

Econ 361: Advanced Econometrics

Properties of Estimators

Bivariate Linear Regression Model

Size N (Bivariate) Sample: $\{ (Y_i = y_i, X_i = x_i) \}_{i=1}^N$

OLS Predictor of Y given X: $\hat{Y}_{ols} = a^{ols} + b^{ols} X$

Sometimes also expressed as $\hat{Y}_{ols} = \underbrace{b_0^{ols}}_{\text{"intercept"}} + \underbrace{b_1^{ols}}_{\text{"slope"}} X$

OLS Estimators

$$b_0^{ols} = \underbrace{\frac{1}{N} \sum_{i=1}^N Y_i}_{\bar{Y}_N} - b_1^{ols} \underbrace{\frac{1}{N} \sum_{i=1}^N X_i}_{\bar{X}_N}$$

analogous to $E[Y] - \beta^* E[X]$

$$b_1^{ols} = \frac{\frac{1}{N} \sum_{i=1}^N X_i Y_i - \bar{X}_N \bar{Y}_N}{\underbrace{\frac{1}{N} \sum_{i=1}^N X_i^2 - (\bar{X}_N)^2}_{\text{analogous to } \text{Var}(X)}}$$

analogous to $\beta^* = \text{Cov}(X, Y) / \text{Var}(X)$

Estimators, as functions of random variables, are themselves random variables.

OLS Estimates

$$\text{“ } b_0^{ols} \text{ ”} = \underbrace{\frac{1}{N} \sum_{i=1}^N y_i}_{\bar{y}_N} - b_1^{ols} \underbrace{\frac{1}{N} \sum_{i=1}^N x_i}_{\bar{x}_N}$$

$$\text{“ } b_1^{ols} \text{ ”} = \frac{\frac{1}{N} \sum_{i=1}^N x_i y_i - \bar{x}_N \bar{y}_N}{\frac{1}{N} \sum_{i=1}^N x_i^2 - (\bar{x}_N)^2}$$

Estimates, as functions of known constants, are themselves constants.

Expected Value of an Estimator: Bivariate OLS Example

Assume the **Linearity Condition** holds: $E[Y_i|X] = \beta_0 + \beta_1 X_i$

$$\begin{aligned} E[b_1^{ols}|X] &= E\left[\frac{\frac{1}{N} \sum_{i=1}^N X_i Y_i - \bar{X}_N \bar{Y}_N}{\frac{1}{N} \sum_{i=1}^N X_i^2 - (\bar{X}_N)^2} \middle| X\right] \\ &= \frac{1}{\frac{1}{N} \sum_{i=1}^N X_i^2 - (\bar{X}_N)^2} E\left[\frac{1}{N} \sum_{i=1}^N X_i Y_i - \bar{X}_N \bar{Y}_N \middle| X\right] \\ &= \left(\frac{1}{\frac{1}{N} \sum_{i=1}^N X_i^2 - (\bar{X}_N)^2} \right) \left(\frac{1}{N} \sum_{i=1}^N X_i E[Y_i|X] - \bar{X}_N E[\bar{Y}_N|X] \right) \end{aligned}$$

$$\begin{aligned}
&= \left(\frac{1}{\frac{1}{N} \sum_{i=1}^N X_i^2 - (\bar{X}_N)^2} \right) \\
&\quad \left(\underbrace{\frac{1}{N} \sum_{i=1}^N X_i (\beta_0 + \beta_1 X_i) - \bar{X}_N (\beta_0 + \beta_1 \bar{X}_N)}_{= \bar{X}_N \beta_0 + \beta_1 \frac{1}{N} \sum_{i=1}^N X_i^2} \right) \\
&= \left(\frac{1}{\frac{1}{N} \sum_{i=1}^N X_i^2 - (\bar{X}_N)^2} \right) \beta_1 \left(\frac{1}{N} \sum_{i=1}^N X_i^2 - (\bar{X}_N)^2 \right) \\
&= \beta_1
\end{aligned}$$

$$\begin{aligned}
E[b_0^{ols}|X] &= E[\bar{Y}_N - b_1^{ols} \bar{X}_N|X] \\
&= E[\bar{Y}_N|X] - \beta_1 \bar{X}_N \\
&= (\beta_0 + \beta_1 \bar{X}_N) - \beta_1 \bar{X}_N \\
&= \beta_0
\end{aligned}$$

$$\begin{aligned}
\text{Note: } E[\bar{Y}_N|X] &= E\left[\frac{1}{N} \sum_{i=1}^N Y_i|X\right] = \frac{1}{N} \sum_{i=1}^N E[Y_i|X] \\
&= \frac{1}{N} \sum_{i=1}^N (\beta_0 + \beta_1 X_i) = \beta_0 + \beta_1 \bar{X}_N
\end{aligned}$$

Expected Value of an Estimator: Multivariate OLS Example

Assume **Full Rank** and **Linearity Conditions** hold:

$$b^{ols} = (X'X)^{-1}X'Y \text{ and } E[Y|X] = X\beta$$

$$\begin{aligned} E[b^{ols}|X] &= E[(X'X)^{-1}X'Y|X] \\ &= (X'X)^{-1}X' \underbrace{E[Y|X]}_{=X\beta} = \underbrace{(X'X)^{-1}X'X}_{I_N} \beta = \beta \end{aligned}$$

Variance of an Estimator: Multivariate OLS Example

Assume **all three Gauss-Markov Assumptions** hold:

$$b^{ols} = (X'X)^{-1}X'Y \text{ and } E[Y|X] = X\beta \text{ and } \text{Var}(Y|X) = \sigma^2 I_N$$

$$\begin{aligned}\text{Var}[b^{ols}|X] &= \text{Var}\left[\overbrace{(X'X)^{-1}X'Y}^A | X \right] \\ &= \underbrace{(X'X)^{-1}X'}_A \underbrace{\text{Var}(Y|X)}_{\sigma^2 I_N} \underbrace{X(X'X)^{-1}}_{A'} \\ &= \sigma^2 (X'X)^{-1} X' I_N X (X'X)^{-1} \\ &= \sigma^2 (X'X)^{-1}\end{aligned}$$

Note: $(X'X)$ is a symmetric matrix, as is $(X'X)^{-1}$

Variance of an Estimator: Bivariate OLS Example

Assume **all three Gauss-Markov Assumptions** hold:

$$b^{ols} = (X'X)^{-1}X'Y \text{ and } E[Y|X] = X\beta \text{ and } \text{Var}(Y|X) = \sigma^2 I_N$$

$$\begin{aligned}\text{Var}(b_1^{ols}|X) &= \frac{\sigma^2}{\sum_{i=1}^N (X_i - \bar{X}_N)^2} \\ \text{Var}(b_0^{ols}|X) &= \frac{\sigma^2}{N} \frac{\sum_{i=1}^N X_i^2}{\sum_{i=1}^N (X_i - \bar{X}_N)^2}\end{aligned}$$

Leave the full derivation as an exercise to reader