

## Ch 7

Extra Sums of squares: The marginal reduction in sum of squared errors when one or several variables are added to a model

$$\begin{aligned} \text{i.e. } SSR(X_2|X_1) &= \text{The marginal reduction in SSE when we add } X_2 \text{ to a model containing } X_1 \\ &= SSE(X_1) - SSE(X_1, X_2) \\ &= SSR(X_1, X_2) - SSR(X_1) \end{aligned}$$

$$\begin{aligned} \text{i.e. } SSR(X_3|X_1, X_2) &= SSE(X_1, X_2) - SSE(X_1, X_2, X_3) \\ &= SSR(X_1, X_2, X_3) - SSE(X_1, X_2) \end{aligned}$$

$$\begin{aligned} \text{i.e. } SSR(X_2, X_3|X_1) &= SSE(X_1) - SSE(X_1, X_2, X_3) \\ &= SSR(X_1, X_2, X_3) - SSR(X_1) \end{aligned}$$

↑ We can get these in either proc reg or proc glm through the linear regression ANOVA Table

$$\boxed{SSTO} = SSR + SSE$$

$$\boxed{SSR(X_1, X_2)} = SSR(X_1) + SSR(X_2|X_1) = SSR(X_2) + SSR(X_1|X_2)$$

Note:  $SSTO(X_1, X_2) = SSR(X_1) + SSR(X_2|X_1) + SSE(X_1, X_2)$

\* Proc glm output Type I and Type III page 25

$$\boxed{MSR(X_2|X_1)} = \frac{SSR(X_2|X_1)}{1}$$

$$\boxed{MSR(X_2, X_3|X_1)} = \frac{SSR(X_2, X_3|X_1)}{2}$$

T test  $\beta_k = 0$

$H_0: \beta_k = 0$  simultaneous

$H_a: \beta_k \neq 0$

$$t^* = \frac{b_k}{SE(b_k)}$$

\* Given in parameter estimate tables in glm; reg

F test  $\beta_k = 0$

$H_0: \beta_k = 0$  given  $X_1, X_2, \dots, X_{k-1}$  are already in the model

$H_a: \beta_k \neq 0$

$$F^* = \frac{SSR(X_k | X_1, X_2)}{1} \div \frac{SSE(X_1, X_2, X_3)}{n-4} = \frac{MSR(X_k | X_1, X_2)}{MSE(X_1, X_2, X_3)}$$

\* Given in type I and type III test tables in glm

F test  $\beta_1 = \beta_2 = \beta_3 = 0$

$H_0: \beta_1 = \beta_2 = \beta_3 = 0$

$H_a: \text{At least one } \neq 0$

$$F^* = \frac{SSE(X_1) - SSE(X_1, X_2, X_3)}{(n-2) - (n-4)} \div \frac{SSE(X_1, X_2, X_3)}{n-4}$$

$$= \frac{SSR(X_2, X_3 | X_1)}{2} \div \frac{SSE(X_1, X_2, X_3)}{n-4} = \frac{MSR(X_2, X_3 | X_1)}{MSE(X_1, X_2, X_3)}$$

\* Add 'test  $x_2 = x_3 = 0$ ;

$$R^2_{Y|123} = \frac{SSR(X_1 | X_2, X_3)}{SSR(X_2, X_3)}$$

= The proportionate reduction in the variation in Y remaining in a model including  $X_2$  and  $X_3$  when  $X_1$  is added

$$r_{Y|123} = \pm \sqrt{R^2_{Y|123}}$$

Multicollinearity - when predictors carry the same information  
 ie when  $\text{corr}(x, y)$  is high,  $r^2$  is high  
 \* To see whether or not this is an issue  
 look at the scatter plot matrix and correlation  
 tables on pg 28.

Effects

- 1) Estimated coefficients vary greatly over samples
- 2) Coefficients may be deemed statistically not significant even though a statistical relationship.
- 3) Our general w/ 'one unit increase in x' interpretation might not make sense if effect is spread across correlated variables

4) On Extra Sums of Squares

$SSR(x_1) = 350$   $\triangleright$  if  $x_1, x_2$  are highly correlated  
 $SSR(x_2|x_1) = 2$  ie multicollinearity exists

5) On  $R^2$

$R^2_{y|1} = \frac{SSR(x_1)}{SSTO} = .75$   $\triangleright$  if  $x_1, x_2$  are highly correlated  
 $R^2_{y|12} = \frac{SSR(x_1, x_2)}{SSTO} = .02$  ie multicollinearity exists

6) On  $se(b_k)$

Variables in Model	$se(b_1)$	$se(b_2)$	
$x_1$	.10	—	* se inflates as we add variables to the model
$x_2$	—	.12	
$x_1, x_2$	.3	.31	
$x_1, x_2, x_3$	3	3.2	

Test for multicollinearity - VIF  $VIF > 10 \rightarrow$  Multicollinearity

$Tolerance = 1/VIF < .1 \rightarrow$  Multicollinearity

\* Sas code

```
proc reg;
  model y = x1 x2 x3 / VIF tol;
```