Simple Linear Regression: Estimation

EC 320: Introduction to Econometrics

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Prologue

Housekeeping

Midterm:

- Midterm 1 is on Wednesday January 29th
- Will have extra office hours, announced through email

Where Are We?

Where we've been

High Concepts

- Reviewed core ideas from statistics
- Developed a framework for thinking about causality

Also, **R**.

Where Are We?

Where we're going

The Weeds!

- Learn the mechanics of *how* OLS works
- Interpret regression results (mechanically and critically)
- Extend ideas about causality to a regression context
- Think more deeply about statistical inference
- Lay a foundation for more-sophisticated regression techniques.

Also, **more R**.

Simple Linear Regression

Example: Effect of police on crime

Policy Question: Do on-campus police reduce crime on campus?

- **Empirical Question:** Does the number of on-campus police officers affect campus crime rates? If so, by how much?

How can we answer these questions?

- Prior beliefs.
- Theory.
- **Data!**

Example: Effect of police on crime

Search:

	Police per 1000 Students	Crimes per 1000 students
1	20.42	1.1
2	0.15	2
3	0.47	1.41
4	14.68	2.06
5	23.75	1.52
6	7.68	2.76

Showing 1 to 6 of 96 entries

Previous Next

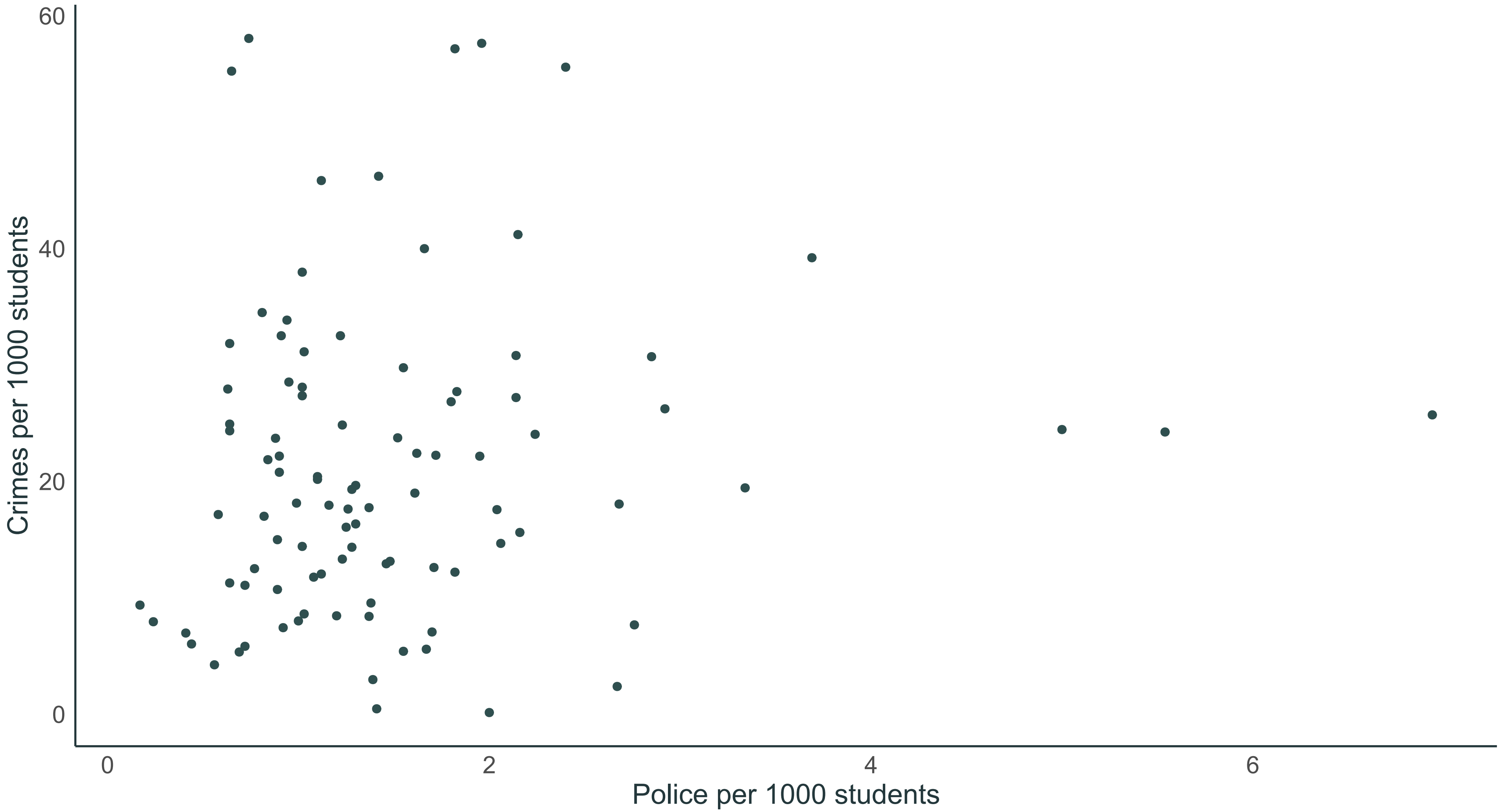
Example: Effect of police on crime

"Looking" at data wasn't especially helpful.

Let's try using a scatter plot.

- Plot each data point in (X, Y) -space.
- `Police` on the X -axis.
- `Crime` on the Y -axis.

Example: Effect of police on crime



Example: Effect of police on crime

The scatter plot tells us more than the spreadsheet.

- Somewhat weak *positive* relationship.
- Sample correlation coefficient of 0.14 confirms this.

But our question was

> Does the number of on-campus police officers affect campus crime rates? If so, by how much?

- The scatter plot and correlation coefficient provide only a partial answer.

Example: Effect of police on crime

Our next step is to estimate a **statistical model.**

To keep it simple, we will relate an **explained variable** Y to an **explanatory variable** X in a linear model.

Simple Linear Regression Model

We express the relationship between a **explained variable** and an **explanatory variable** as linear:

$$Y_i = \beta_1 + \beta_2 X_i + u_i.$$

- β_1 is the **intercept** or constant.
- β_2 is the **slope coefficient**.
- u_i is an **error term** or disturbance term.

Simple = Only one explanatory variable.

Simple Linear Regression Model

The **intercept** tells us the expected value of Y_i when $X_i = 0$.

$$Y_i = \beta_1 + \beta_2 X_i + u_i$$

Usually not the focus of an analysis.

Simple Linear Regression Model

The **slope coefficient** tells us the expected change in Y_i when X_i increases by one.

$$Y_i = \beta_1 + \beta_2 X_i + u_i$$

"A one-unit increase in X_i is associated with a β_2 -unit increase in Y_i ."

Under certain (strong) assumptions about the error term, β_2 is the *effect of* X_i *on* Y_i .

- Otherwise, it's the *association of* X_i *with* Y_i .

Simple Linear Regression Model

The **error term** reminds us that X_i does not perfectly explain Y_i .

$$Y_i = \beta_1 + \beta_2 X_i + u_i$$

Represents all other factors that explain Y_i .

- Useful mnemonic: pretend that u stands for *"unobserved"* or *"unexplained."*

Example: Effect of police on crime

How might we apply the simple linear regression model to our question about the effect of on-campus police on campus crime?

- Which variable is X ? Which is Y ?

$$\text{Crime}_i = \beta_1 + \beta_2 \text{Police}_i + u_i.$$

- β_1 is the crime rate for colleges without police.
- β_2 is the increase in the crime rate for an additional police officer per 1000 students.

Example: Effect of police on crime

How might we apply the simple linear regression model to our question?

$$\text{Crime}_i = \beta_1 + \beta_2 \text{Police}_i + u_i$$

β_1 and β_2 are the population parameters we want, but we cannot observe them.

Instead, we must estimate the population parameters using our $\textbf{\textit{data sample}}$.

$$\text{Crime}_i = \text{b}_1 + \text{b}_2 \text{Police}_i + e_i$$

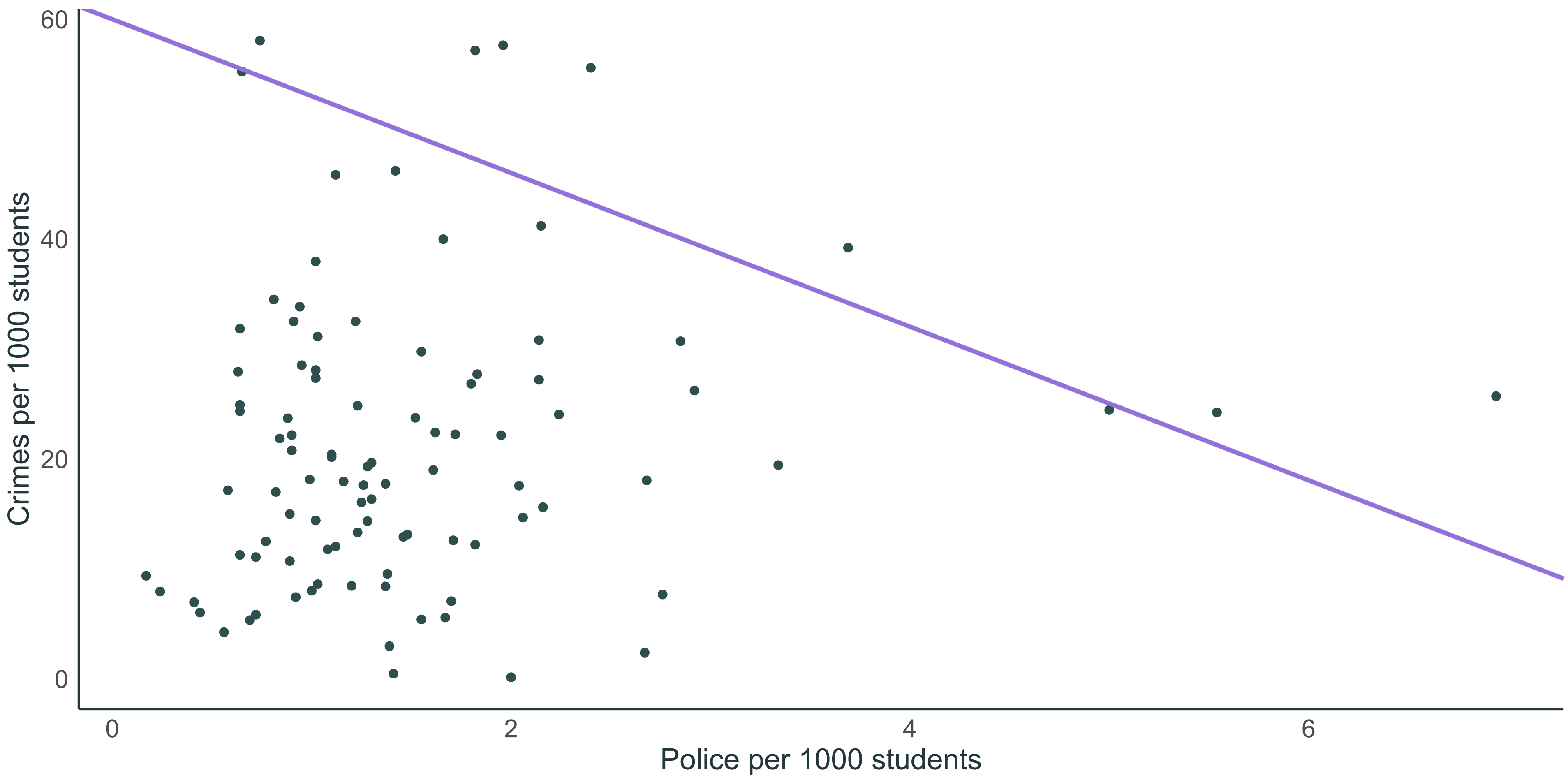
But, is $\boldsymbol{b_1} = \beta_1$ and $\boldsymbol{b_2} = \beta_2$?

Using our estimates, we can make predictions:

- $\hat{\beta}_1$ and $\hat{\beta}_2$ generate predictions of $\mathbf{Crime}_i$ called $\hat{\mathbf{Crime}}_i$.
- We call the predictions of the dependent variable **fitted values.**
- Together, these trace a line: $\hat{\mathrm{Crime}}_i = \hat{\beta}_1 + \hat{\beta}_2 \mathrm{Police}_i$.

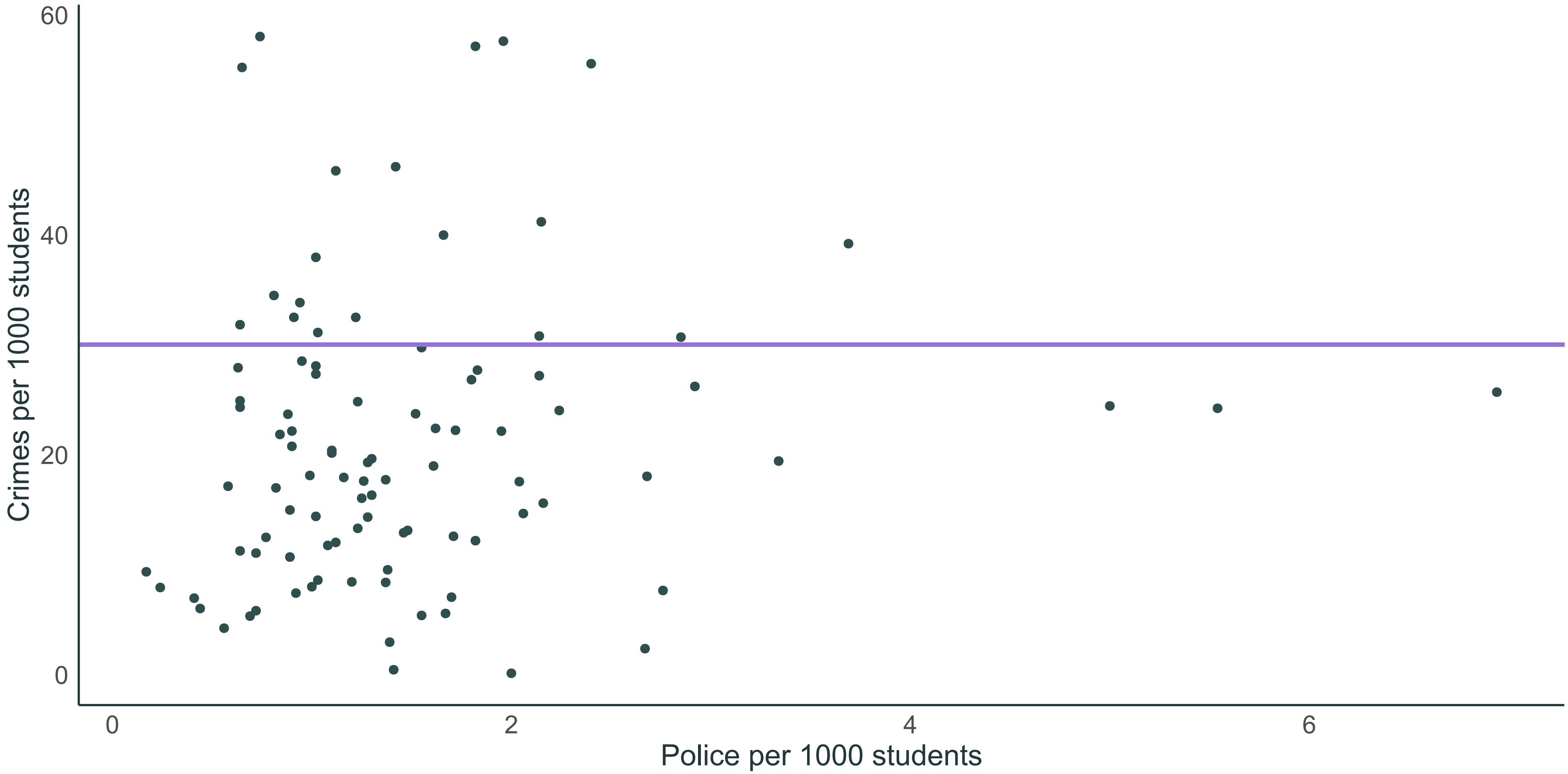
Example: Effect of police on crime

Guess: $\hat{\beta}_1 = \mathbf{60}$ and $\hat{\beta}_2 = -\mathbf{7}$.



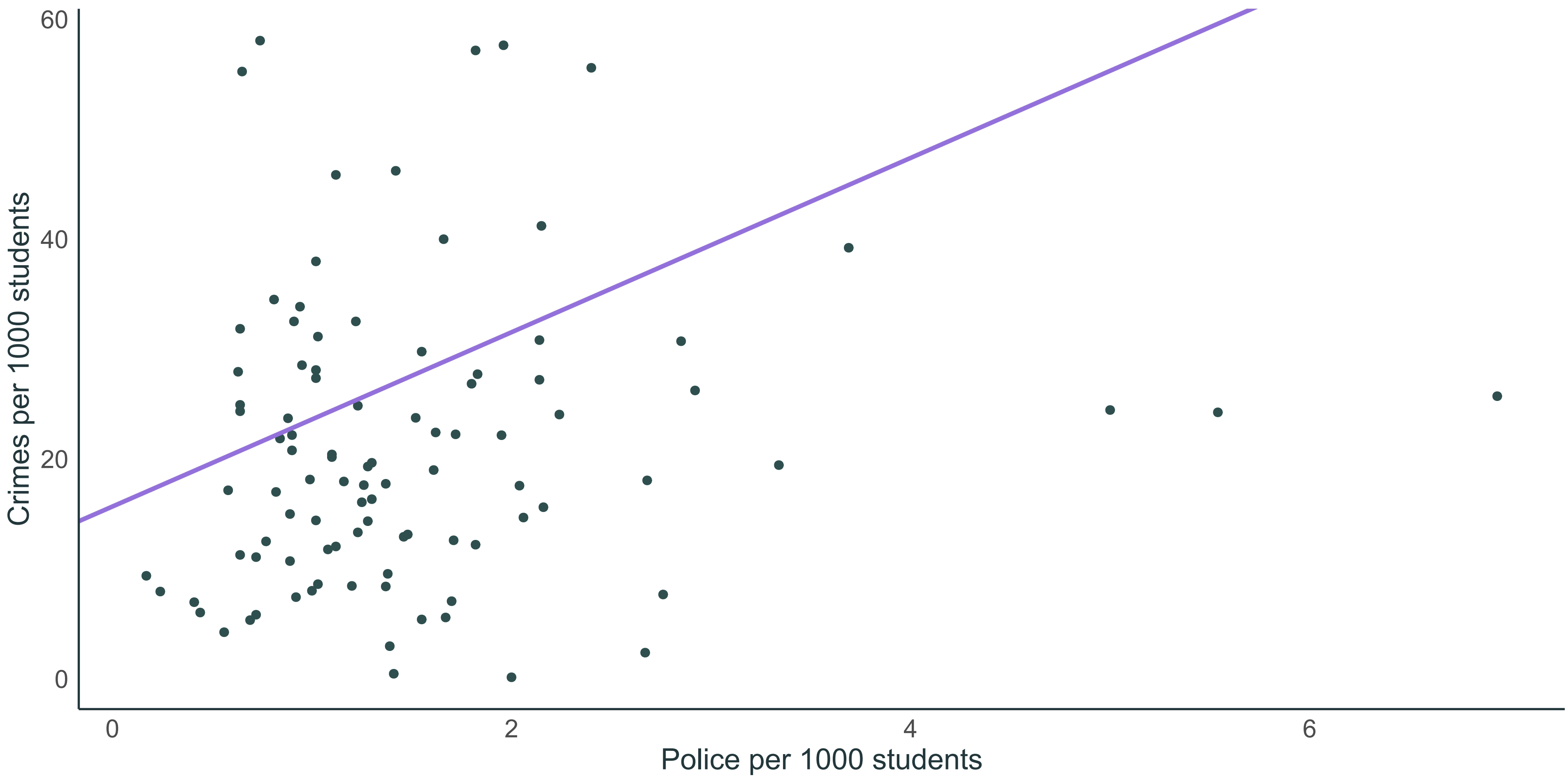
Example: Effect of police on crime

Guess: $\hat{\beta}_1 = \mathbf{30}$ and $\hat{\beta}_2 = \mathbf{0}$.



Example: Effect of police on crime

Guess: $\hat{\beta}_1 = \mathbf{15.6}$ and $\hat{\beta}_2 = \mathbf{7.94}$.



Residuals

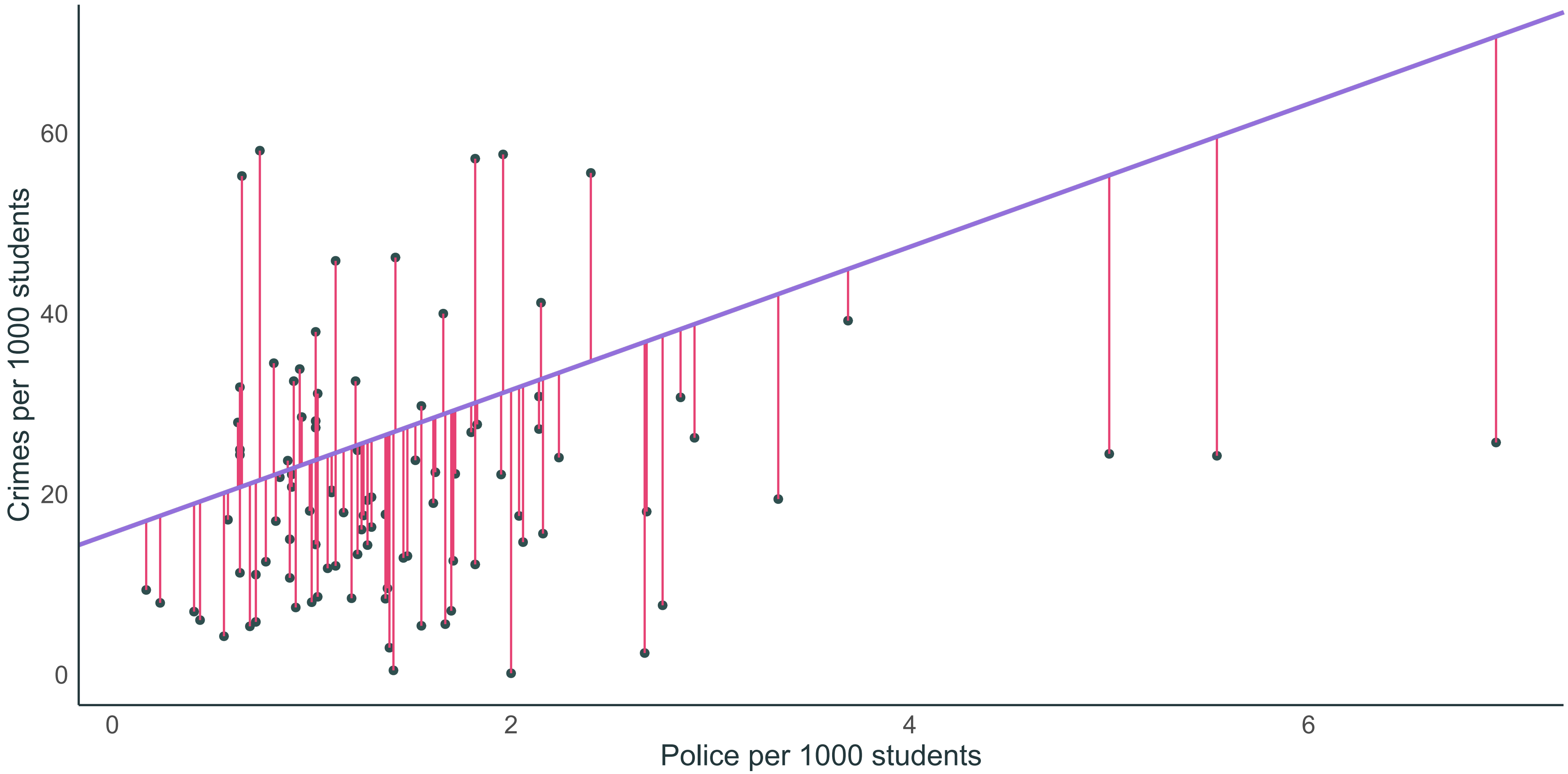
Using $\hat{\beta}_1$ and $\hat{\beta}_2$ to make $\hat{Y}_i$ generates misses called **residuals**:

$$\hat{u}_i = Y_i - \hat{Y}_i.$$

- Sometimes called e_i .

Example: Effect of police on crime

Using $\hat{\beta}_1 = \mathbf{15.6}$ and $\hat{\beta}_2 = \mathbf{7.94}$ to make $\hat{\text{Crime}}_i$ generates **residuals**.



Residuals

We want an estimator that makes fewer big misses.

Why not minimize $\sum_{i=1}^{n} \hat{u}_i$?

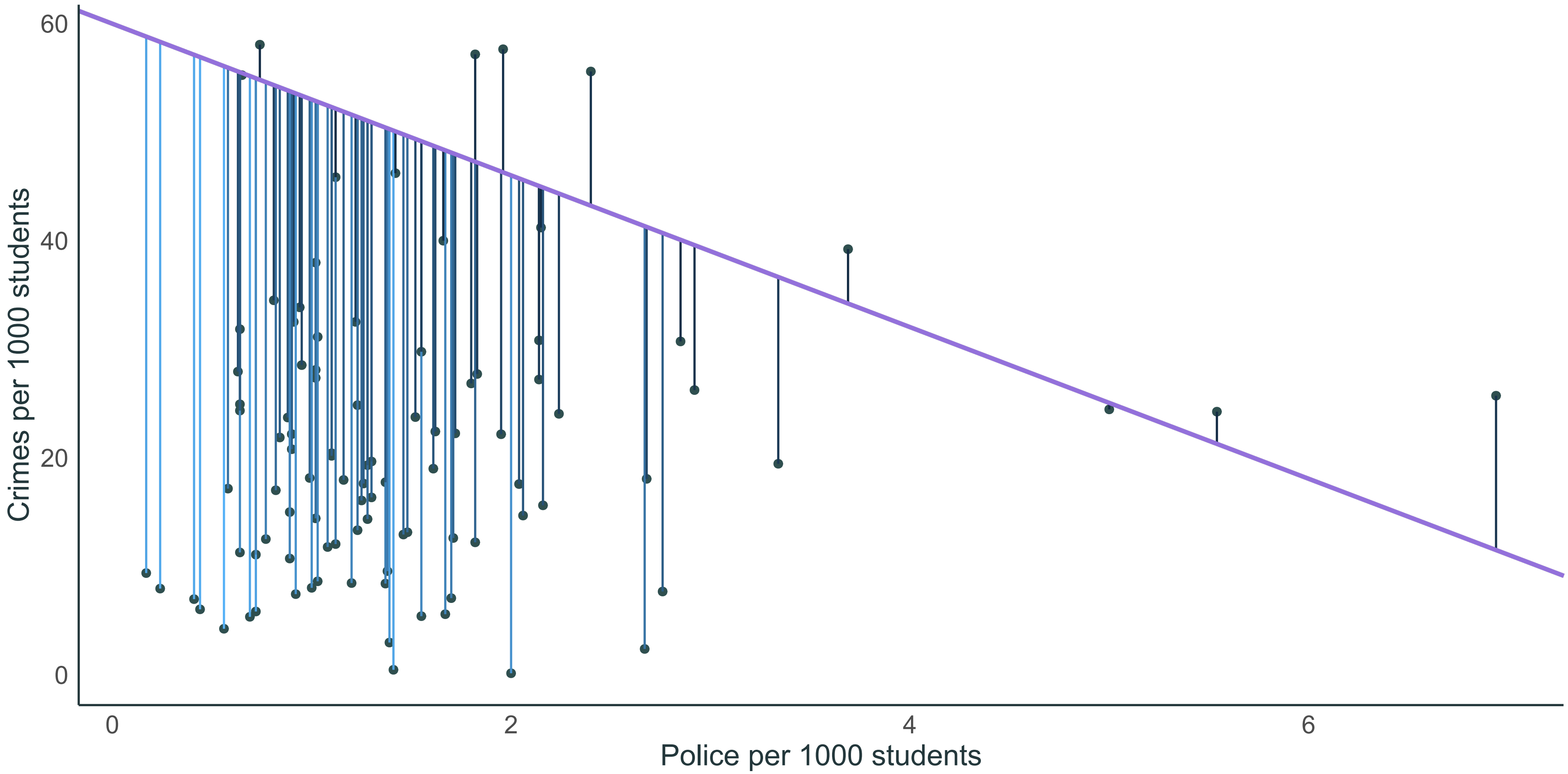
- There are positive *and* negative residuals $\implies$ no solution (can always find a line with more negative residuals).

Alternative: Minimize the sum of squared residuals a.k.a. the **residual sum of squares (RSS)**.

- Squared numbers are never negative.

Example: Effect of police on crime

RSS gives bigger penalties to bigger residuals.



Minimizing RSS

We could test thousands of guesses of $\hat{\beta}_1$ and $\hat{\beta}_2$ and pick the pair that minimizes RSS.

- Or we just do a little math and derive some useful formulas that give us RSS-minimizing coefficients without the guesswork.

Ordinary Least Squares (OLS)

OLS

The **OLS estimator** chooses the parameters $\hat{\beta}_1$ and $\hat{\beta}_2$ that minimize the **residual sum of squares (RSS)**:

$$\min_{\hat{\beta}_1,\, \hat{\beta}_2} \quad \sum_{i=1}^{n} \hat{u}_i^2$$

This is why we call the estimator ordinary **least squares.**

Outline

Step 1. Replace $\sum_{i=1}^{n} \hat{u}_i^2$ with an equivalent expression involving $\hat{\beta}_1$ and $\hat{\beta}_2$.

Step 2. Take partial derivatives of our RSS expression with respect to $\hat{\beta}_1$ and $\hat{\beta}_2$ and set each one equal to zero (first-order conditions).

Step 3. Use the first-order conditions to solve for $\hat{\beta}_1$ and $\hat{\beta}_2$ in terms of data on $\boldsymbol{Y_i}$ and $\boldsymbol{X_i}$
.

Step 4. Check second-order conditions to make sure we found the $\hat{\beta}_1$ and $\hat{\beta}_2$ that minimize RSS.

OLS Formulas

For details, see the handout posted on Canvas.

Slope coefficient

$$\hat{\beta}_2 = \frac{\sum_{i=1}^{n}(Y_i - \bar{Y})(X_i - \bar{X})}{\sum_{i=1}^{n}(X_i - \bar{X})^2}$$

Intercept

$$\hat{\beta}_1 = \bar{Y} - \hat{\beta}_2 \bar{X}$$

Slope coefficient

The slope estimator is equal to the sample covariance divided by the sample variance of X :

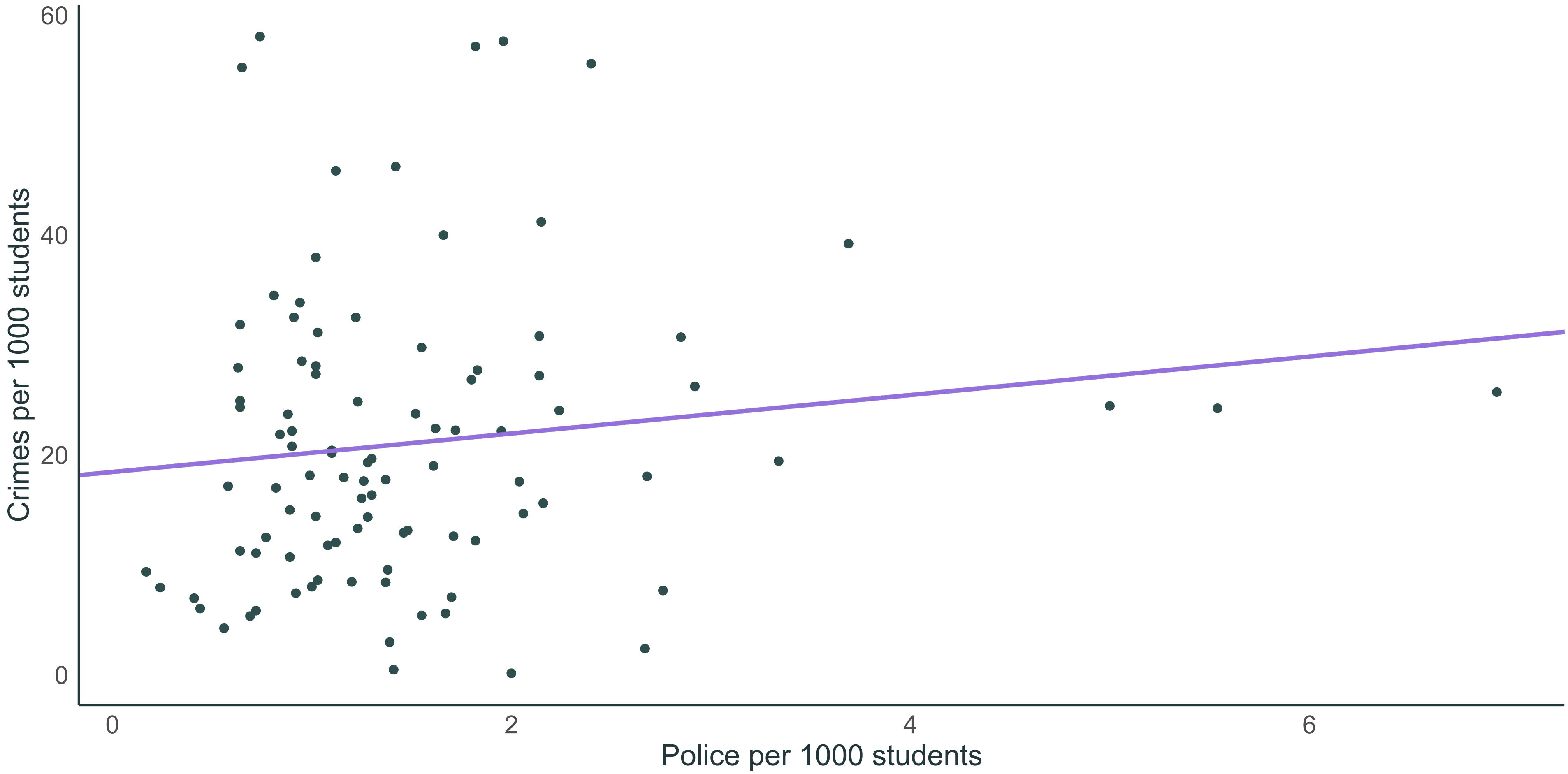
$$\hat{\beta}_2 = \frac{\sum_{i=1}^n (Y_i - \bar{Y})(X_i - \bar{X})}{\sum_{i=1}^n (X_i - \bar{X})^2}$$

$$= \frac{\frac{1}{n-1}\sum_{i=1}^n (Y_i - \bar{Y})(X_i - \bar{X})}{\frac{1}{n-1}\sum_{i=1}^n (X_i - \bar{X})^2}$$

$$= \frac{S_{XY}}{S_X^2}.$$

Example: Effect of police on crime

Using the OLS formulas, we get $\hat{\beta}_1$ = 18.41 and $\hat{\beta}_2$ = 1.76.



Example: Effect of police on crime

Using OLS gives us the fitted line

$$\hat{\text{Crime}}_i = \hat{\beta}_1 + \hat{\beta}_2 \text{Police}_i.$$

What does $\hat{\beta}_1$ = 18.41 tell us?

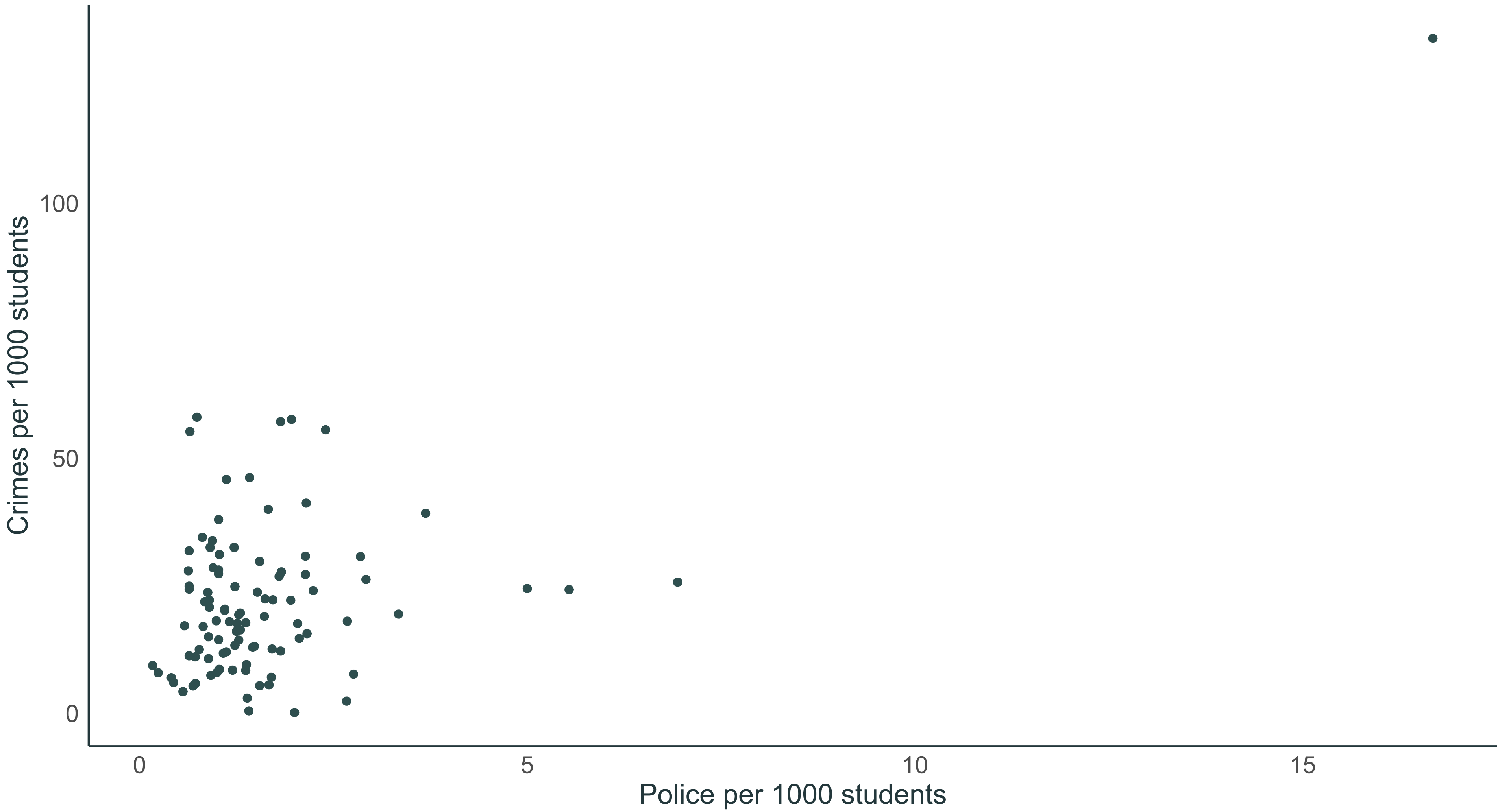
What does $\hat{\beta}_2$ = 1.76 tell us?

Gut check: Does this mean that police *cause* crime?

- Probably not. **Why?**

Outliers

Example: Association of police with crime



Example: Association of police with crime

Fitted line without outlier. **Fitted line** with outlier.