Omitted Variables Bias (OVB) and Causal Inference

ECON 490

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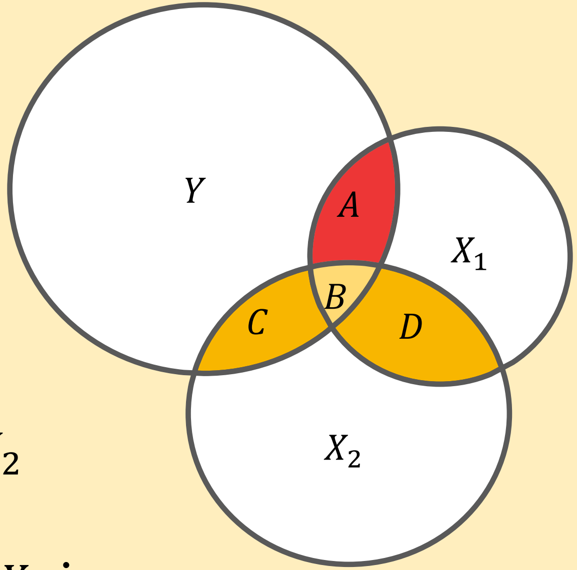
Slides Overview

In these slides, we'll discuss:

- Defining omitted variables bias (OVB)
- Introducing causal inference
- Fixed effects and OVB

Isolating Variation

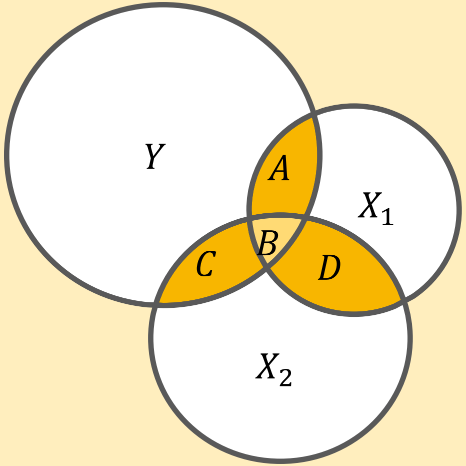


A represents covariance of Y and X_1 that is unrelated to X_2

In a regression of Y on X_1 and X_2, our estimated effect of X_1 is determined by the ***unique*** effect of X_1 on Y

The question for this week – what happens if we ***don't*** control for X_2?

Omitted Variables Bias (OVB)

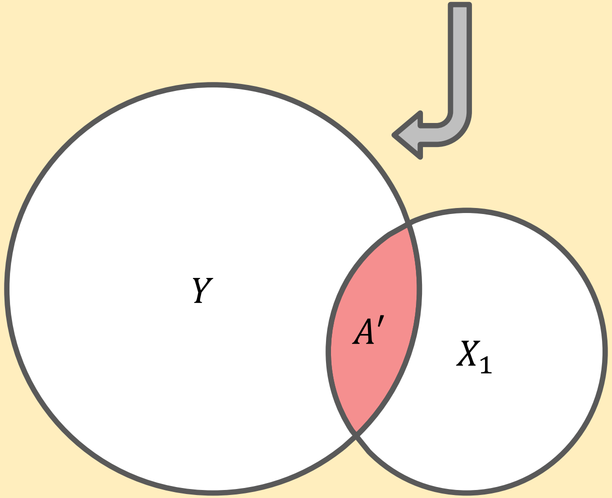


Let's suppose our initial Venn diagram is the "true" model

- What happens if we don't have data for X_2?
- Then we're stuck with just observing X_1

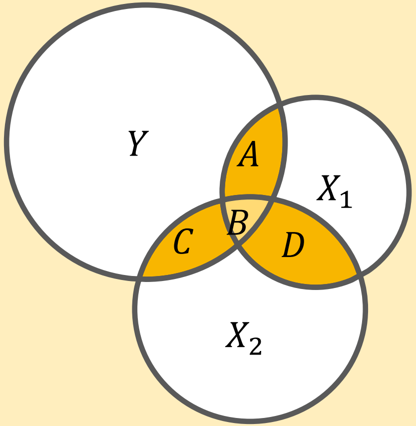
The "effect" of X_1 in our ***new*** diagram is A'

- But we know that's too big – it includes B!



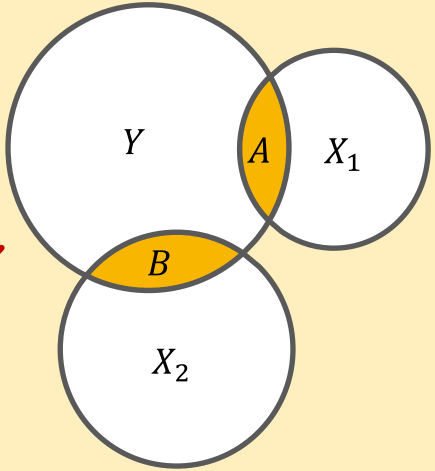
We ***incorrectly*** estimate the effect of X_1 because we ***couldn't*** observe X_2 – this is OVB

Two Key Components of OVB



OVB requires ***two*** conditions:

1) Omitted X_2 must covary with Y
2) Omitted X_2 must covary with X_1



If this is the true model, there's no OVB!

Direction of Bias

The ***bias*** in OVB means that our estimated OLS coefficient is wrong

- In other words, our estimated regression coefficient is too big or too small
- The direction of the bias depends on the underlying relationships

Suppose the true model is given by $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + u$

We can refer to the following as the OVB model: $Y = \alpha_0 + \alpha_1^{OVB} X_1 + e$

Direction of Bias Table

Given the definitions from the last slide, we can compare β_1 to α_1^{OVB}

- Table tells us, “What happens if we omit X_2 from our regression?”

	X_1 and X_2 are ***positively*** correlated	X_1 and X_2 are ***negatively*** correlated
Y and X_2 are ***positively*** correlated	Positive Bias ($\beta_1 < \alpha_1^{OVB}$)	Negative Bias ($\beta_1 > \alpha_1^{OVB}$)
Y and X_2 are ***negatively*** correlated	Negative Bias ($\beta_1 > \alpha_1^{OVB}$)	Positive Bias ($\beta_1 < \alpha_1^{OVB}$)

OVB and Descriptive vs. Causal Statements

Descriptive statement = *"The correlation between* X_1 *and* Y *is* A*"*

- OVB provides helpful context – we know other factors probably matter!
- But claims are still informative – exploring data, relationships, patterns, etc.

Causal statement = *"*X_1 ***causes*** A *change in* Y*"*

- Now OVB is a big deal – ***can't*** make (credible) causal claims if we have OVB
- Causal inference is broadly a set of tools for dealing with OVB

OVB Example

What's the impact of a financial grant program on student GPAs?

- Give some students grants in Fall but not others, observe GPAs in Spring
- We want to estimate the following:

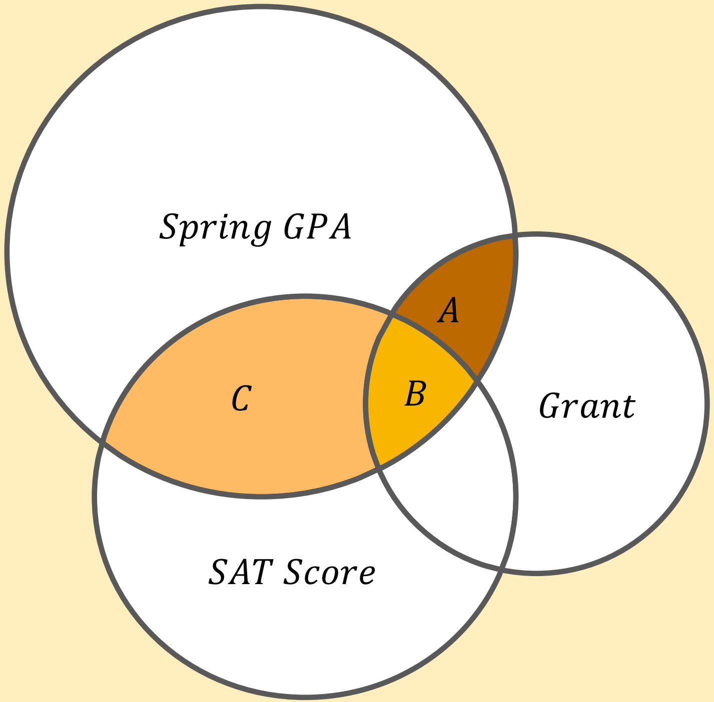
$$Spring\ GPA = \alpha_0 + \alpha_1 Fall\ Grant + u$$

Two possible ways of assigning grants:

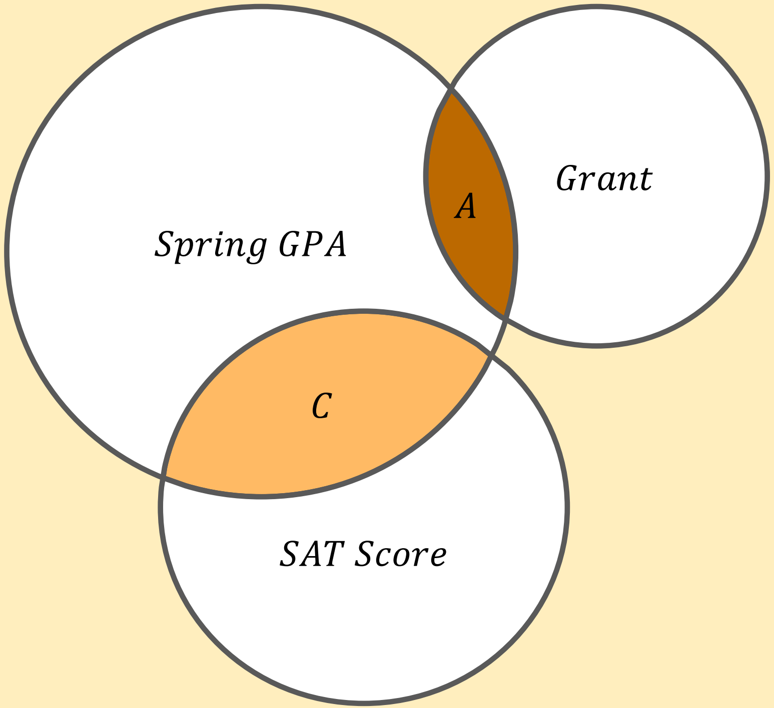
- Give to students with highest SAT scores
- Assign via coin flip

OVB Example – *Two Cases*

Assigned to highest SAT scores



Assigned via coin flip



Causal Inference without Randomization

Randomization solves the OVB problem by assigning values of X_1

- Implemented via Randomized Controlled Trials (RCTs)
- Classic example = pharmaceutical trials

Economics often involves questions where randomization isn't feasible

Causal inference with observational data is the process of “finding” randomization

Causal Inference with Observational Data

“Finding” randomization broadly means one of two things:

1. Identifying situations where treatment assignment is effectively random
2. Controlling for omitted variables to address OVB problem

We can broadly group causal inference models into the above categories

- (1) Includes instrumental variables (IV) & regression discontinuity (RD)
- (2) Includes fixed effects, event studies, diff-in-diff (DiD), etc.

Group (1) – Finding Randomized Treatment

Instrumental Variables (IV) typically gets a lot of coverage in metrics classes

- Used to be more popular in applied research than it is now
- Why? Mix of new methods, potential for things to go wrong, etc.

Regression Discontinuity (RD) tries to “imitate” RCTs

- If we can’t randomize treatment, find something that does it for us
- Laws, administrative rules, etc. that assign treatment based on cutoffs

Regression Discontinuity (RD)

Let's return to our financial grants example

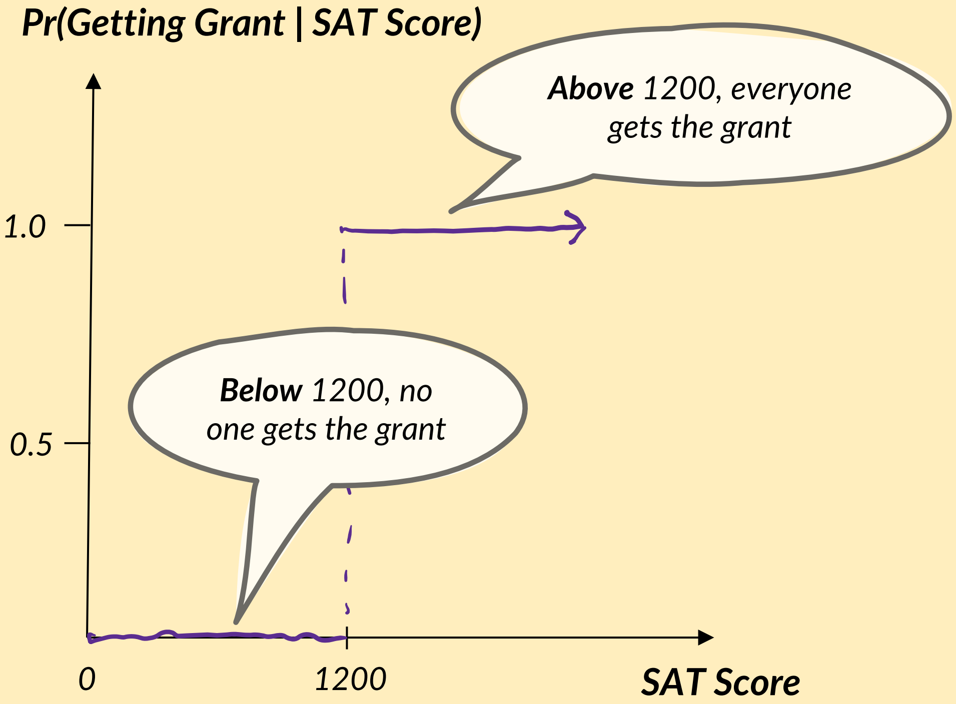
- Suppose everyone with SAT > 1200 gets the grant
- OVB intuition – getting a grant is correlated with omitted factors

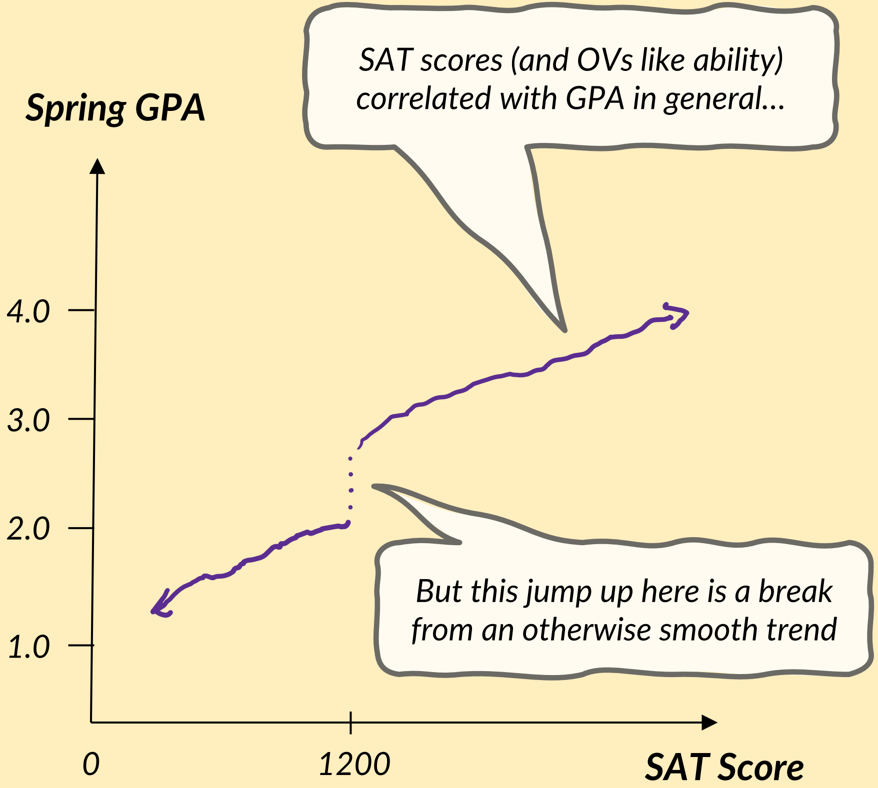
But what if we "zoom in" on SAT scores right around 1200?

- Difference between getting a 1190 vs. 1200 is mostly just luck
- Misread a single question, accidentally mark the wrong answer, etc.

Grant assignment ***effectively random*** around 1200 threshold

RD in Two Pictures





Group (2) – Controlling for Omitted Variables

As a starting point, consider the following:

$$Y = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + u$$

Suppose we ***knew*** that this was the "true" regression equation

- Would we need to worry about OVB?
- No! Regression identifies ***unique*** effect of X_1 ***controlling*** for X_2

Group (2) – Controlling for Omitted Variables (Con't)

In practice, we almost never know the "true" model

- How do we know what to control for?
- Think about the potential "structure" of omitted variables

Do we think omitted variables…

- Differ across groups in a fixed or constant fashion? *(fixed effects)*
- Differ by group and across time? *(DiD, event studies, etc.)*

We can see how this works by considering an example using fixed effects

Fixed Effects Example

What's the relationship between hours spent studying and test scores?

- Suppose we've got data for two students, A and B, for two tests
- Gives us (1) time studying and (2) test scores

Student	Test	Hours Studying	Test Score
A	1	2	90
A	2	3	96
B	1	5	78
B	2	7	83

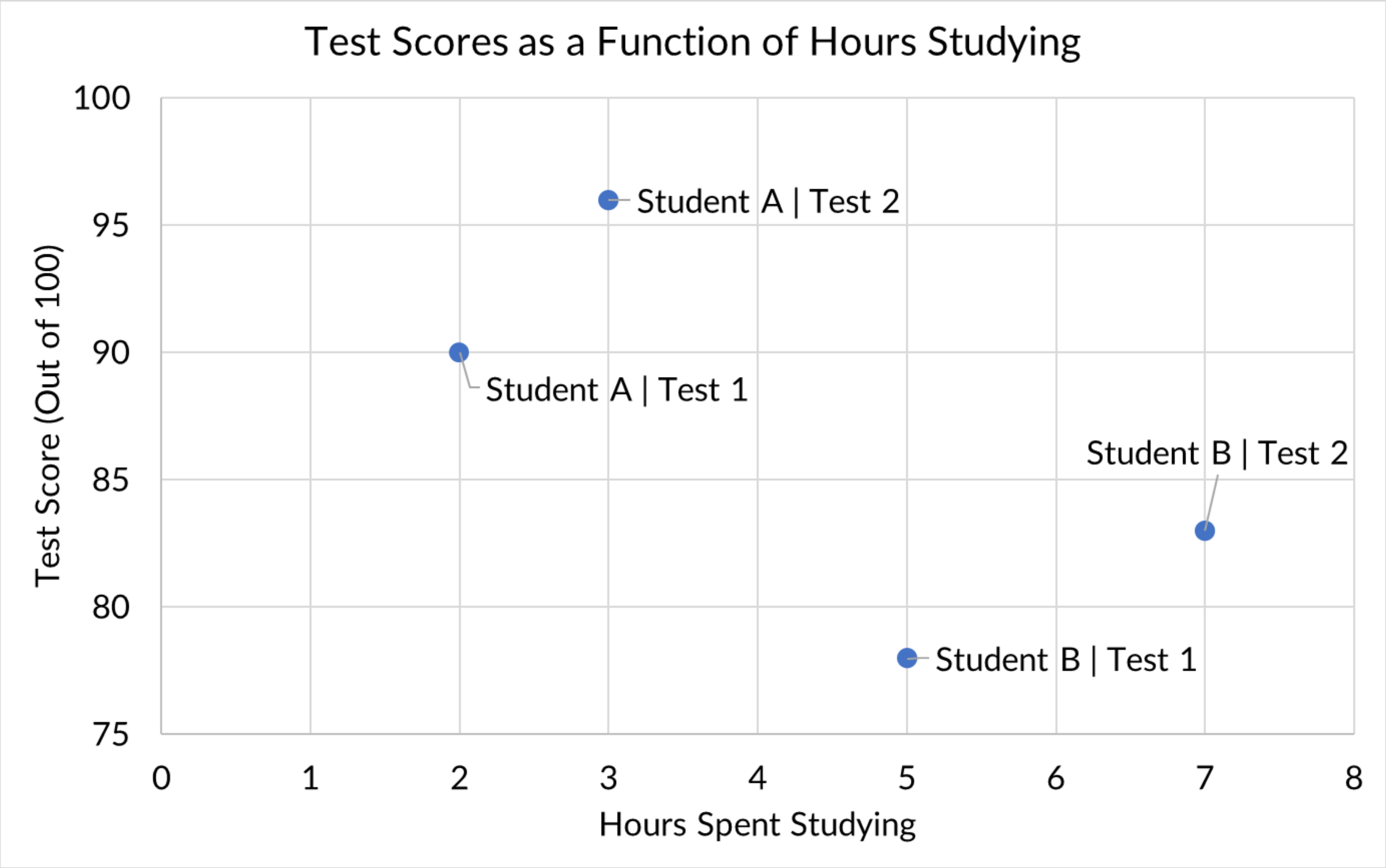
Fixed Effects Example (Con't)

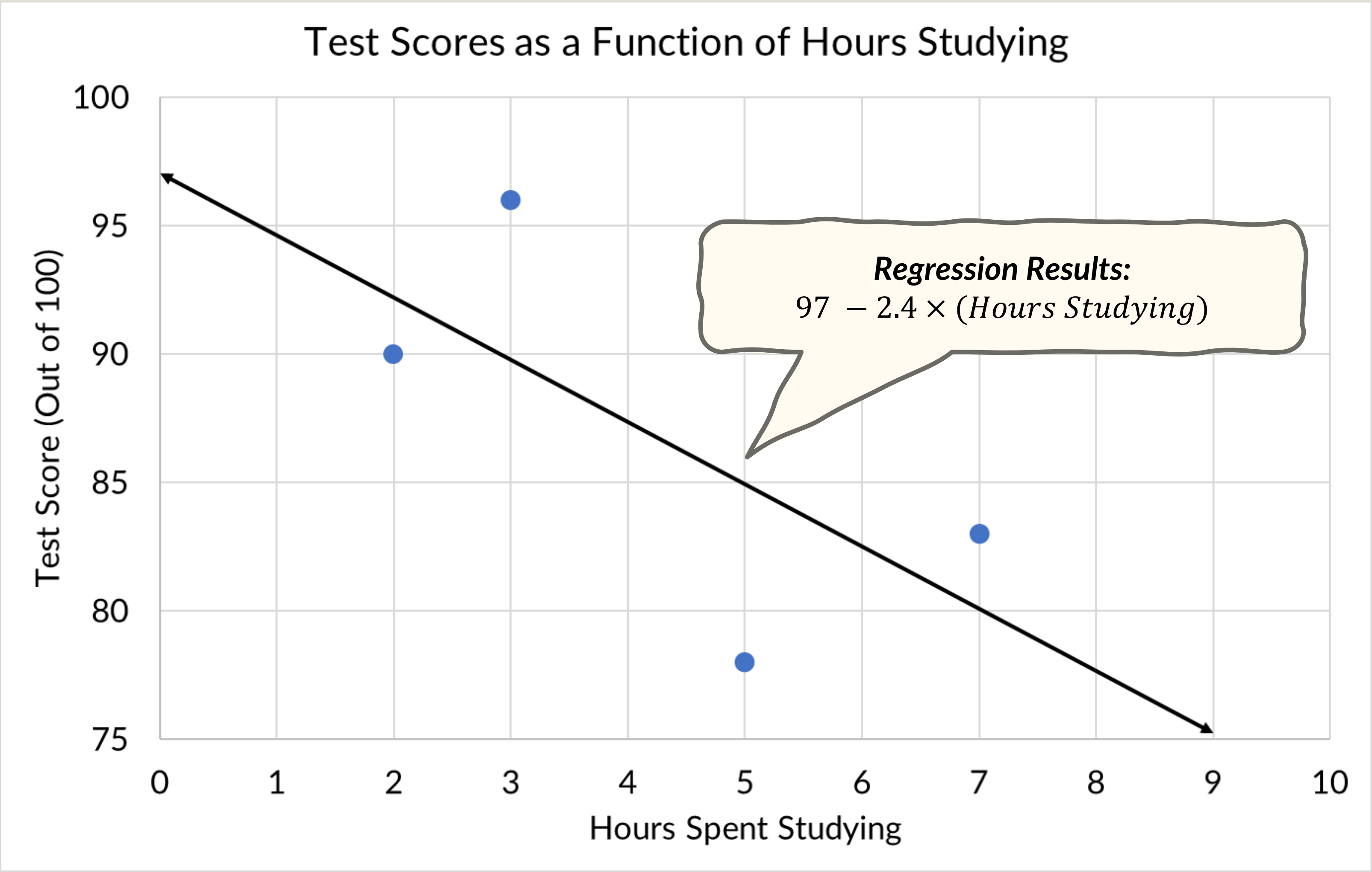
Given our data set, we can run the following regression:

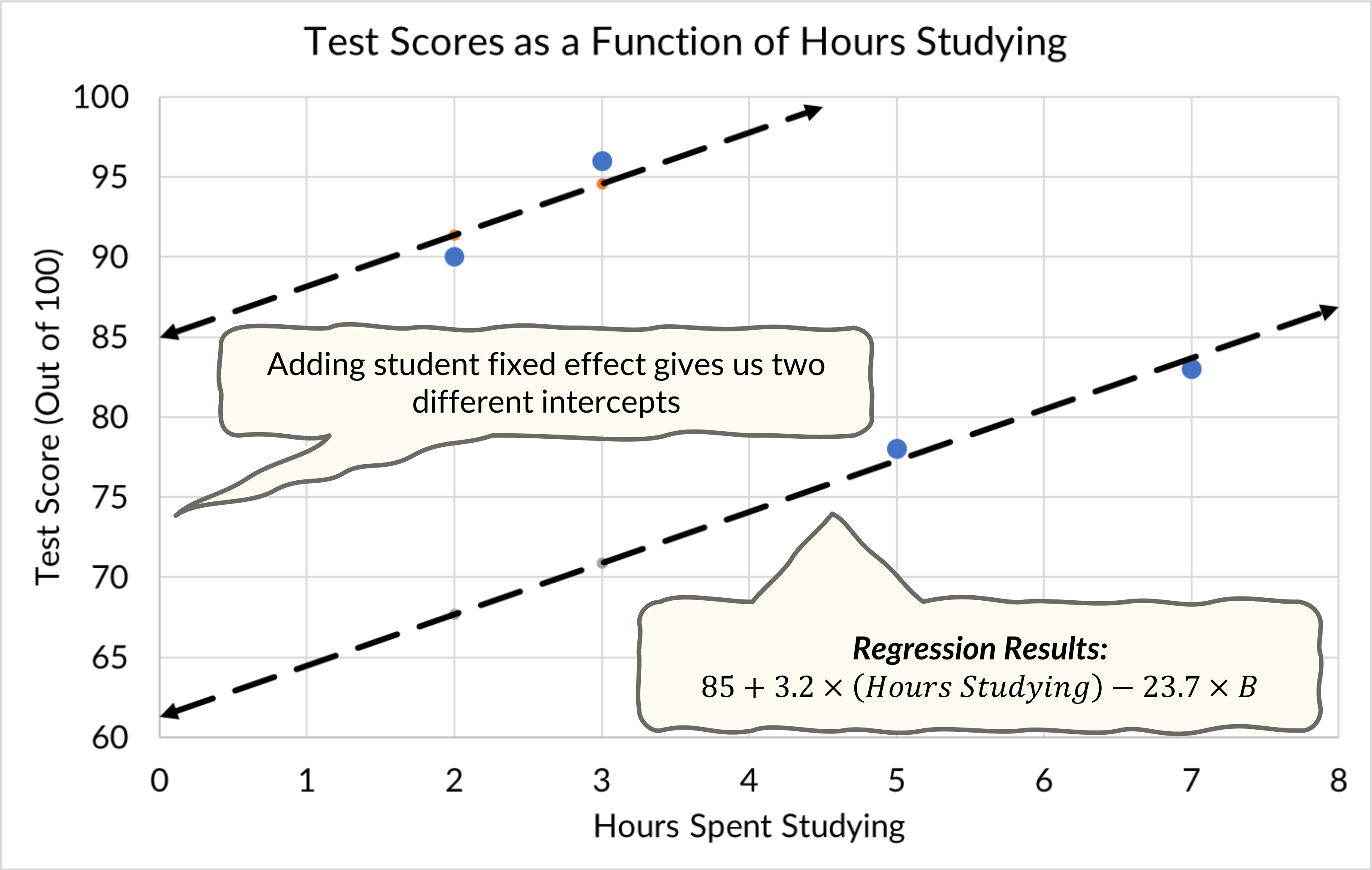
$$Test\ Score_i = \beta_0 + \beta_1 Hours\ Studying_i + u_i$$

Two ways of interpreting our regression results:

- β_1 tells us the change in avg. scores associated with studying 1 more hour
- We can ***predict*** test scores given X hours studying using $\hat{\beta}_0 + \hat{\beta}_1 X$


Test Scores as a Function of Hours Studying
Test Score (Out of 100)
100
95
90
85
80
75
Student A | Test 2
Student A | Test 1
Student B | Test 2
Student B | Test 1
0
1
2
3
4
5
6
7
8
Hours Spent Studying


Test Scores as a Function of Hours Studying
Regression Results:
$97 - 2.4 \times (Hours\ Studying)$
Test Score (Out of 100)
100
95
90
85
80
75
0
1
2
3
4
5
6
7
8
9
10
Hours Spent Studying


Test Scores as a Function of Hours Studying
Test Score (Out of 100)
100
95
90
85
80
75
70
65
60
0
1
2
3
4
5
6
7
8
Hours Spent Studying
Adding student fixed effect gives us two different intercepts
Regression Results:
$85 + 3.2 \times (Hours\ Studying) - 23.7 \times B$

Interpreting Fixed Effects (FEs)

Student FE controlled for avg. differences between students

- In general, we say FEs ***absorb*** variation
- Here, our FE absorbed variation across students in avg. hours + scores

A key question if we’re absorbing variation – what variation is left over?

- Refer to this as ***residual variation***
- We can see what this looks like in our example

Residual Variation

Student	Test	Hours	Score	Student Avg. Test Score	Residual Score Variation	Student Avg. Hours	Residual Hours Variation
A	1	2	90	93	-3	2.5	-0.5
A	2	3	96	93	3	2.5	0.5
B	1	5	78	80.5	-2.5	6	-1
B	2	7	83	80.5	2.5	6	1

Bias in Regression

In our example, students systematically differed in both:

- (1) avg. time spent studying and (2) avg. test performance
- This means “student” (broadly defined) was an omitted variable (OV)

Structure of OV in this example = fixed or constant difference in average Y and X

By creating a fixed effect for student, we solved the OVB problem

- Lets us ***identify*** the causal effect of time studying on test performance

FEs and Causal Inference

FEs are the “building blocks” of research designs like DiD, event studies, etc.

In our example, student FE let us identify the causal effect of studying…

- So long as the ***only*** source of OVB was avg. differences between students
- This kind of reasoning underlies interpreting all group (2) methods

What might cause OVB? Do we have FEs that absorb that kind of variable?

- We can have fixed effects for time, place, people, etc.
- Adding them can solve OVB… but we still need residual variation!