STA 235 - Causal Inference: Differences-in-Differences

Spring 2021

McCombs School of Business, UT Austin

Another identification strategy

- We have seen:

RCTs

Selection on observables

Natural experiments

Differences-in-Differences

Two wrongs make a right

Raising the minimum wage

What happens if we raise the minimum wage

Economic theory says there should be fewer jobs

New Jersey in 1992

\$4.25 → \$5.05

Before vs After

Avg. # of jobs per fast food restaurant in NJ

$\text{New Jersey}_{\text{before}} = 20.44$

$\text{New Jersey}_{\text{after}} = 21.03$

$\Delta = 0.59$

Is this a causal effect?

Treatment vs Control

Avg. # of jobs per fast food restaurant

$\text{Pennsylvania}_{\text{after}} = 21.17$

$\text{New Jersey}_{\text{after}} = 21.03$

$\Delta = -0.14$

Is this a causal effect?

Problems

Before vs After

Only looking at the treatment group

Impossible to separate changes because of treatment or time

Treatment vs Control

Only looking at post-treatment values

Impossible to separate changes because of treatment or differences in growth

Differences-in-Differences

The idea of a **DD** analysis is to take the **within-unit growth**...

	Pre mean	Post mean	(post - pre)
Control	**A** (never treated)	**B** (never treated)	**B - A**
Treatment	**C** (not yet treated)	**D** (treated)	**D - C**

Δ (post – pre) = within-unit growth

Differences-in-Differences

... and the **across-group growth**...

	Pre mean	Post mean	(post - pre)
Control	**A** (never treated)	**B** (never treated)	
Treatment	**C** (not yet treated)	**D** (treated)	
(treatment - control)	**C - A**	**D - B**	

∆ (treatment – control) = across-group growth

Differences-in-Differences

... and **combine them!**

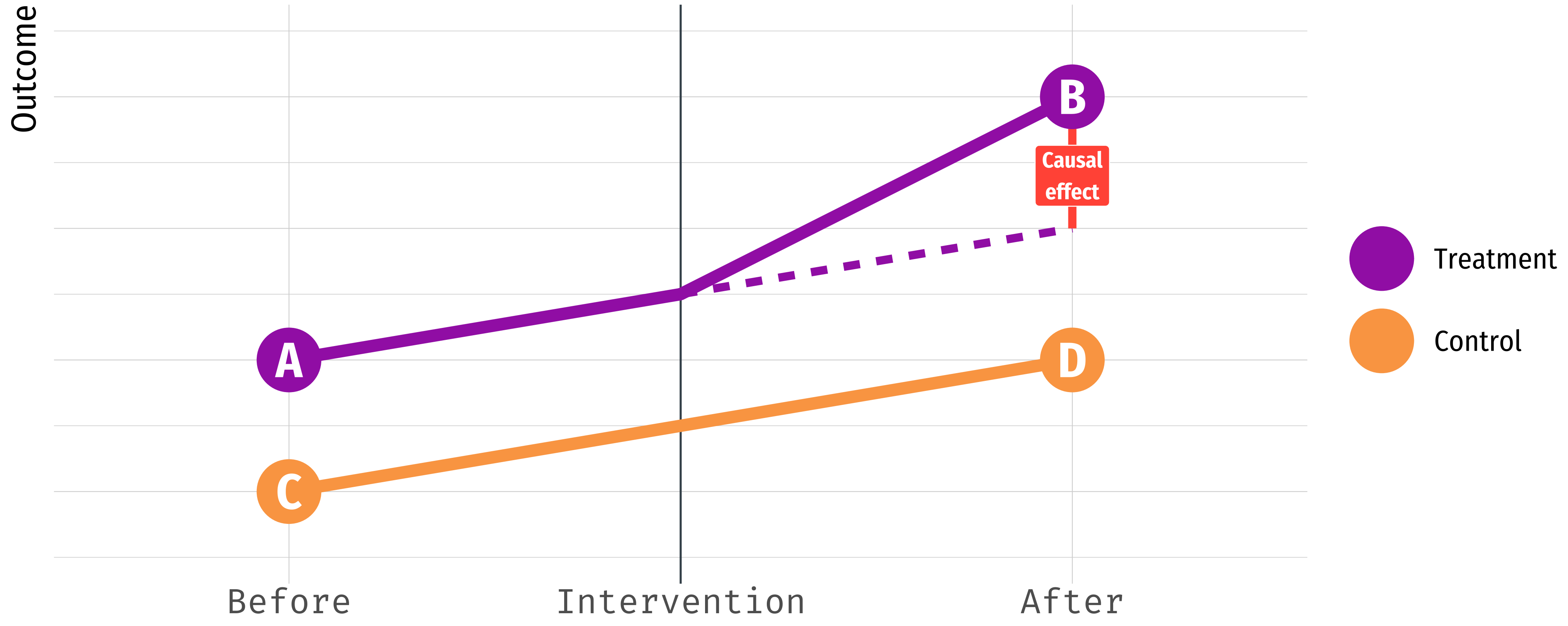
	Pre mean	Post mean	(post - pre)
Control	**A** (never treated)	**B** (never treated)	**B - A**
Treatment	**C** (not yet treated)	**D** (treated)	**D - C**
(treatment - control)	**C - A**	**D - B**	(D - C) - (B - A) *or* (D - B) - (C - A)

$\Delta_{\text{within units}} - \Delta_{\text{across groups}} =$
Difference-in-differences =
causal effect!

Coming back to New Jersey

	Pre mean	Post mean	(post - pre)
Pennsylvania	**23.33** A	**21.17** B	**-2.16** B - A
New Jersey	**20.44** C	**21.03** D	**0.59** D - C
(NJ - PA)	**-2.89** C - A	**-0.14** D - B	**(0.59) - (-2.16) =** **2.76**

How does it look in a plot?



Differences-in-Differences in practice

- There's no need to manually estimate all group means..

We can use regressions!

- If the **two dimensions** for our DD are *time* and *treatment*:

$$Y_i = \beta_0 + \beta_1 Treat_i + \beta_2 Post_i + \beta_3 Treat_i \times Post_i + \varepsilon_i$$

where $Treat = 1$ for the treatment group, and $Post = 1$ for the after period.

Can you identify the different coefficients?

Differences-in-Differences in practice

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where $Treat = 1$ for the treatment group, and $Post = 1$ for the after period.

β_3 is the causal effect!

Some examples: Pokemon Go!

RESEARCH

Gotta catch'em all! Pokémon GO and physical activity among young adults: difference in differences study

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ABSTRACT

OBJECTIVE

To estimate the effect of playing Pokémon GO on the number of steps taken daily up to six weeks after installation of the game.

DESIGN

Cohort study using online survey data.

PARTICIPANTS

Survey participants of Amazon Mechanical Turk (n=1182) residing in the United States, aged 18 to 35 years and using iPhone 6 series smartphones.

MAIN OUTCOME MEASURES

Number of daily steps taken each of the four weeks before and six weeks after installation of Pokémon

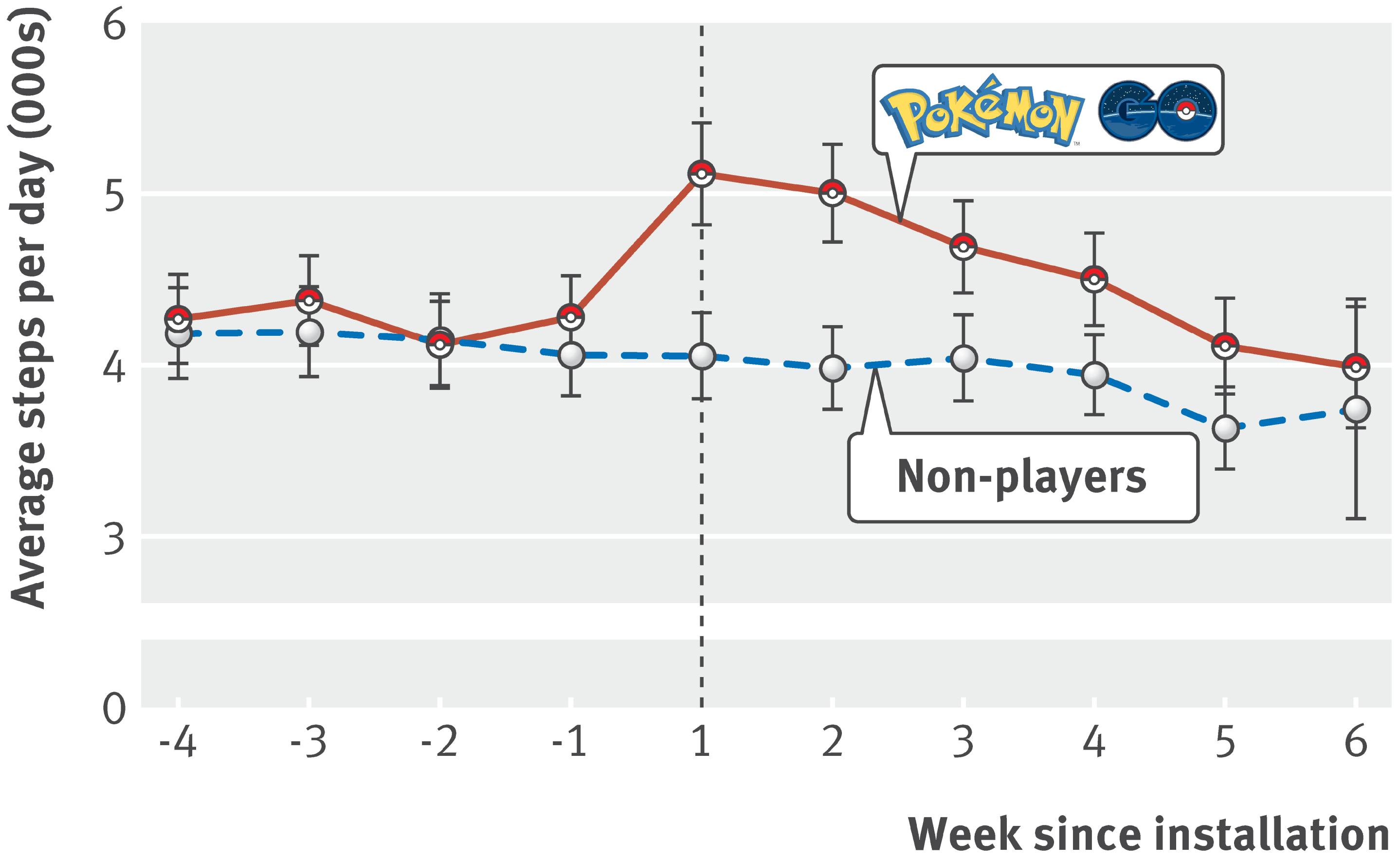
CONCLUSIONS

Pokémon GO was associated with an increase in the daily number of steps after installation of the game. The association was, however, moderate and no longer observed after six weeks.

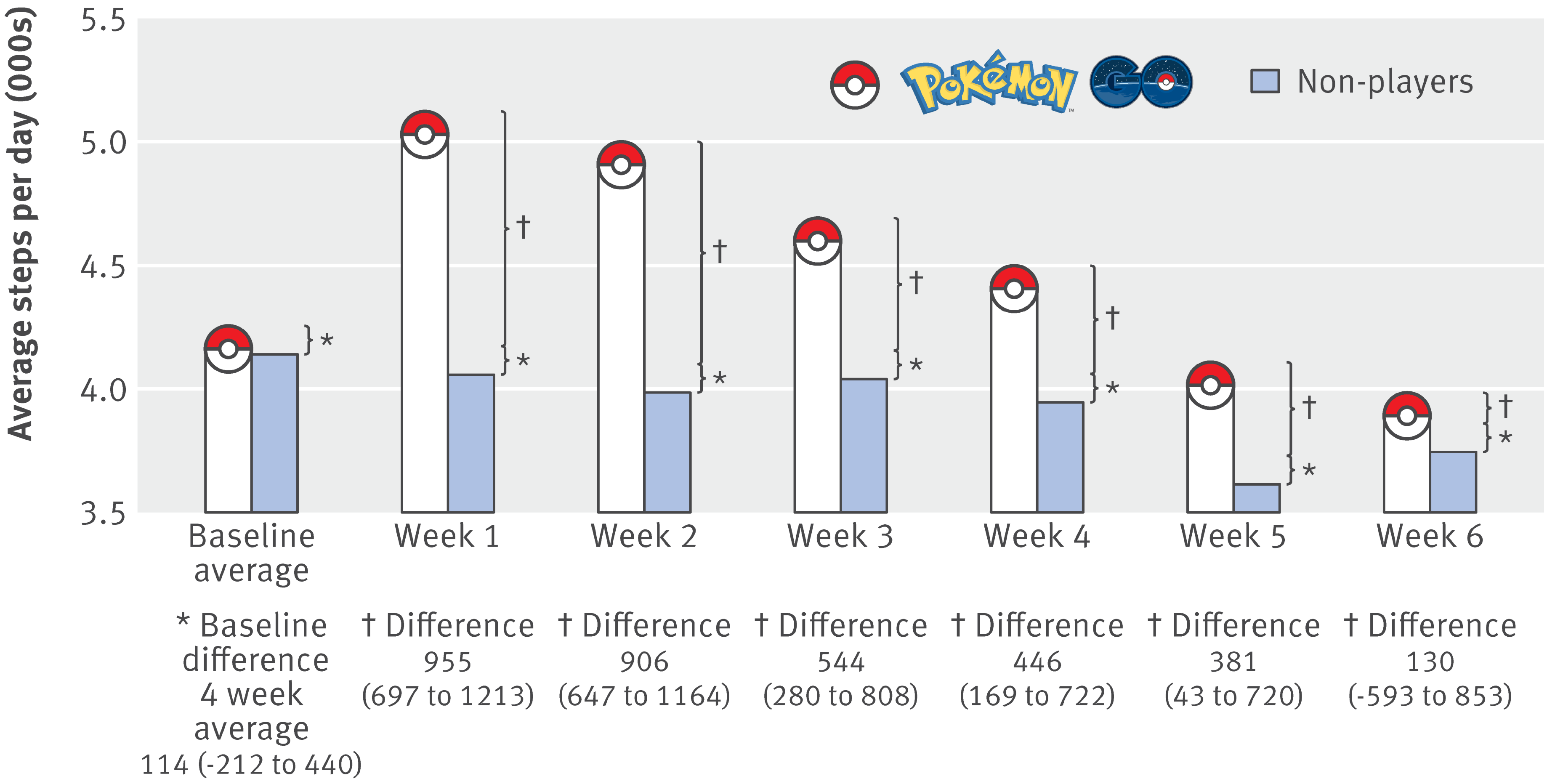
Introduction

Pokémon GO is an augmented reality game in which players search real world locations for cartoon characters appearing on their smartphone screen. Since its launch in July 2016, the game has been downloaded over 500 million times worldwide.

Games that incentivise exercise might have the potential to promote and sustain physical activity habits.[1,2] Because walking is encouraged while playing,



Average steps per day (000s)
6
5
4
3
0
-4
-3
-2
-1
1
2
3
4
5
6
Week since installation
Non-players

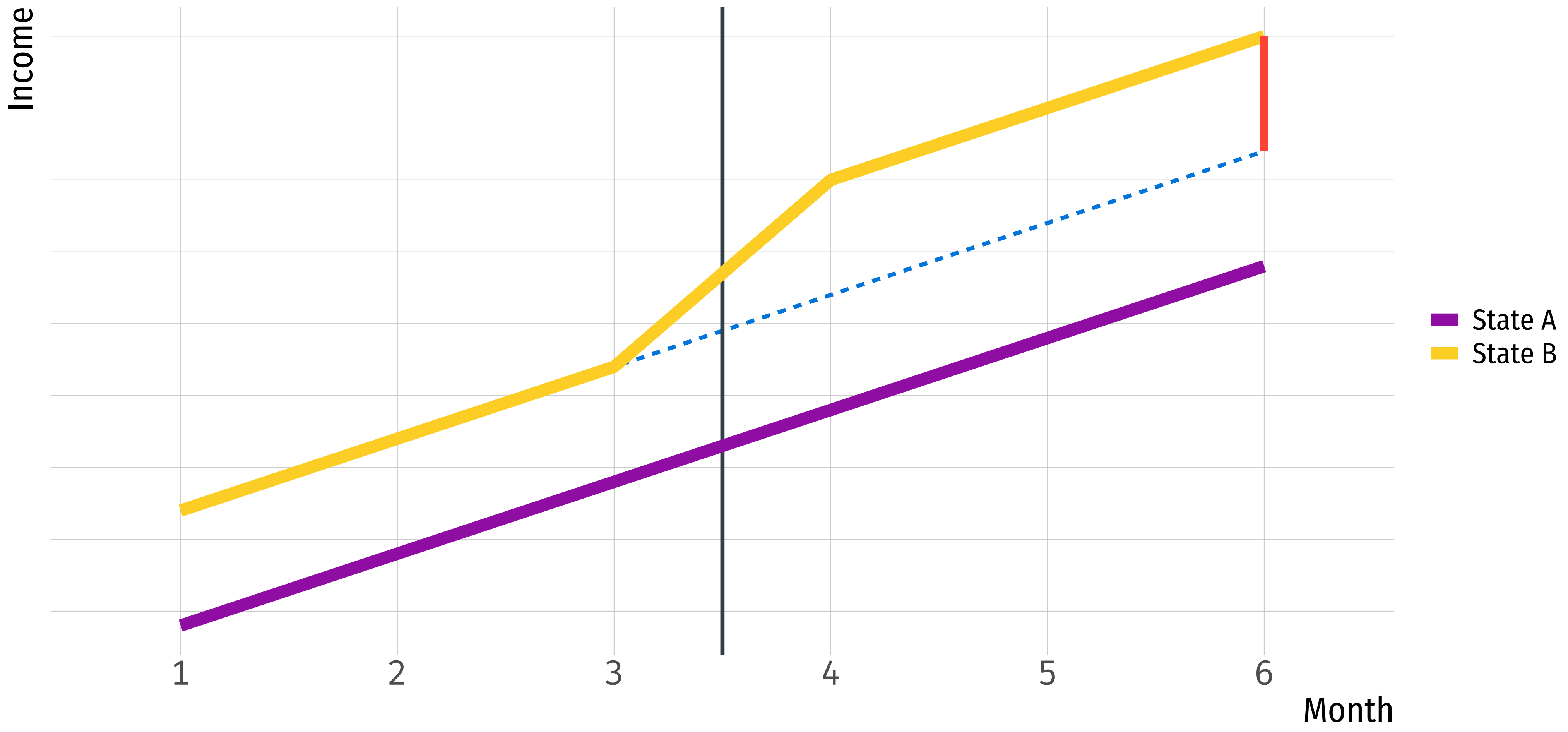

Average steps per day (000s)
5.5
5.0
4.5
4.0
3.5
Non-players
Baseline average
Week 1
Week 2
Week 3
Week 4
Week 5
Week 6
* Baseline difference 4 week average 114 (-212 to 440)
† Difference 955 (697 to 1213)
† Difference 906 (647 to 1164)
† Difference 544 (280 to 808)
† Difference 446 (169 to 722)
† Difference 381 (43 to 720)
† Difference 130 (-593 to 853)

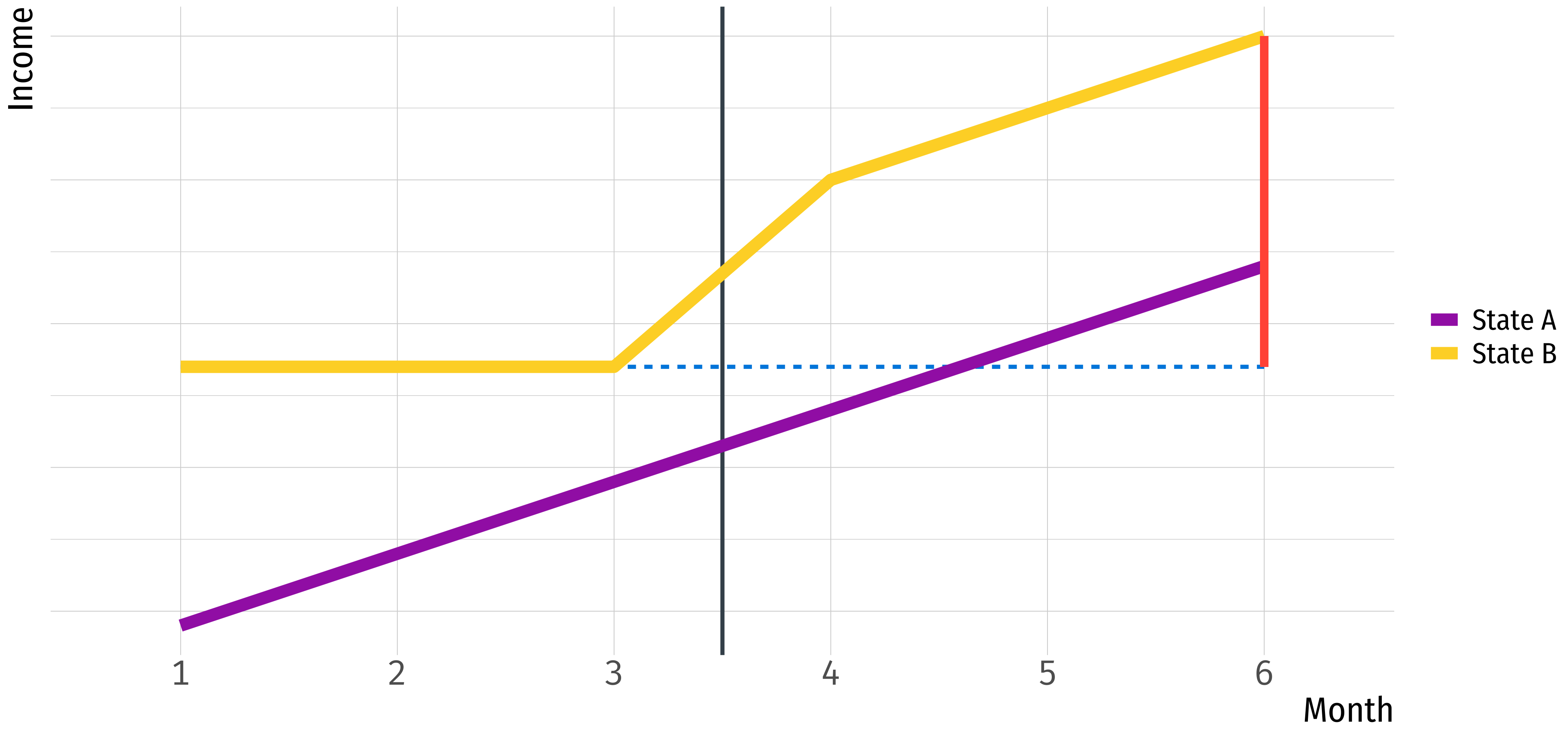
Diff-in-Diff Assumptions

Assumptions

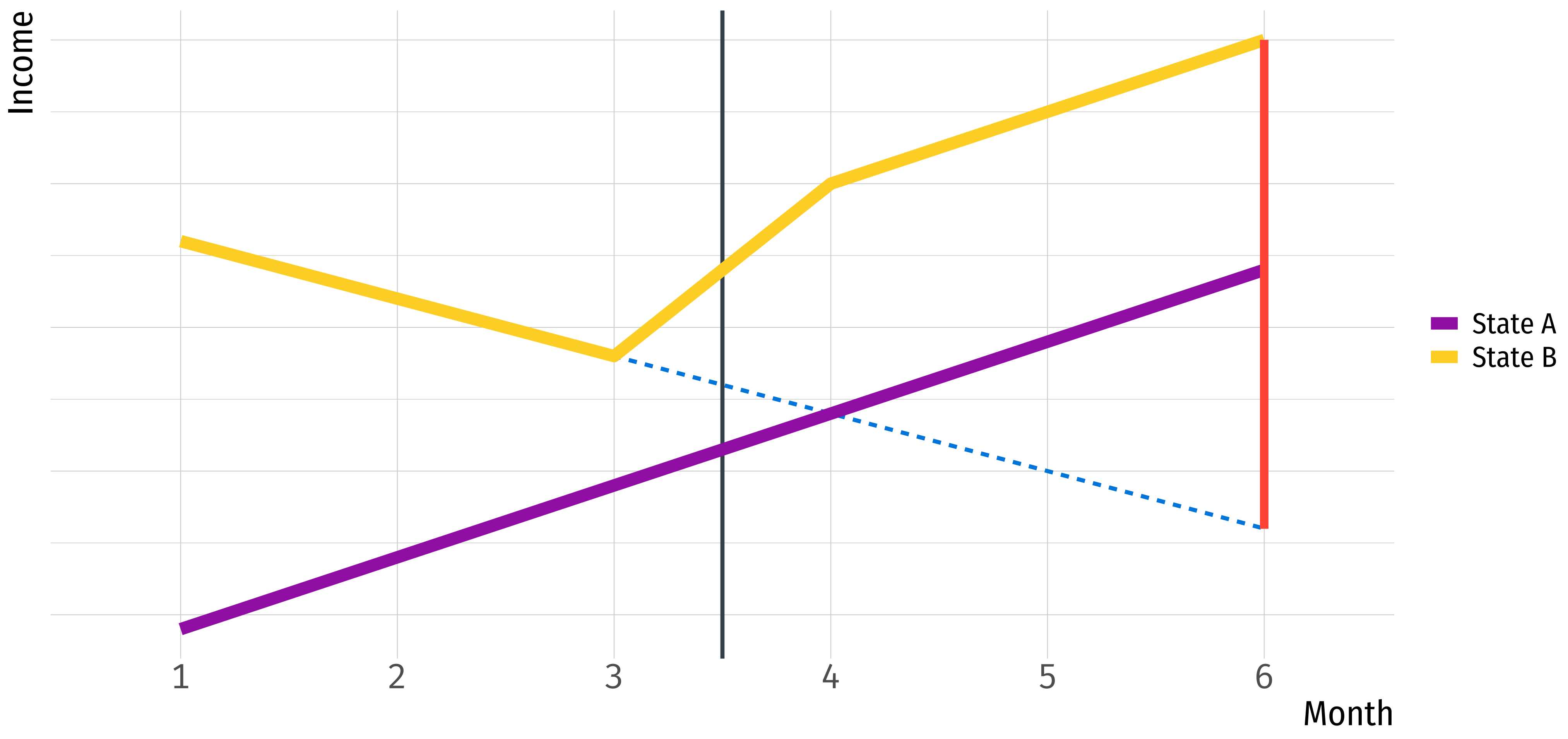
Parallel Trends

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



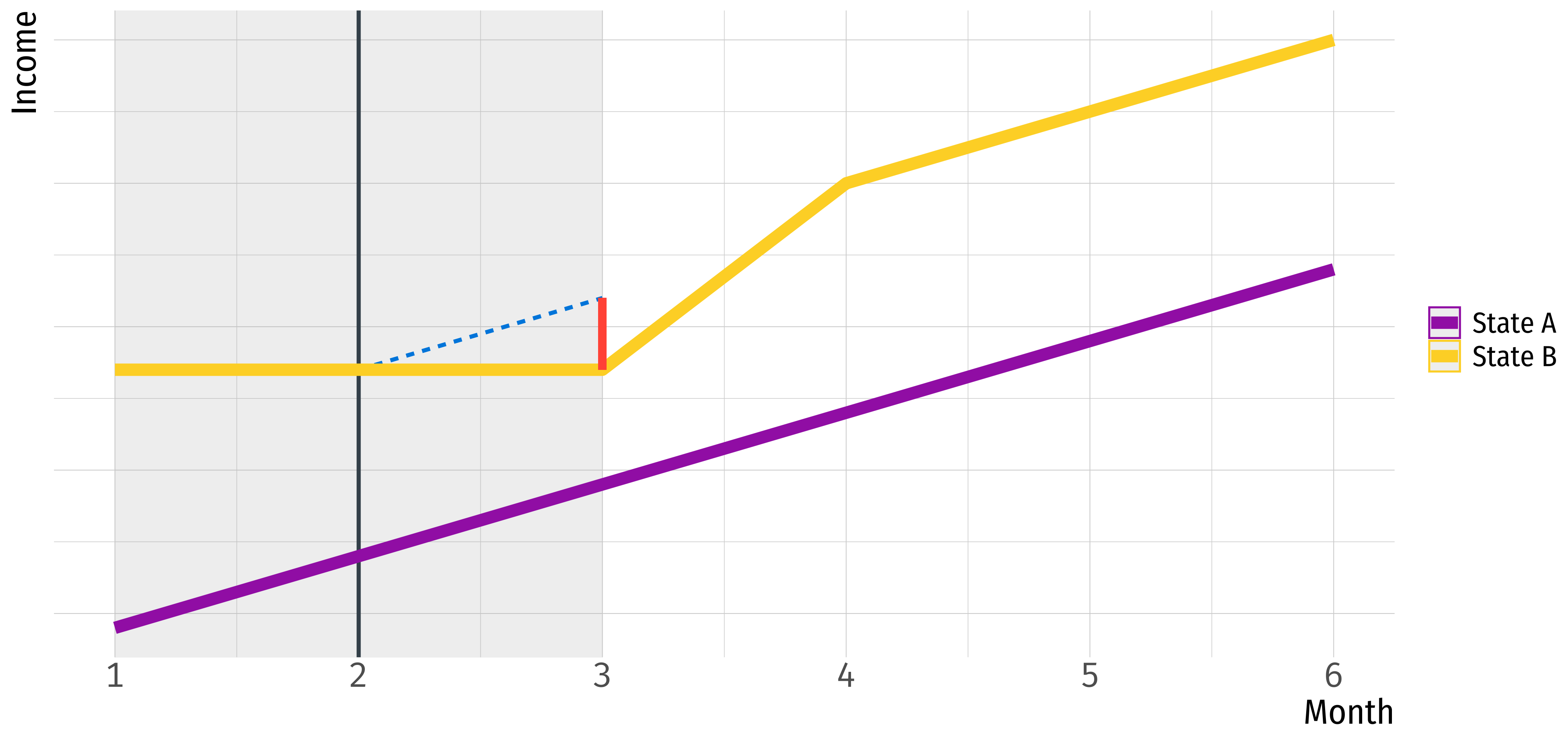
Income
1
2
3
4
5
6
Month
State A
State B


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

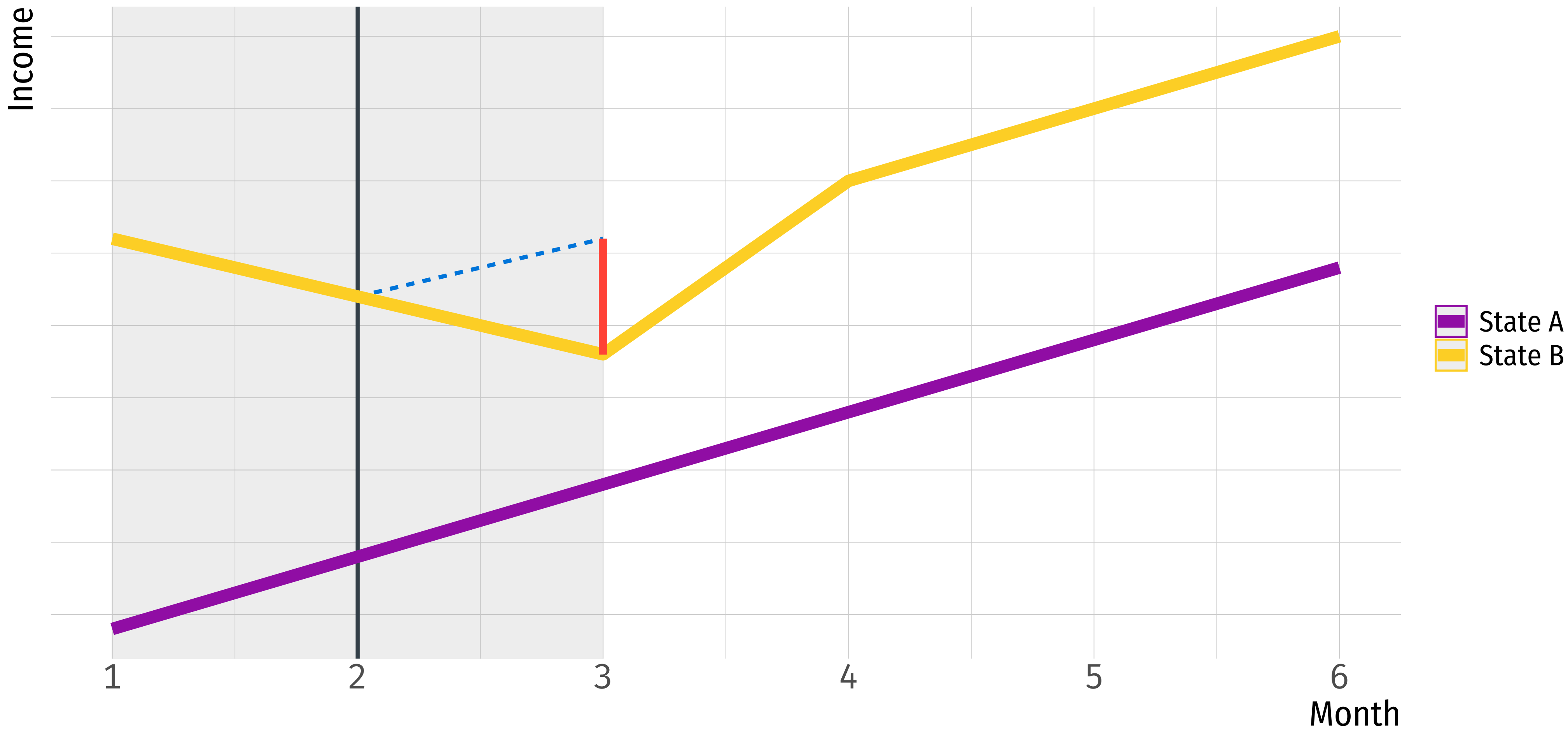
Robustness Check

Parallel Trends

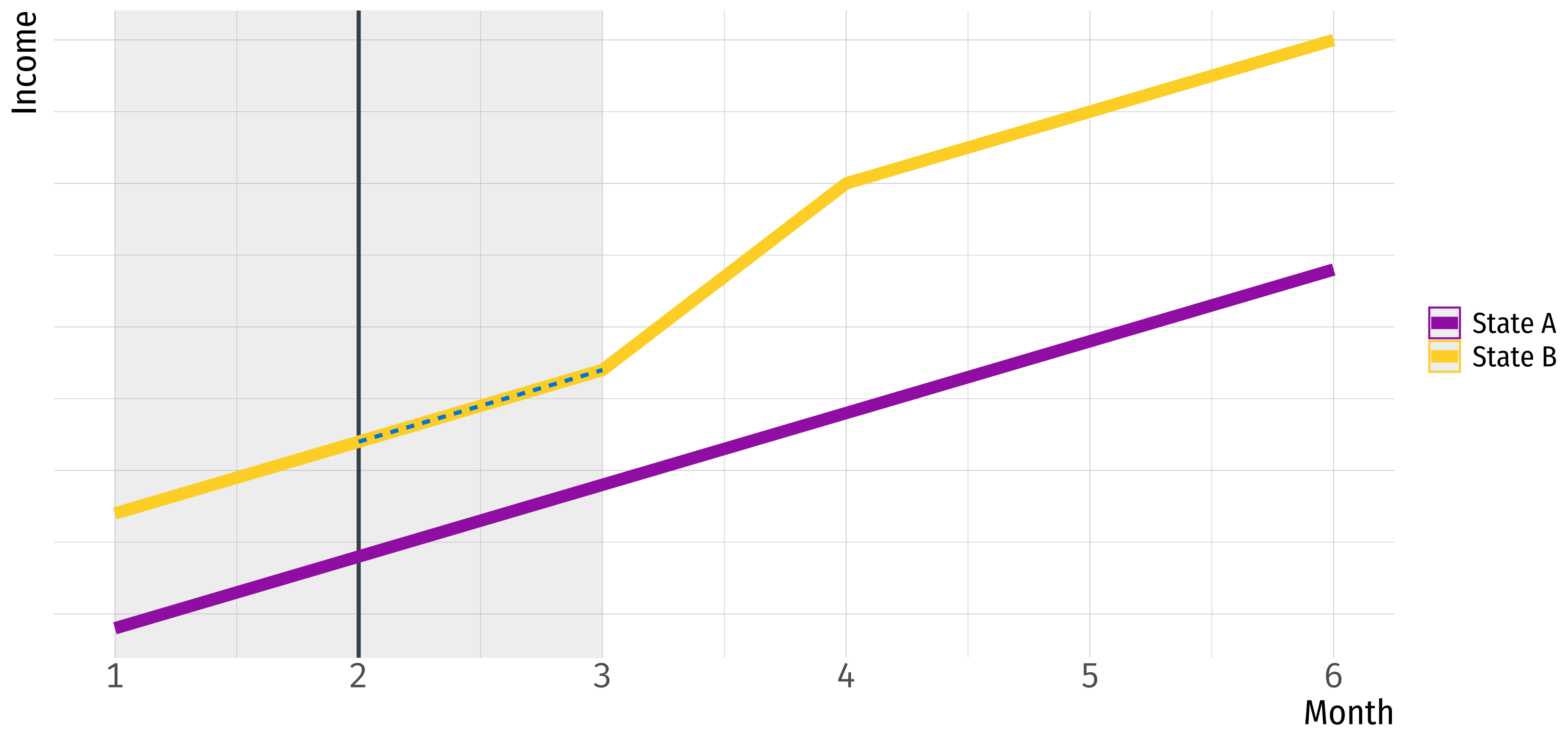
Check by pretending the treatment happened earlier; if there's an effect, there's likely an underlying trend



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



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

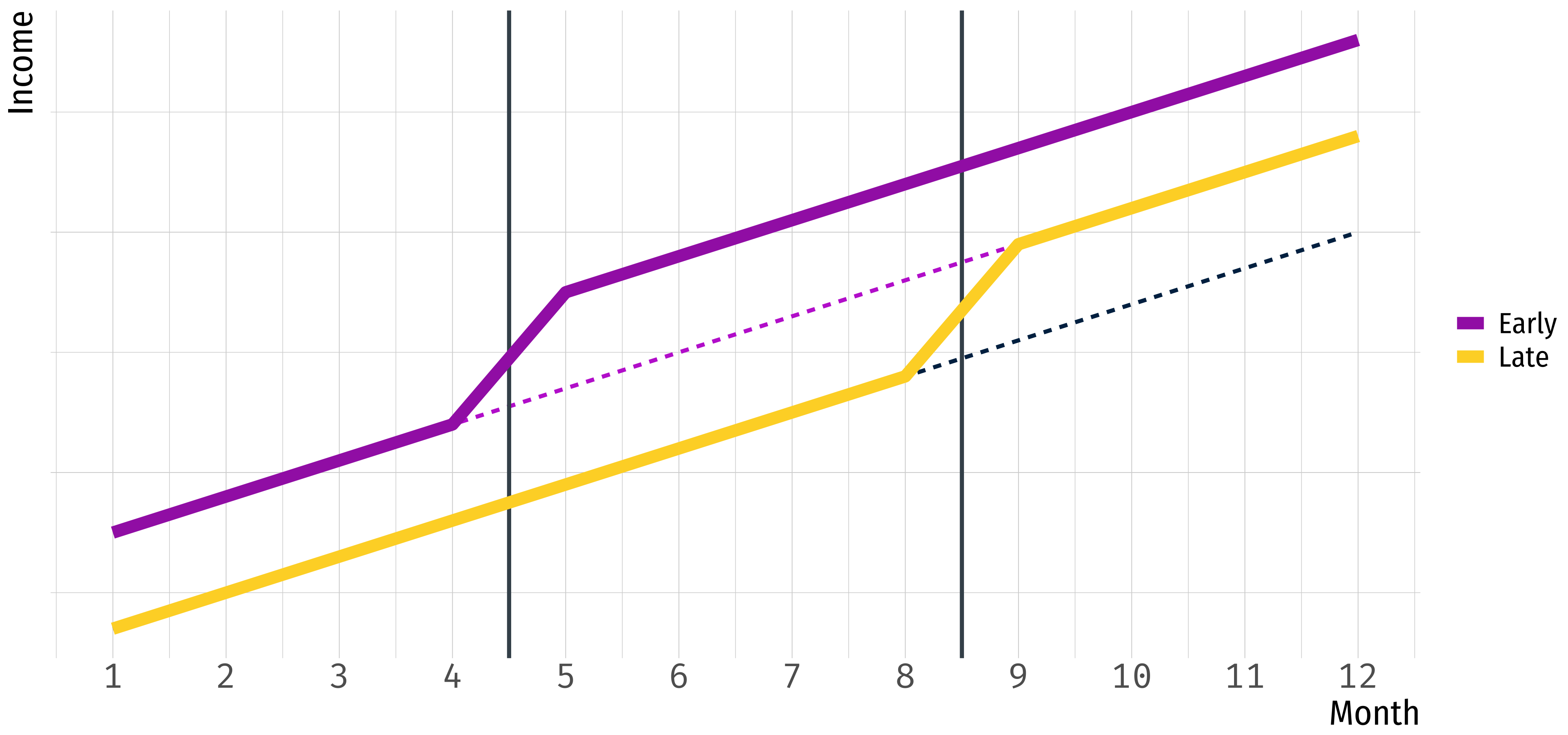


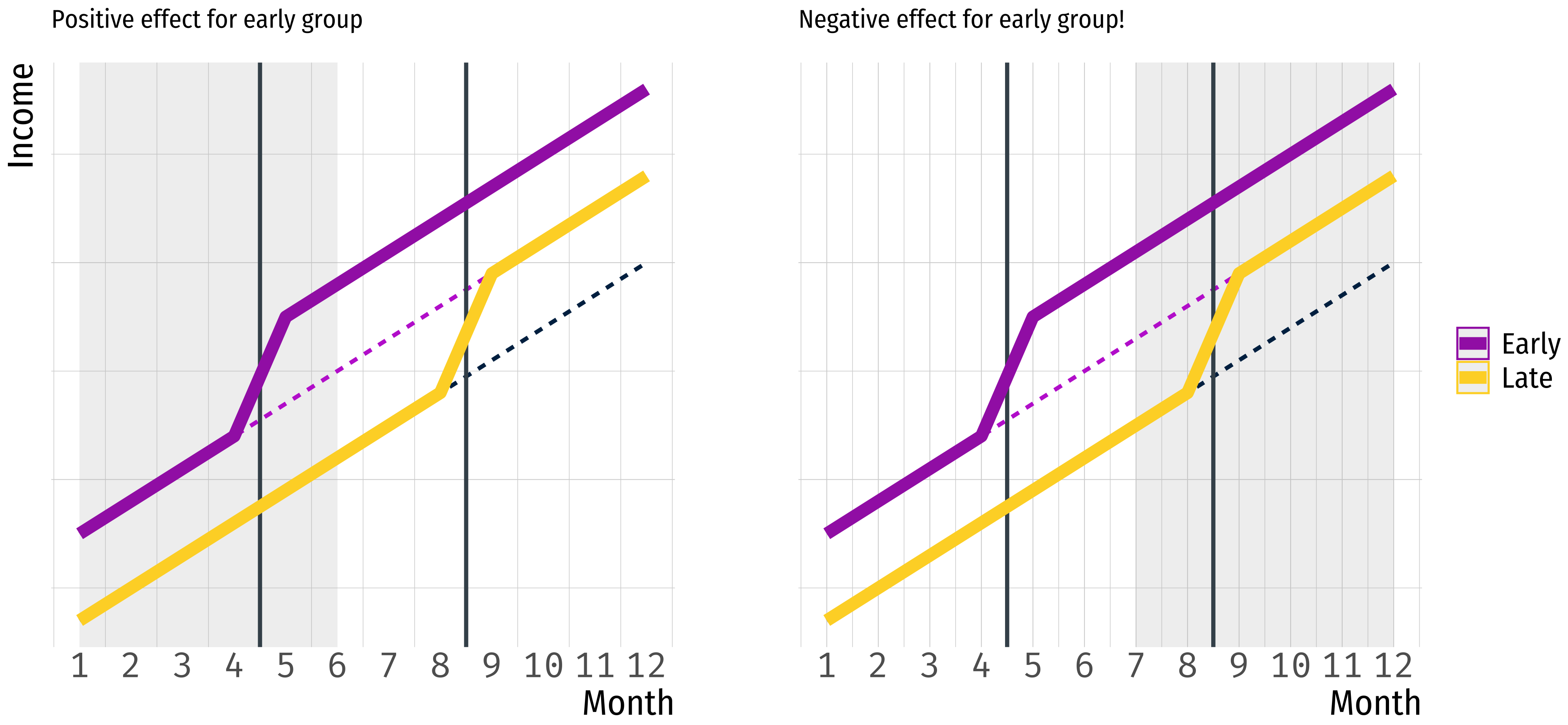
Income
1
2
3
4
5
6
Month
State A
State B

Assumptions

Treatment timing

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


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



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

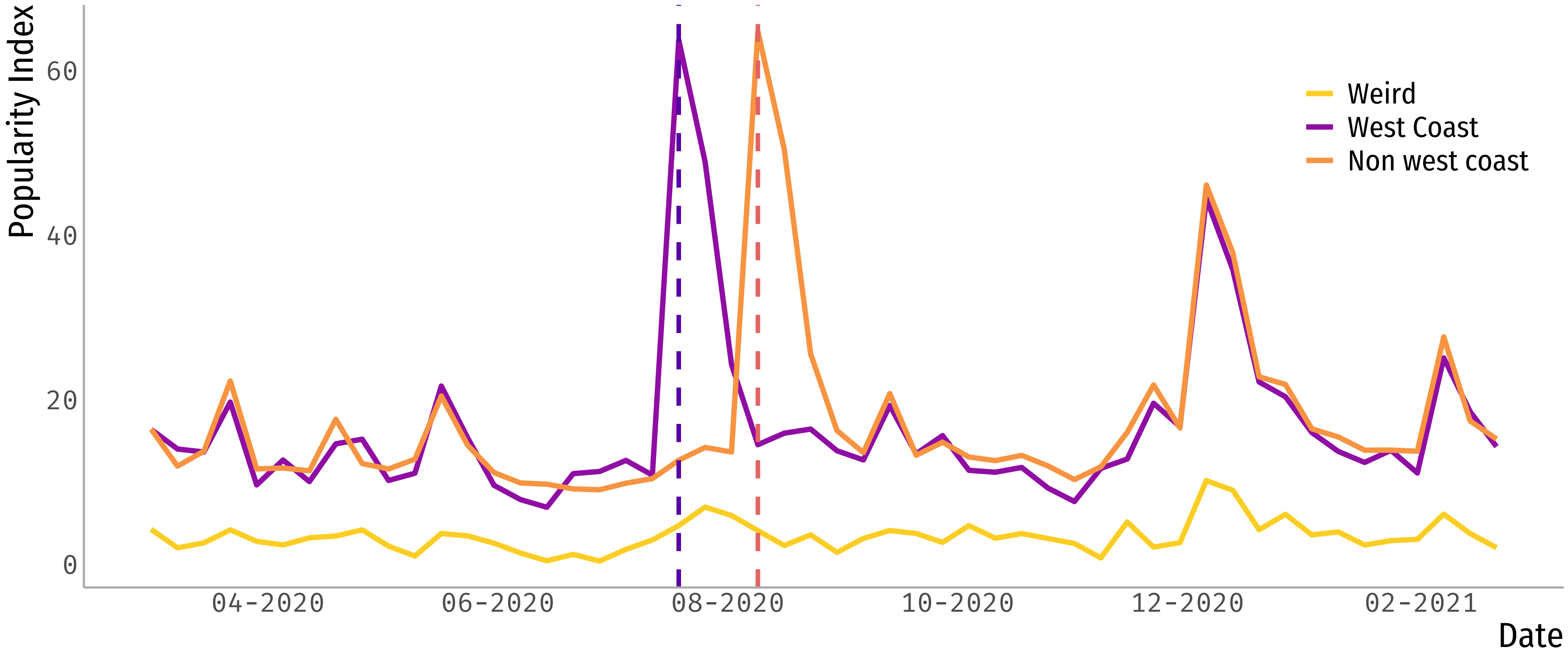
July 2019

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.

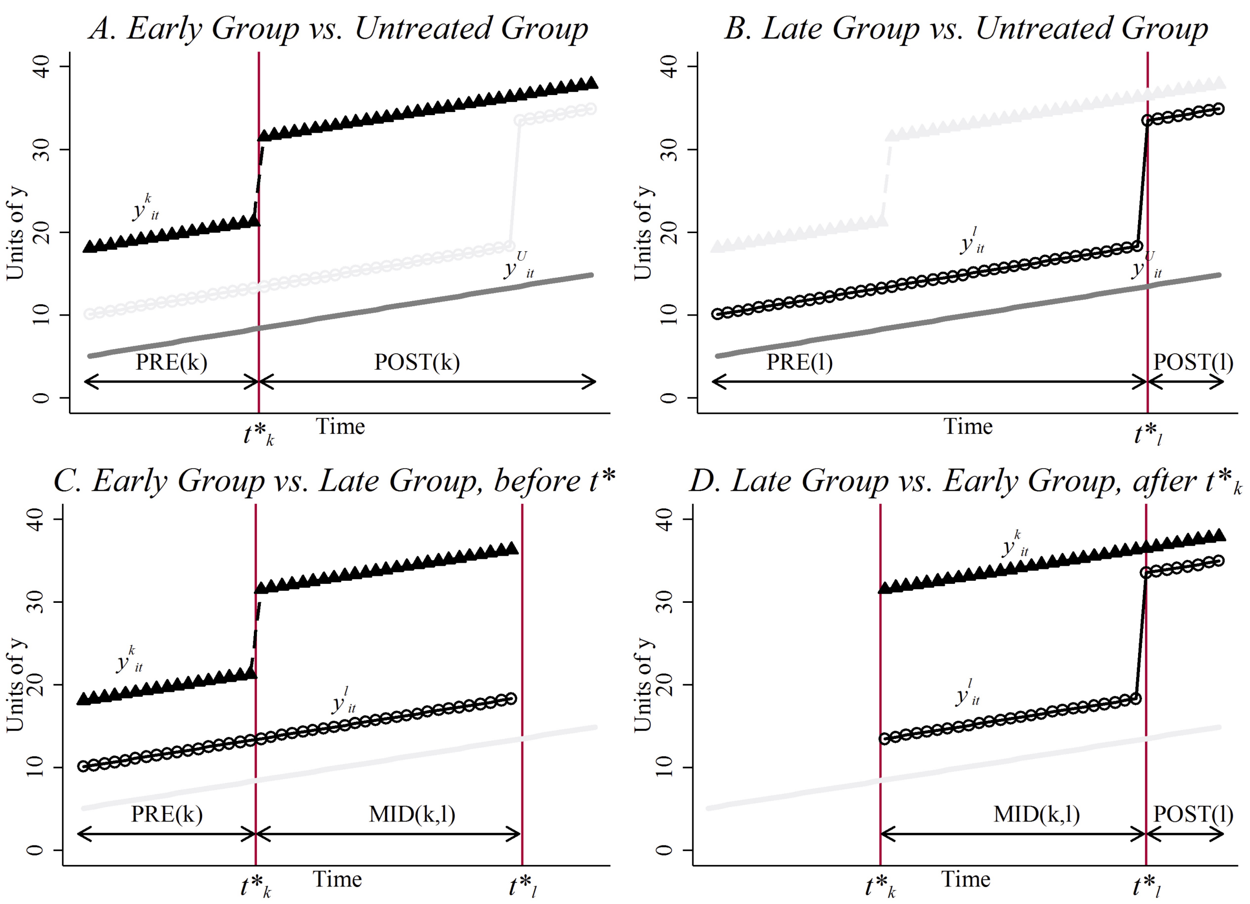
Let's look at an example

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*.