

ASSUMPTIONS OF GENERAL LINEAR REGRESSION MODEL:

(1) Assumption 1:

$E(u) = 0$, where u is a $n \times 1$ column ~~at which~~ ^{matrix} and 0 is a $n \times 1$ column null matrix.

$$\therefore E(u) = 0$$

$$\Rightarrow E \begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{pmatrix}_{n \times 1} = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}_{n \times 1}$$

$$\Rightarrow \begin{pmatrix} E(u_1) \\ E(u_2) \\ \vdots \\ E(u_n) \end{pmatrix}_{n \times 1} = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}_{n \times 1}$$

(2) Assumption 2:

$E(uu') = \sigma^2 I_n$; where σ^2 is a scalar and I_n is an identity matrix of a order $n \times n$.

$$\therefore E(uu') = E \begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{pmatrix}_{n \times 1} \begin{pmatrix} u_1 & u_2 & \dots & u_n \end{pmatrix}_{1 \times n}$$

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$$= E \begin{bmatrix} U_1^2 & U_1 U_2 & \dots & U_1 U_n \\ U_1 U_2 & U_2^2 & \dots & U_2 U_n \\ \vdots & \vdots & \ddots & \vdots \\ U_1 U_n & U_2 U_n & \dots & U_n^2 \end{bmatrix}_{n \times n}$$

$$= \begin{bmatrix} E(U_1^2) & E(U_1 U_2) & \dots & E(U_1 U_n) \\ E(U_1 U_2) & E(U_2^2) & \dots & E(U_2 U_n) \\ \vdots & \vdots & \ddots & \vdots \\ E(U_1 U_n) & E(U_2 U_n) & \dots & E(U_n^2) \end{bmatrix}_{n \times n}$$

$$= \begin{bmatrix} \sigma^2 & 0 & \dots & 0 \\ 0 & \sigma^2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma^2 \end{bmatrix}_{n \times n}$$

$$= \sigma^2 \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix}_{n \times n}$$

$$= \sigma^2 I_n$$

$$\therefore E(UU') = \sigma^2 I_n$$

(ii) Assumption (i) :-

$$E(U_i^2) = \sigma^2$$

where $i = 1, 2, \dots, n$; this assumption is known as homoscedasticity

(iii) Assumption (ii) :-

$E(U_i U_j) = 0$; this means that the random term of different observations are independent. This assumption is known as assumption of no autocorrelation.

(iv) Assumption (iii) :- $U \sim N(0, \sigma^2 I_n)$ that means the

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random disturbance term follows the normal distribution.

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ESTIMATION OF PARAMETERS BY OLS METHOD IN CASE OF MULTIPLE LINEAR REGRESSION

Let us consider following k variable linear regression model.

$$Y_t = \beta_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_k X_k +$$

$$u_t \rightarrow (1)$$

$$\text{where } t = 1, 2, \dots, n$$

Now, to estimate the unknown parameters $\beta_1, \beta_2, \dots, \beta_k$ let us first write the estimated regression model.

$$\hat{Y}_t = \hat{\beta}_1 + \hat{\beta}_2 X_2 + \hat{\beta}_3 X_3 + \dots + \hat{\beta}_k X_k + \rightarrow (2)$$

where, $\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \dots, \hat{\beta}_k$ are the estimated values of $\beta_1, \beta_2, \beta_3, \dots, \beta_k$ respectively.

The main principle of OLS method is to estimate the unknown parameters in such a way that the sum square of the residuals is least or minimum.

[The sum square of the residuals is given by ———]

$$\sum \hat{u}_t^2 = \text{where}$$

$$\hat{u}_t = Y_t - \hat{Y}_t$$

$$= Y_t - \hat{\beta}_1 - \hat{\beta}_2 X_2 - \hat{\beta}_3 X_3 + \dots - \hat{\beta}_k X_k$$

$$\sum \hat{u}_t^2 = \sum (Y_t - \hat{\beta}_1 - \hat{\beta}_2 X_2 - \hat{\beta}_3 X_3 + \dots - \hat{\beta}_k X_k)^2$$

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For minimisation of first order condition is

$$\frac{\partial \sum \hat{u}_t^2}{\partial \hat{\beta}_1} = 0, \quad \frac{\partial \sum \hat{u}_t^2}{\partial \hat{\beta}_2} = 0, \quad \dots, \quad \frac{\partial \sum \hat{u}_t^2}{\partial \hat{\beta}_k} = 0$$

$$\Rightarrow \frac{\partial \sum \hat{u}_t^2}{\partial \hat{\beta}_1} = 2 \sum (y_t - \hat{\beta}_1 - \hat{\beta}_2 x_{2t} - \dots - \hat{\beta}_k x_{kt}) (-1) = 0$$

$$\Rightarrow \frac{\partial \sum \hat{u}_t^2}{\partial \hat{\beta}_2} = 2 \sum (y_t - \hat{\beta}_1 - \hat{\beta}_2 x_{2t} - \dots - \hat{\beta}_k x_{kt}) (-x_{2t}) = 0$$

Last,

$$\Rightarrow \frac{\partial \sum \hat{u}_t^2}{\partial \hat{\beta}_k} = 2 \sum (y_t - \hat{\beta}_1 - \hat{\beta}_2 x_{2t} - \dots - \hat{\beta}_k x_{kt}) (-x_{kt}) = 0$$

The set of equation can be written as

$$\Rightarrow n \hat{\beta}_1 + \hat{\beta}_2 \sum x_{2t} + \hat{\beta}_3 \sum x_{3t} + \dots + \hat{\beta}_k \sum x_{kt} = \sum y_t$$

$$\Rightarrow \hat{\beta}_1 \sum x_{2t} + \hat{\beta}_2 \sum x_{2t}^2 + \hat{\beta}_3 \sum x_{2t} x_{3t} + \dots + \hat{\beta}_k \sum x_{2t} x_{kt} = \sum x_{2t} y_t$$

$$\Rightarrow \hat{\beta}_1 \sum x_{kt} + \hat{\beta}_2 \sum x_{2t} x_{kt} + \hat{\beta}_3 \sum x_{3t} x_{kt} + \dots + \hat{\beta}_k \sum x_{kt}^2 = \sum x_{kt} y_t$$

The set of equation (4) can be arranged in the following matrix form

$$\begin{bmatrix} n & \sum x_{2t} & \sum x_{3t} & \dots & \sum x_{kt} \\ \sum x_{2t} & \sum x_{2t}^2 & \sum x_{2t} x_{3t} & \dots & \sum x_{2t} x_{kt} \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ \sum x_{kt} & \sum x_{2t} x_{kt} & \sum x_{3t} x_{kt} & \dots & \sum x_{kt}^2 \end{bmatrix} \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \dots \\ \hat{\beta}_k \end{bmatrix} = \begin{bmatrix} \sum y_t \\ \sum x_{2t} y_t \\ \dots \\ \sum x_{kt} y_t \end{bmatrix}$$

$\underbrace{\hspace{10em}}_{k \times k}$
 $\underbrace{\hspace{10em}}_{k \times 1}$

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$$= \begin{bmatrix} 1 & 1 & \dots & 1 \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{k1} & x_{k2} & \dots & x_{kn} \end{bmatrix}_{k \times n} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}_{n \times 1}$$

$$= \begin{bmatrix} 1 & 1 & 1 \\ x_{21} & x_{22} & x_{2n} \\ \dots & \dots & \dots \\ x_{k1} & x_{k2} & x_{kn} \end{bmatrix}_{k \times n} \times \begin{bmatrix} 1 & x_{21} & \dots & x_{k1} \\ 1 & x_{22} & \dots & x_{k2} \\ \dots & \dots & \dots & \dots \\ 1 & x_{2n} & \dots & x_{kn} \end{bmatrix}_{n \times k}$$

$$X \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \vdots \\ \hat{\beta}_k \end{bmatrix}_{k \times 1} = \begin{bmatrix} 1 & 1 & 1 \\ x_{21} & x_{22} & x_{2n} \\ \dots & \dots & \dots \\ x_{k1} & x_{k2} & x_{kn} \end{bmatrix}_{k \times n} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}_{n \times 1}$$

$$\Rightarrow X'X\hat{\beta} = X'y$$

multiplying both side of the above equation by $(X'X)^{-1}$

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

$$\Rightarrow \hat{\beta} = (X'X)^{-1}X'y.$$