

# Least Squares Estimation Methods

Ordinary Least Squares (OLS)

Generalized Least Squares (GLS)

Feasible Generalized Least Squares (FGLS)

- Weighted Least Squares (WLS)

Heteroscedasticity

- Cochrane-Orcutt Technique

Autocorrelation

Other Least Squares Methods

- Nonlinear Least Squares (NLS)

- System Equation Estimation Methods

# OLS Matrix Approach

**Scalar Notation**  $Y_i = \beta_1 + \beta_2 X_{2i} + \beta_3 X_{3i} + \dots + \beta_k X_{ki} + u_i$   
where  $i = 1, 2, 3, \dots, n$

**Matrix Notation**  $y = X \beta + u$   
 $n \times 1$     $n \times k$     $k \times 1$     $n \times 1$

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_{21} & x_{31} & \cdots & x_{k1} \\ 1 & x_{22} & x_{32} & \cdots & x_{k2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{2n} & x_{3n} & \cdots & x_{kn} \end{bmatrix} \cdot \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_k \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix}$$

# OLS Estimation

## Estimated Regression Coefficients

3-variable  
scalar  
notation

$$\hat{\beta}_2 = \frac{\left(\sum y_i x_{2i}\right)\left(\sum x_{3i}^2\right) - \left(\sum y_i x_{3i}\right)\left(\sum x_{2i} x_{3i}\right)}{\left(\sum x_{2i}^2\right)\left(\sum x_{3i}^2\right) - \left(\sum x_{2i} x_{3i}\right)^2}$$

k-variable  
matrix  
notation

$$\hat{\beta}_{k \times 1} = \left( \underset{k \times k}{X'X} \right)^{-1} \underset{k \times n}{X'} \underset{n \times 1}{y}$$

Assume normal distribution:

$$u \sim N(0, \sigma^2 I)$$

# Variance-Covariance Matrix

## Under OLS Assumptions

$$\sum_{n \times n} = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_2^2 & \sigma_{23} & \cdots & \sigma_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \sigma_{n3} & \cdots & \sigma_n^2 \end{bmatrix} = \begin{bmatrix} \sigma^2 & 0 & 0 & \cdots & 0 \\ 0 & \sigma^2 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sigma^2 \end{bmatrix} = \sigma^2 I$$

## Under Heteroscedasticity Problem

$$\sum_{n \times n} = \begin{bmatrix} \sigma_1^2 & 0 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sigma_n^2 \end{bmatrix}$$

# Weighted Least Squares (WLS)

Scalar  $Y_i = \beta_1 + \beta_2 X_i + u_i$

$$\frac{Y_i}{\sigma_i} = \beta_1 \left( \frac{1}{\sigma_i} \right) + \beta_2 \left( \frac{X_i}{\sigma_i} \right) + \left( \frac{u_i}{\sigma_i} \right)$$

$$Y_i^* = \beta_1^* X_{0i}^* + \beta_2^* X_i^* + u_i^*$$

Matrix

$$\hat{\beta}_{k \times 1} = \left( \begin{matrix} X' & \Sigma^{-1} & X \\ k \times n & n \times n & n \times k \end{matrix} \right)^{-1} \begin{matrix} X' & \Sigma^{-1} & y \\ k \times n & n \times n & n \times 1 \\ & & k \times 1 \end{matrix}$$

# Autocorrelation: Cochrane-Orcutt

Scalar  $Y_t = \beta_1 + \beta_2 X_t + u_t$

$$u_t = \rho u_{t-1} + \varepsilon_t$$

1. Estimate model using OLS and obtain

estimated  $u_t$   $\hat{u}_t = \hat{\rho} \hat{u}_{t-1} + v_t$

2. Compute

3.  $(Y_t - \hat{\rho} Y_{t-1}) = \beta_1 (1 - \hat{\rho}) + \beta_2 (X_t - \hat{\rho} X_{t-1}) + \varepsilon_t$

$$Y_t^* = \beta_1^* + \beta_2^* X_t^* + \varepsilon_t^*$$

4. Iterative procedure to estimate  $\rho$

# Autocorrelation: Cochrane-Orcutt

Variance-Covariance Matrix  $\Sigma = \sigma^2 \Omega_{n \times n}$

where

$$\Omega_{n \times n} = \begin{bmatrix} 1 & \rho & \rho^2 & \rho^3 & \dots & \rho^{n-1} \\ \rho & 1 & \rho & \rho^2 & \dots & \rho^{n-2} \\ \rho^2 & \rho & 1 & \rho & \dots & \rho^{n-3} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho^{n-1} & \rho^{n-2} & \rho^{n-3} & \dots & \rho & 1 \end{bmatrix}$$

Matrix

$$\hat{\beta}_{k \times 1} = \left( \begin{matrix} X' & \hat{\Omega}^{-1} & X \\ k \times n & n \times n & n \times k \\ & k \times k & \end{matrix} \right)^{-1} \begin{matrix} X' & \hat{\Omega}^{-1} & y \\ k \times n & n \times n & n \times 1 \\ & k \times 1 & \end{matrix}$$

# OLS vs GLS vs FGLS

## OLS Estimation

$$\Sigma = \sigma^2 I_{n \times n}$$

$$\hat{\beta}_{k \times 1} = \left( \begin{matrix} X'X \\ k \times k \end{matrix} \right)^{-1} \begin{matrix} X' \\ k \times n \end{matrix} \begin{matrix} y \\ n \times 1 \end{matrix}$$

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## WLS Estimation

$$\Sigma = \hat{\sigma}_i^2 I_{n \times n}$$

$$\hat{\beta}_{k \times 1} = \left( \begin{matrix} X' \hat{\Sigma}^{-1} X \\ k \times n \quad n \times n \quad n \times k \end{matrix} \right)^{-1} \begin{matrix} X' \hat{\Sigma}^{-1} y \\ k \times n \quad n \times n \quad n \times 1 \end{matrix}$$

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## Cochrane-Orcutt

$$\Sigma = \sigma^2 \hat{\Omega}_{n \times n}$$

$$\hat{\beta}_{k \times 1} = \left( \begin{matrix} X' \hat{\Omega}^{-1} X \\ k \times n \quad n \times n \quad n \times k \end{matrix} \right)^{-1} \begin{matrix} X' \hat{\Omega}^{-1} y \\ k \times n \quad n \times n \quad n \times 1 \end{matrix}$$

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## FGLS Estimation

$$\Sigma \text{ is not known}$$

$$\hat{\beta}_{k \times 1} = \left( \begin{matrix} X' \hat{\Sigma}^{-1} X \\ k \times n \quad n \times n \quad n \times k \end{matrix} \right)^{-1} \begin{matrix} X' \hat{\Sigma}^{-1} y \\ k \times n \quad n \times n \quad n \times 1 \end{matrix}$$

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## GLS Estimation

$$\Sigma \text{ is known}$$

$$\hat{\beta}_{k \times 1} = \left( \begin{matrix} X' \Sigma^{-1} X \\ k \times n \quad n \times n \quad n \times k \end{matrix} \right)^{-1} \begin{matrix} X' \Sigma^{-1} y \\ k \times n \quad n \times n \quad n \times 1 \end{matrix}$$