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Properties of OLS estimators (multiple regression):

① Property of linearity: The OLS estimator $\hat{\beta}$ is given by

$$\hat{\beta} = (X'X)^{-1} X'Y$$

Let, $A = (X'X)^{-1} X'$ is a matrix of order $n \times k$

$$\hat{\beta} = AY$$

$\hat{\beta}$ is a linear function of Y since A is a $k \times n$ matrix of fix elements.

② Property of unbiasedness: - We have the OLS estimator —

$$\hat{\beta} = (X'X)^{-1} X'Y \quad \text{--- (1)}$$

We know that $Y = X\beta + u \rightarrow$ (2)

Now, substituting equation (2) in (1)

$$\begin{aligned}\hat{\beta} &= (X'X)^{-1} X'(X\beta + u) \\ &= (X'X)^{-1} X'X\beta + (X'X)^{-1} X'u \\ &= \beta + (X'X)^{-1} X'u\end{aligned}$$

$$\begin{aligned}\text{Now, } E(\hat{\beta}) &= \beta + (X'X)^{-1} X'E(u) \\ &= \beta \quad \left[\because E(u) = 0 \right]\end{aligned}$$

Thus, the OLS estimator $\hat{\beta}$ is an unbiased estimator of β .

③ Property of minimum variance: - Here, we have to prove that the OLS estimator $\hat{\beta}$ has the smallest variance. For this we have to first obtain the variance $\text{var-cov}(\hat{\beta})$.

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$$\begin{aligned}
\text{var} - \text{cov}(\hat{\beta}) &= E \left[\{\hat{\beta} - E(\hat{\beta})\} \{\hat{\beta} - E(\hat{\beta})\}' \right] \\
&= E \left[\{\hat{\beta} - \beta\} \{\hat{\beta} - \beta\}' \right] \\
&= E \left[\{(X'X)^{-1}X'u\} \{(X'X)^{-1}X'u\}' \right] \\
&= E \left[(X'X)^{-1}X'u u'X (X'X)^{-1} \right] \\
&= \left[(X'X)^{-1}X'E(uu')X (X'X)^{-1} \right] \\
&= (X'X)^{-1}X'6^2I_nX (X'X)^{-1} \\
&= 6^2(X'X)^{-1}X'I_nX (X'X)^{-1} \\
&= 6^2(X'X)^{-1}X'X (X'X)^{-1} \quad [I_n X = X] \\
&= 6^2(X'X)^{-1}
\end{aligned}$$

[In order to compare, let us consider b is an arbitrary estimates of β such that

$$b = (c+A)y \rightarrow (1)$$

$A = (X'X)^{-1}X'$ and c is a matrix of order $(k \times n)$

Since b is a linear function of y therefore, substituting

$$y = X\beta + u \text{ in (1) we get}$$

$$\begin{aligned}
b &= (c+A)(X\beta + u) \\
&= cX\beta + cu + AX\beta + Au \\
&= cX\beta + AX\beta + cu + Au \\
&= (cX + AX)\beta + (c+A)u \quad (2)
\end{aligned}$$

$$\begin{aligned}
\text{Now, } E(b) &= E[(cX + AX)\beta + (c+A)u] \\
&= [(cX + AX)\beta + (c+A)E(u)] \\
&= (cX + AX)\beta \quad \left[\because A'X = (X'X)^{-1}X'X = I \right] \\
&= (cX + I)\beta
\end{aligned}$$

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$\therefore E(b) = \beta$ iff $EX = 0$ [iff $\rightarrow$ if and only if]
 Thus b is an unbiased estimator of β .

From equation (2) if $EX = 0$ then we get

$$= (A'X)\beta + (e' + A')U$$

$$= \beta + (e' + A')U$$

Now,

$$\text{Var} - \text{cov}(b) = E[(b - E(b))(b - E(b))']$$

$$= E[(b - \beta)(b - \beta)']$$

$$= E[(e' + A')U(e' + A')U']$$

$$\therefore b - \beta = (e' + A')U$$

$$= E[(e' + A')U U' (e' + A)']$$

$$= [(e' + A') E(UU') (e' + A)']$$

$$= \{(e' + A') \sigma^2 I_n (e' + A)'\}$$

$$= \sigma^2 (e' + A') (e' + A) [\because I_n = I]$$

$$= \sigma^2 (ee' + eA' + Ae' + AA')$$

$$= \sigma^2 (ee' + AA')$$

$$= \sigma^2 ee' + \sigma^2 AA'$$

$$= \sigma^2 ee' + \sigma^2 (X'X)^{-1}$$

$$= \sigma^2 ee' + \text{var-cov}(\hat{\beta})$$

Thus, $\text{var-cov}(b) = \sigma^2 \cdot ee' + \text{var-cov}(\hat{\beta})$;
 which means $\text{var-cov}(\hat{\beta}) < \text{var-cov}(b)$. Thus

OLS estimator possess the smallest variance.
 Hence it is the best estimator. This is also
 known as the Gauss-Markov theorem.