

Dudin George, group 201, data: 04

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Model: $M_i = \beta K_i + \alpha_i$, where: K_i - # of orders
 M_i - money earned

$$1. b = \frac{\widehat{\text{Cov}}(M, K)}{\widehat{\text{Var}}(K)}$$

We have no intercept, therefore I think, that the better choice would be:

$$b_{OLS}^* = \frac{\sum_{i=1}^n M_i K_i}{\sum_{i=1}^n K_i^2}$$

a) Linear? $b_{OLS}^* = \sum_{i=1}^n M_i K_i \cdot \frac{1}{\sum_{i=1}^n K_i^2} \Rightarrow$
 \Rightarrow it's linear. \nearrow non-stochastic

b) Unbiased?

$$E(b_{OLS}^*) = E\left(\frac{\sum_{i=1}^n M_i K_i}{\sum_{i=1}^n K_i^2}\right) =$$

$$= E\left(\frac{\sum_{i=1}^n B \cdot K_i}{\sum_{i=1}^n K_i^2}\right) + E\left(\frac{\sum_{i=1}^n K_i \alpha_i}{\sum_{i=1}^n K_i^2}\right) = B \Rightarrow$$

\Rightarrow unbiased

Let's check the same for b :

a) Linear? $b = \sum a_i m_i \leftarrow$ from presentation

$$a_i = \frac{M_i - \bar{M}}{\sum_{j=1}^n (K_j - \bar{K})^2} \quad \begin{matrix} K_i = K_i - \bar{K} \\ m_i = M_i - \bar{M} \end{matrix}$$

$$b = \frac{\sum (K_i - \bar{K})(M_i - \bar{M})}{\sum (K_i - \bar{K})^2} = \frac{\sum K_i m_i}{\sum K_i^2} = \sum a_i m_i$$

$$\Rightarrow b = \sum a_i \cdot (M_i - \bar{M}) = \sum a_i M_i - \sum a_i \bar{M} \Rightarrow$$

\Rightarrow **linear**

b) Unbiased? $E(b) = E(B + \sum a_i u_i) =$
Unbiased. $\leftarrow = B + \underbrace{E(\sum a_i u_i)}_{=0} = B$

$$\begin{aligned} 2. \text{Var}(b_{OLS}^*) &= E((b_{OLS}^* - B)^2) = E\left(\left(\frac{\sum K_i u_i}{\sum K_i^2}\right)^2\right) = \\ &= \frac{E\left(\sum K_i^2 u_i^2 + \sum_{i=1}^n \sum_{j \neq i}^n K_i K_j u_i u_j\right)}{(\sum K_i^2)^2} \end{aligned}$$

$$= \frac{\sum K_i^2 \cdot \sigma_u^2}{(\sum K_i^2)^2} = \frac{\sigma_u^2}{\sum K_i^2}$$

$$\text{Var}(b) = \frac{G_u^2}{\sum (k_i - \bar{k})^2} = \frac{G_u^2}{\sum k_i^2 - n\bar{k}} \geq \text{Var}(b_{OLS}^*)$$

$\Rightarrow b^*$ is better estimator, than b

from Gauss-Markov theorem: b^* - BLUE

3. If $n \rightarrow \infty$: is b_{OLS}^* - consistent?

$$\text{plim}(b_{OLS}^*) = \text{plim}\left(\frac{\sum k_i M_i}{\sum k_i^2}\right) =$$

$$= \text{plim}\left(\frac{B \sum k_i^2 + \sum k_i u_i}{\sum k_i^2}\right) =$$

$$= \text{plim}\left(B + \frac{E(ku)}{E(k)}\right) =$$

$$= \text{plim}\left(B + \frac{\underbrace{E(k)}_{=0} \underbrace{E(u)}_{=0} + \text{Cor}(k, u)}{E(k^2)}\right) =$$

$$= B \rightarrow \text{consistent.}$$

$\sqrt{2}$.

$$1. \quad y_i = \beta_1 + \beta_2 X_i + u_i$$

$$TSS_n = \sum_{i=1}^n (y_i - \bar{y})^2$$

$$R_n^2 = \frac{\sum_{i=1}^n (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

$$TSS_{n+1} - TSS_n = (y_{n+1} - \bar{y})^2 \geq 0 \Rightarrow$$

\Rightarrow TSS won't decrease

$$R_{n+1}^2 = \frac{\sum_{i=1}^n (\hat{y}_i - \bar{y})^2 + (\hat{y}_{n+1} - \bar{y})^2}{\sum_{i=1}^n (y_i - \bar{y})^2 + (y_{n+1} - \bar{y})^2} \Rightarrow$$

$\Rightarrow R^2$ could either increase or decrease

2. a) Of course don't throw away observations. They could represent a "new" class of schools, which were not in the base-dataset.

b) Researcher should check if the data is correct

c) Researched should try to increase the dataset to cover more schools

d) This would slightly affect the OLS slope.