

# I'll show you how valuable exam reviews can be!

## API 202: TF Exam Review

# ALL

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February 21, 2024



*Do you remember those four amazing hours we spent learning linear regression in Friday TF section?*



*Well this is so much better than that!*

We've finally made it. It's Legally Blonde day!

# Practice set 1

# Practice questions!

You work for the governor of Massachusetts. She plans to roll out free universal pre-K to 26 communities in the state by 2026. She wants to know if her plan will improve high school (H.S.) graduation rates.

You have data on Boston students who graduated H.S. from 1996–2007 and run this regression, where graduation and pre-K are coded as 0/1:

$$(graduation)_i = \hat{\beta}_0 + \hat{\beta}_1 (pre\_K)_i + \hat{u}_i$$

Which is the “best” interpretation of  $\beta_1 = 0.17$  (SE = 0.05, P<0.001)?

- A. Attending pre-K is associated with a 17% higher high school graduation rate. It is statistically significant.
- B. A 1-unit change in pre-K is associated with a 0.17 pp higher high school graduation rate. It is statistically significant.
- C. Attending pre-K is associated with a 0.17% higher high school graduation rate. It is statistically significant.
- D. Attending pre-K is associated with a 17 pp higher high school graduation rate. It is statistically significant.

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- D. Attending pre-K is associated with a 17 pp higher high school graduation rate. It is statistically significant.

Here, we have a linear probability model with a binary outcome.

As a result, we have to interpret the outcome in percentage points.

When the outcome is 0 or 1, we also have to multiply the coefficient by 100.

Because the 95% confidence interval does not include “0”, the result is statistically significant (i.e. P<0.05).

Lastly, when we have a dummy predictor, it makes more sense to just compare the groups, rather than refer to a “1-unit change.” Even though a “1-unit change” is technically correct, it’s clunky!

# Practice questions!

Original regression:  $(graduation)_i = \hat{\alpha}_0 + \hat{\alpha}_1(pre\_K)_i + \hat{\nu}_i$

Original estimate:  $\alpha_1 = 0.17$  (SE = 0.05, P<0.001)

You're worried about omitted variable bias.

In particular, you know that children with higher household incomes are more likely to attend pre-K. You also know that children with higher household incomes are more likely to graduate high school.

Using this information, sign the omitted variable bias for household income.

	$\gamma_1$	$\beta_2$	Bias sign	Bias size
A.	(+)	(+)	(+)	Understatement/sign flip
B.	(+)	(+)	(+)	Overstatement/sign flip
C.	(+)	(-)	(-)	Overstatement
D.	(+)	(-)	(+)	Understatement
E.	(-)	(-)	(+)	Understatement/sign flip
F.	(-)	(+)	(-)	Overstatement

# Practice questions!

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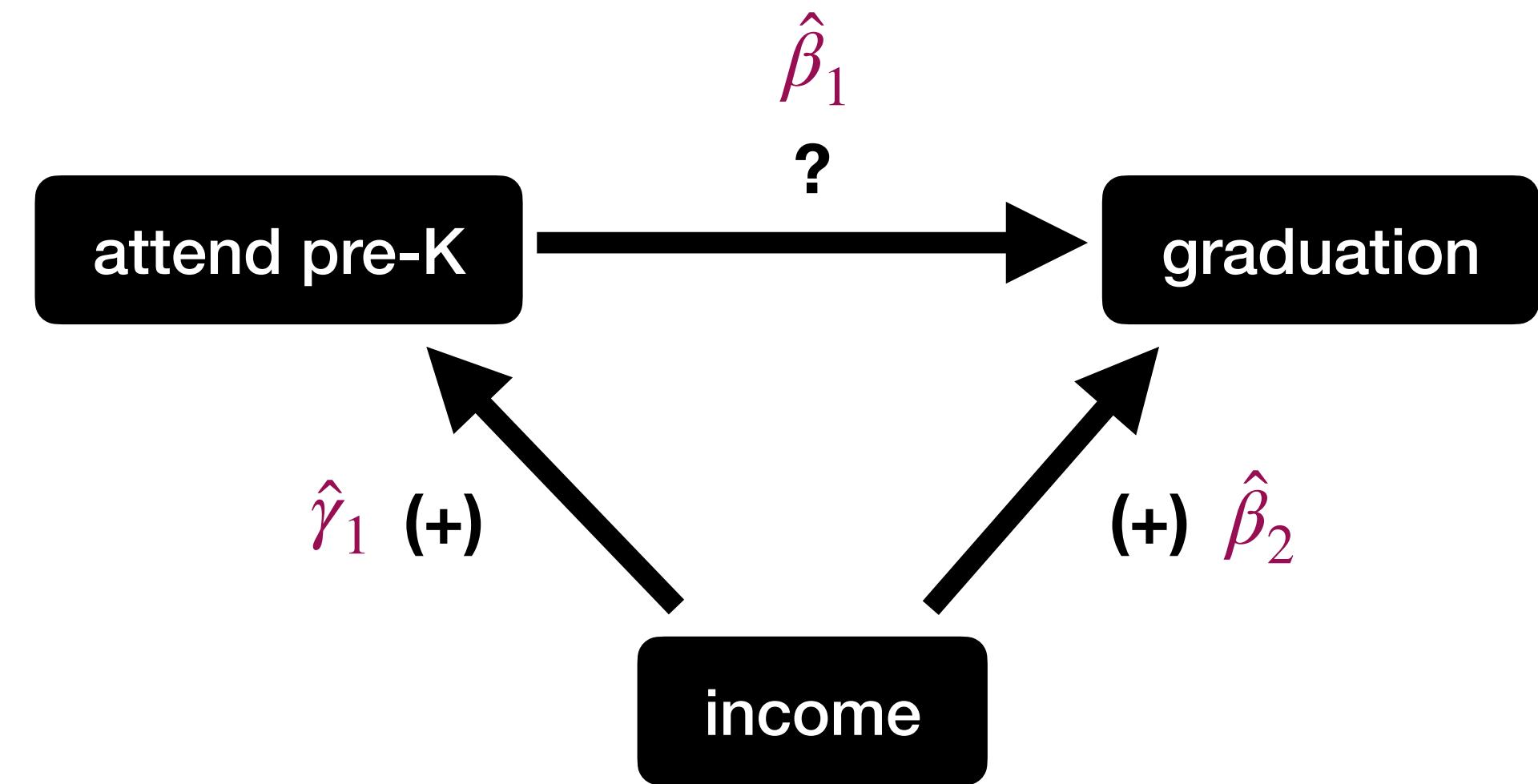
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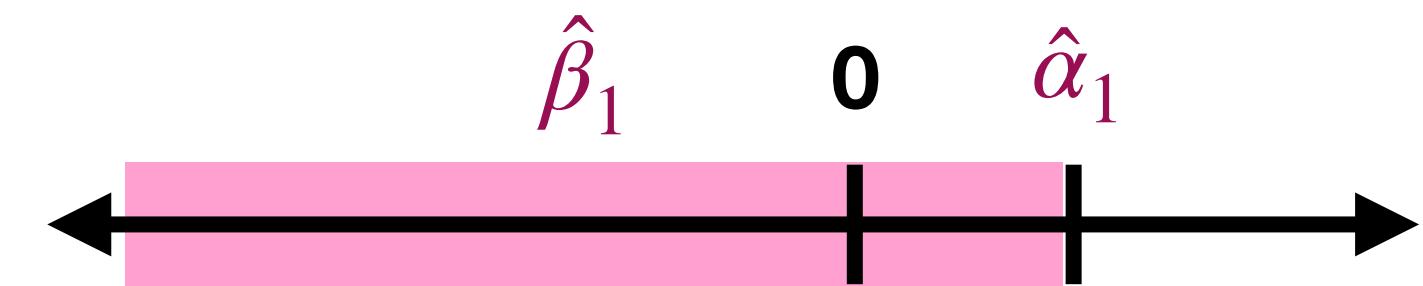
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F.	(-)	(+)	(-)	Overstatement



## Bias formula

$$\alpha_1 - \beta_1 = \beta_2 * \gamma_1 = (+)(+) = (+)$$

We know that  $\alpha_1 > 0$  and must be to the right of  $\beta_1$ . However, we don't know exactly where  $\beta_1$  is.



So we have an overstatement or sign flip, depending on the degree of bias.

# Bias: sign or size?

**Overstatement**

i.e.  $\alpha_1$  is farther from 0

**Understatement**

i.e.  $\alpha_1$  is closer to 0

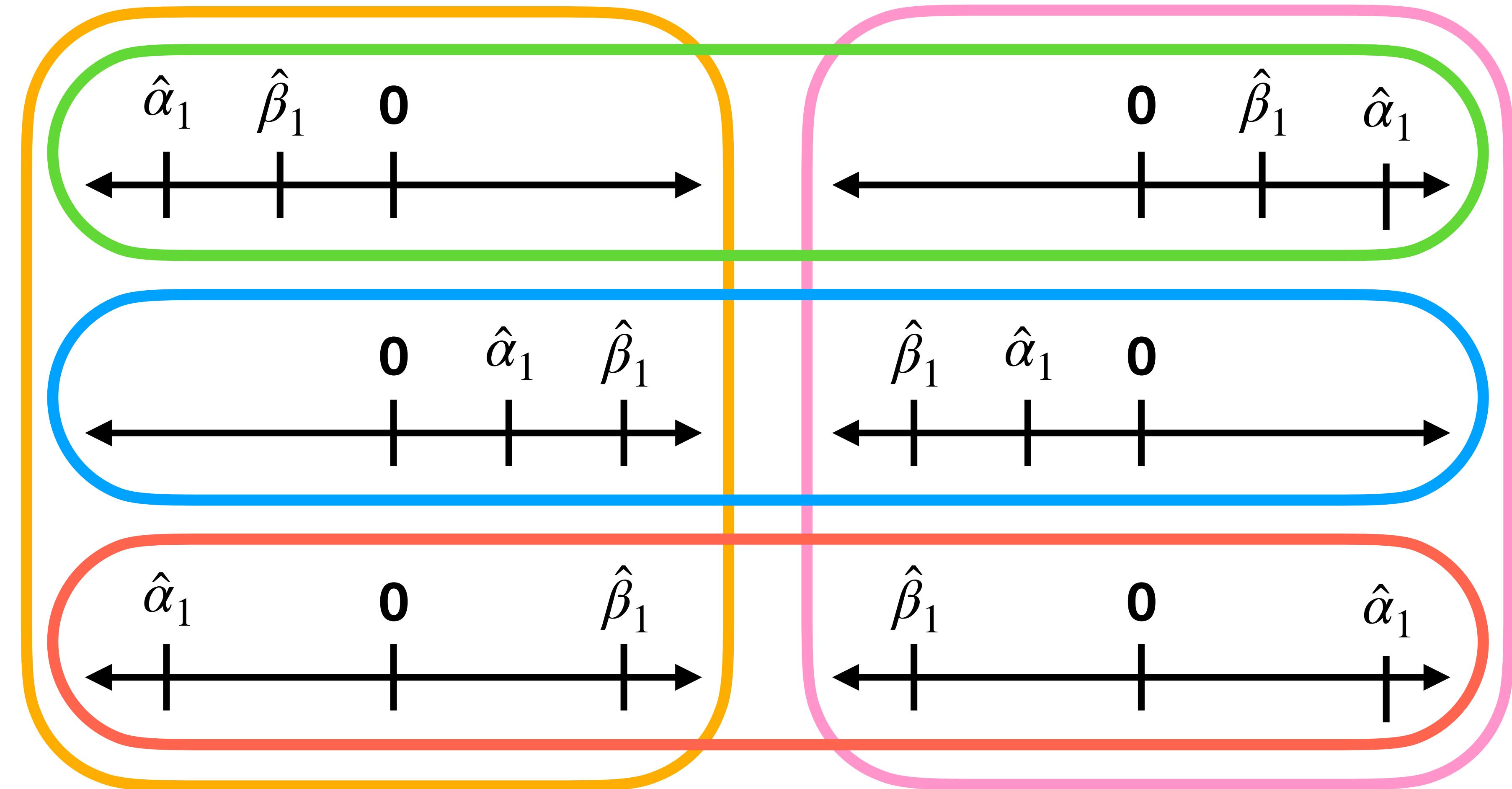
**Sign flip!**

**Negative bias (-)**

i.e.  $\alpha_1$  is to the left of  $\beta_1$

**Positive bias (+)**

i.e.  $\alpha_1$  is to the right of  $\beta_1$



# Practice questions!

You decide to not only control for income but add an interaction term on the hunch that the association between pre-K and high school graduation might be different for low- and high-income families:

$$(graduation)_i = \hat{\beta}_0 + \hat{\beta}_1(pre\_K)_i + \hat{\beta}_2(high\_inc)_i + \hat{\beta}_3(pre\_K * high\_inc)_i + \hat{u}_i$$

Both pre-K and high income are 0/1 dummy variables.

Write the combinations of betas that represent the predicted high school graduation rates for each of the following groups:

Low-income children who didn't go to pre-K:

Low-income children who went to pre-K:

High-income children who didn't go to pre-K:

High-income children who went to pre-K:

# Practice questions!

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Write the combinations of betas that represent the predicted high school graduation rates for each of the following groups:

Low-income children who didn't go to pre-K:  $\hat{\beta}_0$

Low-income children who went to pre-K:  $\hat{\beta}_0 + \hat{\beta}_1$

High-income children who didn't go to pre-K:  $\hat{\beta}_0 + \hat{\beta}_2$

High-income children who went to pre-K:  $\hat{\beta}_0 + \hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3$

The secret sauce here is just setting each variable equal to 0 or 1 based on the groups we're interested in.

So if we want low-income children, we have to set "high\_inc" = 0.

Meanwhile, if we want high-income children, we set "high\_inc" = 1.

The same goes for "pre-K".

Then, we just drop the term(s) that have a "0" for any of the variables.



*Isn't the first cardinal rule of* interpreting interactions **that**  
**you** write out the regression functions for each relevant group so that  
you're not *at the risk of* accidentally  
misinterpreting what each beta represents ?

Yes, I kind of butchered this one.

# Practice questions!

$$(graduation)_i = \hat{\beta}_0 + \hat{\beta}_1(pre\_K)_i + \hat{\beta}_2(high\_inc)_i + \hat{\beta}_3(pre\_K * high\_inc)_i + \hat{u}_i$$

**Given this exact equation, for which of the following pairs of groups can we conduct hypothesis testing?**

**Select all that apply.**

- A. Low-income/no pre-K vs. low-income/pre-K
- B. Low-income/no pre-K vs. high-income/no pre-K
- C. Low-income/no pre-K vs. high-income/pre-K
- D. Low-income/pre-K vs. high-income/no pre-K
- E. Low-income/pre-K vs. high-income/pre-K
- F. High-income/no pre-K vs. high-income/pre-K

# Practice questions!

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Given this exact equation, for which of the following pairs of groups can we conduct hypothesis testing?

Select all that apply.

A. Low-income/no pre-K vs. low-income/pre-K  $\hat{\beta}_1$

B. Low-income/no pre-K vs. high-income/no pre-K  $\hat{\beta}_2$

C. Low-income/no pre-K vs. high-income/pre-K

D. Low-income/pre-K vs. high-income/no pre-K

E. Low-income/pre-K vs. high-income/pre-K

F. High-income/no pre-K vs. high-income/pre-K

When we have a dummy-dummy interaction model, we can get the differences in predicted values between all combinations of groups.

However, we can only conduct hypothesis testing (i.e. p-values) for comparisons that vary by one — and only one — beta, at least without doing additional work.

In this case, that only applies to a few potential comparisons.

Low-income children who didn't go to pre-K:  $\hat{\beta}_0$

Low-income children who went to pre-K:  $\hat{\beta}_0 + \hat{\beta}_1$

High-income children who didn't go to pre-K:  $\hat{\beta}_0 + \hat{\beta}_2$

High-income children who went to pre-K:  $\hat{\beta}_0 + \hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3$

We could get the other comparisons by re-defining our dummy variables!



**(OK look, making these memes isn't  
easy and they aren't all winners.)**

# Practice questions!

You're also worried about the external validity of your model.

Which of the following is true about external validity in this context:

- A. Because there are many potential omitted variables, we aren't sure whether our model is externally valid.
- B. Because we only have data on students in Boston, we aren't sure whether the same relationship is true in rural areas.
- C. Because our data is 15 years old, we aren't sure whether the same relationship is true for Bostonian children today.
- D. A. and B.
- E. A. and C.
- F. B. and C.
- G. All the above.

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- D. A. and B.
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- F. B. and C.
- G. All the above.

External validity is about the generalizability of our model, or how well it apply to contexts other than the one we studied.

We might think about whether another population is similar to our study in geography, demography, economics, and even time.

As a result, we might worry about different factors in rural areas that could affect the pre-K–graduation rate relationship (B.), as well as how those relationships might have changed over time (C.).

Omitted variables are a problem for internal validity or causality, less so for external validity (A.).

# Practice questions!

You propose that the governor randomly selects the 26 communities that will receive free, universal pre-K to evaluate its efficacy.

What of the following statements are true about a randomized trial?

Select all that apply.

- A. A randomized trial guarantees balance on all potential omitted variables that could bias our study's estimates.
- B. A randomized trial will produce balance in omitted variables *on average*, but with only 26 communities, we still could have bias.
- C. A randomized trial allows us to make causal claims that we couldn't with our simple, cross-sectional estimate.
- D. A randomized trial might be politically infeasible if communities that don't receive pre-K perceive it as unfair.
- E. We should only conduct randomized trials when we are genuinely unsure whether pre-K will help or hurt participants.
- F. A randomized trial is always better than a high-quality, causal observational study, like a difference-in-differences.

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- E. We should only conduct randomized trials when we are genuinely unsure whether pre-K will help or hurt participants.\*
- F. A randomized trial is always better than a high-quality, causal observational study, like a difference-in-differences.

Randomization produces balance in omitted variables *on average*, assuming a reasonably large sample (B.). With 26 communities, we could end with an imbalance just due to chance (A.).

Randomized trials have several benefits over “low-quality” studies, like our cross-sectional regression. The most important is that we can make causal claims that we couldn’t before (C.).

However, randomized trials can be imperfect. Failures in randomization or other design flaws can introduce bias and threaten their causal claims, potentially enough to make them “worse” than high-quality observational studies (F.).

Meanwhile, randomized trials can be expensive or politically or ethically infeasible (D.). One important ethical issue is “equipoise,” meaning we shouldn’t experiment on people when we already know what works or doesn’t (E.).

\*OK some students rightly pointed out that there are other circumstances for which we might do a randomized trial even when we “know” an intervention is beneficial, e.g. we don’t have enough resources to give it to everyone. This answer choice is ambiguous, but the point about equipoise still stands: When possible, we should avoid putting people in control groups when there’s an available treatment known to improve their well-being.

# Practice questions!

You search the literature and find one randomized trial for pre-K: the Tennessee Voluntary Pre-K Program in 1996, which randomized 3,000 low-income families to the opportunity to attend pre-K or not.

The study found that students who won the pre-K lottery performed better on achievement tests at the end of pre-K. However, by the end of kindergarten, the control group caught up to the pre-K group.

The study followed students into third grade and still found the groups to be comparable. The study did not follow them beyond grade 3.

Thinking about external validity, describe how this study does and does not inform the Massachusetts governor's plan to expand universal pre-K to all schools in 26 select communities.

# Practice questions!

Lots of possible answers here.

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Top of my mind are:

1. The effects were null, so at baseline, I would expect relatively small effects of pre-K on student achievement in MA communities.
2. The study didn't follow families beyond third grade. The fact that the results were null for several years makes it unlikely that we'd see an effect on H.S. graduation rates (which is even further in the future), but we can't be sure.
3. The study randomized families, not entire communities. Perhaps directing resources to an entire community would increase the effect?
4. The study is fairly old. Perhaps pre-K instruction is more impactful now than in 1996?
5. Is Tennessee similar to Massachusetts?

# Practice questions!

**Let's say that several savvy families in the control group were able to get their children into other pre-K programs.**

**On average, these savvy families were better educated and higher-income than the rest of the families in the trial.**

**What is the expected direction of the bias?**

- A. Toward the null.**
- B. Away from the null.**
- C. No expected bias.**

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**This is an example of noncompliance in a randomized trial: Some families in one of the groups didn't "comply" with their assigned group. In this case, some of the control children ended up getting "treated" by pre-K.**

**We estimated that pre-K had a modestly positive effect on academic achievement.**

**Since some of the control group was also treated, our estimate is probably smaller than the "true" effect of pre-K on achievement.**

**This is akin to "raising the floor" of the control group estimate, making the gap between the two groups smaller.**

# Practice questions!

Let's say that several families who won the lottery for pre-K ended up deciding not to send their children to it.

Which of the following is true about this scenario?

- A. To avoid introducing bias in our estimate, we should keep these families in the “treatment” group of our analysis.
- B. To avoid introducing bias in our estimate, we should move these families to the “control” group of our analysis.
- C. To avoid introducing bias in our estimate, we should drop these families from our analyses entirely.
- D. To avoid introducing bias in our estimate, we should adjust these children’s academic scores by what we think they would have been if the children had attended pre-K.

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- D. To avoid introducing bias in our estimate, we should adjust these children’s academic scores by what we think they would have been if the children had attended pre-K.

This is an “intention to treat” question.

Randomized trials only solve the issue of omitted variable bias when they preserve the original randomization.

Even though some of the “treatment” children didn’t actually get treated, we still have to include them in their assigned group for our analyses.

The inclination not to attend is, itself, an omitted variable, so dropping, moving, or altering those children’s values would introduce bias in our estimate.

Note: In this scenario, the causal effect we’re estimating is now that of winning a lottery for pre-K, not of pre-K itself!

This estimate is unbiased. To get an unbiased estimate of pre-K itself, we’d have to do more advanced statistics (namely, an instrumental variable).

# Practice set 2

# Practice questions!

You were just hired by Vot-ER, a non-profit organization that works to increase the participation of “sicker” people in politics.

You have cross-sectional data on turnout (0 = didn’t vote or 1 = voted) and self-reported health (1 = very bad to 5 = excellent).

You run this regression:  $(turnout)_i = \hat{\beta}_0 + \hat{\beta}_1(health)_i + \hat{u}_i$

Interpret  $\beta_1 = 0.04$  (95% CI, -0.01 to 0.09).

- A. Every 1-unit improvement in health is associated with a 4% increase in the probability of voting. It's not statistically significant.
- B. Every 1-unit improvement in health is associated with a 4 pp increase in the probability of voting. It's not statistically significant.
- C. Every 1-unit improvement in health is associated with a 0.04% increase in the probability of voting. It's not statistically significant.
- D. Every 1-unit improvement in health is associated with a 0.04 pp increase in the probability of voting. It's statistically significant.

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- C. Every 1-unit improvement in health is associated with a 0.04% increase in the probability of voting. It's not statistically significant.
- D. Every 1-unit improvement in health is associated with a 0.04 pp increase in the probability of voting. It's statistically significant.

Here, we have a linear probability model with a binary outcome.

As a result, we have to interpret the outcome in percentage points.

When the outcome is 0 or 1, we have to multiply the coefficient by 100.

Lastly, because the 95% confidence interval includes “0”, the result is not statistically significant (i.e.  $P>0.05$ ).

# Practice questions!

**Original regression:**  $(turnout)_i = \hat{\alpha}_0 + \hat{\alpha}_1(health)_i + \hat{\nu}_i$

**Original estimate:**  $\alpha_1 = 0.04$  (95% CI, -0.01 to 0.09)

You're worried about omitted variable bias. You know that older people tend to be less healthy and also tend to vote more.

Sign the bias of age as an omitted variable.

	$\gamma_1$	$\beta_2$	Bias sign	Bias size
A.	(+)	(+)	(+)	Understatement
B.	(+)	(-)	(-)	Overstatement/sign flip
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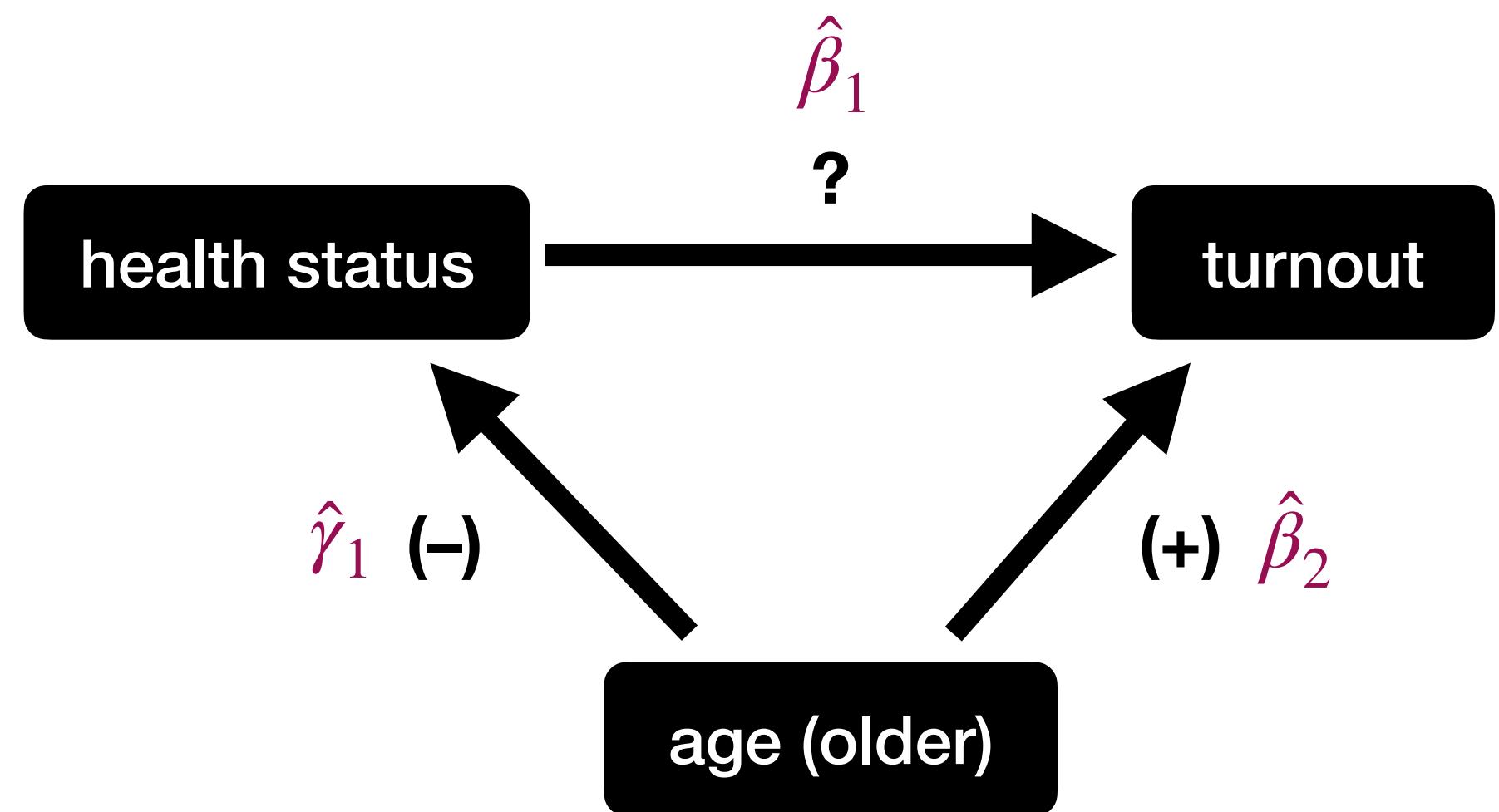
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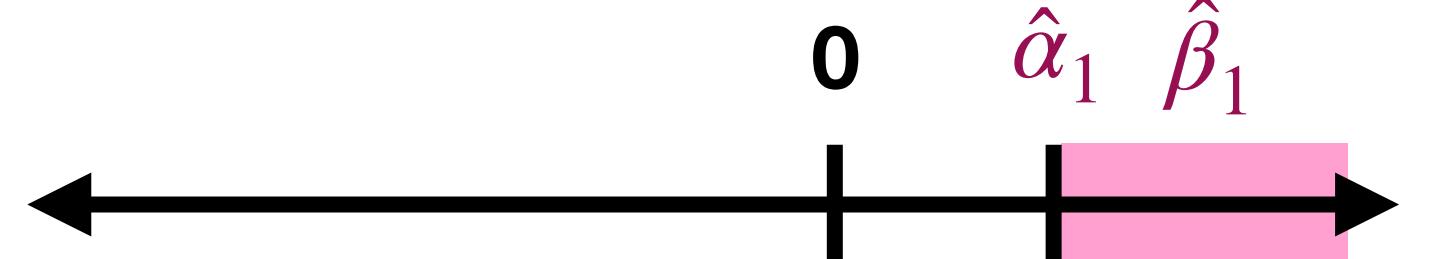
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## Bias formula

$$\alpha_1 - \beta_1 = \beta_2 * \gamma_1 = (-)(+) = (-)$$

We know that  $\alpha_1 > 0$  and must be to the left of  $\beta_1$ .



So we have an understatement.

# Bias: sign or size?

**Overstatement**

i.e.  $\hat{\alpha}_1$  is farther from 0

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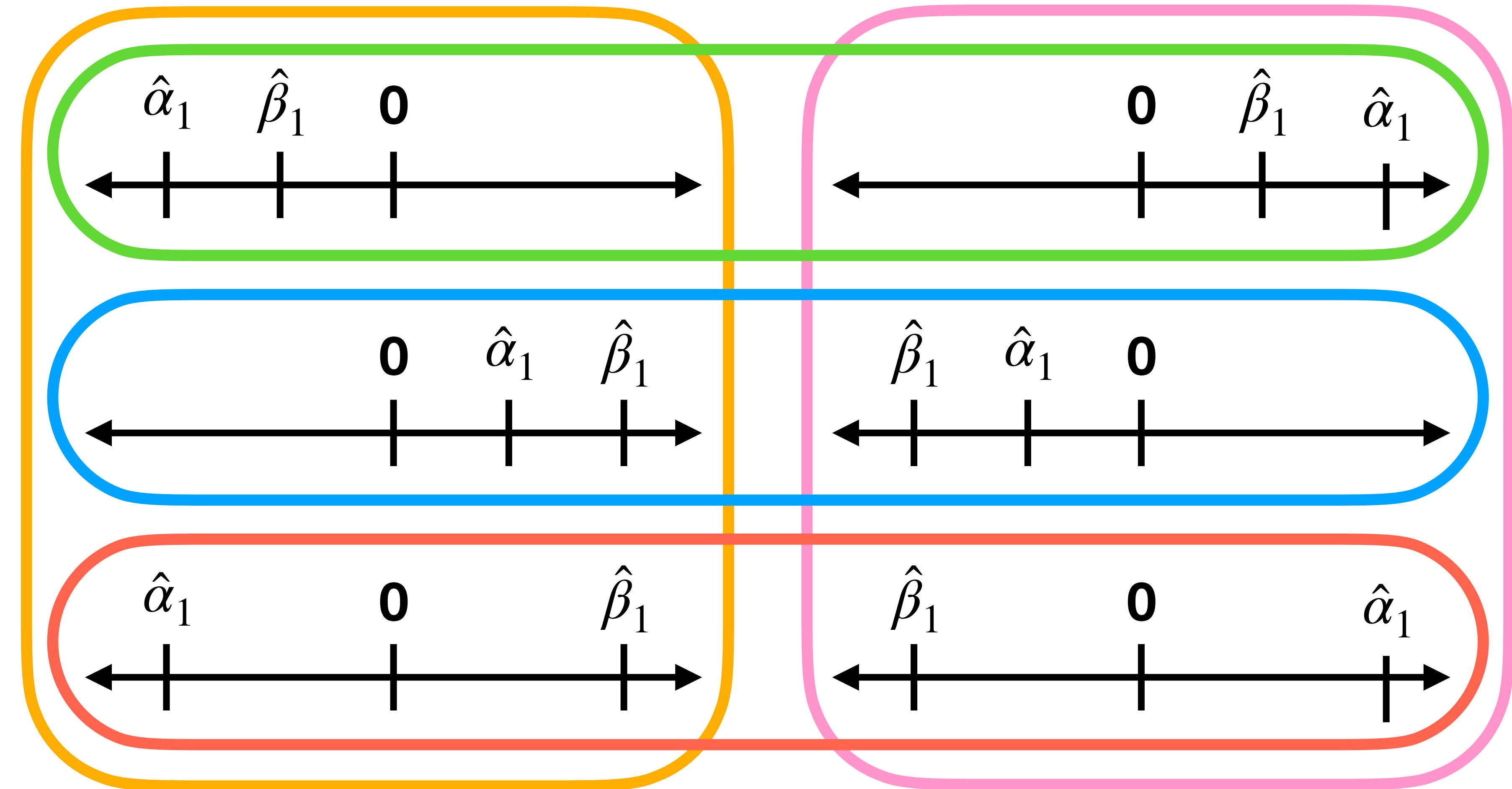
**Sign flip!**

**Negative bias (-)**

i.e.  $\hat{\alpha}_1$  is to the left of  $\beta_1$

**Positive bias (+)**

i.e.  $\hat{\alpha}_1$  is to the right of  $\beta_1$



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**You're worried about other omitted variables. Propose a potential omitted variable and sign the likely bias.**

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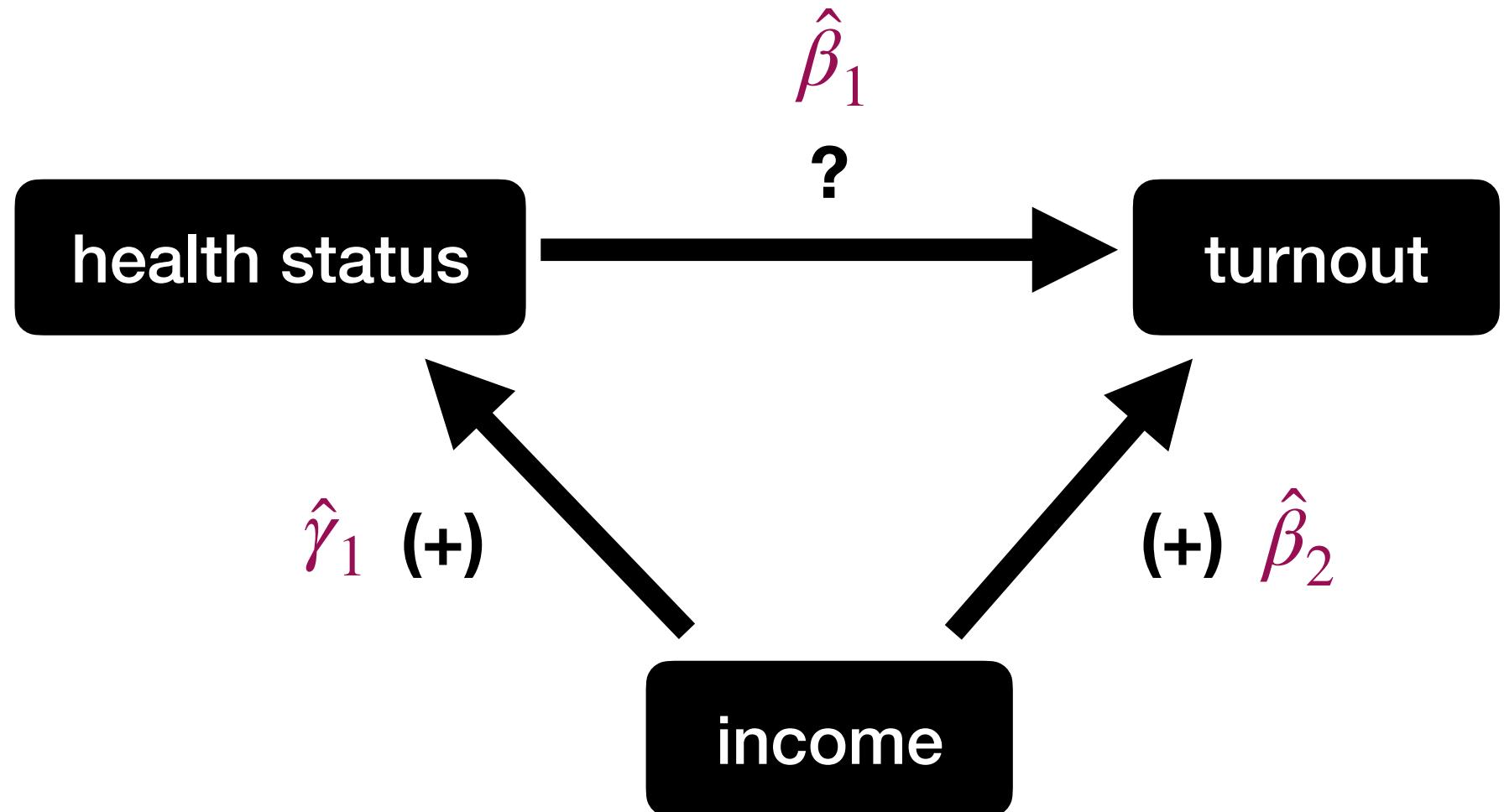
Let's say we're concerned about income.

Wealthier people tend to be healthier, so  $\gamma_1 > 0$ .

Wealthier people tend to vote more often, so  $\beta_2 > 0$ .

Thus, the bias is positive, meaning  $\alpha_1$  must be to the right of  $\beta_1$ .

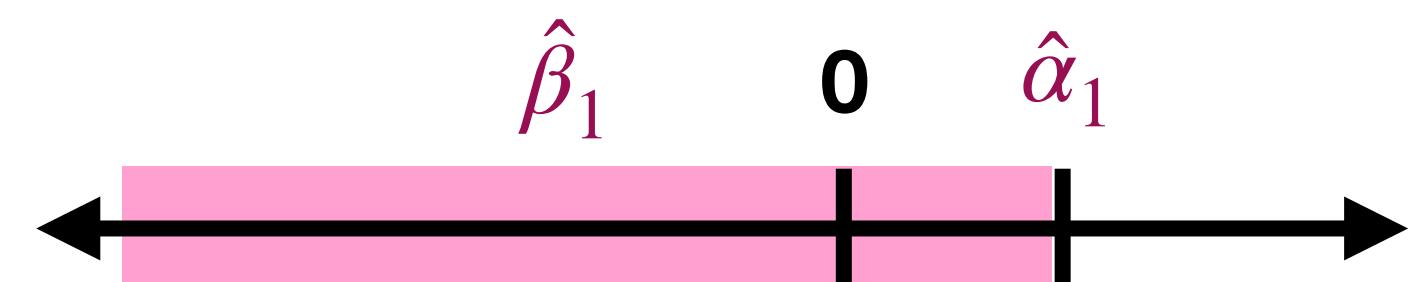
Since  $\alpha_1 > 0$ , we can have an overestimate or sign flip.



## Bias formula

$$\alpha_1 - \beta_1 = \beta_2 * \gamma_1 = (+)(+) = (+)$$

We know that  $\alpha_1 > 0$  and must be to the right of  $\beta_1$ . However, we don't know exactly where  $\beta_1$  is.



So we have an overestimate or sign flip.



# Practice questions!

You collect data on people who \*randomly\* got sick, e.g. got in a car crash, between the 2018 and 2020 elections. You have access to their voting records and the voting records of their neighbors.

You estimate the following difference-in-differences model:

$$(turnout)_i = \hat{\beta}_0 + \hat{\beta}_1(got\_sick)_i + \hat{\beta}_2(post\_2018)_i + \hat{\beta}_3(got\_sick * post\_2018)_i + \hat{u}_i$$

Which of the following omitted variables threaten your estimate?

Select all that apply.

- A. People's genes
- B. National changes in turnout during the 2020 election
- C. People's job, which might change during the study period
- D. The fact that 2020 was a presidential election and 2018 was a midterm
- E. People's political upbringing

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C. People's job, which might change during the study period

D. The fact that 2020 was a presidential election and 2018 was a midterm

E. People's political upbringing

In a diff-in-diff, we are only worried about time-unit-varying omitted variables.

People's jobs (C.) is the only choice that fits this description, as treatment and control units can experience different job pressures.

Our model controls for unit-invariant omitted variables, like genes (A.) or upbringing (E.), as these don't change over time.

Our model also controls for time-varying omitted variables that affect all units equally, like the political environment (B. and D.).

# Practice questions!

You get the following output (see to the right).

$$(turnout)_i = \hat{\beta}_0 + \hat{\beta}_1(got\_sick)_i + \hat{\beta}_2(post\_2018)_i + \hat{\beta}_3(got\_sick * post\_2018)_i + \hat{u}_i$$

What is the predicted turnout of...

The control group in 2018?

The control group in 2020?

The treatment group in 2018?

The treatment group in 2020?

What is the effect of getting sick on turnout? Is it significant?

	Model 1
Intercept	0.40 (0.03)
got_sick	0.02 (0.04)
post_2018	0.21 (0.04)
got_sick * post_2018	-0.15 (0.04)
Num.Obs.	1450
R2	0.042
R2 Adj.	0.041

# Practice questions!

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$$(turnout)_i = \hat{\beta}_0 + \hat{\beta}_1(got\_sick)_i + \hat{\beta}_2(post\_2018)_i + \hat{\beta}_3(got\_sick * post\_2018)_i + \hat{u}_i$$

What is the predicted turnout of...

The control group in 2018?  $\beta_0 = 40\%$

The control group in 2020?  $\beta_0 + \beta_2 = 40 + 21 = 61\%$

The treatment group in 2018?  $\beta_0 + \beta_1 = 40 + 2 = 42\%$

The treatment group in 2020?  $\beta_0 + \beta_1 + \beta_2 + \beta_3 = 48\%$

What is the effect of getting sick on turnout? Is it significant?

$\beta_3 = -15$  pp, and yes (95% CI,  $-15 \pm 1.96*4 = -23$  to  $-7$ )

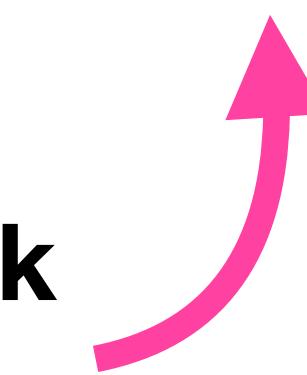
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See the next slide for a review of the coefficients in diff-in-diffs!

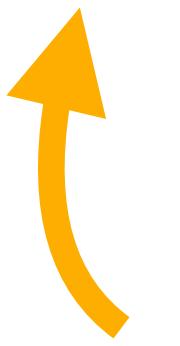
# Let's do a difference-in-differences!

$$(turnout)_i = \hat{\beta}_0 + \hat{\beta}_1(got\_sick)_i + \hat{\beta}_2(post\_2018)_i + \hat{\beta}_3(got\_sick * post\_2018)_i + \hat{u}_i$$

**dummy for getting sick**  
 1 = Randomly got sick  
 0 = Didn't get sick



**dummy for time**  
 1 = 2020 election  
 0 = 2018 election



**interaction**  
 i.e. the diff-in-diff

	2018 election post_2018 = 0	2020 election post_2018 = 1	Difference
<b>Didn't get sick</b> got_sick = 0	$\beta_0$	$\beta_0 + \beta_2$	$\beta_2$
<b>Randomly got sick</b> got_sick = 1	$\beta_0 + \beta_1$	$\beta_0 + \beta_1 + \beta_2 + \beta_3$	$\beta_2 + \beta_3$
<b>Difference</b>	$\beta_1$	$\beta_1 + \beta_3$	$\beta_3$

# Practice questions!

Which of the following statement(s) most accurately interpret(s) the R-squared in this context?

- A. Our regression model explains about 4% of the variation in turnout for our 1,450 respondents.
- B. Because the R-squared is so low, our model wouldn't do a great job predicting turnout for any given respondent.
- C. Because the R-squared is so low, we shouldn't think of these estimates as causal, only as correlational.
- D. A. and B.
- E. A. and C.
- F. B. and C.
- G. All of the above.

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# Practice questions!

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- E. A. and C.
- F. B. and C.
- G. All of the above.

By definition, R-squared quantifies the proportion of variation in our outcome variable explained by our model.

It's a useful metric for evaluating predictions, but it doesn't confirm (or deny) whether our estimates are causal.

Causality is more about study design, and we have a quasi-random diff-in-diff, which is pretty good!

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R2	0.042
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Elle, if I'm going to be  
a senator...



I need to have a Jackie (causal study)  
not a Marilyn (just correlational)

# Good luck!

