

$$\boxed{N = 2}$$

(a) since β is non-random then $E(\hat{\beta}) = \beta$

$$y = X\beta + u$$

$$u = y - X\beta$$

First, let's derive β :

" β should be such that it gives us minimal value of SSR"

$$\begin{aligned} SSR &= u^T u = (y - X\beta)^T (y - X\beta) = (y^T - X^T \beta^T) (y - X\beta) = \\ &= y^T y - \underline{y^T X \beta} - \underline{\beta^T X^T y} + \underline{\beta^T X^T X \beta} \end{aligned}$$

$$\begin{array}{c} Y^T X \beta \\ \downarrow \quad \downarrow \quad \downarrow \\ (n \times 1)^T \quad n \times K \quad K \times 1 \\ \text{---} \quad \text{---} \quad \text{---} \\ 1 \times h \quad n \times 1 \quad n \times 1 \\ \text{---} \quad \text{---} \quad \text{---} \\ n \times 1 \end{array} \quad \begin{array}{l} \text{- scalar} \Rightarrow \text{scalar} = \text{scalar transposed} \Rightarrow \\ \Rightarrow \underline{Y^T X \beta} = (Y^T X \beta)^T = \underline{\beta^T X^T Y} \end{array}$$

$$SSR = \mathbf{y}^T \mathbf{y} - \beta^T \mathbf{x}^T \mathbf{y} - \beta^T \mathbf{x}^T \mathbf{x} \beta + \beta^T \mathbf{x}^T \mathbf{x} \beta = \mathbf{y}^T \mathbf{y} - 2\beta^T \mathbf{x}^T \mathbf{y} + \beta^T \mathbf{x}^T \mathbf{x} \beta \rightarrow \min_{\beta}$$

$$\frac{\partial SSR}{\partial \beta} = 0 - 2 \cdot 1 \cdot \mathbf{x}^T \mathbf{y} + 2\beta \cdot \mathbf{x}^T \mathbf{x} = -2\mathbf{x}^T \mathbf{y} + 2\beta \mathbf{x}^T \mathbf{x} = 0$$

$$\beta \cdot \mathbf{x}^T \mathbf{x} = \mathbf{x}^T \mathbf{y}$$

$$\boxed{\beta = \frac{\mathbf{x}^T \mathbf{y}}{\mathbf{x}^T \mathbf{x}}} \quad \text{OR} \quad (\mathbf{x}^T \mathbf{x})^{-1} \mathbf{x}^T \mathbf{y}$$

$$\hat{\beta} = (\mathbf{x}^T \mathbf{x})^{-1} \mathbf{x}^T \mathbf{y} = (\mathbf{x}^T \mathbf{x})^{-1} \mathbf{x}^T (\mathbf{x}\beta + \mathbf{u}) = (\cancel{\mathbf{x}^T \mathbf{x}})^{-1} (\cancel{\mathbf{x}^T \mathbf{x}}) \beta + (\mathbf{x}^T \mathbf{x})^{-1} \mathbf{x}^T \mathbf{u} = \\ = \beta + \mathbf{x}^{-1} (\mathbf{x}^T)^{-1} \mathbf{x}^T \mathbf{u} = \beta + \mathbf{x}^{-1} \mathbf{u}$$

$$\mathbb{E}(\hat{\beta} | \mathbf{x}) = \beta + \mathbf{x}^{-1} \cdot \mathbb{E}(\mathbf{u} | \mathbf{x}) = \beta + \mathbf{x}^{-1} \cdot \mathbf{0} = \beta + \mathbf{0} = \beta$$

$$(b) \hat{\beta} = \beta + \mathbf{x}^{-1} \mathbf{u}$$

$$\text{Var}(\hat{\beta} | \mathbf{x}) = \text{Var}(\beta + \mathbf{x}^{-1} \mathbf{u} | \mathbf{x}) = 0 + \text{Var}(\mathbf{x}^{-1} \mathbf{u} | \mathbf{x}) = \\ = (\mathbf{x}^{-1})^2 \cdot \text{Var}(\mathbf{u} | \mathbf{x}) = \mathbf{x}^{-2} \cdot \sigma^2 \mathbf{W}$$

(c) Standard confidence interval assumes homoscedasticity

i.e. $\text{Var}(\mathbf{u} | \mathbf{x}) = \sigma^2 \mathbf{I}$. However, we've got $\text{Var}(\mathbf{u} | \mathbf{x}) = \sigma^2 \mathbf{W}$,

i.e. heteroscedasticity \Rightarrow the standard confidence interval will be invalid in this case.

$$(d) \text{Cov}(y, \hat{\beta} | x) = \text{Cov}\left(y, \underbrace{(x^T x)^{-1} x^T y}_{\text{Var}(y|x)} | x\right) = (x^T x)^{-1} x^T \cdot \text{Var}(y|x)$$

$$= (x^T x)^{-1} x^T \cdot \text{Var}(x\beta + u | x) = (x^T x)^{-1} x^T \cdot \text{Var}(u | x) = (x^T x)^{-1} x^T \sigma^2 w$$