## **CHAPTER 4**

4.1  

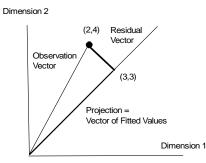
$$X'X = \begin{bmatrix} 10 & 55 \\ 55 & 385 \end{bmatrix}; (X'X)^{-1} = \begin{bmatrix} 0.4667 & -0.0667 \\ -0.0667 & 0.0121 \end{bmatrix};$$

$$V(\hat{\boldsymbol{\beta}}) = \sigma^{2} \begin{bmatrix} 0.4667 & -0.0667 \\ -0.0667 & 0.0121 \end{bmatrix}$$

$$V(\hat{\boldsymbol{\beta}}_{0}) = (0.4667)\sigma^{2}; V(\hat{\boldsymbol{\beta}}_{1}) = (0.0121)\sigma^{2}$$

**4.2** L(1) represents the 45 degree line through the origin in two-dimensional space. Projecting the observation vector  $\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} 2 \\ 4 \end{bmatrix}$  onto the subspace L(1) results in the fitted values  $\hat{\mu} = \begin{bmatrix} 3 \\ 3 \end{bmatrix} = 3 \begin{bmatrix} 1 \\ 1 \end{bmatrix}$  and the least squares estimate  $\hat{\beta}_0 = 3$ . The residual vector  $\boldsymbol{e} = \begin{bmatrix} 2 \\ 4 \end{bmatrix} - \begin{bmatrix} 3 \\ 3 \end{bmatrix} = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$  and the projection  $\hat{\mu} = \begin{bmatrix} 3 \\ 3 \end{bmatrix}$  are orthogonal. The picture is given below.





**4.3** L(X) is the two-dimensional subspace in three-dimensional space that is described by all linear combinations of the two vectors,  $\mathbf{1} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$  and  $\mathbf{x} = \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix}$ . You need to

visualize this as a plane in three-dimensional space. The orthogonal projection of the observation vector  $\mathbf{y} = \begin{bmatrix} 2.2 \\ 3.9 \\ 3.1 \end{bmatrix}$  onto this plane results in the vector of fitted values (the projection)  $\hat{\boldsymbol{\mu}} = \begin{bmatrix} 2.21667 \\ 3.91667 \\ 3.06667 \end{bmatrix}$  and the least squares estimates  $\hat{\boldsymbol{\beta}} = \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \end{bmatrix} = \begin{bmatrix} 1.36667 \\ 0.85000 \end{bmatrix}$ , satisfying  $\hat{\boldsymbol{\mu}} = \begin{bmatrix} 2.21667 \\ 3.91667 \\ 3.06667 \end{bmatrix} = \mathbf{X}\hat{\boldsymbol{\beta}} = \begin{bmatrix} 1 & 1 \\ 1 & 3 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} 1.36667 \\ 0.85000 \end{bmatrix}$ . The residual vector  $\mathbf{e} = \begin{bmatrix} 2.1 - 2.21667 \\ 3.9 - 3.91667 \\ 3.1 - 3.06667 \end{bmatrix} = \begin{bmatrix} -0.01667 \\ -0.01667 \\ 0.03333 \end{bmatrix}$  and the projection  $\hat{\boldsymbol{\mu}} = \begin{bmatrix} 2.21667 \\ 3.91667 \\ 3.91667 \\ 3.06667 \end{bmatrix}$  are orthogonal.

The difference of the data vector y and the projection  $\hat{\mu}$  is quite small, indicating that the data vector is almost in the plane spanned by the matrix X.

**4.4** L(X) is the two-dimensional subspace in three-dimensional space that is described by all linear combinations of the two vectors,  $\mathbf{1} = \begin{bmatrix} 1\\1\\1 \end{bmatrix}$  and  $\mathbf{x} = \begin{bmatrix} 1\\3\\2 \end{bmatrix}$ . You need to visualize this as a plane in three-dimensional space. The orthogonal projection of the observation vector  $\mathbf{y} = \begin{bmatrix} 2\\4\\6 \end{bmatrix}$  onto this plane results in the vector of fitted values (the projection)  $\hat{\boldsymbol{\mu}} = \begin{bmatrix} 3\\5\\4 \end{bmatrix}$  and the least squares estimates  $\hat{\boldsymbol{\beta}} = \begin{bmatrix} \hat{\beta}_0\\\hat{\beta}_1 \end{bmatrix} = \begin{bmatrix} 2\\1 \end{bmatrix}$ , satisfying

$$\hat{\boldsymbol{\mu}} = \begin{bmatrix} 3\\5\\4 \end{bmatrix} = X\hat{\boldsymbol{\beta}} = \begin{bmatrix} 1 & 1\\1 & 3\\1 & 2 \end{bmatrix} \begin{bmatrix} 2\\1 \end{bmatrix}.$$
 The residual vector  $\boldsymbol{e} = \begin{bmatrix} 2-3\\4-5\\6-4 \end{bmatrix} = \begin{bmatrix} -1\\-1\\2 \end{bmatrix}$  and the projection  $\hat{\boldsymbol{\mu}} = \begin{bmatrix} 3\\5\\4 \end{bmatrix}$  are orthogonal.

Note that the difference of the data vector and the projection is larger here than in Exercise 4.3. The data vector is not close to the space spanned by the matrix X.

4.5

- (a)  $V(\hat{\beta}_1) = 18$ (b)  $Cov(\hat{\beta}_1, \hat{\beta}_3) = 1.2$
- (c)  $\operatorname{Corr}(\hat{\beta}_1, \hat{\beta}_3) = 0.0943$
- (d)  $V(\hat{\beta}_1 \hat{\beta}_3) = V(\hat{\beta}_1) + V(\hat{\beta}_3) 2Cov(\hat{\beta}_1, \hat{\beta}_3) = 24.6$

# 4.6

- (a)  $V(\hat{\beta}_2) = 4$ ; s.e. $(\hat{\beta}_2) = 2$
- (b)  $t(\hat{\beta}_2) = \hat{\beta}_2 / \text{s.e.}(\hat{\beta}_2) = 15/2 = 7.5$ ; p-value = 2P(t(12)  $\ge 7.5$ ) < 0.001; reject  $\beta_2 = 0$  in favor of  $\beta_2 \neq 0$

(c) 
$$\text{Cov}(\hat{\beta}_1, \hat{\beta}_2) = -0.05$$

(d) Test  $\beta_1 - \beta_2 = 0$ ;  $V(\hat{\beta}_1 - \hat{\beta}_2) = V(\hat{\beta}_1) + V(\hat{\beta}_2) - 2Cov(\hat{\beta}_1, \hat{\beta}_2) = 1 + 4 + 1 = 6$ ;  $\hat{\beta}_1 - \hat{\beta}_2 / s.e.(\hat{\beta}_1 - \hat{\beta}_2) = -3/\sqrt{6} = -1.22$ ; p-value =  $2P(t(12) \le -1.22) = 0.136$ ; conclude  $\beta_1 - \beta_2 = 0$ , or  $\beta_1 = \beta_2$ .

95% confidence interval for  $\beta_1 - \beta_2$ :  $-3 \pm (2.179)\sqrt{6}$  or (-8.34, 2.34) covers zero.

(e) SST = 120, SSE = 2(15-3) = 24, and SSR = 96; F = (96/2)/(24/12) = 24; very small p-value; reject  $\beta_1 - \beta_2 = 0$ .

#### 4.7

- (a)  $R^2 = 0.9324$
- (b) F-statistic = 110.35; p-value = 0.000; reject  $\beta_1 = \beta_2 = \beta_3 = 0$
- (c) 95% confidence interval for β<sub>taxes</sub>: (0.074, 0.306); reject β<sub>taxes</sub> = 0; cannot simplify model
  95% confidence Interval for β<sub>baths</sub>: (-16.83, 180.57); can not reject β<sub>baths</sub> = 0; can simplify model by dropping "baths"

# 4.8

- (a)  $R^2 = 500074/541119 = 0.9241$
- (b) F-statistic = 152.29; p-value = 0.000; reject  $\beta_1 = \beta_2 = 0$
- (c) t-ratio for taxes = 0.24237 / 0.04884 = 4.96; p-value = P(t(25)  $\ge 4.96$ ) = 0.0000 reject  $\beta_{\text{taxes}} = 0$ ; response is related to taxes.

## 4.9

- (a) From  $\hat{\beta} = (X'X)^{-1}X'y$ , we obtain  $\hat{\beta}_0 = 885.161, \hat{\beta}_1 = -6.571, \hat{\beta}_2 = -1.374$ ; s = 36.49; From  $V(\hat{\beta}) = s^2 (X'X)^{-1}$ : s.e. $(\hat{\beta}_0) = 61.75$ , s.e. $(\hat{\beta}_1) = 0.5832$ , s.e. $(\hat{\beta}_2) = 0.1943$
- (b)  $t(\hat{\beta}_0) = 14.33, t(\hat{\beta}_1) = -11.27, t(\hat{\beta}_2) = -7.07$ ; 97.5<sup>th</sup> percentile: t(27, 0.975) = 2.052; can reject  $\beta_1 = 0$ ; can reject  $\beta_2 = 0$ .
- (c)  $R^2 = 0.841$

## 4.10

- (a) Estimated equation:  $\hat{\mu} = 3.453 + 0.496x_1 + 0.0092x_2$ ;  $s^2 = 4.7403$ ; s.e.( $\hat{\beta}_0$ ) = 2.431, s.e.( $\hat{\beta}_1$ ) = 0.00605, s.e.( $\hat{\beta}_2$ ) = 0.00097
- (b)  $t(\hat{\beta}_1) = 0.496/0.00605 = 81.89$ ; p-value (2-sided) = 2 P(t(12) > 81.89) = 0.000, which is very small. We reject the null hypothesis  $\beta_1 = 0$ .

 $t(\hat{\beta}_2) = 0.009191/0.00097 = 9.49$ ; p-value (2-sided) = 0.000, which is very small. We reject the null hypothesis  $\beta_2 = 0$ .

Neither of the two explanatory variables can be omitted from the model.

#### 4.11

```
(a) Minitab output:
The regression equation is
Y = 295 - 481 X1 - 829 X2 + 0.00794 X3 + 2.36 X4
            CoefSE CoefT295.3340.187.35-480.8150.4-3.20-829.4196.5-4.220.0079360.0035542.232.36030.76163.10
                                                           Ρ
Predictor
                                            7.35 0.000
Constant
                                                    0.006
Xl
X2
                                                      0.001
Х3
                                                      0.041
X4
                                                      0.007
S = 46.77
                R-Sq = 88.3% R-Sq(adj) = 85.1%
```

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	4	246538	61635	28.18	0.000
Residual Error	15	32807	2187		
Total	19	279345			

(b) Test  $\beta_1 = 0$ : t( $\hat{\beta}_1$ ) = -3.20; p-value = 0.006; reject  $\beta_1 = 0$ ; the number of beds in for profit hospitals is important.

(c) The observations (for the two time periods for each state) look very similar and, most likely, they are correlated. If the correlation is very high, it is reasonable to discard one of them or average the two observations, and reanalyze the data.

(d) Instead of selecting ten states at random, one could classify the states into three groups according to population size - small, medium, and large - and select three or four hospitals at random from each category.

**4.12** The output from R software, using the function lm(formula = usage ~ TEMP + PROD + DAYS + PAYR + HOUR) is given below:

Coefficients:					
	Estimate	Std. Error	t value	Pr (> t )	
(Intercept)	39.437054	12.110986	3.256	0.00765	
TEMP	0.084067	0.060469	1.390	0.19194	
PROD	0.001876	0.000607	3.091	0.01027	
DAYS	0.131704	0.289800	0.454	0.65833	
PAYS	-0.215677	0.098810	-2.183	0.05162	
HOUR	-0.014475	0.030052	-0.482	0.63949	

Residual standard error: 3.213 on 11 degrees of freedom Multiple R-Squared: 0.6446, Adjusted R-squared: 0.4831 F-statistic: 3.991 on 5 and 11 DF, p-value: 0.02607

 $R^2 = 0.6446$ , and the regression model is significant at 2.6% level. The output indicates that PROD is significant at the 1% level, even if other variables are present in the model. PAYS is also marginally significant (p-value = 0.051). All other variables are not significant when added last to the model. The model can be simplified

(b) In order to test  $\beta_1 = \beta_3 = \beta_5 = 0$ , we need to fit a reduced model that includes just  $x_2$  and  $x_4$ . The R output for the reduced model with lm(formula = USAGE ~ PROD + PAYR) is listed below

Coefficients:				
	Estimate	Std. Error t	value	Pr (> t )
(Intercept)	46.0177241	10.1085905	4.552	0.000452
PROD	0.0020353	0.0005587	3.643	0.002663
PAYR	-0.2157919	0.0895867	-2.409	0.030356
Residual stand Multiple R-Squ F-statistic: 9	ared: 0.5743	, Adjusted R-	squared	: 0.5135

The additional sum of squares = ResidualSS (reduced model) – ResidualSS (full model) = SSR(full model) – SSR(reduced model) = 205.956 –183.48 and  $F = [(205.956 - 183.48)/2]/(3.213)^2 = 1.09$ ; p-value = P(F(2,11) > 1.09) = 0.37; we can not reject  $\beta_1 = \beta_3 = \beta_5 = 0$ .

(c) We prefer the reduced model  $\hat{\mu} = 46.02 + 0.00204$ PROD - 0.216PAYR ; R<sup>2</sup> = 0.574 (only slightly smaller than the R<sup>2</sup> of the full model = 0.6446).

(d) Production has the smallest p-value.

(e) Water usage as linear function of PROD and PAYR. For fixed value of PAYR, each unit increase in production increases water use by 0.0020353 (gallons/100). Similarly, for a fixed value of PROD, a unit increase in PAYR decreases water usage by 0.2157919 (gallons/100).

4.13 (a) Minitab output: The regression equation is Y = 177 + 2.17 X1 + 3.54 X2 - 22.2 X3 + 0.204 X4Predictor COLL Cont 177.229 CoefSE Coef177.2298.7872.17020.67373.53800.1092-22.15830.54540.20350.3189 т Ρ 
 20.17
 0.000

 3.22
 0.009

 32.41
 0.000
 20.17 X1 X2 Х3 -40.63 0.000 0.538 X4 0.64 S = 5.119 R-Sq = 99.7% R-Sq(adj) = 99.6%Analysis of Variance SourceDFSSRegression489285Residual Error10262Total1489547 MS F Ρ 89285 22321 851.72 0.000 26

(b)  $R^2 = 0.997$ ; estimates are part of the output given above

Abraham/Ledolter: Chapter 4

4-6

(c)

- (i) t-ratio = 0.64; p-value = 0.538; conclude  $\beta_4 = 0$
- (ii) F = [(43968 262)/2]/[262/10] = 834.1; p-value = P(F(2,10) > 834.1) = 0.0000; reject  $\beta_3 = \beta_4 = 0$
- (iii) F = (58575 262)/(262/10) = 2,225.7; p-value = P(F(2,10) > 2,225.7) = 0.0000; reject  $\beta_2 = \beta_3$

```
The regression equation is 
Y = -61 + 4.61 \times 1 + 3.05 \times 2+\times 3 + 2.54 \times 4
```

Predictor Constant X1 X2+X3 X4	Coef -61.4 4.613 3.051 2.541	SE Coef 102.4 9.575 1.549 4.490	T -0.60 0.48 1.97 0.57	P 0.561 0.639 0.075 0.583	
S = 72.97 Analysis of Var	R-Sq = 3	34.6% R-S	Sq(adj) = 10	5.7%	
Source Regression Residual Error Total	DF 3 11 14	SS 30972 58575 89547	MS 10324 5325	F 1.94	P 0.182

(iv) F = 851.72; p-value = 0.0000; reject  $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ 

```
(d) Minitab output:
```

The regression equation is Y = 179 + 2.11 X1 + 3.56 X2 - 22.2 X3

Predictor Constant X1 X2 X3	Coef 178.521 2.1055 3.56240 -22.1880	SE Coef 8.318 0.6479 0.09945 0.5286	21.46 3.25 35.82	P 0.000 0.008 0.000 0.000	
S = 4.980 Analysis of N	R-Sq = Variance	99.7%	R-Sq(adj) =	99.6%	
Source Regression Residual Erro Total	DF 3 or 11 14	SS 89274 273 89547	MS 29758 25	F 1200.14	P 0.000

(e) 95% prediction interval for sales when  $x_1 = 3, x_2 = 45, x_3 = 10$ : (111.46, 135.08)

4.14 (a) 81.82 115.40 13.00 59.43 59.43 394.73 360.66 522.08 X'X =81.82 360.66 576.73 728.31 115.40 522.08 728.31 1035.96  $(X'X)^{-1} = \begin{bmatrix} 8.06479464 & -0.082592705 \\ -0.08259271 & 0.008479816 \\ -0.09419511 & 0.001716687 \\ 0.70052555 \end{bmatrix}$ -0.082592705 -0.094195115 -0.7905268760.001716687 0.003720020 0.016629424 -0.002063308-0.790526880.003720020 -0.0020633080.088601286  $\mathbf{X'} \mathbf{y} = \begin{vmatrix} 1877.911 \\ 2247.285 \end{vmatrix}$ 

(c) Estimated equation:  $\hat{\mu} = 39.482 + 1.0092x_1 - 1.873x_2 - 0.367x_3$ 

(d) (i) (22.802, 25.653); 90% confidence interval for the mean value of y when  $x_1 = 3$ ,  $x_2 = 8$  and  $x_2 = 9$  can be obtained with the software R directly using the function "predict".

u	predict .		
	Mean value	Lower limit	Upper limit
	24.22764	22.80225	25.65302

There is also an option in Minitab.

(ii) (20.109, 28.346); 90% prediction interval for an individual value of y when  $x_1 = 3$ ,  $x_2 = 8$  and  $x_2 = 9$  can also be obtained from the software R directly using the function "predict".

(e) F-statistic = 30.08; p-value = 0.000; reject  $\beta_1 = \beta_2 = \beta_3 = 0$ .

# 4.15

- (a) Linear relationship between y and x<sub>1</sub>; perhaps some curvature in the scatter plot of y against x<sub>2</sub> (see part (e))
- (b)  $\hat{\beta}_0 = 2.59; \hat{\beta}_1 = -0.378; \hat{\beta}_2 = 0.877$ Fitted equation:  $\hat{\mu} = 2.59 - 0.378x_1 + 0.877x_2$
- (c) Significant relationship between y and the variables  $x_1$  and  $x_2$

The regression equation is Y = 2.59 - 0.378 X1 + 0.877 X2

 
 Predictor
 Coef
 SE Coef
 T
 P

 Constant
 2.58810
 0.08349
 31.00
 0.000

 X1
 -0.37802
 0.06630
 -5.70
 0.000
 0.8768 0.1723 X2 5.09 0.000 S = 0.06263 R-Sq = 90.8% R-Sq(adj) = 89.3% Analysis of Variance DF SS 2 0.46419 12 0.047 Source Regression Source MS F Ρ MS 0.23210 0.00392 59.16 0.000 Residual Error 0.00392 Total 14 0.51127

- (d) Model with  $x_1$ :  $R^2 = 0.709$ . Model with  $x_2$ :  $R^2 = 0.659$ . Prefer model with  $x_2$
- (e) Prefer model with both x<sub>1</sub> and x<sub>2</sub> as neither variable can be omitted from the model (see t-ratios in (c)).

No need to add  $(x_2)^2$  to the model; t-ratio = 0.24; p-value = 0.815

4.16

$$(X'X)^{-1} = \begin{vmatrix} 9.61093203 & 0.008587789 & -0.27914754 & -0.04452169 \\ 0.00858779 & 0.509964070 & -0.25886359 & 0.00077654 \\ -0.27914754 & -0.25886359 & 0.13949996 & 0.00073956 \\ -0.04452169 & 0.00077654 & 0.00073956 & 0.00036978 \end{vmatrix}$$

Correction Factor =  $45^2/9 = 225$ SST = y'y - CF = 285 - 225 = 60SSR =  $\hat{\beta}X'y$  - CF = 282.9725 - 225 = 57.9725SSE = SST - SSR = 60 - 57.9725 = 2.0275

ANOVA table:

Source	DF	SS	MS	F	P
Regression	3	57.9725	19.3242	47.66	2.129815e-05
Residual	5	2.0275	0.4055		
Total	8	60.0000			

F-statistic = 47.66; reject  $\beta_1 = \beta_2 = \beta_3 = 0$ (b) Estimated equation:  $\hat{\mu} = -1.16346 + 0.13527x_1 + 0.01995x_2 + 0.12195x_3$ ;  $s^2 = 0.4055$ ; s.e. $(\hat{\beta}_0) = 1.974$ ; s.e. $(\hat{\beta}_1) = 0.45474$ ; s.e. $(\hat{\beta}_2) = 0.23784$ ; s.e. $(\hat{\beta}_3) = 0.01225$ t $(\hat{\beta}_1) = 0.295$ ; p-value = 0.78; can not reject  $\beta_1 = 0$ 

 $t(\hat{\beta}_2) = 0.084$ ; p-value = 0.94; can not reject  $\beta_2 = 0$  $t(\hat{\beta}_3) = 9.955$ ; p-value = 0.000; reject  $\beta_3 = 0$ 

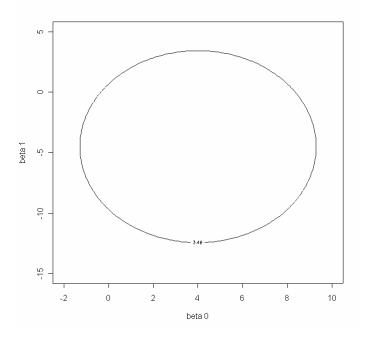
## 4.17

(a) t(0.975;20) = 2.086

95% confidence interval for  $\beta_0$ : 4 ± (2.086)(2) or (-0.17, 8.17); covers  $\beta_0 = 0$ , but just barely.

95% confidence interval for  $\beta_1$ : -4.5 ± (2.086)(3) or (-10.76, 1.76); covers  $\beta_1 = 0$ 

(b) 95% confidence region is given below. The point  $(\beta_0 = 0, \beta_1 = 0)$  is very close to the 95% contour (it is just barely within the 95% confidence region). This indicates that neither model A and B are particularly worthwhile.



(c) There is no conflict between the results in (a) and (b). In general there could have been a conflict if  $\text{Cov}(\hat{\beta}_0, \hat{\beta}_1)$  was not zero.

**4.18** Cov $(e, \hat{\mu}) =$  Cov $((I - H)y, Hy) = \sigma^2(I - H)H = O$ , a (n x n) matrix of zeros. Vectors e and  $\hat{\mu}$  are linear functions of y and are normal. Hence e and  $\hat{\mu}$  are statistically independent.

(a) 
$$\hat{\beta}^{\text{WLS}} = \sum (y_i x_i / x_i^2) / \sum (x_i^2 / x_i^2) = \sum (y_i / x_i) / n; \ V(\hat{\beta}^{\text{WLS}}) = \sigma^2 / n$$
  
(b)  $\hat{\beta}^{\text{WLS}} = 30/12 = 2.5; \ V(\hat{\beta}^{\text{WLS}}) = \sigma^2 / 12$ 

4.20  
(a) 
$$\hat{\beta}^{WLS} = \sum y_i / \sum x_i$$
;  $V(\hat{\beta}^{WLS}) = \sigma^2 / \sum x_i$   
(b)  $\hat{\beta}^{WLS} = 30/2 = 15$ ;  $V(\hat{\beta}^{WLS}) = \sigma^2 / 150$ 

#### **4.21** See Exercise 4.9. Minitab output:

The regression equation is y = 885 - 6.57 x1 - 1.37 x2Predictor Coef SE Coef Т Ρ 61.75 885.16 14.33 0.000 Constant -6.5708 x1 0.5832 -11.27 0.000 0.1943 -1.3743 x2 -7.07 0.000 S = 36.49R-Sq = 84.0% R-Sq(adj) = 82.8% Analysis of Variance DF SS F Source MS Ρ 189062 71.00 0.000 2 94531 Regression Residual Error 27 35950 1331 Total 29 225011

95 percent confidence interval for the mean abrasion loss for rubber with hardness 70 and tensile strength 200: (134.65, 166.03)

## 4.22

(a) Linear model not appropriate.

(b) Fitted equation: TensileStrength = -6.674 + 11.764 Hardwood - 0.635 (Hardwood)<sup>2</sup>

Source	DF	SS	MS	F	P
Regression	2	3104.2	1552.1	79.43	0.000
Residual Error	16	312.6	19.5		
Total	18	3416.9			

Model adequate; quadratic term needed; increases  $R^2$  from 0.305 to 0.909. 95% confidence interval for mean response when hardwood 6 percent: (38.14, 44.00) Prediction intervals are for individual observations while confidence intervals are for the mean value. Confidence intervals are shorter than the corresponding prediction intervals. 95% prediction interval for tensile strength for a batch of paper with 6 percent hardwood concentration: (31.25, 50.88).

The maximum hardwood concentration in the data set used to fit the model is 7 percent, which is very low compared to 20 percent. It is not advisable to use the fitted model to predict the mean tensile strength of paper for 20 percent hardwood concentration.

# 4.23

Quadratic model. Estimated equation:  $\hat{\mu} = 82.385 - 38.310x + 4.703x^2$ 

Regression significant; adequate fit.

Stars with ln(surface temperature) < 4 appear different and should be investigated separately. Without these stars, a linear model is appropriate.

Predictor Constant x	Coef 82.385 -38.310				
x2	4.7025	0.5939	7.92	0.000	
S = 0.3667	R-Sq =	60.6%	R-Sq(adj) =	58.8%	
Analysis of Va	riance				
Source	DF	SS	MS	F	P
Regression	2	9.0945	4.5472	33.82	0.000
Residual Error	44	5.9165	0.1345		
Total	46	15.01			
4.24					
<pre>(a) Minitab regree The regression Y = 31.4 + 9.3</pre>	equation	n is			

Predictor	Coef	SE Coef	Т	P
Constant	31.373	2.461	12.75	0.000
UFFI	9.312	2.133	4.37	0.000
Tight	2.8545	0.3764	7.58	0.000
S = 5.223	R-Sq = 7	'8.3% R-9	Sq(adj) = 70	6.2%

Abraham/Ledolter: Chapter 4

4-12

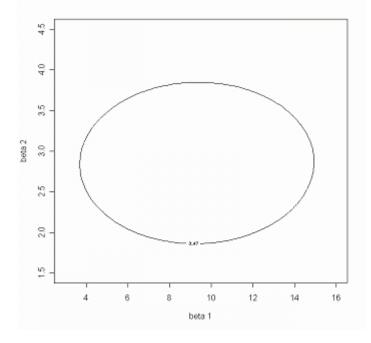
Analysis of Variance

DF Source SS MS F Ρ 37.82 2 2063.3 1031.6 0.000 Regression Residual Error 21 572.9 27.3 23 2636.1 Total (b)  $\begin{bmatrix} 0.221946 & -0.085569 & -0.026828 \end{bmatrix}$ 24 12 123  $(X'X) = \begin{vmatrix} 12 & 12 & 61 \end{vmatrix}; (X'X)^{-1} = \begin{vmatrix} -0.085569 & 0.166703 \end{vmatrix}$ 0.000433 ; 123 61 823 -0.026828 0.000433 0.005193

$$\mathbf{V}(\hat{\boldsymbol{\beta}}) = \mathbf{s}^{2} (\mathbf{X}'\mathbf{X})^{-1} = \begin{bmatrix} 6.05462 & -2.33430 & -0.73187 \\ -2.33430 & 4.54761 & 0.01180 \\ -0.73187 & 0.01180 & 0.14165 \end{bmatrix}$$

s.e.
$$(\hat{\beta}_0) = \sqrt{6.05462} = 2.461$$
; s.e. $(\hat{\beta}_1) = \sqrt{4.54761} = 2.133$ ;  
s.e. $(\hat{\beta}_2) = \sqrt{0.14165} = 0.376$ 

(c) The 95 percent confidence region for  $(\beta_1, \beta_2)$  is shown below. The point  $(\beta_1 = 0, \beta_2 = 0)$  is far from this region.



Abraham/Ledolter: Chapter 4

