Diff-in-diff I

March 4, 2020

PMAP 8521: Program Evaluation for Public Service
Andrew Young School of Policy Studies
Spring 2020

Fill out your reading report on iCollege!

Plan for today

Quasi-experiments

Interactions & regression

Two wrongs make a right

DiD assumptions

Quasi-experiments

RCTs are great!

Super impractical to do all the time though!

Quasi-experiments

You can't always randomly assign people to do things

So let other people (or the government, or nature) do it

Quasi-experiments

Quasi-experiment = a situation where you, as researcher, did not assign people to treatment/control

External validity 👍

Selection 👎

Assignment to treatment is “as if” random

Quasi-experiments

Difference-in-differences
(DiD; DD; diff-in-diff)

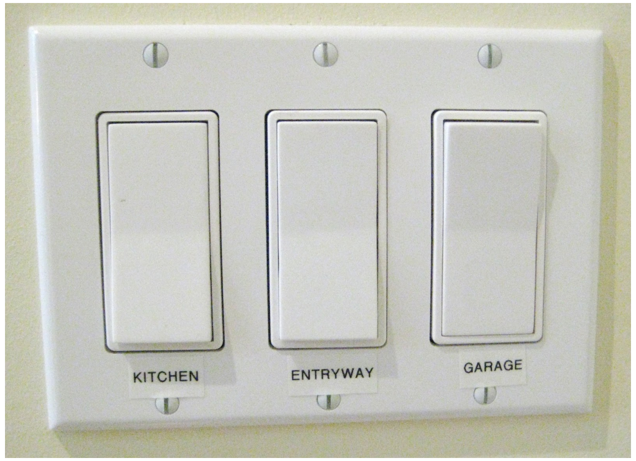
Regression discontinuity
(RDD)

Instrumental variables
(IV)

Interactions & regression

Sliders and switches

$$\hat{\text{happiness}} = \beta_0 + \beta_1 \text{life expectancy} + \epsilon$$



$$\begin{aligned}\hat{\text{happiness}} = \beta_0 + \beta_1 \text{Europe} + \beta_2 \text{Latin America} +\\ \beta_3 \text{MENA} + \beta_4 \text{North America} +\\ \beta_5 \text{South Asia} + \beta_6 \text{Sub-Saharan Africa} + \epsilon\end{aligned}$$

```r
model_life_school_region <-
  lm(happiness_score ~ life_expectancy + school_enrollment + region,
     data = world_happiness)
```

term	estimate	std_error	statistic	p_value
intercept	-2.821	1.355	-2.083	0.04
life_expectancy	0.102	0.017	5.894	0
school_enrollment	0.008	0.01	0.785	0.435
regionEurope & Central Asia	0.031	0.255	0.123	0.902
regionLatin America & Caribbean	0.732	0.294	2.489	0.015
regionMiddle East & North Africa	0.189	0.317	0.597	0.552
regionNorth America	1.114	0.581	1.917	0.058
regionSouth Asia	-0.249	0.45	-0.553	0.582
regionSub-Saharan Africa	0.326	0.407	0.802	0.425

$$\widehat{\text{happiness}} = \beta_0 + \beta_1 \text{life expectancy} + \beta_2 \text{school enrollment} +$$
$$\beta_3 \text{Europe} + \beta_4 \text{Latin America} + \beta_5 \text{MENA} +$$
$$\beta_6 \text{North America} + \beta_7 \text{South Asia} + \beta_8 \text{SSA} + \epsilon$$

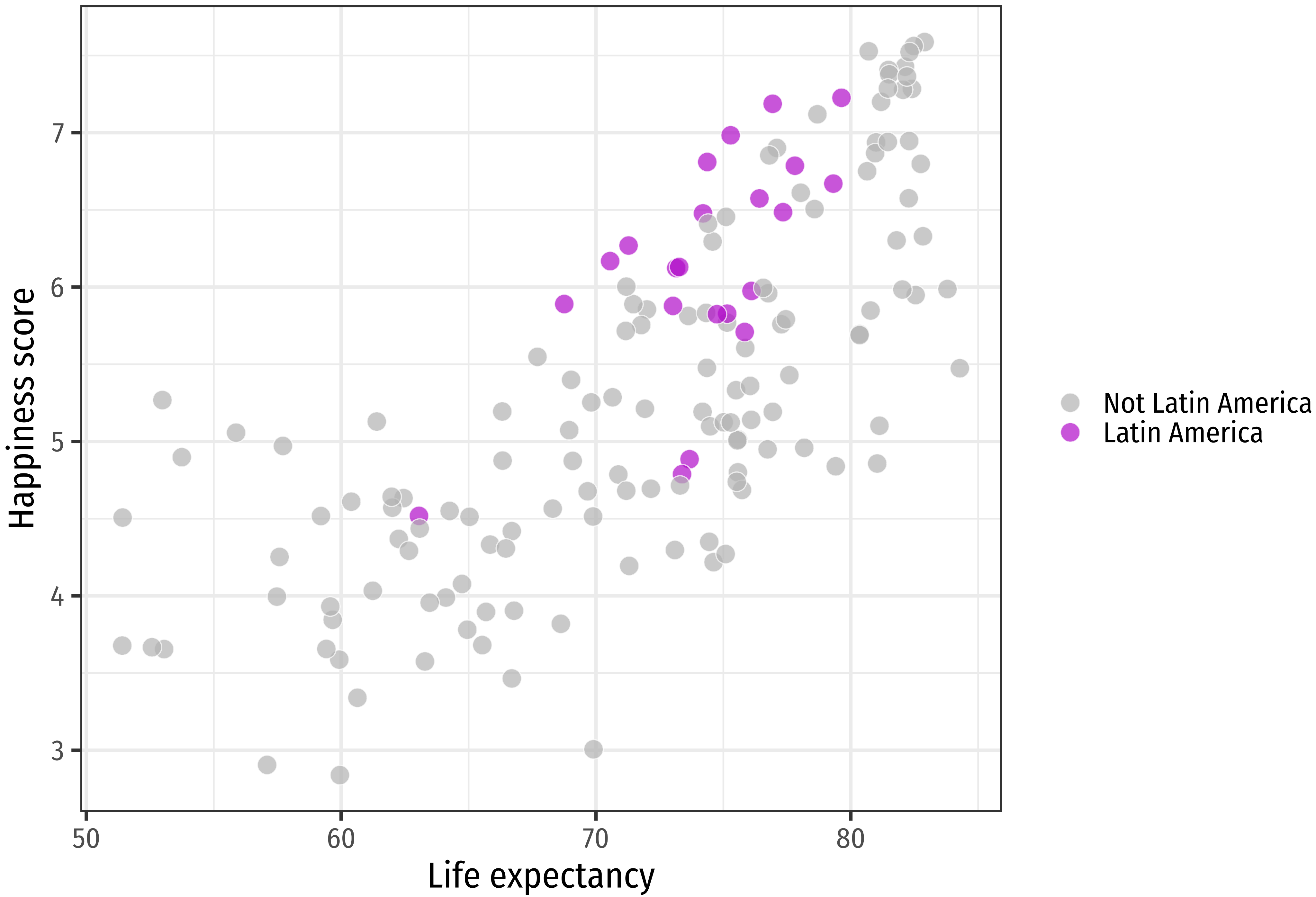
Indicators and interactions

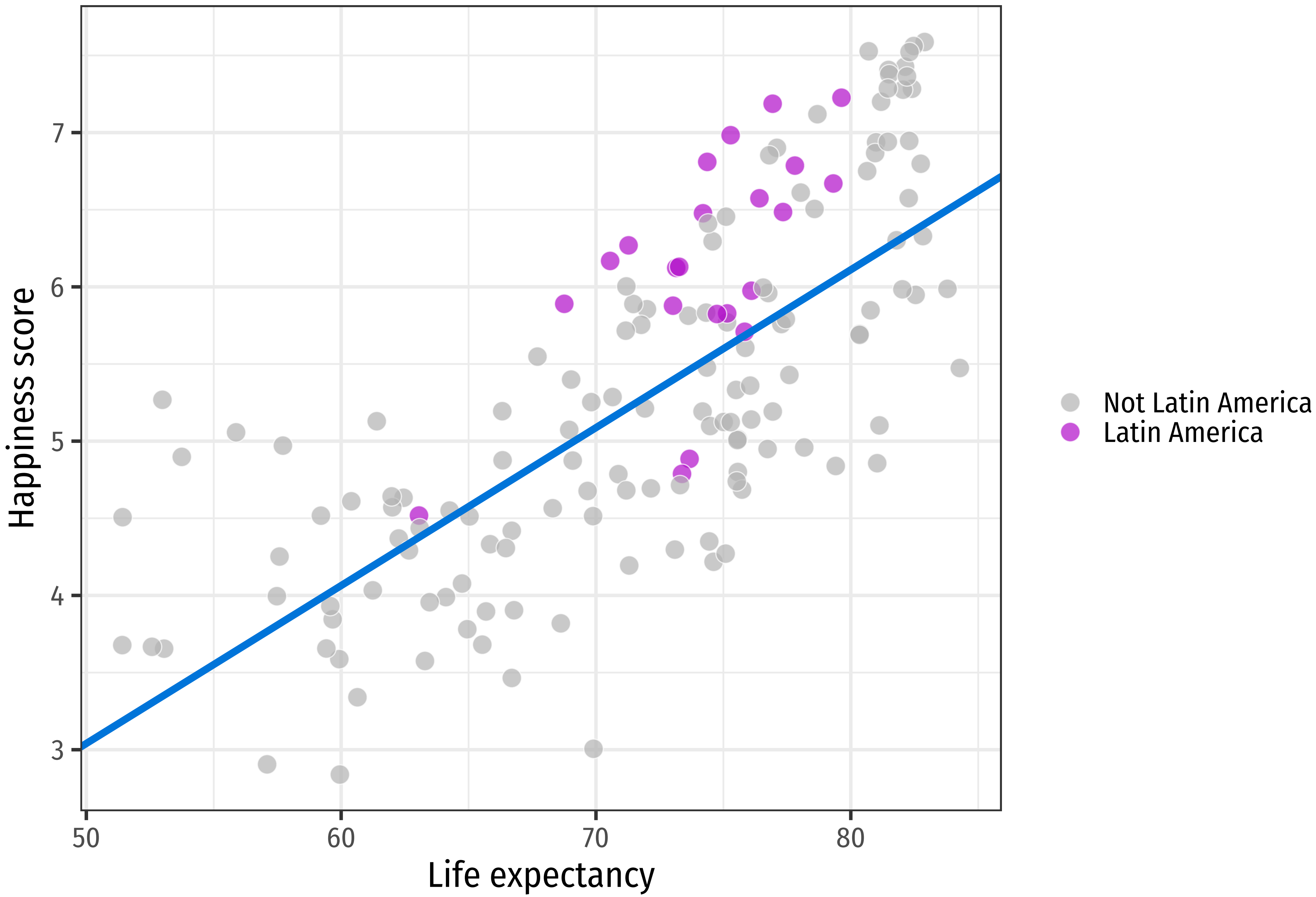
Indicators (dummies)

Change in **intercept** for specific group

Interactions

Change in **slope** for specific group


Happiness score
7
6
5
4
3
50
60
70
80
Life expectancy
Not Latin America
Latin America



Happiness score
7
6
5
4
3
50
60
70
80
Life expectancy
Not Latin America
Latin America

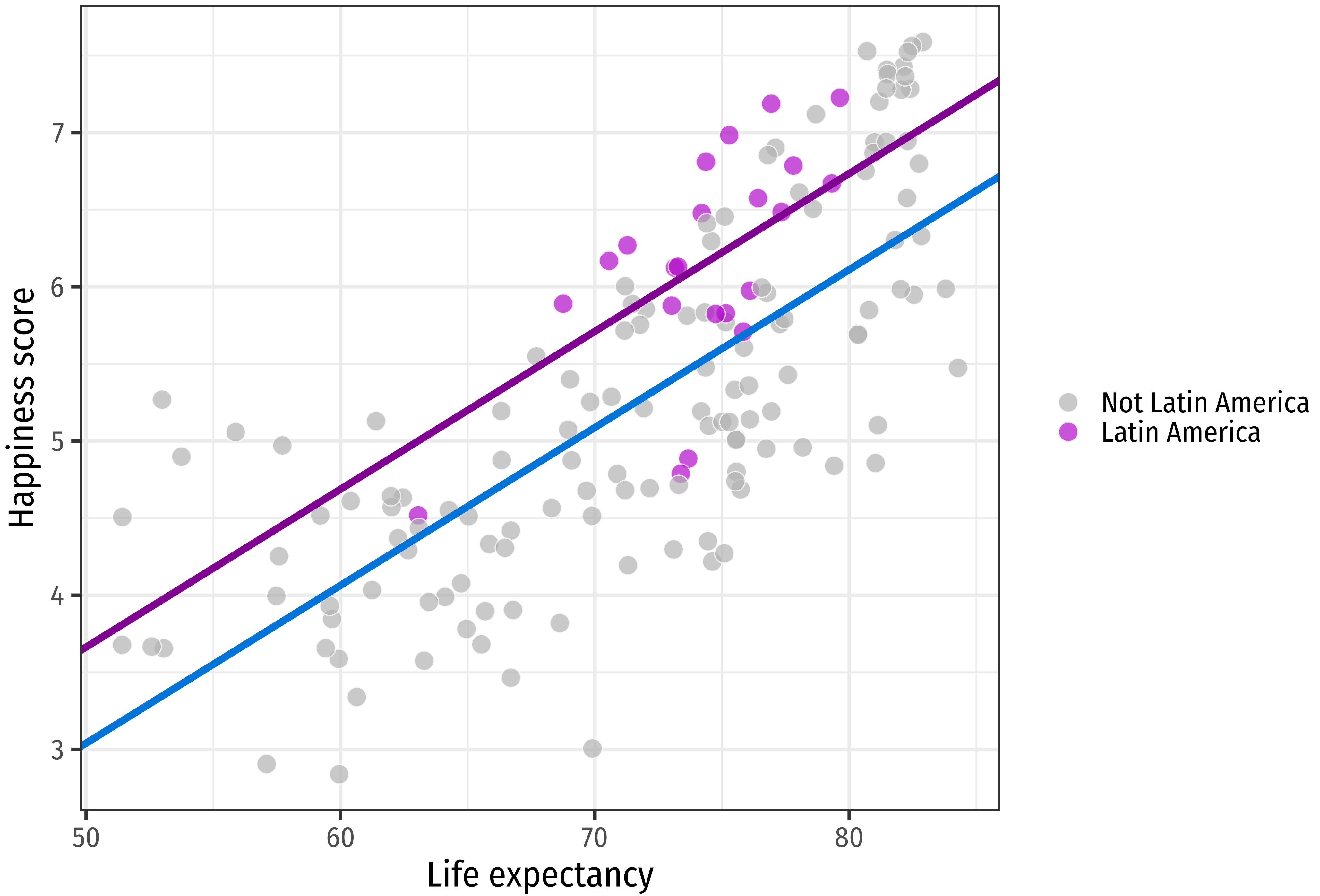
```r
model_life_la <-
  lm(happiness_score ~ life_expectancy + latin_america, data = world_happiness)
```

term <chr>	estimate <dbl>	std.error <dbl>	statistic <dbl>	p.value <dbl>
(Intercept)	-2.0770858	0.536773852	-3.869573	1.613712e-04
life_expectancy	0.1023494	0.007449708	13.738707	1.954881e-28
latin_americaTRUE	0.6234255	0.172757872	3.608666	4.171373e-04

3 rows

Effect for everyone:
0.102 more happiness for every 1 year increase in life expectancy

Effect for Latin America:
0.102 more happiness for every 1 year increase in life expectancy, and 0.623 higher on average



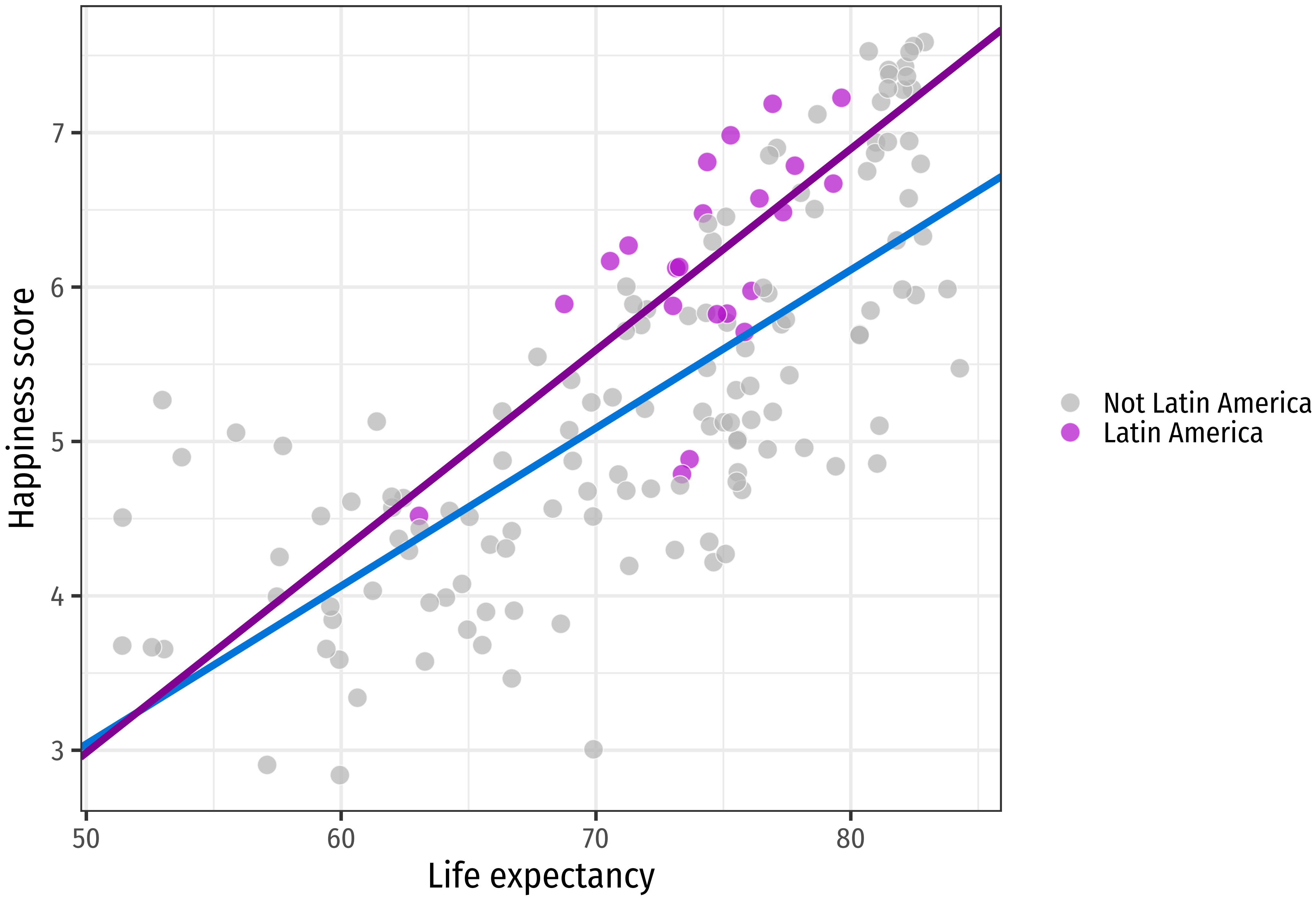
Happiness score
7
6
5
4
3
50
60
70
80
Life expectancy
Not Latin America
Latin America

```r
model_life_la_int <-
  lm(happiness_score ~ life_expectancy + latin_america +
                       (life_expectancy * latin_america), data = world_happiness)
```

term <chr>	estimate <dbl>	std.error <dbl>	statistic <dbl>	p.value <dbl>
(Intercept)	-2.01948544	0.545386030	-3.7028551	2.983292e-04
life_expectancy	0.10154408	0.007570767	13.4126556	1.649813e-27
latin_americaTRUE	-1.51554651	3.364657434	-0.4504311	6.530456e-01
life_expectancy:latin_americaTRUE	0.02884127	0.045307973	0.6365606	5.253749e-01

Effect for everyone:
0.102 more happiness for every 1 year increase in life expectancy

Effect for Latin America:
(0.102 + 0.29 = 0.13) more happiness for every 1 year increase in life expectancy, and the intercept is -1.52 lower (but that's kinda meaningless)



Happiness score
Life expectancy
3
4
5
6
7
50
60
70
80
Not Latin America
Latin America

Interactions

What would happen if you ran this?

```
lm(happiness_score ~ life_expectancy * latin_america,
   data = world_happiness)
```

term <chr>	estimate <dbl>	std.error <dbl>	statistic <dbl>	p.value <dbl>
(Intercept)	-2.01948544	0.545386030	-3.7028551	2.983292e-04
life_expectancy	0.10154408	0.007570767	13.4126556	1.649813e-27
latin_americaTRUE	-1.51554651	3.364657434	-0.4504311	6.530456e-01
life_expectancy:latin_americaTRUE	0.02884127	0.045307973	0.6365606	5.253749e-01

Both terms have to be in the model individually

(R will do it for you if you don't)

Interactions

What would happen if you ran this?

```
lm(happiness_score ~ life_expectancy * region,
   data = world_happiness)
```

term <chr>	estimate <dbl>	std.error <dbl>
(Intercept)	-2.81064813	2.05113076
life_expectancy	0.11167591	0.02707855
regionEurope & Central Asia	-2.77773410	2.75966053
regionLatin America & Caribbean	-0.72438382	3.71820127
regionMiddle East & North Africa	-3.12948812	3.14006737
regionNorth America	2.88162771	23.16756884
regionSouth Asia	4.97845115	5.54389159
regionSub-Saharan Africa	6.32760556	2.47876135
life_expectancy:regionEurope & Central Asia	0.03666426	0.03606854
life_expectancy:regionLatin America & Caribbean	0.01870945	0.04974234
life_expectancy:regionMiddle East & North Africa	0.04095460	0.04186202
life_expectancy:regionNorth America	-0.02210927	0.28819726
life_expectancy:regionSouth Asia	-0.07683819	0.07904406
life_expectancy:regionSub-Saharan Africa	-0.10074346	0.03542467

Changes in slopes and intercepts for each region

Is there a discount when combining cheese and chili?

What is the cheese effect?

What is the chili effect?

What is the chili × cheese effect?

R time!

Two wrongs make a right


I ♥ federalism
(for the natural experiments)

Raising the minimum wage

What happens if you raise the minimum wage?

Economic theory says there should be fewer jobs

New Jersey in 1992

$4.25 → $5.05

Before vs. after

Average fast food jobs in NJ

Before: 20.44

After: 21.03

Δ: 0.59

Is this the causal effect?

Treatment vs. control

Average fast food jobs in states

PA_{after}: 21.17

NJ_{after}: 21.03

Δ: −0.14

Is this the causal effect?

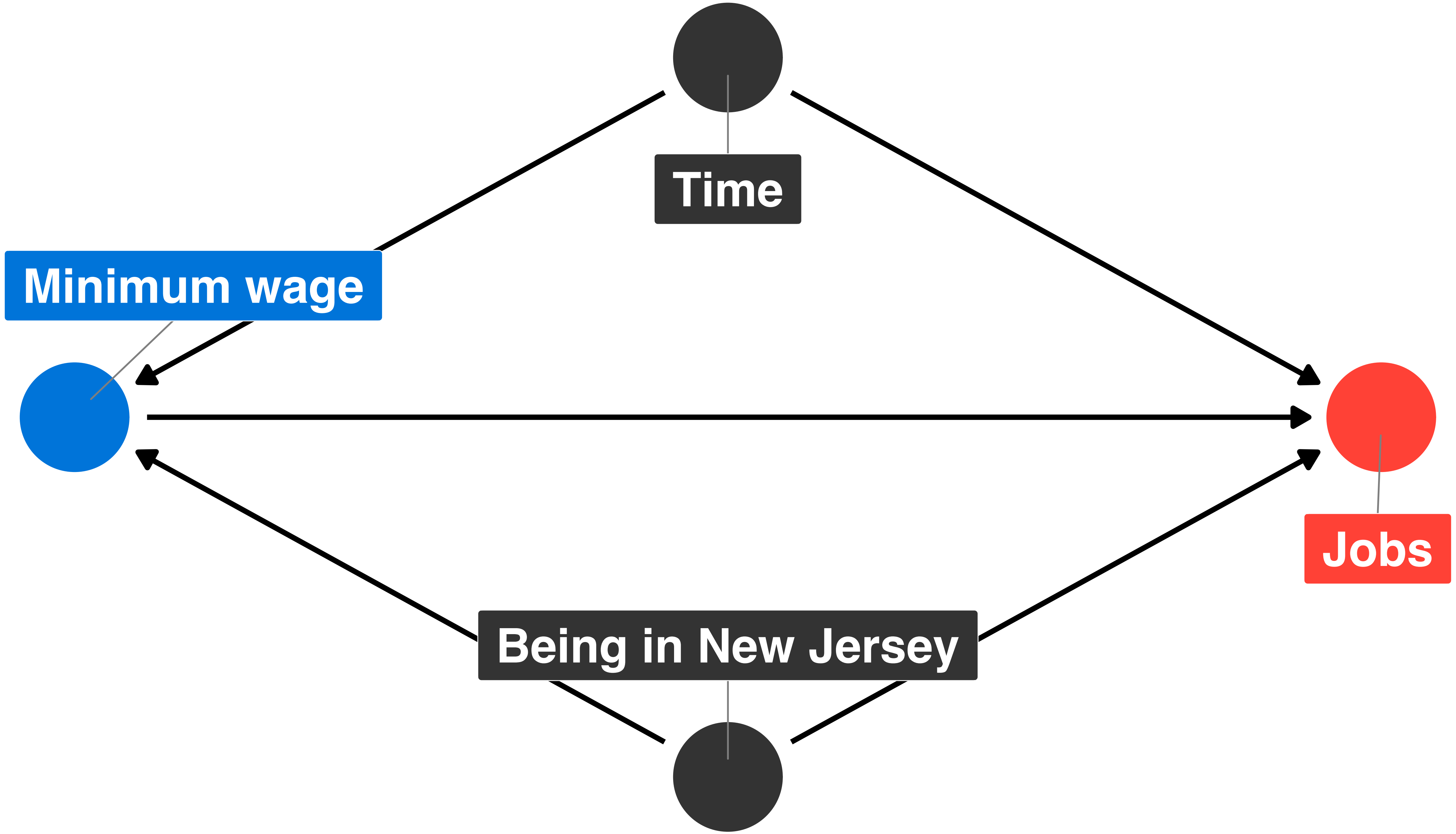
Problems

Comparing only before/after

Impossible to know if growth happened because of treatment or just naturally

Comparing only treatment/control

Impossible to know if any changes happened because of natural growth


Time
Minimum wage
Jobs
Being in New Jersey

	Pre mean	Post mean
Treatment	A (not yet treated)	B (treated)
Control	C (never treated)	D (never treated)

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

Growth!

	Pre mean	Post mean
Treatment	A (not yet treated)	B (treated)
Control	C (never treated)	D (never treated)
Δ (trtmt−ctrl)	A−C	B−D

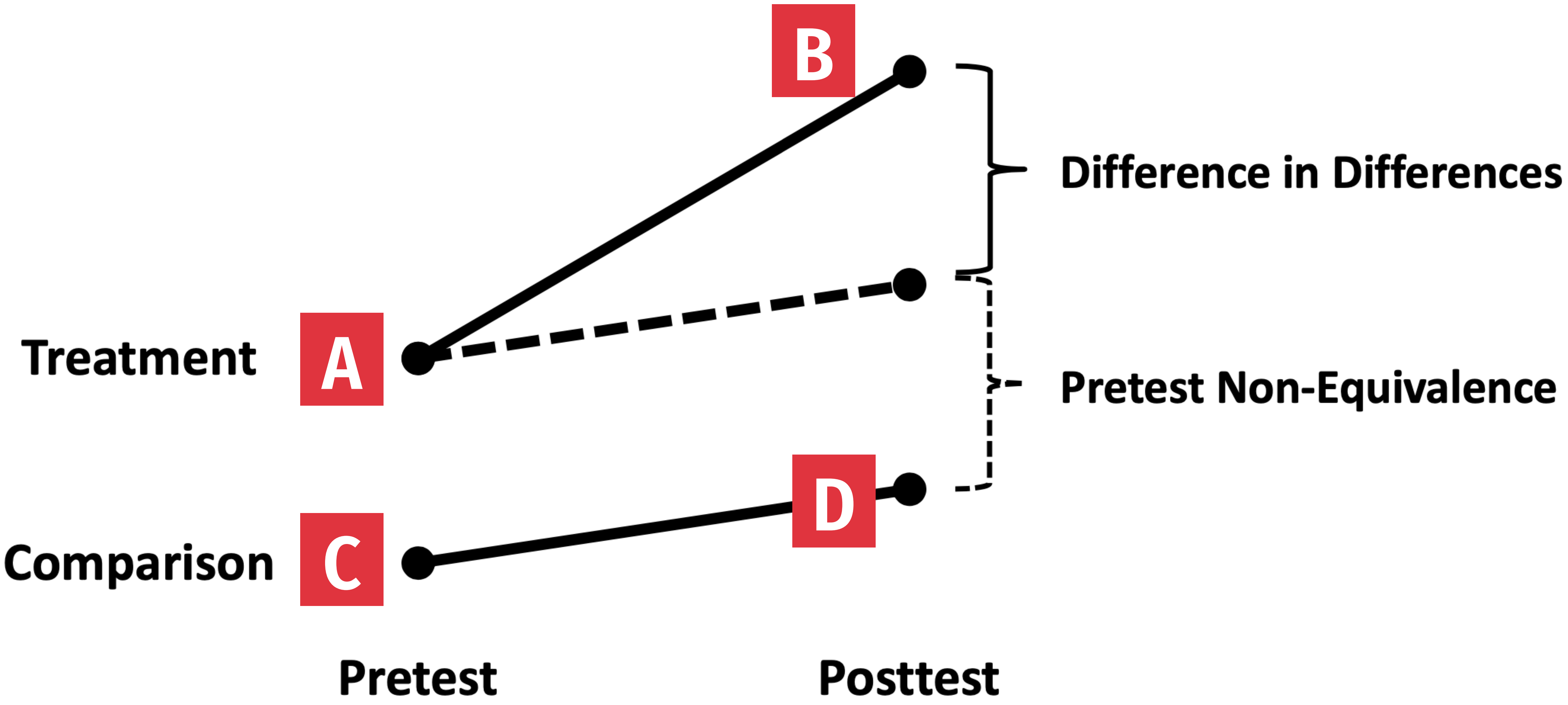
Within-group effects

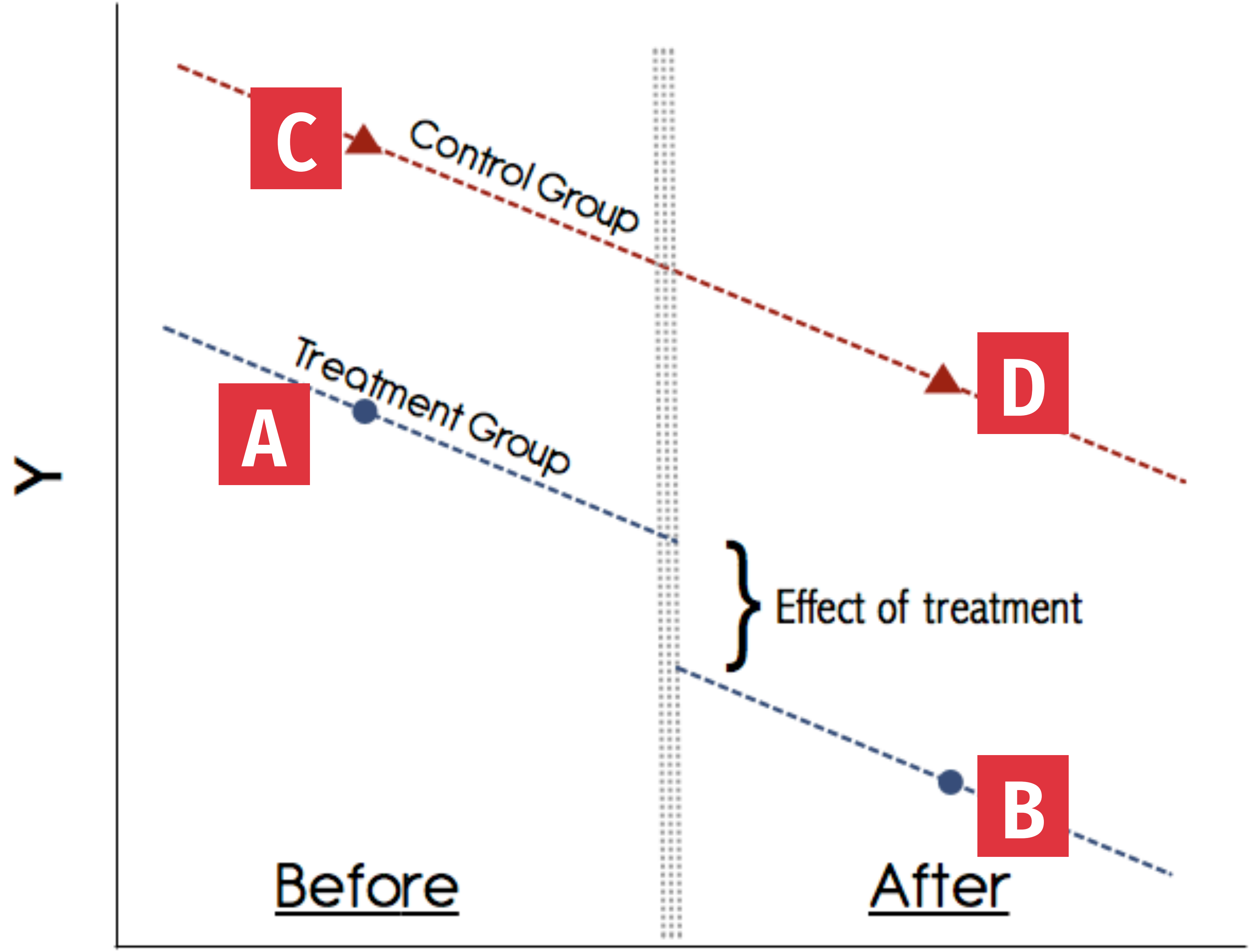
	Pre mean	Post mean	Δ (post−pre)
Treatment	A (not yet treated)	B (treated)	B−A
Control	C (never treated)	D (never treated)	D−C
Δ (trtmt−ctrl)	A−C	B−D	(B−A) − (D−C)

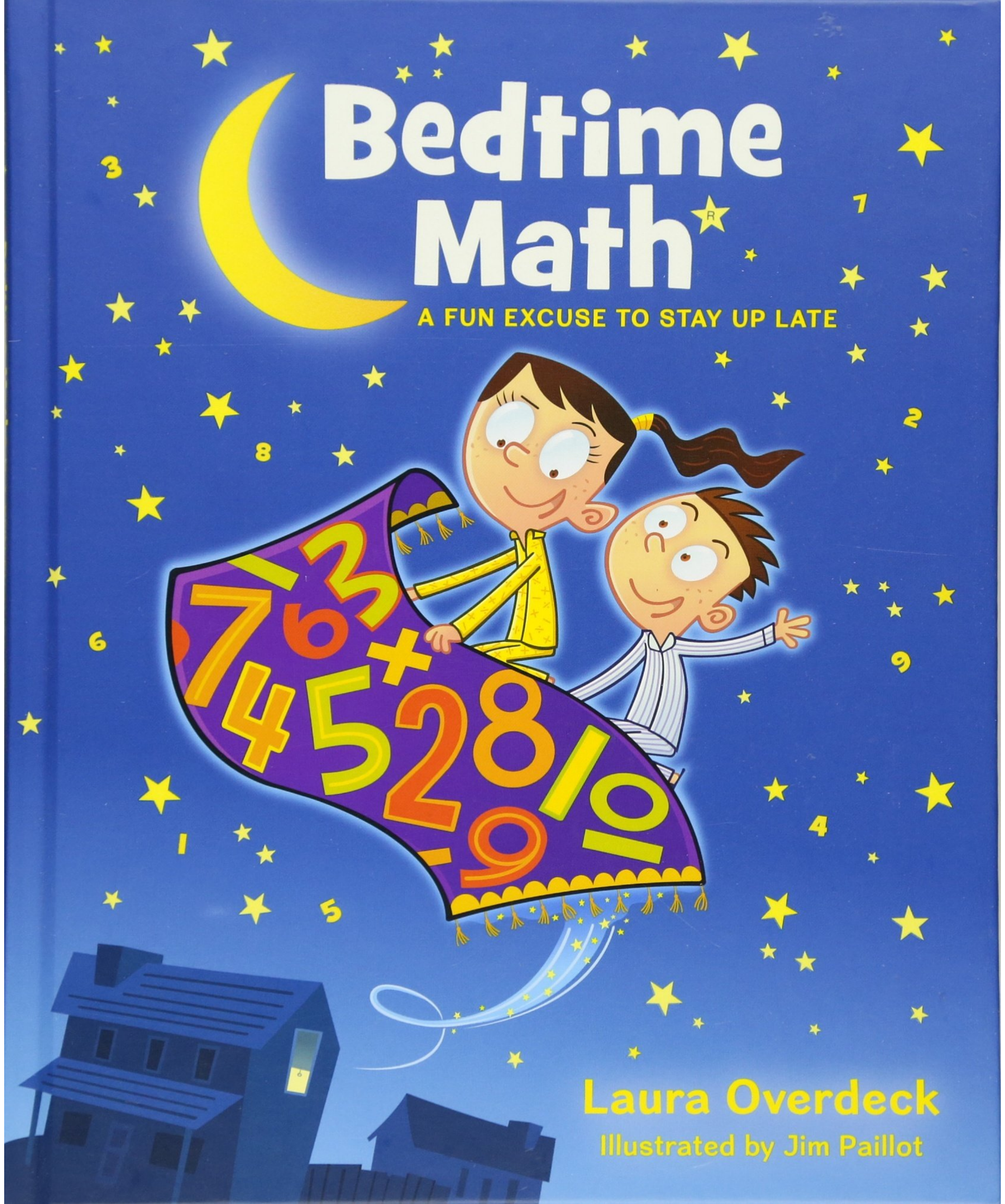
Growth of treatment − growth of control (DiD!)

$$
\begin{aligned}
\mathrm{DD} = & \left(\bar{x}_{\text{treatment, post}} - \bar{x}_{\text{treatment, pre}}\right) \\
& - \left(\bar{x}_{\text{control, post}} - \bar{x}_{\text{control, pre}}\right)
\end{aligned}
$$

	Pre mean	Post mean	Δ (post−pre)
NJ	A **20.44**	B **21.03**	B−A **0.59**
PA	C **23.33**	D **21.17**	D−C **−2.16**
Δ (trtmt−ctrl)	A−C **−2.89**	B−D **−0.14**	**(0.59) − (−2.16) = 2.76**

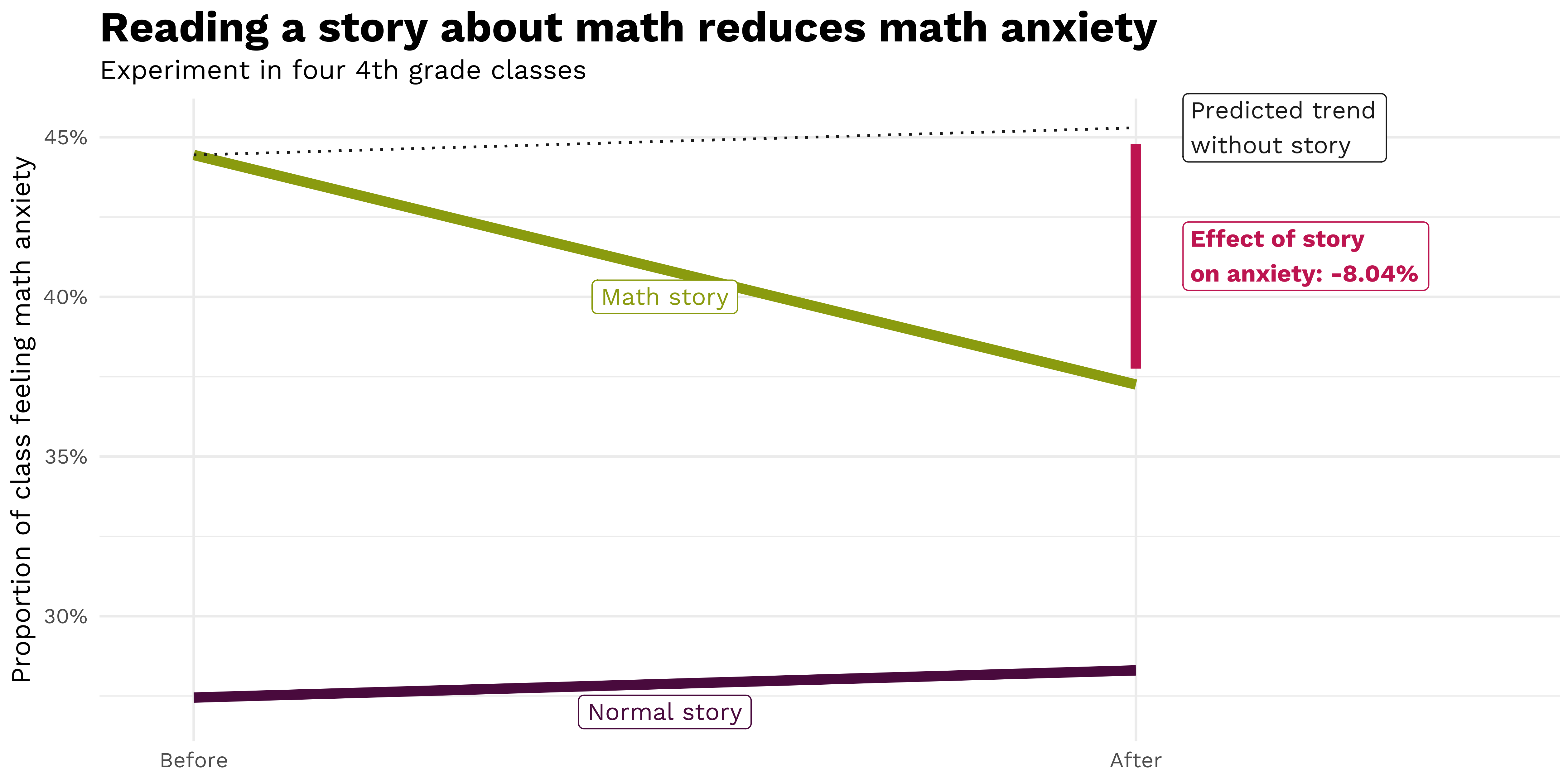

B
Difference in Differences
Treatment
A
Pretest Non-Equivalence
D
Comparison
C
Pretest
Posttest


Y
C
Control Group
A
Treatment Group
D
Effect of treatment
B
Before
After


Bedtime Math®
A FUN EXCUSE TO STAY UP LATE
Laura Overdeck
Illustrated by Jim Paillot

	Pre mean	Post mean	Δ (post–pre)
Math story	A	B	B–A
Normal story	C	D	D–C
Δ (trtmt–ctrl)	A–C	B–D	(B–A) – (D–C)

R time!



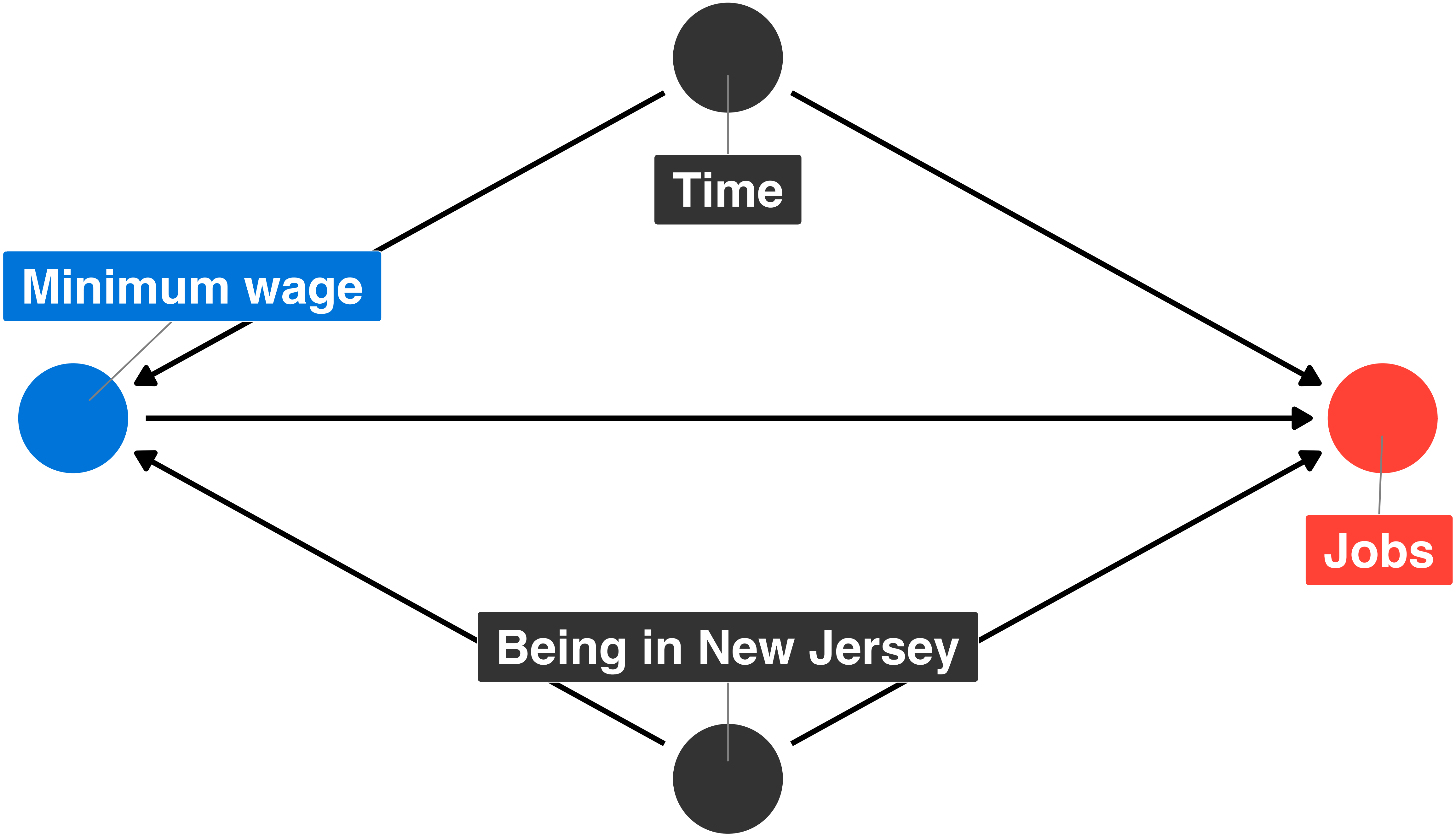
Reading a story about math reduces math anxiety
Experiment in four 4th grade classes
Predicted trend without story
Effect of story on anxiety: -8.04%
Math story
Normal story
45%
40%
35%
30%
Proportion of class feeling math anxiety
Before
After

Finding all the group means is tedious though!

What if there are other backdoors to worry about?

Regression to the rescue!


HOT DOGS
PLAIN $2.00
CHEESE $2.35
CHILI $2.35
CHILI CHEESE $2.70


Time
Minimum wage
Jobs
Being in New Jersey

$$
\begin{aligned}
Y_{it} =& \alpha + \beta \ \text{Group}_i + \gamma \ \text{Time}_t + \\
& \delta \ (\text{Group}_i \times \text{Time}_t) + \epsilon_{it}
\end{aligned}
$$

```r
model <- lm(outcome ~ group + time + group * time)
```

Group = 1/TRUE if treatment

Time = 1/TRUE if after

$$Y_{it} = \alpha + \beta \ \text{Group}_i + \gamma \ \text{Time}_t + \delta \ (\text{Group}_i \times \text{Time}_t) + \epsilon_{it}$$

```
model <- lm(outcome ~ group + time + group * time)
```

α = Mean of control, pre-treatment

β = Increase in outcome across groups

γ = Increase in outcome across time

δ = Difference in differences!

$$Y_{it} = \alpha + \beta \ \text{Group}_i + \gamma \ \text{Time}_t + \delta \ (\text{Group}_i \times \text{Time}_t) + \epsilon_{it}$$

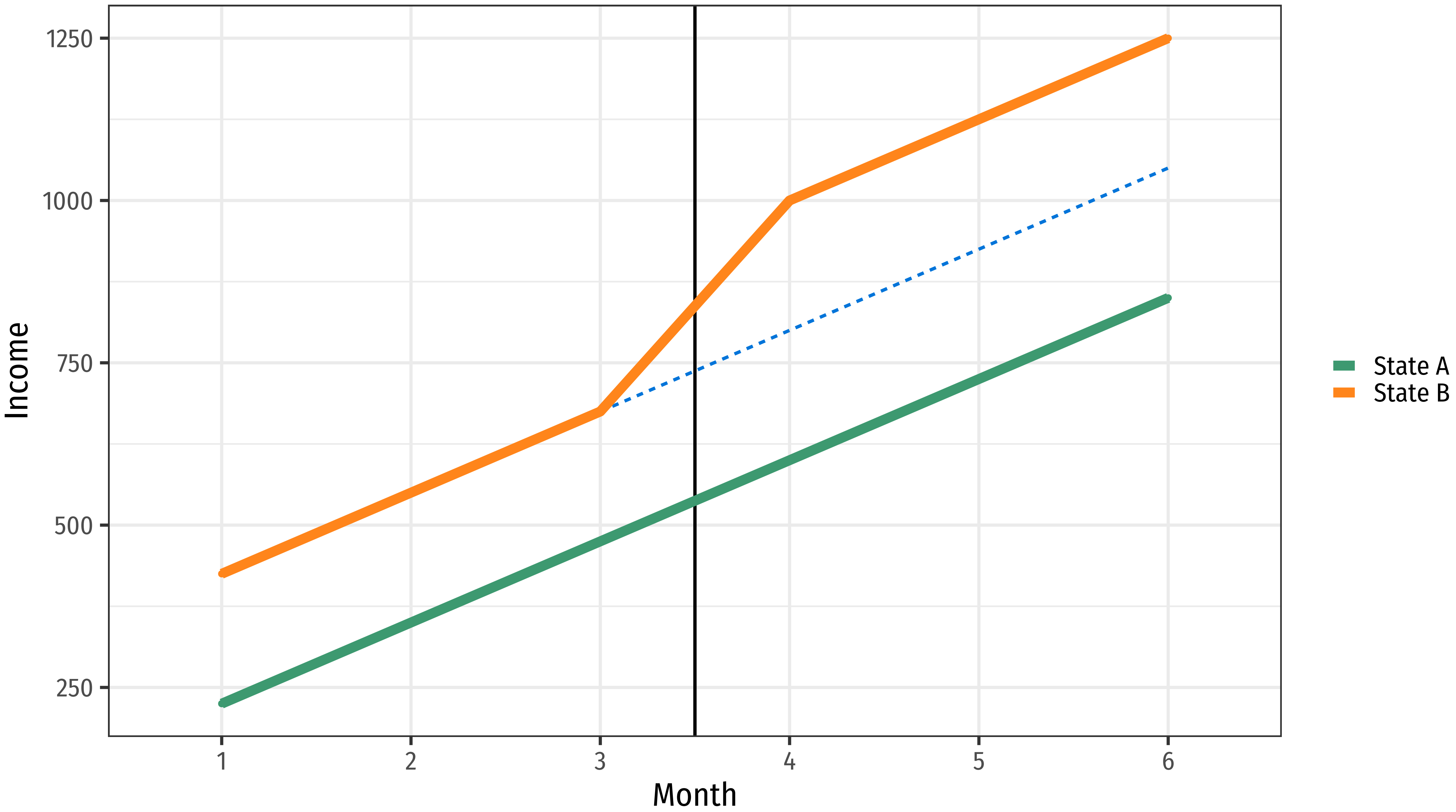
	Pre mean	Post mean	Δ (post−pre)
Control	α	α + γ	γ
Treatment	α + β	α + β + γ + δ	γ + δ
Δ (trtmt−ctrl)	β	β + δ	δ

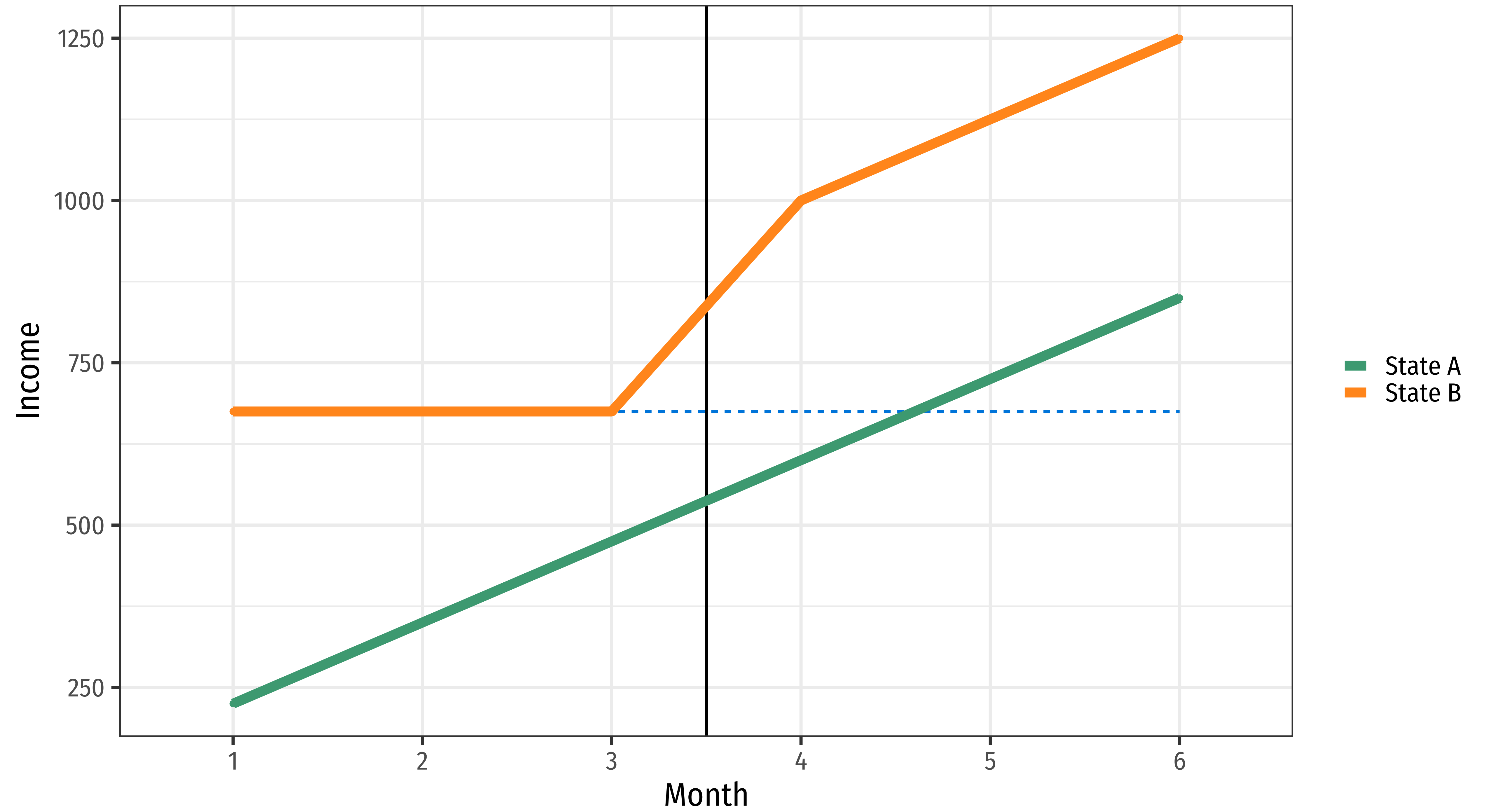
DiD assumptions

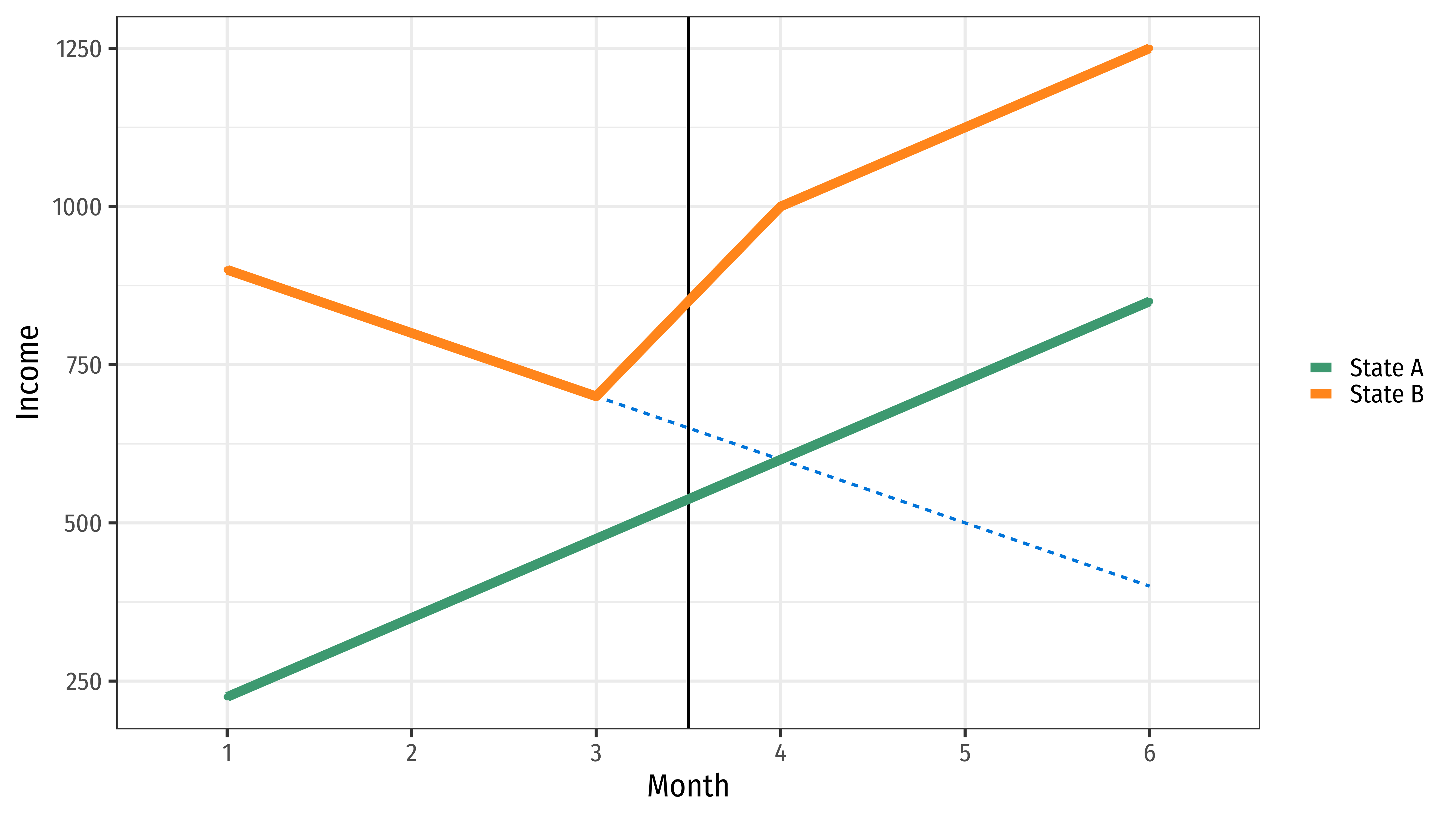
Assumptions

Parallel trends

Treatment and control might have different values at first, but we assume treatment group would have changed like control in absence of treatment


1250
1000
750
500
250
Income
1
2
3
4
5
6
Month
State A
State B

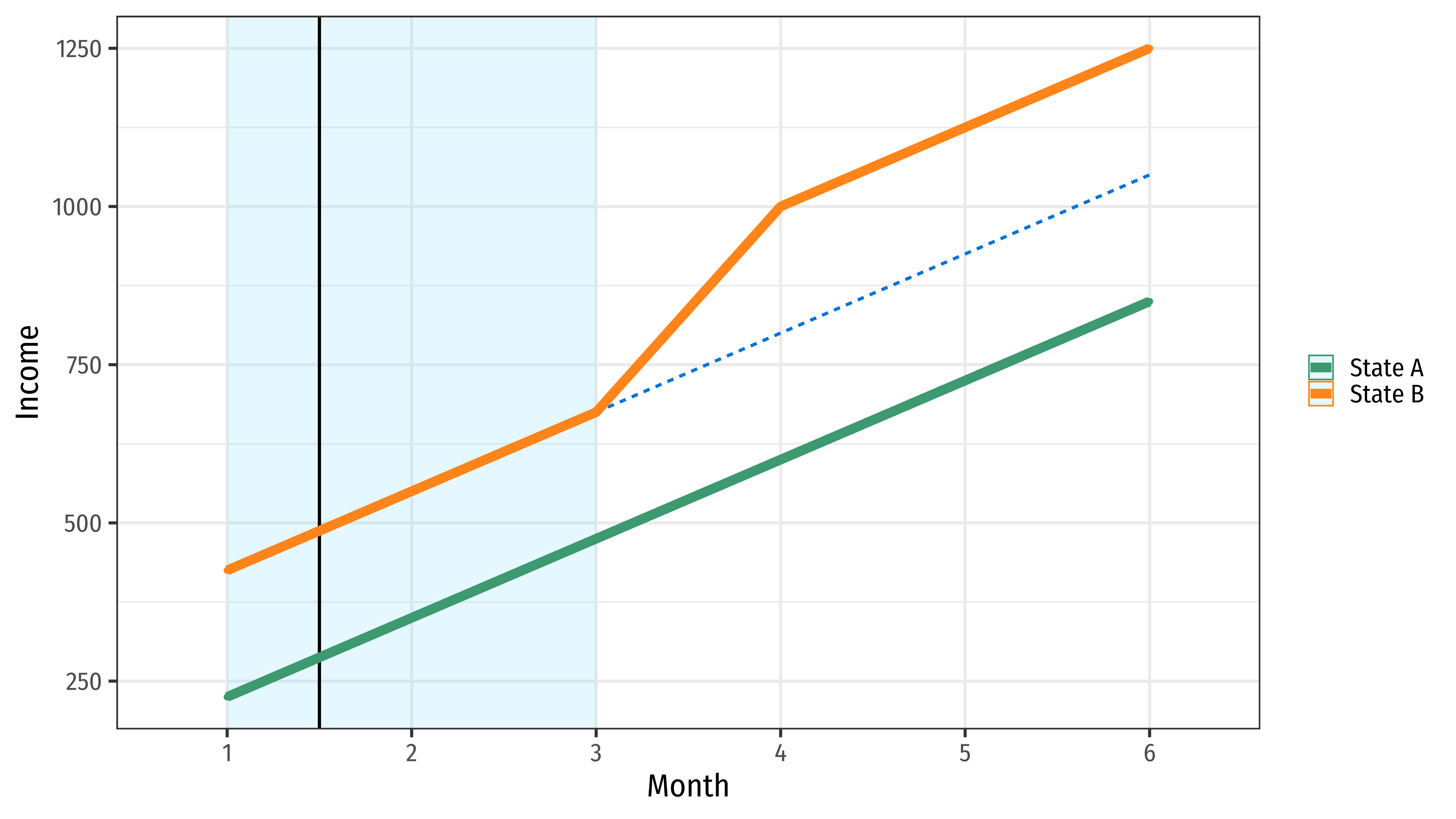

Income
Month
1250
1000
750
500
250
1
2
3
4
5
6
State A
State B

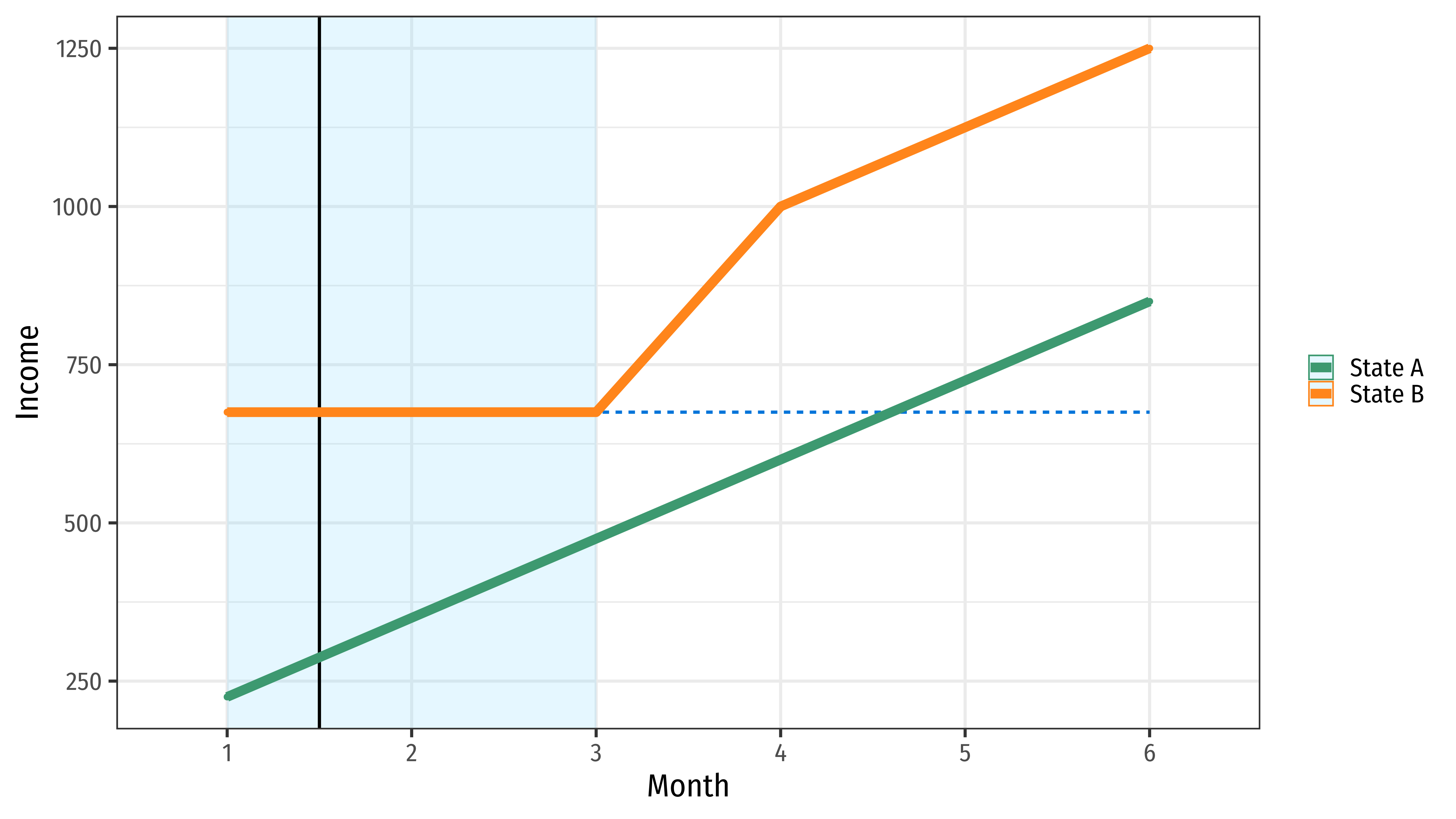

1250
1000
750
500
250
Income
1
2
3
4
5
6
Month
State A
State B

Assumptions

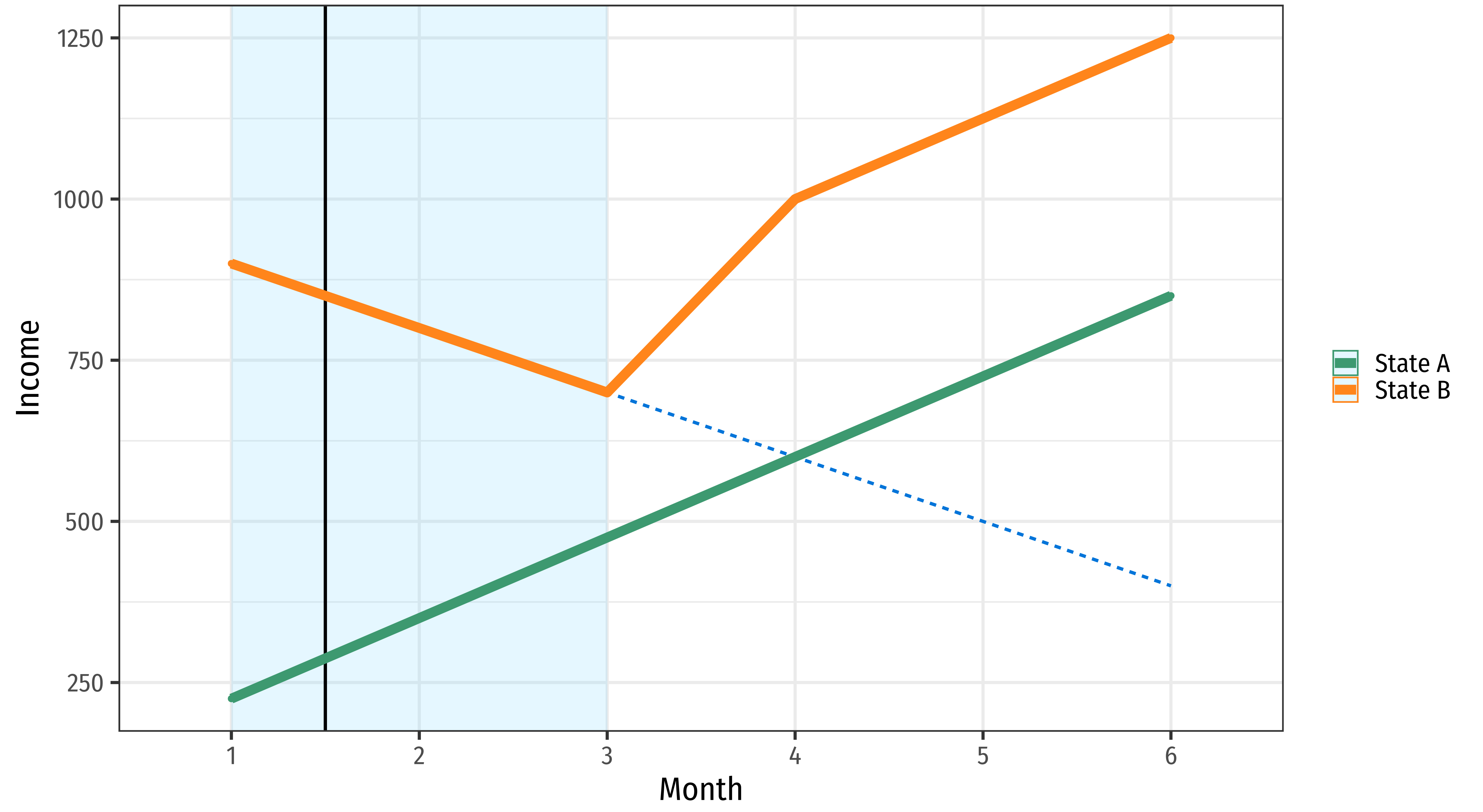
Parallel trends

Check by pretending the treatment happened earlier. If there's an effect, there's an underlying trend.


Income
Month
1250
1000
750
500
250
1
2
3
4
5
6
State A
State B



1250
1000
750
500
250
Income
1
2
3
4
5
6
Month
State A
State B

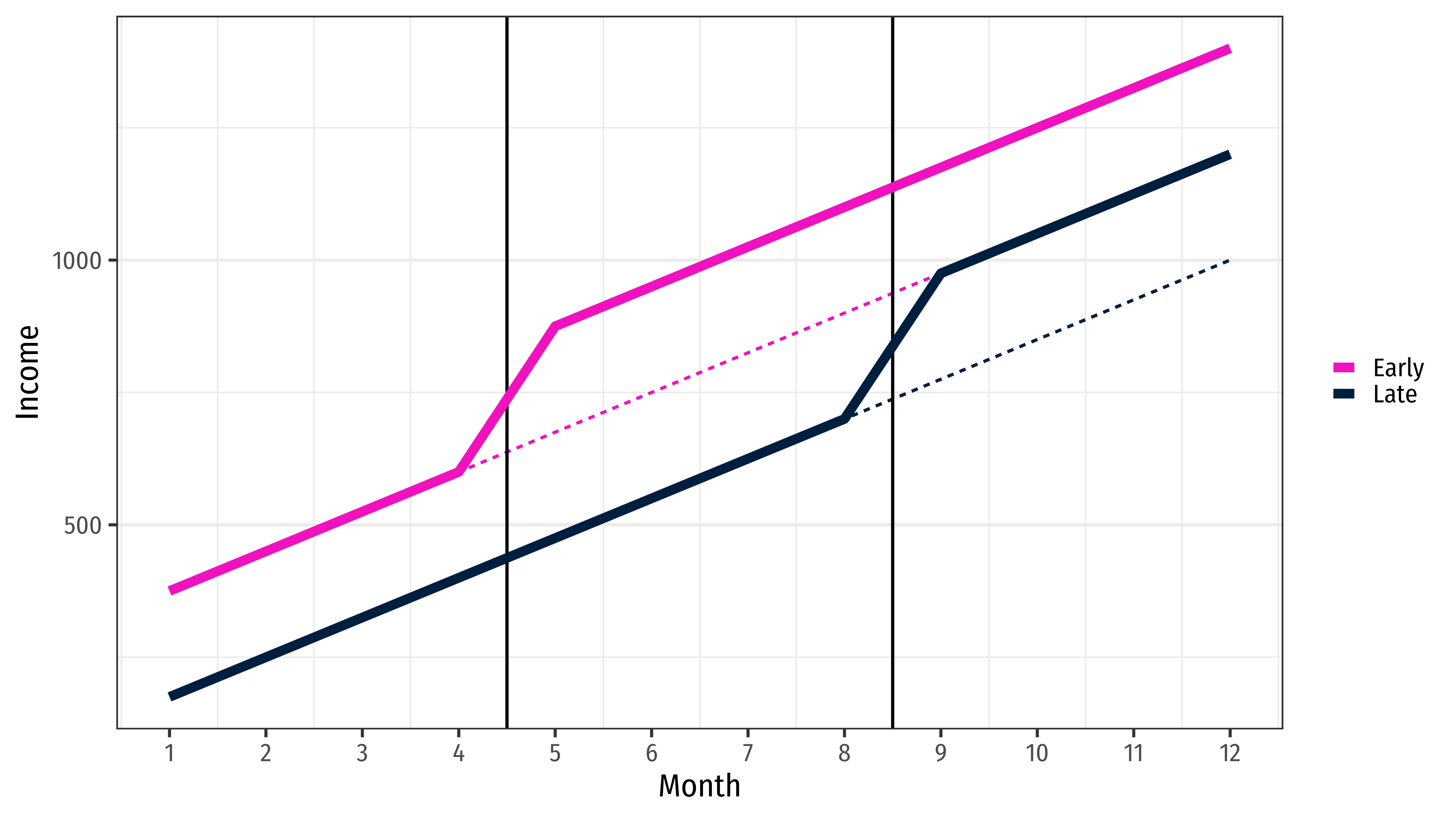


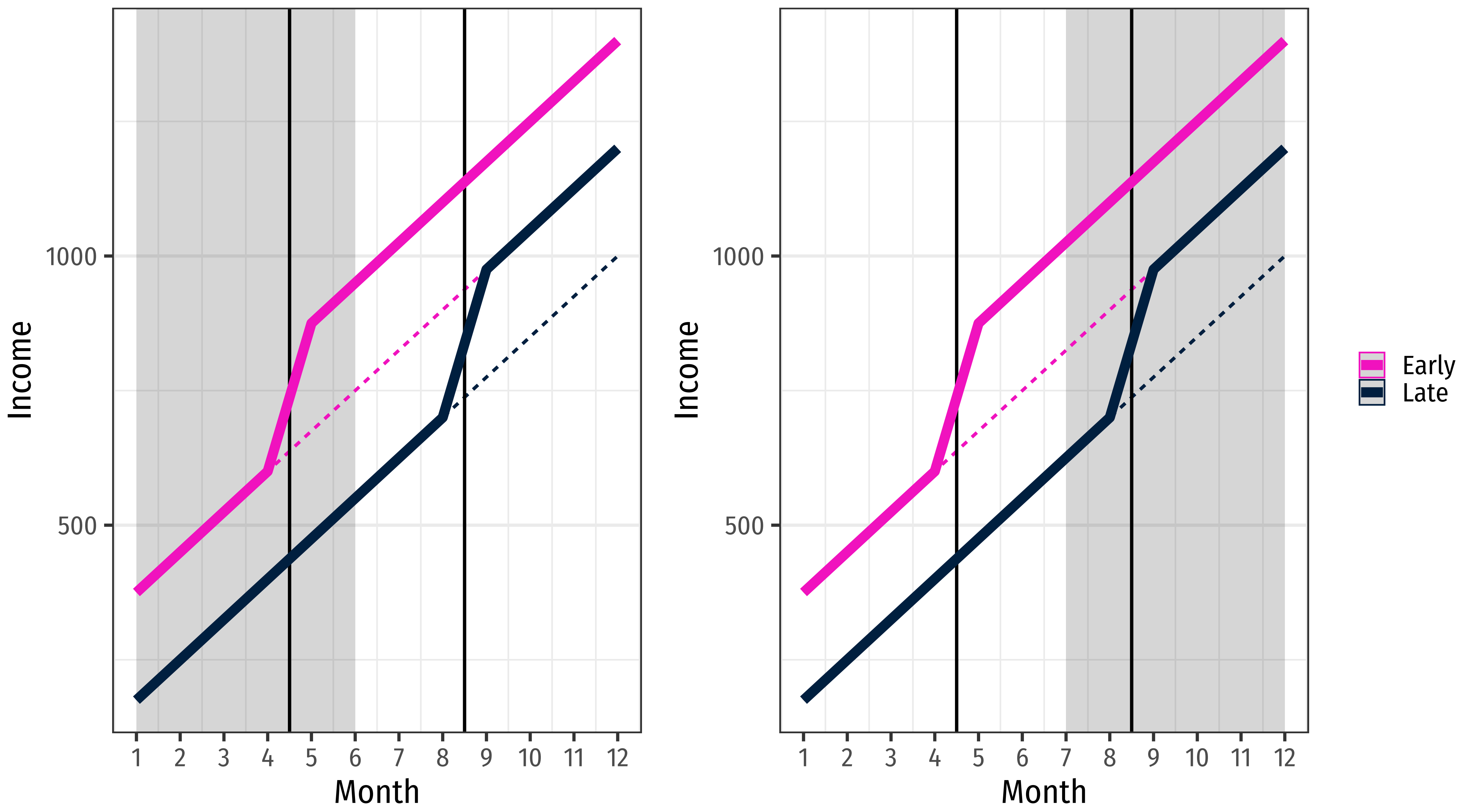
1250
1000
750
500
250
Income
1
2
3
4
5
6
Month
State A
State B

Assumptions

Treatment timing

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


Income
1000
500
Month
1
2
3
4
5
6
7
8
9
10
11
12
Early
Late



1000
500
Income
1 2 3 4 5 6 7 8 9 10 11 12
Month
1000
500
Income
1 2 3 4 5 6 7 8 9 10 11 12
Month
Early
Late

Assumptions

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

Working Paper 25018
http://www.nber.org/papers/w25018

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2018

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 GO, automatically recorded in the "Health" application of the iPhone 6 series smartphones and reported by the participants. A difference in difference regression model was used to estimate the change in

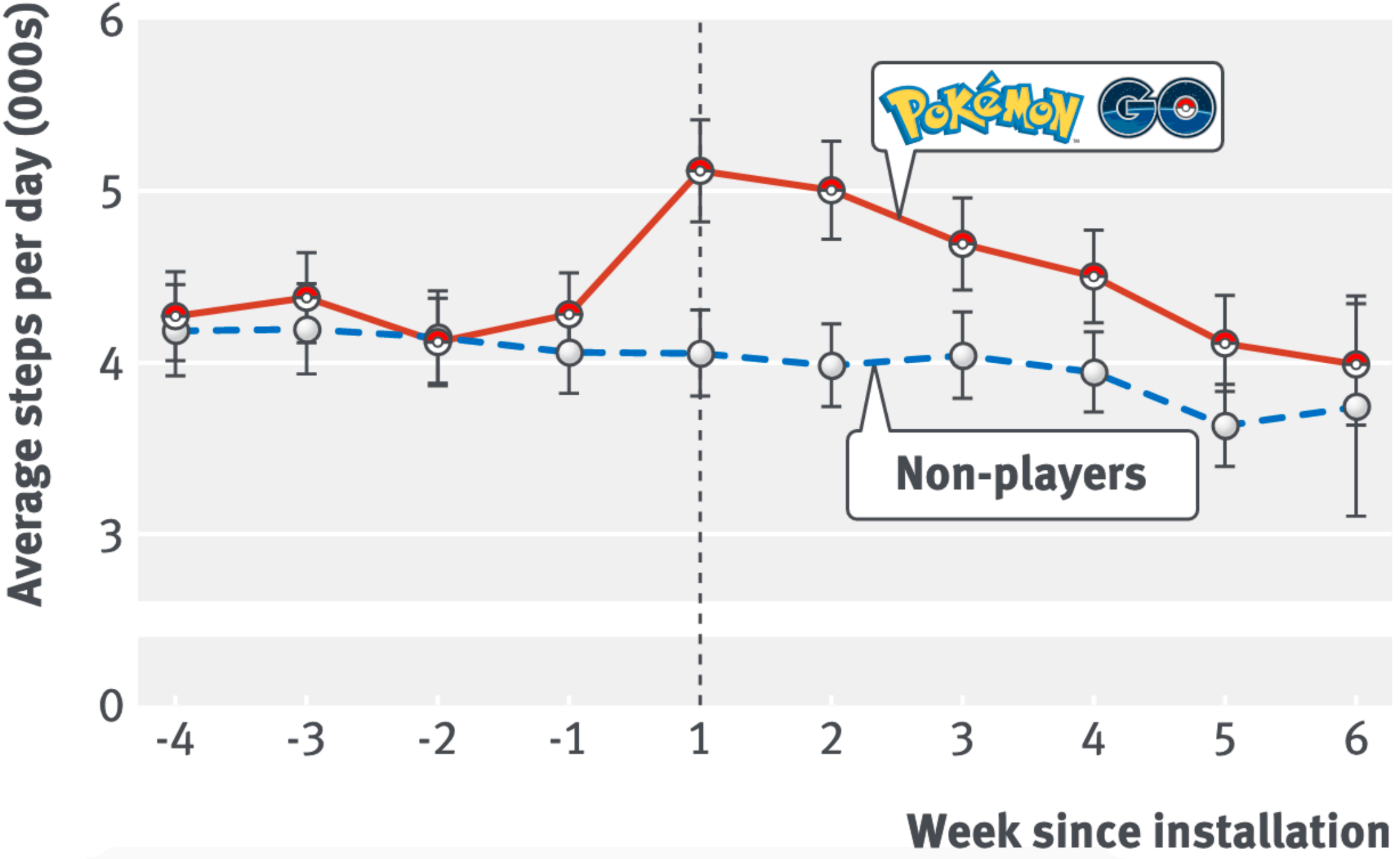
CONCLUSIONS

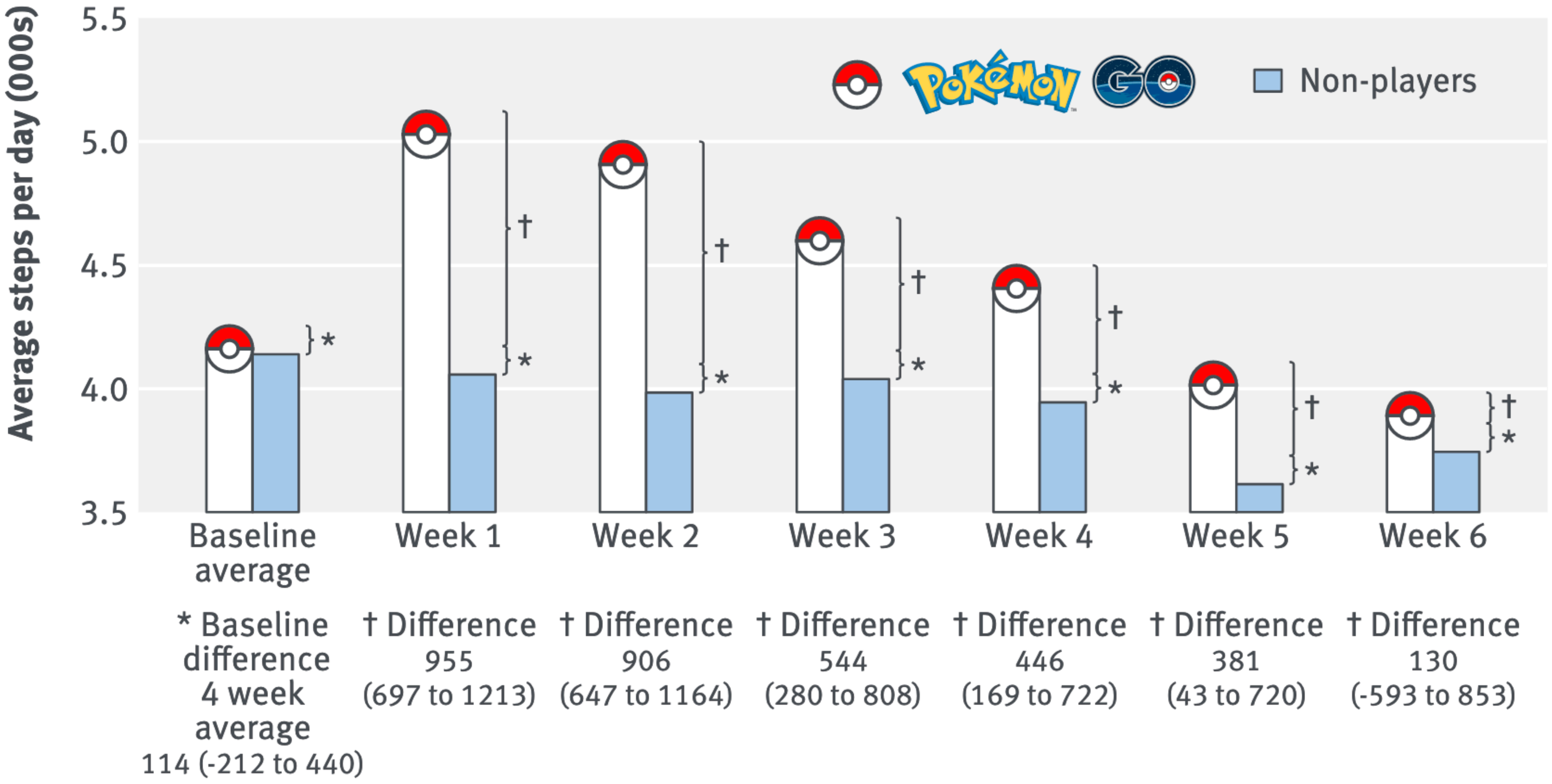
Pokémon GO was associated with an increase in the daily number of steps after installation of the game. The association was, however, moderate and no longer observed after six weeks.

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, Pokémon GO has been suggested to increase physical activity and improve public health, but these claims have been based on anecdotal evidence.[3-5]


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


Average steps per day (000s)
5.5
5.0
4.5
4.0
3.5
Pokémon GO
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)

R time!