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**ECON 351\* -- Addendum to NOTE 17**
**General F-Tests of Linear Coefficient Restrictions: An Example**
**1. An Example**
**Multiple Linear Regression Model 1**

*The PRE* (population regression equation) for Model 1 is:

$$\text{price}_i = \beta_1 + \beta_2 \text{wgt}_i + \beta_3 \text{wgt}_i^2 + \beta_4 \text{mpg}_i + \beta_5 \text{mpg}_i^2 + \beta_6 \text{wgt}_i \text{mpg}_i + u_i. \quad (1)$$

$$k = 6; \quad k - 1 = 5.$$

- *Marginal effect of wgt<sub>i</sub>*

$$\frac{\partial \text{price}_i}{\partial \text{wgt}_i} = \frac{\partial E(\text{price}_i | \text{wgt}_i, \text{mpg}_i)}{\partial \text{wgt}_i} = \frac{\partial E(\text{price}_i | \bullet)}{\partial \text{wgt}_i} = \beta_2 + 2\beta_3 \text{wgt}_i + \beta_6 \text{mpg}_i.$$

- *Marginal effect of mpg<sub>i</sub>*

$$\frac{\partial \text{price}_i}{\partial \text{mpg}_i} = \frac{\partial E(\text{price}_i | \text{wgt}_i, \text{mpg}_i)}{\partial \text{mpg}_i} = \frac{\partial E(\text{price}_i | \bullet)}{\partial \text{mpg}_i} = \beta_4 + 2\beta_5 \text{mpg}_i + \beta_6 \text{wgt}_i.$$

***Proposition to test***

The *marginal effect of mpg<sub>i</sub> on price<sub>i</sub> is zero*: i.e., *mpg<sub>i</sub> has no effect on price<sub>i</sub>*; or *car price<sub>i</sub> is unrelated to fuel efficiency* as measured by *mpg<sub>i</sub>*.

Examine the above expression for the **marginal effect of mpg<sub>i</sub> on price<sub>i</sub>**. We see that a sufficient condition for the proposition to be true for all cars (regardless of their values for wgt<sub>i</sub> and mpg<sub>i</sub>) is that the **three coefficients β<sub>4</sub>, β<sub>5</sub> and β<sub>6</sub> all equal zero**.

$$\text{If } \beta_4 = 0 \text{ and } \beta_5 = 0 \text{ and } \beta_6 = 0, \text{ then } \frac{\partial \text{price}_i}{\partial \text{mpg}_i} = \beta_4 + 2\beta_5 \text{mpg}_i + \beta_6 \text{wgt}_i = 0 \quad \forall i.$$

***Null and Alternative Hypotheses***

$$\text{price}_i = \beta_1 + \beta_2 \text{wgt}_i + \beta_3 \text{wgt}_i^2 + \beta_4 \text{mpg}_i + \beta_5 \text{mpg}_i^2 + \beta_6 \text{wgt}_i \text{mpg}_i + u_i. \quad (1)$$

$$\frac{\partial \text{price}_i}{\partial \text{mpg}_i} = \frac{\partial E(\text{price}_i | \text{wgt}_i, \text{mpg}_i)}{\partial \text{mpg}_i} = \frac{\partial E(\text{price}_i | \bullet)}{\partial \text{mpg}_i} = \beta_4 + 2\beta_5 \text{mpg}_i + \beta_6 \text{wgt}_i.$$

- $H_0: \beta_4 = 0 \text{ and } \beta_5 = 0 \text{ and } \beta_6 = 0 \Rightarrow \frac{\partial \text{price}_i}{\partial \text{mpg}_i} = \beta_4 + 2\beta_5 \text{mpg}_i + \beta_6 \text{wgt}_i = 0$

**Restricted model** corresponding to  $H_0$ : set  $\beta_4 = 0$  and  $\beta_5 = 0$  and  $\beta_6 = 0$  in the unrestricted model given by PRE (1).

$$\text{price}_i = \beta_1 + \beta_2 \text{wgt}_i + \beta_3 \text{wgt}_i^2 + u_i \quad (2)$$

$$k_0 = 3; \quad k_0 - 1 = 2; \quad N - k_0 = 74 - 3 = 71.$$

$$\text{RSS}_0 = 384779934; \quad \text{df}_0 = N - k_0 = 71; \quad R_R^2 = 0.3941.$$

**The OLS SRE for the *Restricted Model* – Model 2**

. regress price wgt wgtsq

Source	SS	df	MS	Number of obs =	74
Model	250285462	2	125142731	F( 2, 71) =	23.09
Residual	<b>384779934</b>	<b>71</b>	5419435.69	Prob > F =	0.0000
				<b>R-squared =</b>	<b>0.3941</b>
				Adj R-squared =	0.3770
Total	635065396	73	8699525.97	Root MSE =	2328.0

price	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
wgt	-7.273097	2.691747	-2.702	0.009	-12.64029	-1.905906
wgtsq	.0015142	.0004337	3.491	0.001	.0006494	.002379
_cons	13418.8	3997.822	3.357	0.001	5447.372	21390.23

- $H_1: \beta_4 \neq 0 \text{ and/or } \beta_5 \neq 0 \text{ and/or } \beta_6 \neq 0 \Rightarrow \frac{\partial \text{price}_i}{\partial \text{mpg}_i} = \beta_4 + 2\beta_5 \text{mpg}_i + \beta_6 \text{wgt}_i$

*Unrestricted model* corresponding to  $H_1$ : is PRE (1).

$$\text{price}_i = \beta_1 + \beta_2 \text{wgt}_i + \beta_3 \text{wgt}_i^2 + \beta_4 \text{mpg}_i + \beta_5 \text{mpg}_i^2 + \beta_6 \text{wgt}_i \text{mpg}_i + u_i \quad (1)$$

$$k = 6; \quad k - 1 = 5; \quad N - k = 74 - 6 = 68.$$

$$\text{RSS}_1 = 326680563; \quad \text{df}_1 = N - k = 68; \quad R_U^2 = 0.4856.$$

**The OLS SRE for the *Unrestricted Model* – Model 1**

```
. regress price wgt wgtsq mpg mpgsq wgtmpg
```

Source	SS	df	MS			
Model	308384833	5	61676966.6	Number of obs =	74	
Residual	<b>326680563</b>	<b>68</b>	4804125.93	F( 5, 68) =	12.84	
Total	635065396	73	8699525.97	Prob > F =	0.0000	
				<b>R-squared</b> =	<b>0.4856</b>	
				Adj R-squared =	0.4478	
				Root MSE =	2191.8	

  

price	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
wgt	-31.88985	9.148215	-3.486	0.001	-50.14483	-13.63487
wgtsq	.0034574	.0008629	4.007	0.000	.0017355	.0051792
mpg	-3549.495	1126.464	-3.151	0.002	-5797.318	-1301.672
mpgsq	38.74472	12.62339	3.069	0.003	13.55514	63.9343
wgtmpg	.5421927	.1971854	2.750	0.008	.1487154	.9356701
_cons	92690.55	25520.53	3.632	0.001	41765.12	143616

## 2. The General F-Statistic

- **Usage:** Can be used to test *any linear* restrictions on the regression coefficients in a linear regression model.
- **Formula 1** for the general F-statistic is:

$$F = \frac{(RSS_0 - RSS_1)/(df_0 - df_1)}{RSS_1/df_1} = \frac{(RSS_0 - RSS_1)/(k - k_0)}{RSS_1/(N - k)} \sim F[df_0 - df_1, df_1] \quad (\text{F1})$$

where:

$RSS_0$  = the *residual sum of squares* for the restricted OLS-SRE;

$RSS_1$  = the *residual sum of squares* for the unrestricted OLS-SRE;

$k_0$  = the *number of free regression coefficients* in the restricted model;

$k$  = the *number of free regression coefficients* in the unrestricted model;

$k - k_0$  = the *number of independent linear coefficient restrictions* specified by the null hypothesis  $H_0$ ;

$N - k$  = the *degrees of freedom* for  $RSS_1$ , the unrestricted RSS.

$df_0 = N - k_0$  = the *degrees of freedom* for  $RSS_0$ , the restricted RSS;

$df_1 = N - k$  = the *degrees of freedom* for  $RSS_1$ , the unrestricted RSS;

$df_0 - df_1 = N - k_0 - (N - k) = N - k_0 - N + k = k - k_0$ .

*Note:*  $df_0 - df_1 = k - k_0$  = the *number of independent linear coefficient restrictions* specified by the null hypothesis  $H_0$ .

- **Formula 2** for the general F-statistic is:

$$F = \frac{(R_U^2 - R_R^2)/(df_0 - df_1)}{(1 - R_U^2)/df_1} = \frac{(R_U^2 - R_R^2)/(k - k_0)}{(1 - R_U^2)/(N - k)} \sim F[df_0 - df_1, df_1]. \quad (\text{F2})$$

where:

$R_R^2$  = the *R-squared value* for the restricted OLS-SRE;

$R_U^2$  = the *R-squared value* for the unrestricted OLS-SRE.

### 3. Performing a General F-Test of Exclusion Restrictions

*Calculate the sample value of the general F-statistic using formula 1*

$$RSS_0 = 384779934; \quad df_0 = N - k_0 = 71; \quad R_R^2 = 0.3941.$$

$$RSS_1 = 326680563; \quad df_1 = N - k = 68; \quad R_U^2 = 0.4856.$$

$$\begin{aligned} F_0 &= \frac{(RSS_0 - RSS_1)/(df_0 - df_1)}{RSS_1/df_1} \\ &= \frac{(384779934 - 326680563)/(71 - 68)}{326680563/68} \\ &= \frac{58099371/3}{326680563/68} \\ &= \mathbf{4.031} \end{aligned}$$

*Calculate the sample value of the general F-statistic using formula 2*

$$\begin{aligned} F_0 &= \frac{(R_U^2 - R_R^2)/(df_0 - df_1)}{(1 - R_U^2)/df_1} \\ &= \frac{(0.4856 - 0.3941)/3}{(1 - 0.4856)/68} \\ &= \frac{0.0915/3}{0.5144/68} \\ &= \mathbf{4.032} \end{aligned}$$

**Result:  $F_0 = 4.032$**

**Decision Rule -- Formulation 1**

Let  $F_\alpha[df_0 - df_1, df_1]$  = the  $\alpha$ -level *critical value* of the  $F[df_0 - df_1, df_1]$  distribution.

**Retain  $H_0$**  at significance level  $\alpha$  if  $F_0 \leq F_\alpha[df_0 - df_1, df_1]$ .

**Reject  $H_0$**  at significance level  $\alpha$  if  $F_0 > F_\alpha[df_0 - df_1, df_1]$ .

- **Critical values of  $F[3, 68]$**

$$\alpha = 0.05: \quad F_{0.05}[3, 68] = 2.79$$

$$\alpha = 0.01: \quad F_{0.01}[3, 68] = 4.08$$

```
. display invFtail(3, 68, 0.05)
2.794891
```

```
. display invFtail(3, 68, 0.01)
4.083395
```

***Inference:***

- $F_0 = 4.032 > 2.79 = F_{0.05}[3, 68] \Rightarrow$  **reject  $H_0$**  at **5%** significance level

- $F_0 = 4.032 < 4.08 = F_{0.01}[3, 68] \Rightarrow$  **retain  $H_0$**  at **1%** significance level

**Decision Rule -- Formulation 2**

**Retain  $H_0$**  at significance level  $\alpha$  if the **p-value for  $F_0 \geq \alpha$** .

**Reject  $H_0$**  at significance level  $\alpha$  if the **p-value for  $F_0 < \alpha$** .

- **p-value for  $F_0 = 0.0106$**

```
. display Ftail(3, 68, 4.032)
.01062773
```

***Inference:***

- p-value for  $F_0 = 0.0106 < 0.05 \Rightarrow$  **reject  $H_0$**  at **5%** significance level

- p-value for  $F_0 = 0.0106 > 0.01 \Rightarrow$  **retain  $H_0$**  at **1%** significance level

### Computing this General F-Test with *Stata*

The *Stata test* command computes general F-tests of any set of coefficient restrictions on linear regression models.

#### The OLS SRE for the Unrestricted Model – Model 1

```
. regress price wgt wgtsq mpg mpgsq wgtmpg
```

Source	SS	df	MS	Number of obs =	74
Model	308384833	5	61676966.6	<b>F( 5, 68) =</b>	<b>12.84</b>
Residual	326680563	68	4804125.93	<b>Prob &gt; F</b>	<b>= 0.0000</b>
Total	635065396	73	8699525.97	R-squared	= 0.4856
				Adj R-squared	= 0.4478
				Root MSE	= 2191.8

price	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
wgt	-31.88985	9.148215	-3.486	0.001	-50.14483	-13.63487
wgtsq	.0034574	.0008629	4.007	0.000	.0017355	.0051792
mpg	-3549.495	1126.464	-3.151	0.002	-5797.318	-1301.672
mpgsq	38.74472	12.62339	3.069	0.003	13.55514	63.9343
wgtmpg	.5421927	.1971854	2.750	0.008	.1487154	.9356701
_cons	92690.55	25520.53	3.632	0.001	41765.12	143616

```
. test mpg mpgsq wgtmpg
( 1) mpg = 0.0
( 2) mpgsq = 0.0
( 3) wgtmpg = 0.0
```

```

F( 3, 68) = 4.03
Prob > F = 0.0106

```

#### 4. Outline of the General F-Test Procedure

Once the null hypothesis  $H_0$  and the alternative hypothesis  $H_1$  have been formulated, the procedure for testing a set of  $df_0 - df_1 = k - k_0$  independent linear coefficient restrictions consists of **four basic steps**.

**Step 1:** Estimate by OLS the *unrestricted* model implied by the alternative hypothesis  $H_1$  to obtain the *unrestricted* OLS SRE and associated statistics:

$$RSS_1; \quad df_1 = N - k; \quad R_U^2 = ESS_1/TSS = 1 - RSS_1/TSS.$$

**Step 2:** Estimate by OLS the *restricted* model implied by the null hypothesis  $H_0$ , after imposing on the unrestricted PRE the linear coefficient restrictions specified by the null hypothesis. This yields the *restricted* OLS SRE and associated statistics:

$$RSS_0; \quad df_0 = N - k_0; \quad R_R^2 = ESS_0/TSS = 1 - RSS_0/TSS.$$

**Step 3:** Compute the *sample value of either of the general F-statistics*.

$$F = \frac{(RSS_0 - RSS_1)/(df_0 - df_1)}{RSS_1/df_1} = \frac{(R_U^2 - R_R^2)/(df_0 - df_1)}{(1 - R_U^2)/df_1} \sim F[df_0 - df_1, df_1]$$

where:

$$\begin{aligned} df_0 &= N - k_0 = \text{the } \textit{degrees of freedom} \text{ for } RSS_0, \text{ the } \textit{restricted} \text{ RSS}; \\ df_1 &= N - k = \text{the } \textit{degrees of freedom} \text{ for } RSS_1, \text{ the } \textit{unrestricted} \text{ RSS}; \\ df_0 - df_1 &= N - k_0 - (N - k) = N - k_0 - N + k = k - k_0 \\ &= \text{the } \textit{number of coefficient restrictions} \text{ specified by } H_0. \end{aligned}$$

**Step 4:** Apply the conventional decision rule:

- (1) If  $F_0 > F_{\alpha}(k-k_0, N-k)$ , or if the **p-value for  $F_0 < \alpha$** , **reject the coefficient restrictions** specified by the null hypothesis  $H_0$  **at the  $100\alpha\%$  significance level**;
- (2) If  $F_0 \leq F_{\alpha}(k-k_0, N-k)$ , or if the **p-value for  $F_0 \geq \alpha$** , **retain (do not reject) the coefficient restrictions** specified by the null hypothesis  $H_0$  **at the  $100\alpha\%$  significance level**.



## 5. Properties of the Restricted and Unrestricted Coefficient Estimators

The statistical properties of the *restricted* OLS coefficient estimators  $\tilde{\beta}_j$  ( $j = 1, \dots, k$ ) and the *unrestricted* OLS coefficient estimators  $\hat{\beta}_j$  ( $j = 1, \dots, k$ ) depend on whether the linear coefficient restrictions are *true or false*.

**5.1. If the linear coefficient restrictions specified by the null hypothesis  $H_0$  are TRUE, then**

- (1) the restricted coefficient estimators  $\tilde{\beta}_j$  ( $j = 1, \dots, k$ ) are *unbiased* and have *smaller variances* than (i.e., are *efficient* relative to) the unrestricted coefficient estimators  $\hat{\beta}_j$  -- i.e.,

$$E(\tilde{\beta}_j) = \beta_j \quad \text{and} \quad \text{Var}(\tilde{\beta}_j) \leq \text{Var}(\hat{\beta}_j) \quad \text{for all } j = 0, 1, \dots, k;$$

whereas

- (2) the unrestricted coefficient estimators  $\hat{\beta}_j$  ( $j = 1, \dots, k$ ) are also *unbiased*, but have *larger variances* than (i.e., are *inefficient* relative to) the restricted coefficient estimators  $\tilde{\beta}_j$  -- i.e.,

$$E(\hat{\beta}_j) = \beta_j \quad \text{and} \quad \text{Var}(\tilde{\beta}_j) \leq \text{Var}(\hat{\beta}_j) \quad \text{for all } j = 0, 1, \dots, k.$$

**Implication:** If the **linear coefficient restrictions** specified by the null hypothesis are *retained* by an F-test, then the restricted coefficient estimators  $\tilde{\beta}_j$  ( $j = 1, \dots, k$ ) are preferred because they have *smaller variances* than the unrestricted coefficient estimators  $\hat{\beta}_j$  ( $j = 0, \dots, k$ ). **Both estimators are unbiased** if the coefficient restrictions are true.

**5.2. If the linear coefficient restrictions specified by the null hypothesis  $H_0$  are FALSE, then**

- (1) the **restricted coefficient estimators  $\tilde{\beta}_j$  ( $j = 1, \dots, k$ ) are *biased***, although **they still have *smaller* variances** than the unrestricted coefficient estimators  $\hat{\beta}_j$  -- i.e.,

$$E(\tilde{\beta}_j) \neq \beta_j \quad \text{and} \quad \text{Var}(\tilde{\beta}_j) \leq \text{Var}(\hat{\beta}_j) \quad \text{for all } j = 0, 1, \dots, k;$$

whereas

- (2) the **unrestricted coefficient estimators  $\hat{\beta}_j$  ( $j = 1, \dots, k$ ) are *unbiased***, though **they have *larger* variances** than the restricted coefficient estimators  $\tilde{\beta}_j$ .

$$E(\hat{\beta}_j) = \beta_j \quad \text{and} \quad \text{Var}(\tilde{\beta}_j) \leq \text{Var}(\hat{\beta}_j) \quad \text{for all } j = 0, 1, \dots, k.$$

**Implication:** If the **linear coefficient restrictions** specified by the null hypothesis are ***rejected*** by an F-test, then the **unrestricted coefficient estimators  $\hat{\beta}_j$  ( $j = 1, \dots, k$ ) are preferred because they are *unbiased***, even though they have larger variances than the restricted coefficient estimators  $\tilde{\beta}_j$  ( $j = 0, \dots, k$ ).