

## Assumptions

1.  $E(y | X) = X\beta \Rightarrow y = X\beta + \varepsilon$
2.  $X$  is a non-stochastic ( $N \times k$ ) matrix with rank  $k$ .
3.  $E(\varepsilon) = \mathbf{0}$
4.  $E(\varepsilon\varepsilon') = \sigma^2 I$
5.  $\varepsilon \sim N(\mathbf{0}, \sigma^2 I)$

## What can we derive from the assumptions?

- Under (1) and (2);

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

- Under (1) - (3);

$$E(\hat{\beta}) = \beta$$

- Under (1) - (4);

$$\text{Var}(\hat{\beta}) = \sigma^2 (X'X)^{-1}$$

- Under (1) - (4),  $\hat{\beta}$  is BLUE. (*Gauss - Markov Theorem*)
- We can estimate  $\sigma^2$  with

$$s^2 = \frac{1}{N-k} e'e$$

where  $e'e = y'y - \hat{\beta}'X'X\hat{\beta}$ .

- 

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

- $e = y - X\hat{\beta} = My$  where  $M = I - X(X'X)^{-1}X'$
- $M$  is symmetric, idempotent, positive semi-definite with rank  $(N - k)$ .
- The coefficient of determination,  $R^2$ , is defined as

$$R^2 = \frac{ESS}{TSS} = 1 - \frac{RSS}{TSS} = 1 - \frac{e'e}{y'Ay}$$

- Under (1) - (5);

$$\hat{\beta} \sim \left( \beta, \sigma^2 (X'X)^{-1} \right)$$

$$\frac{(N-k)s^2}{\sigma^2} = \frac{e'e}{\sigma^2} \sim \chi^2(N-k)$$

- 

$$F = \frac{\left( R\hat{\beta} - r \right)' \left[ R(X'X)^{-1}R' \right]^{-1} \left( R\hat{\beta} - r \right) / q}{e'e / (N-k)}$$

$$= \frac{\left( R\hat{\beta} - r \right)' \left[ s^2 R(X'X)^{-1}R' \right]^{-1} \left( R\hat{\beta} - r \right)}{q} \sim F(q, N-k)$$

•

$$F = \frac{(e'_R e_R - e'_U e_U) / q}{e'_U e_U / (N - k)} \sim F(q, N - k)$$

## The least squares in mean deviation form

- If we decompose the regression as

$$\begin{aligned} y &= X\beta + \varepsilon \\ &= \mathbf{1}\beta_1 + X_2\beta_2 + \varepsilon \end{aligned}$$

•

$$\hat{\beta}_2 = (X_2' A X_2)^{-1} X_2' A y$$

•

$$\text{Var}(\hat{\beta}_2) = \sigma^2 (X_2' A X_2)^{-1}$$

- We can estimate  $\sigma^2$  with

$$s^2 = \frac{e'e}{(N - k)}$$

where  $e'e = y' A y - \hat{\beta}'_2 X_2' A X_2 \hat{\beta}_2 = y' A y - \hat{\beta}'_2 X_2' A y$

•

$$R^2 = \frac{\hat{\beta}'_2 X_2' A X_2 \hat{\beta}_2}{y' A y} = \frac{\hat{\beta}'_2 X_2' A y}{y' A y} = 1 - \frac{e'e}{y' A y}$$

## Constrained least squares estimator

- Under the constraint,

$$E(b) = E\left(\hat{\beta} + (X'X)^{-1} R' \left[ R(X'X)^{-1} R' \right]^{-1} (r - R\hat{\beta})\right) = \beta$$

- Under the constraint,

$$\text{Var}(b) = \sigma^2 \left[ (X'X)^{-1} - (X'X)^{-1} R' \left[ R(X'X)^{-1} R' \right]^{-1} R (X'X)^{-1} \right] \leq \text{Var}(\hat{\beta})$$

## Specification error

- Exclusion of relevant regressors results in the biased estimator of the included variables.
- Inclusion of irrelevant regressors does not affect the Unbiasedness of the relevant regressors but we lose some efficiency.