

Lecture 22

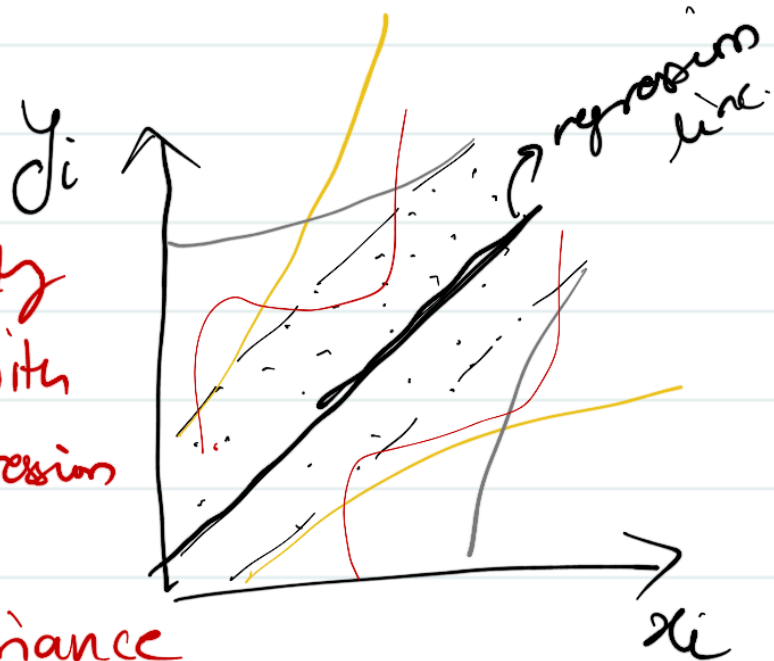
16.04.2021

Econometrics - 1

Heteroskedasticity

- Impact of heteroskedasticity
 - does not interfere with the unbiasedness of regression coefficient estimates

- does impact the variance estimate of ^{regression} coefficients, and hence statistical inference.



- OLS fails (no longer BLUE)

GLS is apt

Generalized
least
squares



$$y_i = \beta_0 + \beta_1 x_i + u_i$$

$$V(u_i | x_i) = \sigma_i^2 \quad i = 1, 2, \dots, N$$

Heteroskedastic
structure.

Variance-Covariance matrix of regression errors

$$\sigma_i^2 = \begin{bmatrix} \sigma_1^2 & & & \\ & \sigma_2^2 & & \\ & & \ddots & \\ & & & \sigma_N^2 \end{bmatrix}$$

$$= \sigma^2 \begin{bmatrix} \sigma_1^2/\sigma^2 & & & \\ & \sigma_2^2/\sigma^2 & & \\ & & \ddots & \\ & & & \sigma_N^2/\sigma^2 \end{bmatrix}$$

$$\sigma^2 \Omega_{N \times N} =$$

$$\underline{y} = \underline{X} \underline{\beta} + \underline{u}$$

$N \times 1$ $N \times K$ $K \times 1$ $N \times 1$

$$V(\underline{u} | X) = \sigma^2 \underline{\Omega}$$

$N \times 1$ \downarrow $N \times N$
 scalar
 (1×1)

Then,

$$\underline{\hat{\beta}}_{GLS} = \left(\underbrace{\underline{X}' \underline{\Omega}^{-1} \underline{X}}_{K \times K} \right)^{-1} \underbrace{\underline{X}' \underline{\Omega}^{-1} \underline{y}}_{K \times 1}$$

$K \times 1$ $K \times N$ $N \times N$ $N \times K$ $K \times N$ $N \times N$ $N \times 1$

$$V(\underline{\hat{\beta}}_{GLS}) = \sigma^2 \left(\underbrace{\underline{X}' \underline{\Omega}^{-1} \underline{X}}_{K \times K} \right)^{-1} < \sigma^2 (\underline{X}' \underline{X})^{-1} = V(\underline{\hat{\beta}}_{OLS})$$

$K \times 1$ $K \times N$ $N \times N$ $N \times K$

Contrast GLS estimators w/ OLS counterparts

$$\underline{\hat{\beta}}_{OLS} = \underbrace{(\underline{X}' \underline{X})^{-1} \underline{X}' \underline{y}}_{E(\underline{\hat{\beta}}_{OLS}) = E(\underline{\hat{\beta}}_{GLS}) = \underline{\beta}}$$

$$V(\underline{\hat{\beta}}_{OLS}) = \sigma^2 (\underline{X}' \underline{X})^{-1}$$

Q. why/how does the GLS work?

* Suppose \exists a $N \times N$ matrix $\underline{T}_{N \times N}$ s.t.

$$\underline{T} \underline{\Omega} \underline{T}' = \underline{I}_N$$

* Now, for our model $\underline{y} = \underline{x} \underline{\beta} + \underline{u}$

we transform each component in the following manner:-

Define

$$\begin{aligned}\underline{y}_{N \times 1}^{NEW} &= \underline{T}_{N \times N} \underline{y}_{N \times 1} \\ \underline{x}_{N \times K}^{NEW} &= \underline{T}_{N \times N} \underline{x}_{N \times K} \\ \underline{u}_{N \times 1}^{NEW} &= \underline{T}_{N \times N} \underline{u}_{N \times 1}\end{aligned}$$

* Consider estimating the transformed model

$$\underline{y}^{NEW} = \underline{x}^{NEW} \underline{\beta} + \underline{u}^{NEW}$$

$$\underline{y}^{NEW} = X^{NEW} \underline{\beta} + \underline{u}^{NEW}$$

$$T \underline{y} = T X \underline{\beta} + T \underline{u} \quad \left\{ \begin{array}{l} \text{original} \\ \text{model} \\ \text{premultiplied} \\ \text{by } T_{N \times N} \end{array} \right.$$

$$V(T \underline{u}) = E[(T \underline{u})(T \underline{u})']$$

$$= E[T \underline{u} \underline{u}' T']$$

$$= T \underbrace{E[\underline{u} \underline{u}']}_{= \sigma^2 \Omega} T'$$

$$= T \sigma^2 \Omega T'$$

$$= \sigma^2 T \Omega T'$$

$$\boxed{V(T \underline{u}) = \sigma^2 I_N}$$

So, the transformed model is HOMOSKEDASTIC.

\Rightarrow We can ^{efficiently} estimate the transformed model using OLS.

$$T\underline{y} = TX\underline{\beta} + T\underline{u}$$

$$V(T\underline{u}) = \sigma^2 I_n$$

Hence The OLS estimators of

$$\underline{y}^{NEW} = X^{NEW}\underline{\beta} + \underline{u}^{NEW}$$

are efficient.

$$\begin{aligned} \overset{\text{transformed}}{\underline{\beta}}_{OLS} &= (X^{NEW'} X^{NEW})^{-1} X^{NEW'} \underline{y}^{NEW} \\ &= [(TX)' (TX)]^{-1} (TX)' T\underline{y} \\ &= [X' \underbrace{T' T}_I X]^{-1} X' T' T\underline{y} \\ &= (X' \Omega^{-1} X)^{-1} X' \Omega^{-1} \underline{y} \equiv \hat{\underline{\beta}}_{GLS} \quad \star \end{aligned}$$

$$\begin{aligned}
 V(\hat{\beta}_{OLS}^{\text{transformed}}) &= \sigma^2 (X^{\text{NEW}'} X^{\text{NEW}})^{-1} \\
 &= \sigma^2 ((TX)' TX)^{-1} \\
 &= \sigma^2 [X' \Omega^{-1} X]^{-1} \\
 &\equiv V(\hat{\beta}_{GLS})
 \end{aligned}$$

$$\hat{\beta}_{GLS} = (X' \underbrace{\Omega^{-1}}_{\text{unknown!}} X)^{-1} X' \underbrace{\Omega^{-1}}_{\text{unknown!}} y$$

$$V(\hat{\beta}_{GLS}) = \sigma^2 (X' \underbrace{\Omega^{-1}}_{\text{unknown!}} X)^{-1}$$

$$V(u_i | x_i) = \sigma^2 \Omega \rightarrow \text{True } \Omega \text{ is not known}$$

Hence, we don't know Ω ! Then how do we estimate GLS?

Feasible Generalized Least Squares

FGLS

Step 1: estimate $\hat{\Omega}$ from the data $\{y, \vec{x}_i\}_{i=1}^n$

Step 2: get \hat{T} s.t. $\hat{\Omega}^{-1} = \hat{T}' \hat{T}$

Step 3: given \hat{T} , define

$$\underline{y}^m = \hat{T} \underline{y}$$

$$\underline{x}^m = \hat{T} \underline{x}$$

Step 4: Run OLS with y^m as dependent variable
and x^m as explanatory variables.

$$\hat{\beta}_{\text{GLS}} = (X^m{}' X^m)^{-1} X^m{}' y^m$$

$$= [(\hat{T}X)' \hat{T}X]^{-1} (\hat{T}X)' \hat{T}y$$

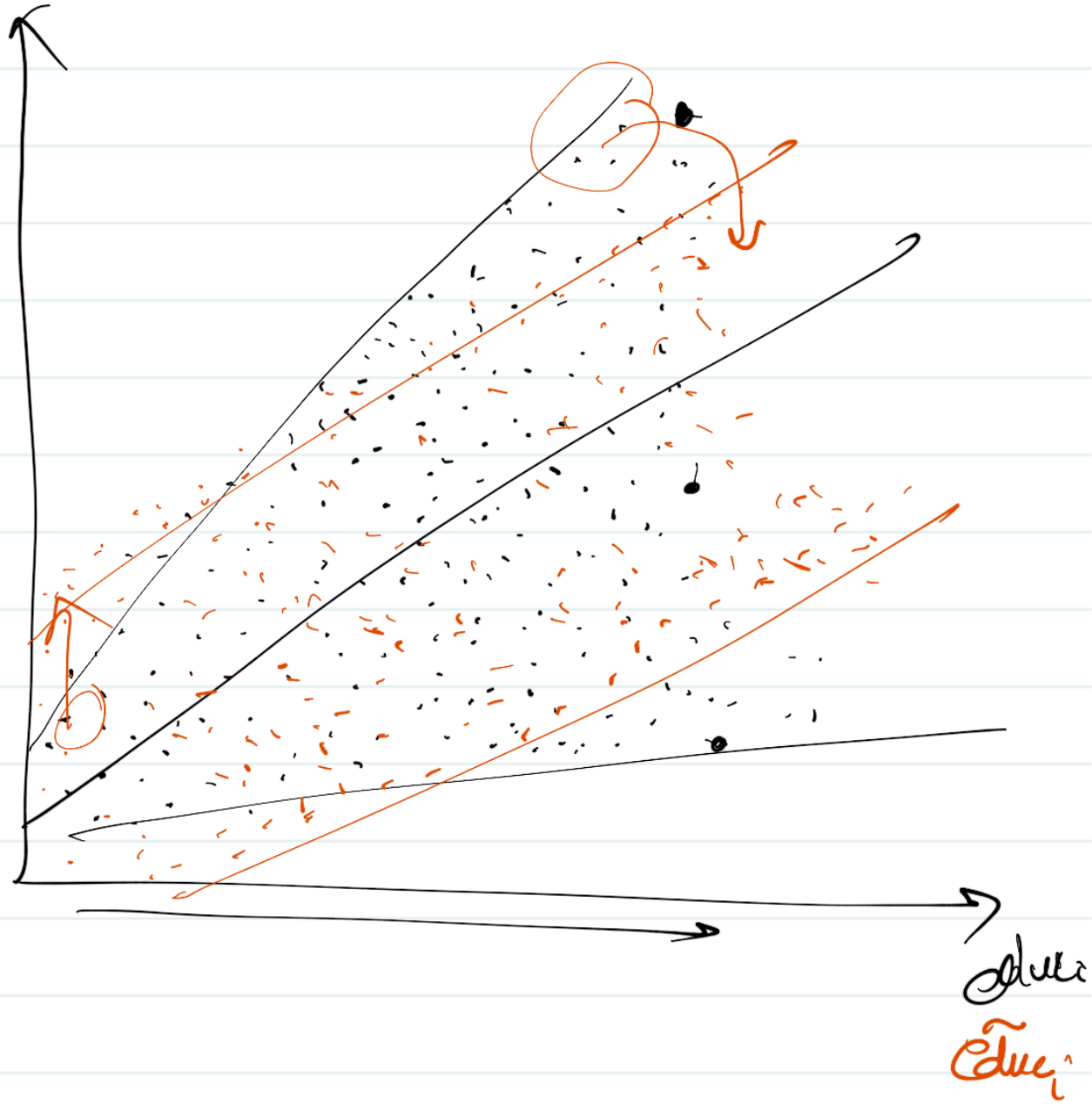
$$\hat{\beta}_{\text{GLS}} = \left(X' \underbrace{\hat{T}' \hat{T}}_{\hat{\Omega}^{-1}} X \right)^{-1} X' \underbrace{\hat{T}' \hat{T}}_{\hat{\Omega}^{-1}} y$$

$$\hat{\beta}_{\text{GLS}} = \left(X' \underbrace{\hat{\Omega}^{-1}}_{\substack{\text{Replace} \\ \text{with } \hat{\Omega}^{-1}}} X \right)^{-1} X' \underbrace{\hat{\Omega}^{-1}}_{\substack{\text{Replace} \\ \text{with } \hat{\Omega}^{-1}}} y$$

Replace
with $\hat{\Omega}^{-1}$

model
what does the transformation achieve?
(Intuition)

\tilde{wage}_i
 $wage_i$



Example 1:

GROUPWISE HETEROSKEDASTICITY

$$y = \beta_1 + \beta_2 x_{2i} + \beta_3 x_{3i} + u_i$$

$$i = 1, 2, \dots, N$$

The data can be divided in 3 strata:-

$$i = \underbrace{1, 2, \dots, N_1}_{\text{group 1}}, \underbrace{N_1+1, N_1+2, \dots, N_1+N_2}_{g_2}, \underbrace{N_1+N_2+1, \dots, N}_{g_3}$$

$$V(\underline{u}) = \begin{bmatrix} \sigma_1^2 & & & \\ & \ddots & & \\ & & \sigma_1^2 & \\ & & & \ddots & \\ & & & & \sigma_2^2 & \\ & & & & & \ddots & \\ & & & & & & \sigma_2^2 & \\ & & & & & & & \ddots & \\ & & & & & & & & \sigma_3^2 & \\ & & & & & & & & & \ddots & \\ & & & & & & & & & & \sigma_3^2 \end{bmatrix}$$

$\left. \begin{array}{c} \text{ } \end{array} \right\} N_1 \text{ rows}$
 $\left. \begin{array}{c} \text{ } \end{array} \right\} N_2 \text{ rows}$
 $\left. \begin{array}{c} \text{ } \end{array} \right\} N - N_1 - N_2 = N_3 \text{ rows.}$

H₀: $\sigma_1^2 = \sigma_2^2 = \sigma_3^2$; i.e., No heteroskedasticity

we have

Ω

but we need

$\hat{\Omega}$

in the next lecture.
(Apply FALS).