

Exercise C

Consider a model in which $IE[y_i] = \beta x_i$, $var(y_i) = \sigma^2 x_i$, with $x_i > 0$. By definition:

$$a. \hat{\beta}_{wes} = \underset{\beta \in \mathbb{R}}{\operatorname{argmin}} \sum_{i=1}^n \frac{1}{x_i} (y_i - \beta x_i)^2 = \underset{\beta \in \mathbb{R}}{\operatorname{argmin}} e_{wes}(\beta).$$

$$e'_{wes}(\beta) = -\sum_{i=1}^n \frac{2}{x_i} (y_i - \beta x_i) \cancel{\times} = -2 \sum_{i=1}^n (y_i - x_i \beta)$$

$$\Rightarrow -2 \sum_{i=1}^n y_i = -2 \beta \sum_{i=1}^n x_i$$

$$\Rightarrow \hat{\beta}_{wes} = \frac{\bar{y}}{\bar{x}}.$$

(This is indeed a maximum. .
or it can be checked from the
second derivative)

$$IE[\hat{\beta}_{wes}] = \frac{IE[\bar{y}]}{\bar{x}} = \frac{\frac{1}{m} \sum_{i=1}^m IE[\beta x_i]}{\bar{x}} = \beta \frac{\bar{x}}{\bar{x}} = \beta.$$

$$var(\hat{\beta}_{wes}) = \frac{1}{\bar{x}^2} \cdot var\left(\frac{1}{m} \sum_{i=1}^m y_i\right) = \frac{1}{m^2 \bar{x}^2} \sum_{i=1}^m var(y_i) = \frac{\sigma^2 \sum_{i=1}^m x_i}{m^2 \bar{x}^2} = \frac{\sigma^2 m \bar{x}}{m^2 \bar{x}^2}$$

Independence of y_i .

$$= \frac{\sigma^2}{m \bar{x}} = \frac{\sigma^2}{\sum_{i=1}^m x_i}.$$

b. The ordinary least square is obtained as

$$\hat{\beta}_{ols} = \underset{\beta \in \mathbb{R}}{\operatorname{argmin}} \sum_{i=1}^n (y_i - x_i \beta)^2$$

$$\Rightarrow e'(\beta) = -2 \sum_{i=1}^n (y_i - x_i \beta) x_i \Rightarrow -2 \sum_{i=1}^n x_i y_i = -2 \beta \sum_{i=1}^n x_i^2.$$

$$\Rightarrow \hat{\beta}_{ols} = \frac{\frac{1}{m} \sum_{i=1}^m x_i y_i}{\frac{1}{m} \sum_{i=1}^m x_i^2} = \bar{x}_2$$

$$var(\hat{\beta}_{ols}) = var\left(\frac{\frac{1}{m} \sum_{i=1}^m x_i y_i}{\bar{x}_2}\right) = \frac{1}{m^2 \bar{x}_2} var\left(\sum_{i=1}^m x_i y_i\right) = \frac{1}{m^2 \bar{x}_2} \sum_{i=1}^m x_i var(y_i)$$

Independence

$$= \frac{\sigma^2 \sum_{i=1}^n x_i^3}{m^2 \bar{x}_2} = \frac{\sigma^2}{m} \frac{\bar{x}_3}{\bar{x}_2^2}, \text{ where } \bar{x}_3 = \frac{1}{m} \sum_{i=1}^n x_i^3; \bar{x}_2 = \frac{1}{m} \sum_{i=1}^n x_i^2.$$

c. We want to show that $\text{var}(\hat{\beta}_{\text{WLS}}) \leq \text{var}(\hat{\beta}_{\text{OLS}})$ that is

$$\cancel{\frac{\sigma^2}{m}} \cdot \frac{1}{\bar{x}} \leq \cancel{\frac{\sigma^2}{m}} \frac{\bar{x}_3}{\bar{x}_2^2} \iff \frac{1}{\bar{x}} \leq \frac{\bar{x}_3}{\bar{x}_2^2} \iff \boxed{\bar{x}_3 \bar{x} \geq \bar{x}_2^2}$$

Set

$$y_i = x_i^{3/2}, \quad z_i = x_i^{1/2}, \quad i = 1, \dots, m.$$

Consequently, using Cauchy-Schwarz

$$\left(\frac{1}{m} \sum_{i=1}^m y_i z_i \right)^2 \leq \left(\frac{1}{m} \sum_{i=1}^m y_i^2 \right) \left(\frac{1}{m} \sum_{i=1}^m z_i^2 \right)$$

Substituting:

$$\left(\frac{1}{m} \sum_{i=1}^m x_i^{3/2} x_i^{1/2} \right)^2 \leq \left(\frac{1}{m} \sum_{i=1}^m x_i^{3/2 \cdot 2} \right) \left(\frac{1}{m} \sum_{i=1}^m x_i^{1/2 \cdot 2} \right)$$

$$\left(\frac{1}{m} \sum_{i=1}^m x_i^3 \right)^2 \leq \left(\frac{1}{m} \sum_{i=1}^m x_i^3 \right) \left(\frac{1}{m} \sum_{i=1}^m x_i \right)$$

$$\boxed{\bar{x}_2^2 \leq \bar{x}_3 \bar{x}}.$$

Which implies that $\text{var}(\hat{\beta}_{\text{WLS}}) \leq \text{var}(\hat{\beta}_{\text{OLS}})$.