

Simple Linear Regression: Inference

EC 320: Introduction to Econometrics

Winter 2022

Prologue

Housekeeping

- Lab today & Ex05 due today
- Midterm 1 solution posted
- Extra OH 7pm-8pm on Zoom

Last Time

We discussed the **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. **Random Sampling:** We have a random sample from the population of interest.
4. **Exogeneity:** The X variable is exogenous (*i.e.*, $\mathbb{E}(u|X) = 0$).
5. **Homoskedasticity:** The error term has the same variance for each value of the independent variable (*i.e.*, $\text{Var}(u|X) = \sigma^2$).
6. **Normality:** The population error term is normally distributed with mean zero and variance σ^2 (*i.e.*, $u \sim N(0, \sigma^2)$)

We restricted our attention to the first 5 assumptions.

Classical Assumptions

Last Time

1. We used the first 4 assumptions to show that OLS is unbiased:

$$\mathbb{E}[\hat{\beta}] = \beta$$

2. We used the first 5 assumptions to derive a formula for the **variance** of the OLS estimator: $\text{Var}(\hat{\beta}) = \frac{\sigma^2}{\sum_{i=1}^n (X_i - \bar{X})^2}$.

Classical Assumptions

Today

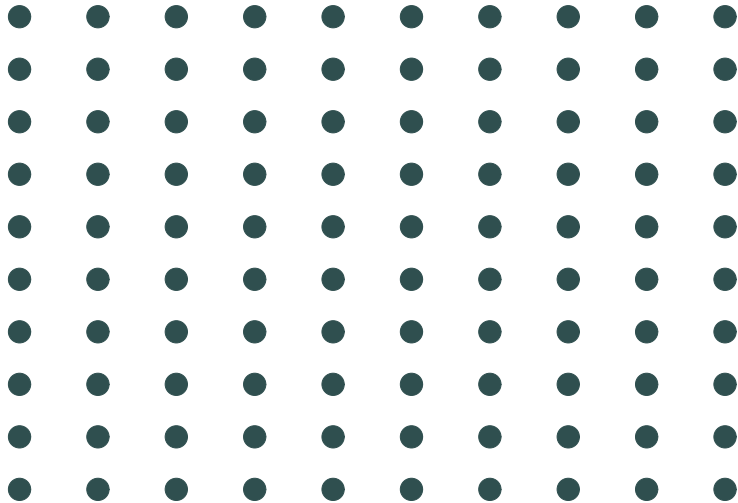
We will use the sampling distribution of $\hat{\beta}_1$ to conduct hypothesis tests.

- Can use all 6 classical assumptions to show that OLS is normally distributed:

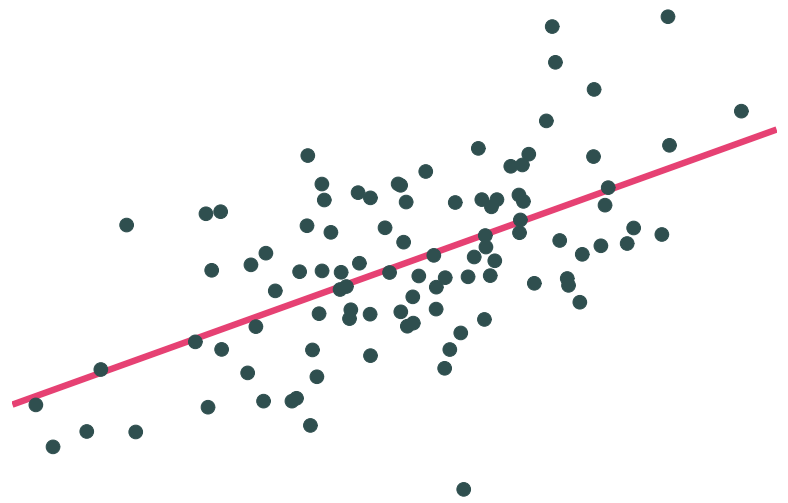
$$\hat{\beta}_1 \sim N\left(\beta_1, \frac{\sigma^2}{\sum_{i=1}^n (X_i - \bar{X})^2}\right)$$

- We'll "prove" this using R.

Simulation



Population

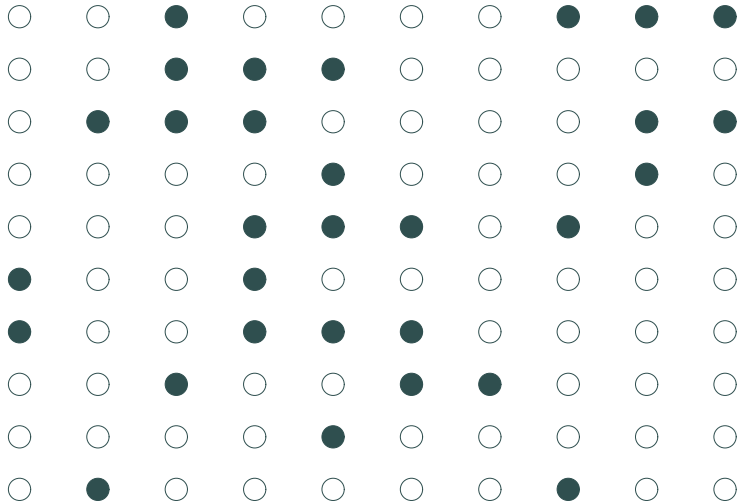


Population relationship

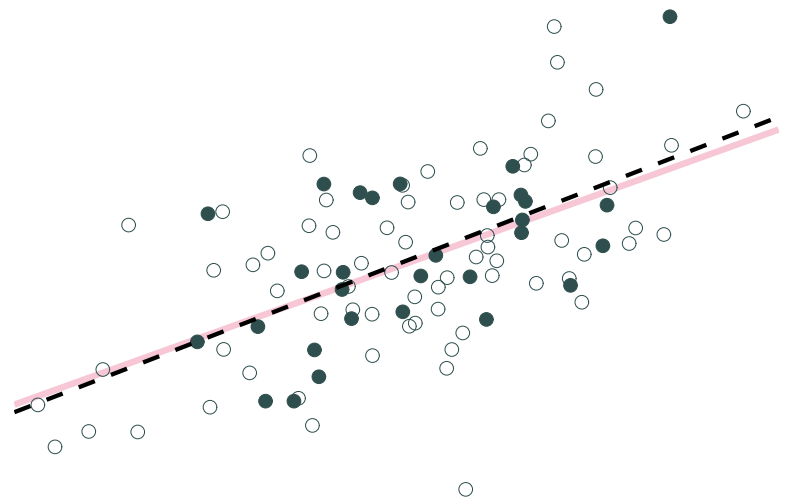
$$Y_i = 2.53 + 0.57X_i + u_i$$

$$Y_i = \beta_0 + \beta_1 X_i + u_i$$

Simulation



Sample 1: 30 random individuals



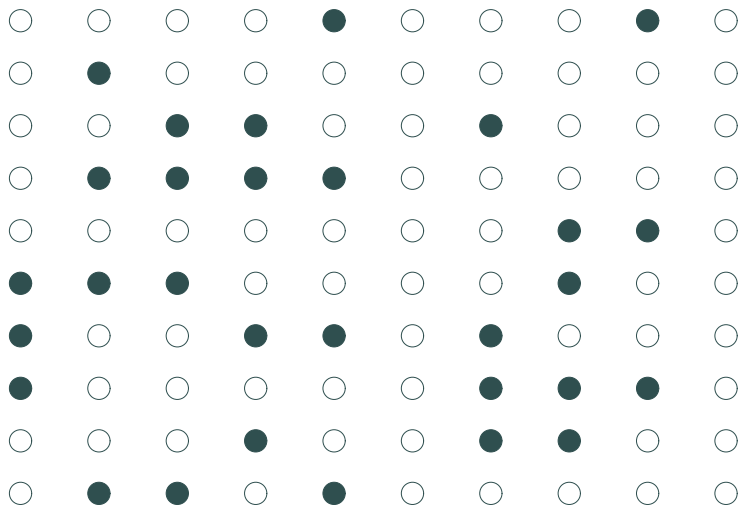
Population relationship

$$Y_i = 2.53 + 0.57X_i + u_i$$

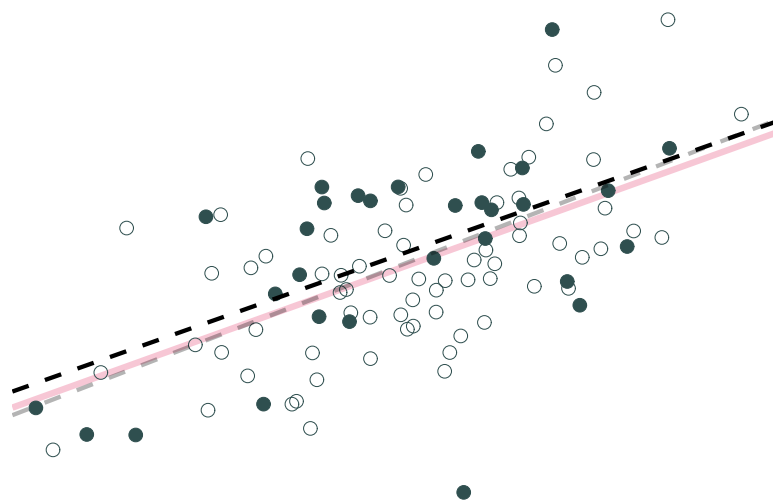
Sample relationship

$$\hat{Y}_i = 2.36 + 0.61X_i$$

Simulation



Sample 2: 30 random individuals



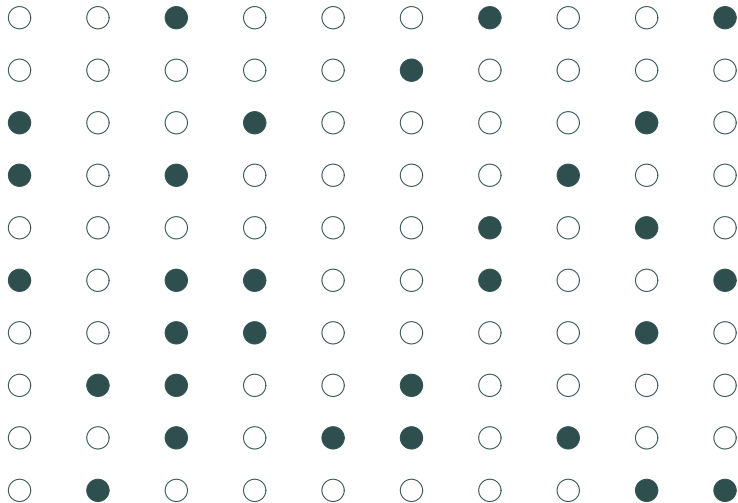
Population relationship

$$Y_i = 2.53 + 0.57X_i + u_i$$

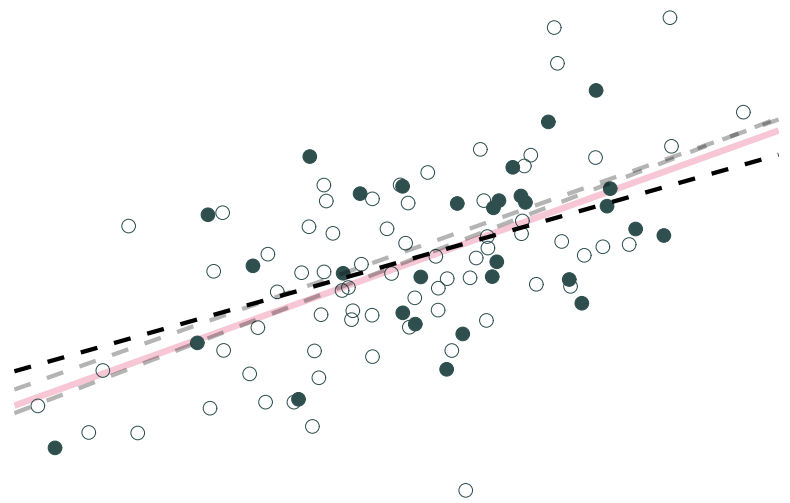
Sample relationship

$$\hat{Y}_i = 2.79 + 0.56X_i$$

Simulation



Sample 3: 30 random individuals



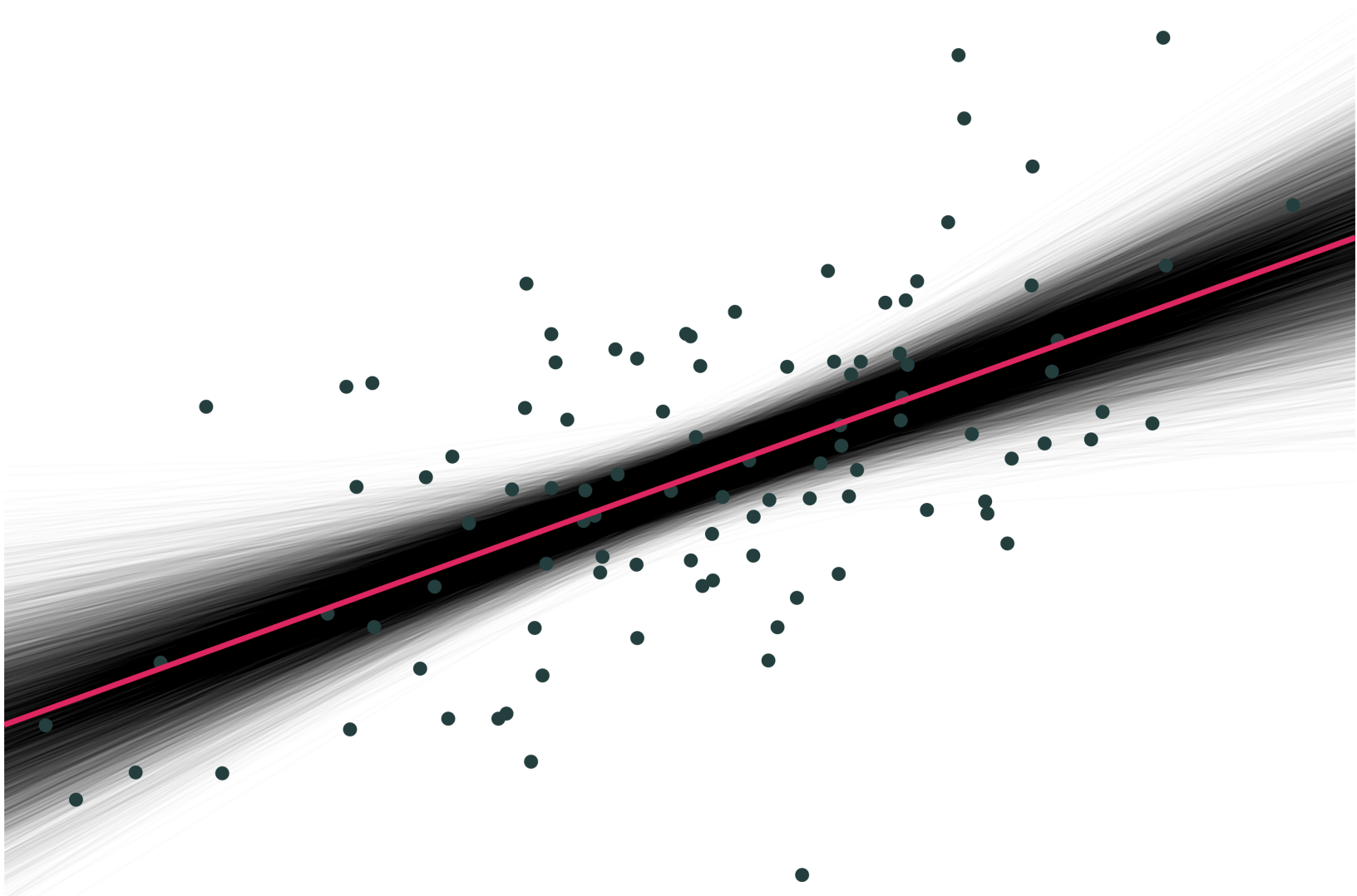
Population relationship

$$Y_i = 2.53 + 0.57X_i + u_i$$

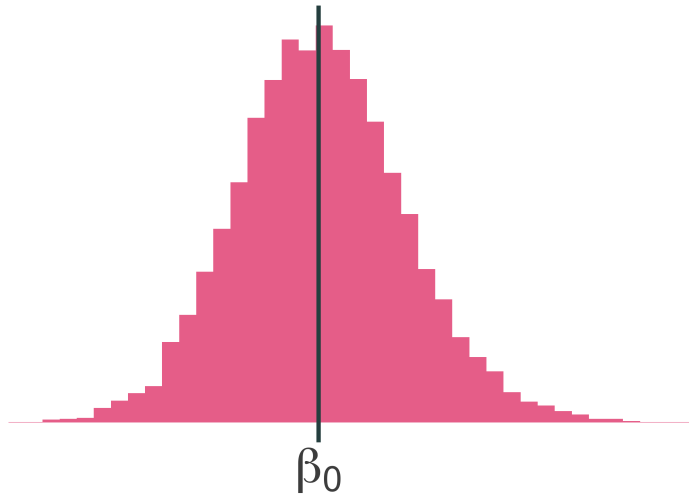
Sample relationship

$$\hat{Y}_i = 3.21 + 0.45X_i$$

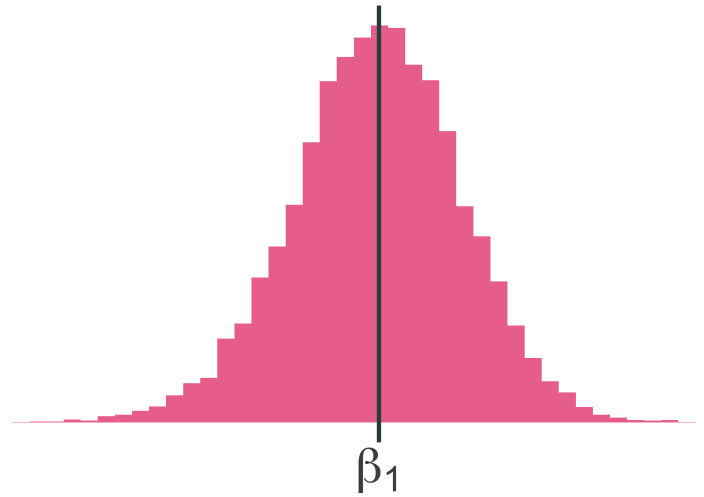
Repeat **10,000 times** (Monte Carlo simulation).



Intercept Estimates



Slope Estimates



Simulation

Can you spot the classical assumptions?

```
# Set population and sample sizes
n_p ← 100
n_s ← 30
# Generate population data
pop_df ← tibble(
  x = rnorm(n_p, mean = 5, sd = 1.5),
  e = rnorm(n_p, mean = 0, sd = 1),
  y = 2.53 + 0.57 * x + e
)
# Define simulation procedure
sim_ols ← function(x, size = n_s) {
  lm(y ~ x, data = pop_df %>% sample_n(size = size)) %>%
    tidy() %>%
    mutate(iteration = x)
}
# Run simulation
sim_df ← map_df(1:10000, ~sim_ols(.x, size = n_s))
```

Inference

Motivation

What does statistical evidence say about existing theories?

We want to test hypotheses posed by politicians, economists, scientists, people with foil hats, *etc.*

- Does building a giant wall **reduce crime**?
- Does shutting down a government **adversely affect the economy**?
- Does legal cannabis **reduce drunk driving** or **reduce opioid use**?
- Do air quality standards **improve health** or **reduce jobs**?

While uncertainty exists, we can still conduct *reliable* statistical tests (rejecting or failing to reject a hypothesis).

Inference

We know OLS has some nice properties, and we know how to estimate an intercept and slope coefficient using OLS.

Our current workflow:

- Get data (points with X and Y values).
- Regress Y on X .
- Plot the fitted values (*i.e.*, $\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i$) and report the estimates.

But how do we actually **learn** something from this exercise?

- Based upon our value of $\hat{\beta}_1$, can we rule out previously hypothesized values?
- How confident should we be in the precision of our estimates?

We need to be able to deal with uncertainty. Enter: **Inference**.

Inference

We use the standard error of $\hat{\beta}_1$, along with $\hat{\beta}_1$ itself, to learn about the parameter β_1 .

After deriving the distribution of $\hat{\beta}_1$,[†] we have two (related) options for formal statistical inference (learning) about our unknown parameter β_1 :

- **Hypothesis tests:** Determine whether there is statistically significant evidence to reject a hypothesized value or range of values.
- **Confidence intervals:** Use the estimate and its standard error to create an interval that, when repeated, will generally^{††} contain the true parameter.

[†] Hint: It's normal with mean β_1 and variance $\frac{\sigma^2}{\sum_{i=1}^n (X_i - \bar{X})^2}$.

^{††} E.g., similarly constructed 95% confidence intervals will contain the true parameter 95% of the time.

OLS Variance

Hypothesis tests and confidence intervals require information about the variance of the OLS estimator:

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

Problem

- The variance formula has a population parameter: σ^2 (a.k.a. error variance).
- We can't observe population parameters.
- **Solution:** Estimate σ^2 .

Estimating Error Variance

Learning from our (prediction) errors

We can estimate the variance of u_i (a.k.a. σ^2) using the sum of squared residuals:

$$s_u^2 = \frac{\sum_i \hat{u}_i^2}{n - k}$$

where k gives the number of regression parameters.

- In a simple linear regression, $k = 2$.
- s_u^2 is an unbiased estimator of σ^2 .

OLS Variance, Take 2

With $s_u^2 = \frac{\sum_i \hat{u}_i^2}{n - k}$, we can calculate

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

Taking the square root, we get the **standard error** of the OLS estimator:

$$\text{SE}(\hat{\beta}_1) = \sqrt{\frac{s_u^2}{\sum_{i=1}^n (X_i - \bar{X})^2}}.$$

- Standard error = standard deviation of an estimator.

Standard Errors

R's `lm()` function estimates standard errors out of the box:

```
tidy(lm(y ~ x, pop_df))
```

```
#> # A tibble: 2 × 5
#>   term          estimate std.error statistic  p.value
#>   <chr>          <dbl>    <dbl>    <dbl>    <dbl>
#> 1 (Intercept)    2.53      0.422      6.00 3.38e- 8
#> 2 x              0.567     0.0793     7.15 1.59e-10
```

I won't ask you to estimate standard errors by hand!

Hypothesis Tests

Hypothesis Tests

Null hypothesis (H_0): $\beta_1 = 0$

Alternative hypothesis (H_a): $\beta_1 \neq 0$

There are four possible outcomes of our test:

1. We **fail to reject** the null hypothesis and the null is true.
2. We **reject** the null hypothesis and the null is false.
3. We **reject** the null hypothesis, but the null is actually true (**Type I error**).
4. We **fail to reject** the null hypothesis, but the null is actually false (**Type II error**).

Hypothesis Tests

Goal: Make a statement about β_1 using information on $\hat{\beta}_1$.

$\hat{\beta}_1$ is random: it could be anything, even if $\beta_1 = 0$ is true.

- But if $\beta_1 = 0$ is true, then $\hat{\beta}_1$ is unlikely to take values far from zero.
- As the standard error shrinks, we are even less likely to observe "extreme" values of $\hat{\beta}_1$ (assuming $\beta_1 = 0$).

Our test should take **extreme values** of $\hat{\beta}_1$ as **evidence against the null hypothesis**, but it should also weight them by what we know about the variance of $\hat{\beta}_1$.

Hypothesis Tests

Null hypothesis

$$H_0: \beta_1 = 0$$

Alternative hypothesis

$$H_a: \beta_1 \neq 0$$

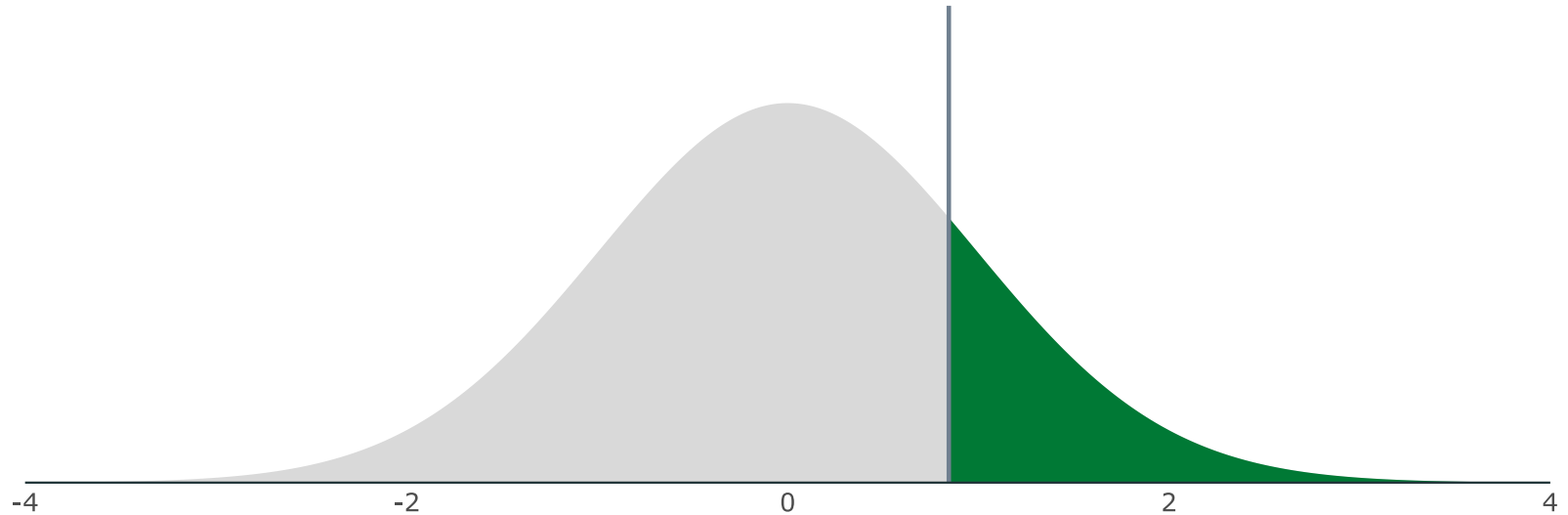
To conduct the test, we calculate a t -statistic:

$$t = \frac{\hat{\beta}_1 - \beta_1^0}{\text{SE}(\hat{\beta}_1)}$$

- Distributed according to a t -distribution with $n - 2$ degrees of freedom.
- β_1^0 is the value of β_1 in our null hypothesis (e.g., $\beta_1^0 = 0$).

Hypothesis Tests

Next, we use the t -**statistic** to calculate a p -**value**.



Describes the probability of seeing a t -statistic as extreme as the one we observe *if the null hypothesis is actually true*.

But...we still need some benchmark to compare our p -value against.

Hypothesis Tests

We worry mostly about false positives, so we conduct hypothesis tests based on the probability of making a Type I error.

How? We select a **significance level α** that specifies our tolerance for false positives. This is the probability of Type I error we choose to live with.



Hypothesis Tests

We then compare α to the p -value of our test.

- If the p -value is less than α , then we **reject the null hypothesis** at the $\alpha \cdot 100$ percent level.
- If the p -value is greater than α , then we **fail to reject the null hypothesis**.
- **Note:** *Fail to reject \neq accept.*

Hypothesis Tests

Example: Are campus police associated with campus crime?

```
lm(crime ~ police, data = campus) %>% tidy()
```

```
#> # A tibble: 2 × 5  
#>   term          estimate std.error statistic  p.value  
#>   <chr>          <dbl>    <dbl>    <dbl>    <dbl>  
#> 1 (Intercept)    18.4      2.38     7.75 1.06e-11  
#> 2 police         1.76      1.30     1.35 1.81e- 1
```

$H_0: \beta_{\text{Police}} = 0$ v.s. $H_a: \beta_{\text{Police}} \neq 0$

Significance level: $\alpha = 0.05$ (i.e., 5 percent test)

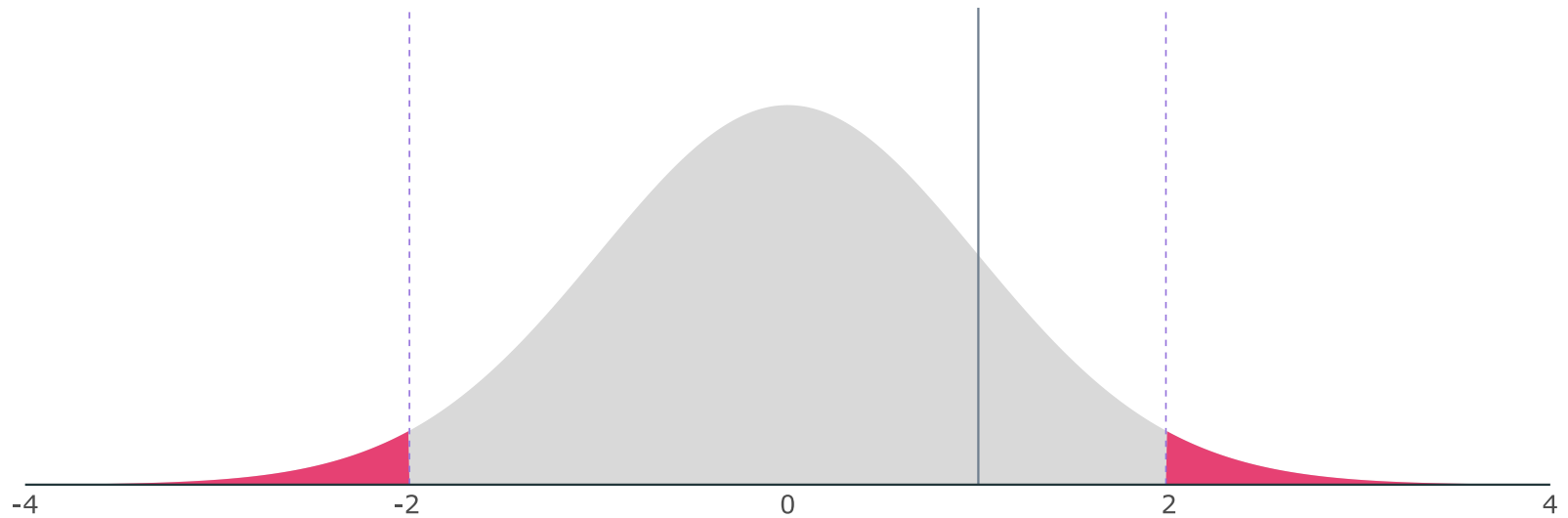
Test Condition: Reject H_0 if $p < \alpha$

$p = 0.18$. **Do we reject the null hypothesis?**

Hypothesis Tests

p -values are difficult to calculate by hand.

Alternative: Compare t -statistic to **critical values** from the t -distribution.



Hypothesis Tests

Notation: $t_{1-\alpha/2, n-2}$ or t_{crit} .

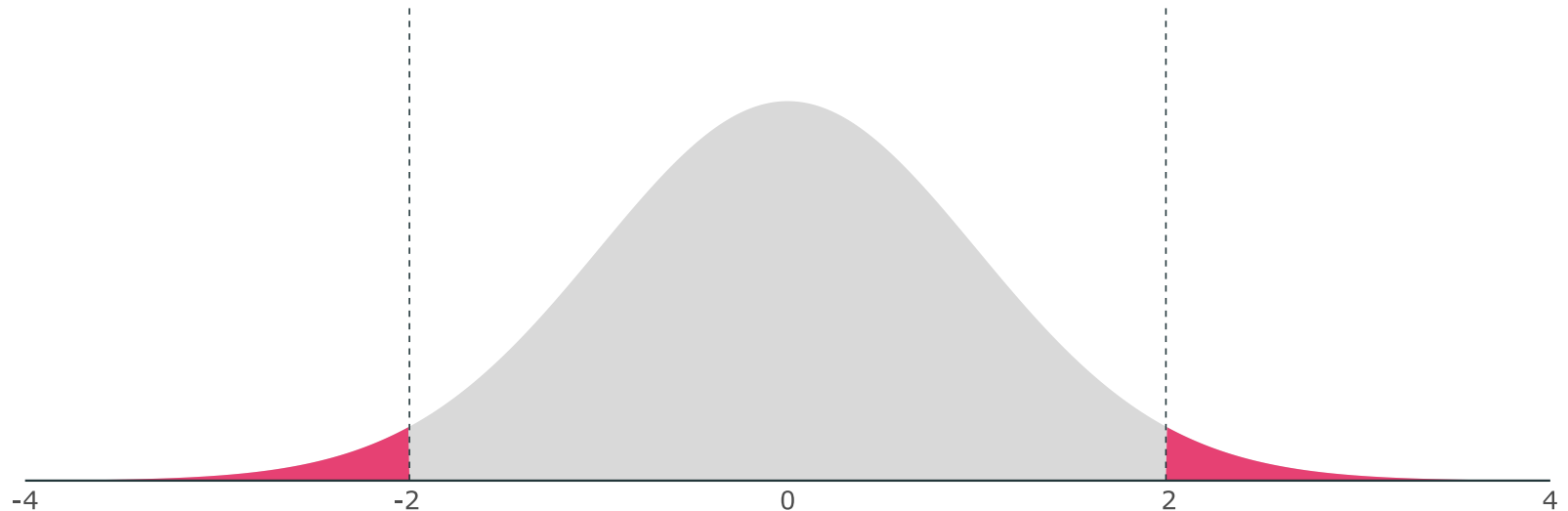
- Find in a t table using the significance level α and $n - 2$ degrees of freedom.

Compare the the critical value to your t -statistic:

- If $|t| > |t_{1-\alpha/2, n-2}|$, then **reject the null**.
- If $|t| < |t_{1-\alpha/2, n-2}|$, then **fail to reject the null**.

Two-Sided Tests

Based on a critical value of $t_{1-\alpha/2, n-2} = t_{0.975, 100} = 1.98$, we can identify a **rejection region** on the t -distribution.



If our t statistic is in the rejection region, then we reject the null hypothesis at the 5 percent level.

Two-Sided Tests

R defaults to testing hypotheses against the null hypothesis of zero.

```
lm(y ~ x, data = pop_df) %>% tidy()
```

```
#> # A tibble: 2 × 5  
#>   term          estimate std.error statistic  p.value  
#>   <chr>          <dbl>    <dbl>    <dbl>    <dbl>  
#> 1 (Intercept)    2.53      0.422      6.00 3.38e- 8  
#> 2 x              0.567     0.0793     7.15 1.59e-10
```

$H_0: \beta_1 = 0$ vs. $H_a: \beta_1 \neq 0$

Significance level: $\alpha = 0.05$ (*i.e.*, 5 percent test)

$t_{\text{stat}} = 7.15$ and $t_{0.975, 28} = 2.05$, which implies that $p < 0.05$.

Therefore, we **reject H_0** at the 5% level.

Two-Sided Tests

Example: Are campus police associated with campus crime?

```
lm(crime ~ police, data = campus) %>% tidy()
```

```
#> # A tibble: 2 × 5  
#>   term          estimate std.error statistic  p.value  
#>   <chr>          <dbl>    <dbl>    <dbl>    <dbl>  
#> 1 (Intercept)    18.4      2.38     7.75 1.06e-11  
#> 2 police         1.76      1.30     1.35 1.81e- 1
```

$H_0: \beta_{\text{Police}} = 0$ v.s. $H_a: \beta_{\text{Police}} \neq 0$

Significance level: $\alpha = 0.1$ (i.e., 10 percent test)

Test Condition: Reject H_0 if $|t| > t_{\text{crit}}$

$t = 1.35$ and $t_{\text{crit}} = 1.66$. **Do we reject the null hypothesis?**

One-Sided Tests

Sometimes we are confident that a parameter is non-negative or non-positive.

A **one-sided** test assumes that values on one side of the null hypothesis are impossible.

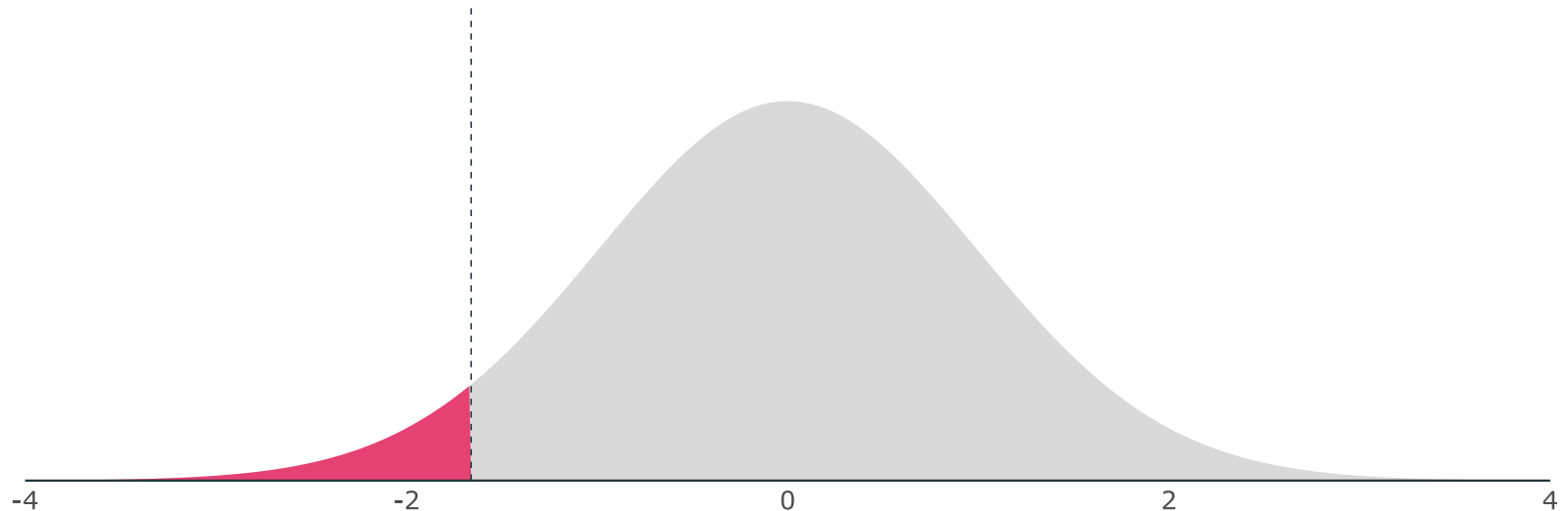
- **Option 1:** $H_0: \beta_1 = 0$ vs. $H_a: \beta_1 > 0$
- **Option 2:** $H_0: \beta_1 = 0$ vs. $H_a: \beta_1 < 0$

If this assumption is reasonable, then our rejection region changes.

- Same α .

One-Sided Tests

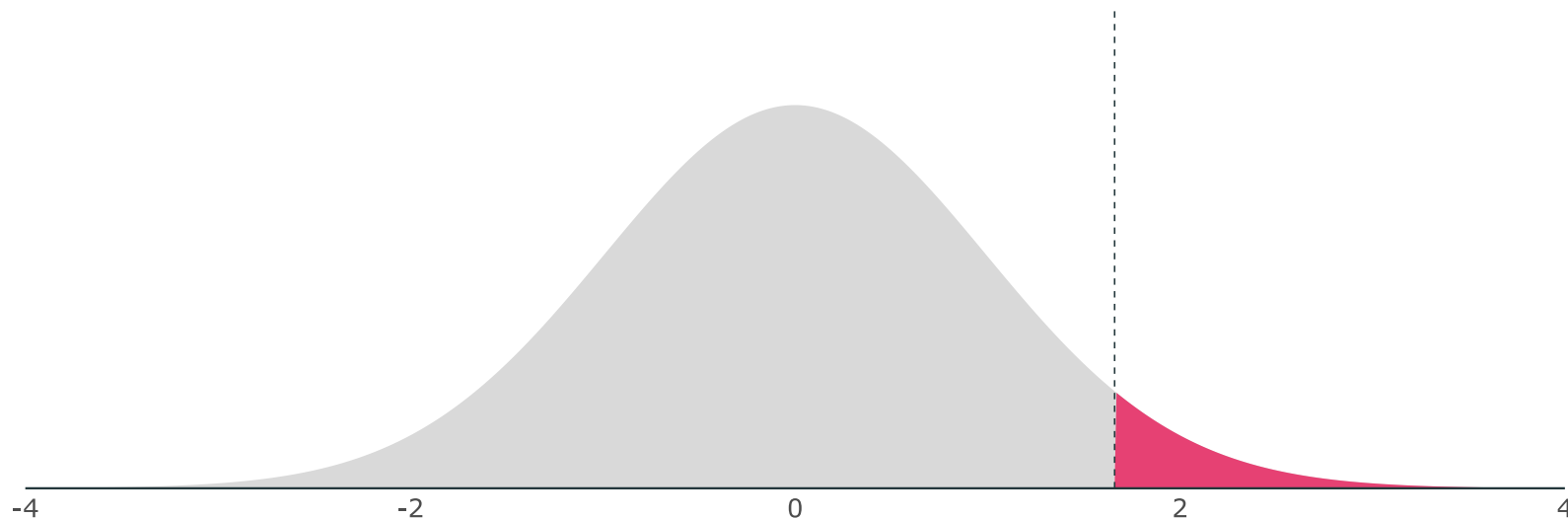
Left-tailed: Based on a critical value of $t_{1-\alpha, n-2} = t_{0.95, 100} = 1.66$, we can identify a **rejection region** on the t -distribution.



If our t statistic is in the rejection region, then we reject the null hypothesis at the 5 percent level.

One-Sided Tests

Right-tailed: Based on a critical value of $t_{1-\alpha, n-2} = t_{0.95, 100} = 1.66$, we can identify a **rejection region** on the t -distribution.



If our t statistic is in the rejection region, then we reject the null hypothesis at the 5 percent level.

One-Sided Tests

Example: Do campus police deter campus crime?

```
lm(crime ~ police, data = campus) %>% tidy()
```

```
#> # A tibble: 2 × 5
#>   term          estimate std.error statistic  p.value
#>   <chr>          <dbl>    <dbl>    <dbl>    <dbl>
#> 1 (Intercept)    18.4      2.38     7.75 1.06e-11
#> 2 police         1.76      1.30     1.35 1.81e- 1
```

$H_0: \beta_{\text{Police}} = 0$ v.s. $H_a: \beta_{\text{Police}} < 0$

Significance level: $\alpha = 0.1$ (i.e., 10 percent test)

Test Condition: Reject H_0 if $t < -t_{\text{crit}}$

$t = 1.35$ and $t_{\text{crit}} = 1.29$. **Do we reject the null hypothesis?**

Confidence Intervals

Confidence Intervals

Until now, we have considered **point estimates** of population parameters.

- Sometimes a range of values is more interesting/honest.

We can construct $(1 - \alpha) \cdot 100$ -percent level confidence intervals for β_1

$$\hat{\beta}_1 \pm t_{1-\alpha/2, n-2} \text{SE}(\hat{\beta}_1)$$

$t_{1-\alpha/2, n-2}$ denotes the $1 - \alpha/2$ quantile of a t distribution with $n - 2$ degrees of freedom.

Confidence Intervals

Q: Where does the confidence interval formula come from?

A: The confidence interval formula comes from the rejection condition of a two-sided test.

Reject H_0 if $|t| > t_{\text{crit}}$

The test condition implies

Fail to reject H_0 if $|t| \leq t_{\text{crit}}$

which is equivalent to

Fail to reject H_0 if $-t_{\text{crit}} \leq t \leq t_{\text{crit}}$.

Confidence Intervals

Replacing t with its formula gives

$$\text{Fail to reject } H_0 \text{ if } -t_{\text{crit}} \leq \frac{\hat{\beta}_1 - \beta_1^0}{\text{SE}(\hat{\beta}_1)} \leq t_{\text{crit}}.$$

Standard errors are always positive, so the inequalities do not flip when we multiply by $\text{SE}(\hat{\beta}_1)$:

$$\text{Fail to reject } H_0 \text{ if } -t_{\text{crit}} \text{SE}(\hat{\beta}_1) \leq \hat{\beta}_1 - \beta_1^0 \leq t_{\text{crit}} \text{SE}(\hat{\beta}_1).$$

Subtracting $\hat{\beta}_1$ yields

$$\text{Fail to reject } H_0 \text{ if } -\hat{\beta}_1 - t_{\text{crit}} \text{SE}(\hat{\beta}_1) \leq -\beta_1^0 \leq -\hat{\beta}_1 + t_{\text{crit}} \text{SE}(\hat{\beta}_1).$$

Confidence Intervals

Multiplying by -1 and rearranging gives

Fail to reject H_0 if

$$\hat{\beta}_1 - t_{\text{crit}} \hat{\text{SE}}(\hat{\beta}_1) \leq \beta_1^0 \leq \hat{\beta}_1 + t_{\text{crit}} \hat{\text{SE}}(\hat{\beta}_1).$$

Replacing β_1^0 with β_1 and dropping the test condition yields the interval

$$\hat{\beta}_1 - t_{\text{crit}} \hat{\text{SE}}(\hat{\beta}_1) \leq \beta_1 \leq \hat{\beta}_1 + t_{\text{crit}} \hat{\text{SE}}(\hat{\beta}_1)$$

which is equivalent to

$$\hat{\beta}_1 \pm t_{\text{crit}} \hat{\text{SE}}(\hat{\beta}_1).$$

Confidence Intervals

Insight: A confidence interval is related to a two-sided hypothesis test.

- If a 95 percent confidence interval contains zero, then we fail to reject the null hypothesis at the 5 percent level.
- If a 95 percent confidence interval does not contain zero, then we reject the null hypothesis at the 5 percent level.
- **Generally:** A $(1 - \alpha) \cdot 100$ percent confidence interval embeds a two-sided test at the $\alpha \cdot 100$ level.

Confidence Intervals

Example

```
lm(y ~ x, data = pop_df) %>% tidy()
```

```
#> # A tibble: 2 × 5  
#>   term          estimate std.error statistic  p.value  
#>   <chr>          <dbl>     <dbl>     <dbl>    <dbl>  
#> 1 (Intercept)    2.53      0.422      6.00 3.38e- 8  
#> 2 x              0.567     0.0793     7.15 1.59e-10
```

```
# find degrees of freedom  
dof ← summary(lm(y ~ x, data = pop_df))$df[2]  
# return critical value  
qt(0.975, dof)
```

```
#> [1] 1.984467
```

95% confidence interval for β_1 is $0.567 \pm 1.98 \times 0.0793 = [0.410, 0.724]$

Confidence Intervals

We have a confidence interval for β_1 , i.e., $[0.410, 0.724]$.

What does it mean?

Informally: The confidence interval gives us a region (interval) in which we can place some trust (confidence) for containing the parameter.

More formally: If we repeatedly sample from our population and construct confidence intervals for each of these samples, then $(1 - \alpha) \cdot 100$ percent of our intervals (e.g., 95%) will contain the population parameter *somewhere in the interval*.

Now back to our simulation...

Confidence Intervals

We drew 10,000 samples (each of size $n = 30$) from our population and estimated our regression model for each sample:

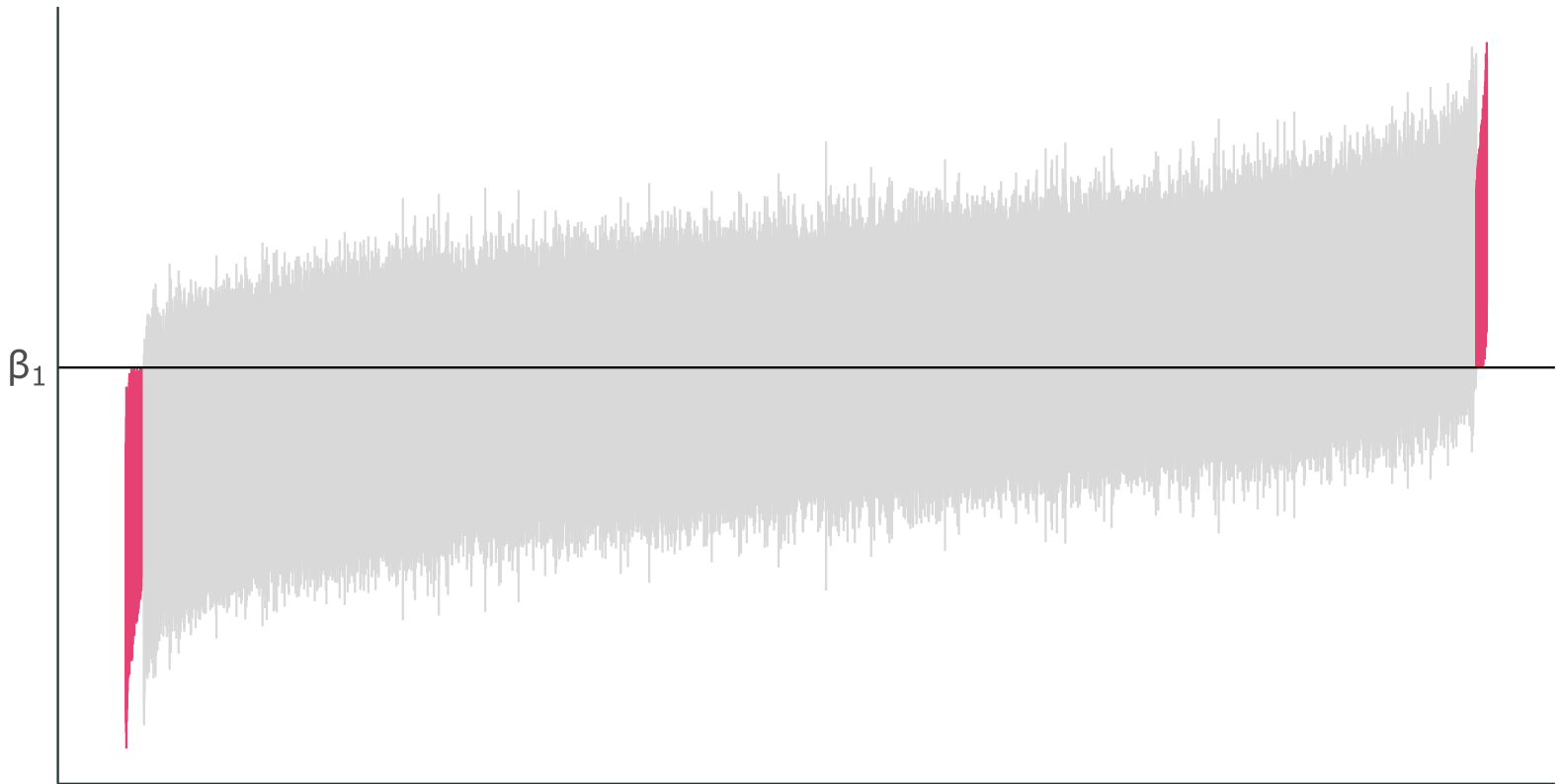
$$Y_i = \hat{\beta}_1 + \hat{\beta}_1 X_i + \hat{u}_i$$

(repeated 10,000 times)

Now, let's estimate 95% confidence intervals for each of these intervals...

Confidence Intervals

From our previous simulation: 97.9% of 95% confidence intervals contain the true parameter value of β_1 .



Confidence Intervals

Example: Association of police with crime

You can instruct `tidy` to return a 95 percent confidence interval for the association of campus police with campus crime:

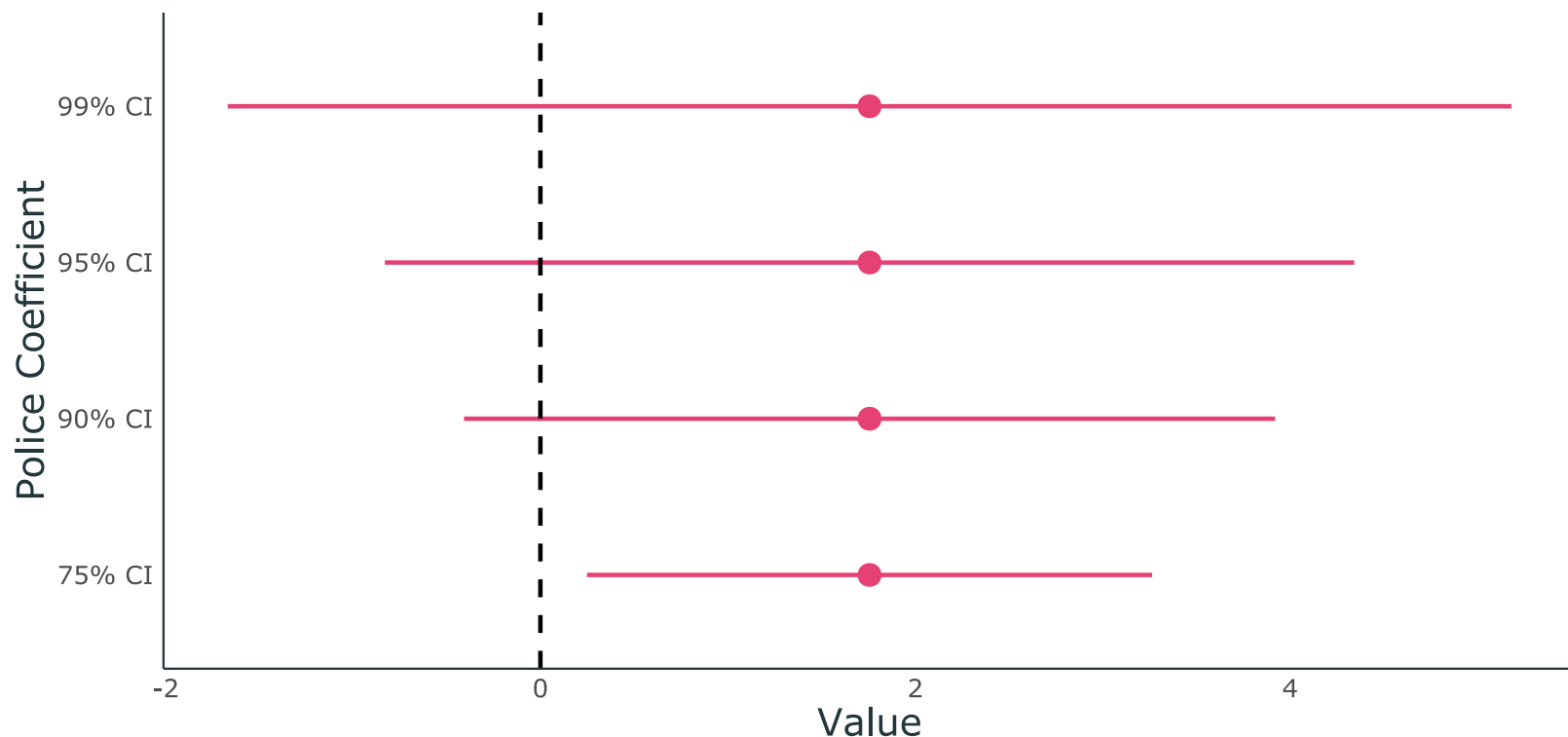
```
lm(crime ~ police, data = campus) %>% tidy(conf.int = TRUE, conf.level = 0.95)
```

```
#> # A tibble: 2 × 7
```

#>	term	estimate	std.error	statistic	p.value	conf.low	conf.high
#>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
#> 1	(Intercept)	18.4	2.38	7.75	1.06e-11	13.7	23.1
#> 2	police	1.76	1.30	1.35	1.81e- 1	-0.830	4.34

Confidence Intervals

Example: Association of police with crime



Four confidence intervals for the same coefficient.