

# Regression in Action: Bias, squares, and measurement error

Econ 140, Section 3

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# Roadmap

1. Recap
2. Selection bias in action: Omitted Variable Bias
3. Quadratic Terms
4. Measurement Error

Any questions?

... Remember – Every question is useful!

## Recap

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# Recap: Selection bias

We saw that whenever we do a difference-in-means comparison (or a regression), we get:

## Estimating the effect of iPads on grades

Let us start with a difference-in-means comparison:

$$\Delta = E[\text{Grade}_i | \text{iPad}_i = 1] - E[\text{Grade}_i | \text{iPad}_i = 0]$$

Add and subtract  $E[\text{Grade}_i | \text{iPad}_i = 1]$ :

$$\begin{aligned} &= E[\text{Grade}_i | \text{iPad}_i = 1] - E[\text{Grade}_i | \text{iPad}_i = 1] + \\ &\quad E[\text{Grade}_i | \text{iPad}_i = 1] - E[\text{Grade}_i | \text{iPad}_i = 0] \end{aligned}$$

Use properties of expectations:

$$\begin{aligned} &= E[\text{Grade}_i | \text{iPad}_i = 1] - E[\text{Grade}_i | \text{iPad}_i = 1] + \\ &\quad E[\text{Grade}_i | \text{iPad}_i = 1] - E[\text{Grade}_i | \text{iPad}_i = 0] \\ &= \text{ATT} + \text{Selection bias} \end{aligned}$$

Selection bias: Students with and without iPad have different potential grades: **even if they both had iPads, they would be different.**

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Causal Effect  
+  
Selection Bias

- We cannot observe them - so we can never be sure!
- Econometrics is all about uncertainty. You can **always** state that there are different possibilities and you cannot know for sure

## Recap: How to think about Selection Bias

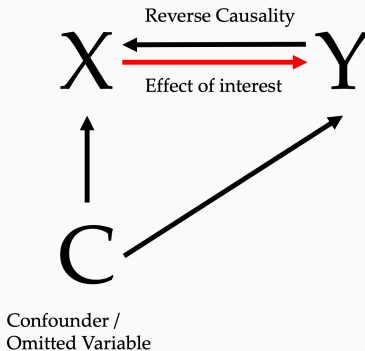


Figure 1: Selection bias

## Selection bias in action: Omitted Variable Bias

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# Omitted Variable Bias (OVV)

Let's go through an example:

You are doing a summer internship with San-Francisco based tech company "Chirp", when your boss asks you to help evaluating the effect of "performance-based" or "incentive" pay on employees' job satisfaction. When you analyze the data, you realize that it's a mess. Until now, every manager could decide on the performance pay system in their team. Can you run a regression of job satisfaction on whether or not an individual works in a team that has a performance bonus in place?

You believe that:

$$\text{Satisfaction}_i = \beta_0 + \beta_1 \text{Performance pay}_i + \beta_2 \text{Manager quality}_i + u_i$$

$$\text{Manager quality}_i = \gamma_0 + \gamma_1 \text{Performance pay}_i + v_i$$



## OVB Question

1. Run a "short" regression of satisfaction ( $S_i$ ) on pay ( $P_i$ ):

$$S_i = \alpha_0 + \alpha_1 P_i + e_i$$

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$$\alpha_1 = \frac{\text{Cov}(S_i, P_i)}{\text{Var}(P_i)} = \frac{\text{Cov}(\beta_0 + \beta_1 P_i + \beta_2 M_i + u_i, P_i)}{\text{Var}(P_i)}$$

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$$\begin{aligned}\alpha_1 &= \frac{\text{Cov}(S_i, P_i)}{\text{Var}(P_i)} = \frac{\text{Cov}(\beta_0 + \beta_1 P_i + \beta_2 M_i + u_i, P_i)}{\text{Var}(P_i)} \\ &= \beta_1 \underbrace{\frac{\text{Cov}(P_i, P_i)}{\text{Var}(P_i)}}_{=1} + \beta_2 \underbrace{\frac{\text{Cov}(M_i, P_i)}{\text{Var}(P_i)}}_{=\gamma_1} + \underbrace{\frac{\text{Cov}(u_i, P_i)}{\text{Var}(P_i)}}_{=0, \text{ by assumption}}\end{aligned}$$

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# The most important slide of this course (until the midterm)

We can summarize everything of OVB in three equations. Let  $Y_i$  be the outcome variable,  $X_i$  our regressor of interest, and  $Z_i$  the "omitted" variable.

$$\text{[Long regression]} \quad Y_i = c_1 + \beta_L X_i + \delta Z_i + e_i$$

$$\text{[Short regression]} \quad Y_i = c_2 + \beta_S X_i + u_i$$

$$\text{[Auxiliary regression]} \quad Z_i = c_3 + \gamma X_i + v_i$$

Then, the **Omitted variable bias formula** states that:

$$\underbrace{\beta_S}_{\text{Short}} = \underbrace{\beta_L}_{\text{Long}} + \underbrace{\delta}_{\text{Omitted}} \cdot \underbrace{\gamma}_{\text{Included}}$$

We call  $\delta\gamma$  the **omitted variable bias**. We can appraise the direction of the bias by multiplying our guesses for the signs of  $\delta$  and  $\gamma$ .

# Wait a minute!

We saw that the OLS coefficient in the short regression is:

$$\alpha_1 = \underbrace{\beta_1}_{\text{Actual effect}} + \underbrace{\beta_2 \gamma_1}_{\text{Omitted variable bias}}$$

This looks awfully much like:

Estimating the effect of iPads on grades

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Add and subtract  $E[\text{Grade}_i(0) | \text{iPad}_i = 1]$  :

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Use properties of expectations:

$$\begin{aligned} &= E[\text{Grade}_i(1) - \text{Grade}_i(0) | \text{iPad}_i = 1] + \\ &\quad E[\text{Grade}_i(0) | \text{iPad}_i = 1] - E[\text{Grade}_i(0) | \text{iPad}_i = 0] \\ &= \text{ATT} + \text{Selection bias} \end{aligned}$$

Selection bias: Students with and without iPad have different potential grades: **even if they both had iPads, they would be different.**



# Control variables

Control variables are additional variables (or covariates) **included in a regression**. We do this for **various reasons** (in decreasing order of importance):

- To remove selection bias / omitted variable bias
- To increase precision of our estimates
- To know about the (conditional/partial) correlation of other variables
- To better predict the outcome

Let's see graphically how control variables work.

Any questions?

... Remember – Every question is useful!

# Attendance and Evaluation

Please fill out a very short evaluation form here:

<https://forms.gle/7neuAJbkAv17mSEp6>



## Quadratic Terms

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See in *RStudio*

# Measurement Error

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See on Blackboard and in *RStudio*.  
If time permits, see on [chatGPT](#).