Classical Assumptions

EC 320: Introduction to Econometrics

Winter 2022

Prologue

Housekeeping

- Problem Set 02 due today by 11:59 pm on Canvas
- The solution to the problem set will be released on Wednesday.
- Midterm grade appeal until tomorrow. Solution posted tomorrow. No appeals will be addressed after the solution is being posted.

Agenda

Last Week

How does OLS estimate a regression line?

- Minimize RSS.

What are the direct consequences of minimizing RSS?

- Residuals sum to zero.
- Residuals and the explanatory variable X are uncorrelated.
- Mean values of X and Y are on the fitted regression line.

Whatever do we mean by *goodness of fit*?

- What information does R^2 convey? "The proportion of the variance explained by the regression line"

Agenda

Today

Under what conditions is OLS *desirable*?

- **Desired properties:** Unbiasedness, efficiency, and ability to conduct hypothesis tests.
- **Cost:** Six **classical assumptions** about the population relationship and the sample.

Returns to Schooling

Policy Question: How much should the state subsidize higher education?

- Could higher education subsidies increase future tax revenue?
- Could targeted subsidies reduce income inequality and racial wealth gaps?
- Are there positive externalities associated with higher education?

Empirical Question: What is the monetary return to an additional year of education?

- Focuses on the private benefits of education. Not the only important question!
- Useful for learning about the econometric assumptions that allow causal interpretation.

Returns to Schooling

Step 1: Write down the population model.

$$\log(\mathbf{Earnings}_i) = \beta_0 + \beta_1 \mathbf{Education}_i + u_i$$

Step 2: Find data.

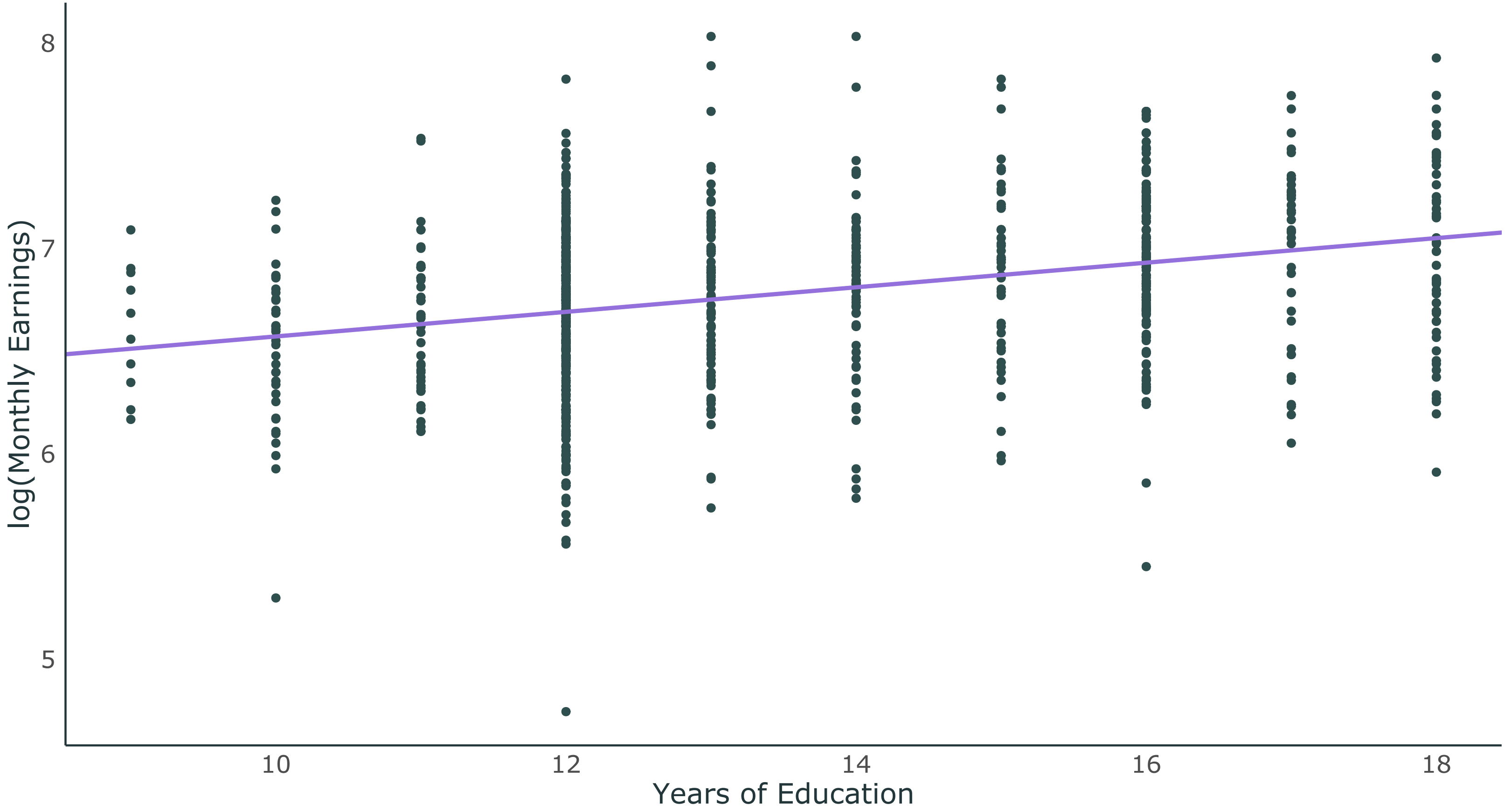
- *Source:* Blackburn and Neumark (1992).

Step 3: Run a regression using OLS.

$$\hat{\log(\mathbf{Earnings}_i)} = \hat{\beta}_0 + \hat{\beta}_1 \mathbf{Education}_i$$

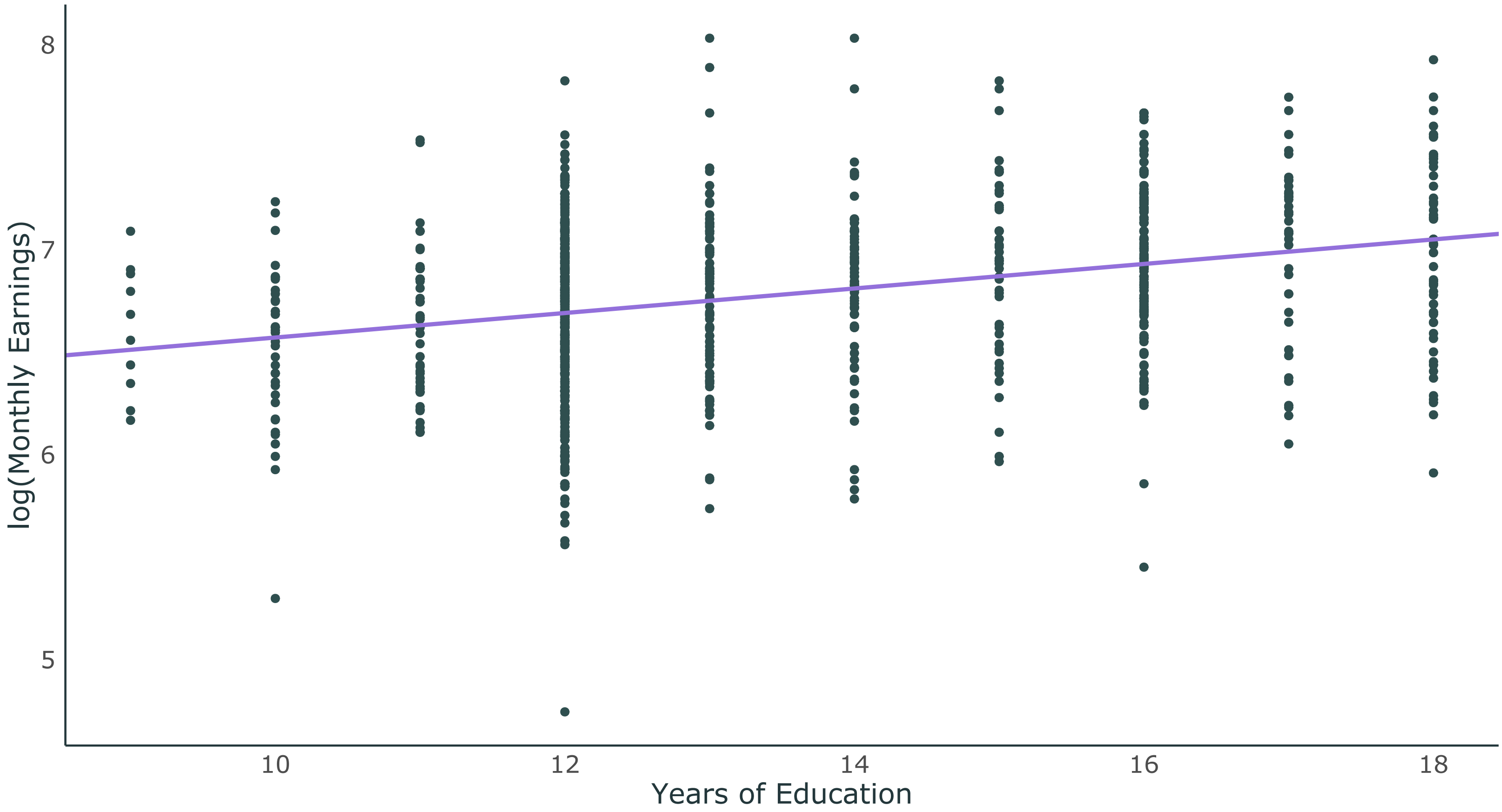
Returns to Schooling

$$\widehat{\log(\text{Earnings}_i)} = \mathbf{5.97} + \mathbf{0.06} \times \text{Education}_i.$$



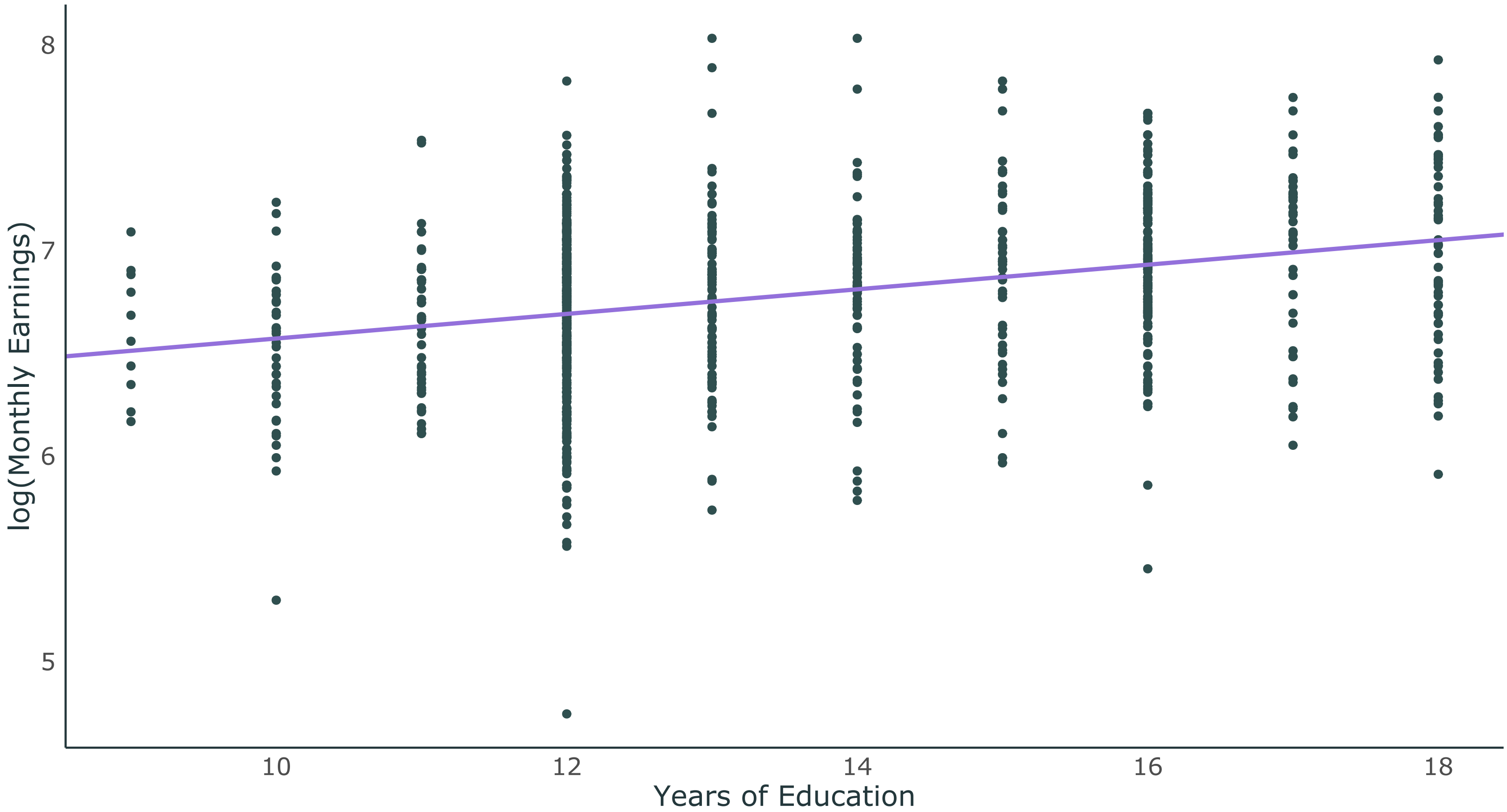
Returns to Schooling

Additional year of school associated with a **6%** increase in earnings.



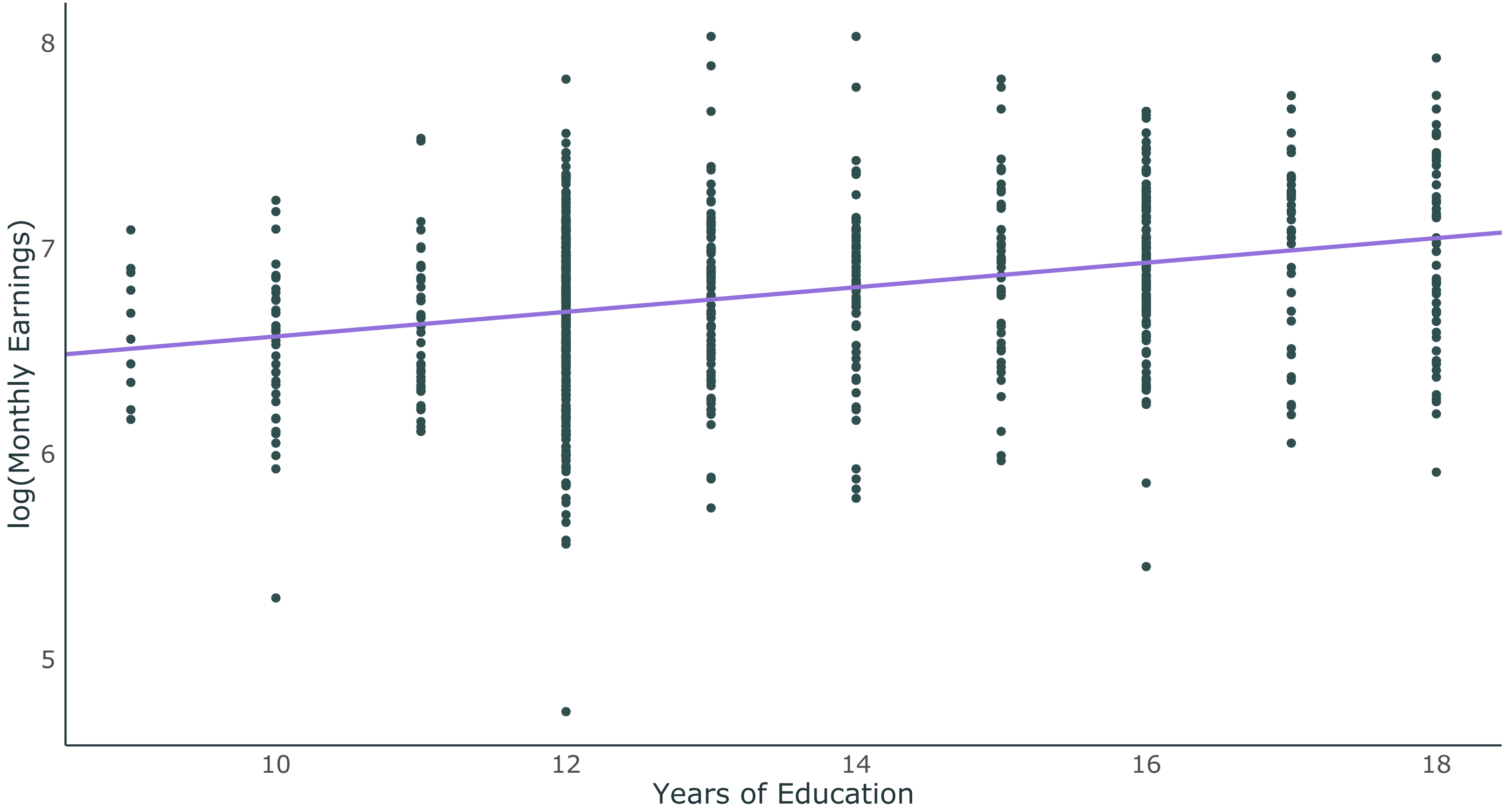
Returns to Schooling

$R^2 =$ **0.097**.



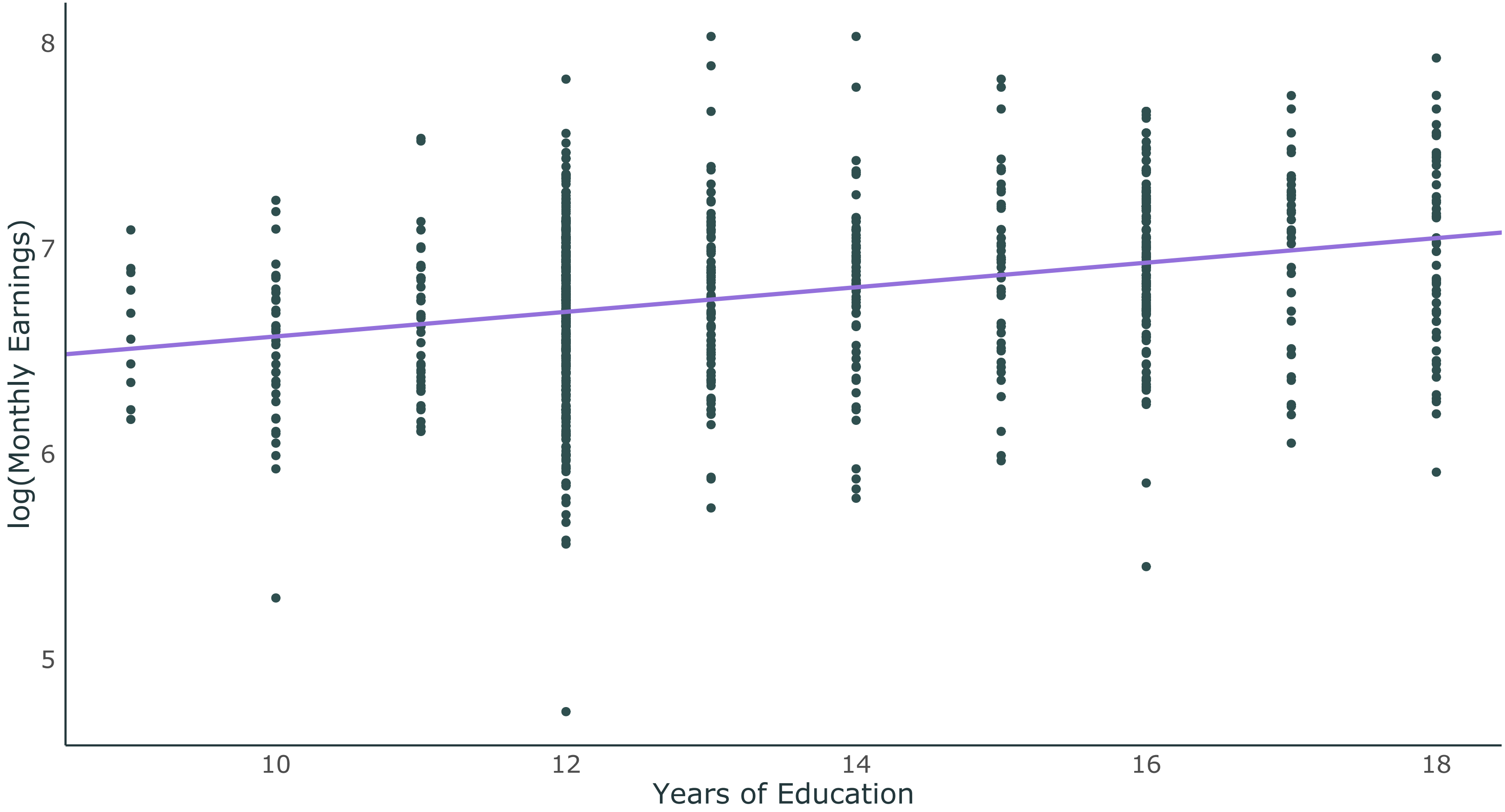
Returns to Schooling

Education explains **9.7%** of the variation in wages.



Returns to Schooling

What must we **assume** to interpret $\hat{\beta}_1 = \mathbf{0.06}$ as the return to schooling?



Residuals *vs.* Errors

The most important assumptions concern the error term u_i.

Important: An error u_i and a residual $\hat{u}_i$ are related, but different.

Population

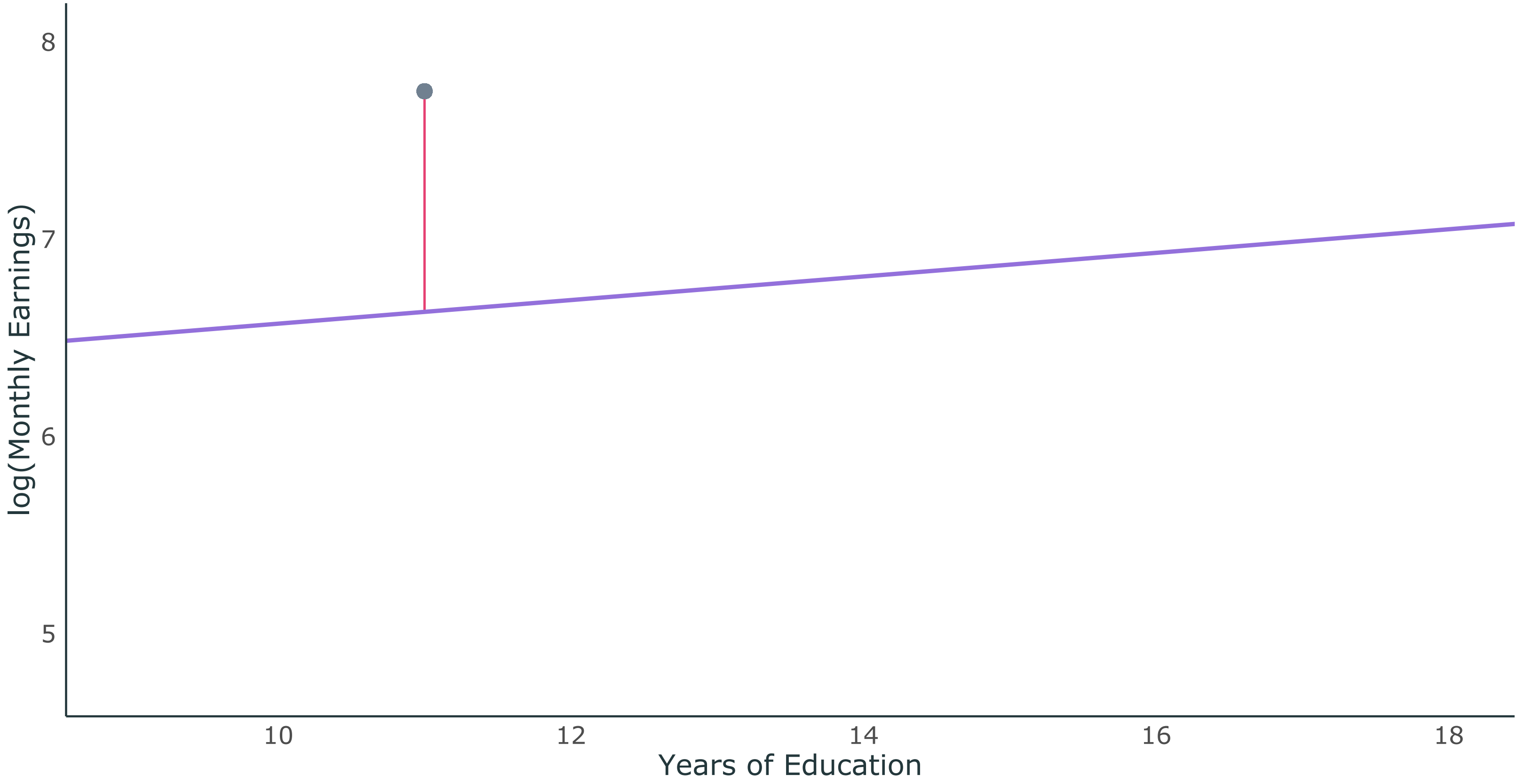
- $Y_i = \beta_0 + \beta_1 X_i + u_i$
- **Error:** Difference between the wage of a worker with 16 years of education and the **expected wage** with 16 years of education.

Sample

- $Y_i = \hat{\beta}_0 + \hat{\beta}_1 X_i + \hat{u}_i$
- **Residual:** Difference between the wage of a worker with 16 years of education and the **average wage** of workers with 16 years of education.

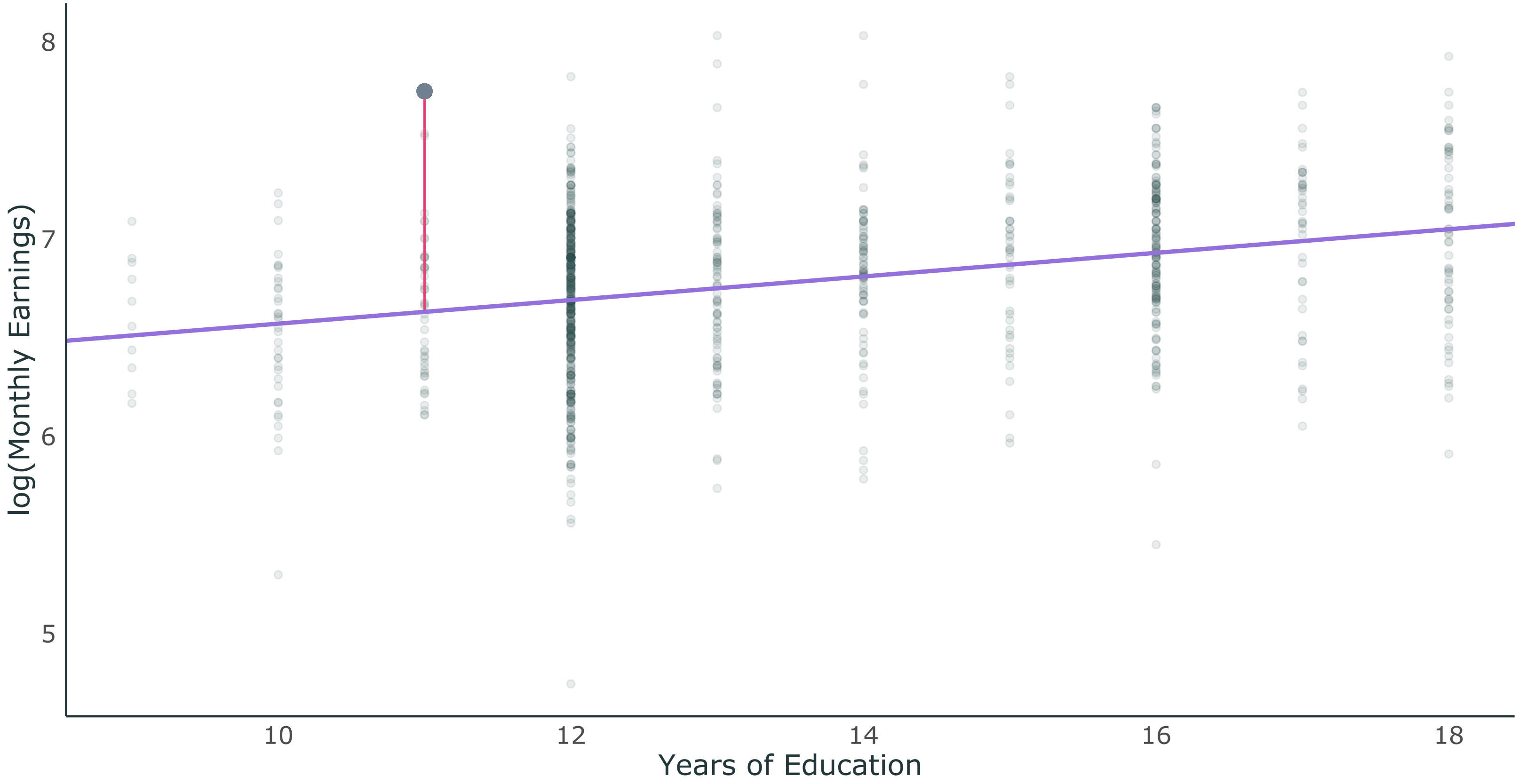
Residuals *vs.* Errors

A **residual** tells us how a **worker**'s wages compare to the average wages of workers in the **sample** with the same level of education.



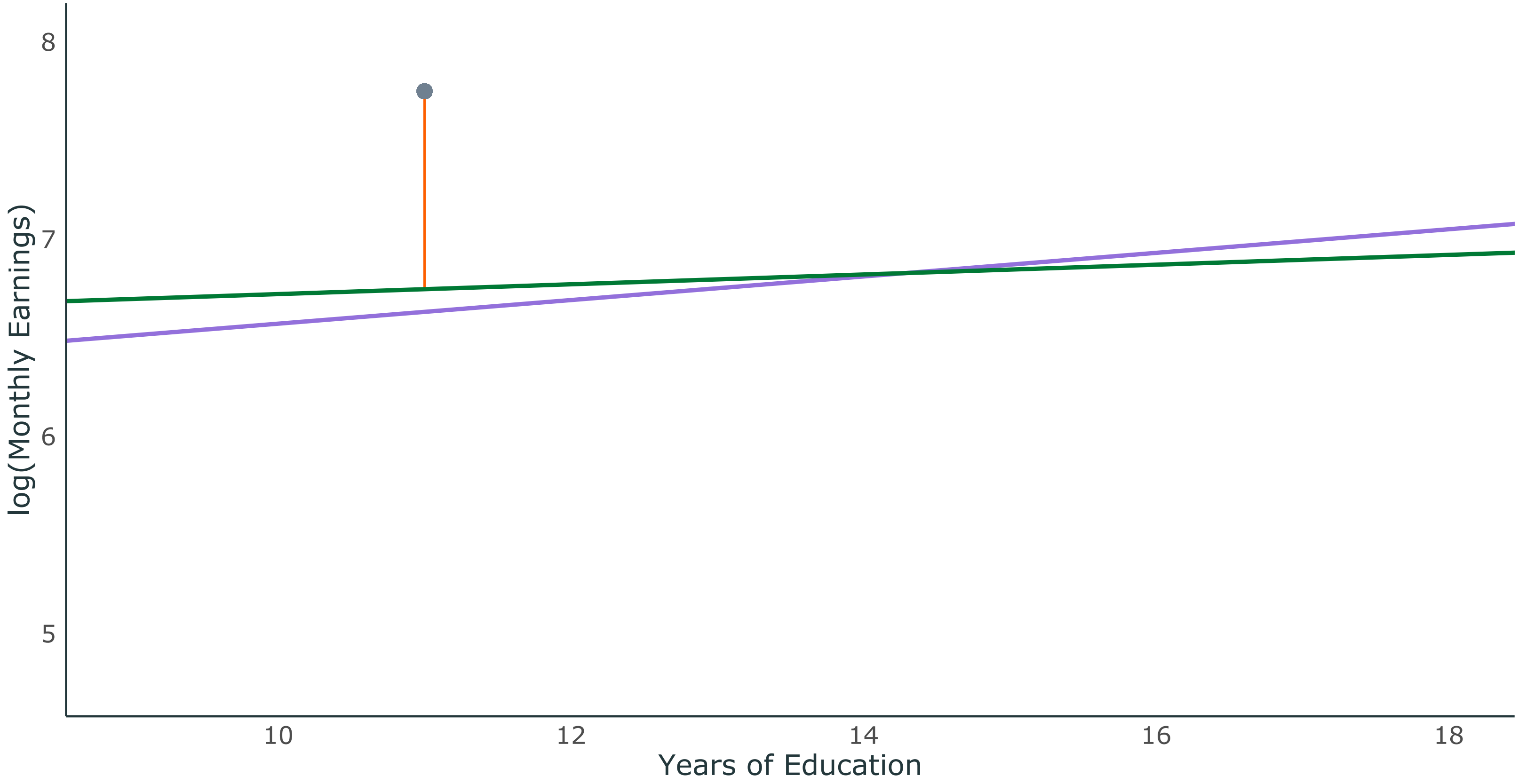
Residuals *vs.* Errors

A **residual** tells us how a **worker**'s wages compare to the average wages of workers in the **sample** with the same level of education.



Residuals *vs.* Errors

An **error** tells us how a **worker**'s wages compare to the expected wages of workers in the **population** with the same level of education.



Classical Assumptions

Classical Assumptions of OLS

1. **Linearity:** The population relationship is **linear in parameters** with an additive error term.

2. **Sample Variation:** There is variation in X.

3. **Exogeneity:** The X variable is **exogenous** (*i.e.*, $\mathbb{E}(u|X) = 0$).[†]

4. **Homoskedasticity:** The error term has the same variance for each value of the independent variable (*i.e.*, $\text{Var}(u|X) = \sigma^2$).

5. **Non-autocorrelation:** The values of error terms have independent distributions (*i.e.*, $E[u_i u_j] = 0, \forall i \text{ s.t. } i \neq j$)

6. **Normality:** The population error term is normally distributed with mean zero and variance σ^2 (*i.e.*, $u \sim N(0, \sigma^2)$)

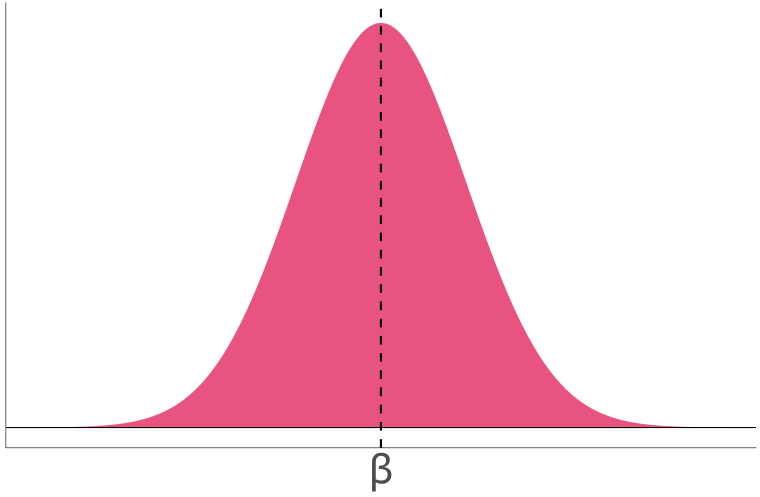
[†] **Random Sampling:** We have a random sample from the population of interest.

When Can We Trust OLS?

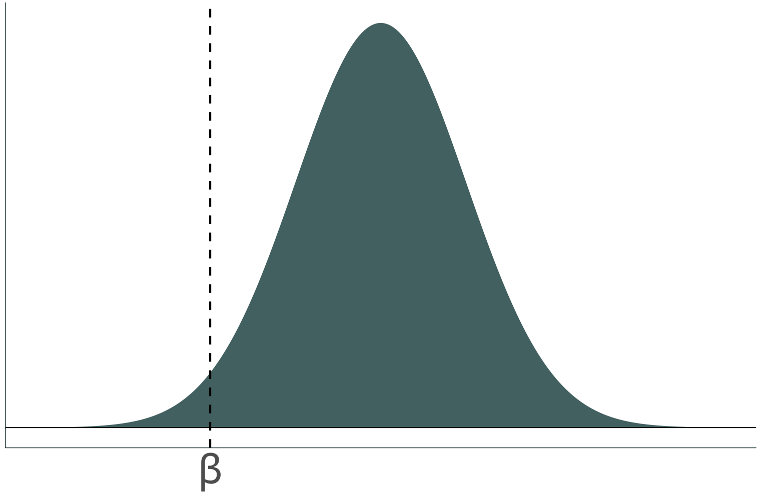
Bias

An estimator is **biased** if its expected value is different from the true population parameter.

Unbiased estimator: $\mathbb{E}\left[\hat{\beta}\right] = \beta$



Biased estimator: $\mathbb{E}\left[\hat{\beta}\right] \neq \beta$



When is OLS Unbiased?

Assumptions

1. **Linearity:** The population relationship is **linear in parameters** with an additive error term.

2. **Sample Variation:** There is variation in X.

3. **Random Sampling:** We have a random sample from the population of interest.

4. **Exogeneity:** The X variable is **exogenous** (*i.e.*, $\mathbb{E}(u|X) = 0$).

Result

OLS is unbiased.

Linearity

Assumption

The population relationship is **linear in parameters** with an additive error term.

Examples

- $\text{Wage}_i = \beta_0 + \beta_1 \text{Experience}_i + u_i$
- $\log(\text{Happiness}_i) = \beta_0 + \beta_1 \log(\text{Money}_i) + u_i$
- $\sqrt{\text{Convictions}_i} = \beta_0 + \beta_1 (\text{Early Childhood Lead Exposure})_i + u_i$
- $\log(\text{Earnings}_i) = \beta_0 + \beta_1 \text{Education}_i + u_i$

Linearity

Assumption

The population relationship is **linear in parameters** with an additive error term.

Violations

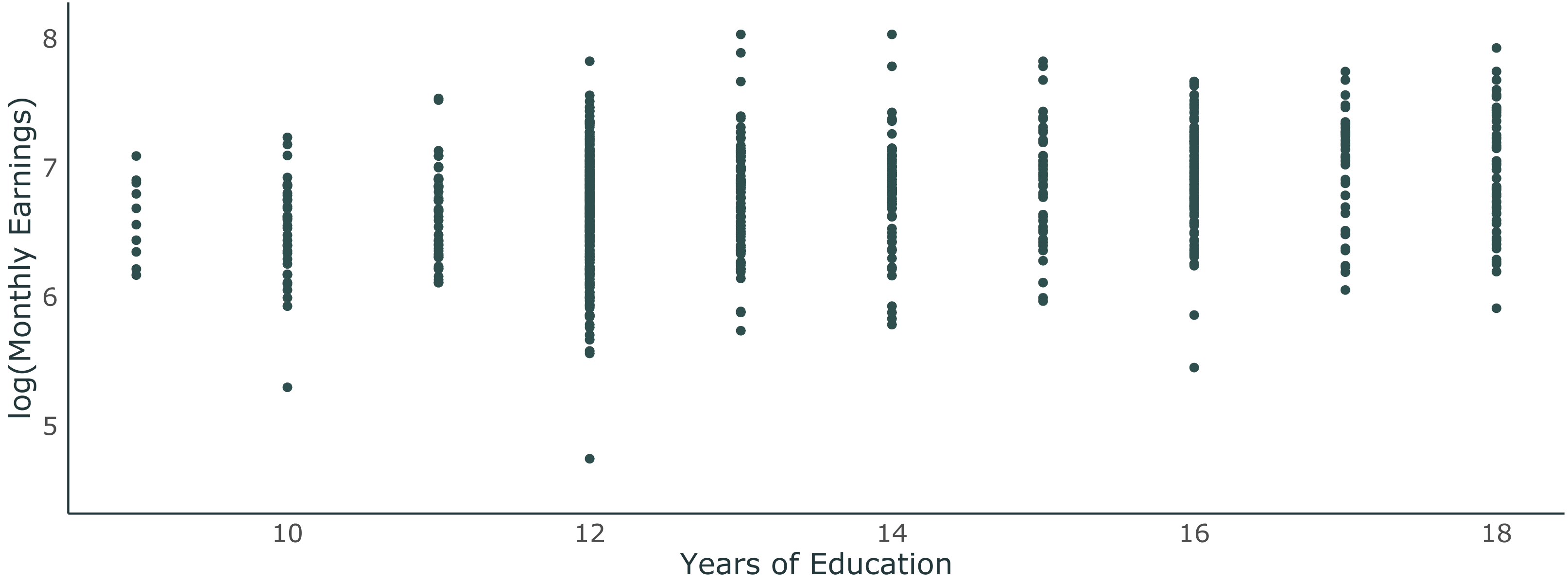
- $\text{Wage}_i = (\beta_0 + \beta_1 \text{Experience}_i) u_i$
- $\text{Consumption}_i = \frac{1}{\beta_0 + \beta_1 \text{Income}_i} + u_i$
- $\text{Population}_i = \frac{\beta_0}{1 + e^{\beta_1 + \beta_3 \text{Food}_i}} + u_i$
- $\text{Batting Average}_i = \beta_0 (\text{Wheaties Consumption})_i^{\beta_1} + u_i$

Sample Variation

Assumption

There is variation in X.

Example

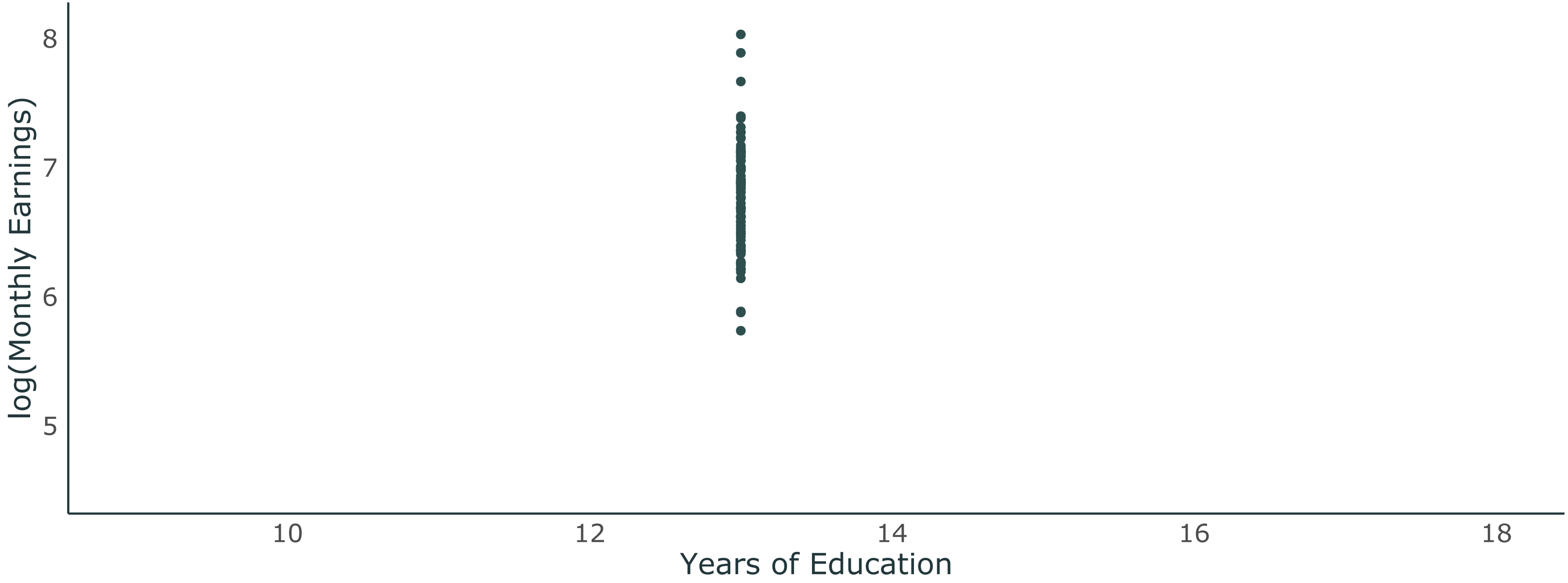


Sample Variation

Assumption

There is variation in X.

Violation



Random Sampling

Assumption

We have a random sample from the population of interest.

Examples

Random sampling generates many cross-sectional datasets (especially surveys).

- Government surveys (*e.g.*, Current Population Survey, American Community Survey).
- Scientific surveys (*e.g.*, General Social Survey, American National Election Study).
- High-quality political polls (*e.g.*, YouGov, Quinnipiac University, Gallup).

Random Sampling

Assumption

We have a random sample from the population of interest.

Violations

- Data collected from non-probability sampling (*e.g.* snowball sampling).
- Most (all?) time-series data.
- Self-selected samples.

Exogeneity

Assumption

The X variable is **exogenous:** $\mathbb{E}(u|X) = 0$.

- For *any* value of X, the mean of the error term is zero.

The most important assumption!

Really two assumptions bundled into one:

1. On average, the error term is zero: $\mathbb{E}(u) = 0$.
2. The mean of the error term is the same for each value of X: $\mathbb{E}(u|X) = \mathbb{E}(u)$.

Exogeneity

Assumption

The X variable is **exogenous:** $\mathbb{E}(u|X) = 0$.

- The assignment of X is effectively random.
- **Implication:** **no selection bias** and **no omitted-variable bias**.

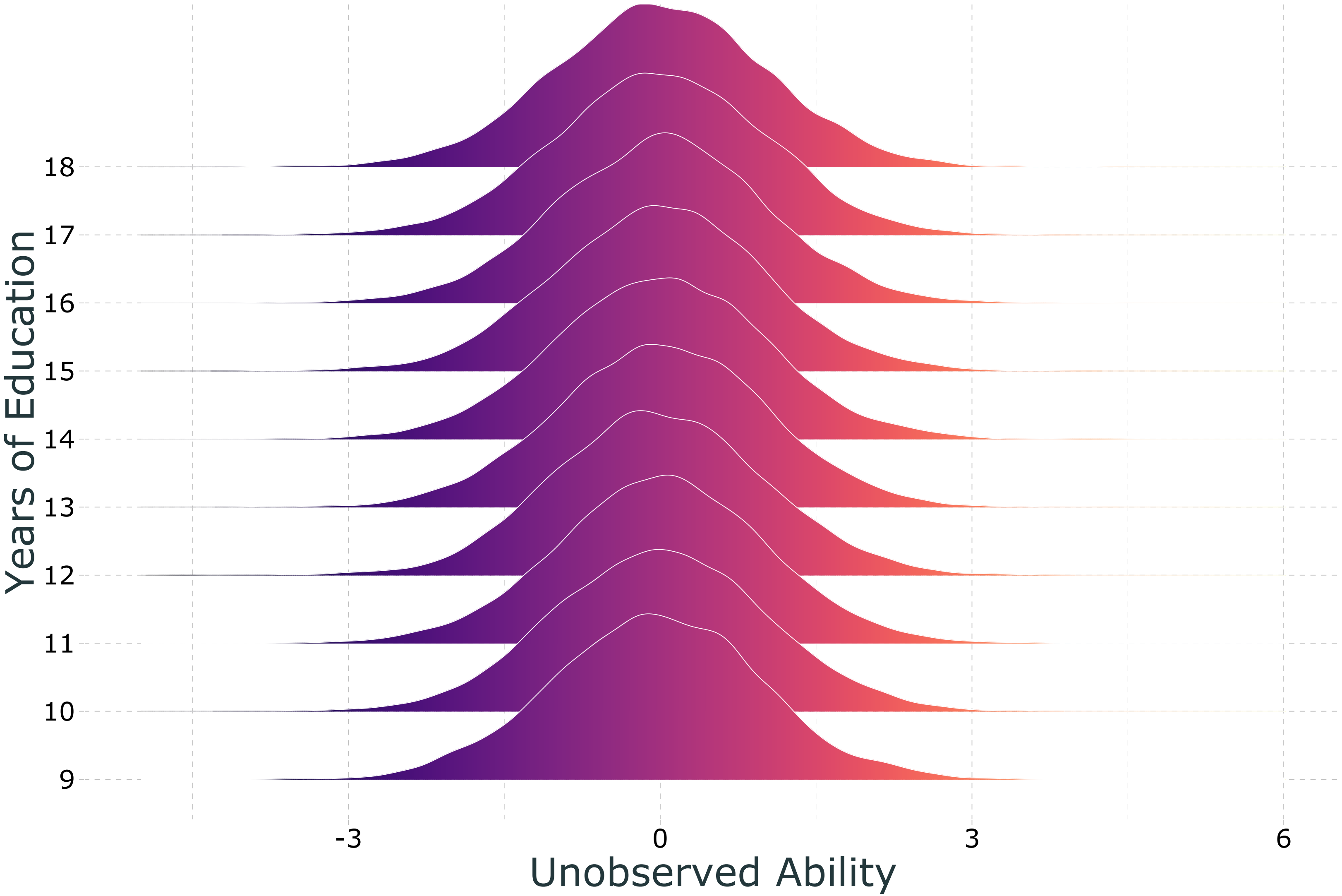
Examples

In the labor market, an important component of u is unobserved ability.

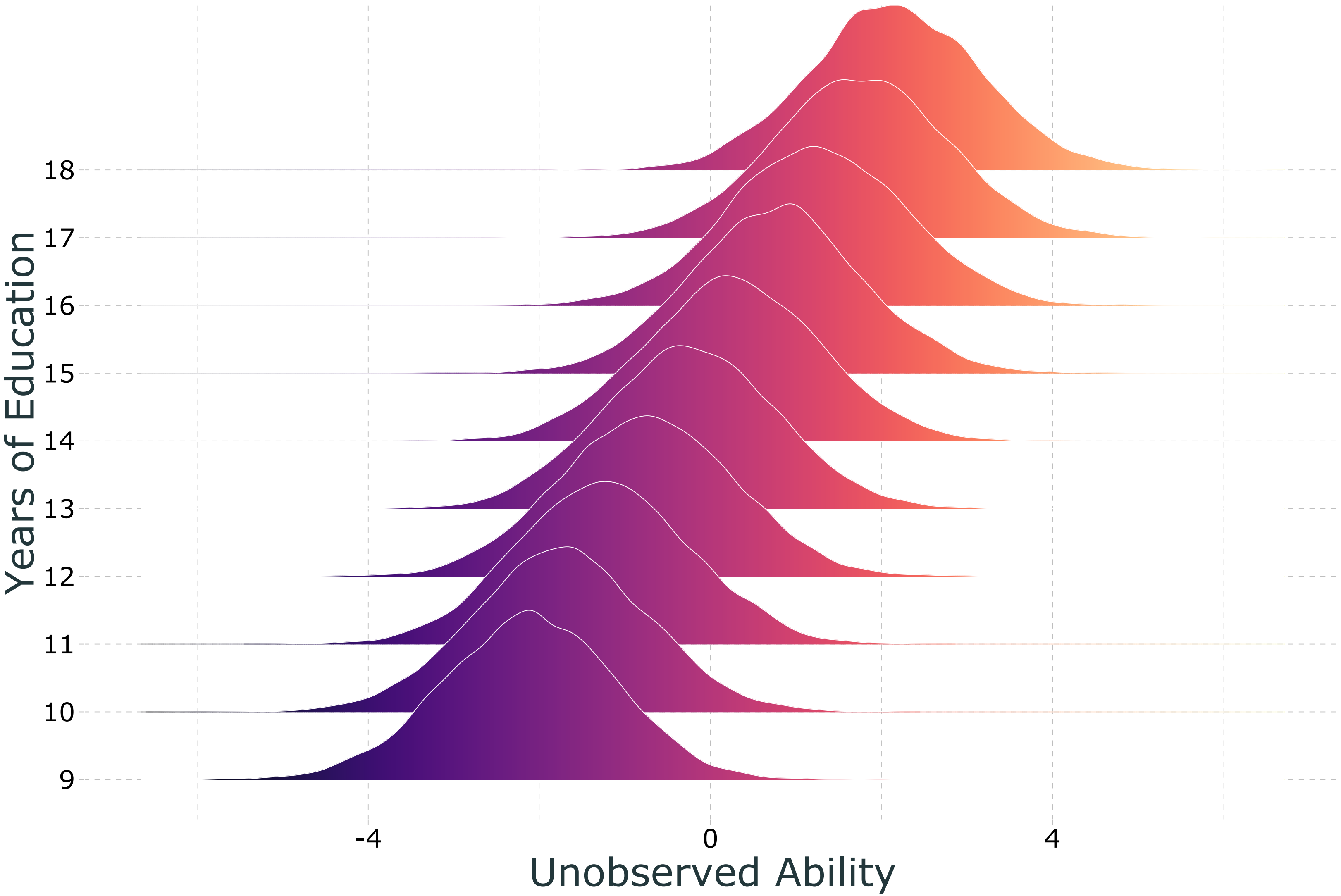
- $\mathbb{E}(u|\text{Education} = 12) = 0$ and $\mathbb{E}(u|\text{Education} = 20) = 0$.
- $\mathbb{E}(u|\text{Experience} = 0) = 0$ and $\mathbb{E}(u|\text{Experience} = 40) = 0$.
- **Do you believe this?**

Graphically...

Valid exogeneity, *i.e.*, $\mathbb{E}(u \mid X) = 0$



Invalid exogeneity, *i.e.*, $\mathbb{E}(u \mid X) \neq 0$



Variance Matters, Too

Why Variance Matters

Unbiasedness tells us that OLS gets it right, *on average*.

- But we can't tell whether our sample is "typical."

Variance tells us how far OLS can deviate from the population parameter.

- How tight is OLS centered on its expected value?

The smaller the variance, the closer OLS gets to the true population parameters *on any sample*.

- Given two unbiased estimators, we want the one with smaller variance.

OLS Variance

To calculate the variance of OLS, we need:

1. The same four assumptions we made for unbiasedness.
2. **Homoskedasticity**
3. **Non-autocorrelation**

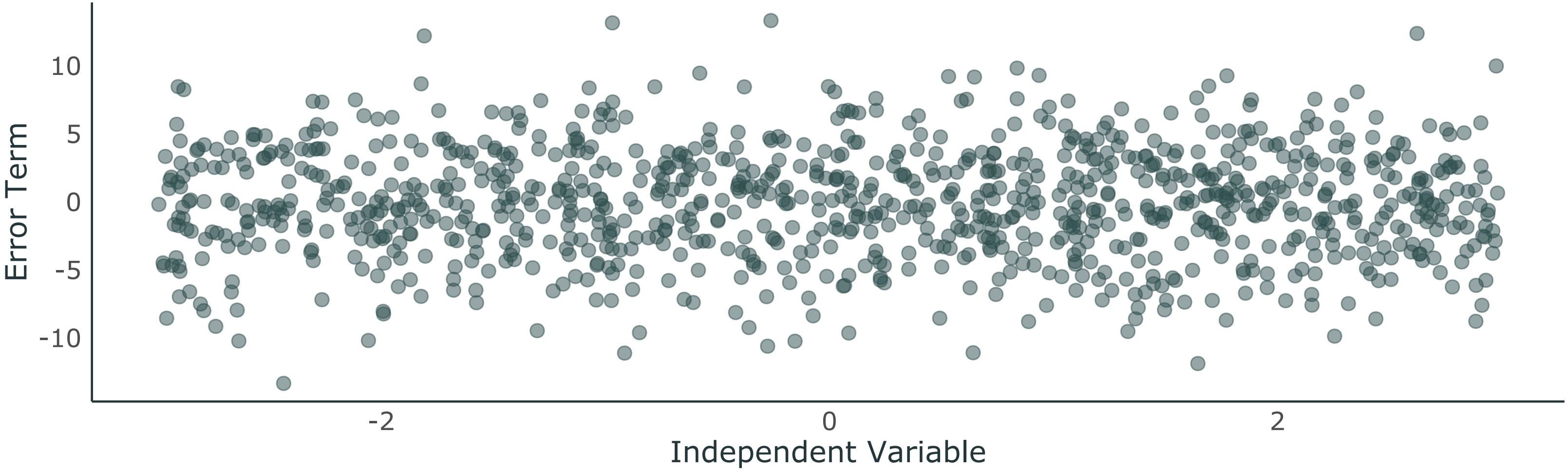
Homoskedasticity

Assumption

The error term has the same variance for each value of the independent variable:

$$\mathrm{Var}(u|X) = \sigma^2.$$

Example



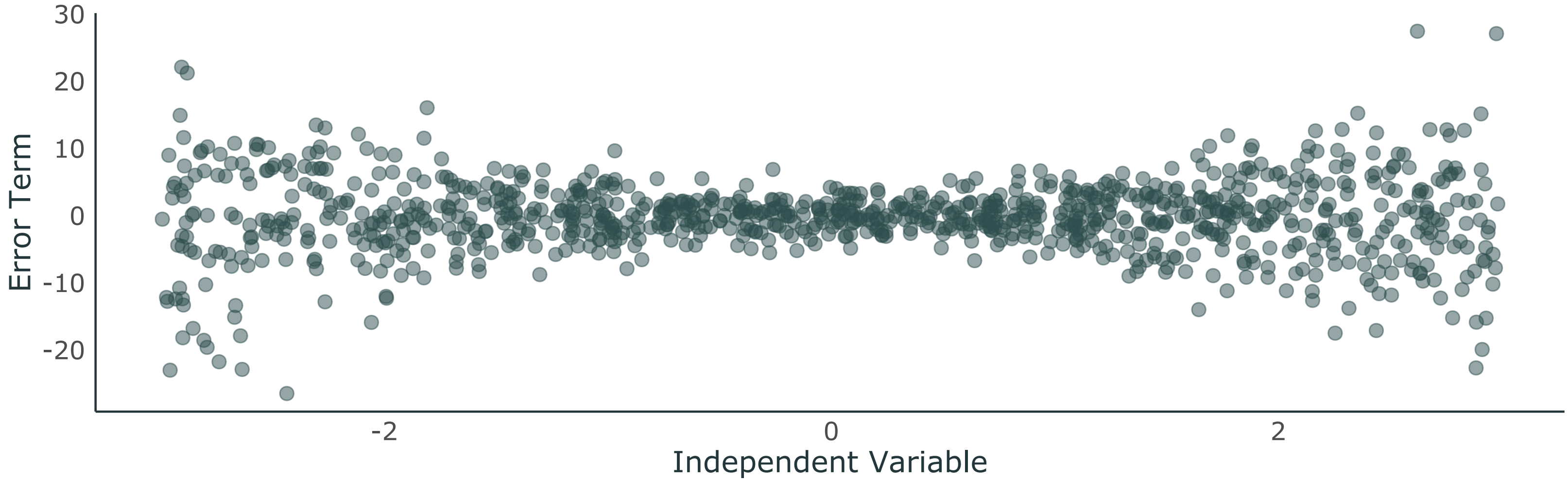
Homoskedasticity

Assumption

The error term has the same variance for each value of the independent variable:

$$\mathrm{Var}(u|X) = \sigma^2.$$

Violation: Heteroskedasticity



Non-Autocorrelation

Assumption

The population covariance between u_i and u_j is zero, meaning that any individual's error term is drawn independently of other error terms.

$$\begin{aligned}\mathrm{Cov}(u_i, u_j) &= E[(u_i - \mu_u)(u_j - \mu_u)] \\ &= E[u_i u_j] = E[u_i]E[u_j] = 0, \text{where } i \neq j\end{aligned}$$

- This implies no systematic association between error term values for any pair of individuals. The values of the error term should be independent of one another.
- If this assumption is not satisfied, OLS gives inefficient estimates.
- Example: The magnitude and the sign of disturbance term in one observation should not lead to a tendency of determining magnitude and the sign of the disturbance term in the next.

OLS Variance

Variance of the slope estimator:

$$\mathbf{Var}(\hat{\beta}_1) = \frac{\sigma^2}{\sum_{i=1}^{n}(X_i - \bar{X})^2}.$$

- As the error variance increases, the variance of the slope estimator increases.

- As the variation in X increases, the variance of the slope estimator decreases.

- Larger sample sizes exhibit more variation in $X \implies \mathbf{Var}(\hat{\beta}_1)$ falls as n rises.

Gauss-Markov

Gauss-Markov Theorem

OLS is the **Best Linear Unbiased Estimator (BLUE)** when:

1. **Linearity:** The population relationship is **linear in parameters** with an additive error term.
2. **Sample Variation:** There is variation in X.
3. **Exogeneity:** The X variable is **exogenous** (*i.e.*, $\mathbb{E}(u|X) = 0$).
4. **Homoskedasticity:** The error term has the same variance for each value of the independent variable (*i.e.*, $\text{Var}(u|X) = \sigma^2$).
5. **Non-Autocorrelation:** Any pair of error terms are drawn independently of each other (*i.e.*, $\text{E}(u_i u_j) = 0 \; \forall \; i \text{ s.t. } i \neq j$)

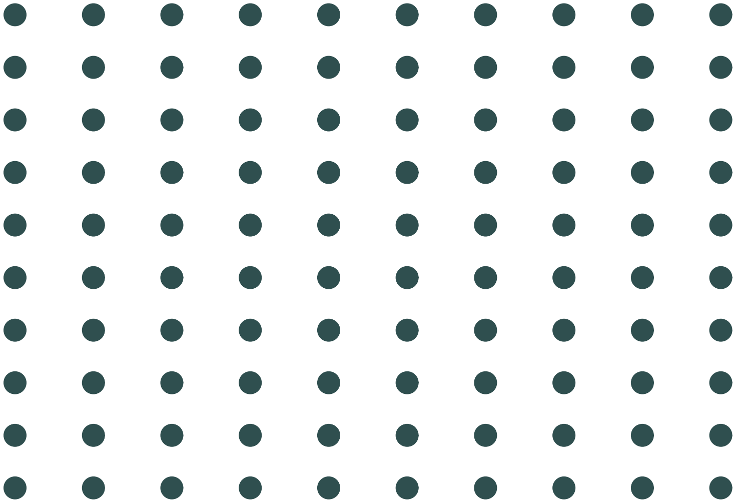
Gauss-Markov Theorem

OLS is the **Best Linear Unbiased Estimator (BLUE)**

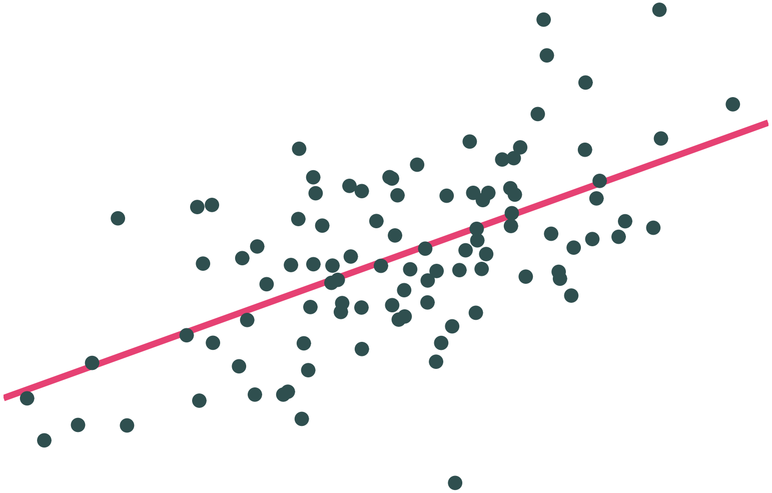
Population *vs.* Sample, Revisited

Population *vs.* Sample

Question: Why do we care about *population vs. sample*?



Population



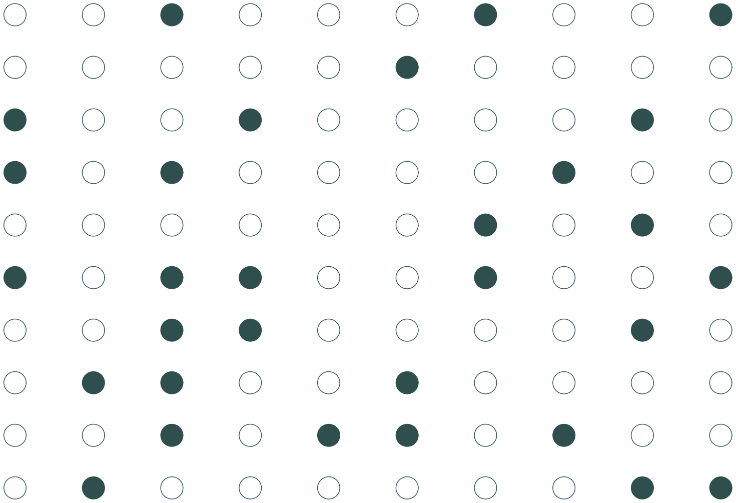
Population relationship

$$y_i = 2.53 + 0.57 x_i + u_i$$

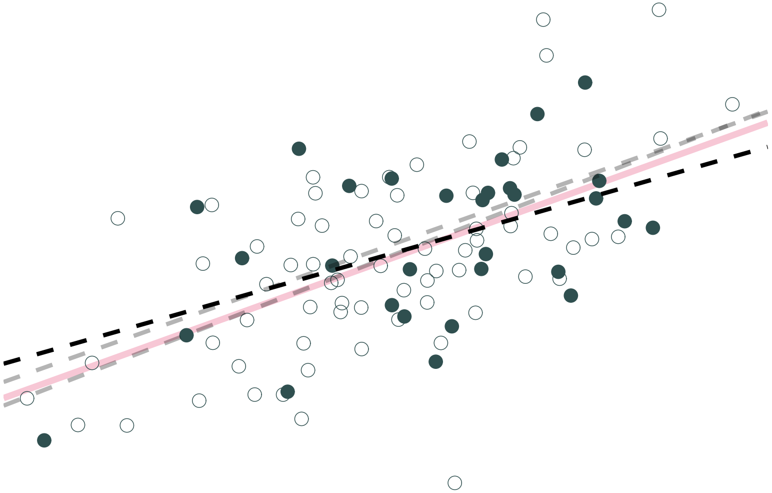
$$y_i = \beta_0 + \beta_1 x_i + u_i$$

Population *vs.* Sample

Question: Why do we care about *population vs. sample*?



Sample 3: 30 random individuals



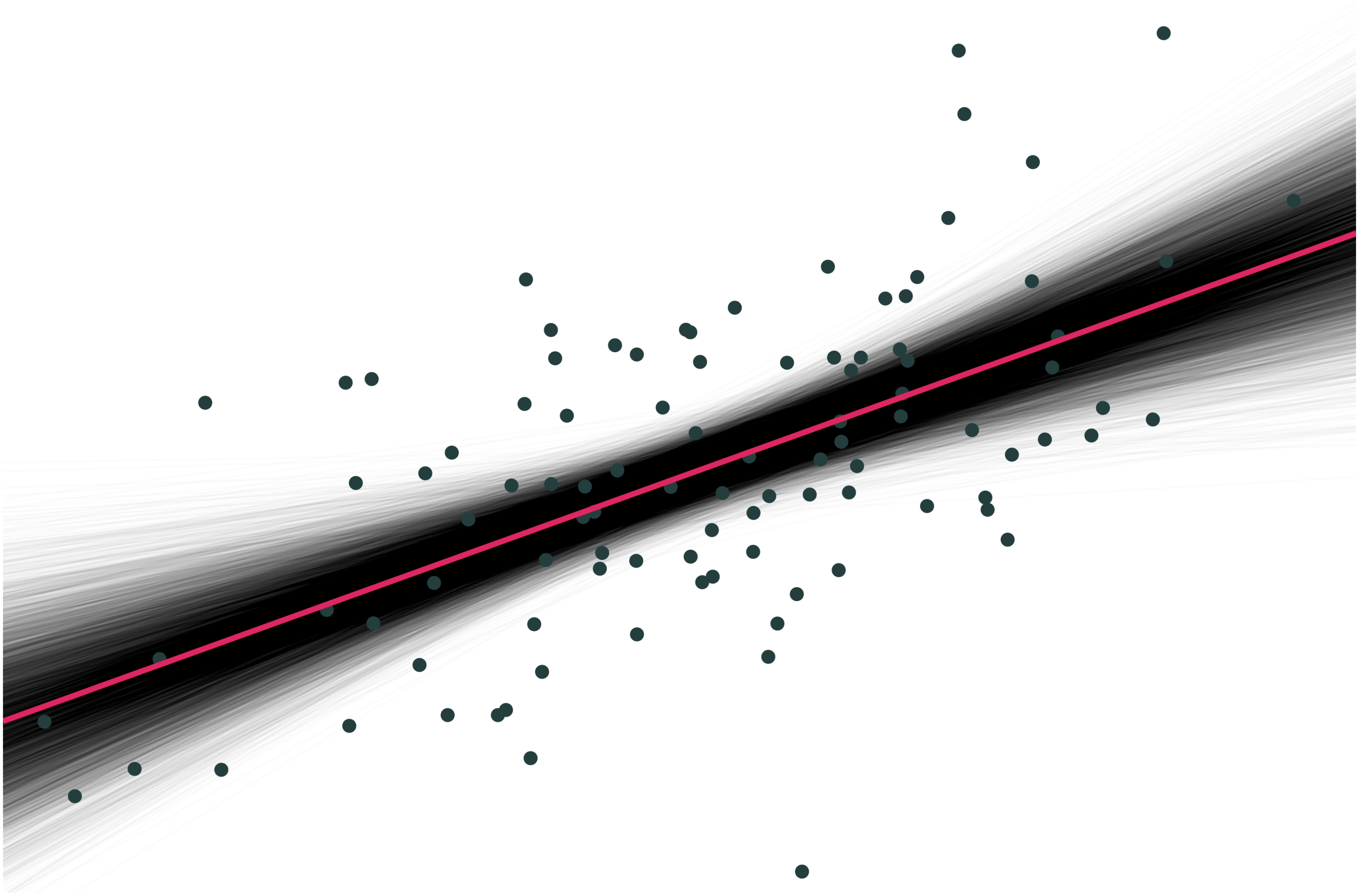
Population relationship

$$y_i = 2.53 + 0.57 x_i + u_i$$

Sample relationship

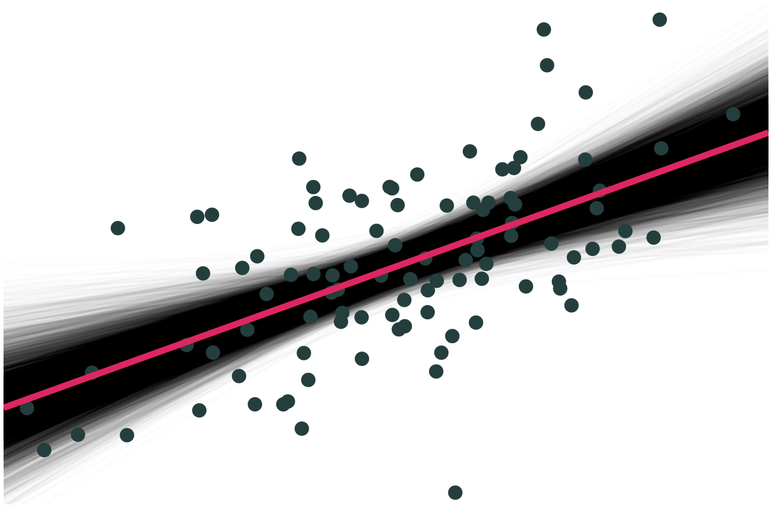
$$\hat{y}_i = 3.21 + 0.45 x_i$$

Repeat **10,000 times** (Monte Carlo simulation).



Population *vs.* Sample

Question: Why do we care about *population vs. sample*?



- On **average**, the regression lines match the population line nicely.
- However, **individual lines** (samples) can miss the mark.
- Differences between individual samples and the population create **uncertainty**.

Population *vs.* Sample

Question: Why do we care about *population vs. sample*?

Answer: Uncertainty matters.

$\hat{\beta}_0$ and $\hat{\beta}_1$ are random variables that depend on the random sample.

We can't tell if we have a "good" sample (similar to the population) or a "bad sample" (very different than the population).

Next time, we will leverage all six classical assumptions, including **normality**, to conduct hypothesis tests.