LECTURE 5

Introduction to Econometrics

Hypothesis testing

October 18, 2016

◆□ ▶ < @ ▶ < ≧ ▶ < ≧ ▶ ≧ りへで 1/26

ON TODAY'S LECTURE

- We are going to discuss how hypotheses about coefficients can be tested in regression models
- ► We will explain what significance of coefficients means
- We will learn how to read regression output
- Readings for this week:
 - ► Studenmund, Chapter 5.1 5.4
 - Wooldridge, Chapter 4

QUESTIONS WE ASK

- ► What conclusions can we draw from our regression?
- What can we learn about the real world from a sample?
- Is it likely that our results could have been obtained by chance?
- If our theory is correct, what are the odds that this particular outcome would have been observed?

HYPOTHESIS TESTING

- We cannot prove that a given hypothesis is "correct" using hypothesis testing
- ► All that can be done is to state that a particular sample conforms to a particular hypothesis
- We can often reject a given hypothesis with a certain degree of confidence
- In such a case, we conclude that it is very unlikely the sample result would have been observed if the hypothesized theory were correct

NULL AND ALTERNATIVE HYPOTHESES

- First step in hypothesis testing: state explicitly the hypothesis to be tested
- Null hypothesis: statement of the range of values of the regression coefficient that would be expected to occur if the researcher's theory were *not* correct
- Alternative hypothesis: specification of the range of values of the coefficient that would be expected to occur if the researcher's theory were correct
- In other words: we define the null hypothesis as the result we do not expect

NULL AND ALTERNATIVE HYPOTHESES

► Notation:

- $H_0 \dots$ null hypothesis
- H_A ... alternative hypothesis
- ► Examples:
 - ► One-sided test ► Two-sided test

TYPE I AND TYPE II ERRORS

- It would be unrealistic to think that conclusions drawn from regression analysis will always be right
- There are two types of errors we can make
 - ► Type I : We reject a true null hypothesis
 - ► Type II : We do not reject a false null hypothesis
- ► Example:
 - $H_0: \beta = 0$
 - $H_A: \beta \neq 0$
 - Type I error: it holds that $\beta = 0$, we conclude that $\beta \neq 0$
 - Type II error: it holds that $\beta \neq 0$, we conclude that $\beta = 0$

TYPE I AND TYPE II ERRORS

- ► Example:
 - H_0 : The defendant is innocent
 - H_A : The defendant is guilty
 - ► Type I error = Sending an innocent person to jail
 - ► Type II error = Freeing a guilty person
- Obviously, lowering the probability of Type I error means increasing the probability of Type II error
- In hypothesis testing, we focus on Type I error and we ensure that its probability is not unreasonably large

DECISION RULE

- 1. Calculate sample statistic
- 2. Compare sample statistic with the *critical value* (from the statistical tables)
- The critical value divides the range of possible values of the statistic into two regions: *acceptance region* and *rejection region*
 - ► If the sample statistic falls into the rejection region, we reject *H*₀
 - ► If the sample statistic falls into the acceptance region, we do not reject *H*₀
- ► The idea is that if the value of the coefficient does not support H₀, the sample statistic should fall into the rejection region

ONE-SIDED REJECTION REGION

- $H_0: \beta \leq 0$ vs $H_A: \beta > 0$
- Distribution of $\hat{\beta}$:



TWO-SIDED REJECTION REGION

- $H_0: \beta = 0$ vs $H_A: \beta \neq 0$
- Distribution of $\hat{\beta}$:



THE *t*-TEST

- We use *t*-test to test hypothesis about individual regression slope coefficients
- ► Test of more than one coefficient at a time (joint hypotheses) are typically done with the *F*-test (see next lecture)
- The *t*-test is appropriate to use when the stochastic error term is normally distributed and when the variance of that distribution is unknown
 - These are the usual assumptions in regression analyses
- The *t*-test accounts for differences in the units of measurement of the variables

THE *t*-test

Consider the model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$$

• Suppose we want to test (*b* is some constant)

$$H_0: \beta_1 = b$$
 vs $H_A: \beta_1 \neq b$

 \sim

We know that

$$\widehat{\beta}_1 \sim N\left(\beta_1, Var(\widehat{\beta}_1)\right) \Rightarrow \frac{\widehat{\beta}_1 - \beta_1}{\sqrt{Var(\widehat{\beta}_1)}} \sim N(0, 1)$$

THE *t*-TEST

- Problem: $Var(\hat{\beta}_1)$ depends on the variance of error term σ^2 , which is unobservable and therefore unknown
- It has to be estimated as

$$\hat{\sigma}^2 := s^2 = \frac{\mathbf{e}'\mathbf{e}}{n-k} \; \; ,$$

k is the number of regression coefficients (here k = 3) **e** is the vector of residuals

We denote standard error of β₁ (sample counterpart of standard deviation σ_{β1}) as s.e. (β₁)

THE *t*-TEST

• We define the *t*-statistic

$$t := \frac{\widehat{\beta}_1 - \beta_1}{s.e.\left(\widehat{\beta}_1\right)} \sim t_{n-k}$$

where $\hat{\beta}_1$ is the estimated coefficient and β_1 is the value of the coefficient that is stated in our hypothesis

This statistic depends only on the estimate β
₁, our hypothesis about β₁, and it has a known distribution

TWO-SIDED *t*-TEST

Our hypothesis is

$$H_0: \beta_1 = b$$
 vs $H_A: \beta_1 \neq b$

► Hence, our *t*-statistic is

$$t = \frac{\widehat{\beta}_1 - b}{s.e.\left(\widehat{\beta}_1\right)}$$

- where $\hat{\beta}_1$ is the estimated regression coefficient of β_1
- ► *b* is the constant from our null hypothesis
- *s.e.* $(\widehat{\beta}_1)$ is the estimated standard error of $\widehat{\beta}_1$

TWO-SIDED *t*-TEST

How to determine the *critical value* for this test statistic?

- ► The critical value is the value that distinguishes the acceptance region from the rejection region
- 1. We set the probability of Type I error
 - Let's set the Type I. error to 5%
 - ► We say the *p*-value of the test is 5% or that we have a test at 95% confidence level
- 2. We find the critical values in the statistical tables: $t_{n-k,0.975}$ and $t_{n-k,0.025}$
 - ► The critical value depends on the chosen level of Type I error and *n* − *k*
 - Note that $t_{n-k,0.975} = -t_{n-k,0.025}$

TWO-SIDED *t*-TEST



• We reject H_0 if $|t| > t_{n-k,0.975}$

ONE-SIDED *t***-TEST**

Suppose our hypothesis is

$$H_0: \beta_1 \leq b \quad \text{vs} \quad H_A: \beta_1 > b$$

Our *t*-statistic still is

$$t = \frac{\widehat{\beta}_1 - b}{s.e.\left(\widehat{\beta}_1\right)}$$

- ► We set the probability of Type I error to 5%
- We compare our statistic to the critical value $t_{n-k,0.95}$

ONE-SIDED *t***-TEST**



• We reject H_0 if $t > t_{n-k,0.95}$

SIGNIFICANCE OF THE COEFFICIENT

The most common test performed in regression is

$$H_0: \beta = 0$$
 vs $H_A: \beta \neq 0$

with the *t*-statistic

$$t = \frac{\widehat{\beta}}{s.e.\left(\widehat{\beta}\right)} \sim t_{n-k}$$

- If we reject $H_0: \beta = 0$, we say the coefficient β is *significant*
- This *t*-statistic is displayed in most regression outputs

THE *p*-VALUE

- Classical approach to hypothesis testing: first choose the significance level, then test the hypothesis at the given level of significance (e.g. 5%)
 - ► However, there is no "correct" significance level.
- Or we can ask a more informative question:
 - ► What is the smallest significance level at which the null hypothesis would still be rejected?
 - This level of significance is known as the *p*-value.
 - Remember that the significance level describes the probability of type I. error. The smaller the *p*-value, the smaller the probability of rejecting the true null hypothesis (the bigger the confidence the null hypothesis is indeed correctly rejected).
 - ► The *p*-value for H₀ : β = 0 is displayed in most regression outputs

EXAMPLE

Let us study the impact of years of education on wages:

 $wage = \beta_0 + \beta_1 education + \beta_2 experience + \varepsilon$

Output from Gretl:

Model 3: OLS, using observations 1-526 Dependent variable: wage

	coeffic	cient	std.	erro	r t-ratio	о р	-value	
const	-3.39054		0.766566		-4.423	1	.18e-05	***
educ	0.644272		0.0538061		11.97	2	.28e-29	***
exper	0.0700954		0.0109776		6.385	3	.78e-10	***
lean dependent var		5.896103		S.D. dependent va		var	r 3.693086	
Sum squared	resid	5548.1	L60	S.E.	of regress	sion	3.2570	944
R-squared		0.2251	162	Adju	sted R-squa	ared	0.2223	199
(2, 523)		75.989	998	P-va	lue(F)		1.07e	- 29
_og-likeliho	od	-1365.9	969	Akai	ke criterio	on	2737.9	937
Schwarz criterion		2750.733		Hann	an-Quinn		2742.9	948

CONFIDENCE INTERVAL

 A 95% confidence interval of β is an interval centered around β such that β falls into this interval with probability 95%

$$P\left(\widehat{\beta} - c < \beta < \widehat{\beta} + c\right) =$$
$$= P\left(-\frac{c}{s.e.\left(\widehat{\beta}\right)} < \frac{\widehat{\beta} - \beta}{s.e.\left(\widehat{\beta}\right)} < \frac{c}{s.e.\left(\widehat{\beta}\right)}\right) = 0.95$$

• Since $\frac{\widehat{\beta}-\beta}{s.e.(\widehat{\beta})} \sim t_{n-k}$, we derive the confidence interval:

$$\widehat{\beta} \pm t_{n-k,0.975} \cdot s.e.\left(\widehat{\beta}\right)$$

4 ロ ト 4 部 ト 4 差 ト 4 差 ト 差 少 9 (や 24 / 26

CONFIDENCE INTERVAL

Output from Gretl (wage regression):

Model 3: OLS, using observations 1-526 Dependent variable: wage

	coeffic	ient	std.	error	t-ratio	p - v	alue	
const educ exper	-3.3905 0.6442 0.0700	54 272)954	0.76 0.05 0.01	6566 38061 09776	-4.423 11.97 6.385	1.1 2.2 3.7	8e-05 8e-29 8e-10	*** *** ***
Mean depende Sum squared R-squared F(2, 523) Log-likelihe Schwarz cri ¹	ent var resid pod terion	5.896 5548. 0.225 75.98 -1365. 2750.	5103 160 5162 8998 969 733	S.D. d S.E. o Adjust P-valu Akaike Hannan	ependent va f regressio ed R-squarc e(F) criterion -Quinn	ar on ed	3.6930 3.2570 0.2221 1.07e- 2737.9 2742.9)86)44 99 29 37 37

- Confidence interval for coefficient on education: $\hat{\beta} \pm t_{n-k,0.975} \cdot s.e.(\hat{\beta}) = 0.644 \pm 1.960 \cdot 0.054$
- ▶ $\hat{\beta} \in [0.538; 0.750]$ with 95% probability

SUMMARY

- ► We discussed the principle of hypothesis testing
- We derived the *t*-statistic
- ► We defined the concept of the *p*-value
- ► We explained what significance of a coefficient means
- We observed a regression output on an example