

Recap:

- (i) Simple Model: $Y_i = \alpha + \beta X_i + u_i$
 - (ii) Multivariate Model: $Y_i = \beta_1 + \beta_2 X_{2i} + \beta_3 X_{3i} + u_i$
 - (iii) OLS Estimation Technique
 - (iv) Assumptions of the Model $[E(u_i) = 0, \text{Var}(u_i) = \sigma^2 \forall i, \dots]$
 - (v) Properties of the OLS Estimates $[\text{unbiaseness, variance}]$
 - (vi) Gauss Markov Theorem.
- Under the classical assumptions OLS estimates are BLUE.
- (vii) Goodness of Fit measures (R^2 & $\text{Adj } R^2$)
 - (viii) ANOVA Analysis
 - (ix) Testing of Hypothesis.

Violations of OLS Assumptions:-

Simple Model: $Y_i = \alpha + \beta X_i + u_i$

Assumptions:

- (i) $E(u_i) = 0 \quad \forall i$
- ~~(ii)~~ $\text{Var}(u_i) = E(u_i^2) = \sigma^2 \quad \forall i$
- ~~(iii)~~ $\text{Cov}(u_i, u_j) = E(u_i u_j) = 0 \quad \forall i \neq j$
- (iv) $\text{Cov}(X, u) = 0$
- (v) $u_i \overset{\text{iid}}{\sim} N(0, \sigma^2)$ [Needs to be incorporated only during Testing of Hypothesis]

If $\text{Var}(u_i) \neq \sigma^2 \quad \forall i \Rightarrow$ Problem of Heteroskedasticity }
 If $\text{Cov}(u_i, u_j) \neq 0 \quad \forall i \neq j \Rightarrow$ Problem of Autocorrelation }

i.e from the statement of Gauss Markov Theorem, if Heteroskedasticity / Autocorrelation is present in the data, then the OLS estimates will no longer be BLUE.

Heteroskedasticity:

True Model: $Y_i = \alpha + \beta X_i + u_i$

where: $\text{Var}(u_i) = \sigma_i^2$ [Rest Gauss Markov Assumptions hold]

Estimated Model: $\hat{Y}_i = \hat{\alpha}_{OLS} + \hat{\beta}_{OLS} X_i$

$$\text{where } \hat{\beta}_{OLS} = \frac{\sum (Y_i - \bar{Y})(X_i - \bar{X})}{\sum (X_i - \bar{X})^2} \quad \hat{\alpha}_{OLS} = \bar{Y} - \hat{\beta}_{OLS} \bar{X}$$

∴ According to Gauss Markov Th, $\hat{\alpha}_{OLS}$ and $\hat{\beta}_{OLS}$ are not BLUE.

Suppose if we can express $\sigma_i^2 = \sigma^2 z_i^2$.

$$\frac{Y_i}{z_i} = \alpha \left(\frac{1}{z_i} \right) + \beta \frac{X_i}{z_i} + \frac{u_i}{z_i}$$

Transformed Model: $\left(\frac{Y_i}{z_i} \right) = \alpha \left(\frac{1}{z_i} \right) + \beta \left(\frac{X_i}{z_i} \right) + \left(\frac{u_i}{z_i} \right)$

new random disturbance term.

$$\Rightarrow \text{Var} \left(\frac{u_i}{z_i} \right) = \frac{1}{z_i^2} \text{Var}(u_i) = \frac{\sigma_i^2}{z_i^2} = \frac{\sigma^2 \cdot z_i^2}{z_i^2} = \sigma^2$$

∴ $\left(\frac{u_i}{z_i} \right)$ are Homoskedastic.

∴ As Transformed Model is Homoskedastic, applying OLS on the transformed model will give us efficient estimates of α, β .

This is the method of Weighted Least Squares (WLS).

WLS gives us estimates $\hat{\alpha}_{WLS}$ and $\hat{\beta}_{WLS}$.

According to Gauss-Markov Theorem, $\hat{\alpha}_{NLS}$ and $\hat{\beta}_{NLS}$ are efficient.

i.e, under Heteroskedasticity, $\text{Var}(\hat{\beta}_{NLS}) \leq \text{Var}(\hat{\beta}_{OLS})$
 $\text{Var}(\hat{\alpha}_{NLS}) \leq \text{Var}(\hat{\alpha}_{OLS})$

Autocorrelation:

More prominent in time-series data.

$$\text{cov}(u_t, u_{t'}) \neq 0.$$

X_t	Y_t
Pd 1	
Pd 2	
⋮	
Pd T	

True Model: $Y_t = \alpha + \beta X_t + u_t$.

Dependence structure of u_t .

$$u_t = \rho \cdot u_{t-1} + \epsilon_t, \quad \epsilon_t \stackrel{iid}{\sim} N(0, \sigma_\epsilon^2), \quad |\rho| < 1.$$

Auto correlation is present in the data and if OLS estimation is performed on the true model then $\hat{\alpha}_{OLS}$ and $\hat{\beta}_{OLS}$ will be inefficient [From Gauss Markov Theorem].

True Model: Pd 't': $Y_t = \alpha + \beta X_t + u_t$ ----- (i)

Pd 't-1' $\rho Y_{t-1} = \alpha \rho + \beta \rho X_{t-1} + \rho u_{t-1}$ --- (ii)

$$(i) - (ii): (Y_t - \rho Y_{t-1}) = \alpha(1-\rho) + \beta(X_t - \rho X_{t-1}) + \underbrace{(u_t - \rho u_{t-1})}_{\epsilon_t}$$

Transformed Model: $(Y_t - \rho Y_{t-1}) = \alpha(1-\rho) + \beta(X_t - \rho X_{t-1}) + \epsilon_t$

Here $\epsilon_t \sim$ Gauss Markov assumptions. Estimates of α, β from this transformed Model will be efficient.

from this transformed model will be efficient. --- estimates of α, β .

Method of Generalized Least Squares (GLS).

GLS estimates: $\hat{\alpha}_{GLS}, \hat{\beta}_{GLS}$.

From Gauss Markov Theorem: $\text{Var}(\hat{\beta}_{GLS}) \leq \text{Var}(\hat{\beta}_{OLS})$

under Autocorrelation:

$$\text{Var}(\hat{\alpha}_{GLS}) \leq \text{Var}(\hat{\alpha}_{OLS})$$