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## GENERALIZED LEAST SQUARES

- A solution to the following problem:

Suppose  $\text{Cov}(\epsilon) \neq \sigma^2 I_T$

but rather  $= \sigma^2 \Omega$  ,  $\Omega \neq I_T$

i.e.  $\epsilon \sim N(0, \sigma^2 \Omega)$

This violates the ideal conditions.

One or both of the following exists:

① Heteroskedasticity

- nonequal variances of the  $\epsilon$ 's ;
- the diagonal elements of  $\Omega$  are not necessarily equal ;
- $\sigma_t^2 \neq \sigma_{t+1}^2$  .

② Autocorrelation or Serial Correlation

- $\Omega$  is not necessarily a diagonal matrix ;
- $\text{Cov}(\epsilon_t, \epsilon_{t+i}) \neq 0$  ;
- disturbances not independent .

## Properties of OLS:

Thm:  $\hat{\beta} \sim N(\beta, \sigma^2 (X'X)^{-1} X' \Omega X (X'X)^{-1})$

Proof:

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

ie.  $\hat{\beta}$  is linear in  $\epsilon \rightarrow$  (i) l.c. of  $\epsilon_i$ ;  $\therefore \hat{\beta} \sim N$ .

(ii)  $E(\hat{\beta}) = \beta$ ; since  $E(\epsilon) = 0$ ,  $\hat{\beta}$  is unbiased.

$$\begin{aligned} \text{(iii) Cov}(\hat{\beta}) &= E[(\hat{\beta} - \beta)(\hat{\beta} - \beta)'] \\ &= E[(X'X)^{-1} X' \epsilon][\epsilon' X (X'X)^{-1}] \\ &= E(X'X)^{-1} X' E(\epsilon \epsilon') X (X'X)^{-1} \\ &= (X'X)^{-1} X' E(\epsilon \epsilon') X (X'X)^{-1} \\ &= \sigma^2 (X'X)^{-1} X' \Omega X (X'X)^{-1} \end{aligned}$$

QED

Thm:  $\hat{\beta}$  is consistent.

$$\begin{aligned} \text{Proof: } \text{plim } \hat{\beta} &= \text{plim} (\beta + (X'X)^{-1} X' \epsilon) \\ &= \beta + \text{plim} (X'X)^{-1} X' \epsilon \\ &= \beta + \text{plim} \left( \frac{X'X}{T} \right)^{-1} \text{plim} \left( \frac{X' \epsilon}{T} \right) \\ &\quad \uparrow \quad \quad \uparrow \\ &\quad \text{finite} \quad X_i \text{ uncorrel. w/ } \epsilon \end{aligned}$$

Other ideal conditions still hold.

Alternative proof for consistency;

Since  $\hat{\beta}$  unbiased, show that  $\text{Cov}(\hat{\beta}) \rightarrow 0$ .

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

$$\text{plim Cov}(\hat{\beta}) = \lim_{T \rightarrow \infty} \sigma^2 \left(\frac{X'X}{T}\right)^{-1} \frac{X' \Omega X}{T^2} \left(\frac{X'X}{T}\right)^{-1}$$

$$= \sigma^2 \underset{\substack{\uparrow \\ \text{finite}}}{\text{plim} \left(\frac{X'X}{T}\right)^{-1}} \underset{\substack{\uparrow \\ 0 \\ \text{[for any reasonable } \Omega\text{]}}}{\text{plim} \frac{X' \Omega X}{T^2}} \underset{\substack{\uparrow \\ \text{finite}}}{\text{plim} \left(\frac{X'X}{T}\right)^{-1}}$$

QED

$\therefore \hat{\beta}$  unbiased & consistent.

But  $\hat{\beta}$  is not efficient. GLS is better (later).

Thm:  $s^2$  is biased and inconsistent.

$$\begin{aligned} \text{Proof: } s^2 &= \frac{1}{T-K} E' M E \\ &= \frac{1}{T-K} \text{Trace}(E' M E) && [E' M E \text{ a scalar}] \\ &= \frac{1}{T-K} \text{Tr}(M E E') \end{aligned}$$

$$\begin{aligned} \Rightarrow E(s^2) &= \frac{1}{T-K} \text{Tr}(M E(E E')) \\ &= \frac{1}{T-K} \sigma^2 \text{Tr}(M \Omega) \end{aligned}$$

$$\neq \sigma^2 \text{ unless } \text{Tr}(M \Omega) = T-K, \text{ which it isn't, unless } \Omega = I_T.$$

Thus,  $s^2$  is biased.

Pf. of inconsistency is similar.

Implications: The  $t$  &  $F$  tests are incorrect.

- for 2 reasons -

$$\frac{\hat{\beta}_i}{\sqrt{s^2 (X'X)^{-1}_{ii}}}$$

(i)  $s^2$  is biased

(ii)  $(X'X)^{-1}$  is not the appropriate covariance matrix  
-  $(X'X)^{-1} X' \Omega X (X'X)^{-1}$  is!

Summary:

- ①  $\hat{\beta}_{OLS}$  unbiased, consistent, but inefficient.
- ②  $s^2$  biased & inconsistent.
- ③  $t$  &  $F$  tests are incorrect

Now, the Cure for  $\epsilon \sim N(0, \sigma^2 \Omega)$

GLS - Generalized LS

Lemma:  $\exists$  a nonsingular  $T \times T$  matrix  $V$   
 $\exists V'V = \Omega^{-1}$ .

Proof:  $\Omega$  is a covariance matrix,  $\therefore \text{psd.}$

Thus if  $\Omega^{-1}$  exists, it is psd.

Thus  $\exists$  a  $V$   $\exists V'V = \Omega^{-1}$ . (Schmidt p.66)

Thm:

Suppose  $Y = X\beta + \epsilon$  satisfies ideal conditions  
except that  $\text{Cov}(\epsilon) = \sigma^2 \Omega$ .

Let  $V'V = \Omega^{-1}$ . Then

$$(VY) = (VX)\beta + (VE)$$

satisfies the ideal conditions.

Proof: (i)  $VE$  is Normal.

(ii)  $E(VE) = VE(E) = 0$ .

(iii)  $\text{Cov}(VE) = E(VEE'V')$

$$= V(\sigma^2 \Omega)V'$$

$$= \sigma^2 V\Omega V'$$

$$= \sigma^2 I_T$$

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

(ideal conditions)

$$V^T V \Omega V^T = \sigma^2 I$$

~~$V\Omega V^T = I$~~

$$V\Omega V^T = I$$

Intuition:  $V\Omega V^T = I$  since if we premultiply by  $V'$ ,  
 we get  $V'$ .

$$V'(V\Omega V^T) = \Omega^{-1}\Omega V^T = V^T$$

this  $\Rightarrow V\Omega V^T = I$  since  $V'$  is nonsingular.

Click  
 (see next page)

GLS

5 (INSERTA)

$$\begin{aligned}\text{Cov}(VE) &= E[(VE)(VE)'] \\ &= E[VEe'V] \\ &= V \cdot E[e e'] \cdot V' \\ &= V \cdot \sigma^2 \Omega \cdot V' \\ &= \sigma^2 V \Omega V'\end{aligned}$$

Now

$$\begin{aligned}V \Omega V' &= V \Omega V' \cdot I_T \\ &= V \Omega V' \cdot V V^{-1} \quad (V^{-1} \text{ exists since } V \text{ non-singular}) \\ &= V \Omega \cdot V^{-1} V \cdot V^{-1} \\ &= V \Omega \cdot \Omega^{-1} \cdot V^{-1} \\ &= V V^{-1} \\ &= I_T\end{aligned}$$

Hence  $\text{Cov}(VE) = \sigma^2 I_T$  ✓

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Furthermore,  $VX$  is nonstochastic matrix of Rank  $K$   
 $\nexists \lim_{T \rightarrow \infty} \frac{(VX)'(VX)}{T}$  is finite & nonsingular.

$\Rightarrow$  given  $\lim_{T \rightarrow \infty} \frac{X'X}{T}$  is finite,

$$\lim_{T \rightarrow \infty} \frac{X'V'VX}{T} = \lim_{T \rightarrow \infty} \frac{X'\Omega^{-1}X}{T} \text{ is finite}$$

for any reasonable  $\Omega$ .

Thus the transformed equation,  $(VY) = (VX)\beta + (VE)$ ,  
 will have all the optimal properties under the ideal conditions.



Defn: The GLS estimator is  
 the OLS estimator of  $(VY)$  on  $(VX)$ .

$$\begin{aligned} \tilde{\beta} &= [(VX)'(VX)]^{-1} (VX)'(VY) \\ &= (X'V'VX)^{-1} X'V'VY \\ &= \underline{\underline{(X'\Omega^{-1}X)^{-1} X'\Omega^{-1}Y}} \end{aligned}$$

$$\begin{aligned} \tilde{\sigma}^2 &= \frac{1}{T-K} [VY - VX\tilde{\beta}]' [VY - VX\tilde{\beta}] \\ &= \frac{1}{T-K} [Y - X\tilde{\beta}]' V'V [Y - X\tilde{\beta}] \\ &= \frac{1}{T-K} (Y - X\tilde{\beta})' \Omega^{-1} (Y - X\tilde{\beta}) \\ &= \frac{1}{T-K} \tilde{\epsilon}' \Omega^{-1} \tilde{\epsilon} \end{aligned}$$

This is a weighted sum of the squared residuals;  
 weighted by  $\Omega^{-1}$ .

Fact: GLS  $\tilde{\beta}$  minimizes  $SSE_{GLS} = (Y - X\beta)' \Omega^{-1} (Y - X\beta)$ .

This is an algebraic result. — should be able to prove.

Proof: GLS —  $UY = UX\beta + UE$

$$\begin{aligned} \Rightarrow SSE_{GLS} &= (UY - UX\beta)' (UY - UX\beta) \\ &= (Y - X\beta)' \Omega^{-1} (Y - X\beta) \\ &= Y' \Omega^{-1} Y - 2\beta' X' \Omega^{-1} Y + \beta' X' \Omega^{-1} X \beta \end{aligned}$$

$$\frac{\partial SSE_{GLS}}{\partial \beta} = -2X' \Omega^{-1} Y + 2X' \Omega^{-1} X \beta$$

$$\begin{aligned} \Rightarrow \tilde{\beta} &= (X' \Omega^{-1} X)^{-1} X' \Omega^{-1} Y \\ &= \beta + (X' \Omega^{-1} X)^{-1} X' \Omega^{-1} \epsilon \end{aligned}$$

QED

Consider the distribution of GLS  $\tilde{\beta}$ .

Thm:  $\tilde{\beta} \sim N(\beta, \sigma^2 (X' \Omega^{-1} X)^{-1})$

(i)  $\tilde{\beta}$  l.c. of  $\epsilon$ 's ;  $\therefore$  Normal

(ii)  $E(\tilde{\beta}) = \beta$

$$\begin{aligned} \text{(iii) Cov}(\tilde{\beta}) &= E(\tilde{\beta} - \beta)(\tilde{\beta} - \beta)' \\ &= E[(X' \Omega^{-1} X)^{-1} X' \Omega^{-1} \epsilon] [\epsilon' \Omega^{-1} X (X' \Omega^{-1} X)^{-1}]^T \\ &= (X' \Omega^{-1} X)^{-1} X' \Omega^{-1} [\sigma^2 \Omega] \Omega^{-1} X (X' \Omega^{-1} X)^{-1} \\ &= \sigma^2 (X' \Omega^{-1} X)^{-1} \end{aligned}$$

QED



Thus, since the transformed equation satisfies the ideal conditions,

$\tilde{\beta}$  is unbiased, consistent, BLUE, efficient, & asymptotically efficient.

$\tilde{\sigma}^2$  is unbiased, consistent, efficient, & asymptotically efficient.

and, 
$$\frac{(T-K)\tilde{\sigma}^2}{\sigma^2} \sim \chi^2_{T-K}$$

Furthermore,  $\tilde{\sigma}^2$  and  $\tilde{\beta}$  are independent.

∴ Use appropriate  $t$  &  $F$  statistics to test hypotheses.

e.g. 
$$\frac{\tilde{\beta}_i - \beta_i}{\sqrt{\tilde{\sigma}^2 (X' \Omega^{-1} X)^{-1}_{ii}}} \sim t_{T-K}$$

Note: Since  $\tilde{\beta}$  is MLE (see p. 7) [minimizes  $SSE_{GLS}$ ] we have its asymptotic distribution as well;

$$\sqrt{T}(\tilde{\beta} - \beta) \rightarrow N \left[ 0, \sigma^2 \lim_{T \rightarrow \infty} \left( \frac{X' \Omega^{-1} X}{T} \right)^{-1} \right]$$

\* No big deal since we know small sample distribution!

\*\* It is a big deal, because when we estimate  $\hat{\Omega}$ ,

Again, the problem is to find a transformation,  $V$ ,  
 $\exists V'V = \Omega^{-1}$ . Then GLS is nice.

What if  $\Omega$  is unknown? (the usual case)

- ① assume it = something. (tacky)
- ② estimate it.

Problem:  $\Omega$  is  $T \times T$ ;  $\Rightarrow T + \frac{1}{2}T(T-1)$  elements.  
 (it is symmetric)  
 $\rightarrow$  too many to estimate in general.

Solution(s):

- do OLS on  $Y = X\beta + \epsilon$ ; get  $\hat{\beta}$ .  
 let  $\hat{\Omega} = ee'$ .

$\hat{\beta}$  unbiased & consistent, but inefficient.

In other words, look at the OLS residuals.  
 Do they behave nicely?

- constant variance ?
- no autocorrelation ?

The residuals are a good Diagnostic to reveal any such problems.

$\therefore$  Look for problem [heterosked.?, autocorrel?],  
 $\neq$  then look for an appropriate  $V$ .

More Rigorous Solution: (than letting  $\hat{\Omega} = ee'$ )

It is "better" to assume  $\Omega = f(\theta)$   
 where  $\theta$  is p x 1; i.e.  $\Omega$  is determined by a few parameters

e.g. Heteroskedasticity;  
 assume variance of  $\epsilon_t$  is a  $f(x_t), \dots$   
 e.g.  $\text{Var}(Y) = f(\text{age})$

Autocorrelation;  
 assume correlation between  $\epsilon_t$  &  $\epsilon_{t-1}$   
 is  $f(\text{something}), \dots$

--- More on this later!

Then estimate  $\theta$  with  $\hat{\theta}$ .

Thm:

If  $\hat{\theta}$  is a consistent estimate of  $\theta$ ,  
 then  $\hat{\Omega} = f(\hat{\theta})$  is consistent estimate of  $\Omega$ ,  
 (by Slutsky Thm)

and then  $\tilde{\beta}^* = (X' \hat{\Omega}^{-1} X)^{-1} X' \hat{\Omega}^{-1} Y$   
 is a consistent estimate of  $\beta$ ,

and  $\tilde{\beta}^* \neq \tilde{\beta}$  will have the same  
 asymptotic distribution.

$\implies \therefore \tilde{\beta}^*$  will be asymptotically efficient.

[See Maddala, ECON, 1971.]

$\therefore$  better than  $\hat{\beta}_{OLS}$

$\beta$   
 (it's the MLE)