

# The multiple regression model: Inference

Chapters 4: Introductory Econometrics 771

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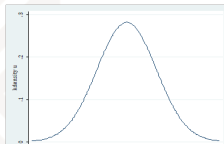
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- 1 Distributional assumptions about  $\hat{\beta}$
- 2 Testing hypotheses about a single population parameter: The T-test
  - One-sided alternatives
  - Two-sided alternatives
- 3 Confidence intervals
- 4 Testing hypotheses about a single linear combination of parameters
- 5 Testing multiple linear restrictions – the F test
- 6 Testing General Linear Restrictions

$\hat{\beta}_j$  is estimated using **one** possible sample of **many** from the population: they are therefore **random variables**

- ▶ Statistical **theory**: estimates unbiased  $E(\hat{\beta}_j|X) = \beta_j$  under **MLR 1-4**
- ▶ Adding **MLR5** gives a formula for how "spread" out the distributions of the random variables are:  $Var(\hat{\beta}_j|X) = (X'X)^{-1} \sigma^2$ 
  - Only *one* of many possible samples observed (=no variation), need formula
- ▶ Still don't know about the **shape** of the distribution
  - All we know: distribution of  $\hat{\beta}_j$  depends on distribution of  $\hat{u}$
- ▶ Add **MLR.6 – NORMALITY**
  - Errors normally distributed  $u \sim N(0; \sigma^2)$  & independent of  $X$



## ► Recall

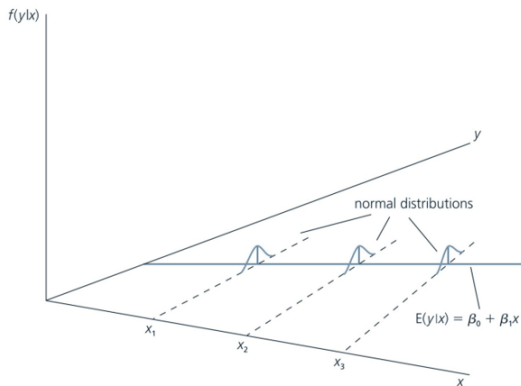
$$\begin{aligned}\hat{\beta} &= \beta + (X'X)^{-1}X'u \\ &= \beta + \sum_{i=1}^n (\mathbf{x}_i\mathbf{x}_i')^{-1}\mathbf{x}_iu_i\end{aligned}$$

- ...or a function of a sum containing  $u_i$
  - A linear combination of  $u_i \sim N$  is normally distributed
  - Therefore  $\hat{\beta}$  is normally distributed if we assume  $u_i \sim N$
- Put it all together:
- From MLR1-4:  $E(\hat{\beta}_j|X) = \beta_j$
  - From MLR5: we get formula for  $Var(\hat{\beta}_j|X)$
  - Now add MLR6:  $\hat{\beta}_j \sim N(\beta_j; Var(\beta_j))$

$$u \sim N(0; \sigma^2)$$
$$\Rightarrow y|\mathbf{x} \sim N(\beta_0 + \beta_1 x_1 + \dots + \beta_k x_k; \sigma^2) \text{ if MLR1-6 hold}$$

FIGURE 4.1

The homoskedastic normal distribution with a single explanatory variable.



- ▶ Generally valid by the **Central Limit Theorem**
  - Residuals represent unmodelled variables
  - Sum of many independently distributed variables  $\rightarrow$  normal distribution when  $n$  is “large”
  - But we need to establish empirically whether this holds ( $S \rightarrow 0; K \rightarrow 3$ )
  - Sometimes transformations of variables can introduce normality
    - ▶  $\log(\text{Price}), \log(\text{Income})$
- ▶ But also convenient
  - Now  $\hat{\beta}_j$  are also normally distributed by properties of normal distribution (linear combination of normal residuals are normally distributed)
  - Normal distribution defined completely by its mean and variance
  - Normality allows us to construct other test statistics ( $F$ ,  $T$  and  $\chi^2$ ) to test a variety of hypotheses

- ▶ Slight adjustment: if  $u \sim \text{Normal} \Rightarrow \hat{\beta}_j$  has a *t-distribution* **when** we **estimate**  $\hat{\sigma}^2 = \frac{SSR}{n-k-1}$  which is contained in  $se(\hat{\beta}_j)$  - this is *usually* the case

$$T = \frac{\hat{\beta}_j - \beta_j}{se(\hat{\beta}_j)}$$

- ▶ Normality is only a valid assumption if population  $\sigma^2$  is known
  - *t*-distribution is flatter and wider to account for additional uncertainty that comes from estimating  $\hat{\sigma}^2$
  - As  $n$  grows large, a *t* distribution tends towards a normal distribution (it grows flatter and more symmetric)
    - ▶ Normal is a relevant and frequent special case of the *t* distribution

► Hypotheses about **population** parameters

- Question: is it possible that a **sample** estimate could have been drawn from a population with hypothesised properties?

$$PRF : \log(wage) = \beta_0 + \beta_1 educ + \beta_2 exp + \beta_3 tenure + u$$

- Does tenure influence wages once we have controlled for education and experience? **OR** is  $\beta_3 = 0$  in the population?



- ▶ Hypothesise a population value of estimate ( $\beta^*$ )

$$H_0 : \beta_j = \beta^*$$

$$H_a : \beta_j \neq \beta^*$$

- How “close” is estimated value to the hypothesised population value?
  - ▶ Too far – **reject** the possibility
  - ▶ Close enough – **do not reject**
- How close is “close” – depends on **distribution** of estimate
- ▶ Particular case:
  - Does x have an influence on y once other variables are controlled for?

$$H_0 : \beta_j = 0$$

$$H_a : \beta_j \neq 0$$

Insert hypothesised value:  $T = \frac{\hat{\beta}_j - 0}{se(\hat{\beta}_j)} \sim t_{n-(k+1)}$

- ▶ We assume (hypothesise) a specific population distribution
  - Then we “place” the estimate in the context of the hypothesised distribution
  - If the hypothesised value is “too far” from the mean of this distribution, then we reject this hypothesised population value
    - ▶ Gives us a sense of what probability that estimate could be drawn from specific population
  - For instance, a large  $T$  value will be far from 0 in absolute value
    - ▶ Because  $\hat{\beta}$  is large and  $se(\hat{\beta})$  is low
  - We then reject that the estimate is 0 (ie there **IS** a relationship)
  - Statistically SIGNIFICANT
- ▶ Note that we do not “accept” a hypothesis if it is “too close”
  - We simply “do not reject”

$$H_0 : \beta_j = 0$$

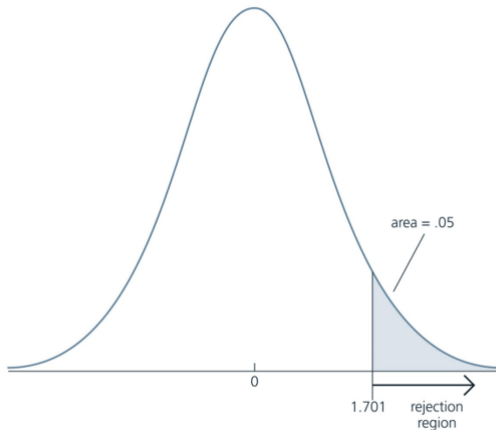
$$H_a : \beta_j > 0$$

- ▶ Choose *significance level* ( $\alpha$ )
  - The probability of rejecting  $H_0$  when it could be true
    - ▶ Usually 1%, 5%, 10%
  - Acknowledging that we could be making mistakes in the process
- ▶ Establish “sufficiently” large value of  $\hat{\beta}_j$  where we conclude that it is “sufficiently” likely to be larger than zero
  - CRITICAL value
  - 95th percentile of *theoretical*  $t$ -distribution if 5% level of significance
- ▶ Rejection rule
  - If *calculated*  $T$  is larger than *critical*  $t$ , reject  $H_0$  in favour of  $H_a$

- ▶ Degrees of freedom (see tables)
  - $n - k - 1$
- ▶ Level of significance ( $\alpha$ ) chosen
  - "Statistically (in)significant"
- ▶ Whether it is a one or two-tailed test
  - Always draw a picture and make sure how you split the distribution
  - Will see later...

FIGURE 4.2

5% rejection rule for the alternative  $H_1: \beta_1 > 0$  with 28 df.



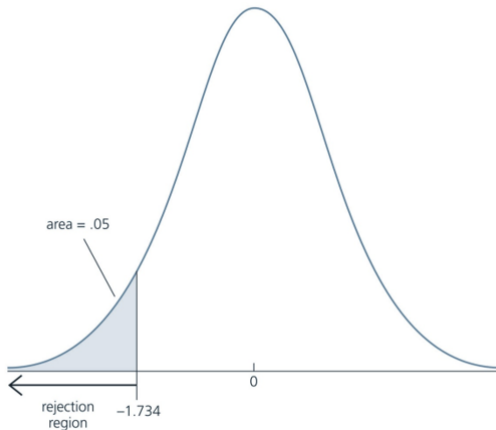
$$H_0 : \beta_j = 0$$

$$H_a : \beta_j < 0$$

- ▶ Very similar for testing whether estimate is negative
- ▶ Except now our rejection region is in bottom tail of distribution
  - And critical  $t$  is just the negative of the previous
  - Now if calculated value is *smaller* than the critical value, reject  $H_0$  in favour of  $H_a$ 
    - ▶ Same as taking the absolute value of the critical value and rejecting if calculated  $T$  is larger
    - ▶ Symmetry of T-distribution

FIGURE 4.3

5% rejection rule for the alternative  $H_1: \beta_1 < 0$  with 18 df.



- ▶ Test whether  $H_0 : \beta_{educ} = 0$  or  $H_a : \beta_{educ} > 0$  at a 5% level of significance

$$T = \frac{\hat{\beta}_{educ} - 0}{se(\hat{\beta}_{educ})} = \frac{0.1816909 - 0}{0.0019129} = 94.981$$

$$d.f. = n - (k + 1) = 23436 - (3 + 1) = 23432$$

$$t_{23432;0.95} = 1.645$$

$T > t \Rightarrow$  Reject  $H_0 \Rightarrow$  Statistically significant at a 100-95%=5% level

```
. reg lwage educ exp exp2
```

Source	SS	df	MS
Model	8719.68073	3	2906.56024
Residual	20693.8116	23432	.883143204
Total	29413.4923	23435	1.25510955

Number of obs = 23436  
F( 3, 23432) = 3291.15  
Prob > F = 0.0000  
R-squared = 0.2965  
Adj R-squared = 0.2964  
Root MSE = .93976

lwage1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
educ	.1816909	.0019129	94.98	0.000	.1779414 .1854404
exp	.0365736	.0018376	19.90	0.000	.0329718 .0401754
exp2	-.0002069	.0000351	-5.89	0.000	-.0002757 -.0001381
_cons	-.3953021	.0299979	-13.18	0.000	-.4540999 -.3365043



- ▶ Test whether  $H_0 : \beta_{\text{exper}^2} = 0$  or  $H_a : \beta_{\text{exper}^2} < 0$  at a 1% level of significance

$$T = \frac{\hat{\beta}_{\text{educ}} - 0}{\text{se}(\hat{\beta}_{\text{educ}})} = \frac{-0.0002069 - 0}{0.0000351} = -5.8946 \Rightarrow |T| = 5.8646$$

$$d.f. = n - (k + 1) = 23436 - (3 + 1) = 23432$$

$$t_{23432;0.99} = 2.326$$

$|T| > t \Rightarrow \text{Reject } H_0 \Rightarrow \text{Statistically significant}$

```
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```

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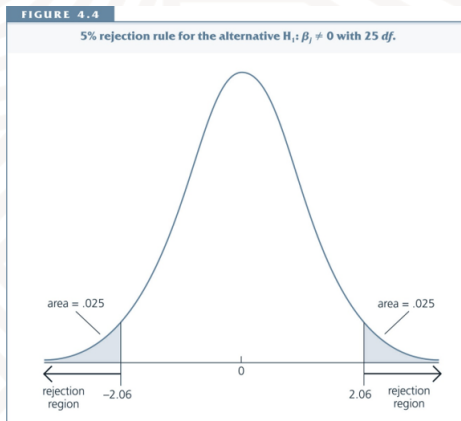
$$H_0 : \beta_j = 0$$

$$H_a : \beta_j \neq 0$$

- ▶ This is the usual format used in hypothesis testing
  - Do not specify whether the effect is positive or negative a priori
  - We say it could be larger OR smaller than 0

“Split” the critical area:  $0.025 + 0.025 = 0.05 \Rightarrow 5\%$  level of significance

- ▶ **Reject** if  $T$  is *above* the *upper* critical value **or** *below* lower critical value
- ▶ Equivalent to checking whether  $|T|$  is larger than upper critical value



- Test whether  $H_0 : \beta_{\text{experience}} = 0$  or  $H_a : \beta_{\text{experience}} \neq 0$

$$T = \frac{\hat{\beta}_{\text{exp}} - 0}{\text{se}(\hat{\beta}_{\text{exp}})} = \frac{0.0365736 - 0}{0.0018376} = 19.90$$

$$d.f. = n - (k + 1) = 23436 - (3 + 1) = 23432$$

$$t_{23432; 0.995} = 2.576 \text{ (where } 0.995 = 0.005 + 0.99)$$

$|T| > t \Rightarrow \text{Reject } H_0 \Rightarrow \text{Statistically significant at 1\% level}$

. reg lwage educ exp exp2

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► Test for  $\beta_{\text{numeracy}}$ ?

$$T = -0.08$$

$$t_{19;0.975} = 2.093$$

$|T| < t \Rightarrow$  Do **not** reject  $H_0 \Rightarrow$  Statistically **insignificant** at **5%** level

. reg lwages educ numeracy if age==21

Source	SS	df	MS
Model	7.14221169	2	3.57110584
Residual	28.3220949	19	1.49063657
Total	35.4643066	21	1.6887765

Number of obs = 22  
F( 2, 19) = 2.40  
Prob > F = 0.1181  
R-squared = 0.2014  
Adj R-squared = 0.1173  
Root MSE = 1.2209

lwages	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
educ	.3901161	.1802502	2.16	0.043	.012848 .7673841
numeracy	-.0191996	.2461784	-0.08	0.939	-.534457 .4960577
_cons	-1.961189	1.946364	-1.01	0.326	-6.034976 2.112598

- For instance, test that an elasticity (from a log-log model) equals  $\alpha_j = 1$

$$H_0 : \beta_j = \alpha_j$$

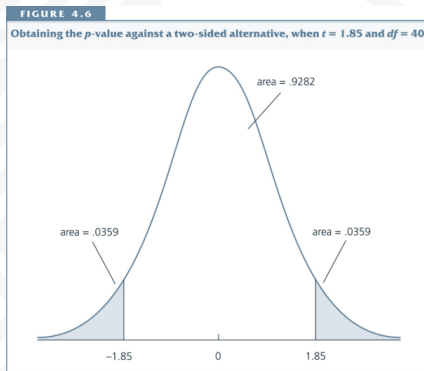
$$T = \frac{\hat{\beta}_j - \alpha_j}{se(\hat{\beta}_j)} \sim t_{n-(k+1)}$$

$$T = \frac{\text{estimate} - \text{hypothesised}}{se}$$

## ► $p$ -value

- Exact level of significance  $P(|T| > |t|)$
- The lowest level of significance at which one would reject  $H_0$
- Allows us to see what the conclusion would be at all levels of significance
- Example:  $p$ -value = 0.04 (ie probability above calculated  $T$ -value is 0.04)
  - Draw a graph for yourself
  - At 1% that  $T$  value is not in rejection region
  - 3.9% do not reject
  - 4% reject
  - 4.1% reject
  - 5% reject
  - 10% reject
- Small  $p$ -values lead to rejection of  $H_0$

- ▶ Two-sided: Add area in both tails
- ▶ One-sided
  - Take only area in relevant tail according to  $H_a$
  - Packages compute two-sided alternative
  - But for one-sided just divide by 2





- ▶ “Rejecting” and “Non-rejecting”
  - Never “accept” a hypothesis
  - As evident from confidence intervals (later), a range of possibilities could be the “true” population value
    - ▶ Which do we therefore “accept”?
  - Formulating null and alternative
    - ▶ Theory guides
    - ▶ Testing statistical properties (eg T-test of significance)

## Choosing $\alpha$

- ▶ Usually 1%, 5% and 10%
- ▶ “conventional” levels of statistical significance
  - But not grounded on any statistical basis

$\alpha = P(\text{Type I Error}) = P(\text{Reject true hypothesis}) = \text{“false positive”}$

$P(\text{Type II Error}) = P(\text{Not Rejecting false hypothesis}) = \text{“false negative”}$

- Trade-off!
- Power of Test =  $1 - P(\text{Type II Error})$ 
  - ▶ In practise: just choose  $\alpha$ , but realise that you sacrifice power

## Economic vs Statistical Significance

- ▶ McCloskey
- ▶ An estimate can “mean something” in economic magnitude even if it marginally fails a statistical test
- ▶ But, if two different values are statistically plausible, they may have varying practical implications
  - Eg small differences in MPC could have large impacts on consumption multiplier
- ▶ Often have statistically significant coefficient with no economically significant magnitude
  - Or it has the wrong sign
  - Must still go through some introspection of model
    - ▶ Ie don't blindly apply statistical criteria ONLY

- Find a confidence interval for the population  $\beta$

$$P(-t_{\alpha/2} \leq T \leq t_{\alpha/2}) = 1 - \alpha$$

$$\vdots$$

$$P\left(\hat{\beta}_j - t_{\alpha/2}se(\hat{\beta}_j) \leq \beta_j \leq \hat{\beta}_j + t_{\alpha/2}se(\hat{\beta}_j)\right) = 1 - \alpha$$

$$(1 - \alpha)\% \text{ confidence interval} = \hat{\beta}_j \pm t_{\alpha/2}se(\hat{\beta}_j)$$

- High Standard Error = Broad Confidence Interval
- Level of significance ( $\alpha$ ) = 5%
  - Confidence interval of 95%

- ▶ If  $\alpha = 5\%$ , is there a 95% chance that the true  $\beta$  lies within that specific interval? **NO!**
  - If 100 different samples were taken
  - ...would obtain 100 different estimates  $\hat{\beta}$
  - ...and 100 different confidence intervals
  - 95 out of the 100 times the true population  $\beta$  would fall inside the calculated confidence interval (subject to MLR1-6 holding!)
    - ▶ So there is still a 5% chance that a specific confidence interval does NOT contain the true  $\beta$
    - ▶ Remember Type I error?
  - Can use to test hypothesis
    - ▶  $H_0 : \beta = 0$
    - ▶ If 0 lies within confidence interval, we do not reject at  $\alpha\%$

- ▶ Calculate a 95% and a 99% confidence interval for  $\beta_{education}$ 
  - $0.1816909 \pm 1.96 \times 0.0019129 = [0.17794162; 0.18544018]$
  - $0.1816909 \pm 2.576 \times 0.0019129 = [0.17676327; 0.18661853]$
  - Which is wider? Why?
- ▶ We get a “range” of possible population values
  - The reason why we never “accept” a hypothesis!

```
. reg lwage educ exp exp2
```

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## Confidence Intervals vs Test of Significance

- ▶ First gives range of *magnitudes*, while second only offers a *binary* conclusion
  - If test of significance is rejected, then what *is* a plausible value for the population value?
- ▶ However, in the second approach we can use *p*-values, while for confidence intervals we need to specify  $\alpha$  upfront
  - Both approaches are therefore flexible in one sense or the other
- ▶ NB NOTE
  - ALL hypothesis tests depend on **MLR1-6**
    - ▶ If normality of errors is violated,  $\hat{\beta}$  are not *t*-distributed
    - ▶ If homoskedasticity is violated, standard errors are biased, and so are the calculated *T*-stats
    - ▶ If MLR 1-4 are violated, limited value for making conclusions about the population from biased estimates and inferences

- ▶ Does an additional year at school have the same value as an additional year at university?

$$\log(wage) = \beta_0 + \beta_1 school + \beta_2 university + u$$

$$H_0 : \beta_1 = \beta_2 \Leftrightarrow \beta_1 - \beta_2 = 0$$

$$H_a : \beta_1 < \beta_2 \Leftrightarrow \beta_1 - \beta_2 < 0$$

$$T = \frac{(\hat{\beta}_1 - \hat{\beta}_2) - 0}{se(\hat{\beta}_1 - \hat{\beta}_2)}$$

- ▶ Similar approach to before, except  $se$  is not so easy to get from our normal regression output



$$\text{Var}(\hat{\beta}_1 - \hat{\beta}_2) = \text{Var}(\hat{\beta}_1) + \text{Var}(\hat{\beta}_2) - 2\text{Cov}(\hat{\beta}_1; \hat{\beta}_2)$$

$$\text{se}(\hat{\beta}_1 - \hat{\beta}_2) = \sqrt{\text{Var}(\hat{\beta}_1 - \hat{\beta}_2)}$$

- ▶ But we need to dig to find  $\text{Cov}(\hat{\beta}_1; \hat{\beta}_2)$
- ▶ Another way is to estimate a similar but informative model, using resulting coefficient and standard errors with a  $T$  test

$$\log(\text{wage}) = \beta_0 + \beta_1 \text{school} + \beta_2 \text{university} + u$$

Let  $\theta = \beta_1 - \beta_2$ , the parameter we are interested in testing

$$\Rightarrow \beta_1 = \theta + \beta_2$$

$$\begin{aligned}\Rightarrow \log(\text{wage}) &= \beta_0 + (\theta + \beta_2) \text{school} + \beta_2 \text{university} + u \\ &= \beta_0 + \theta \text{school} + \beta_2 (\text{school} + \text{university}) + u\end{aligned}$$

```
. gen school = (educ<=12)*educ
(290 missing values generated)

. gen university = (educ>12)*(educ-12)
(290 missing values generated)

. replace school=12 if university!=0
(4590 real changes made)
```

```
. reg lwage school university
```

Source	SS	df	MS
Model	8343.18513	2	4171.59256
Residual	21070.3072	23433	.899172413
Total	29413.4923	23435	1.25510955

```
Number of obs = 23436
F( 2, 23433) = 4639.37
Prob > F      = 0.0000
R-squared     = 0.2837
Adj R-squared = 0.2836
Root MSE     = .94825
```

lwage1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
school	.1040755	.0017539	59.34	0.000	.1006377	.1075133
university	.4678748	.0082577	56.66	0.000	.4516892	.4840604
_cons	.9226882	.016209	56.92	0.000	.8909175	.954459

- Is the difference statistically significant?

```
. reg lwage school educ
```

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Root MSE = .94825

lwage1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
school	-.3637993	.0089007	-40.87	0.000	-.3812452    -.3463533
educ	.4678748	.0082577	56.66	0.000	.4516892    .4840604
_cons	.9226882	.016209	56.92	0.000	.8909175    .954459

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```
. test school=university
```

```
( 1) school - university = 0
```

```
      F( 1, 23433) = 1670.61  
      Prob > F = 0.0000
```

- ▶ Joint hypothesis: entire subsection of model is equal to zero

$$\log(\text{wage}) = \beta_0 + \beta_1 \text{school} + \beta_2 \text{university} + \beta_3 \text{experience} + \beta_4 \text{tenure} + u$$

**BEFORE JOB MARKET    AFTER JOB MARKET**

- ▶ Test whether learning acquired during the job market has no effect on wages
- ▶ **JOINT** hypothesis

$$H_0 : \beta_3 = \beta_4 = 0$$

$$H_a : H_0 \text{ not true}$$

- ▶ If one of these is different from zero, then the alternative will often hold

$$\text{UR:} \log(\text{wage}) = \beta_0 + \beta_1 \text{school} + \beta_2 \text{university} + \beta_3 \text{experience} + \beta_4 \text{tenure} + u$$

Impose hypothesised restriction by setting  $\beta_3 = \beta_4 = 0$

$$\text{R:} \log(\text{wage}) = \beta_0 + \beta_1 \text{school} + \beta_2 \text{university} + u$$

- ▶  $SSR \downarrow$  when  $k \uparrow$  (or moving from restricted (R) to unrestricted (UR))
  - But is the *relative* drop in  $SSR$  "large enough" to suggest that the variables are relevant to the model?
- ▶  $SSR$  of unrestricted model vs restricted model
  - More parameters vs fewer parameters
  - Lower  $SSR$  vs higher  $SSR$
  - Higher  $R^2$  vs lower  $R^2$

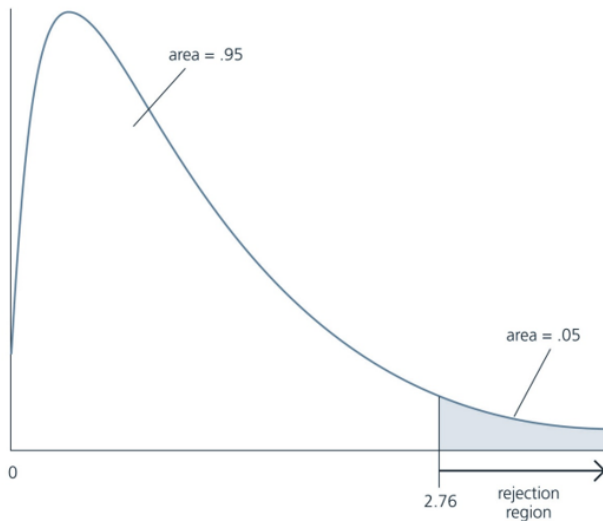
- ▶  $F$  = the relative increase in  $SSR$  by excluding group of variables (scaled by d.f.)

$$F = \frac{(SSR_R - SSR_{UR}) / q}{SSR_{UR} / (n - k - 1)} \sim F_{q; n-k-1}$$

- $F$  always  $> 0$ , therefore only one-sided test
  - $q = [n - (k + 1 - q)] - [n - k - 1]$  = number of restrictions = numerator d.f.
  - $n - k - 1$  = denominator d.f.
- ▶ If  $F$  is “large”: “substantial” enough increase in  $SSR$  to reject  $H_0$ 
    - In other words  $F$  larger than a critical value from the  $F$  theoretical distribution

**FIGURE 4.7**

The 5% critical value and rejection region in an  $F_{3,60}$  distribution.





```
. reg lwage school university exp tenure
```

Source	SS	df	MS			
Model	8632.98807	4	2158.24702	Number of obs = 19734		
Residual	12554.1738	19729	.636330974	F( 4, 19729) = 3391.71		
Total	21187.1619	19733	1.07369188	Prob > F = 0.0000		
				R-squared = 0.4075		
				Adj R-squared = 0.4073		
				Root MSE = .7977		

lwage1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
school	.1325051	.002059	64.36	0.000	.1284693	.1365408
university	.3974043	.007653	51.93	0.000	.3824039	.4124047
exp	.0120163	.0006381	18.83	0.000	.0107656	.013267
tenure	.0311069	.0008276	37.59	0.000	.0294847	.0327291
_cons	.2394071	.0278982	8.58	0.000	.1847243	.2940898

```
. reg lwage school university if e(sample)=1
```

Source	SS	df	MS			
Model	6544.35606	2	3272.17803	Number of obs = 19734		
Residual	14642.8058	19731	.742121829	F( 2, 19731) = 4409.22		
Total	21187.1619	19733	1.07369188	Prob > F = 0.0000		
				R-squared = 0.3089		
				Adj R-squared = 0.3088		
				Root MSE = .86146		

lwage1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
school	.0991527	.0017681	56.08	0.000	.095687	.1026184
university	.4642348	.0081604	56.89	0.000	.4482398	.4802298
_cons	1.005904	.0164882	61.01	0.000	.9735857	1.038222

$$H_0 : \beta_{exp} = \beta_{tenure} = 0$$

$$F = \frac{(SSR_R - SSR_{UR}) / q}{SSR_{UR} / (n - k - 1)} = \frac{(14642.8058 - 12554.1738) / 2}{12554.1738 / 19729} = 1641.1522$$

$$F_{2;19729;0.99} = 4.61$$

$$F > F_{2;19729;0.99} \Rightarrow \text{reject } H_0 \text{ at a 1\% level of significance}$$

$$t_{n-k-1}^2 = F_{1;n-k-1}$$

- ▶ Using  $F$ -stat approach to exclude one variable at a time gives same conclusions as individual  $T$ -tests
- ▶ But  $T$  can test two-sided hypotheses
- ▶  $F$  test is good at testing jointly
  - If joint test shows that whole group is insignificant, it may still be true that one variable does have some important explanatory power

$$F = \frac{(R_{UR}^2 - R_R^2) / q}{(1 - R_{UR}^2) / (n - k - 1)}$$

- ▶ Note the order of the  $R^2$ 's, to ensure that  $F > 0$
- ▶ Interpretation: has relative  $R^2$  increased significantly after adding variables to unrestricted model?

```
. reg lwage school university exp tenure
```

Source	SS	df	MS			
Model	8632.98807	4	2158.24702	Number of obs = 19734		
Residual	12554.1738	19729	.636330974	F( 4, 19729) = 3391.71		
Total	21187.1619	19733	1.07369188	Prob > F = 0.0000		
				R-squared = 0.4075		
				Adj R-squared = 0.4073		
				Root MSE = .7977		

lwage1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
school	.1325051	.002059	64.36	0.000	.1284693	.1365408
university	.3974043	.007653	51.93	0.000	.3824039	.4124047
exp	.0120163	.0006381	18.83	0.000	.0107656	.013267
tenure	.0311069	.0008276	37.59	0.000	.0294847	.0327291
_cons	.2394071	.0278982	8.58	0.000	.1847243	.2940898

```
. reg lwage school university if e(sample)=1
```

Source	SS	df	MS			
Model	6544.35606	2	3272.17803	Number of obs = 19734		
Residual	14642.8058	19731	.742121829	F( 2, 19731) = 4409.22		
Total	21187.1619	19733	1.07369188	Prob > F = 0.0000		
				R-squared = 0.3089		
				Adj R-squared = 0.3088		
				Root MSE = .86146		

lwage1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
school	.0991527	.0017681	56.08	0.000	.095687	.1026184
university	.4642348	.0081604	56.89	0.000	.4482398	.4802298
_cons	1.005904	.0164882	61.01	0.000	.9735857	1.038222

$$H_0: \beta_{exp} = \beta_{tenure} = 0$$

$$F = \frac{(R_{UR}^2 - R_R^2) / q}{(1 - R_{UR}^2) / (n - k - 1)} = \frac{(0.4075 - 0.3089) / 2}{(1 - 0.4075) / 19729} = 1641.15$$

$$F_{2;19729;0.99} = 4.61$$

$$F > F_{2;19729;0.99} \Rightarrow \text{reject } H_0 \text{ at a 1\% level of significance}$$

```
. reg lwage school university exp tenure
```

Source	SS	df	MS
Model	8632.98807	4	2158.24702
Residual	12554.1738	19729	.636330974
Total	21187.1619	19733	1.07369188

Number of obs = 19734  
F( 4, 19729) = 3391.71  
Prob > F = 0.0000  
R-squared = 0.4075  
Adj R-squared = 0.4073  
Root MSE = .7977

lwage1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
school	.1325051	.002059	64.36	0.000	.1284693	.1365408
university	.3974043	.007653	51.93	0.000	.3824039	.4124047
exp	.0120163	.0006381	18.83	0.000	.0107656	.013267
tenure	.0311069	.0008276	37.59	0.000	.0294847	.0327291
_cons	.2394071	.0278982	8.58	0.000	.1847243	.2940898

```
. test exp=tenure=0
```

```
( 1) exp - tenure = 0
( 2) exp = 0
```

F( 2, 19729) = 1641.15  
Prob > F = 0.0000

- ▶  $p\text{-value} = P(F > F_{critical})$
- ▶ Better to use, because size of  $F$ -stat is dependent on d.f.
- ▶ Still same interpretation as other  $p$ -values
  - Small  $p$ -value is evidence against  $H_0$

- Are all the regressors jointly (in)significant?
  - Routinely reported by regression packages

$$H_0 : \beta_1 = \beta_2 = \dots = \beta_k = 0$$

- Same approach as before, with  $k$  restrictions
- The only difference is that the restricted model just has an intercept

- ▶ Test whether coefficients are specific **non-zero** values
  - Rewrite models to do this
  - Cannot always use the  $R^2$  version of the test statistic
    - ▶ Particularly if we have a different dependent variable after rewriting the model

$$H_0 : \beta_{\text{experience}} = 0.01 \text{ and } \beta_{\text{university}} = 3 \times \beta_{\text{school}}$$

## Unrestricted (UR):

$$\log(\text{wage}) = \beta_0 + \beta_1 \text{school} + \beta_2 \text{university} + \beta_3 \text{experience} + \beta_4 \text{tenure} + u$$

## Restricted (R):

$$\begin{aligned} \log(\text{wage}) &= \beta_0 + \beta_1 \text{school} + 3\beta_1 \text{university} + 0.01 \times \text{experience} + \beta_4 \text{tenure} + u \\ \Rightarrow \log(\text{wage}) - 0.01 \times \text{exper} &= \beta_0 + \beta_1 (\text{school} + 3 \times \text{university}) + \beta_4 \text{tenure} + u \end{aligned}$$



```
. reg lwage school university exp tenure
```

Source	SS	df	MS	Number of obs = 19734
Model	8632.98807	4	2158.24702	F( 4, 19729) = 3391.71
Residual	12554.1738	19729	.636330974	Prob > F = 0.0000
Total	21187.1619	19733	1.07369188	R-squared = 0.4075
				Adj R-squared = 0.4073
				Root MSE = .7977

lwage1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
school	.1325051	.002059	64.36	0.000	.1284693 .1365408
university	.3974043	.007653	51.93	0.000	.3824039 .4124047
exp	.0120163	.0006381	18.83	0.000	.0107656 .013267
tenure	.0311069	.0008276	37.59	0.000	.0294847 .0327291
_cons	.2394071	.0278982	8.58	0.000	.1847243 .2940898

```
. gen l_newwage = lwage - 0.01*exp
(42455 missing values generated)
. gen newschool = school+3*university
(290 missing values generated)
. reg l_newwage newschool tenure if e(sample)==1
```

Source	SS	df	MS	Number of obs = 19734
Model	9147.8608	2	4573.9304	F( 2, 19731) = 7184.58
Residual	12561.3759	19731	.63663149	Prob > F = 0.0000
Total	21709.2367	19733	1.10014882	R-squared = 0.4214
				Adj R-squared = 0.4213
				Root MSE = .79789

l_newwage	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
newschool	.1299335	.0011791	110.20	0.000	.1276223 .1322446
tenure	.0325503	.0007075	46.01	0.000	.0311637 .033937
_cons	.2995577	.013601	22.02	0.000	.2728985 .3262168

$$F = \frac{(SSR_R - SSR_{UR}) / q}{SSR_{UR} / (n - k - 1)} = \frac{(12561.3759 - 12554.1738) / 2}{12554.1738 / 19729} = 5.66$$

$$> F_{2;19729;0.99} = 4.61 \Rightarrow \text{Reject } H_0$$

```
. reg lwage school university exp tenure
```

Source	SS	df	MS
Model	8632.98807	4	2158.24702
Residual	12554.1738	19729	.636330974
Total	21187.1619	19733	1.07369188

Number of obs = **19734**  
 F( 4, 19729) = **3391.71**  
 Prob > F = **0.0000**  
 R-squared = **0.4075**  
 Adj R-squared = **0.4073**  
 Root MSE = **.7977**

lwage1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
school	.1325051	.002059	64.36	0.000	.1284693	.1365408
university	.3974043	.007653	51.93	0.000	.3824039	.4124047
exp	.0120163	.0006381	18.83	0.000	.0107656	.013267
tenure	.0311069	.0008276	37.59	0.000	.0294847	.0327291
_cons	.2394071	.0278982	8.58	0.000	.1847243	.2940898

```
. test (exp=0.01) (university=3*school)
```

```
( 1) exp = .01
( 2) - 3*school + university = 0
```

F( 2, 19729) = **5.66**  
 Prob > F = **0.0035**

- ▶ Coefficients
  - With economic interpretation
    - ▶ Elasticity, semi-elasticity, unit changes
  - Add significance stars for easy reading:  $*p < 0.1$ ,  $**p < 0.05$ ,  $***p < 0.01$
- ▶ Standard errors (usually in parentheses below coefficients)
  - Help us compute confidence intervals,  $T$ -stats and  $p$ -values
- ▶  $R^2$  and  $n$
- ▶ In Stata
  - `ssc install esttab`
  - `help esttab`