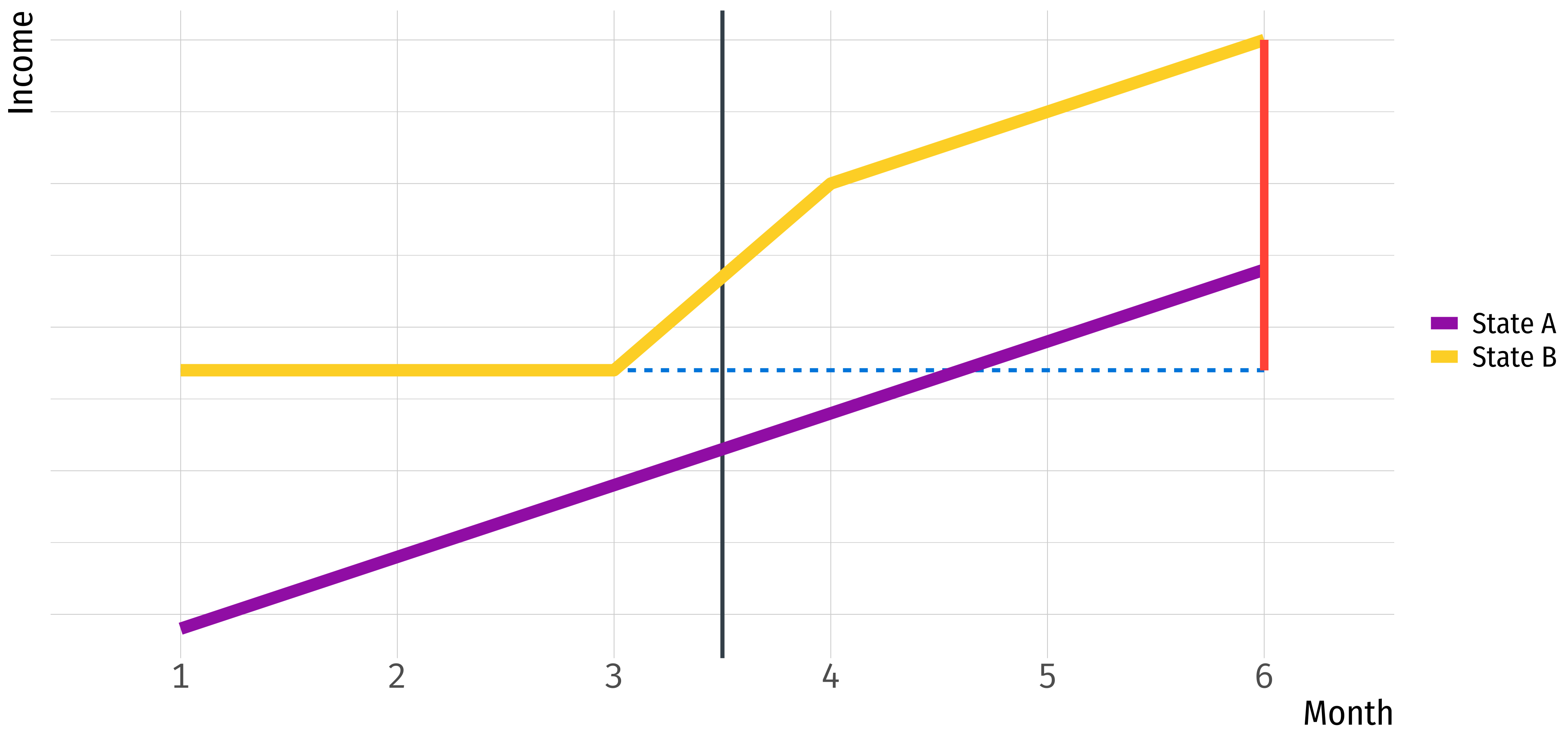
Diff-in-Diff Assumptions

Assumptions

Parallel Trends

In the absence of the intervention, treatment and control group would have changed in the same way


Income
1
2
3
4
5
6
Month
State A
State B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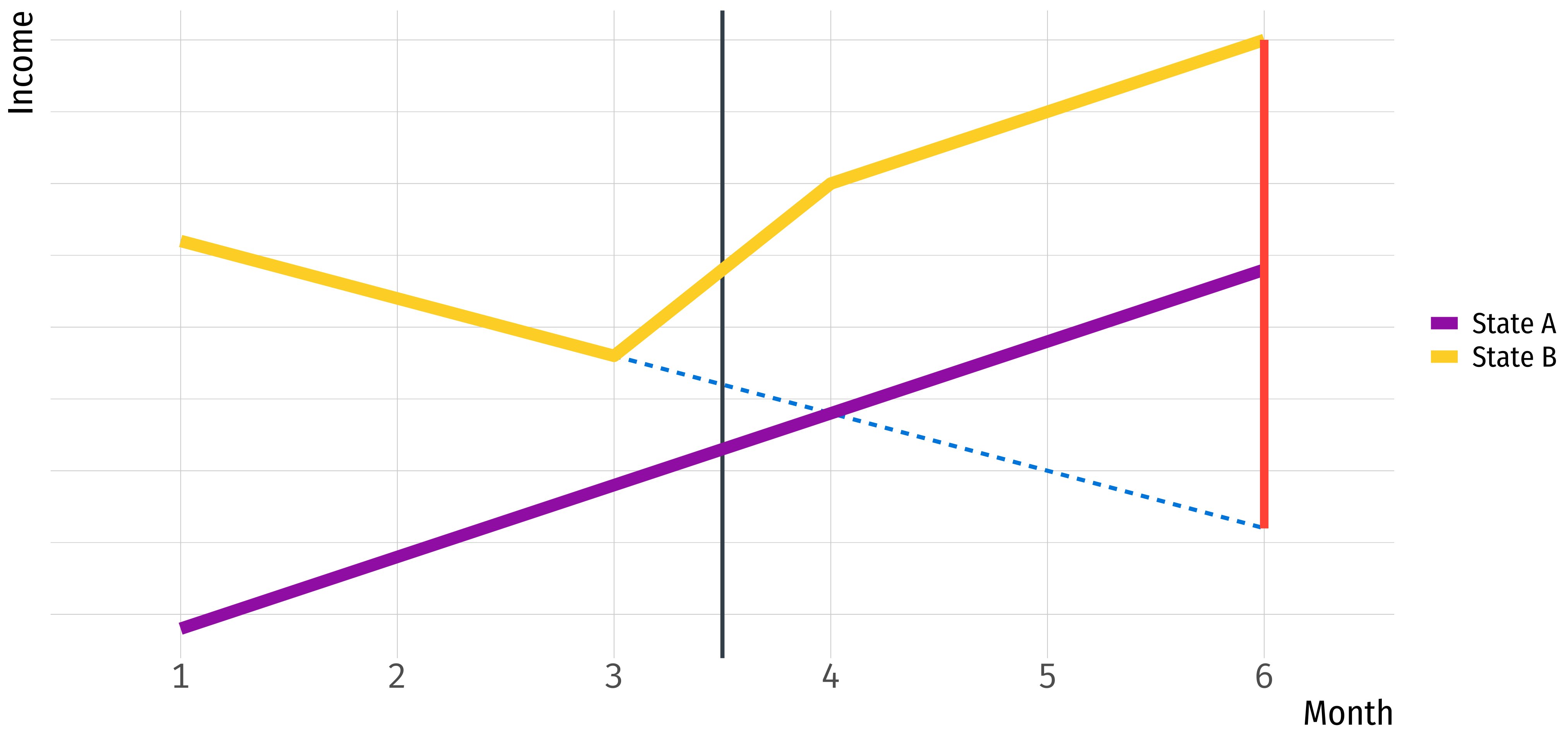
Income
1
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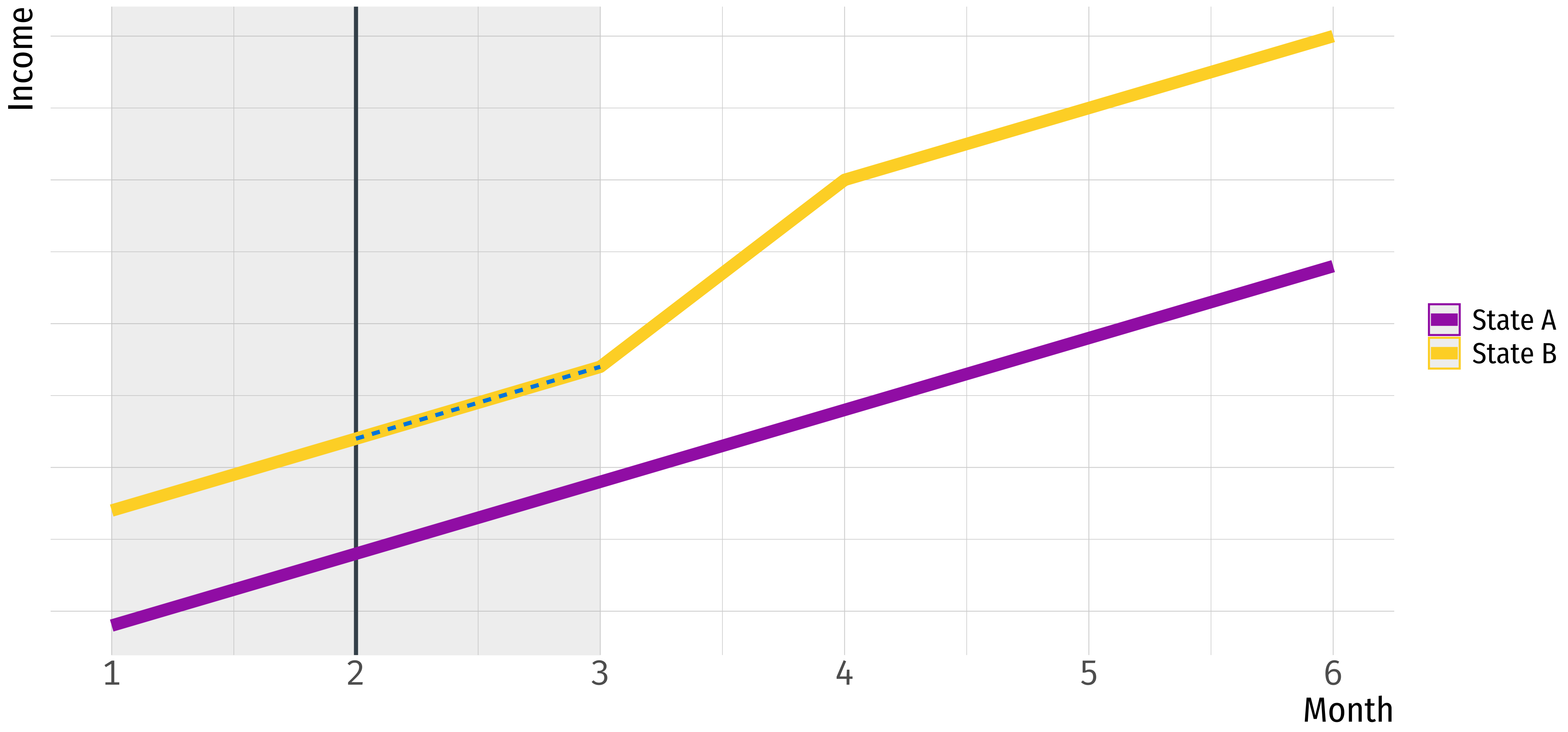
Month
State A
State B

Looking at the previous plots, what is the estimand of interest?

Robustness Check

Parallel Trends

Check by pretending the treatment happened earlier; if there's an effect, there's likely an underlying trend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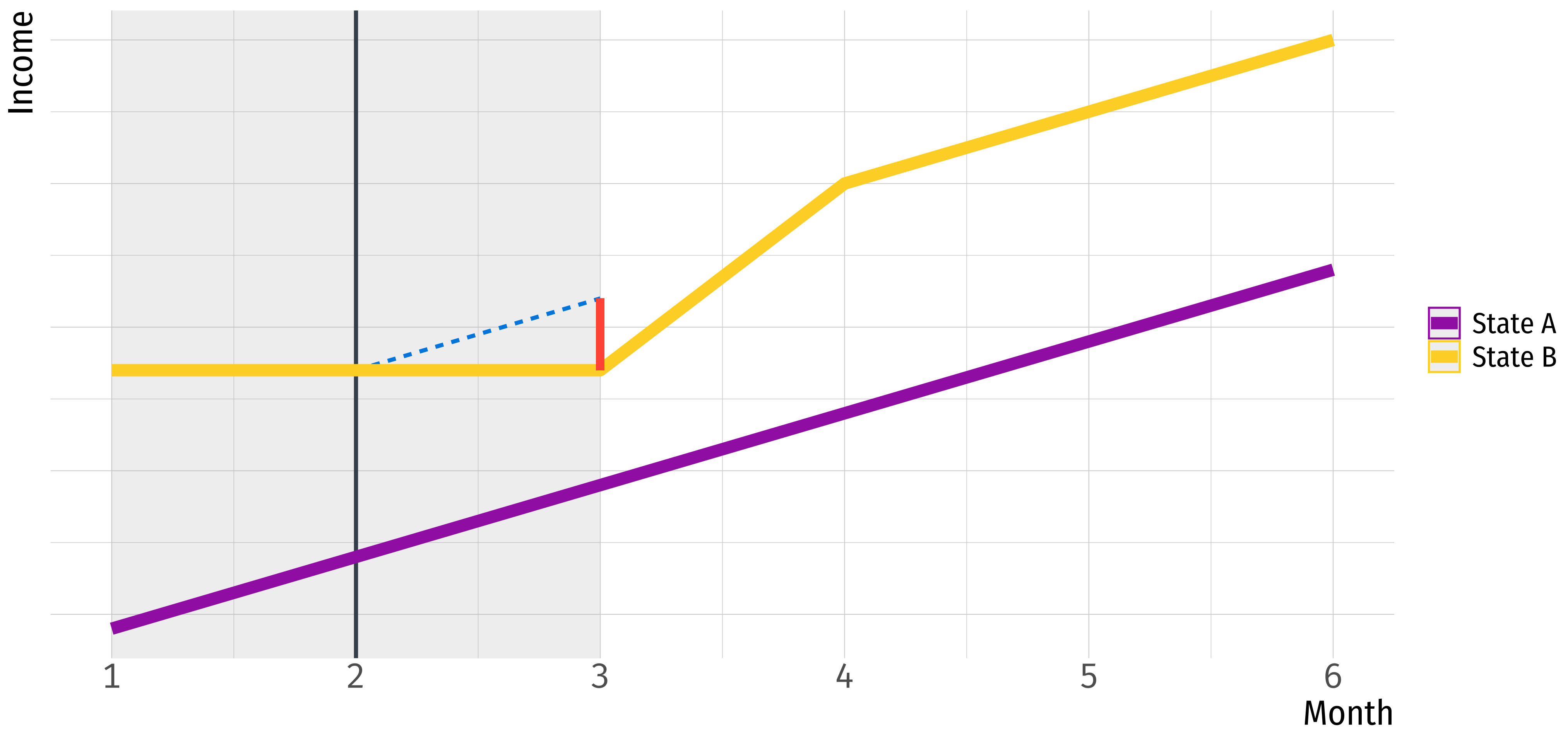
Month
State A
State B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4
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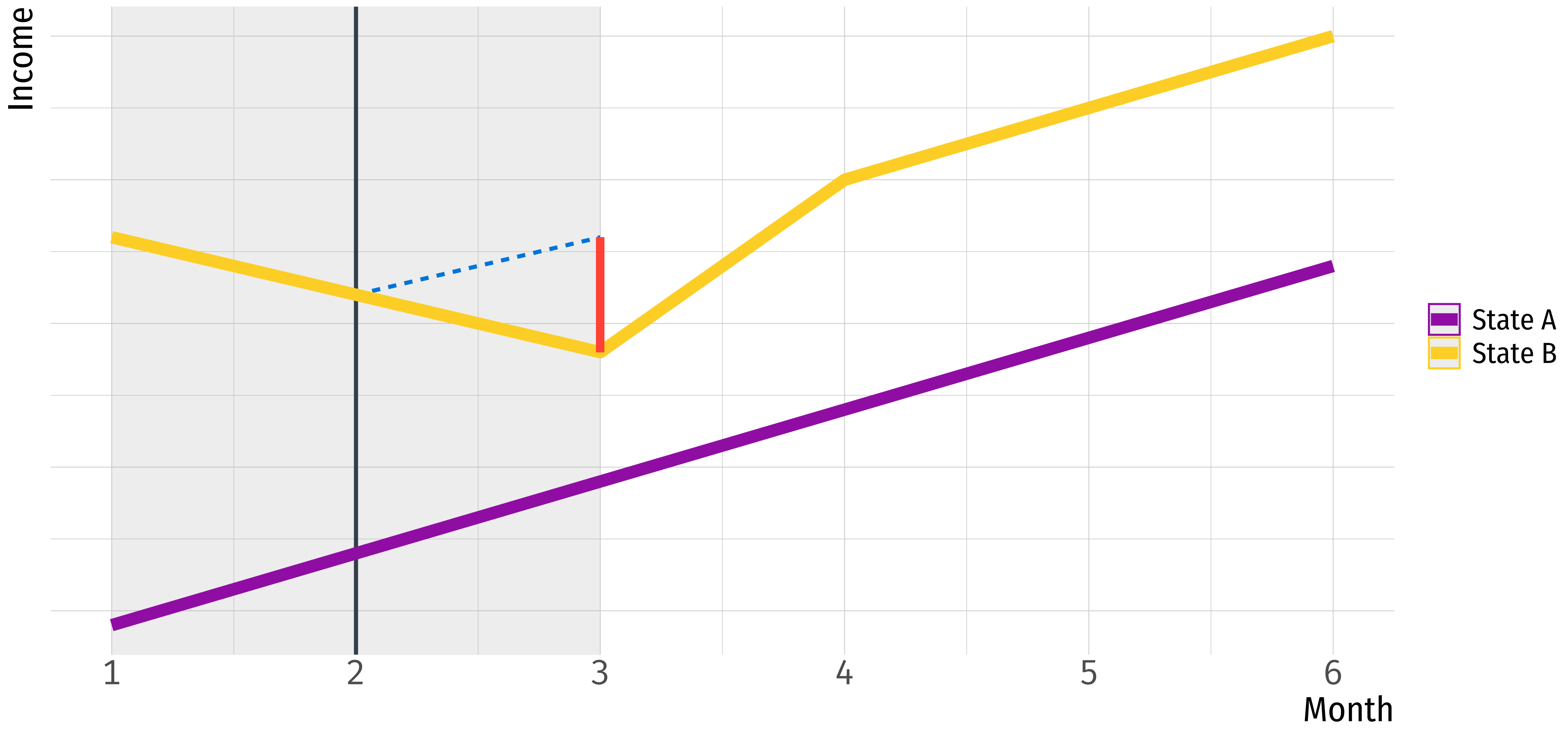
Month
State A
State B

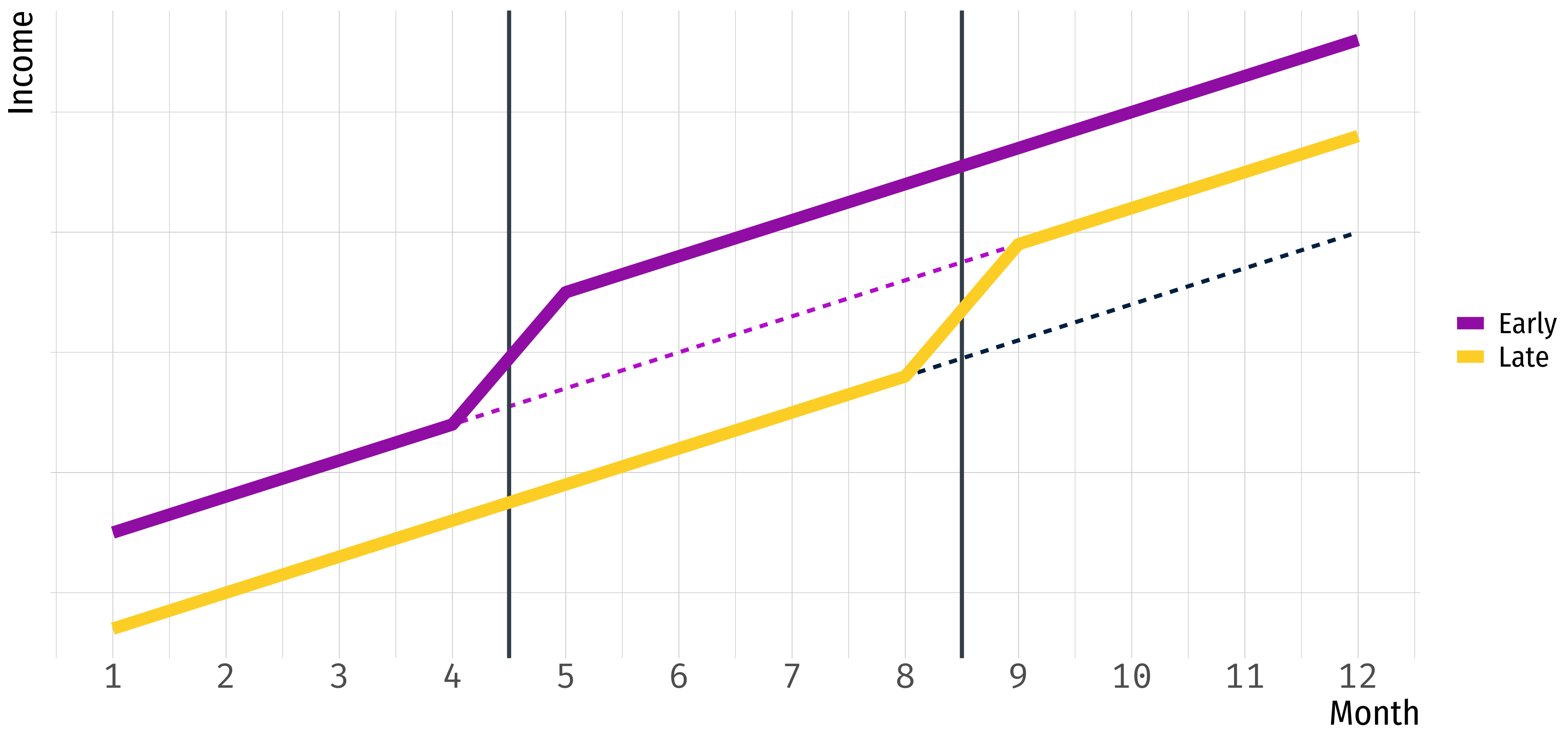


Income
State A
State B
1
2
3
4
5
6
Month

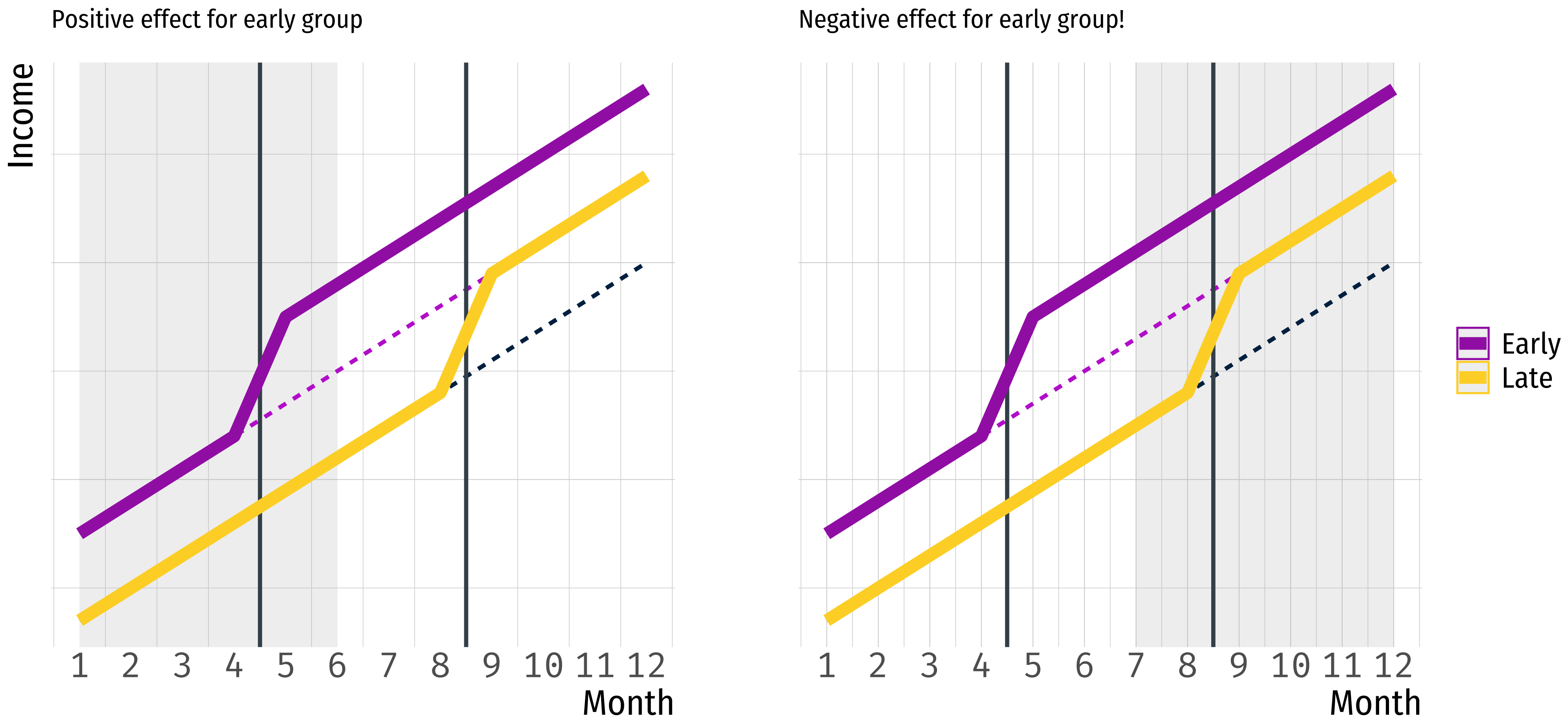
Assumptions

Treatment timing

Units often receive treatment at different times, which can distort your estimate!



Income
Early
Late
1
2
3
4
5
6
7
8
9
10
11
12
Month


Positive effect for early group
Negative effect for early group!
Income
1 2 3 4 5 6 7 8 9 10 11 12
Month
1 2 3 4 5 6 7 8 9 10 11 12
Month
Early
Late

Staggered treatment adoptions

- Units receive treatment at **different points in time**
- Common solution so far has been a Two-Way Fixed Effect (TWFE) model

$$Y_i = \alpha_i + \alpha_t + \beta^{DD} D_{it} + \varepsilon_{it}$$

- **Problem**: Weighted average of treatment effects

Not easily interpretable

Staggered treatment adoptions

You can check how big of an issue this is with Goodman-Bacon decomposition

R package: `bacondecomp`

DIFFERENCE-IN-DIFFERENCES WITH VARIATION IN TREATMENT TIMING*

Andrew Goodman-Bacon

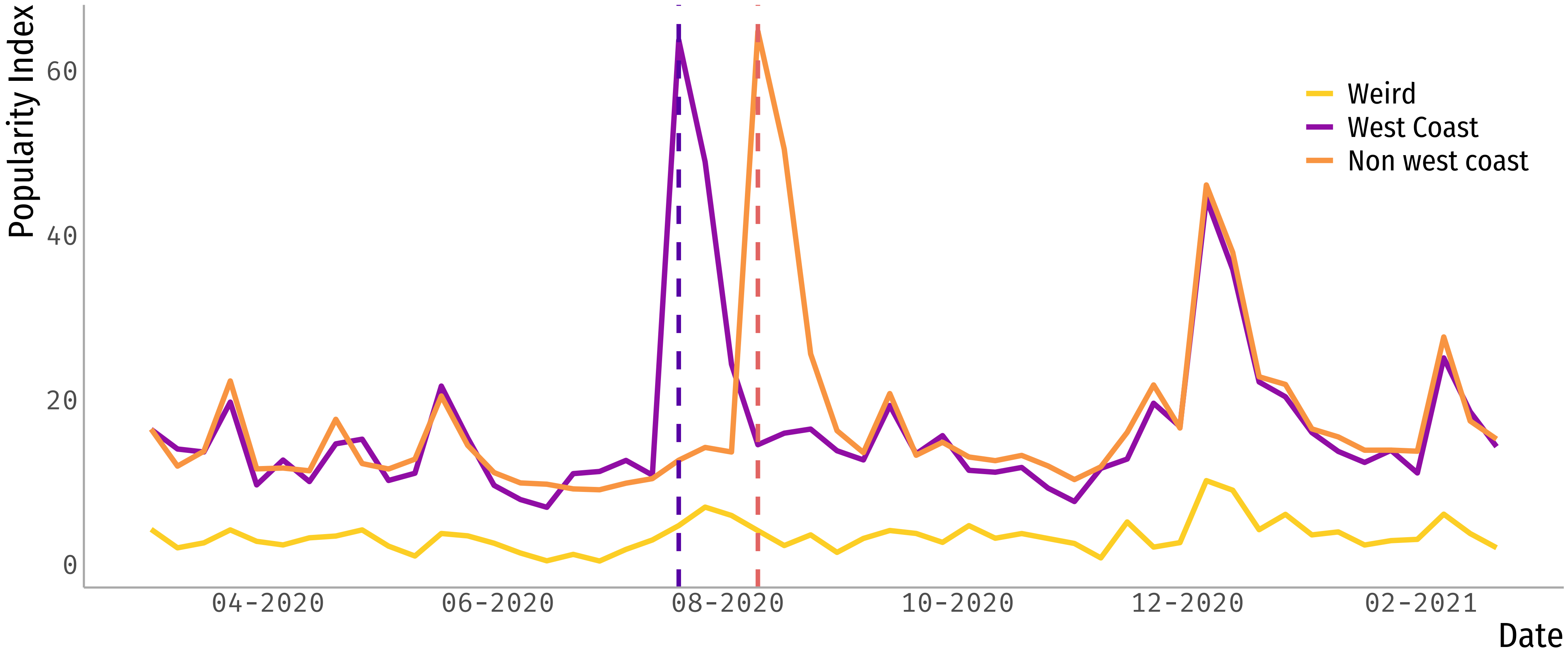
July 2019

Abstract: The canonical difference-in-differences (DD) estimator contains two time periods, "pre" and "post", and two groups, "treatment" and "control". Most DD applications, however, exploit variation across groups of units that receive treatment at different times. This paper shows that the general estimator equals a weighted average of all possible two-group/two-period DD estimators in the data. This defines the DD estimand and identifying assumption, a generalization of common trends. I discuss how to interpret DD estimates and propose a new balance test. I show how to decompose the difference between two specifications, and provide a new analysis of models that include time-varying controls.

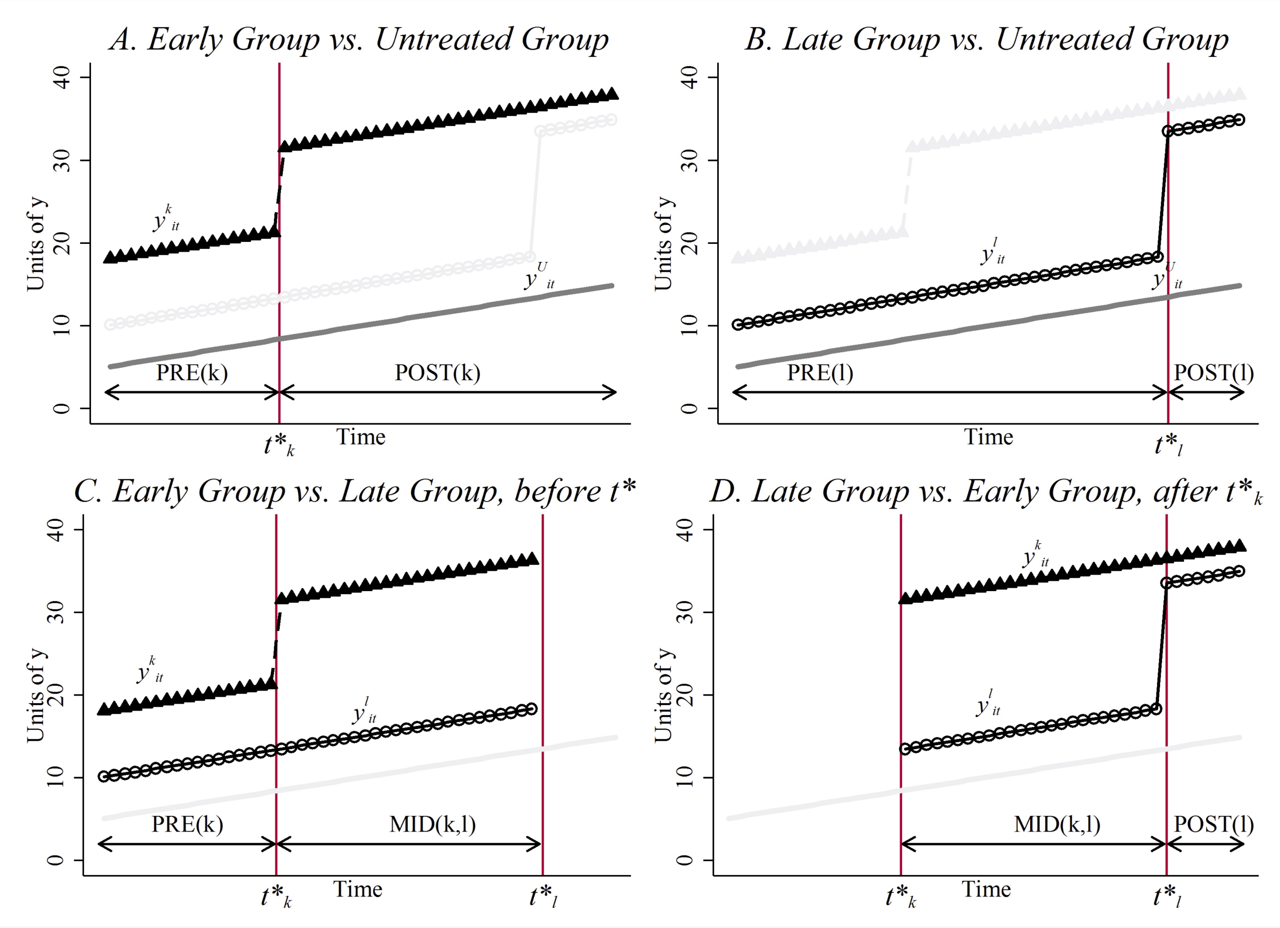
Let's look at an example

Look at what T.S. made me do

- Like in the JITT, we will have data for Taylor Swift's popularity in the past 12 months.



How many comparisons can we do?



Let's go to R

Takeaway points

- There are other ways to **estimate causal effects beyond randomization**
- Always be careful of the **assumptions**.
  - Run robustness checks!
- Don't confuse *assignment mechanisms* with *identification assumptions*
  - Note: Assignment mechanisms might make our identification assumption credible, **but they are not the same thing!**

References

- Angrist, J. and S. Pischke. (2015). "Mastering Metrics". *Chapter 5*.
- Baker, A. (2019). "Difference-in-Differences Methodology".
- Goodman-Bacon, A. (2019). "Difference-in-Differences with variation in treatment timing". *NBER working paper*.
- Heiss, A. (2020). "Program Evaluation for Public Policy". *Class 8-9: Diff-in-diff I and II, Course at BYU*.