

## L06 Best restricted estimator

### 1. Restricted Model

(1) Model under restrictions

Consider linear model (A)

$$Y = X\beta + \epsilon \text{ with } \epsilon \sim (0, \sigma^2\Sigma) \text{ under the constraint } G\beta = b.$$

(2) The restriction

If  $G\beta = b$  is consistent, then

$$\beta \in G^+b + \mathcal{N}(G) = \{G^+b + (I - G^+G)\eta : \eta \in R^p\}.$$

**Proof.** Suppose  $G\beta = b$  has a solution  $\beta_0$ . Then

$$\begin{aligned} G\beta = b &\iff G\beta = b = G\beta_0 = GG^+G\beta_0 = GG^+b \iff G(\beta - G^+b) = 0 \\ &\iff \beta - G^+b \in \mathcal{N}(G) \iff \beta \in G^+b + \mathcal{N}(G). \end{aligned}$$

But  $\mathcal{N}(G) = \mathcal{N}(G^+G) = \mathcal{R}(I - G^+G) = \{(I - G^+G)\eta : \eta\}$ . Thus

$$G\beta = b \iff \beta \in G^+b + \mathcal{N}(G) = \{G^+b + (I - G^+G)\eta : \eta\}$$

(3) Transformed model

Let  $Y_* = Y - XG^+b$ ,  $X_* = X(I - G^+G)$  and  $\beta = G^+b + (I - G^+G)\eta$ . Then Model (A) with the restriction is transformed to Model (B)  $Y_* = X_*\eta + \epsilon$ ,  $\epsilon \sim (0, \sigma^2\Sigma)$  without restrictions.

$$\textbf{Proof. (A): } \begin{cases} Y = X\beta + \epsilon, \epsilon \sim (0, \sigma^2\Sigma) \\ G\beta = b \end{cases} \iff \begin{cases} Y = X\beta + \epsilon, \epsilon \sim (0, \sigma^2\Sigma) \\ \beta = G^+b + (I - G^+G)\eta, \eta \in R^p \end{cases}$$

$$\iff Y = XG^+b + X(I - G^+G)\eta + \epsilon, \epsilon \sim (0, \sigma^2\Sigma)$$

$$\iff \text{(B): } Y_* = X_*\eta + \epsilon, \epsilon \sim (0, \sigma^2\Sigma)$$

### 2. Restricted GLSE

(1) Definition

$\hat{\beta}$  is a restricted GLSE (RGLSE) under  $G\beta = b$  with respect to  $U = \Sigma^{-1}$  if

$$G\hat{\beta} = b \text{ and } \|Y - X\hat{\beta}\|_{\Sigma^{-1}}^2 \leq \|Y - X\beta\|_{\Sigma^{-1}}^2 \text{ for all } \beta \text{ under } G\beta = b.$$

(2) Formula

Let  $\hat{\beta} = G^+b + [\Sigma^{-1/2}X(I - G^+G)]^+ \Sigma^{-1/2}(Y - XG^+b)$ . Then the collection of all RGLSE under  $G\beta = b$  is

$$\text{RGLSE}_{\Sigma^{-1}}(\beta) = \hat{\beta} + (I - G^+G)\mathcal{N}(X(I - G^+G))$$

$$\textbf{Proof. } \tilde{\beta} \in \text{RGLSE}_{\Sigma^{-1}}(\beta) \stackrel{\text{def}}{\iff} \begin{cases} G\tilde{\beta} = b \\ \|Y - X\tilde{\beta}\|_{\Sigma^{-1}}^2 \leq \|Y - X\beta\|_{\Sigma^{-1}}^2 \text{ for all } G\beta = b \end{cases}$$

$$\iff \begin{cases} \tilde{\beta} = G^+b + (I - G^+G)\tilde{\eta} \\ \|Y - X\tilde{\beta}\|_{\Sigma^{-1}}^2 \leq \|Y - X\beta\|_{\Sigma^{-1}}^2 \text{ for all } \beta = G^+b + (I - G^+G)\eta \text{ for all } \eta \end{cases}$$

$$\iff \begin{cases} \tilde{\beta} = G^+b + (I - G^+G)\tilde{\eta} \\ \|Y_* - X_*\tilde{\eta}\|_{\Sigma^{-1}}^2 \leq \|Y_* - X_*\eta\|_{\Sigma^{-1}}^2 \text{ for all } \eta \end{cases} \iff \begin{cases} \tilde{\beta} = G^+b + (I - G^+G)\tilde{\eta} \\ \tilde{\eta} \in \text{GLSE}_{\Sigma^{-1}}(\eta) \text{ in B} \end{cases}$$

$$\iff \begin{cases} \tilde{\beta} = G^+b + (I - G^+G)\tilde{\eta} \\ \tilde{\eta} \in (\Sigma^{-1/2}X_*)^+ \Sigma^{-1/2}Y_* + \mathcal{N}(X_*) \end{cases} \iff \tilde{\beta} \in \hat{\beta} + (I - G^+G)\mathcal{N}(X(I - G^+G))$$

### 3. Best restricted estimator

#### (1) Definitions

$LY + d$  is a P1UE for  $H\beta$  under  $G\beta = b$

$$\stackrel{def}{\iff} E(LY + d) = H\beta \text{ for all } \beta \text{ under consistent } G\beta = b$$

$H\beta$  is P1EU estimable under  $G\beta = b$

$$\stackrel{def}{\iff} H\beta \text{ has a P1UE } LY + d \text{ under } G\beta = b$$

$L_0Y + d_0$  is the best P1UE for  $H\beta$  under  $G\beta = b$

$$\stackrel{def}{\iff} \begin{cases} L_0Y + d_0 \text{ is a P1UE for } H\beta \text{ under } G\beta = b \\ \text{Cov}(L_0Y + d_0) \leq \text{Cov}(LY + d) \text{ for all P1UE } LY + d. \end{cases}$$

#### (2) Sufficient and necessary conditions

$LY + d$  is a P1UE for  $H\beta$  under  $G\beta = b$

$$\stackrel{def}{\iff} E(LY + d) = H\beta \text{ for all } \beta \text{ under consistent } G\beta = b$$

$$\iff LX(I - G^+G) = H(I - G^+G) \text{ and } d = (H - LX)G^+b$$

$H\beta$  is P1EU estimable under  $G\beta = b$

$$\iff LX(I - G^+G) = H(I - G^+G) \text{ and } d = (H - LX)G^+b \text{ for some } L \text{ and } d$$

#### (3) Best P1UE

With PIUE estimable  $H\beta$  under  $G\beta = b$ , and  $\hat{\beta}$  in (2) of 2,  $H\hat{\beta}$  is the best restricted P1UE for  $H\beta$ .

**Proof.**  $H\beta$  is P1UE estimable under  $G\beta = b$ . So

$$H(I - G^+G) = L_1X(I - G^+G) \text{ and } d_1 = (H - L_1X)G^+b \text{ for some } L_1 \text{ and } d_1.$$

$$H\hat{\beta} = L_0Y + d_0 \text{ where } L_0 = H [\Sigma^{-1/2}X(I - G^+G)]^+ \Sigma^{-1/2} \text{ and } d_0 = (H - L_0X)G^+b.$$

But with  $T = \Sigma^{-1/2}X(I - G^+G)$ ,

$$\begin{aligned} L_0X(I - G^+G) &= HT^+T = H(I - G^+G)T^+T = L_1X(I - G^+G)T^+T \\ &= L_1\Sigma^{1/2}TT^+T = L_1\Sigma^{1/2}T = L_1\Sigma^{1/2}\Sigma^{-1/2}X(I - G^+G) \\ &= L_1X(I - G^+G) = H(I - G^+G). \end{aligned}$$

So  $H\hat{\beta}$  is a PIUE for  $H\beta$  under  $G\beta = b$ .

If  $LY + d$  is also PIUE for  $H\beta$  under  $G\beta = b$ , i.e.,  $LX(I - G^+G) = H(I - G^+G)$  and  $d = (H - LX)G^+b$ , we need to show

$$\text{Cov}(LY + d) - \text{Cov}(L_0Y + d_0) = \sigma^2(L\Sigma L' - L_0\Sigma L'_0) \geq 0.$$

$$\begin{aligned} \text{Write } L_0 &= HT^+\Sigma^{-1/2} = H(I - G^+G)T^+\Sigma^{-1/2} = LX(I - G^+G)T^+\Sigma^{-1/2} \\ &= L\Sigma^{1/2}TT^+\Sigma^{-1/2} \end{aligned}$$

So  $L_0\Sigma L'_0 = (L\Sigma^{1/2})TT^+(L\Sigma^{1/2})'$ . Therefore

$$\begin{aligned} \text{Then } \text{Cov}(LY + d) - \text{Cov}(L_0Y + d_0) &= \sigma^2(L\Sigma L' - L_0\Sigma L'_0) \\ &= \sigma^2(L\Sigma^{1/2})(I - TT^+)(L\Sigma^{1/2})' \geq 0 \end{aligned}$$

since symmetric idempotent  $I - TT^+ \geq 0$ .