A First Guide to Hypothesis Testing in Linear Regression Models

A Generic Linear Regression Model: Scalar Formulation of Population Regression Equation

For the i-th population (or sample) observation, the scalar formulation of the PRE, is written as:

$$\begin{aligned} \mathbf{Y}_{i} &= \beta_{0} + \beta_{1} \mathbf{X}_{i1} + \beta_{2} \mathbf{X}_{i2} + \dots + \beta_{k} \mathbf{X}_{ik} + \mathbf{u}_{i} \qquad \forall i \\ &= \beta_{0} + \sum_{j=1}^{j=k} \beta_{j} \mathbf{X}_{ij} + \mathbf{u}_{i} \qquad \forall i \\ &= \sum_{i=0}^{j=k} \beta_{j} \mathbf{X}_{ij} + \mathbf{u}_{i} , \qquad \mathbf{X}_{i0} = 1 \ \forall i \qquad \forall i \end{aligned}$$

$$(1)$$

where

 $Y_i =$ the i-th population value of the regressand, or dependent variable;

 $X_{ij} \equiv$ the i-th population value of the j-th regressor, or independent variable;

 $\beta_i \equiv$ the partial regression coefficient of X_{ij} ;

 $u_i \equiv$ the i-th population value of the *unobservable* random error term.

<u>Note</u>:

(1) Lower case "k" denotes the number of *slope* coefficients in the PRF (population regression function).

(2) Upper case "K" denotes the *total* number of regression coefficients in the PRF.

(3) Therefore: $\mathbf{K} = \mathbf{k} + \mathbf{1}$.

Scalar Formulation of the Ordinary Least Squares (OLS) Sample Regression Equation

For the i-th sample observation, the scalar formulation of the OLS SRE is written as:

$$\begin{split} \mathbf{Y}_{i} &= \hat{\beta}_{0} + \hat{\beta}_{1} \mathbf{X}_{i1} + \hat{\beta}_{2} \mathbf{X}_{i2} + \dots + \hat{\beta}_{k} \mathbf{X}_{ik} + \hat{\mathbf{u}}_{i} \qquad \forall \ i = 1, \dots, N \\ &= \hat{\beta}_{0} + \sum_{j=1}^{j=k} \hat{\beta}_{j} \mathbf{X}_{ij} + \hat{\mathbf{u}}_{i} \qquad \forall \ i = 1, \dots, N \\ &= \hat{\mathbf{Y}}_{i} + \hat{\mathbf{u}}_{i} \qquad \forall \ i = 1, \dots, N \end{split}$$
(2)

where

 $Y_i \equiv$ the i-th sample value of the regressand, or dependent variable;

 $X_{ij} \equiv$ the i-th sample value of the j-th regressor, or independent variable;

 $\hat{\beta}_{i} \equiv$ the **OLS estimator or estimate** of the regression coefficient β_{j} ;

 $\hat{u}_i \equiv$ the i-th **OLS sample residual**;

 $\hat{Y}_i = \hat{\beta}_0 + \sum_{j=1}^{j=k} \hat{\beta}_j X_{ij} \equiv$ the **OLS sample regression function (SRF)** for the i-th sample observation.

1. Tests of One Coefficient Restriction: One Restriction on One Coefficient

H₀ specifies *only one equality* restriction on *one coefficient*.

□ <u>*Two-Tail* Tests of One Restriction on One Coefficient</u>

- *Example:* H_0 : $\beta_j = b_j$ versus H_1 : $\beta_j \neq b_j$ where b_j is a specified constant.
- Use: either a two-tail t-test or an F-test.
- Test Statistics:

$$\Rightarrow t(\hat{\beta}_{j}) = \frac{\hat{\beta}_{j} - \beta_{j}}{s\hat{e}(\hat{\beta}_{j})} \sim t[N - K] \qquad \Rightarrow sample value = t_{0}(\hat{\beta}_{j}) = \frac{\hat{\beta}_{j} - b_{j}}{s\hat{e}(\hat{\beta}_{j})}.$$

$$\Rightarrow F(\hat{\beta}_{j}) = \frac{\left(\hat{\beta}_{j} - \beta_{j}\right)^{2}}{V\hat{a}r(\hat{\beta}_{j})} \sim F[1, N - K] \Rightarrow sample value = F_{0}(\hat{\beta}_{j}) = \frac{\left(\hat{\beta}_{j} - b_{j}\right)^{2}}{V\hat{a}r(\hat{\beta}_{j})}.$$

$$Note: \left[t(\hat{\beta}_{j})\right]^{2} = F(\hat{\beta}_{j}) \text{ or } t(\hat{\beta}_{j}) = \sqrt{F(\hat{\beta}_{j})} \text{ and } \left[t_{\alpha/2}[N - K]\right]^{2} = F_{\alpha}[1, N - K]$$

• Decision Rules – Two-Tail Tests of One Coefficient Restriction on One Coefficient:

Reject \mathbf{H}_{0} if $|\mathbf{t}_{0}| > \mathbf{t}_{\alpha/2}[\mathbf{N} - \mathbf{K}]$ or two-tail *p*-value for $\mathbf{t}_{0} = \Pr(|\mathbf{t}| > |\mathbf{t}_{0}| |\mathbf{H}_{0} \text{ is true}) < \alpha$; $\mathbf{F}_{0} > \mathbf{F}_{\alpha}[\mathbf{1}, \mathbf{N} - \mathbf{K}]$ or *p*-value for $\mathbf{F}_{0} = \Pr(\mathbf{F} > \mathbf{F}_{0} |\mathbf{H}_{0} \text{ is true}) < \alpha$.

Retain \mathbf{H}_{0} if $|\mathbf{t}_{0}| \leq \mathbf{t}_{\alpha/2}[\mathbf{N} - \mathbf{K}]$ or two-tail *p*-value for $\mathbf{t}_{0} = \Pr(|\mathbf{t}| > |\mathbf{t}_{0}| |\mathbf{H}_{0} \text{ is true}) \geq \alpha$; $F_{0} \leq F_{\alpha}[\mathbf{1}, \mathbf{N} - \mathbf{K}]$ or *p*-value for $F_{0} = \Pr(\mathbf{F} > F_{0} |\mathbf{H}_{0} \text{ is true}) \geq \alpha$.

<u>Two-tail t test</u>: rejection and non-rejection regions

Two-tail critical values of t[50] distribution at 5% significance level ($\alpha = 0.05$, $\alpha/2 = 0.025$)

- *upper* 0.025 critical value of $t[50] = t_{\alpha/2}[50] = t_{0.025}[50] = 2.0086$
- *lower* 0.025 critical value of $t[50] = -t_{\alpha/2}[50] = -t_{0.025}[50] = -2.0086$

Stata commands to compute *upper* 0.025 critical value of $t[50] = t_{0.025}[50]$

```
. display invttail(50, 0.025)
2.0085591
. display ttail(50, 2.0086)
.02499776
. display 2*ttail(50, 2.0086)
.04999551
```

two-tail rejection region is $|\mathbf{t}| > \mathbf{t}_{\alpha/2}$: Pr($|\mathbf{t}| > \mathbf{t}_{\alpha/2}$ | H₀ is true) = $\alpha = 0.05$

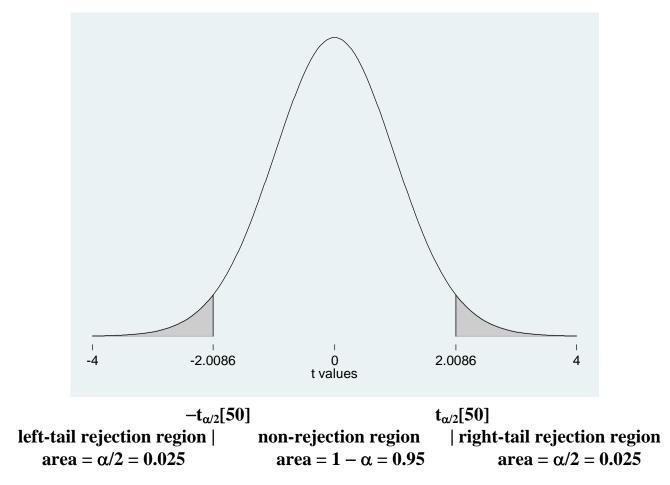
right-tail rejection region is $\mathbf{t} > \mathbf{t}_{\alpha/2}$: Pr($\mathbf{t} > \mathbf{t}_{\alpha/2} \mid \mathbf{H}_0$ is true) = $\alpha/2 = 0.05/2 = 0.025$ *left-tail rejection* region is $\mathbf{t} < -\mathbf{t}_{\alpha/2}$: Pr($\mathbf{t} < -\mathbf{t}_{\alpha/2} \mid \mathbf{H}_0$ is true) = $\alpha/2 = 0.05/2 = 0.025$

non-rejection region is $-t_{\alpha/2} \le t \le t_{\alpha/2}$:

 $\Pr(-t_{\alpha/2} \le t \le t_{\alpha/2} | H_0 \text{ is true}) = \Pr(|t| \le t_{\alpha/2} | H_0 \text{ is true}) = 1 - \alpha = 1 - 0.05 = 0.95$

<u>Two-tail t test</u>: rejection and non-rejection regions (continued)

At 5% significance level, $\alpha = 0.05$ and $\alpha/2 = 0.025$: $t_{0.025}[50] = 2.0086$; $-t_{0.025}[50] = -2.0086$



M.G. Abbott

<u>F test</u>: rejection and non-rejection regions

Critical value of F[1,50] at 5% significance level ($\alpha = 0.05$) = F_a[1,50] = F_{0.05}[1,50] = 4.0343

• 0.05 critical value of $F[1,50] = F_{\alpha}[1,50] = F_{0.05}[1,50] = 4.0343$

Stata commands to compute 0.05 critical value of $F[1,50] = F_{0.05}[1,50]$

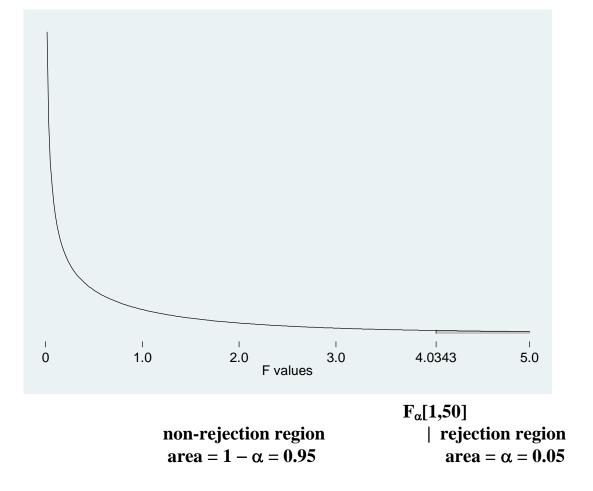
```
. display invFtail(1, 50, 0.05)
4.0343097
. display Ftail(1, 50, 4.0343)
.05000027
```

rejection region is $\mathbf{F} > \mathbf{F}_{\alpha}$: Pr(F > F_{α} | H₀ is true) = α = 0.05

non-rejection region is $\mathbf{F} \leq \mathbf{F}_{\alpha}$: Pr(F $\leq F_{\alpha} \mid \mathbf{H}_{0}$ is true) = 1 - α = 1 - 0.05 = 0.95

<u>F test</u>: rejection and non-rejection regions (continued)

At 5% significance level, $\alpha = 0.05$: 0.05 (5%) critical value of F[1,50] = F_{0.05}[1,50] = 4.0343



□ <u>One-Tail Tests of One Restriction on One Coefficient</u>

- *Examples:* $H_0: \beta_j = b_j \text{ (or } \beta_j \ge b_j \text{) versus } H_1: \beta_j < b_j \text{ a } \underline{\textit{left-tail}} \text{ test}$ $H_0: \beta_j = b_j \text{ (or } \beta_j \le b_j \text{) versus } H_1: \beta_j > b_j \text{ a } \underline{\textit{right-tail}} \text{ test}$
- Use: a one-tail t-test.
- Test Statistic:

$$\Rightarrow t(\hat{\beta}_{j}) = \frac{\hat{\beta}_{j} - \beta_{j}}{s\hat{e}(\hat{\beta}_{j})} \sim t[N - K] \implies sample \ value = t_{0}(\hat{\beta}_{j}) = \frac{\hat{\beta}_{j} - b_{j}}{s\hat{e}(\hat{\beta}_{j})}.$$

• Decision Rules -- <u>left-tail</u> t-test:

Reject \mathbf{H}_{0} if $\mathbf{t}_{0} < -\mathbf{t}_{\alpha}[\mathbf{N} - \mathbf{K}]$ or left-tail *p*-value for $\mathbf{t}_{0} = \Pr(\mathbf{t} < \mathbf{t}_{0} \mid \mathbf{H}_{0} \text{ is true}) < \alpha$; **Retain** \mathbf{H}_{0} if $\mathbf{t}_{0} \ge -\mathbf{t}_{\alpha}[\mathbf{N} - \mathbf{K}]$ or left-tail *p*-value for $\mathbf{t}_{0} = \Pr(\mathbf{t} < \mathbf{t}_{0} \mid \mathbf{H}_{0} \text{ is true}) \ge \alpha$.

• Decision Rules -- <u>right-tail</u> t-test:

Reject \mathbf{H}_{0} if $t_{0} > t_{\alpha}[N-K]$ or **right-tail p-value** for $t_{0} = Pr(t > t_{0} | H_{0} \text{ is true}) < \alpha$;

Retain \mathbf{H}_{0} if $t_{0} \leq t_{\alpha}[N-K]$ or **right-tail p-value** for $t_{0} = Pr(t > t_{0} | H_{0} \text{ is true}) \geq \alpha$.

<u>Left-tail t test</u>: rejection and non-rejection regions

Left-tail critical value of t[50] distribution at 5% significance level ($\alpha = 0.05$)

• *lower* (left-tail) 0.05 critical value of $t[50] = -t_{\alpha}[50] = -t_{0.05}[50] = -1.6759$

Stata commands to compute *lower* 0.05 critical value of $t[50] = -t_{0.05}[50]$

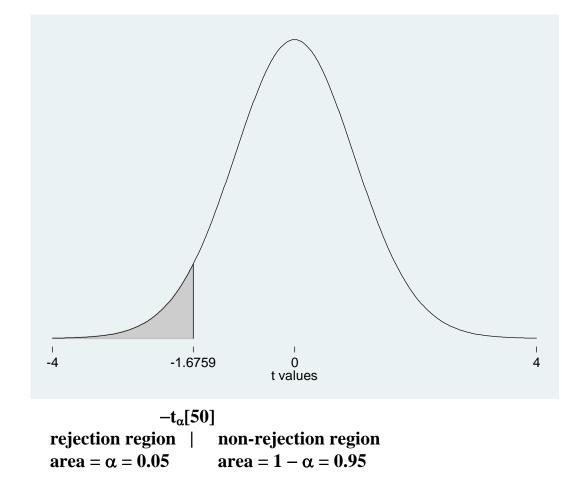
```
. display -1*invttail(50, 0.05)
-1.675905
. display ttail(50, -1.6759)
.9499995
. display 1 - ttail(50, -1.6759)
.0500005
```

rejection region is $t < -t_{\alpha}$: Pr(t < -t_{\alpha} | H_0 is true) = $\alpha = 0.05$

non-rejection region is $t \ge -t_{\alpha}$: $\Pr(t \ge -t_{\alpha} \mid H_0 \text{ is true}) = 1 - \alpha = 1 - 0.05 = 0.95$

<u>Left-tail t test</u>: rejection and non-rejection regions (continued)

At 5% significance level, $\alpha = 0.05$: $-t_{0.05}[50] = -1.6759$



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<u>Right-tail t test</u>: rejection and non-rejection regions

Right-tail critical value of t[50] distribution at 5% significance level ($\alpha = 0.05$)

• *upper* (right-tail) 0.05 critical value of $t[50] = t_{\alpha}[50] = t_{0.05}[50] = 1.6759$

Stata commands to compute *upper* 0.05 critical value of $t[50] = t_{0.05}[50]$

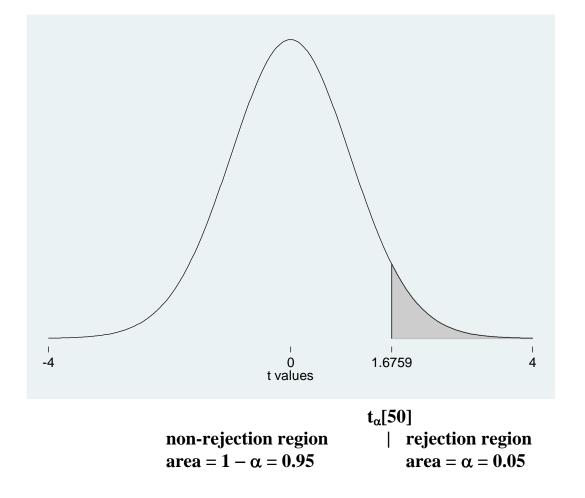
```
. display invttail(50, 0.05)
1.675905
. display ttail(50, 1.6759)
.0500005
```

rejection region is $\mathbf{t} > \mathbf{t}_{\alpha}$: Pr(t > t_{α} | H₀ is true) = α = 0.05

non-rejection region is $\mathbf{t} \leq \mathbf{t}_{\alpha}$: Pr($\mathbf{t} \leq \mathbf{t}_{\alpha} \mid \mathbf{H}_{0}$ is true) = 1 - α = 1 - 0.05 = 0.95

<u>Right-tail t test</u>: rejection and non-rejection regions (continued)

At 5% significance level, $\alpha = 0.05$: $t_{0.05}[50] = 1.6759$



2. <u>Tests of One Linear Restriction on Two or More Coefficients</u>

H₀ specifies *only one* linear restriction on *two or more* regression coefficients.

□ <u>*Two-Tail* Tests of *One* Linear Restriction on *Two* Coefficients</u>

- **Example:** $H_0: c_j\beta_j + c_h\beta_h = c_0$ versus $H_1: c_j\beta_j + c_h\beta_h \neq c_0$.
- Use: either a two-tail t-test or an F-test.
- Test Statistics:

t-statistic

$$\Rightarrow t\left(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h}\right) = \frac{(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h})-(c_{j}\beta_{j}+c_{h}\beta_{h})}{s\hat{e}(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h})} \sim t[N-K] = t[N-K_{1}]$$
where: $s\hat{e}(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h}) = \sqrt{V\hat{a}r(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h})}$

$$V\hat{a}r(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h}) = c_{j}^{2}V\hat{a}r(\hat{\beta}_{j}) + c_{h}^{2}V\hat{a}r(\hat{\beta}_{h}) + 2c_{j}c_{h}C\hat{o}v(\hat{\beta}_{j},\hat{\beta}_{h}).$$

$$sample \ value = t_{0}\left(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h}\right) = \frac{(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h})-c_{0}}{s\hat{e}(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h})}.$$

□ <u>*Two-Tail* Tests of *One* Linear Restriction on *Two* Coefficients (continued)</u>

<u>F-statistic</u>

$$\Rightarrow F\left(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h}\right) = \frac{\left[\left(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h}\right)-\left(c_{j}\beta_{j}+c_{h}\beta_{h}\right)\right]^{2}}{V\hat{a}r(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h})} \sim F[1, N-K] = F[1, N-K_{1}]$$
where: $V\hat{a}r(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h}) = c_{j}^{2}V\hat{a}r(\hat{\beta}_{j}) + c_{h}^{2}V\hat{a}r(\hat{\beta}_{h}) + 2c_{j}c_{h}C\hat{o}v(\hat{\beta}_{j}, \hat{\beta}_{h}).$

$$sample \ value = F_{0}\left(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h}\right) = \frac{\left[\left(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h}\right)-c_{0}\right]^{2}}{V\hat{a}r(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h})}$$

• Decision Rules – Two-Tail Tests of One Coefficient Restriction on Two Coefficients:

Reject
$$\mathbf{H_0}$$
 if $|\mathbf{t}_0| > \mathbf{t}_{\alpha/2}[\mathbf{N} - \mathbf{K}]$ or two-tail p-value for $\mathbf{t}_0 = \Pr(|\mathbf{t}| > |\mathbf{t}_0| |\mathbf{H}_0 \text{ is true}) < \alpha$;
 $F_0 > F_{\alpha}[\mathbf{1}, \mathbf{N} - \mathbf{K}]$ or p-value for $F_0 = \Pr(\mathbf{F} > F_0 |\mathbf{H}_0 \text{ is true}) < \alpha$.

Retain
$$\mathbf{H}_{0}$$
 if $|\mathbf{t}_{0}| \leq \mathbf{t}_{\alpha/2}[\mathbf{N} - \mathbf{K}]$ or two-tail p-value for $\mathbf{t}_{0} = \Pr(|\mathbf{t}| > |\mathbf{t}_{0}| |\mathbf{H}_{0} \text{ is true}) \geq \alpha$;
 $\mathbf{F}_{0} \leq \mathbf{F}_{\alpha}[\mathbf{1}, \mathbf{N} - \mathbf{K}]$ or p-value for $\mathbf{F}_{0} = \Pr(\mathbf{F} > \mathbf{F}_{0} |\mathbf{H}_{0} \text{ is true}) \geq \alpha$.

- Example of Tests of One Linear Restriction on Two Coefficients: Stata Commands
- Consider the *linear regression model* given by the population regression equation, or PRE, (1): $Y_{i} = \beta_{0} + \beta_{1}X_{i1} + \beta_{2}X_{i2} + \beta_{3}X_{i3} + \beta_{4}X_{i4} + \beta_{5}X_{i5} + u_{i}$
- Estimate the PRE (1) by OLS (Ordinary Least Squares) using the following Stata regress command: regress y x1 x2 x3 x4 x5
- Perform individual two-tail t-test of H_0 : $\beta_2 = \beta_4$ versus H_1 : $\beta_2 \neq \beta_4$ using the Stata *lincom* command:

```
lincom x2 - x4
or
lincom _b[x2] - _b[x4]
```

• Perform individual F-test of H_0 : $\beta_2 = \beta_4$ versus H_1 : $\beta_2 \neq \beta_4$ using the Stata *test* command:

```
test x^2 = x^4
or
test x^2 - x^4 = 0
```

(1)

Example of Tests of One Linear Restriction on Two Coefficients: Stata Commands (continued)

• How is t_0 statistic produced by *lincom* command related to F_0 statistic produced by *test* command?

lincom command computes:

$$t_0(\hat{\beta}_2 - \hat{\beta}_4) = \frac{(\hat{\beta}_2 - \hat{\beta}_4) - 0}{\hat{se}(\hat{\beta}_2 - \hat{\beta}_4)} = \frac{(\hat{\beta}_2 - \hat{\beta}_4)}{\hat{se}(\hat{\beta}_2 - \hat{\beta}_4)} \sim t[N - 6] \text{ under } H_0$$

test command computes:

$$F_0(\hat{\beta}_2 - \hat{\beta}_4) = \frac{\left[(\hat{\beta}_2 - \hat{\beta}_4) - 0\right]^2}{V\hat{a}r(\hat{\beta}_2 - \hat{\beta}_4)} = \frac{(\hat{\beta}_2 - \hat{\beta}_4)^2}{V\hat{a}r(\hat{\beta}_2 - \hat{\beta}_4)} \sim F[1, N - 6] \text{ under } H_0$$

• Relationship between t and F tests: they yield identical inferences because

$$F_0(\hat{\beta}_2 - \hat{\beta}_4) = (t_0(\hat{\beta}_2 - \hat{\beta}_4))^2 \quad \text{and} \quad F_\alpha[1, N - 6] = (t_{\alpha/2}[N - 6])^2$$

p-value for $\mathbf{F}_0 = two-tail p-value$ for \mathbf{t}_0

□ <u>One-Tail Tests of One Linear Restriction on Two Coefficients</u>

- *Examples:* $H_0: c_j\beta_j + c_h\beta_h = c_0$ versus $H_1: c_j\beta_j + c_h\beta_h < c_0$ a <u>*left-tail*</u> test $H_0: c_j\beta_j + c_h\beta_h = c_0$ versus $H_1: c_j\beta_j + c_h\beta_h > c_0$ a <u>*right-tail*</u> test
- Use: a one-tail t-test.
- Test Statistic:

$$\Rightarrow t\left(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h}\right) = \frac{(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h})-(c_{j}\beta_{j}+c_{h}\beta_{h})}{s\hat{e}(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h})} \sim t[N-K] = t[N-K_{1}]$$
where $s\hat{e}(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h}) = \sqrt{V\hat{a}r(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h})}$

$$V\hat{a}r(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h}) = c_{j}^{2}V\hat{a}r(\hat{\beta}_{j}) + c_{h}^{2}V\hat{a}r(\hat{\beta}_{h}) + 2c_{j}c_{h}C\hat{o}v(\hat{\beta}_{j},\hat{\beta}_{h}).$$

$$sample \ value = t_{0}\left(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h}\right) = \frac{(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h})-c_{0}}{s\hat{e}(c_{j}\hat{\beta}_{j}+c_{h}\hat{\beta}_{h})}.$$

□ <u>One-Tail Tests of One Linear Restriction on Two Coefficients</u> (continued)

• Decision Rules -- <u>left-tail</u> t-test:

Reject \mathbf{H}_{0} if $t_{0} < -t_{\alpha}[N-K]$ or **left-tail p-value** for $t_{0} = \Pr(t < t_{0} \mid H_{0} \text{ is true}) < \alpha$;

Retain \mathbf{H}_{0} if $t_{0} \ge -t_{\alpha}[N-K]$ or **left-tail p-value** for $t_{0} = \Pr(t < t_{0} \mid H_{0} \text{ is true}) \ge \alpha$.

• Decision Rules -- <u>right-tail</u> t-test:

Reject \mathbf{H}_{0} if $t_{0} > t_{\alpha}[N-K]$ or **right-tail p-value** for $t_{0} = Pr(t > t_{0} | H_{0} \text{ is true}) < \alpha$;

Retain $\mathbf{H}_{\mathbf{0}}$ if $\mathbf{t}_{0} \leq \mathbf{t}_{\alpha}[\mathbf{N} - \mathbf{K}]$ or **right-tail p-value** for $\mathbf{t}_{0} = \Pr(\mathbf{t} > \mathbf{t}_{0} \mid \mathbf{H}_{0} \text{ is true}) \geq \alpha$.

3. <u>Tests of Two or More Linear Coefficient Restrictions</u>

H₀ specifies *two or more* linear coefficient restrictions on the PRE given by (1):

$$Y_{i} = \beta_{0} + \beta_{1}X_{i1} + \beta_{2}X_{i2} + \beta_{3}X_{i3} + \beta_{4}X_{i4} + \beta_{5}X_{i5} + u_{i}$$
(1)

We consider two different sets of two or more coefficient restrictions on PRE (1).

- *Example 1:* $H_0: \beta_2 = \beta_4$ and $\beta_3 = \beta_5$ (number of restrictions = 2) $H_1: \beta_2 \neq \beta_4$ and/or $\beta_3 \neq \beta_5$
- *Example 2:* $H_0: \beta_3 = 0$ and $\beta_4 = 0$ and $\beta_5 = 0$ (number of restrictions = 3) $H_1: \beta_3 \neq 0$ and/or $\beta_4 \neq 0$ and/or $\beta_5 \neq 0$
- Use: a general F-test; only an F-test can be used to test jointly two or more coefficient restrictions.

□ <u>*Tests* of *Two or More* Linear Coefficient Restrictions</u> (continued)

• *Test Statistics:* Either of the following two forms of the general F-statistic.

$$\Rightarrow F = \frac{(RSS_0 - RSS_1)/(df_0 - df_1)}{RSS_1/df_1} = \frac{(RSS_0 - RSS_1)/(K - K_0)}{RSS_1/(N - K)}$$
$$\Rightarrow F = \frac{(R_U^2 - R_R^2)/(df_0 - df_1)}{(1 - R_U^2)/df_1} = \frac{(R_U^2 - R_R^2)/(K - K_0)}{(1 - R_U^2)/(N - K)}.$$

 $RSS_{0} = \text{the } restricted \text{ OLS residual sum of squares for the } restricted \text{ model implied by } \mathbf{H}_{0};$ $RSS_{1} = \text{the } unrestricted \text{ OLS residual sum of squares for the } unrestricted \text{ model implied by } \mathbf{H}_{1};$ $df_{0} = N - K_{0} = df \text{ for } RSS_{0}; \qquad df_{1} = N - K = df \text{ for } RSS_{1};$ $R_{R}^{2} = \text{the } R^{2} \text{ value for the } restricted \text{ model implied by } \mathbf{H}_{0};$ $R_{U}^{2} = \text{the } R^{2} \text{ value for the } unrestricted \text{ model implied by } \mathbf{H}_{1}.$

- *Null distribution:* $F \sim F[df_0 df_1, df_1] = F[K K_0, N K].$
- *Sample value* of F-statistic under $H_0 = F_0$.

□ <u>*Tests* of *Two or More* Linear Coefficient Restrictions</u> (continued)

• Decision Rules:

Reject \mathbf{H}_0 if $F_0 > F_{\alpha}[df_0 - df_1, df_1] = F_{\alpha}[K - K_0, N - K]$ or *p***-value for F_0 = \Pr(F > F_0 \mid H_0 \text{ is true}) < \alpha.**

Retain \mathbf{H}_{0} if $F_{0} \leq F_{\alpha}[df_{0} - df_{1}, df_{1}] = F_{\alpha}[K - K_{0}, N - K]$ or

*p***-value** for $F_0 = Pr(F > F_0 | H_0 \text{ is true }) \ge \alpha$.

□ <u>*Tests* of *Two* Linear Coefficient Restrictions: Example 1</u>

- *Example 1:* $H_0: \beta_2 = \beta_4$ and $\beta_3 = \beta_5$ (number of restrictions = 2) $H_1: \beta_2 \neq \beta_4$ and/or $\beta_3 \neq \beta_5$
- *Unrestricted model* is given by PRE (1):

$$Y_{i} = \beta_{0} + \beta_{1}X_{i1} + \beta_{2}X_{i2} + \beta_{3}X_{i3} + \beta_{4}X_{i4} + \beta_{5}X_{i5} + u_{i}$$
(1)

• Restricted model is given by PRE (2): set $\beta_4 = \beta_2$ and $\beta_5 = \beta_3$ in PRE (1): $Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \beta_4 X_{i4} + \beta_5 X_{i5} + u_i$ (1) $Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \beta_2 X_{i4} + \beta_3 X_{i5} + u_i$ $Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 (X_{i2} + X_{i4}) + \beta_3 (X_{i3} + X_{i5}) + u_i$ (2)

□ <u>*Tests* of *Two* Linear Coefficient Restrictions: Example 1</u> (continued)

• OLS estimation of (1) yields the *unrestricted SRE* (1*): $Y_{i} = \hat{\beta}_{0} + \hat{\beta}_{1}X_{i1} + \hat{\beta}_{2}X_{i2} + \hat{\beta}_{3}X_{i3} + \hat{\beta}_{4}X_{i4} + \hat{\beta}_{5}X_{i5} + \hat{u}_{i}$ (1*)

$$RSS_1 = \sum_{i=1}^{N} \hat{u}_i^2 = \hat{u}^T \hat{u}$$
 with $df_1 = N - K = N - 6$ since $K = 6$..

• OLS estimation of (2) yields the *restricted SRE* (2*):

$$Y_{i} = \widetilde{\beta}_{0} + \widetilde{\beta}_{1}X_{i1} + \widetilde{\beta}_{2}(X_{i2} + X_{i4}) + \widetilde{\beta}_{3}(X_{i3} + X_{i5}) + \widetilde{u}_{i}$$

$$\widetilde{\beta}_{4} = \widetilde{\beta}_{2} \quad \text{and} \quad \widetilde{\beta}_{5} = \widetilde{\beta}_{3}$$

$$RSS_{0} = \sum_{i=1}^{N} \widetilde{u}_{i}^{2} = \widetilde{u}^{T}\widetilde{u} \quad \text{with} \quad df_{0} = N - K_{0} = N - 4 \quad \text{since } K_{0} = 4.$$

$$(2^{*})$$

• Substitute values of RSS₁, RSS₀, df₁ and df₀ into formula for general F-statistic:

$$F = \frac{(RSS_0 - RSS_1)/(df_0 - df_1)}{RSS_1/df_1} = \frac{(RSS_0 - RSS_1)/(K - K_0)}{RSS_1/(N - K)}$$

- Null distribution of F: $F \sim F[df_0 df_1, df_1] = F[K K_0, N K] = F[2, N K].$
- Apply decision rule.

□ <u>*Tests* of *Two* Linear Coefficient Restrictions: Example 1</u>

• *Example 1:* $H_0: \beta_2 = \beta_4$ and $\beta_3 = \beta_5$ (number of restrictions = 2) $H_1: \beta_2 \neq \beta_4$ and/or $\beta_3 \neq \beta_5$

<u>F test</u>: rejection and non-rejection regions

Critical value of F[2,1000] at 5% significance level ($\alpha = 0.05$) = F_{\alpha}[2,1000] = F_{0.05}[2,1000] = 3.0047

• 0.05 critical value of $F[2,1000] = F_{\alpha}[2, 1000] = F_{0.05}[2, 1000] = 3.0047$

Stata commands to compute 0.05 critical value of $F[2,1000] = F_{0.05}[2,1000]$

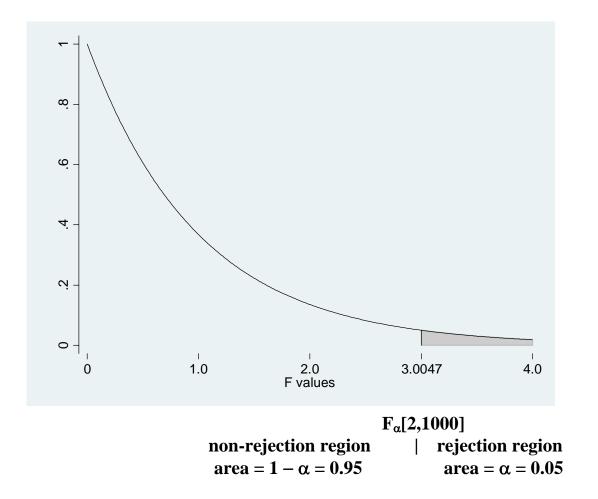
```
. display invFtail(2, 1000, 0.05)
3.0047246
. display Ftail(2, 1000, 3.0047)
.05000122
```

rejection region is $\mathbf{F} > \mathbf{F}_{\alpha}$: Pr(F > F_{α} | H₀ is true) = $\alpha = 0.05$

non-rejection region is $\mathbf{F} \leq \mathbf{F}_{\alpha}$: Pr(F $\leq F_{\alpha}$ | H₀ is true) = 1 - α = 1 - 0.05 = 0.95

<u>F test</u>: rejection and non-rejection regions: Example 1 (continued)

At 5% significance level, $\alpha = 0.05$: 0.05 (5%) critical value of F[2,1000] = F_{0.05}[2,1000] = 3.0047



- *Example 1:* $H_0: \beta_2 = \beta_4$ and $\beta_3 = \beta_5$ (number of restrictions = 2) $H_1: \beta_2 \neq \beta_4$ and/or $\beta_3 \neq \beta_5$
- *Unrestricted model* is given by PRE (1):

$$Y_{i} = \beta_{0} + \beta_{1}X_{i1} + \beta_{2}X_{i2} + \beta_{3}X_{i3} + \beta_{4}X_{i4} + \beta_{5}X_{i5} + u_{i}$$
(1)

• Estimate *unrestricted model* given by PRE (1) by OLS using the **Stata** *regress* command:

regress y x1 x2 x3 x4 x5

• Perform **joint F-test** of H₀ versus H₁ using the following **Stata** *test* commands:

```
test x^2 = x^4, notest
test x^3 = x^5, accumulate
or
test x^2 - x^4 = 0, notest
test x^3 - x^5 = 0, accumulate
```

□ <u>*Tests* of *Three* Linear Coefficient Restrictions: Example 2</u>

- *Example 2:* $H_0: \beta_3 = 0$ and $\beta_4 = 0$ and $\beta_5 = 0$ (number of restrictions = 3) $H_1: \beta_3 \neq 0$ and/or $\beta_4 \neq 0$ and/or $\beta_5 \neq 0$
- *Unrestricted model* is given by PRE (1):

$$\mathbf{Y}_{i} = \beta_{0} + \beta_{1} \mathbf{X}_{i1} + \beta_{2} \mathbf{X}_{i2} + \beta_{3} \mathbf{X}_{i3} + \beta_{4} \mathbf{X}_{i4} + \beta_{5} \mathbf{X}_{i5} + \mathbf{u}_{i}$$
(1)

• *Restricted model* is given by PRE (3): set $\beta_3 = 0$ and $\beta_4 = 0$ and $\beta_5 = 0$ in PRE (1): $Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \beta_4 X_{i4} + \beta_5 X_{i5} + u_i$ (1) $Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + 0 X_{i3} + 0 X_{i4} + 0 X_{i5} + u_i$ (2) $Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + u_i$ (3)

□ <u>*Tests* of *Three* Linear Coefficient Restrictions: Example 2</u> (continued)

- OLS estimation of (1) yields the *unrestricted SRE* (1*): $Y_{i} = \hat{\beta}_{0} + \hat{\beta}_{1}X_{i1} + \hat{\beta}_{2}X_{i2} + \hat{\beta}_{3}X_{i3} + \hat{\beta}_{4}X_{i4} + \hat{\beta}_{5}X_{i5} + \hat{u}_{i}$ $RSS_{1} = \sum_{i=1}^{N} \hat{u}_{i}^{2} = \hat{u}^{T}\hat{u} \quad \text{with} \quad df_{1} = N - K = N - 6 \quad \text{since } K = 6.$ (1*)
- OLS estimation of (3) yields the *restricted SRE* (3*):

$$\begin{split} \mathbf{Y}_{i} &= \widetilde{\beta}_{0} + \widetilde{\beta}_{1} \mathbf{X}_{i1} + \widetilde{\beta}_{2} \mathbf{X}_{i2} + \widetilde{\mathbf{u}}_{i} \\ &\widetilde{\beta}_{3} = 0 \quad \text{and} \quad \widetilde{\beta}_{4} = 0 \quad \text{and} \quad \widetilde{\beta}_{5} = 0 \\ &\text{RSS}_{0} = \sum_{i=1}^{N} \widetilde{\mathbf{u}}_{i}^{2} = \widetilde{\mathbf{u}}^{T} \widetilde{\mathbf{u}} \quad \text{with} \quad df_{0} = \mathbf{N} - \mathbf{K}_{0} = \mathbf{N} - \mathbf{3} \text{ since } \mathbf{K}_{0} = \mathbf{3}. \end{split}$$
(3*)

• Substitute values of RSS₁, RSS₀, df₁ and df₀ into formula for general F-statistic:

$$F = \frac{(RSS_0 - RSS_1)/(df_0 - df_1)}{RSS_1/df_1} = \frac{(RSS_0 - RSS_1)/(K - K_0)}{RSS_1/(N - K)}$$

- **Null distribution of F:** $F \sim F[df_0 df_1, df_1] = F[K K_0, N K] = F[3, N K].$
- Apply decision rule.

□ <u>*Tests* of *Three* Linear Coefficient Restrictions: Example 2</u>

• *Example 2:* $H_0: \beta_3 = 0$ and $\beta_4 = 0$ and $\beta_5 = 0$ (number of restrictions = 3) $H_1: \beta_3 \neq 0$ and/or $\beta_4 \neq 0$ and/or $\beta_5 \neq 0$

<u>F test</u>: rejection and non-rejection regions

Critical value of F[3,1000] at 5% significance level ($\alpha = 0.05$) = F_{α}[3,1000] = F_{0.05}[3,1000] = 2.6138

• 0.05 critical value of $F[3,1000] = F_{\alpha}[3, 1000] = F_{0.05}[3, 1000] = 2.6138$

Stata commands to compute 0.05 critical value of $F[3,1000] = F_{0.05}[3,1000]$

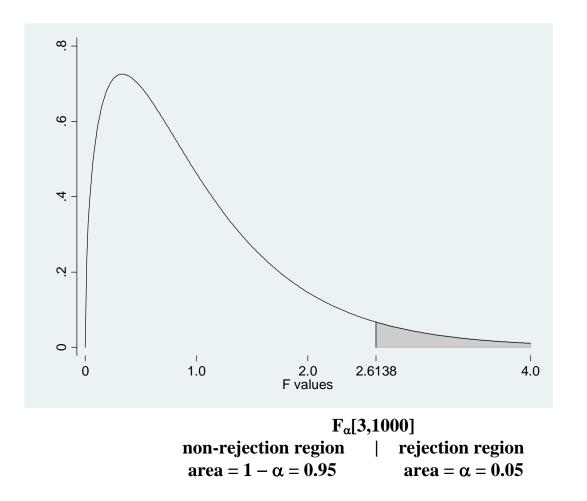
```
. display invFtail(3, 1000, 0.05)
2.6138036
. display Ftail(3, 1000, 2.6138)
.05000024
```

rejection region is $\mathbf{F} > \mathbf{F}_{\alpha}$: Pr(F > F_{α} | H₀ is true) = α = 0.05

non-rejection region is $\mathbf{F} \leq \mathbf{F}_{\alpha}$: Pr(F $\leq F_{\alpha} \mid \mathbf{H}_{0}$ is true) = 1 - α = 1 - 0.05 = 0.95

<u>F test</u>: rejection and non-rejection regions: Example 2 (continued)

At 5% significance level, $\alpha = 0.05$: 0.05 (5%) critical value of F[3,1000] = F_{0.05}[3,1000] = 2.6138



- *Example 2:* $H_0: \beta_3 = 0$ and $\beta_4 = 0$ and $\beta_5 = 0$ (number of restrictions = 3) $H_1: \beta_3 \neq 0$ and/or $\beta_4 \neq 0$ and/or $\beta_5 \neq 0$
- *Unrestricted model* is given by PRE (1):

$$Y_{i} = \beta_{0} + \beta_{1}X_{i1} + \beta_{2}X_{i2} + \beta_{3}X_{i3} + \beta_{4}X_{i4} + \beta_{5}X_{i5} + u_{i}$$
(1)

• Estimate *unrestricted model* given by PRE (1) by OLS using the following **Stata** *regress* command:

```
regress y x1 x2 x3 x4 x5
```

• Perform **joint F-test** of H₀ versus H₁ using the following **Stata** *test* command(s):

```
test x3 x4 x5
or (the long way)
test x3 = 0, notest
test x4 = 0, accumulate notest
test x5 = 0, accumulate
```