STA 235H - Difference-in-Differences

Fall 2021

McCombs School of Business, UT Austin

Another identification strategy

- We have seen:

RCTs

Selection on observables

Natural experiments

Difference-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

Difference-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

Difference-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

Difference-in-Differences

… and **combine them!**

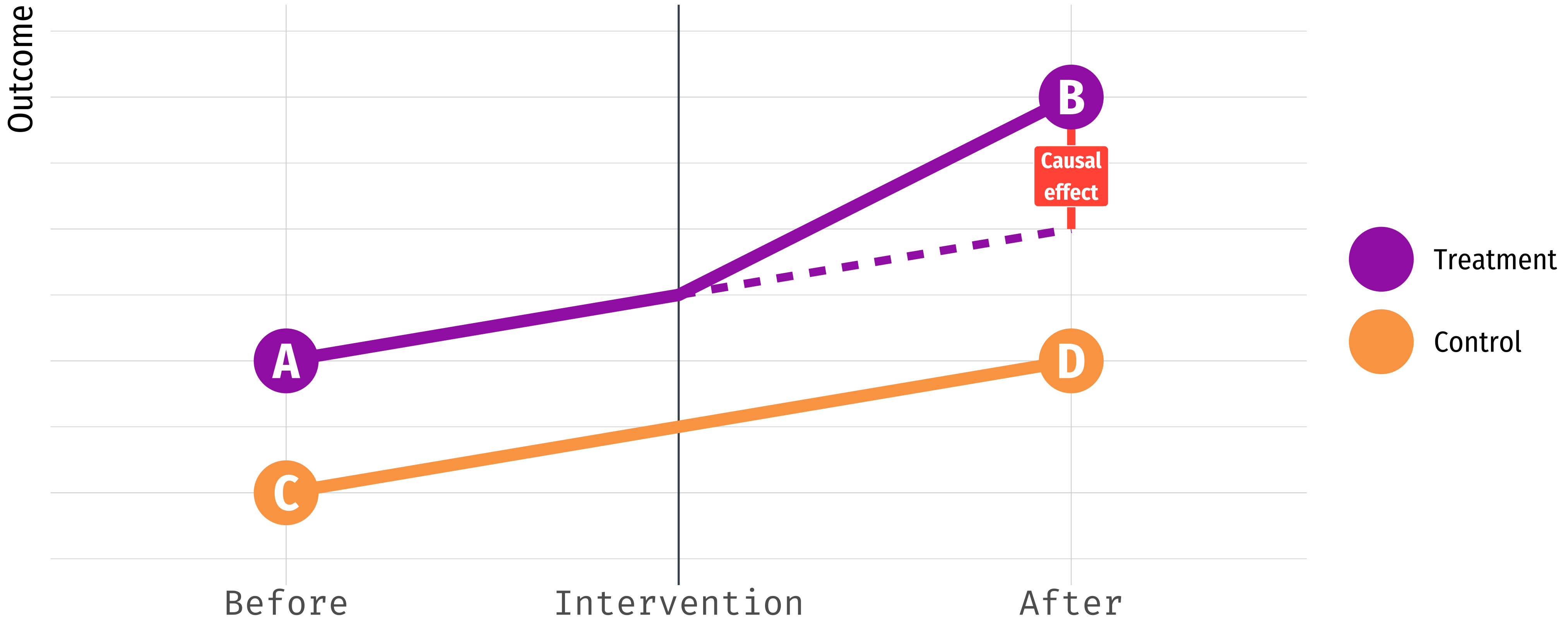
	Pre mean	Post mean	(post - pre)
Control	A (never treated)	B (never treated)	B - A
Treatment	C (not yet treated)	D (treated)	D - C
(treatment - control)	C - A	D - B	(D - C) - (B - A) *or* (D - B) - (C - A)

$\Delta_{\text{within units}} - \Delta_{\text{across groups}}$ =
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?



Difference-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?

Difference-in-Differences in practice

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

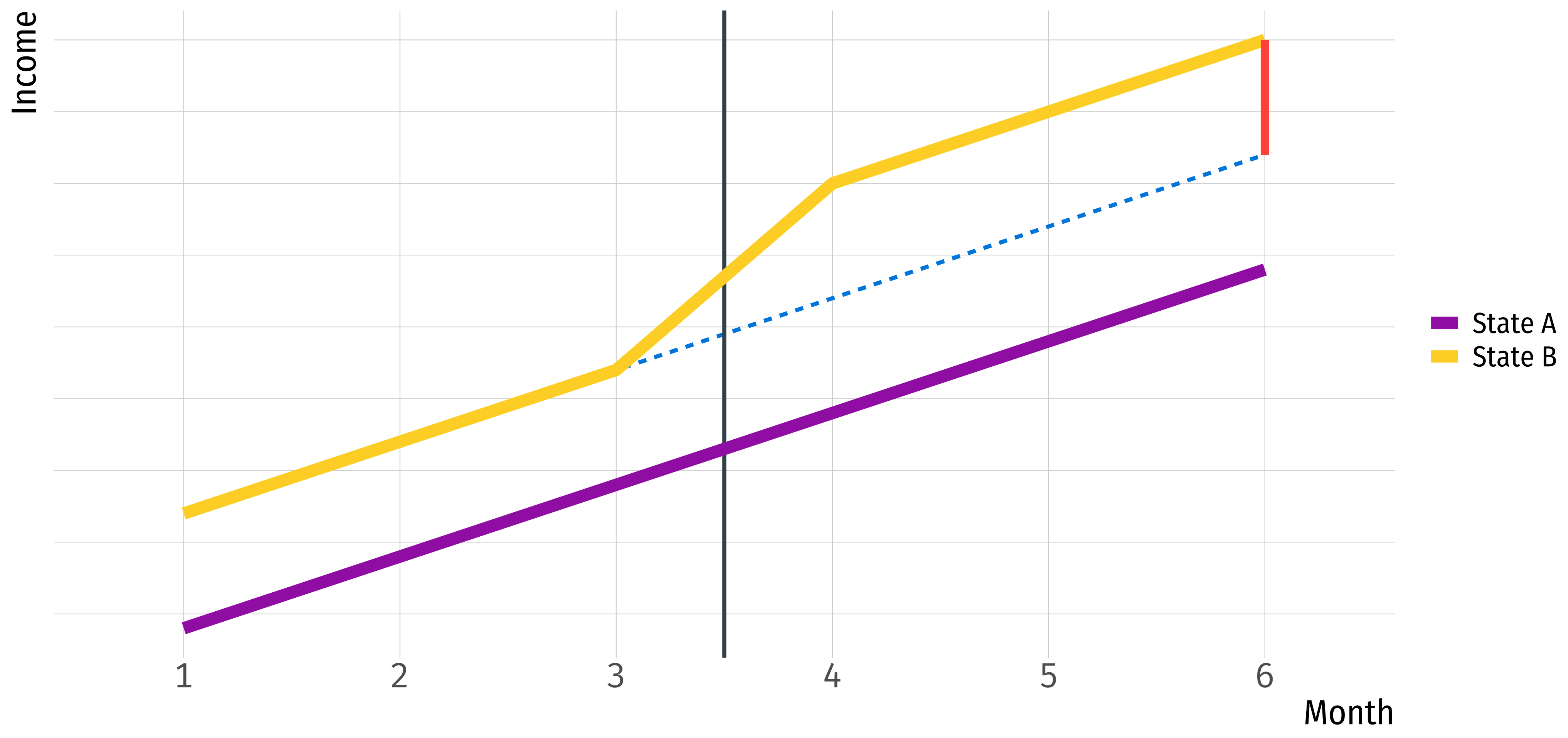
β_3 is the causal effect!

Diff-in-Diff Assumptions

Assumptions

Parallel Trends

In the absence of the intervention, treatment and control group would have changed in the same way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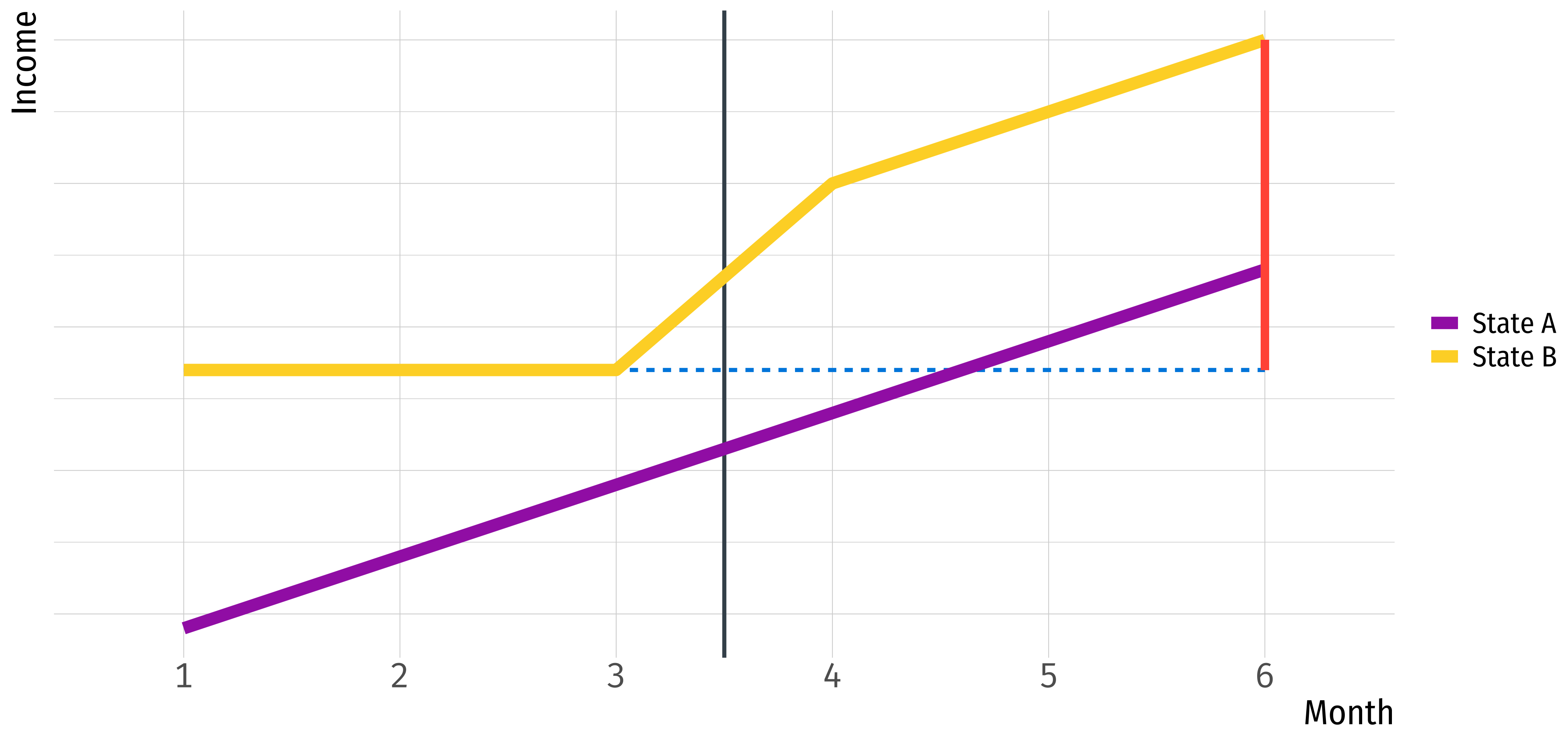
Month
State A
State B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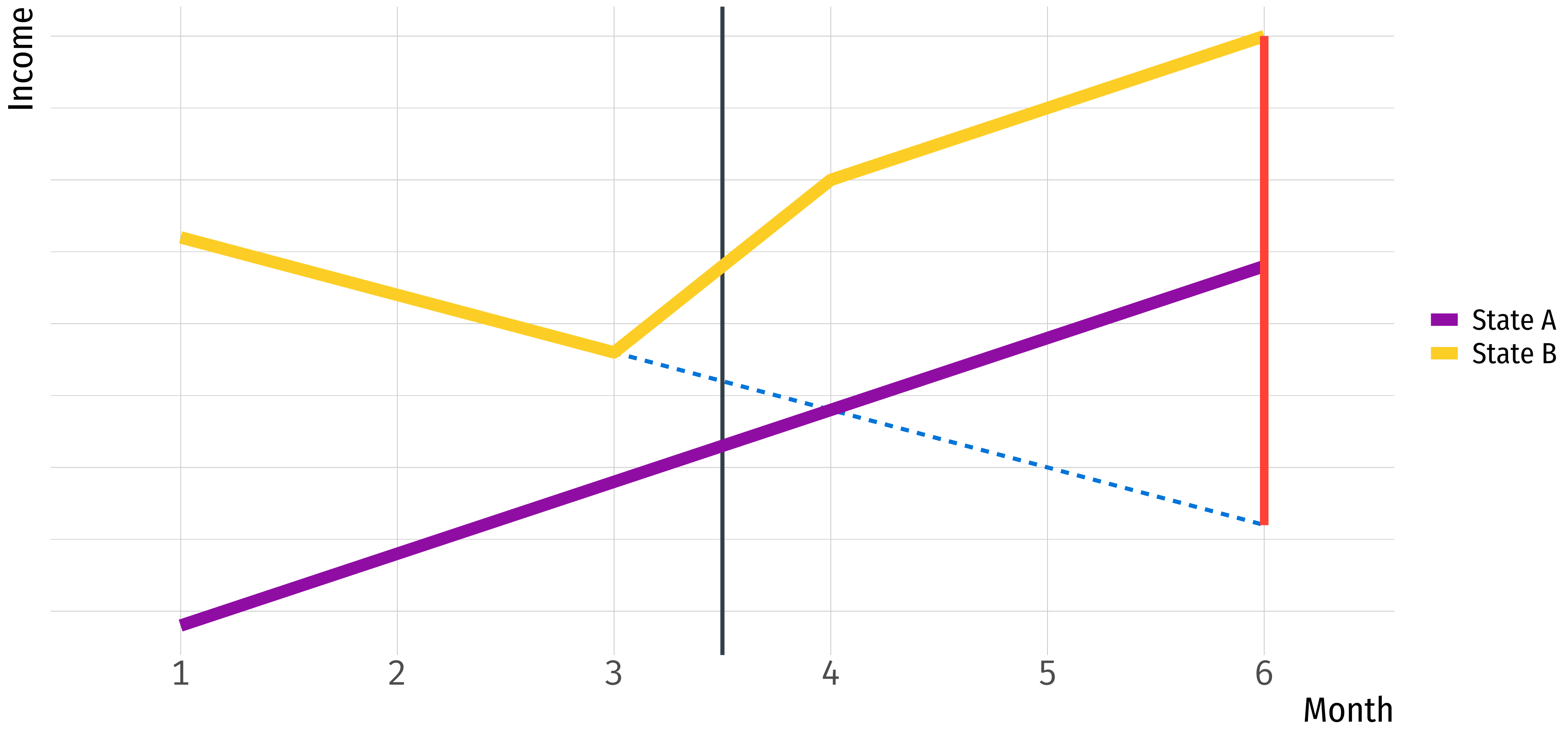
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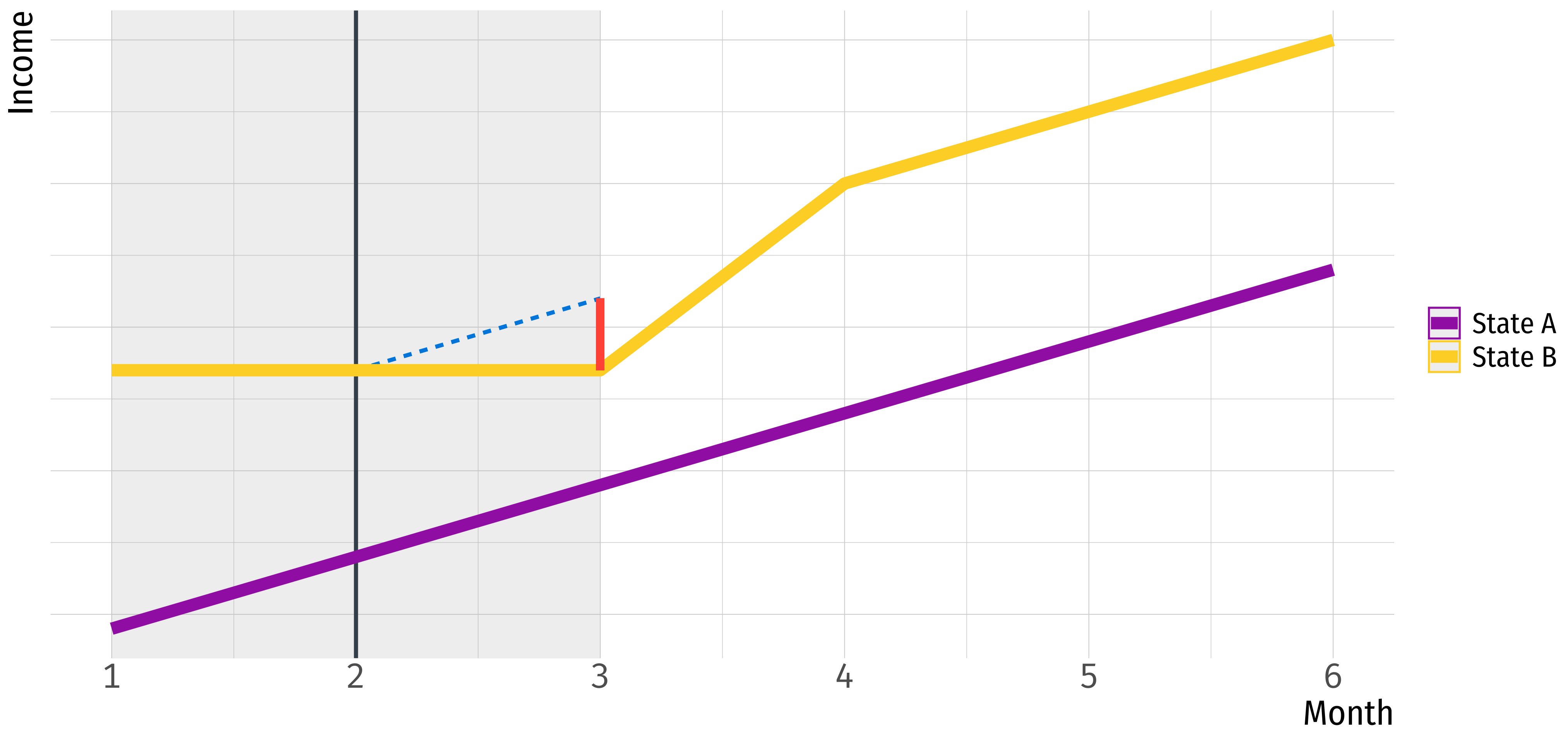
Robustness Check

Parallel Trends

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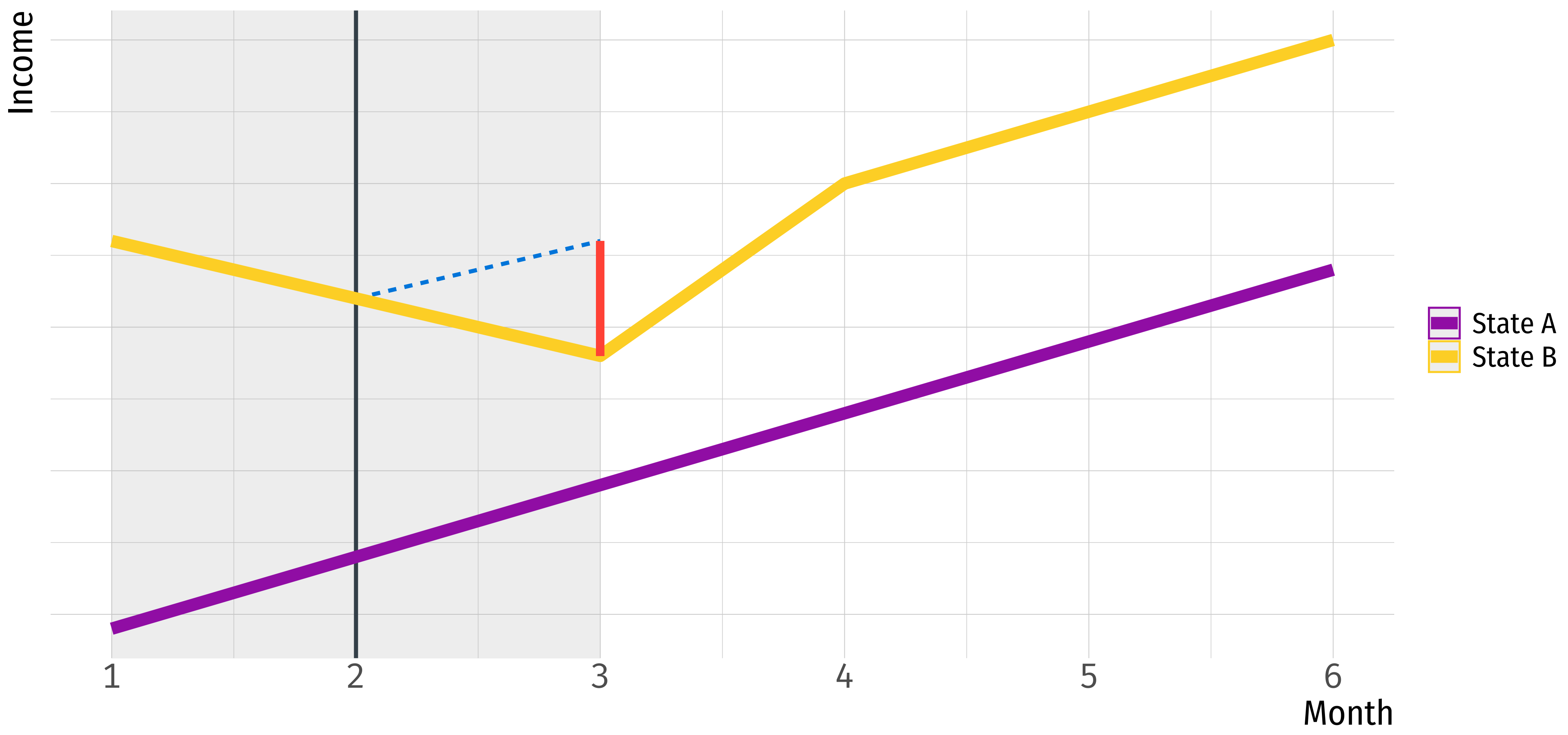
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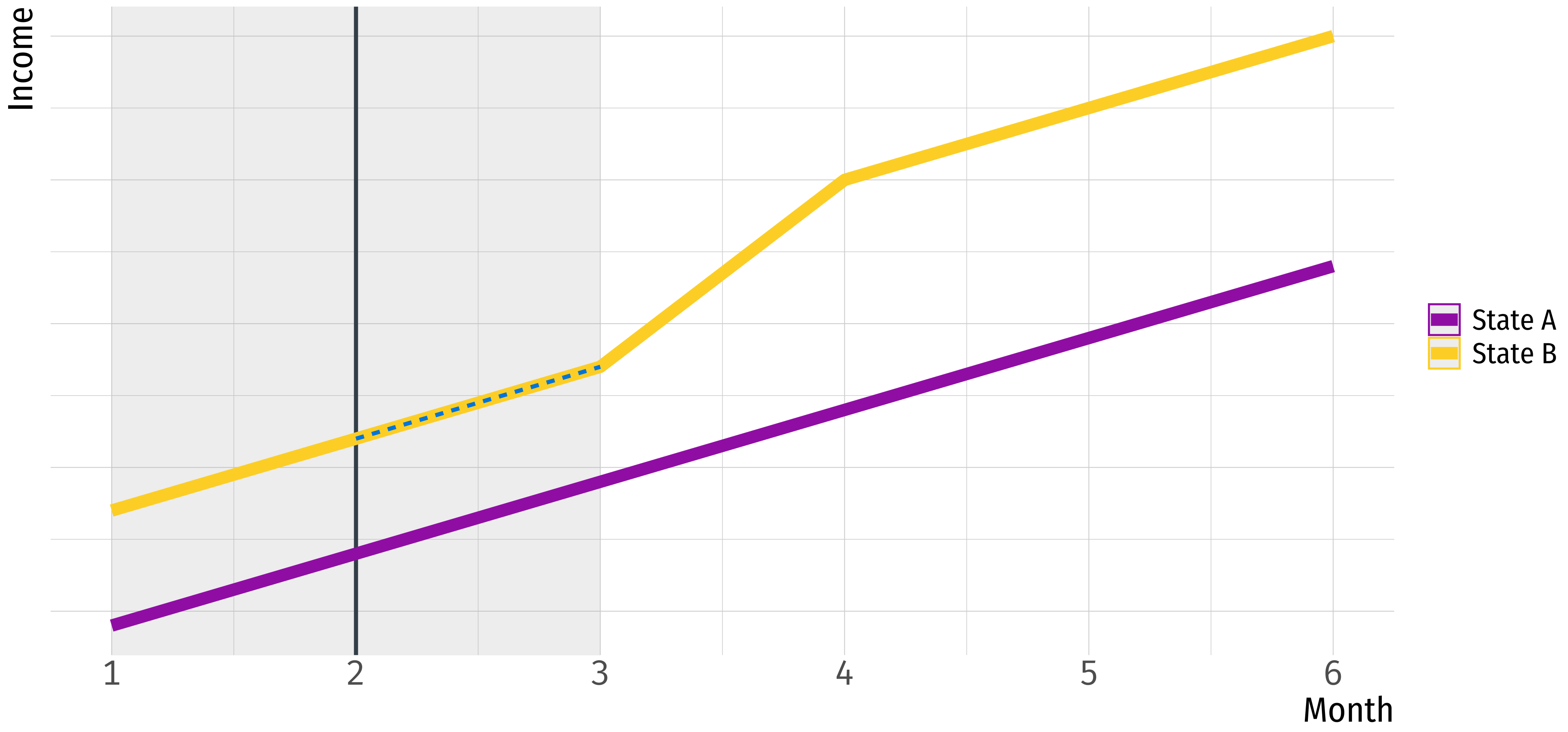

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Month
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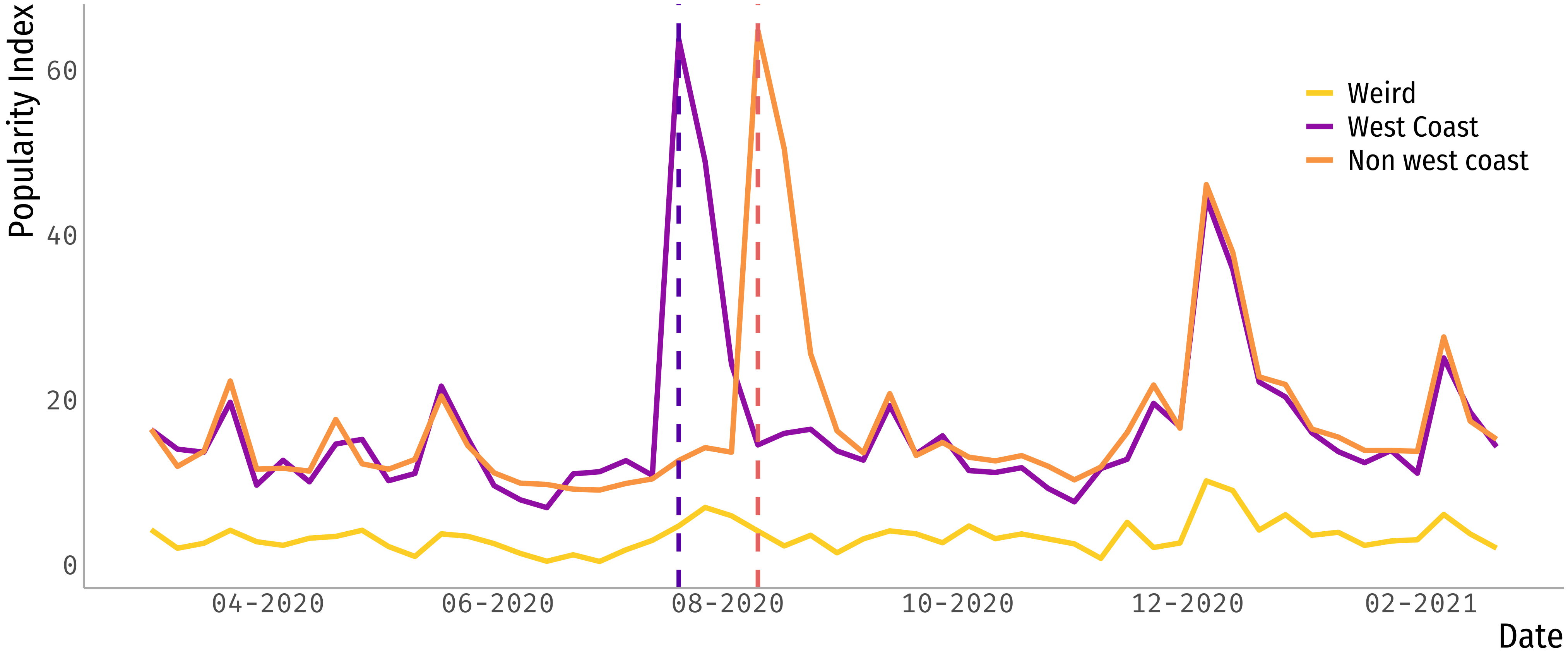
State B

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.



Staggered treatment adoption

- We have three groups:
  - West Coast: Received the album early because of a glitch.
  - Non west-coast: Received the album a bit later.
  - Weird: Two fictional states that are not connected to the US (independent), and do not get Taylor Swift.
- What are the two dimensions we will leverage here?

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".
- Callaway, B. and P. Sant'Anna (2020). "Difference-in-Differences with multiple time periods". *Journal of Econometrics*.
- Heiss, A. (2020). "Program Evaluation for Public Policy". *Class 8-9: Diff-in-diff I and II, Course at BYU*.