STA 235H - Natural Experiments & Difference-In-Differences

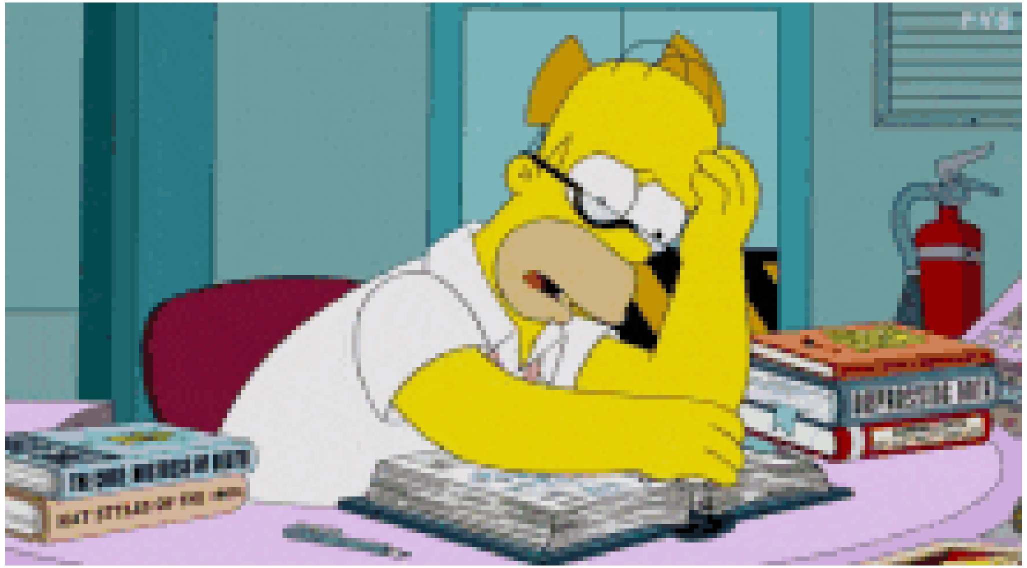
Fall 2022

McCombs School of Business, UT Austin

Announcements

- Grades for Homework 3 will be posted this week.
    - Review the Answer Key on the course website.
- Midterm will be posted on Friday (12.00pm):
    - Take it as an in-class exam (try to finish it in two hours) --> You have 24 hrs.
    - Only clarification questions for the midterm (<u>no questions on Chatter</u>).
- Reminder that collaboration on assignments is not permitted.
    - Every student is responsible for their own work, <u>especially in the Midterm</u>.
- Review session this Friday 10am (UTC 3.102).
    - Slides will be posted with answers on the course website.
- As a reminder:
    - Announcements are official communications.
    - Office hours go from 3.30pm - 5.30pm Tue and Thur.

Last week



- Finished with randomized controlled trials.
  - Limitations in Generalizability and Interference.
- Introduced observational studies:
  - Controlling for observable confounders (e.g. matching)

Today

- Talk about other **Observational Studies**:
  - Natural Experiments
  - Difference-in-Differences
- **First half**: Material
- **Second half**: You will tackle an exercise.

Recap from last week

What did we see last week?

- Limitations in RCTs:
  - Generalizability
  - Breaking SUTVA: Spillover effects and General Equilibrium Effects.
- Introduced Observational Studies:
  - Matching

Identification strategies (designs) we have seen so far...

Randomized Controlled trials (RCTs)

- Treatment assignment is <u>randomized</u>
- Ignorability assumption holds by design: Groups are comparable in obs. and unobs. characteristics.
- Analysis? (i) Check balance and (ii) difference in means.

Selection on Observables (Matching, Regressions with covariates):

- Treatment assignment is <u>not randomized</u>
- Ignorability assumption holds <u>if we can control for all confounders</u> (assumes all confounders are observed)
  - *After adjusting for covariates*, assignment to treatment is as good as random (*Is this a credible assumption?*).
- Analysis? (i) Compare balance before matching, (ii) compare balance after matching, and (iii) difference in means for the matched sample.

Is there randomness out there?

Finding "RCTs" in the wild

- Given that we can't run RCTs for everything, the next best thing is finding a source of random variation that, for all practical purposes, **would work as an RCT**

Natural Experiments

You, as a researcher, did not assign units to treatment levels

1. **Random**: Assignment to an intervention is random (e.g. lottery)

2. **As if random**: Assignment to an intervention is not random, but it's not correlated with potential outcomes.

Context matters!

Examples of natural experiments

- Oregon Health experiment: Lotteries for Medicaid expansion.
- Vietnam Draft: Impact of military service/education (GI Bill) on earnings.
- Lottery winners: Impact of unearned income on labor earnings.
- GreatSchool ranking availability: Roll-out between states.

What do we do if we have something like a natural experiment but <u>both our groups are not necessarily balanced</u>?

Two wrongs make a right

Raising the minimum wage

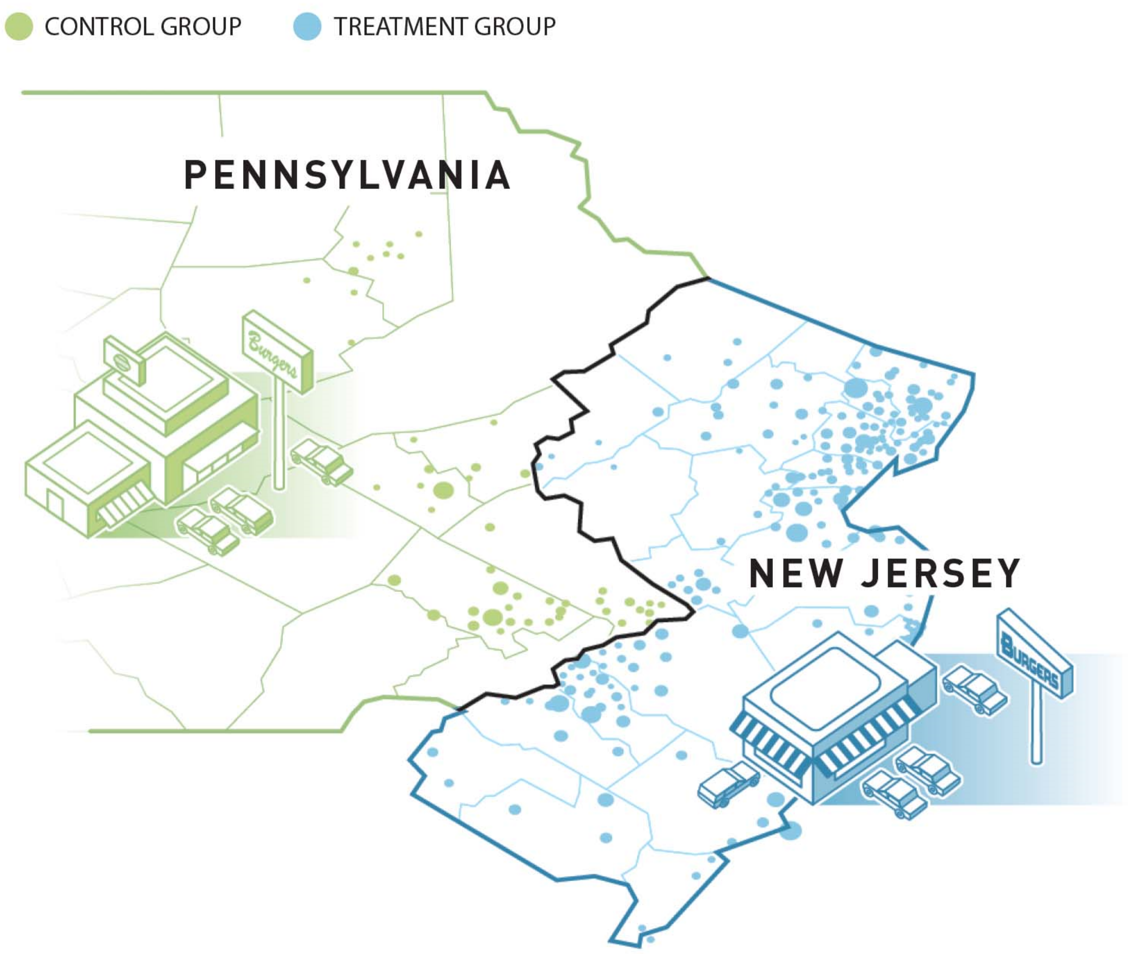
What happens if we raise the minimum wage

Economic theory says there should be fewer jobs

New Jersey in 1992

$4.25 → $5.05

The setup


CONTROL GROUP
TREATMENT GROUP
PENNSYLVANIA
NEW JERSEY
Burgers
BURGERS

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	

Δ (treatment – control) = across-group growth

Difference-in-Differences

… and combine them!

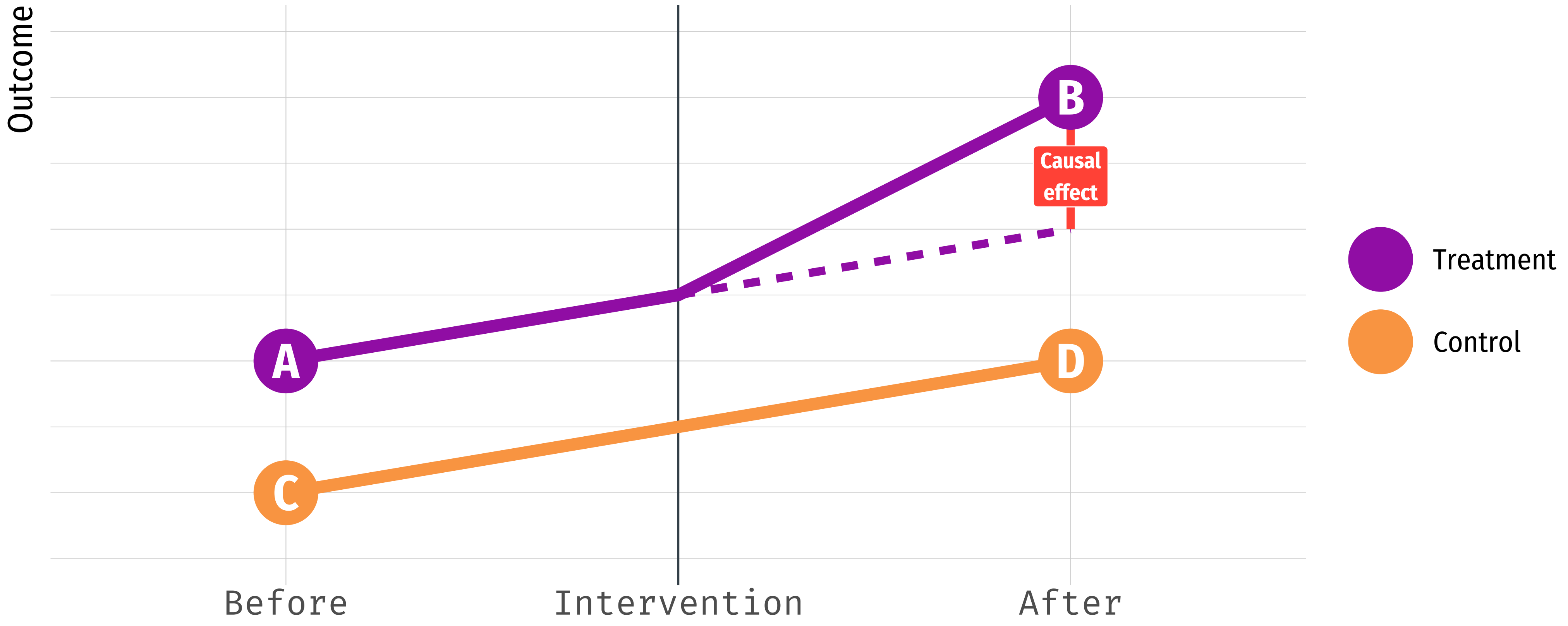
	Pre mean	Post mean	(post - pre)
Control	A (never treated)	B (never treated)	B - A
Treatment	C (not yet treated)	D (treated)	D - C
(treatment - control)	C - A	D - B	(D - C) - (B - A) *or* (D - B) - (C - A)

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

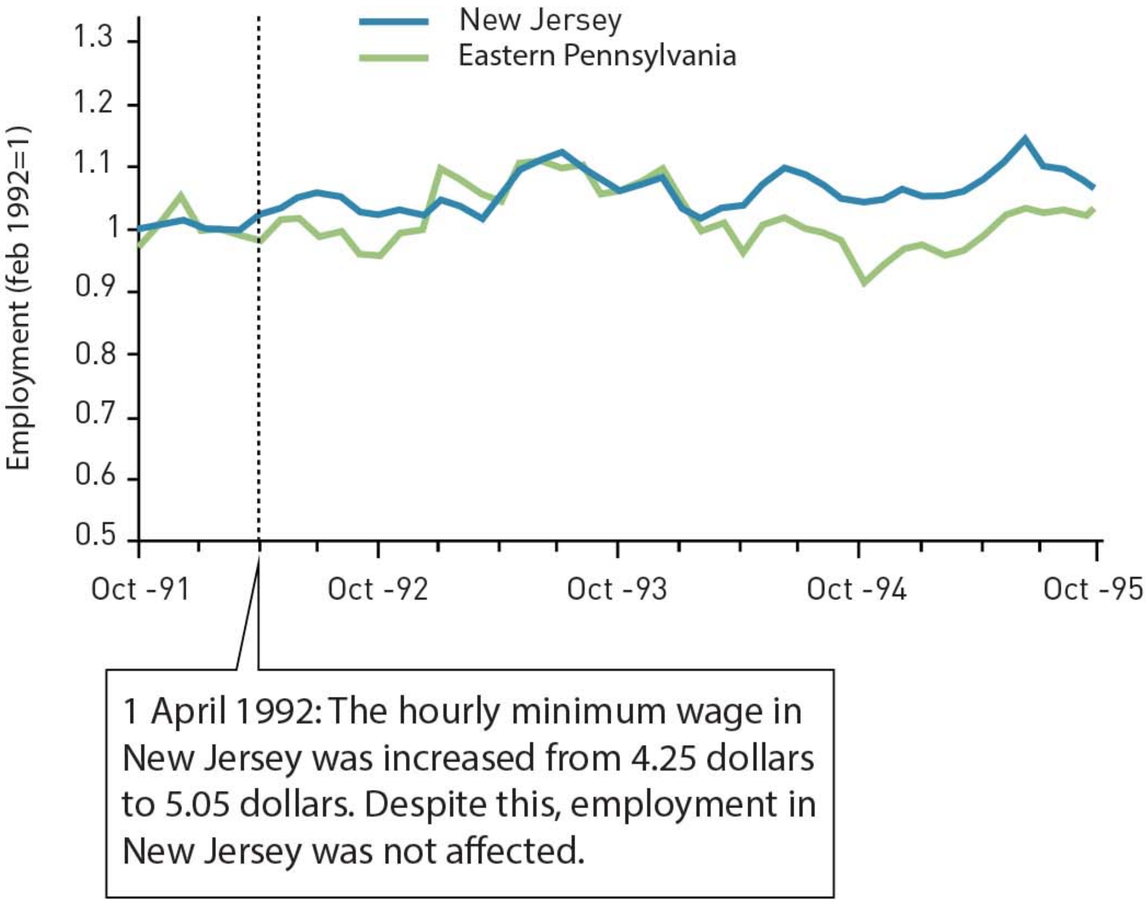
Coming back to New Jersey

	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?



... And the real 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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$$Y_i = \beta_0 + \beta_1 Treat_i + \beta_2 Post_i + \beta_3 Treat_i \times Post_i + \varepsilon_i$$

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

β_3 is the causal effect!

Let's see it with data

```
minwage <- read.csv("https://raw.githubusercontent.com/maibennett/sta235/main/exampleSite/content/C

minwage <- minwage %>% mutate(treat = ifelse(location=="PA", 0, 1), # treat group: the treated stat
                              post = ifelse(date=="nov1992", 1, 0)) # post: time after treatment wa

head(minwage)
```

```
##        chain location wage full part    date treat post
## 1     wendys       PA 5.00   20   20 feb1992     0    0
## 2     wendys       PA 5.50    6   26 feb1992     0    0
## 3 burgerking       PA 5.00   50   35 feb1992     0    0
## 4 burgerking       PA 5.00   10   17 feb1992     0    0
## 5        kfc       PA 5.25    2    8 feb1992     0    0
## 6        kfc       PA 5.00    2   10 feb1992     0    0
```

Let's see it with data

```
summary(lm(full ~ treat*post, data = minwage))
```

```
##
## Call:
## lm(formula = full ~ treat * post, data = minwage)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -10.664  -5.971  -2.405   3.653  52.029
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   10.664      1.007  10.589   <2e-16 ***
## treat         -2.693      1.117  -2.411   0.0162 *
## post          -2.493      1.424  -1.750   0.0805 .
## treat:post     2.927      1.580   1.853   0.0643 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.243 on 712 degrees of freedom
## Multiple R-squared:  0.008207,    Adjusted R-squared:  0.004028
## F-statistic: 1.964 on 3 and 712 DF,  p-value: 0.118
```

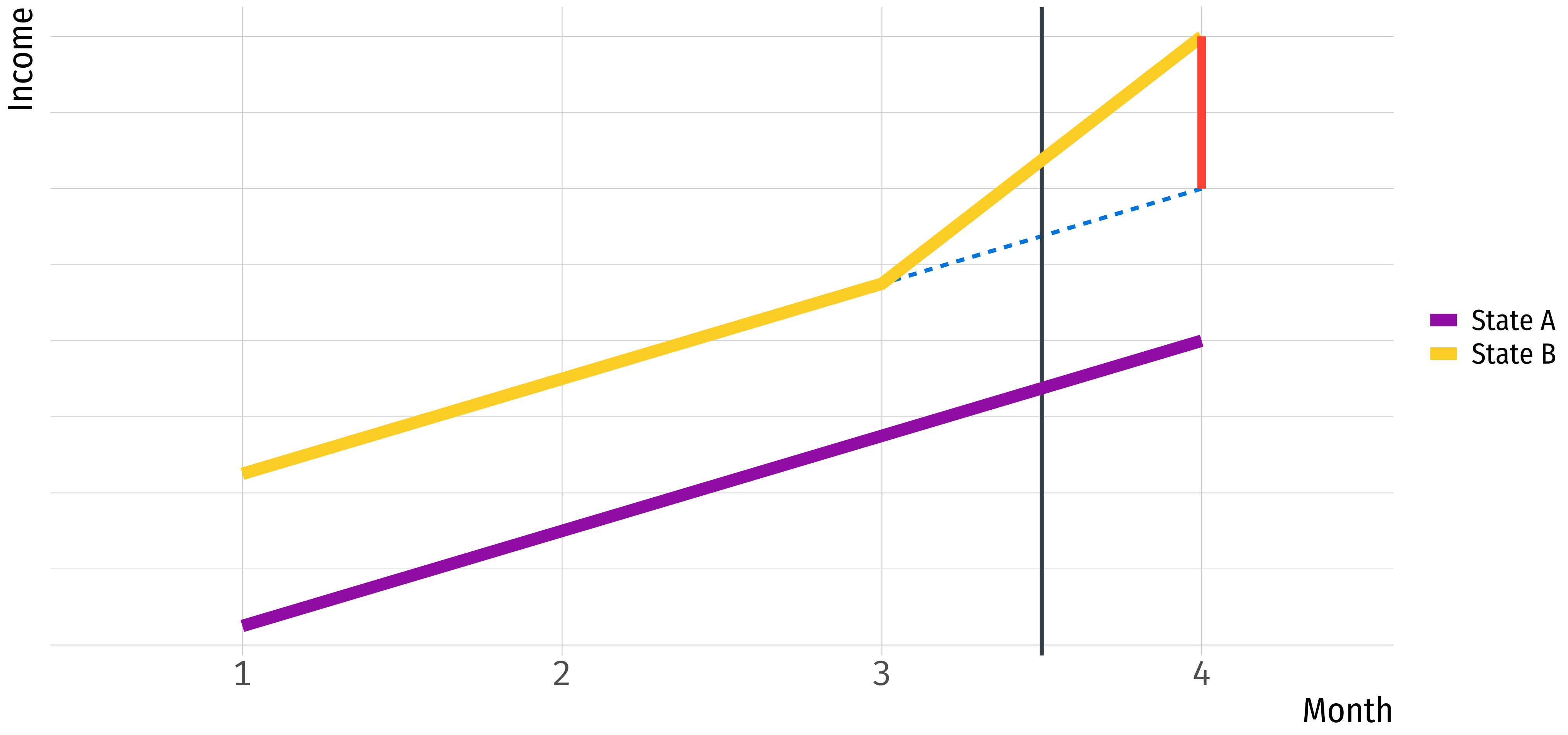
- Can you interpret the treatment effect?

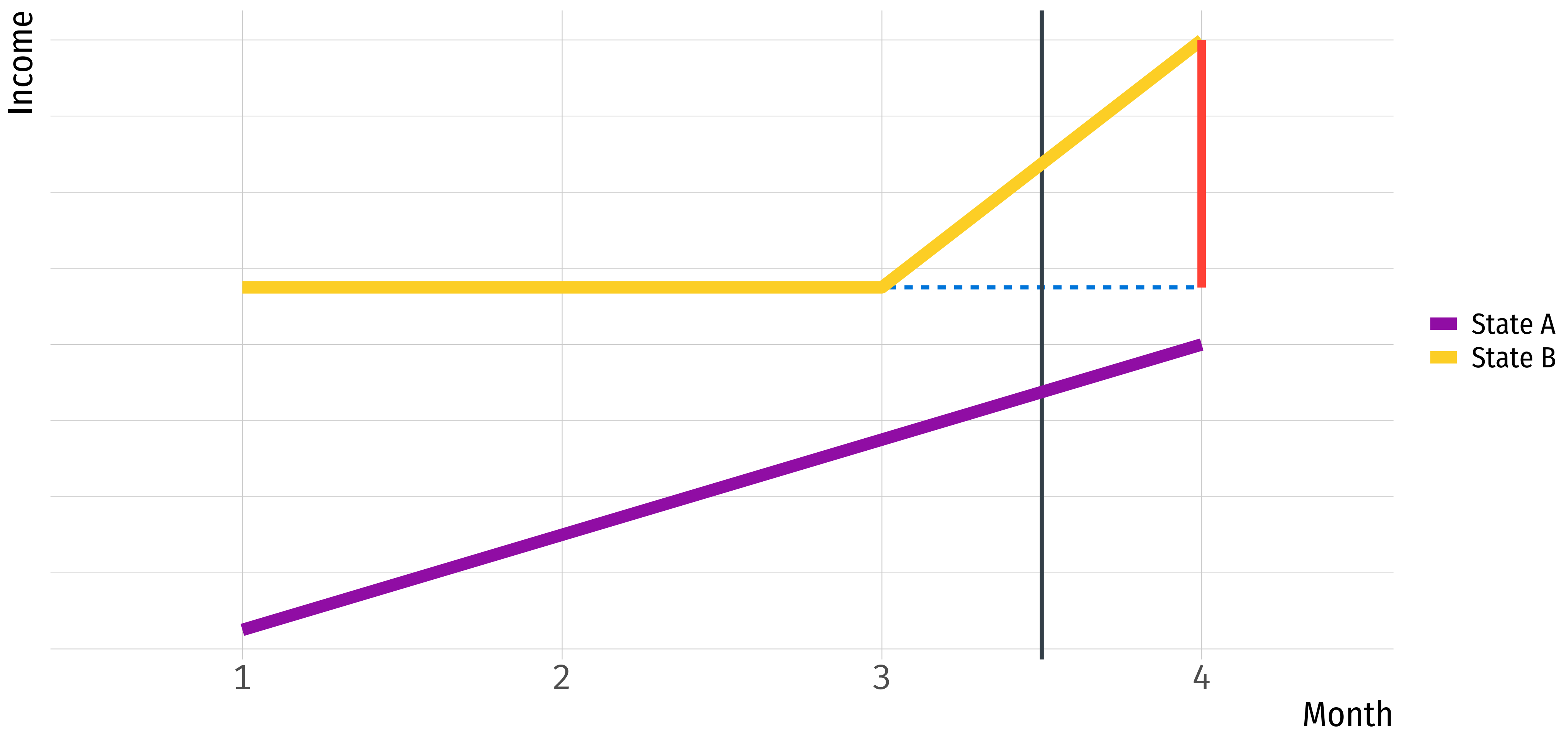
Diff-in-Diff Assumptions

Assumptions

Parallel Trends

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


Income
1
2
3
4
Month
State A
State B


Income
1
2
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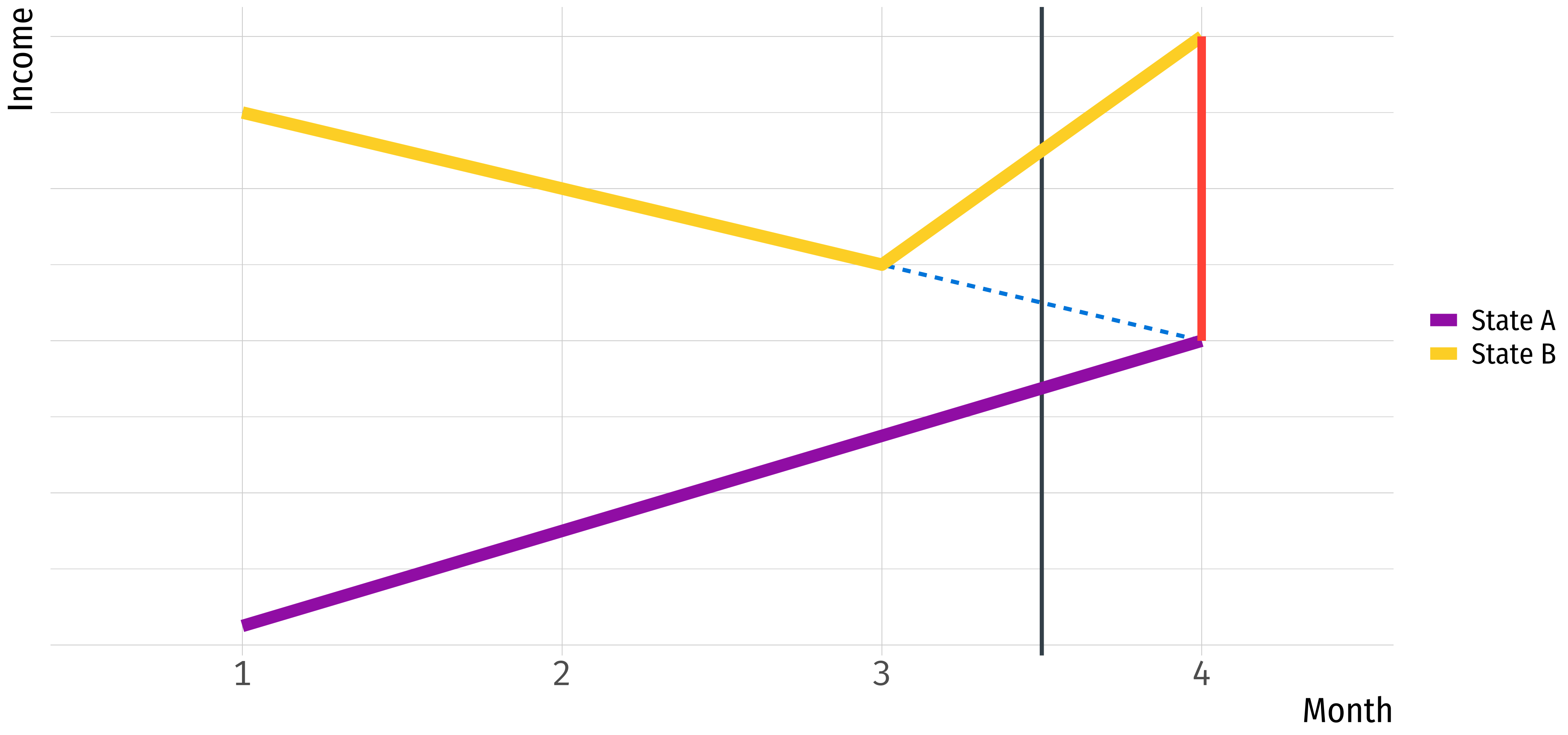
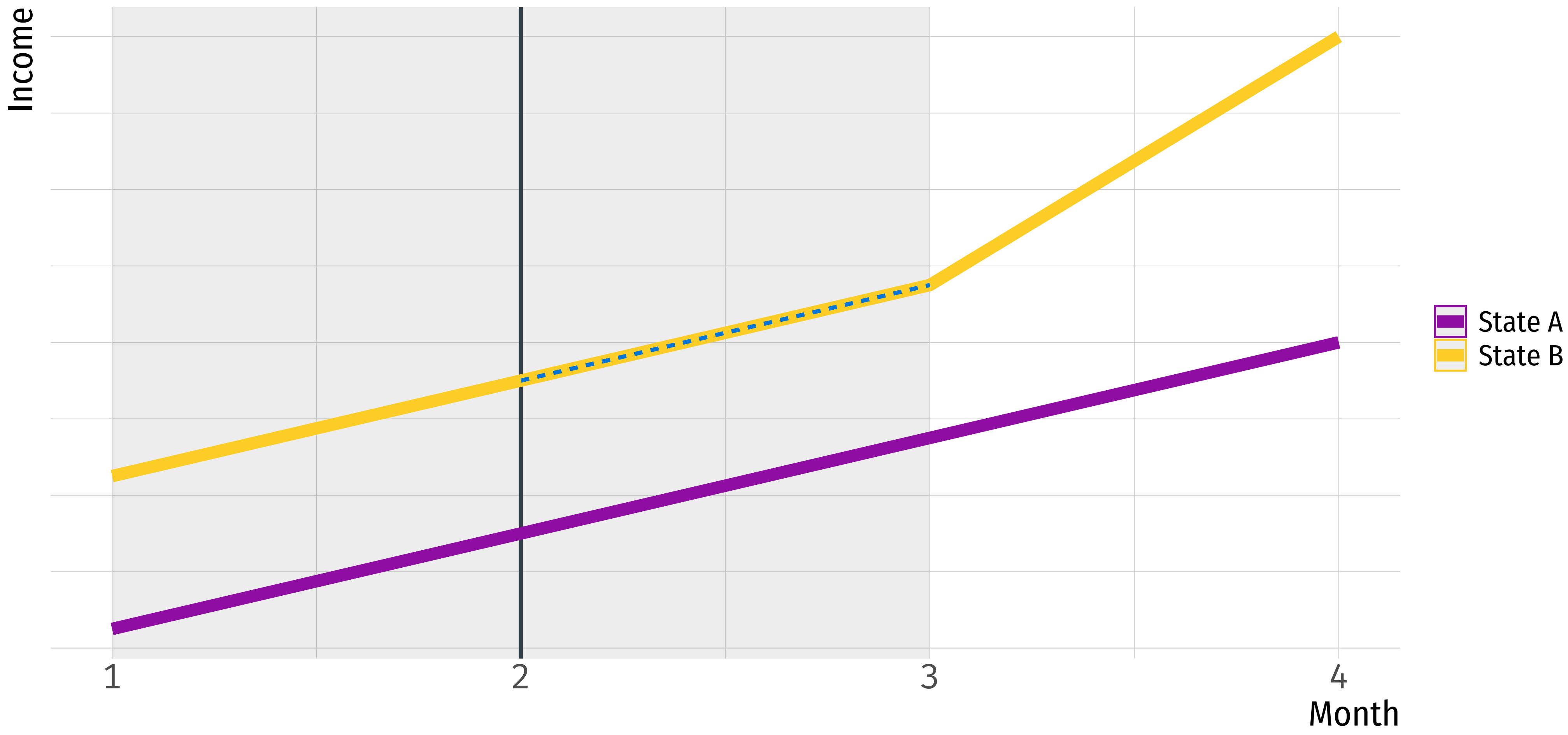
Month
State A
State B

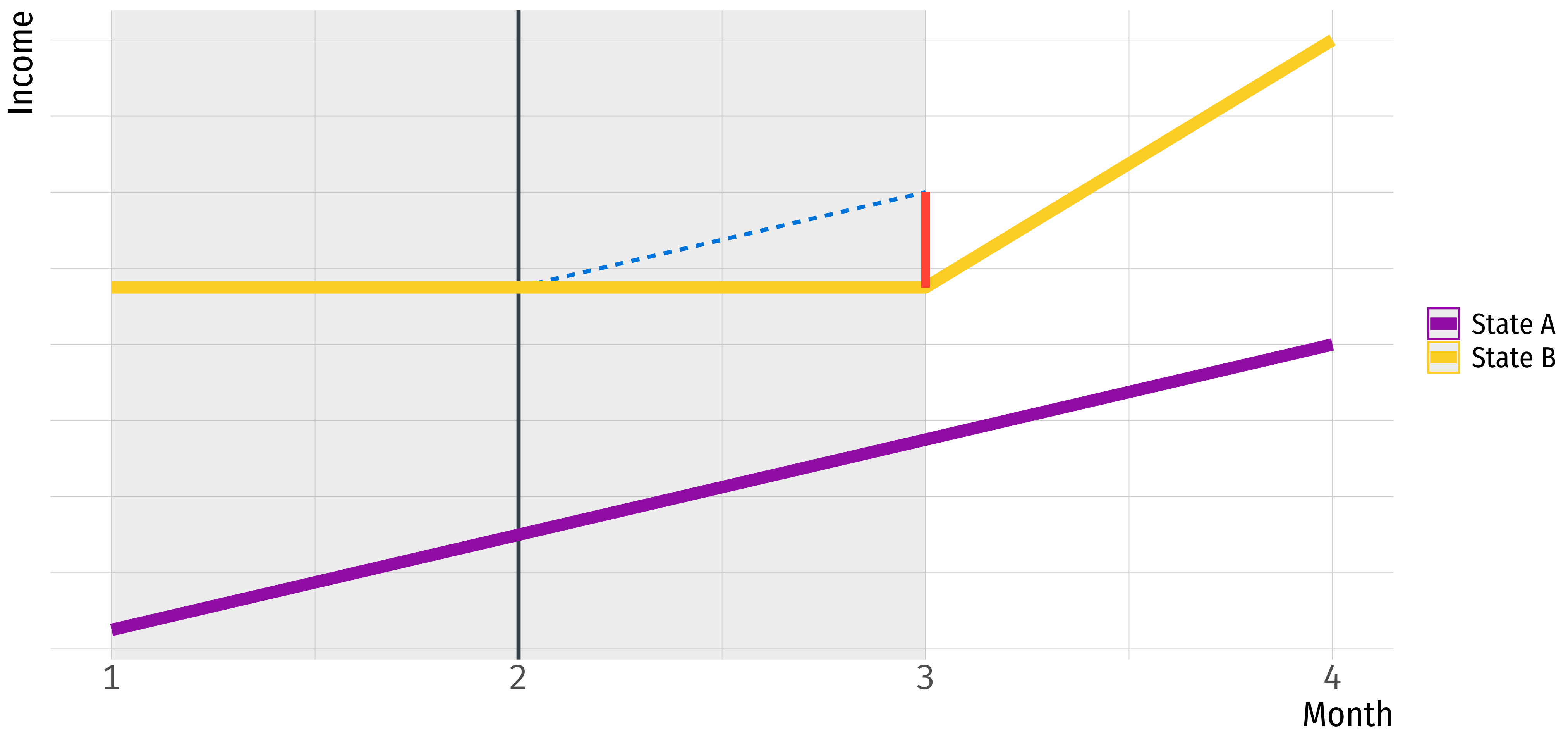

Income
1
2
3
4
Month
State A
State B

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
Month
State A
State B



Income
1
2
3
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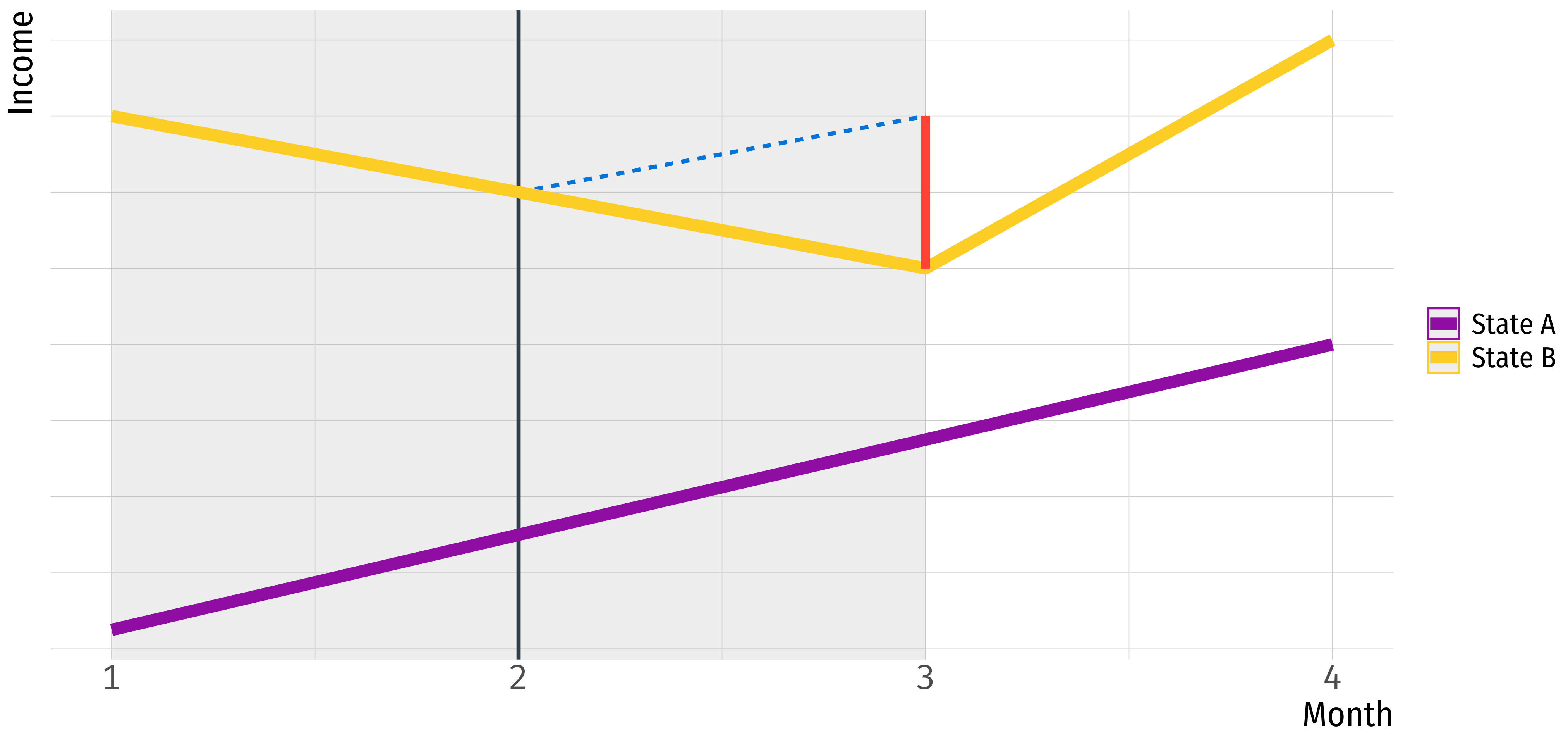
Month
State A
State B



Income
1
2
3
4
Month
State A
State B

Wrapping up

- We don't always need **randomization** to make causal inference
- If we think the **parallel trend assumption holds**, we can find an Average Treatment Effect for the treated group (ATT)
    - Remember that we can't say anything about the treatment effect for the control group!
- Next week we will see **more identification strategies.**

References

- Angrist, J. and S. Pischke. (2015). "Mastering Metrics". *Chapter 2*.
- Angrist, J. and S. Pischke. (2015). "Mastering Metrics". *Chapter 5*.
- Heiss, A. (2020). "Program Evaluation for Public Policy". *Class 8-9: Diff-in-diff I and II, Course at BYU*.