

Introduction to Econometrics, 5th edition

Chapter 2: Properties of the Regression Coefficients and Hypothesis Testing

$$Y = \beta_1 + \beta_2 X + u$$

$$(Y - \overline{Y})^2 = (Y - \overline{Y})^2 + (X - \overline{Y})^2 + (X - \overline{Y})^2 + (X - \overline{Y})^2$$

In an earlier sequence it was demonstrated that the sum of the squares of the actual values of Y(TSS): total sum of squares) could be decomposed into the sum of the squares of the fitted values (ESS: explained sum of squares) and the sum of the squares of the residuals.

Model

$$Y = \beta_1 + \beta_2 X + u$$

$$(\hat{Y} - \overline{Y})^2 = (\hat{Y} - \overline{Y})^2 + (\hat{Y} - \overline{$$

$$R^{2} = \frac{ESS}{TSS} = \frac{(\hat{Y}_{i} - \overline{Y})^{2}}{(\hat{Y}_{i} - \overline{Y})^{2}}$$

 R^2 , the usual measure of goodness of fit, was then defined to be the ratio of the explained sum of squares to the total sum of squares.

Model

$$Y = \beta_1 + \beta_2 X + u$$

$$(\hat{Y} - \overline{Y})^2 = (\hat{Y} - \overline{Y})^2 + (\hat{Y} - \overline{$$

$$R^{2} = \frac{ESS}{TSS} = \frac{(\hat{Y}_{i} - \overline{Y})^{2}}{(\hat{Y}_{i} - \overline{Y})^{2}}$$

The null hypothesis that we are going to test is that the model has no explanatory power.

$$Y = \beta_1 + \beta_2 X + u$$

Null hypothesis:

$$H_0: \beta_2 = 0$$

Alternative hypothesis: $H_1: \beta_2 \neq 0$

$$H_1: \beta_2 \neq 0$$

$$(\hat{Y} - \overline{Y})^2 = (\hat{Y} - \overline{Y})^2 + (\hat{Y})^2$$

$$TSS = ESS + RSS$$

$$R^{2} = \frac{ESS}{TSS} = \frac{(\hat{Y}_{i} - \overline{Y})^{2}}{(\hat{Y}_{i} - \overline{Y})^{2}}$$

Since X is the only explanatory variable at the moment, the null hypothesis is that Y is not determined by X. Mathematically, we have H_0 : $\beta_2 = 0$

Model

$$Y = \beta_1 + \beta_2 X + u$$

Null hypothesis:

$$H_0: \beta_2 = 0$$

Alternative hypothesis: $H_1: \beta_2 \neq 0$

$$H_1: \beta_2 \neq 0$$

$$(\hat{Y} - \overline{Y})^2 = (\hat{Y} - \overline{Y})^2 + (\hat{Y})^2$$

$$TSS = ESS + RSS$$

$$R^{2} = \frac{ESS}{TSS} = \frac{\hat{Y}_{i} - \overline{Y}^{2}}{\hat{Y}_{i} - \overline{Y}^{2}}$$

$$F(k-1,n-k) = \frac{ESS/(k-1)}{RSS/(n-k)} = \frac{\frac{ESS}{TSS}/(k-1)}{\frac{RSS}{TSS}/(n-k)} = \frac{R^2/(k-1)}{(1-R^2)/(n-k)}$$

Hypotheses concerning goodness of fit are tested via the F statistic, defined as shown. k is the number of parameters in the regression equation, which at present is just 2.

Model

$$Y = \beta_1 + \beta_2 X + u$$

Null hypothesis:

$$H_0: \beta_2 = 0$$

Alternative hypothesis:

$$H_1: \boldsymbol{\beta}_2 \neq \mathbf{0}$$

$$(\widehat{Y} - \overline{Y})^2 = (\widehat{Y} - \overline{Y})^2 + (\widehat{Y} - \overline{Y})^2$$

$$TSS = ESS + RSS$$

$$R^{2} = \frac{ESS}{TSS} = \frac{\hat{Y}_{i} - \overline{Y}^{2}}{\hat{Y}_{i} - \overline{Y}^{2}}$$

$$F(k-1,n-k) = \frac{ESS/(k-1)}{RSS/(n-k)} = \frac{\frac{ESS}{TSS}/(k-1)}{\frac{RSS}{TSS}/(n-k)} = \frac{R^2/(k-1)}{(1-R^2)/(n-k)}$$

n-k is, as with the t statistic, the number of degrees of freedom (number of observations less the number of parameters estimated). For simple regression analysis, it is n-2.

$$Y = \beta_1 + \beta_2 X + u$$

Null hypothesis:

$$H_0: \beta_2 = 0$$

Alternative hypothesis: $H_1: \beta_2 \neq 0$

$$H_1$$
: $\beta_2 \neq 0$

$$\bigcirc Y -$$

$$(\hat{Y} - \overline{Y})^2 = (\hat{Y} - \overline{Y})^2 + (\hat{Y})^2$$

$$TSS = ESS + RSS$$

$$R^{2} = \frac{ESS}{TSS} = \frac{\hat{Y}_{i} - \overline{Y}^{2}}{\hat{Y}_{i} - \overline{Y}^{2}}$$

$$F(k-1,n-k) = \frac{ESS/(k-1)}{RSS/(n-k)} = \frac{\frac{ESS}{TSS}/(k-1)}{\frac{RSS}{TSS}/(n-k)} = \frac{R^2/(k-1)}{(1-R^2)/(n-k)}$$

The F statistic may alternatively be written in terms of R^2 . First divide the numerator and denominator by TSS.

$$Y = \beta_1 + \beta_2 X + u$$

Null hypothesis:

$$H_0: \beta_2 = 0$$

Alternative hypothesis:

$$H_1: \beta_2 \neq 0$$

$$(\hat{Y} - \overline{Y})^2 = (\hat{Y} - \overline{Y})^2 + (\hat{Y})^2$$

$$TSS = ESS + RSS$$

$$R^{2} = \frac{ESS}{TSS} = \frac{(\hat{Y}_{i} - \overline{Y})^{2}}{(Y_{i} - \overline{Y})^{2}}$$

$$F(k-1,n-k) = \frac{ESS/(k-1)}{RSS/(n-k)} = \frac{\frac{ESS}{TSS}/(k-1)}{\frac{RSS}{TSS}/(n-k)} = \frac{R^2/(k-1)}{(1-R^2)/(n-k)}$$

We can now rewrite the F statistic as shown. The R^2 in the numerator comes straight from the definition of R^2 .

$$\frac{RSS}{TSS} = \frac{TSS - ESS}{TSS} = 1 - \frac{ESS}{TSS} = 1 - R^2$$

$$(Y - \overline{Y})^2 = (Y - \overline{Y})^2 + (Y -$$

$$TSS = ESS + RSS$$

$$R^{2} = \frac{ESS}{TSS} = \frac{\hat{Y}_{i} - \overline{Y}^{2}}{\hat{Y}_{i} - \overline{Y}^{2}}$$

$$F(k-1,n-k) = \frac{ESS/(k-1)}{RSS/(n-k)} = \frac{\frac{ESS}{TSS}/(k-1)}{\frac{RSS}{TSS}/(n-k)} = \frac{R^2/(k-1)}{(1-R^2)/(n-k)}$$

It is easily demonstrated that RSS/TSS is equal to $1 - R^2$.

Model

$$Y = \beta_1 + \beta_2 X + u$$

Null hypothesis:

$$H_0: \beta_2 = 0$$

Alternative hypothesis:

$$H_1: \beta_2 \neq 0$$

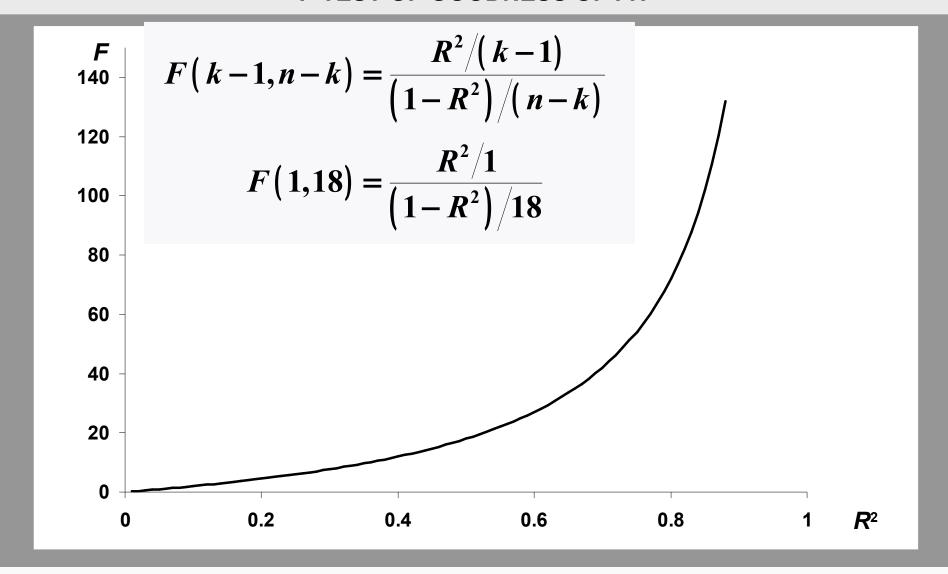
$$(Y - \overline{Y})^2 = (Y - \overline{Y})^2 + (X - \overline{Y})^2$$

$$TSS = ESS + RSS$$

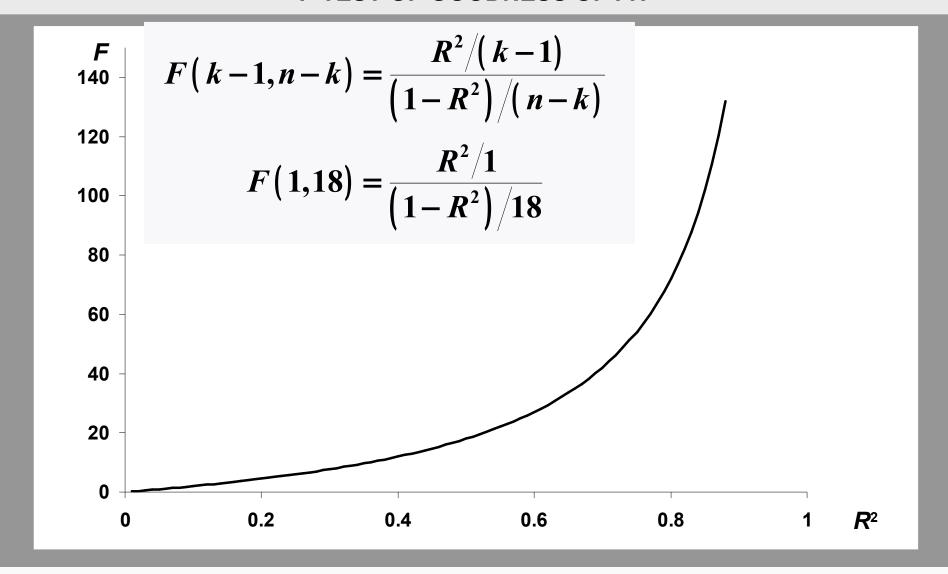
$$R^{2} = \frac{ESS}{TSS} = \frac{(\hat{Y}_{i} - \overline{Y})^{2}}{(Y_{i} - \overline{Y})^{2}}$$

$$F(k-1,n-k) = \frac{ESS/(k-1)}{RSS/(n-k)} = \frac{\frac{ESS}{TSS}/(k-1)}{\frac{RSS}{TSS}/(n-k)} = \frac{R^2/(k-1)}{(1-R^2)/(n-k)}$$

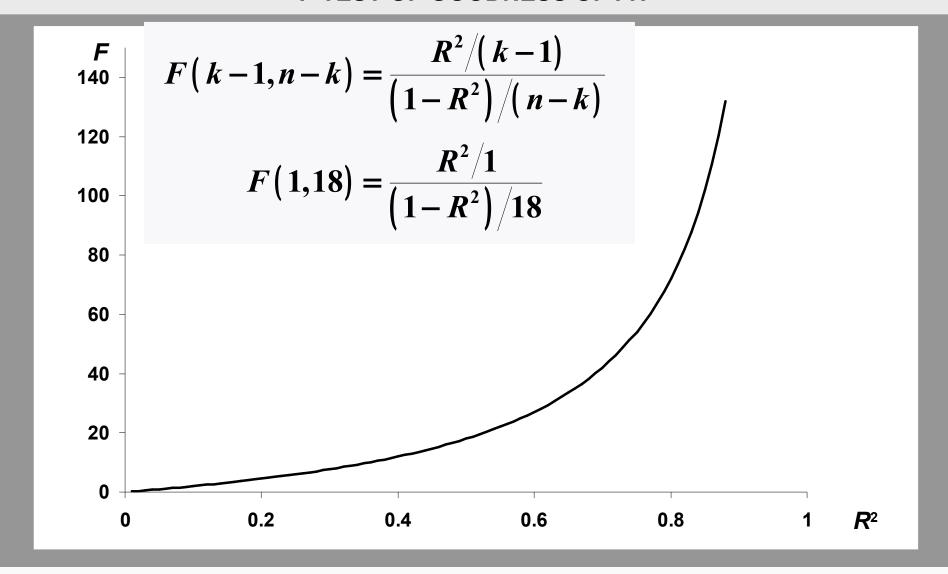
F is a monotonically increasing function of R^2 . As R^2 increases, the numerator increases and the denominator decreases, so for both of these reasons F increases.



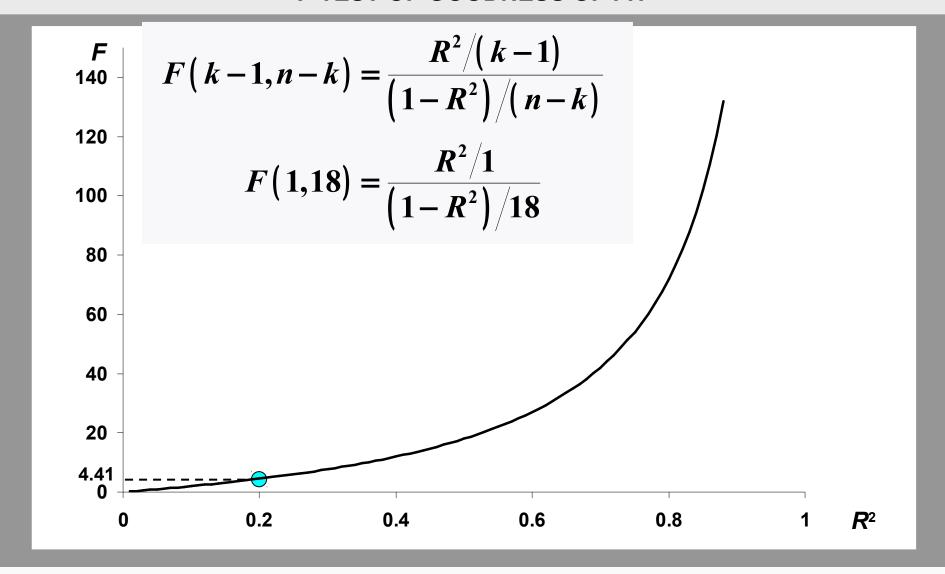
Here is F plotted as a function of R^2 for the case where there is 1 explanatory variable and 20 observations. Since k = 2, n - k = 18.



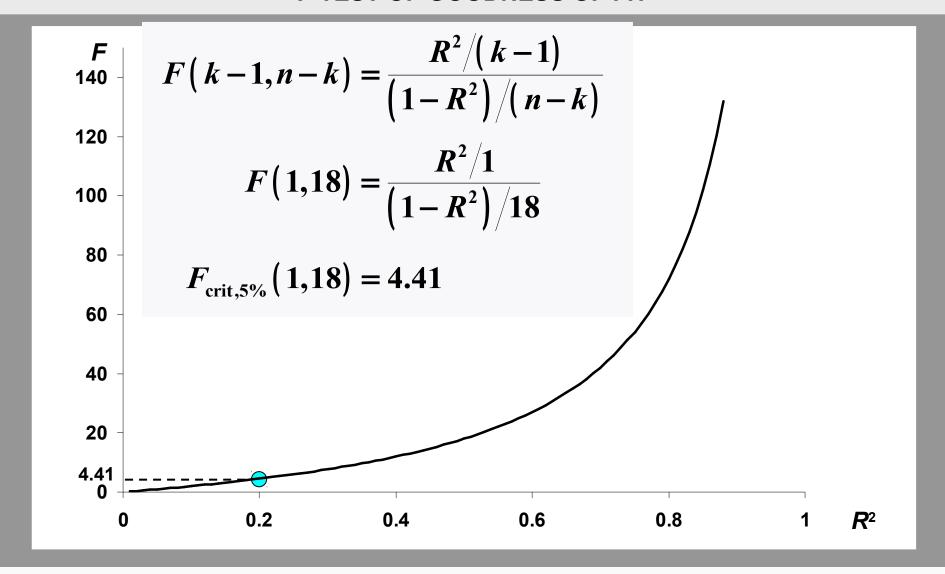
If the null hypothesis is true, *F* will have a random distribution.



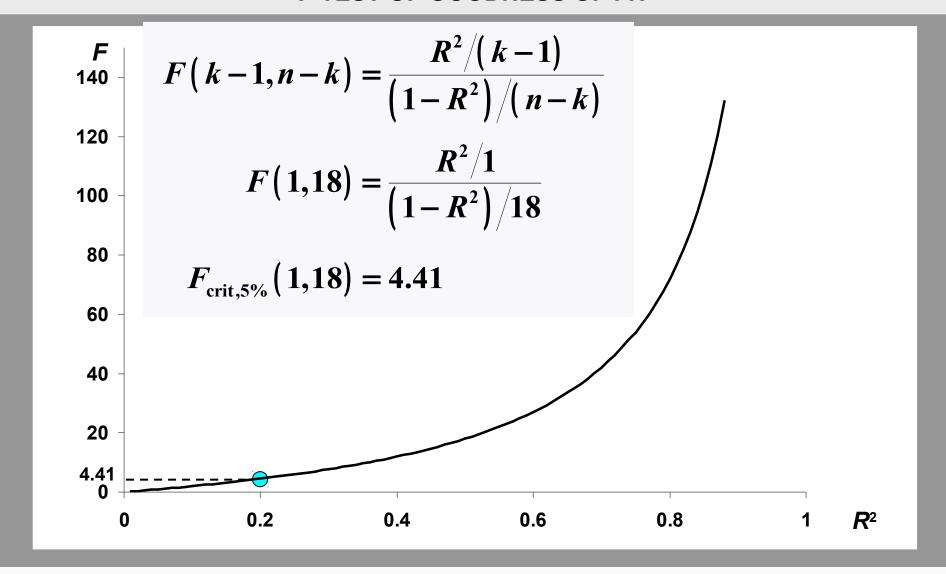
There will be some critical value which it will exceed, as a matter of chance, only 5 percent of the time. If we are performing a 5 percent significance test, we will reject H_0 if the F statistic is greater than this critical value.



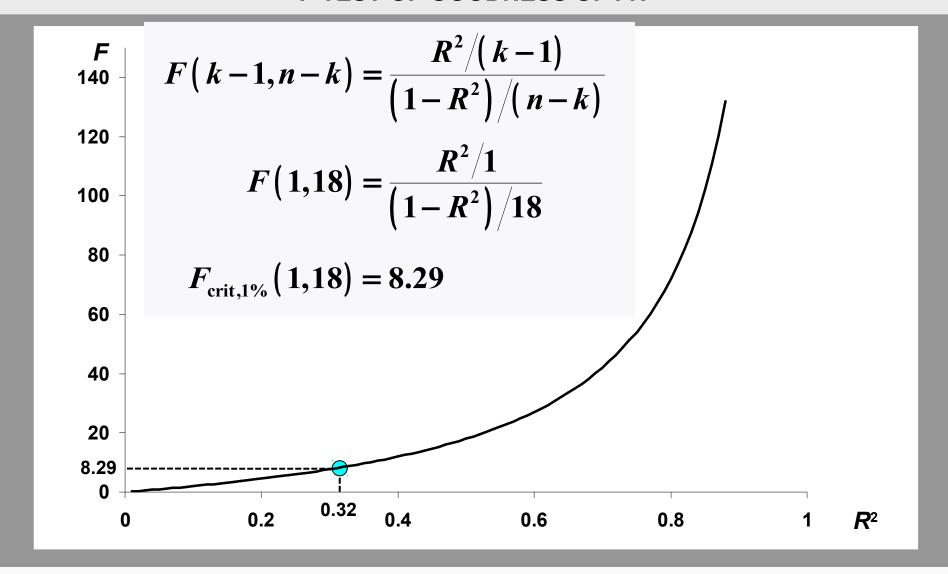
In the case of an *F* test, the critical value depends on the number of explanatory variables as well as the number of degrees of freedom. When there is one explanatory variable and 18 degrees of freedom, the critical value of *F* at the 5 percent significance level is 4.41.



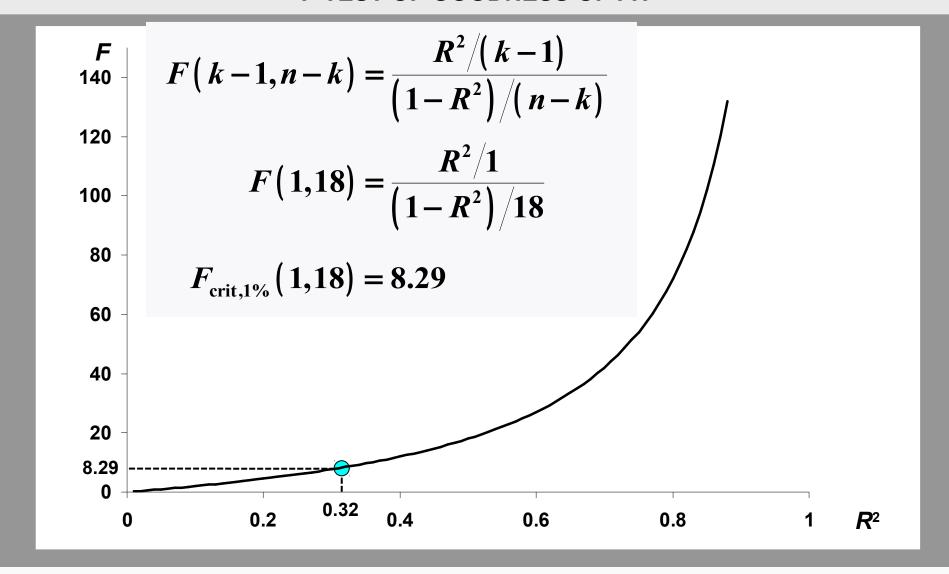
For one explanatory variable and 18 degrees of freedom, F = 4.41 when $R^2 = 0.20$.



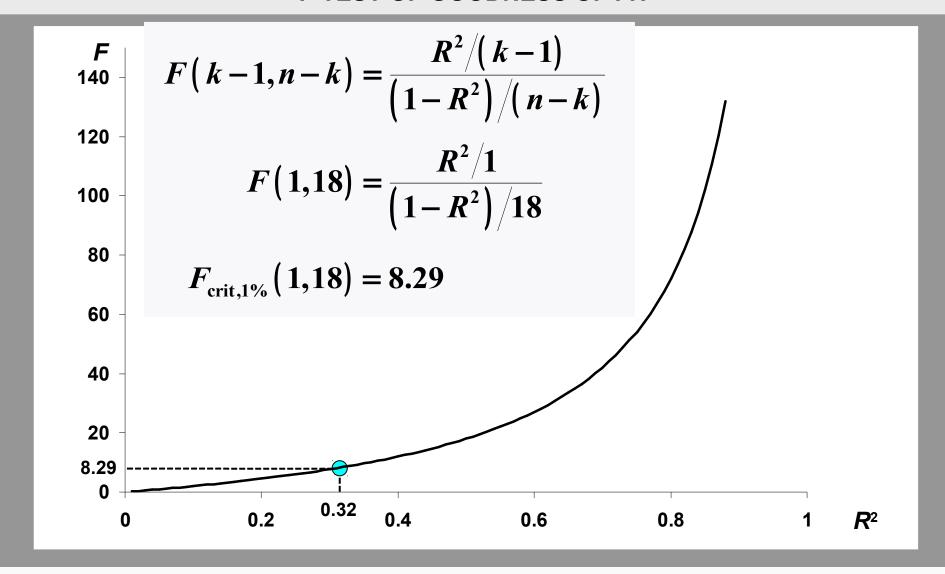
If R^2 is higher than 0.20, F will be higher than 4.41, and we will reject the null hypothesis at the 5 percent level.



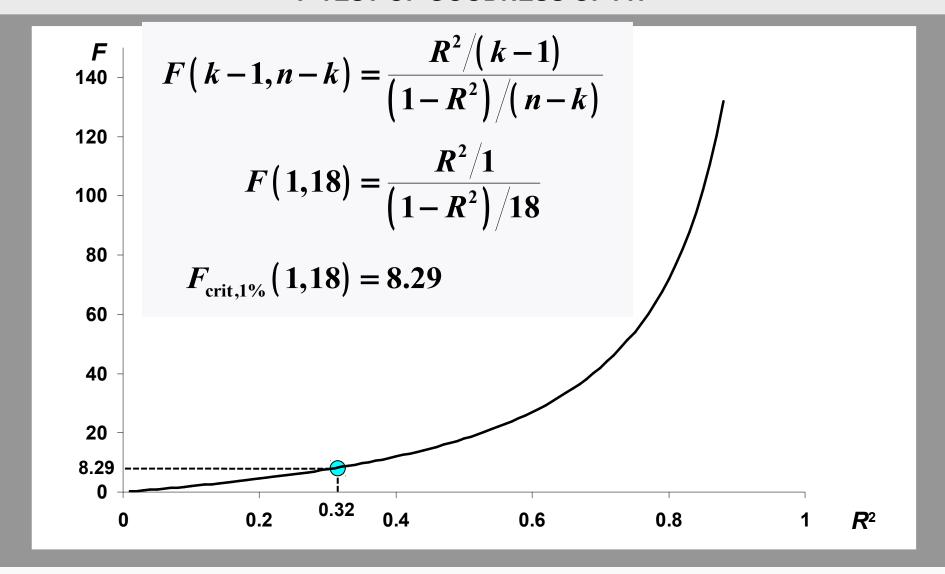
If we were performing a 1 percent test, with one explanatory variable and 18 degrees of freedom, the critical value of F would be 8.29. F = 8.29 when, R² = 0.32.



If R^2 is higher than 0.32, F will be higher than 8.29, and we will reject the null hypothesis at the 1 percent level.



Why do we perform the test indirectly, through F, instead of directly through R^2 ? After all, it would be easy to compute the critical values of R^2 from those for F.



The reason is that an *F* test can be used for several tests of analysis of variance. Rather than have a specialized table for each test, it is more convenient to have just one.

$$Y = \beta_1 + \beta_2 X + u$$

Null hypothesis:

$$H_0: \beta_2 = 0$$

Alternative hypothesis: $H_1: \beta_2 \neq 0$

$$H_1$$
: $\beta_2 \neq 0$

$$(\mathbf{\hat{Y}} - \overline{Y})^2 = (\mathbf{\hat{Y}} - \overline{Y})^2 + (\mathbf{\hat{Y}})^2$$

$$TSS = ESS + RSS$$

$$R^{2} = \frac{ESS}{TSS} = \frac{\hat{Y}_{i} - \overline{Y}^{2}}{\hat{Y}_{i} - \overline{Y}^{2}}$$

$$F(k-1,n-k) = \frac{ESS/(k-1)}{RSS/(n-k)} = \frac{\frac{ESS}{TSS}/(k-1)}{\frac{RSS}{TSS}/(n-k)} = \frac{R^2/(k-1)}{(1-R^2)/(n-k)}$$

Note that, for simple regression analysis, the null and alternative hypotheses are mathematically exactly the same as for a two-tailed t test. Could the F test come to a different conclusion from the t test?

Model

$$Y = \beta_1 + \beta_2 X + u$$

Null hypothesis:

$$H_0: \beta_2 = 0$$

Alternative hypothesis: $H_1: \beta_2 \neq 0$

$$H_1: \beta_2 \neq 0$$

$$(Y - \overline{Y})^2 = (Y - \overline{Y})^2 + (X - \overline{Y})^2$$

$$TSS = ESS + RSS$$

$$R^{2} = \frac{ESS}{TSS} = \frac{(\hat{Y}_{i} - \overline{Y})^{2}}{(Y_{i} - \overline{Y})^{2}}$$

$$F(k-1,n-k) = \frac{ESS/(k-1)}{RSS/(n-k)} = \frac{\frac{ESS}{TSS}/(k-1)}{\frac{RSS}{TSS}/(n-k)} = \frac{R^2/(k-1)}{(1-R^2)/(n-k)}$$

The answer, of course, is no. We will demonstrate that, for simple regression analysis, the F statistic is the square of the t statistic.

Demonstration that $F = t^2$

$$F = \frac{ESS}{RSS/(n-2)} = \frac{\hat{\boldsymbol{\chi}}(\hat{Y}_i - \bar{Y})^2}{\hat{\boldsymbol{\chi}}_i^2/(n-2)}$$

$$= \frac{\hat{\boldsymbol{\chi}}((\hat{\beta}_1 + \hat{\beta}_2 X_i) - (\hat{\beta}_1 + \hat{\beta}_2 \bar{X}))^2}{\hat{\boldsymbol{\sigma}}_u^2} = \frac{1}{\hat{\boldsymbol{\sigma}}_u^2} \hat{\boldsymbol{\beta}}_2^2 (X_i - \bar{X})^2$$

$$= \frac{\hat{\boldsymbol{\beta}}_2^2}{\hat{\boldsymbol{\sigma}}_u^2} \hat{\boldsymbol{\chi}} X_i - \bar{X})^2 = \frac{\hat{\boldsymbol{\beta}}_2^2}{\hat{\boldsymbol{\sigma}}_u^2/\hat{\boldsymbol{\chi}} X_i - \bar{X})^2} = \frac{\hat{\boldsymbol{\beta}}_2^2}{(s.e.(\hat{\beta}_2))^2} = t^2$$

We start by replacing ESS and RSS by their mathematical expressions.

Demonstration that $F = t^2$

$$F = \frac{ESS}{RSS/(n-2)} = \frac{\hat{\boldsymbol{Q}}(\hat{Y}_i - \bar{Y})^2}{\hat{\boldsymbol{Q}}\hat{u}_i^2/(n-2)}$$

$$= \frac{\hat{\boldsymbol{Q}}(\hat{\boldsymbol{\beta}}_1 + \hat{\boldsymbol{\beta}}_2 X_i) - (\hat{\boldsymbol{\beta}}_1 + \hat{\boldsymbol{\beta}}_2 \bar{X})^2}{\hat{\boldsymbol{\sigma}}_u^2} = \frac{1}{\hat{\boldsymbol{\sigma}}_u^2} \hat{\boldsymbol{\beta}}_2^2 (X_i - \bar{X})^2$$

$$= \frac{\hat{\boldsymbol{\beta}}_2^2}{\hat{\boldsymbol{\sigma}}_u^2} \hat{\boldsymbol{Q}} X_i - \bar{X})^2 = \frac{\hat{\boldsymbol{\beta}}_2^2}{\hat{\boldsymbol{\sigma}}_u^2/\hat{\boldsymbol{Q}} X_i - \bar{X})^2} = \frac{\hat{\boldsymbol{\beta}}_2^2}{(s.e.(\hat{\boldsymbol{\beta}}_2))^2} = t^2$$

The denominator is the expression for $\hat{\sigma}_u^2$, the estimator of σ_u^2 , for the simple regression model. We expand the numerator using the expression for the fitted relationship.

Demonstration that $F = t^2$

$$F = \frac{ESS}{RSS/(n-2)} = \frac{\hat{\mathbf{x}}(\hat{Y}_i - \overline{Y})^2}{\hat{\mathbf{x}}_i^2/(n-2)}$$

$$= \frac{\hat{\mathbf{x}}((\hat{\beta}_1 + \hat{\beta}_2 X_i) - (\hat{\beta}_1 + \hat{\beta}_2 \overline{X}))^2}{\hat{\sigma}_u^2} = \frac{1}{\hat{\sigma}_u^2} \hat{\mathbf{x}} \hat{\beta}_2^2 (X_i - \overline{X})^2$$

$$= \frac{\hat{\beta}_2^2}{\hat{\sigma}_u^2} \hat{\mathbf{x}} X_i - \overline{X})^2 = \frac{\hat{\beta}_2^2}{\hat{\sigma}_u^2/\hat{\mathbf{x}} X_i - \overline{X})^2} = \frac{\hat{\beta}_2^2}{(s.e.(\hat{\beta}_2))^2} = t^2$$

The $\hat{m{eta}}_1$ terms in the numerator cancel. The rest of the numerator can be grouped as shown.

Demonstration that $F = t^2$

$$F = \frac{ESS}{RSS/(n-2)} = \frac{\hat{\boldsymbol{\chi}}(\hat{Y}_i - \bar{Y})^2}{\hat{\boldsymbol{\sigma}}_i^2/(n-2)}$$

$$= \frac{\hat{\boldsymbol{\chi}}((\hat{\beta}_1 + \hat{\beta}_2 X_i) - (\hat{\beta}_1 + \hat{\beta}_2 \bar{X}))^2}{\hat{\boldsymbol{\sigma}}_u^2} = \frac{1}{\hat{\boldsymbol{\sigma}}_u^2} \hat{\boldsymbol{\beta}}_2^2 (X_i - \bar{X})^2$$

$$= \frac{\hat{\boldsymbol{\beta}}_2^2}{\hat{\boldsymbol{\sigma}}_u^2} \hat{\boldsymbol{\chi}} X_i - \bar{X})^2 = \frac{\hat{\boldsymbol{\beta}}_2^2}{\hat{\boldsymbol{\sigma}}_u^2/\hat{\boldsymbol{\chi}} X_i - \bar{X})^2} = \frac{\hat{\boldsymbol{\beta}}_2^2}{(s.e.(\hat{\beta}_2))^2} = t^2$$

We take the $\hat{\beta}_2^2$ term out of the summation as a factor.

Demonstration that $F = t^2$

$$F = \frac{ESS}{RSS/(n-2)} = \frac{\hat{\boldsymbol{\chi}}(\hat{Y}_i - \bar{Y})^2}{\hat{\boldsymbol{\chi}}_i^2/(n-2)}$$

$$= \frac{\hat{\boldsymbol{\chi}}((\hat{\beta}_1 + \hat{\beta}_2 X_i) - (\hat{\beta}_1 + \hat{\beta}_2 \bar{X}))^2}{\hat{\boldsymbol{\sigma}}_u^2} = \frac{1}{\hat{\boldsymbol{\sigma}}_u^2} \hat{\boldsymbol{\beta}}_2^2 (X_i - \bar{X})^2$$

$$= \frac{\hat{\boldsymbol{\beta}}_2^2}{\hat{\boldsymbol{\sigma}}_u^2} \hat{\boldsymbol{\chi}} X_i - \bar{X})^2 = \frac{\hat{\boldsymbol{\beta}}_2^2}{\hat{\boldsymbol{\sigma}}_u^2/\hat{\boldsymbol{\chi}} X_i - \bar{X})^2} = \frac{\hat{\boldsymbol{\beta}}_2^2}{(s.e.(\hat{\beta}_2))^2} = t^2$$

We move the term involving X to the denominator.

Demonstration that $F = t^2$

$$F = \frac{ESS}{RSS/(n-2)} = \frac{\hat{\boldsymbol{\chi}}(\hat{Y}_i - \bar{Y})^2}{\hat{\boldsymbol{\chi}}_i^2/(n-2)}$$

$$= \frac{\hat{\boldsymbol{\chi}}((\hat{\beta}_1 + \hat{\beta}_2 X_i) - (\hat{\beta}_1 + \hat{\beta}_2 \bar{X}))^2}{\hat{\boldsymbol{\sigma}}_u^2} = \frac{1}{\hat{\boldsymbol{\sigma}}_u^2} \hat{\boldsymbol{\beta}}_2^2 (X_i - \bar{X})^2$$

$$= \frac{\hat{\boldsymbol{\beta}}_2^2}{\hat{\boldsymbol{\sigma}}_u^2} \hat{\boldsymbol{\chi}} X_i - \bar{X})^2 = \frac{\hat{\boldsymbol{\beta}}_2^2}{\hat{\boldsymbol{\sigma}}_u^2/\hat{\boldsymbol{\chi}} X_i - \bar{X})^2} = \frac{\hat{\boldsymbol{\beta}}_2^2}{(s.e.(\hat{\beta}_2))^2} = t^2$$

The denominator is the square of the standard error of $\hat{oldsymbol{eta}}_2$.

Demonstration that $F = t^2$

$$F = \frac{ESS}{RSS/(n-2)} = \frac{\hat{\boldsymbol{Q}}(\hat{Y}_i - \bar{Y})^2}{\hat{\boldsymbol{Q}}\hat{u}_i^2/(n-2)}$$

$$= \frac{\hat{\boldsymbol{Q}}((\hat{\beta}_1 + \hat{\beta}_2 X_i) - (\hat{\beta}_1 + \hat{\beta}_2 \bar{X}))^2}{\hat{\boldsymbol{\sigma}}_u^2} = \frac{1}{\hat{\boldsymbol{\sigma}}_u^2} \hat{\boldsymbol{Q}}\hat{\boldsymbol{\beta}}_2^2 (X_i - \bar{X})^2$$

$$= \frac{\hat{\boldsymbol{\beta}}_2^2}{\hat{\boldsymbol{\sigma}}_u^2} \hat{\boldsymbol{Q}} X_i - \bar{X})^2 = \frac{\hat{\boldsymbol{\beta}}_2^2}{\hat{\boldsymbol{\sigma}}_u^2/\hat{\boldsymbol{Q}} X_i - \bar{X})^2} = \frac{\hat{\boldsymbol{\beta}}_2^2}{(s.e.(\hat{\beta}_2))^2} = t^2$$

Hence we obtain $\hat{\beta}_2^2$ divided by the square of the standard error of $\hat{\beta}_2$. This is the *t* statistic, squared.

Demonstration that $F = t^2$

$$F = \frac{ESS}{RSS/(n-2)} = \frac{\hat{Q}(\hat{Y}_i - \overline{Y})^2}{\hat{Q}\hat{u}_i^2/(n-2)}$$

$$= \frac{\hat{Q}(\hat{\beta}_1 + \hat{\beta}_2 X_i) - (\hat{\beta}_1 + \hat{\beta}_2 \overline{X})^2}{\hat{\sigma}_u^2} = \frac{1}{\hat{\sigma}_u^2} \hat{Q}\hat{\beta}_2^2 (X_i - \overline{X})^2$$

$$= \frac{\hat{\beta}_2^2}{\hat{\sigma}_u^2} \hat{Q}(X_i - \overline{X})^2 = \frac{\hat{\beta}_2^2}{\hat{\sigma}_u^2/\hat{Q}(X_i - \overline{X})^2} = \frac{\hat{\beta}_2^2}{(s.e.(\hat{\beta}_2))^2} = t^2$$

It can also be shown that the critical value of F, at any significance level, is equal to the square of the critical value of t. We will not attempt to prove this.

Demonstration that $F = t^2$

$$F = \frac{ESS}{RSS/(n-2)} = \frac{\hat{\boldsymbol{\chi}}(\hat{Y}_i - \bar{Y})^2}{\hat{\boldsymbol{\chi}}_i^2/(n-2)}$$

$$= \frac{\hat{\boldsymbol{\chi}}((\hat{\beta}_1 + \hat{\beta}_2 X_i) - (\hat{\beta}_1 + \hat{\beta}_2 \bar{X}))^2}{\hat{\boldsymbol{\sigma}}_u^2} = \frac{1}{\hat{\boldsymbol{\sigma}}_u^2} \hat{\boldsymbol{\beta}}_2^2 (X_i - \bar{X})^2$$

$$= \frac{\hat{\boldsymbol{\beta}}_2^2}{\hat{\boldsymbol{\sigma}}_u^2} \hat{\boldsymbol{\chi}} X_i - \bar{X})^2 = \frac{\hat{\boldsymbol{\beta}}_2^2}{\hat{\boldsymbol{\sigma}}_u^2/\hat{\boldsymbol{\chi}} X_i - \bar{X})^2} = \frac{\hat{\boldsymbol{\beta}}_2^2}{(s.e.(\hat{\beta}_2))^2} = t^2$$

Since the F test is equivalent to a two-sided t test in the simple regression model, there is no point in performing both tests. In fact, if justified, a one-sided t test would be better than either because it is more powerful (lower risk of Type II error if H_0 is false).

Demonstration that $F = t^2$

$$F = \frac{ESS}{RSS/(n-2)} = \frac{\hat{\boldsymbol{\varphi}}(\hat{Y}_i - \bar{Y})^2}{\hat{\boldsymbol{\varphi}}_i^2/(n-2)}$$

$$= \frac{\hat{\boldsymbol{\varphi}}((\hat{\beta}_1 + \hat{\beta}_2 X_i) - (\hat{\beta}_1 + \hat{\beta}_2 \bar{X}))^2}{\hat{\boldsymbol{\sigma}}_u^2} = \frac{1}{\hat{\boldsymbol{\sigma}}_u^2} \hat{\boldsymbol{\varphi}} \hat{\boldsymbol{\beta}}_2^2 (X_i - \bar{X})^2$$

$$= \frac{\hat{\boldsymbol{\beta}}_2^2}{\hat{\boldsymbol{\sigma}}_u^2} \hat{\boldsymbol{\varphi}} X_i - \bar{X})^2 = \frac{\hat{\boldsymbol{\beta}}_2^2}{\hat{\boldsymbol{\sigma}}_u^2/\hat{\boldsymbol{\varphi}} X_i - \bar{X})^2} = \frac{\hat{\boldsymbol{\beta}}_2^2}{(s.e.(\hat{\beta}_2))^2} = t^2$$

The F test will have its own role to play when we come to multiple regression analysis.

. reg EARNING	s s					
Source	SS	df 	MS 		Number of obs F(1, 498)	
Model			.04474		Prob > F	
Residual	64314.9215	498 129.	146429		R-squared	= 0.0855
Total	70328.9662		939812		Adj R-squared Root MSE	= 0.0837 = 11.364
EARNINGS	Coef.	Std. Err.		P> t	-	Interval]
S	1.265712	.1854782	6.82	0.000	.9012959	
_cons	.7646844	2.803765	0.27	0.785 	-4.743982	6.273351

Here is the output for the regression of hourly earnings on years of schooling for the sample of 500 respondents from the National Longitudinal Survey of Youth 1997—.

	reg EARNINGS	SS							
	Source +	ss	df		MS		Number of obs F(1, 498)		
	Model	6014.04474	1	6014	.04474		Prob > F		0.0000
]	Residual	64314.9215	498	129.	146429		R-squared	=	0.0855
							Adj R-squared	=	0.0837
	Total	70328.9662	499	140.	939812		Root MSE	=	11.364
	EARNINGS	Coef.			t	• •	[95% Conf.	In	terval]
	s I	1.265712	.1854		6.82	0.000	.9012959	1	. 630128
	_cons	.7646844	2.803		0.27	0.785	-4.743982		.273351

$$F(1,n-2) = \frac{ESS}{RSS/(n-2)} = \frac{6014}{64315/(500-2)} = \frac{6014}{129.15} = 46.57$$

We shall check that the F statistic has been calculated correctly. The explained sum of squares (described in Stata as the model sum of squares) is 6014.

. reg EARNING	S S					
Source	 SS	df	MS		Number of obs F(1, 498)	
Model Residual	6014.04474 64314.9215	1 6014 498 129.3	.04474 146429		Prob > F R-squared	= 0.0000 = 0.0855
Total	70328.9662				Adj R-squared Root MSE	
EARNINGS	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
S _cons	1.265712 .7646844	.1854782 2.803765	6.82 0.27	0.000 0.785	.9012959 -4.743982	1.630128 6.273351

$$F(1,n-2) = \frac{ESS}{RSS/(n-2)} = \frac{6014}{64315/(500-2)} = \frac{6014}{129.15} = 46.57$$

The residual sum of squares is 64315.

. reg EARNING	GS S					
Source	SS	df	MS		Number of obs	
Model Residual	6014.04474 64314.9215	1 6014 498 129.	.04474		Prob > F R-squared	= 0.0000 = 0.0855
Total	70328.9662	499 140.	939812		Adj R-squared Root MSE	
EARNINGS	Coef.			• •	[95% Conf.	Interval]
S _cons	1.265712 .7646844	.1854782 2.803765	6.82	0.000 0.785	.9012959	1.630128 6.273351

$$F(1,n-2) = \frac{ESS}{RSS/(n-2)} = \frac{6014}{64315/(500-2)} = \frac{6014}{129.15} = 46.57$$

The number of degrees of freedom is 500 - 2 = 498.

. reg EARNING	GS S					
Source	ss	df	MS		Number of obs	
Model Residual		1 6014	.04474		F(1, 498) Prob > F R-squared	= 0.0000 = 0.0855
Total	70328.9662	499 140.9	939812		Adj R-squared Root MSE	
EARNINGS	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
S _cons	1.265712 .7646844	.1854782 2.803765	6.82 0.27	0.000 0.785	.9012959 -4.743982	1.630128 6.273351

$$F(1,n-2) = \frac{ESS}{RSS/(n-2)} = \frac{6014}{64315/(500-2)} = \frac{6014}{129.15} = 46.57$$

The denominator of the expression for F is therefore 129.15. Note that this is an estimate of σ_u^2 . Its square root, denoted in Stata by Root MSE, is an estimate of the standard deviation of u.

. reg EARNIN	GS S					
Source		df	MS		Number of obs	
Model Residual	64314.9215	1 601 498 129	.4.04474 9.146429		F(1, 498) Prob > F R-squared	= 0.0000 = 0.0855
Total	70328.9662				Adj R-squared Root MSE	
EARNINGS	Coef.			• •	[95% Conf.	Interval]
S _cons	1.265712	.1854782 2.803765	6.82	0.000 0.785	.9012959	1.630128 6.273351

$$F(1,n-2) = \frac{ESS}{RSS/(n-2)} = \frac{6014}{64315/(500-2)} = \frac{6014}{129.15} = \frac{46.57}{129.15}$$

Our calculation of *F* agrees with that in the Stata output.

. reg EARNING	S S					
Source	SS	df	MS		Number of obs	
Model		1 6014	.04474		F(1, 498) Prob > F	= 0.0000
Residual	64314.9215				R-squared Adj R-squared	
Total	70328.9662	499 140.	939812 		Root MSE	= 11.364
EARNINGS	Coef.			• •	[95% Conf.	Interval]
s I	1.265712 .7646844	.1854782 2.803765	6.82	0.000 0.785	.9012959	1.630128 6.273351
_cons	. 7040044				-4./4J90Z	0.273331

$$F(1,n-2) = \frac{R^2}{(1-R^2)/(n-2)} = \frac{0.0855}{(1-0.0855)/(500-2)} = 46.56$$

We will also check the F statistic using the expression for it in terms of R^2 . We see again that it agrees, apart from rounding error.

. reg EARNING	s s					
Source	SS	df	MS		Number of obs	= 500
+-					F(1, 498)	= 46.57
Model	6014.04474	1 601	4.04474		Prob > F	= 0.0000
Residual	64314.9215	498 129	.146429		R-squared	= 0.0855
+-					Adj R-squared	= 0.0837
Total	70328.9662	499 140	.939812		Root MSE	= 11.364
EARNINGS	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
s I	1.265712	.1854782	6.82	0.000	.9012959	1.630128
cons	.7646844	2.803765	0.32	0.785	-4.743982	6.273351
	.,040044					

We will also check the relationship between the *F* statistic and the *t* statistic for the slope coefficient.

. reg EARNING	s s					
Source	ss	df	MS		Number of obs	= 500
+-					F(1, 498)	= 46.57
Model	6014.04474	1 6014	.04474		Prob > F	= 0.0000
Residual	64314.9215	498 129.	146429		R-squared	= 0.0855
+-					Adj R-squared	= 0.0837
Total	70328.9662	499 140.	939812		Root MSE	= 11.364
EARNINGS	Coef.			P> t	[95% Conf.	_
s I	1.265712	.1854782	6.82	0.000		
cons	.7646844	2.803765	0.32	0.785		6.273351
	. 7040044					

$$6.82^2 = 46.51$$

Obviously, this is correct as well, apart from rounding error.

. reg EARNING	SS S							
Source	SS	df	М	_		Number of obs		
Model Residual		1 498	6014.0 129.14	4474 6429		F(1, 498) Prob > F R-squared Adj R-squared	= =	0.0000 0.0855
Total	70328.9662			9812		Root MSE		11.364
EARNINGS	Coef.			t	P> t	[95% Conf.	In	terval]
S _cons	1.265712 .7646844	.18547 2.8037	782	6.82	0.000 0.785	.9012959		.630128 .273351

$$F_{\text{crit, 0.1\%}}(1,500) = 10.96$$
 $t_{\text{crit, 0.1\%}}(500) = 3.31$ $10.96 = 3.31^2$

And the critical value of F is the square of the critical value of t. (We are using the values for 500 degrees of freedom because those for 498 do not appear in the table.)

. reg EARNING	s s						
Source	SS	df	MS		Number of obs		
·	6014.04474 64314.9215	1 6 498 1	014.04474 29.146429		R-squared	= =	0.0000 0.0855
+- Total			40.939812		Adj R-squared Root MSE		11.364
EARNINGS	Coef.		r. t	P> t	[95% Conf.	Int	erval]
S _cons	1.265712	.185478 2.80376	6.82	0.000 0.785	.9012959	_	630128 273351

$$F_{\text{crit, 0.1\%}}(1,500) = 10.96$$
 $t_{\text{crit, 0.1\%}}(500) = 3.31$ $10.96 = 3.31^2$

The relationship is shown for the 0.1% significance level, but obviously it is also true for any other significance level.

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