

# Discussion Section

Week 4

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## Test

- I haven't started grading them. Hopefully I will be done with it and the homeworks by the middle of next week
- Study the answer key, understand the questions that you got wrong, none of these concepts are going away

## Office Hours

- I **WILL NOT** have office hours on Monday as it is Labor Day. I will have make-up office hours in the same room (SSH 2143) from 10-11 on Tuesday

# Hypothesis Testing

What is hypothesis testing in a nutshell?

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- Remember that we talked about  $b_0$  and  $b_k$  being random variables
  - That is, they will change with each sample we take from the population
  - The population parameter  $\beta$  will not change and is thus not a random variable
  - This is the same for all random variables and their population parameters (like  $\bar{X}$  and  $\mu_X$ )
- Since these estimates can vary, we want to understand construct some range for  $b$  that we think is “believable”

# Hypothesis Testing

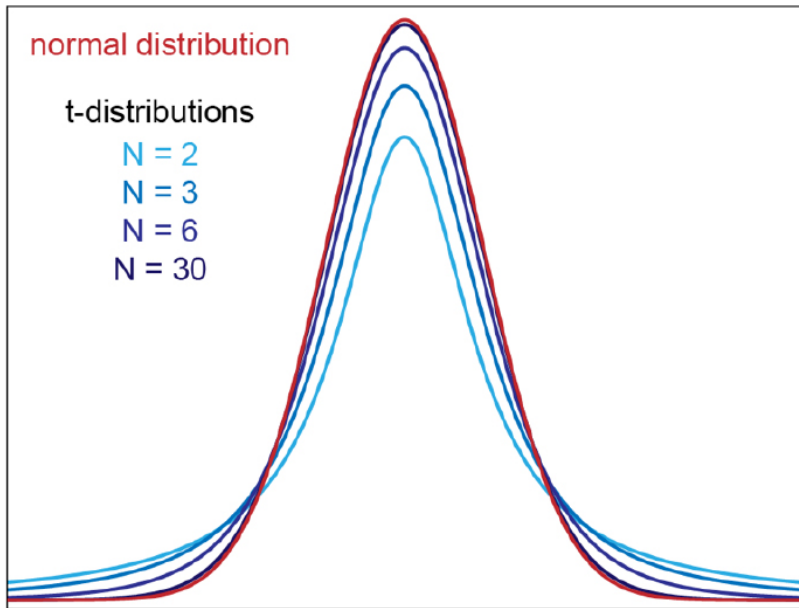
How do we find this range of believable values?

# Hypothesis Testing

How do we find this range of believable values?

- There are a couple of different methods, that will tell us the same result
  - Its good to know all of them since they will tell you the same answer, but explain it in a different way
- All three of these methods revolve around the t-distribution
  - The t-distribution is very similar to a normal distribution, but its a bit “fatter”
  - This distribution is supposed to be like a normal distribution that accounts for sample size
  - The larger the sample, the more the t-distribution looks like the normal distribution

# Hypothesis Testing



Why would we base this on the normal distribution?



# Hypothesis Testing

Why would we base this on the normal distribution?

- There is a statistical theorem which essentially states that the average of a random variable is normally distributed
- The OLS  $b$  coefficients can be understood as a type of average
  - This means that the theorem can apply to OLS  $b$  coefficients
- This means that if we collected many samples from a population and ran the same regression on all of them, then plotted the values of the  $bs$  we found it would look like a bell curve
- We can then treat our  $b$  values as a point on a bell curve

# Hypothesis Testing

What can we do with this knowledge?

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- Let's say we run a regression with 100 observations and get the following results:

$$b_0 = 2$$

$$b_1 = 2$$

$$s.e.(b_0) = 2$$

$$s.e.(b_1) = 1$$

- We know that  $b_0$  and  $b_1$  are random variables, what if we want to know the likelihood that  $b_1 = 5$ ?
- We can use the fact that  $b$  is a random variable and is essentially normally distributed to understand how likely this is
- A better way to phrase this question is: "If 5 is the true population  $\beta$ , how likely would it be that I find  $b_1 = 3$  in a random sample?"
  - This type of question is what we call a "hypothesis test"
  - $b_1 = 5$  is called our "null hypothesis ( $H_0$ )" where  $b_1 \neq 5$  is our alternative hypothesis ( $H_A$ )

# Hypothesis Testing

How do we conduct a hypothesis test?

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How do we conduct a hypothesis test?

- To find how likely it is to see our sample estimate, given that our hypothesis is true, we want to “normalize” our data
  - This takes that distribution of  $b$ s we talked about before and makes its mean = 0 and its variance = 1
  - This will allow us to translate our  $b_1$  estimate into “standard deviations from the mean” as opposed to just a number
  - This will let us find the probability of getting  $b_1 = 3$  given the “fact” that  $\beta = 5$
- Since we are asking “If 5 is the true population parameter...” our unnormalized hypothetical distribution would be centered on 5
  - To make its mean = 0, we would have to subtract 5
- We then want to make the variance of the distribution = 1
  - To do this, we would want to just divide by the population standard deviation
  - We don’t have this, so we will divide by the sample standard deviation and use the t-distribution instead of the normal distribution

# Hypothesis Testing

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- From our example:

$$\frac{3 - 5}{1} = -2$$

- From this process we get a “t-score”. Our t-score is -2. This means that **IF** the true  $\beta$  were 5, our estimate would be -2 standard deviations from the mean
- Since we normalized our distribution, we can actually calculate the probability of getting an estimate that is -2 standard deviations from the mean



# Hypothesis Testing

- If we were to look at a t-table and find this probability we would find that there is a roughly 5% chance of this happening
  - This is called a “p-value”
  - We can define a p-value as: “The probability that we would find our estimate (or bigger) from a random sample, conditional on our null hypothesis being true”
  - We would denote this as  $p = .05$
- We then have to ask ourselves if this seems reasonable?
- If our hypothesis is true, we would only expect to see a value this far from the mean one in every 20 samples
- In economics, this is the standard cut-off, although this is up for debate as it is totally subjective
- Typically, if a t-test yields a p-value that is less than or equal to .05, we say that we “reject the null hypothesis”

# Hypothesis Testing

The logic of hypothesis testing is a bit like this:

- Pretend our hypothesis is true
- See how likely/unlikely our sample would have to be to get the estimate that we actually found
- If it seems very unlikely that we would get a sample that would give us the result we found, we say that our hypothesis must be wrong
  - We then “reject” the null hypothesis
- If it seems likely that we would get a sample that would give us the result we found, we say that we can’t necessarily reject the null hypothesis
  - We then “fail to reject” the null hypothesis
- We never say that we “accept” the null hypothesis, this is because we will fail to reject a lot of null hypothesis

# Hypothesis Testing

To understand this, let's look at  $b_0$  from our example regression:

$$b_0 = 2$$

$$b_1 = 2$$

$$s.e.(b_0) = 2$$

$$s.e.(b_1) = 1$$

- Let's test if  $b_0 = 1$
- we can find our t-score first:

$$\frac{2 - 1}{2} = .5$$

- If we were to look up the probability of being .5 standard deviations from the mean on a t-distribution with 99 degrees of freedom we would find  $p = .618$
- This means that in about 60% of samples we would expect to see an estimate this far from the mean
- This falls short of the standard  $p = .05$  cut-off and thus, we would fail to reject the null hypothesis.

# Hypothesis Testing

- What if we instead tested of  $b_0 = 1.1$ ?

$$\frac{2 - 1.1}{2} = .45 \Rightarrow p = .653$$

- We would again fail to reject the null hypothesis
- In fact, we will fail to reject a range of null hypotheses, this range is called a “confidence interval”, it gives us all of the values that we would fail to reject
- To calculate a two sided confidence interval we find:

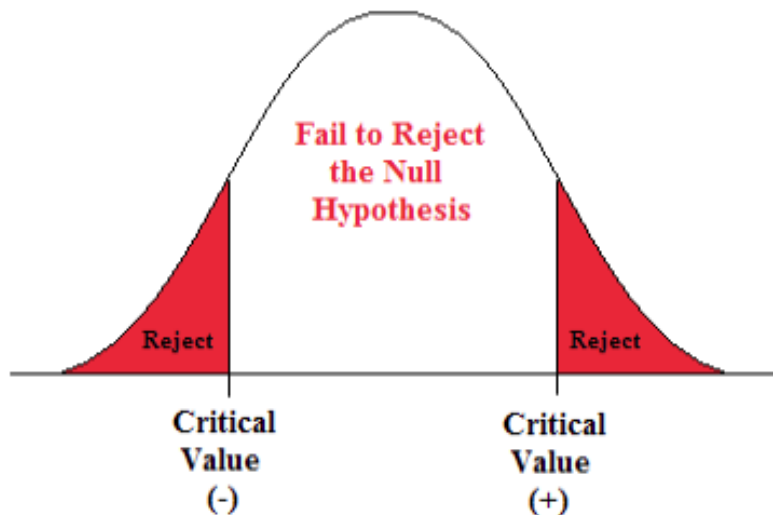
$$b \pm t_{crit} \times s.e.(b)$$

In our example the confidence interval for  $b_0$  is:

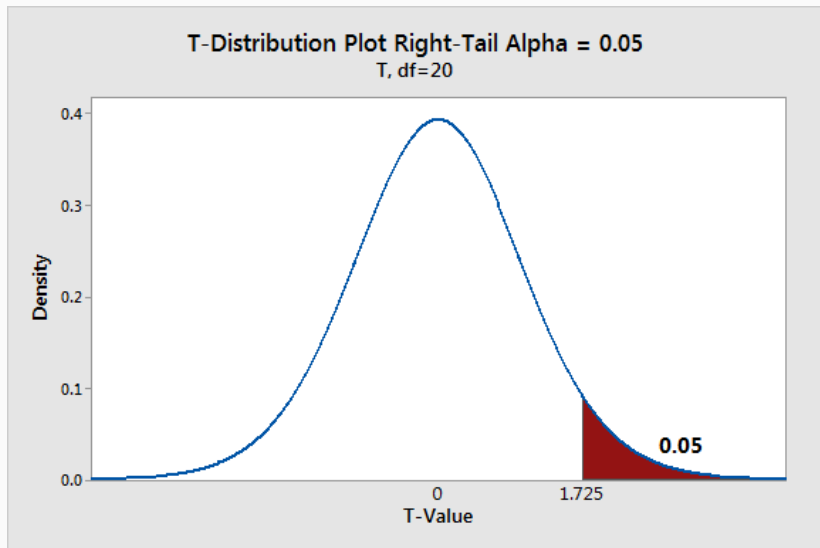
$$2 \pm 2 * 1.96 = (1.92, 5.92)$$

- That means, if you test if  $b_0$  is any number between 1.92 and 5.92, you will fail to reject the null hypothesis
- On the other hand, if you test if  $b_0$  is any number outside of this interval, you will reject the null hypothesis

# Hypothesis Testing



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All of this is so interesting and cool, but why exactly would we do this?

- We typically test to see if a coefficient that we are interested in is “statistically different from 0”
- If  $b$  is statistically different from 0, then if we make 0 our null hypothesis, we would reject the null
- Remember that  $b$  represents the effect of  $x$  on  $y$ , thus if we fail to reject that  $b = 0$  we are failing to reject that **there is no effect**
- When we reject the null we say that the result is *statistically significant*
  - This means that we don't think that the true  $\beta$  could be 0, thus there is some effect of  $x$  on  $y$



## Hypothesis Testing

	coef	std err	t	P> t	[0.025	0.975]
Intercept	3.9650	0.711	5.577	0.000	2.552	5.378
LSAT	0.0329	0.006	5.165	0.000	0.020	0.046
GPA	0.4152	0.141	2.955	0.004	0.136	0.695

# Hypothesis Testing

Another helpful test is the Wald Statistic

- This test allows us to compare two different regression models
- To do this, we essentially compare the  $R^2$  of the regression:

$$\frac{R_{alt}^2 - R_{null}^2}{(1 - R_{alt}^2)/(N - K_{alt} - 1)}$$

- Instead of following a t-distribution, this test statistic will follow a Chi-squared distribution where the degrees of freedom is the number of variables that are different between the regressions
- What this test is actually doing is simultaneously doing a t-test on all of the variables that are in the alt regression but not the null

# Hypothesis Testing

## BIG TAKEAWAYS

- t-test gives us how many standard deviations our estimate would be away from the mean **if** our null hypothesis were true
  - Critical value at 5% confidence level is 1.96 for a two-sided test and 1.645 for a one-sided test (assuming a large sample)
- p-value gives us the probability of getting a sample which would give us our estimate or a more extreme one
  - For either test, the critical p-value is always just  $p = .05$  at the 5% confidence level
- Confidence interval tells us all of the null hypotheses we would not reject (and all of the ones we would)
- Wald statistic lets us compare regressions