

# Chapter 3

## Multiple Linear Regression

$$\begin{aligned} \mathbf{y}'\mathbf{y} &= SS_{Res} + \hat{\beta}' \mathbf{x}'\mathbf{y} & \mathbf{y} = \mathbf{X}\beta + \mathbf{e} \\ \mathbf{y}'\mathbf{y} - n\bar{y}^2 &= SS_{Res} + \hat{\beta}' \underline{\mathbf{x}'\mathbf{y}} - n\bar{y} \\ \sum_{i=1}^n (y_i - \bar{y})^2 &= SS_{Res} + SS_R \\ SS_T &= SS_{Res} + SS_R \end{aligned}$$

# Chapter 3e

Extra-sum-of-squares method (pages 3-7)

Examples A – pr2103 data (pages 8-10)

Examples B – pr2103 data (pages 11-13)

Examples C – pr2103 data (pages 14-16)

Difference between Example A and Example C (page 17)

More examples (pages 18-26)

$$\begin{aligned}SS_R &= SS_R(\beta) - SS_R(\beta_0) \\&= SS_R(\beta_0, \beta_1, \dots, \beta_k) - SS_R(\beta_0) \\&= SS_R(\beta_1, \beta_2, \dots, \beta_k \mid \beta_0)\end{aligned}$$

$\text{H}_0: \beta_1 = \beta_2 = \dots = \beta_k = 0$

$\text{H}_1: \text{At least 1 of } \beta_1, \beta_2, \dots, \beta_k \text{ are non-zero}$

## Extra sum of squares method

1. Consider the multiple linear regression model with  $k$  regressor variables

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \epsilon, \quad p = k + 1$$

$$y = (\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_{k-r} x_{k-r}) + (\beta_{k-r+1} x_{k-r+1} + \dots + \beta_k x_k) + \epsilon$$

In matrix notation:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \epsilon = (\mathbf{X}_1, \mathbf{X}_2) \begin{bmatrix} \boldsymbol{\beta}_1 \\ \boldsymbol{\beta}_2 \end{bmatrix} + \epsilon \quad (\text{Full model})$$

$\boldsymbol{\beta}_1$  contains the first  $p - r$  regression coefficients.

$\boldsymbol{\beta}_2$  contains the last  $r$  regression coefficients.

$$\mathbf{y} = \mathbf{X}_1 \boldsymbol{\beta}_1 + \epsilon \quad (\text{reduced model})$$

$$H_0: \beta_2 = \vec{0} \text{ (zero vector)}$$

4. The F statistic for testing the hypotheses is given as

$$F = \frac{\frac{SS_R(\beta_2|\beta_1)/r}{SS_{Res}(FM)/(n-p)}}{\text{full model } (K \text{ regressor variables})}$$

MSRes

Reject  $H_0$  if  $F > F_{\alpha, r, n-p}$

5. The sum of squares  $SS_R(\beta_2|\beta_1)$  is known as the **extra sum of squares** due to  $\beta_2$  because it measures the increase in the regression sum of squares that results from adding  $\beta_2$  to a model that already contains  $\beta_1$ .

6.  $SS_R(\beta_2|\beta_1)$  can be expressed in terms of residual sum of squares of the two models as

$$SS_R(\beta_2|\beta_1) = SS_{Res}(RM) - SS_{Res}(FM)$$

$$\begin{aligned}
 SS_R(\beta_2|\beta_1) &= SS_R(\beta_1, \beta_2) - SS_R(\beta_1) \\
 &= [SS_R(\beta_1, \beta_2) - SS_R(\beta_0)] - [SS_R(\beta_1) - SS_R(\beta_0)] \\
 &= [SS_T - SS_{Res}(FM)] - [SS_T - SS_{Res}(RM)] \\
 &= SS_{Res}(RM) - SS_{Res}(FM)
 \end{aligned}$$

7. The degrees of freedom (DF) of  $SS_R(\beta_2|\beta_1)$  can be expressed in terms of degrees of freedom of the two models as

$$\text{DF of } SS_R(\beta_2|\beta_1) = \text{DF of } SS_{Res}(RM) - \text{DF of } SS_{Res}(FM)$$

$$\text{DF of } SS_{Res}(RM) - \text{DF of } SS_{Res}(FM)$$

$$= [n - (p - r)] - [n - p]$$

$$= r$$

$$= \text{DF of } SS_R(\beta_2|\beta_1)$$

$$H_0: \beta_2 = 0$$

↑  
r parameters

(vector)

8. R can be used to compare the full and reduced models to obtain extra sum of squares  $SS_R(\beta_2|\beta_1)$ , degrees of freedom and  $p$ -value for testing the hypotheses.

For example, suppose the full and reduced models are given as

$$\text{Full model (FM):} \quad y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \epsilon$$

Reduced model (RM):  $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \epsilon$

We want to test

$$H_0 : \beta_4 = \beta_5 = 0$$

$H_1$  : At least one of the two  $\beta$ 's is not zero

By comparing the full and reduced models, the following R code will produce extra sum of squares  $SS_R(\beta_4, \beta_5 | \beta_0, \beta_1, \beta_2, \beta_3)$ , degrees of freedom and p-value for testing the hypotheses,

## Example A - pr2103 data

Suppose we consider the following multiple linear regression model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \epsilon$$

We want to test

$$H_0 : \beta_4 = \beta_5 = 0$$

$$H_1 : \text{At least one of the } \beta\text{'s is not zero}$$

The  $p$ -value is 0.9224 which is large, so we do not reject  $H_0 : \beta_4 = \beta_5 = 0$ .

*they are not too useful in predicting response*

	rm	fm	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)	(P-value)
rm	Model 1: $y \sim x_1 + x_2 + x_3$		79	8914.3					
fm	Model 2: $y \sim x_1 + x_2 + x_3 + x_4 + x_5$		77	8895.7	2	18.675	0.0808	0.9224	$\frac{18.675}{2}$ MS Res (FM)

*minyj*

$SS_{\text{res}}( \beta_4, \beta_5 | \beta_0, \beta_1, \beta_2, \beta_3 )$

```
1 #ch3_pr2103.R
2 library(MASS)
3 rm(list = ls())
4 dat <- read.csv("D:\\nus_teaching\\st3131\\data\\pr2103.csv",
5                  header = T, sep=",")
6 dat
7 names(dat)
8
9 # to test H0: beta1=beta2=beta3=0
10 anova(lm(y~x1+x2+x3))
11 anova(lm(y~1))
12 anova(lm(y~1),lm(y~x1+x2+x3))
13
14 # to test H0: beta4=beta5=0
15 anova(lm(y~x1+x2+x3+x4+x5))
16 anova(lm(y~x1+x2+x3))
17 anova(lm(y~x1+x2+x3),lm(y~x1+x2+x3+x4+x5))
18
19 # to test H0: beta1=beta2=beta3=0
20 anova(lm(y~x1+x2+x3+x4+x5))
21 anova(lm(y~x4+x5))
22 anova(lm(y~x4+x5),lm(y~x1+x2+x3+x4+x5))
```

```
> # to test H0: beta4=beta5=0  
> anova(lm(y~x1+x2+x3+x4+x5))
```

Analysis of Variance Table

FM

Response: y

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
x1	1	8413.4	8413.4	72.8254	9.510e-13 ***
x2	1	1009.6	1009.6	8.7388	0.004133 **
x3	1	2327.8	2327.8	20.1491	2.474e-05 ***
x4	1	1.5	1.5	0.0129	0.909910
x5	1	17.2	17.2	0.1488	0.700788
Residuals	77	8895.7	115.5		

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

```
> anova(lm(y~x1+x2+x3))
```

Analysis of Variance Table

RM

Response: y

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
x1	1	8413.4	8413.4	74.560	5.028e-13 ***
x2	1	1009.6	1009.6	8.947	0.003706 **
x3	1	2327.8	2327.8	20.629	1.973e-05 ***
Residuals	79	8914.3	112.8		

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

```
> anova(lm(y~x1+x2+x3), lm(y~x1+x2+x3+x4+x5))
```

Analysis of Variance Table

8914.3 - 8895.7 = 18.6

Comparing both models

RM

Model 1: y ~ x1 + x2 + x3

FM

Model 2: y ~ x1 + x2 + x3 + x4 + x5

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	79	8914.3			
2	77	8895.7	2	18.675	0.0808 0.9224

## Example B - pr2103 data

Suppose we consider the following multiple linear regression model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \epsilon$$

We want to test

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

$$H_1 : \text{At least one of the } \beta\text{'s is not zero}$$

The  $p$ -value is  $8.8 \times 10^{-11}$  which is very small, so we reject  $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$ .

rm

$$y \sim x_4 + x_5 + x_1 + x_2 + x_3$$

```
> anova(lm(y~x4+x5), lm(y~x1+x2+x3+x4+x5))
```

Analysis of Variance Table

Model 1:  $y \sim x_4 + x_5$

Model 2:  $y \sim x_1 + x_2 + x_3 + x_4 + x_5$

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	80	16918.4				
2	77	8895.7	3	8022.7	23.148	8.808e-11 ***

```

1 #ch3_pr2103.R
2 library(MASS)
3 rm(list = ls())
4 dat <- read.csv("D:\\nus_teaching\\st3131\\data\\pr2103.csv",
5                  header = T, sep=",")
6 dat
7 names(dat)
8
9 # to test H0: beta1=beta2=beta3=0
10 anova(lm(y~x1+x2+x3))
11 anova(lm(y~1))
12 anova(lm(y~1), lm(y~x1+x2+x3))
```

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon$$

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

```

13
14 # to test H0: beta4=beta5=0
15 anova(lm(y~x1+x2+x3+x4+x5))
16 anova(lm(y~x1+x2+x3))
17 anova(lm(y~x1+x2+x3), lm(y~x1+x2+x3+x4+x5))
18
19 # to test H0: beta1=beta2=beta3=0
20 anova(lm(y~x1+x2+x3+x4+x5)) FM
21 anova(lm(y~x4+x5)) RM
22 anova(lm(y~x4+x5), lm(y~x1+x2+x3+x4+x5))
```

```
> # to test H0: beta1=beta2=beta3=0  
> anova(lm(y~x1+x2+x3+x4+x5))
```

Analysis of Variance Table

Response: y

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
x1	1	8413.4	8413.4	72.8254	9.510e-13 ***
x2	1	1009.6	1009.6	8.7388	0.004133 **
x3	1	2327.8	2327.8	20.1491	2.474e-05 ***
x4	1	1.5	1.5	0.0129	0.909910
x5	1	17.2	17.2	0.1488	0.700788
Residuals	77	8895.7	115.5		

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

```
> anova(lm(y~x4+x5))
```

Analysis of Variance Table

Response: y

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
x4	1	3649.8	3649.8	17.2584	8.113e-05 ***
x5	1	96.9	96.9	0.4581	0.5005
Residuals	80	16918.4	211.5		

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

```
> anova(lm(y~x4+x5), lm(y~x1+x2+x3+x4+x5))
```

Analysis of Variance Table

Model 1: y ~ x4 + x5

Model 2: y ~ x1 + x2 + x3 + x4 + x5

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	80	16918.4			
2	77	8895.7	3	8022.7	23.148 8.808e-11 ***

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

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

## Example C - pr2103 data

Suppose we consider the following multiple linear regression model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \epsilon$$

We want to test

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

$$H_1 : \text{At least one of the } \beta\text{'s is not zero}$$

The  $p$ -value is  $2.056 \times 10^{-14}$  which is very small, so we reject  $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$ .

```
> anova(lm(y~1), lm(y~x1+x2+x3))
Analysis of Variance Table

Model 1: y ~ 1
Model 2: y ~ x1 + x2 + x3
  Res.Df   RSS Df Sum of Sq    F    Pr(>F)
1     82 20665.1
2     79  8914.3  3      11751 34.712 2.056e-14 ***
```

```
1 #ch3_pr2103.R
2 library(MASS)
3 rm(list = ls())
4 dat <- read.csv("D:\\nus_teaching\\st3131\\data\\pr2103.csv",
5                  header = T, sep=",")
6 dat
7 names(dat)
8
9 # to test H0: beta1=beta2=beta3=0
10 anova(lm(y~x1+x2+x3))
11 anova(lm(y~1))
12 anova(lm(y~1),lm(y~x1+x2+x3))
13
14 # to test H0: beta4=beta5=0
15 anova(lm(y~x1+x2+x3+x4+x5))
16 anova(lm(y~x1+x2+x3))
17 anova(lm(y~x1+x2+x3),lm(y~x1+x2+x3+x4+x5))
18
19 # to test H0: beta1=beta2=beta3=0
20 anova(lm(y~x1+x2+x3+x4+x5))
21 anova(lm(y~x4+x5))
22 anova(lm(y~x4+x5),lm(y~x1+x2+x3+x4+x5))
```

```
> # to test H0: beta1=beta2=beta3=0  
> anova(lm(y~x1+x2+x3))
```

Analysis of Variance Table

Response: y

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
x1	1	8413.4	8413.4	74.560	5.028e-13	***
x2	1	1009.6	1009.6	8.947	0.003706	**
x3	1	2327.8	2327.8	20.629	1.973e-05	***
Residuals	79	8914.3	112.8			

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

```
> anova(lm(y~1))
```

Analysis of Variance Table

Response: y

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Residuals	82	20665	252.01		

```
> anova(lm(y~1),lm(y~x1+x2+x3))
```

Analysis of Variance Table

Model 1: y ~ 1

Model 2: y ~ x1 + x2 + x3

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	82	20665.1			
2	79	8914.3	3	11751	34.712 2.056e-14 ***

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

extra sum of sq due to  $\beta_1, \beta_2, \beta_3$

In Example B, we use  $SS_R(\beta_1, \beta_2, \beta_3 | \beta_0, \beta_4, \beta_5)$  to test  $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$  given that  $\beta_4$  and  $\beta_5$  are already included in the model.

In Example C, we use  $SS_R(\beta_1, \beta_2, \beta_3 | \beta_0)$  to test  $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$ , without considering  $\beta_4$  and  $\beta_5$ .

$$y = \beta_0 + \beta_1 x_1 + \varepsilon$$

Anova ( $\text{lm}(y \sim x_1)$ )

$$SS_T = SS_{Res} + SS_R$$

### Analysis of Variance

Source of Variation	Sum of Squares	DF	Mean Square
$x_1$	$SS_R(\beta_0, \beta_1)$	$SS_R(\beta_0   \beta_1) = SS_R$	$MS_R(\beta_0   \beta_1)$
Residual	$SS_{Res}(\beta_0, \beta_1)$	$n - 2$	$MS_{Res}(\beta_0, \beta_1)$
Total	$SST$	$= SS_{Res}$	$n - 1$

$$F = MS_R(\beta_0 | \beta_1) / MS_{Res}(\beta_0, \beta_1)$$

To test  $H_0 : \beta_1 = 0$ , reject  $H_0$  if  $F > F_{\alpha, 1, n-2}$

**Note:**  $SS_{Res}(\beta_0, \beta_1) = SS_{Res}$

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon$$

### Analysis of Variance

Source of Variation	Sum of Squares	DF	Mean Square
$x_1, x_2, x_3$	$SS_R(\beta_1, \beta_2, \beta_3   \beta_0)$	3	$MS_R(\beta_1, \beta_2, \beta_3   \beta_0)$
Residual	$SS_{Res}(\beta_0, \beta_1, \beta_2, \beta_3)$	$n - 4$	$MS_{Res}(\beta_0, \beta_1, \beta_2, \beta_3)$
Total	$SST$	$n - 1$	

$$F = MS_R(\beta_1, \beta_2, \beta_3 | \beta_0) / MS_{Res}(\beta_0, \beta_1, \beta_2, \beta_3)$$

To test  $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$ ,

reject  $H_0$  if  $F > F_{\alpha, 3, n-4}$

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon$$

### Analysis of Variance

Source of Variation	Sum of Squares	DF	Mean Square
$x_1$	$SS_R(\beta_1   \beta_0)$	1	$MS_R(\beta_1   \beta_0)$
$x_2, x_3   x_1$	$SS_R(\beta_2, \beta_3   \beta_0, \beta_1)$	2	$MS_R(\beta_2, \beta_3   \beta_0, \beta_1)$
Residual	$SS_{Res}(\beta_0, \beta_1, \beta_2, \beta_3)$	$n - 4$	$MS_{Res}(\beta_0, \beta_1, \beta_2, \beta_3)$
Total	$SST$	$n - 1$	

$$F = MS_R(\beta_2, \beta_3 | \beta_0, \beta_1) / MS_{Res}(\beta_0, \beta_1, \beta_2, \beta_3)$$

To test  $H_0 : \beta_2 = \beta_3 = 0$ ,

reject  $H_0$  if  $F > F_{\alpha, 2, n-4}$

Note:  $SS_R(\beta_2, \beta_3 | \beta_0, \beta_1) = SS_R(\beta_1, \beta_2, \beta_3 | \beta_0) - SS_R(\beta_1 | \beta_0)$

```
> anova(lm(y ~ x1+x2))
Analysis of Variance Table
```

Test  $H_0 : \beta_1 = 0$

Test  $H_0 : y = \beta_0 + \epsilon$  versus  $H_A : y = \beta_0 + \beta_1 x_1 + \epsilon$

$SS_R(\beta_1 | \beta_0)$

Response: y

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
x1	1	866.50	866.50	87.6186	5.748e-10
x2	1	5.60	5.60	0.5659	0.4584
Residuals	27	267.01	9.89		

$SS_R(\beta_2 | \beta_0, \beta_1)$

Test  $H_0 : \beta_2 = 0$

Test  $H_0 : y = \beta_0 + \beta_1 x_1 + \epsilon$  versus  $H_A : y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon$

An alternative way of getting  $SS_R(\beta_2|\beta_0, \beta_1)$ :

```
> anova(lm(y ~ x1), lm(y ~ x1+x2))
```

Analysis of Variance Table

Model 1:  $y \sim x1$

Model 2:  $y \sim x1 + x2$

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	28	272.61				
2	27	267.01	1	5.5959	0.5659	0.4584

$$SS_R(\beta_2|\beta_0, \beta_1) = SS_{Res}(RM) - SS_{Res}(FM)$$

Reduced Model (RM):

$$y = \beta_0 + \beta_1 x_1 + \epsilon$$

```
> anova(lm(y ~ x1))
Analysis of Variance Table
```

	Response: y	Df	Sum Sq	Mean Sq	F value	Pr(>F)
x1		1	866.50	866.50	88.999	3.429e-10
Residuals	28	272.61		9.74		

Full Model (FM):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon$$

```
> anova(lm(y ~ x1+x2))
Analysis of Variance Table
```

	Response: y	Df	Sum Sq	Mean Sq	F value	Pr(>F)
x1		1	866.50	866.50	87.6186	5.748e-10
x2		1	5.60	5.60	0.5659	0.4584
Residuals	27	267.01		9.89		

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon$$

Test  $H_0 : \beta_1 = \beta_2 = 0$  versus  $H_A : \text{At least one of the } \beta\text{'s is not zero.}$

```
> anova(lm(y ~ 1), lm(y ~ x1+x2))
Analysis of Variance Table
```

Model 1:  $y \sim 1$

Model 2:  $y \sim x1 + x2$

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	29	1139.11				
2	27	267.01	2	872.09	44.092	3.123e-09


$$SS_R(\beta_1, \beta_2 | \beta_0)$$

Full Model ( $FM$ ):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \epsilon$$

Reduced Model ( $RM$ ):

$$y = \beta_0 + \beta_1 x_1 + \epsilon$$

Test  $H_0 : \beta_2 = \beta_3 = 0$  versus  $H_A$  : At least one of the  $\beta$ 's is not zero.

```
> anova(lm(y ~ x1), lm(y ~ x1+x2+x3))
Analysis of Variance Table

Model 1: y ~ x1
Model 2: y ~ x1 + x2 + x3
  Res.Df   RSS Df Sum of Sq      F Pr(>F)
1     28 272.61
2     26 263.31  2  9.2957 0.4589  0.637
```



$$SS_R(\beta_2, \beta_3 | \beta_0, \beta_1)$$

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \epsilon$$

Test  $H_0 : \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = 0$  versus  $H_A : \text{At least one of the } \beta\text{'s is not zero.}$

Reduced Model (*RM*):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \epsilon$$

Full Model (*FM*):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \epsilon$$

```
> anova(lm(y ~ x1+x2+x3), lm(y ~ x1+x2+x3+x4+x5+x6+x7+x8))
Analysis of Variance Table
```

```
Model 1: y ~ x1 + x2 + x3
Model 2: y ~ x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8
  Res.Df   RSS Df Sum of Sq    F Pr(>F)
1     26 263.31
2     21 202.87  5 60.44 1.2513 0.3212
```

  $SS_R(\beta_4, \beta_5, \beta_6, \beta_7, \beta_8 | \beta_0, \beta_1, \beta_2, \beta_3)$

```
> anova(lm(y ~ x1+x2+x3))
Analysis of Variance Table
```

Response: y

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
x1	1	866.50	866.50	85.5590	1.048e-09
x2	1	5.60	5.60	0.5525	0.4639
x3	1	3.70	3.70	0.3653	0.5508
Residuals	26	263.31	10.13		

```
> summary(lm(y ~ x1+x2+x3))
```

Coefficients:

$$F = t^2$$

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	32.620594	2.050397	15.909	6.45e-15
x1	-0.077808	0.036767	-2.116	0.0441
x2	0.007284	0.053111	0.137	0.8920
x3	0.039820	0.065881	0.604	0.5508

$$H_0: \beta_3 \leq 0$$

$$SS_R(\beta_1 | \beta_0)$$

$$SS_R(\beta_2 | \beta_0, \beta_1)$$

$$SS_R(\beta_3 | \beta_0, \beta_1, \beta_2)$$

not the  
same

## Partial or marginal tests

$$SS_R(\beta_1 | \beta_0, \beta_2, \beta_3)$$

$$SS_R(\beta_2 | \beta_0, \beta_1, \beta_3)$$

$$SS_R(\beta_3 | \beta_0, \beta_1, \beta_2)$$

The End