

Econometrics-I

05.02.2021

Lecture 7

STATISTICAL PROPERTIES OF THE OLS estimator:

population model: $y = \beta_0 + \beta_1 x + u$ ✓

↓
"random"

sample is drawn

Size = N , $\{x_i, y_i\}_{i=1}^N$

$$\underline{y_i} = \beta_0 + \beta_1 \underline{x_i} + \underbrace{u_i}_{\text{error.}} ; i = \text{person/state/country/firm}$$

Estimate β_0 and β_1 using OLS strategy.

residual

$$\hat{u}_i$$

$$= y_i - \hat{y}_i = y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i$$

$$\min_{\beta_0, \beta_1} \sum_{i=1}^n u_i^2 \rightarrow$$

$$\hat{\beta}_0(y_i, x_i), \hat{\beta}_1(y_i, x_i)$$

$$\hat{\beta}_{1,OLS} = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

$$= \frac{\sum_{i=1}^N (x_i - \bar{x}) y_i}{\sum_{i=1}^N (x_i - \bar{x})^2} - \frac{\bar{y} \sum_{i=1}^N (x_i - \bar{x})}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

$\nearrow 0$
 $\bar{y} \sum_{i=1}^N (x_i - \bar{x}) = 0$

$$\checkmark \hat{\beta}_{1,OLS} = \frac{\sum_{i=1}^N (x_i - \bar{x}) y_i}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

$\Rightarrow \hat{\beta}_{1,OLS}$
itself a r.v.!!

$$y_i = \underbrace{\beta_0 + \beta_1 x_i}_{\text{random variable}} + \underbrace{u_i}_{\text{random variable}}$$

\downarrow
itself is a random variable

$$E(u_i | x) = 0$$

$$\hat{\beta}_{OLS} = \frac{\sum_{i=1}^N (x_i - \bar{x}) y_i}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

$$y_i = \beta_0 + \beta_1 x_i + u_i \rightarrow \text{population relation}$$

$$\hat{\beta}_{OLS} = \frac{\sum_{i=1}^N (x_i - \bar{x}) (\beta_0 + \beta_1 x_i + u_i)}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

$$= \beta_0 \frac{\sum_{i=1}^N (x_i - \bar{x})}{\sum_{i=1}^N (x_i - \bar{x})^2} + \beta_1 \frac{\sum_{i=1}^N (x_i - \bar{x}) x_i}{\sum_{i=1}^N (x_i - \bar{x})^2} + \frac{\sum_{i=1}^N (x_i - \bar{x}) u_i}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

sum of deviations from mean.

0

$$\hat{\beta}_{OLS} = \beta_1 \frac{\sum_{i=1}^N (x_i - \bar{x}) x_i}{\sum_{i=1}^N (x_i - \bar{x})^2} + \frac{\sum_{i=1}^N (x_i - \bar{x}) u_i}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

T2

T3

$$T2 = \beta_1 \frac{\sum_{i=1}^N (x_i - \bar{x}) x_i}{\sum_{i=1}^N (x_i - \bar{x})(x_i - \bar{x})} = \beta_1 \frac{\sum_{i=1}^N (x_i - \bar{x}) x_i}{\sum_{i=1}^N (x_i - \bar{x}) x_i - \bar{x} \sum_{i=1}^N (x_i - \bar{x})} = \beta_1$$

0

$$\hat{\beta}_{OLS} = \beta_1 + \frac{\sum_{i=1}^N (x_i - \bar{x}) u_i}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

TB = bias \Rightarrow of causality is not attained

$$TB = \frac{\sum_{i=1}^N x_i u_i}{\sum_{i=1}^N (x_i - \bar{x})^2} - \frac{\bar{x} \sum_{i=1}^N u_i}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

≥ 0
by using the assumption

$$E(u|x) = 0$$

≥ 0
by using

$$E(u) = 0$$

$$E(\hat{\beta}_{OLS}) = \beta_1$$

only if $E(u) = 0$
and
 $E(u|x) = 0$

Unbiasedness of the OLS estimator.

$\downarrow \checkmark$
Ceteris paribus
experiment
and
causality.

Bottomline: If $E(u|x)=0$ fails, the OLS is biased

$$E(\hat{\beta}_{OLS}) = \beta, \quad \checkmark$$

$$V(\hat{\beta}_{OLS}) = ?$$

$$\Rightarrow V(\hat{\beta}_{OLS} | x) = V\left(\frac{\sum_{i=1}^N (x_i - \bar{x}) y_i}{\sum_{i=1}^N (x_i - \bar{x})^2}\right)$$

↓ random variable

$$= \frac{1}{\left[\sum_{i=1}^N (x_i - \bar{x})^2\right]^2} V\left(\sum_{i=1}^N (x_i - \bar{x}) y_i\right)$$

$$V(\hat{\beta}_{OLS} | x) = \frac{1}{\left[\sum_{i=1}^N (x_i - \bar{x})^2\right]^2} \sum_{i=1}^N (x_i - \bar{x})^2 V(y_i)$$

$$y_i = \beta_0 + \beta_1 x_i + \underbrace{u_i}_{\text{random error.}}$$

we add an assumption that errors are "homoskedastic".

$$\textcircled{A3} \quad V(u|x) = \sigma^2$$

$$\begin{aligned} V(u|x) &= E_x[u - E_x(u)]^2 \\ &= E_x(u^2) - [E_x(u)]^2 \\ &= E(u^2|x) - \underbrace{[E(u|x)]^2}_{=0} \end{aligned}$$

$$= E(u^2|x) = \sigma^2 \quad \text{💡}$$

Interpretation: Expectation of u^2 is independent of x .

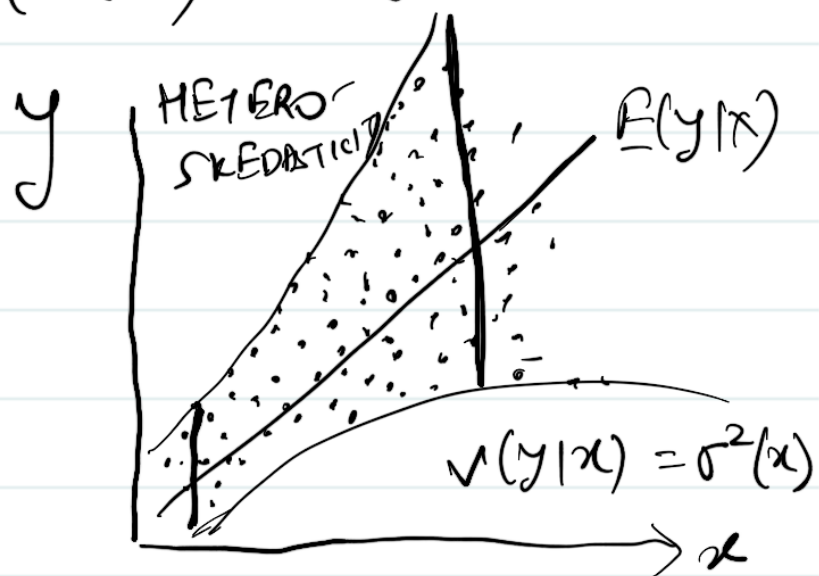
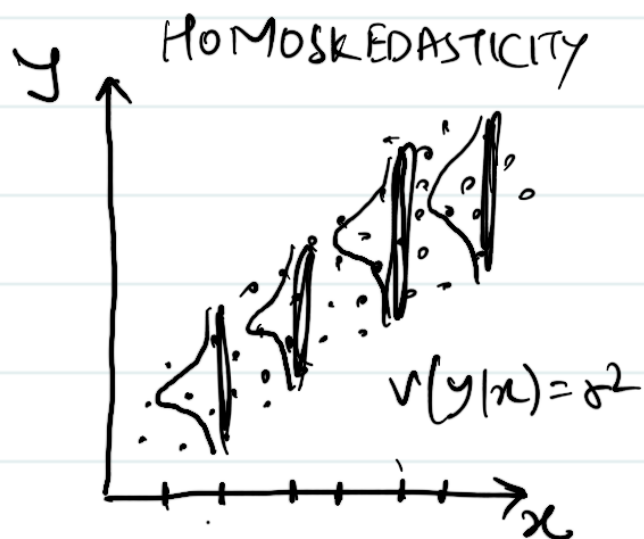
- Remember:
- $A3$ is based on the second moment of the error term
 - It is different from $E(u|x)=0$
 - Homoskedasticity ($A3^R$) is not needed for unbiasedness of the OLS estimator.

Population model:

$$y = \beta_0 + \beta_1 x + u$$

$$E(y|x) = \beta_0 + \beta_1 x$$

$$V(y|x) = V(u|x) = \sigma^2$$



Therefore

$$V(\hat{\beta}_{1,ols} | X) = \frac{1}{\left[\sum_{i=1}^N (x_i - \bar{x})^2 \right]^2} \sum_{i=1}^N (x_i - \bar{x})^2 \cdot \sigma^2$$

$$= \sigma^2 \frac{\sum_{i=1}^N (x_i - \bar{x})^2}{\left[\sum_{i=1}^N (x_i - \bar{x})^2 \right]^2}$$

$$V(\hat{\beta}_{1,ols}) = \frac{\sigma^2}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

$$V(\hat{\beta}_{0,ols}) = \frac{\sigma^2 n^{-1} \sum_{i=1}^N x_i^2}{\sum_{i=1}^N (x_i - \bar{x})^2} \rightarrow \text{Home assignment}$$

Aside (Redone for clarity) ↓

$$\hat{\beta}_{OLS} = \frac{\sum_{i=1}^N (x_i - \bar{x}) y_i}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

$$V(\hat{\beta}_{OLS} | X) = V\left(\frac{\sum_{i=1}^N (x_i - \bar{x}) y_i}{\sum_{i=1}^N (x_i - \bar{x})^2}\right)$$

$$= \frac{1}{\left[\sum_{i=1}^N (x_i - \bar{x})^2\right]^2} V\left(\sum_{i=1}^N (x_i - \bar{x}) y_i\right)$$

$$= \frac{1}{[\cdot]^2} \sum_{i=1}^N \left\{ V[(x_i - \bar{x}) y_i] \right\}$$

$$= \frac{1}{[\cdot]^2} \sum_{i=1}^N (x_i - \bar{x})^2 V(y_i | x_i)$$

$\sigma^2 (By A3)$

$$= \frac{\sigma^2}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

→ x →

By now: $y_i = \beta_0 + \beta_1 x_i + u_i$ $\hat{\beta}_{1,ols}$, $\hat{\beta}_{0,ols}$ \rightarrow functions of data.

$$\checkmark E(\hat{\beta}_{1,ols}) = \beta_1 \quad \left(\begin{smallmatrix} \text{e.g.} \\ A_1, A_2 \end{smallmatrix} \right)$$

$$\checkmark E(\hat{\beta}_{0,ols}) = \beta_0$$

$$\checkmark V(\hat{\beta}_{1,ols}) = \frac{\sigma^2}{\sum_{i=1}^N (x_i - \bar{x})^2}; \quad V(\hat{\beta}_{0,ols}) = \text{HOME ASSIGNMENT}$$

What is $\sigma^2 = ?$

Need $\hat{\sigma}_{ols}^2$ from the data: s.t. $E(\hat{\sigma}^2) = \sigma^2$.

- σ^2 is a second-order moment of u_i $\left[\begin{smallmatrix} V(u_i | x_i) \\ = \sigma^2 \end{smallmatrix} \right]$
- So, the sample estimate can be written as:

$$\checkmark \hat{\sigma}^2 \stackrel{?}{=} \frac{\sum_{i=1}^N \hat{u}_i^2}{N-2} \rightarrow \text{Unbiased sample estimate of } V(u_i | x) = \sigma^2?$$

$\underbrace{N-2}_{\rightarrow ??}$

Aside

we say an unbiased estimator of mean of a r.v. Z is

$$V(Z) = \frac{\sum_{i=1}^N (Z_i - \bar{Z})^2}{N-1}$$

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^N (\hat{u}_i - \bar{\hat{u}})^2}{N-2} = \frac{\sum_{i=1}^N \hat{u}_i^2}{N-2}$$

\downarrow
 $\bar{\hat{u}} = 0$

$\because \sum_{i=1}^N \hat{u}_i = 0$
 $\sum_{i=1}^N \hat{u}_i x_i = 0$ } we know these two conditions will always be true

SAMPLE PROP. OVS estimator

$$E(\hat{\sigma}^2) = \sigma^2$$

★ \rightarrow will Do the proof in next lecture.