

# Problem Set #4

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## Question 1

- (a) The table below displays the coefficient estimates, alongside robust standard errors.

VARIABLES	(1) log(wage)
Education	0.144*** (0.0118)
Experience	0.0426*** (0.0125)
Experience <sup>2</sup>	-0.0951*** (0.0341)
Constant	0.531*** (0.202)
Observations	267
R-squared	0.389
Sum-of-squared Errors	82.50
Robust standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

- (b) In terms of the model parameters, with *experience* = 10,

$$\theta = \frac{\beta_1}{\beta_2 + \frac{1}{5}\beta_3}$$

Using the parameter estimates from the model,

$$\hat{\theta} \approx 6.109$$

- (c) The asymptotic standard error of  $\hat{\theta}$  is the square root of its asymptotic variance. Since  $\theta$  is a function of  $\beta$ , we can use the delta method to solve for the variance of  $\hat{\theta}$  as a function of the variance-covariance matrix of  $\hat{\beta}$ :

$$\sqrt{n}(\hat{\theta} - \theta) \rightarrow_d f'(\hat{\beta})\mathcal{N}(0, V) \equiv \mathcal{N}\left(0, f'(\hat{\beta})'Vf'(\hat{\beta})\right)$$

Where  $V$  is the variance-covariance matrix of  $\hat{\beta}$  and

$$f'(\hat{\beta}) = \begin{pmatrix} \frac{\partial f(\hat{\beta})}{\partial \hat{\beta}_1} \\ \frac{\partial f(\hat{\beta})}{\partial \hat{\beta}_2} \\ \frac{\partial f(\hat{\beta})}{\partial \hat{\beta}_3} \\ \frac{\partial f(\hat{\beta})}{\partial \hat{\beta}_4} \end{pmatrix} = \begin{pmatrix} \frac{1}{\hat{\beta}_2 + \frac{1}{5}\hat{\beta}_3} \\ -\frac{\hat{\beta}_1}{(\hat{\beta}_2 + \frac{1}{5}\hat{\beta}_3)^2} \\ -\frac{\hat{\beta}_1}{5(\hat{\beta}_2 + \frac{1}{5}\hat{\beta}_3)^2} \\ 0 \end{pmatrix}$$

- (d) Using the results from the regression summarized in part (a),

$$s(\hat{\theta}) \approx 1.63$$

$$90\% \text{ c.i.} = [\hat{\theta} - 1.645s(\hat{\theta}), \hat{\theta} + 1.645s(\hat{\theta})] \approx [3.428, 8.790]$$

## Question 2

According to equation (8.3),

$$\tilde{\beta}_{CLS} = \arg \min_{R'\beta=c} \text{SSE}(\beta)$$

Where  $R = \begin{pmatrix} 0 \\ I_{k_2} \end{pmatrix}$  and  $c = 0$ . Then, (8.3) can be simplified as the following unconstrained optimization problem:

$$\tilde{\beta}_{CLS} = \text{argmin} \text{SSE} \begin{pmatrix} \beta_1 \\ 0 \end{pmatrix}$$

And where  $\hat{\beta}_{OLS}$  from the regression of  $Y$  on  $X_1$  is defined as:

$$\hat{\beta}_{OLS} = \text{argmin} \text{SSE}(\beta_1)$$

## Question 3

By equation (8.3),

$$\tilde{\beta}_{CLS} = \arg \min_{R'\beta=c} \text{SSE}(\beta)$$

Where,  $SSE(\beta) = (Y - X\beta)'(Y - X\beta) = (Y - X_1\beta_1 - X_2\beta_2)'(Y - X_1\beta_1 - X_2\beta_2)$   
and, in this case,  $R = \begin{pmatrix} I_k \\ I_k \end{pmatrix}$  and  $c = 0$ . Then,

$$\begin{aligned}\tilde{\beta}_{CLS} &= \arg \min_{R'\beta=c} SSE(\beta)(Y - X\beta)'(Y - X\beta) \\ \mathcal{L} &= (Y - X_1\beta_1 - X_2\beta_2)'(Y - X_1\beta_1 - X_2\beta_2) - \lambda(\beta_1 + \beta_2) \\ \frac{\partial \mathcal{L}}{\partial \beta_1} &= -2X_1'(Y - X_1\beta_1 - X_2\beta_2) - \lambda = 0 \\ \frac{\partial \mathcal{L}}{\partial \beta_2} &= -2X_2'(Y - X_1\beta_1 - X_2\beta_2) - \lambda = 0 \\ \frac{\partial \mathcal{L}}{\partial \lambda} &= \beta_1 + \beta_2 = 0 \\ \beta_1 &= -\beta_2 \\ -2X_1'(Y - X_1\beta_1 - X_2\beta_2) &= -2X_2'(Y - X_1\beta_1 - X_2\beta_2) \\ -2X_1'(Y + X_1\beta_2 - X_2\beta_2) &= -2X_2'(Y + X_1\beta_2 - X_2\beta_2) \\ -2X_1'Y - 2X_1'(X_1 - X_2)\beta_2 &= -2X_2'Y - 2X_2'(X_1 - X_2)\beta_2 \\ 2(X_2 - X_1)'(X_1 - X_2)\beta_2 &= 2(X_1 - X_2)'Y \\ \beta_2 &= [(X_2 - X_1)'(X_1 - X_2)](X_1 - X_2)'Y \\ \beta_1 &= [(X_2 - X_1)'(X_2 - X_1)](X_2 - X_1)'Y\end{aligned}$$

Thus,

$$\tilde{\beta}_{CLS} = \begin{pmatrix} [(X_2 - X_1)'(X_2 - X_1)](X_2 - X_1)'Y \\ [(X_2 - X_1)'(X_1 - X_2)](X_1 - X_2)'Y \end{pmatrix}$$

## Question 4

8.4(a)

## Question 5

8.22

## Question 6

9.1

9.2

## Question 7

9.4

## Question 8

9.7