

Part II
Multivariate Linear Models

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January 2012

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1. Multivariate Regression Models

1.1 The Model

T

$$y'_i = x'_i B + u'_i$$

$i = 1, \dots, n$, n a $\mathbf{1}$ W , $\{y_i\}$ a $\{u_i\}$ ℓ - a, a $\{x_i\}$
 m - a , a a , a, a $m \times \ell$ a B a , ffi . T
 , y_i a x_i , a ,
 , ffi a B . I a , , a a
 a

$$Y = XB + U$$

a a fi a , . . , a a a a a , a
 , .

T $\{u_i\}$ a a $(0, \Sigma)$ a , a . T , $\mathbf{E}u_i u'_j =$
 Σ , $i = j$ a 0 . M , a $(Z) = a (Z)$,

$$a(U) = I_n \otimes \Sigma$$

, a , .

1.2 Multivariate Least Squares

S $\sum_{p,q} z_{pq}^2 = Z'Z$, a a $Z = (z_{pq})$, a (LS) a \hat{B} , B
 fi

$$\hat{B} = a_B (Y - XB)'(Y - XB) \quad (1)$$

I $q(B) = (Y - XB)'(Y - XB)$, a

$$dq(B) = -2 (X'Y - X'XB)' dB$$

a FOC $dq(B) = 0$,

$$\hat{B} = (X'X)^{-1} X'Y$$

S , a, a a a , $\hat{Y} = X\hat{B}$ a $\hat{U} = Y - X\hat{B}$. T

$$\hat{Y} = P_X Y \quad \hat{U} = (I - P_X)Y$$

$P_X = X(X'X)^{-1}X'$, . . , a $\mathcal{R}(X)$, X , a a a

I a a \hat{B} , $\mathbf{1}$ a , (1),

$$q(B) = (Y - X\hat{B})'(Y - X\hat{B}) + (\hat{B} - B)'X'X(\hat{B} - B) \quad (2)$$

where $\Sigma = \hat{\Sigma}$. C, LS, ML

1.4 Statistical Properties of the Estimators

We have $\hat{B} = \hat{\Sigma}$.

Theorem 1 We have

- (a) $\mathbf{E}(\hat{B}) = B$ and $\mathbf{E}(\hat{\Sigma}) = \frac{n-m}{n} \Sigma$

Proof Part (a) is straightforward.

$$\hat{B} = B + (X'X)^{-1}X'U \quad \hat{\Sigma} = B + ((X'X)^{-1}X' \otimes I_\ell) U$$

For (b),

$$\hat{\Sigma} = \frac{1}{n}U'(I - P_X)U = \frac{1}{n}V'V$$

where $V := H'U$, H is a $n \times (n-m)$ matrix with $I - P_X = HH'$ and $H'H = I_{n-m}$.
 Note that $V = (H' \otimes I)U$, so $V = I_{n-m} \otimes \Sigma$, i.e., $v_i = v_i'$,
 V is a $(n-m) \times n$ matrix with Σ on the diagonal.

$$\mathbf{E}V'V = \mathbf{E} \left(\sum_{i=1}^{n-m} v_i v_i' \right) = (n-m) \Sigma$$

Therefore, $\hat{\Sigma} = \frac{1}{n}V'V \rightarrow \frac{n-m}{n} \Sigma$. ■

Thus, \hat{B} is unbiased, and $\hat{\Sigma}$ is biased. However, $\hat{\Sigma}$ is consistent as $n \rightarrow \infty$.

$$\hat{\Sigma} = \frac{1}{n-m}Y'(I - P_X)Y$$

For part (b), we have $\hat{B} = B + (X'X)^{-1}X'U$.
 (a) $\mathbf{E}(\hat{B}) = B + (X'X)^{-1}X' \mathbf{E}U = B$, since $\mathbf{E}U = 0$.
 (b) $\mathbf{E}(\hat{\Sigma}) = \frac{1}{n} \mathbf{E}V'V = \frac{n-m}{n} \Sigma$.

Definition 1 Let $z_i \sim i.i.d. \mathbf{N}(0, \Sigma_p)$. Then

$$\sum_{i=1}^n z_i z_i' \sim \mathcal{W}_p(n, \Sigma)$$

i.e., Wishart distribution with n degrees of freedom and covariance matrix Σ . The p is the dimensionality parameter.

Case: W is a Wishart distribution with n degrees of freedom and covariance matrix Σ .
 For $\hat{\Sigma}$, we have $\hat{\Sigma} = \frac{1}{n-m}Y'(I - P_X)Y$.
 Note that $Y = (I - P_X)Y$, so $\hat{\Sigma} = \frac{1}{n-m}Y'Y$.

Theorem 2 Under normality, we have

- (a) $\hat{B} \sim \mathbf{N}(B, (X'X)^{-1} \otimes \Sigma)$
- () $n\hat{\Sigma} \sim \mathcal{W}_\ell(n-m, \Sigma)$

$$\begin{aligned}
 & \text{ (a) } \frac{X'X}{n} = \sum \frac{x_i x_i'}{n} \xrightarrow{p} M > 0 \quad \text{ () } \frac{X'U}{n} = \sum \frac{x_i u_i'}{n} \xrightarrow{p} 0 \\
 & \hat{B} \xrightarrow{d} \mathbf{N}(B, M^{-1} \otimes \hat{\Sigma}) \\
 & \text{ () } \frac{X'U}{\sqrt{n}} = \sum \frac{x_i u_i'}{\sqrt{n}} \xrightarrow{d} \mathbf{N}(0, M \otimes \Sigma) \\
 & \sqrt{n}(\hat{B} - B) \xrightarrow{d} \mathbf{N}(0, M^{-1} \otimes \Sigma) \tag{3}
 \end{aligned}$$

$$(\hat{B} - B) = ((X'X)^{-1} \otimes I_\ell) \frac{X'U}{\hat{\sigma}^2}$$

1.5 Hypothesis Testing

Let R be a $q \times ml$ matrix of full rank q , where $q < ml$. We consider the hypothesis testing problem

$$H_0: B = r \quad \text{vs} \quad H_1: B \neq r$$

where r is a $q \times 1$ vector. Under H_0 , the distribution of W is

$$W = (R(\hat{B} - r))' (R((X'X)^{-1} \otimes \hat{\Sigma})R')^{-1} (R(\hat{B} - r))$$

Under H_0 , $W \xrightarrow{d} \chi_q^2$

Let $\hat{\Sigma}$ be a $ml \times ml$ matrix. Under H_0 , the distribution of W is

1.6 Exercises

1. Show that:

(a) $\text{tr}(ABC) = \text{tr}(C'A) = \text{tr}(B'C)$.

(b) Let $x = X\alpha$ and $y = Y\beta$. Then

$$\frac{\partial^2}{\partial x \partial y'} X'AYB' = A \otimes B$$

2. Show that the log-likelihood function is

$$\ell(\hat{B}, \Sigma) = -\frac{n}{2} \left(\text{tr}(\Sigma^{-1}\hat{B}) - \frac{n}{2} \right) \Sigma^{-1}\hat{\Sigma},$$

where $\hat{\Sigma} = \hat{B}^{-1}$.

3. Let \hat{B} be the GLS estimator of B based on the model

$$Y = XB + U$$

where $U \sim N(0, \Sigma_1 \otimes \Sigma_2)$ and Σ_1 and Σ_2 are positive definite matrices. Show that

$$\Sigma_2^{-1}(Y - XB)' \Sigma_1^{-1}(Y - XB)$$

is

$$\hat{B} = (X' \Sigma_1^{-1} X)^{-1} X' \Sigma_1^{-1} Y$$

4. Consider the following model

$$y'_i = x'_i B + u'_i$$

where $y'_i = (y_{1i}, y_{2i})$, $x'_i = (x_{1i}, x_{2i})$, $u'_i = (u_{1i}, u_{2i})$,

$$B = \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}$$

and u_i is a zero mean random vector with

$$\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix}$$

Assume that $\sigma_{11} > 0$ and $\sigma_{22} > 0$.

(a) Let $\beta_{21} = 0$. Show that the GLS estimator of B is unbiased and efficient.

where β_{11}, β_{12} and β_{22} .

(b) Let $\beta_{21} = 0$ and $\sigma_{12} = \sigma_{21} = 0$. Show that the GLS estimator of B is unbiased and efficient. (a) a ?

(c) Assume $\Sigma = \sigma^2 I$. Show that $\beta_{11} + \beta_{12} = 1$. (e) a

Was a ff a : OLS a , β_{11} a β_{12} , a

5. C

(A) $y_{ij} = x'_{ij}\beta + \varepsilon_{ij}$

(B) $y_{ij} = x'_{ij}\beta_j + \varepsilon_{ij}$

$i = 1, \dots, n$ a $j = 1, 2$. L $\varepsilon_i = (\varepsilon_{1i}, \varepsilon_{2i})'$ a a a

$$\Sigma_1 = \begin{pmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{pmatrix}, \quad \Sigma_2 = \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{pmatrix}.$$

A , .. :

(a) E , a fi , a , GLS a , β (A)
 a a a Σ_1 .

() F GLS a , $\beta_j, j = 1, 2$, (B)
 a Σ_1 Σ_2 . C a GLS a OLS a a a . W a ,
 $x_{i1} = x_{i2}$ (B)?

2. Seemingly Unrelated Regressions

2.1 The Model

T , , a (SUR) a ,

$$y_k = X_k\beta_k + u_k$$

, $k = 1, \dots, \ell$, y_k, X_k, β_k a u_k a fi a , a a a
 , a a , a k k - , , a
 , a n a . T a a , a , a
 ℓ - a a

$$\begin{pmatrix} y_1 \\ \vdots \\ y_\ell \end{pmatrix} = \begin{pmatrix} X_1 & & \\ & \ddots & \\ & & X_\ell \end{pmatrix} \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_\ell \end{pmatrix} + \begin{pmatrix} u_1 \\ \vdots \\ u_\ell \end{pmatrix}$$

a

$$y = X\beta + u$$

a , . W , $\mathbf{E} u_p u'_q = \sigma_{pq} I$ a $\Sigma = (\sigma_{pq})$. T , .. a a $u = \Sigma \otimes I_n$.
 N a , a a a U a $u = U$ a a $U = a (U) = I_n \otimes \Sigma$.

T a a , SUR, $X_1 = \dots = X_\ell$, .. , SUR a , . I

X_0 , a SUR

$$Y = (I \otimes X_0)B + U$$

fi $y = Y, X = I \otimes X_0, \beta = B, u = U$.

2.2 Estimation

T SUR a GLS,

$$\hat{\beta} = (X'(\Sigma^{-1} \otimes I)X)^{-1} X'(\Sigma^{-1} \otimes I)y \tag{4}$$

T a, SUR a GLS a. W Σ
 a, a, a, GLS a. T a Σ ,
 a $\hat{\beta}_k, \beta_k$ (OLS a) $\hat{u}_k = y_k - X_k \hat{\beta}_k$
 , $k = 1, \dots, l$. U $\{\hat{u}_k\}$, a $\hat{\sigma}_{pq} = \hat{u}'_p \hat{u}_q / n$, $p, q = 1, \dots, l$ a
 a $\hat{\Sigma} = (\hat{\sigma}_{pq})$.

U a, u a a
 U fi u $U = u$. M, y a a
 a, a, U, a k - , U $y_k - X_k \beta_k$. T SUR a
 fi (4), ML a β . G ML a
 , β , ML a Σ a a a a a
 , fi \hat{U}, \hat{u} , ML (SUR, a) a fi U
 , u,

$$\hat{\Sigma} = \frac{1}{n} \hat{U}' \hat{U}$$

T ML a β a Σ a a a
 , a GLS.

I a (SELS). I $\tilde{\beta}$ OLS SUR a β SUR

$$\begin{aligned} \tilde{\beta} &= (X'X)^{-1} X'y \\ &= \begin{pmatrix} (X'_1 X_1)^{-1} X'_1 y_1 \\ \vdots \\ (X'_l X_l)^{-1} X'_l y_l \end{pmatrix} \end{aligned}$$

F SUR, GLS a OLS a a a
 a SUR a OLS a SELS,
 a H a a SUR: W a fi
 , a (a ,)

2.3 Equivalence of SUR and SELS

The SUR model is defined as $y = X\beta + u$, where y is a $n \times 1$ vector, X is a $n \times k$ matrix, β is a $k \times 1$ vector, and u is a $n \times 1$ vector. The SELS model is defined as $y = X\beta + u$, where y is a $n \times 1$ vector, X is a $n \times k$ matrix, β is a $k \times 1$ vector, and u is a $n \times 1$ vector. The SUR model is identical to the SELS model if and only if $\sigma_{pq} = 0$ for all $p \neq q$.

Theorem 3 *The SUR and SELS are identical if and only if*

$$\sigma_{pq} = 0 \quad \mathcal{R}(X_p) = \mathcal{R}(X_q)$$

for all $p \neq q$.

Proof *B* $\mathcal{R}((\Sigma \otimes I)X) = \mathcal{R}(X)$. Since $\mathcal{R}((\Sigma \otimes I)X) \subset \mathcal{R}(X)$, it follows that

$$\mathcal{R}((\Sigma \otimes I)X) \subset \mathcal{R}(X)$$

$$(\Sigma \otimes I)X = XT$$

$$I \quad T = (T_{pq}) \quad \sigma_{pq} X_q = X_p T_{pq}$$

$$\sigma_{pq} = 0 \quad \mathcal{R}(X_p) = \mathcal{R}(X_q)$$

for all $p \neq q$. ■

2.4 Exercises

1. Consider a SUR model

$$\begin{pmatrix} y_1 \\ \vdots \\ y_\ell \end{pmatrix} = \begin{pmatrix} X_1 & & 0 \\ & \ddots & \\ 0 & & X_\ell \end{pmatrix} \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_\ell \end{pmatrix} + \begin{pmatrix} u_1 \\ \vdots \\ u_\ell \end{pmatrix}$$

where y_k ($n \times 1$), X_k ($n \times m$), β_k ($m \times 1$) and u_k ($n \times 1$), $k = 1, \dots, \ell$. We assume $\mathbf{E}u_k = 0$ and $\mathbf{E}u_j u_k' = \sigma_{jk} I_n$, $\sigma_{jk} = 0$ for $j \neq k$. We assume X_k has full rank m for $k = 1, \dots, \ell$. We assume $\mathbf{E}u_k u_k' = \sigma_k I_n$, $\sigma_k > 0$.

$$y = X\beta + u,$$

- y, X, β a u a fi a a a . A , , :
- (a) D a SUR a , $\beta = (\beta_1', \dots, \beta_\ell)'$.
 - () S a SUR a , β a a a a , - - OLS
a $\sigma_{jk} = 0, a, j \neq k.$
 - () S a SUR a , β a a a a , - - OLS
a $X_1 = \dots = X_\ell.$

2. C a a SUR

$$\begin{pmatrix} y_1 \\ \vdots \\ y_\ell \end{pmatrix} = \begin{pmatrix} X_1 & & \\ & \ddots & \\ & & X_\ell \end{pmatrix} \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_\ell \end{pmatrix} + \begin{pmatrix} u_1 \\ \vdots \\ u_\ell \end{pmatrix}$$

a fi Q 1 a . W , $E u_p u_q' = \sigma_{pq} I$ a $\Sigma = (\sigma_{pq})$. A , , $\beta = (\beta_1, \dots, \beta_\ell)'$. E , a a ML a , a a β a Σ ML a . S , a a , a a ML a . R a , a , n - a a a μ a a a Ω

$$p(x) = \left(\frac{1}{2\pi}\right)^{\frac{n}{2}} (\Omega)^{-\frac{1}{2}} \left(-\frac{1}{2}(x - \mu)' \Omega^{-1}(x - \mu)\right)$$

3. C a ,

$$\begin{aligned} y_{1i} &= \alpha' x_{1i} + \varepsilon_{1i} \\ y_{2i} &= \alpha' x_{2i} + \beta' x_{3i} + \varepsilon_{2i} \end{aligned}$$

$\{\varepsilon_i\}, \varepsilon_i = (\varepsilon_{1i}, \varepsilon_{2i})'$, a a $(\varepsilon_i) = \sigma^2 I$. L $\hat{\alpha}_1$ a $\hat{\alpha}_2$ OLS a
a , a $\hat{\alpha}$ OLS a
, α . A , , :

(a) O a $\hat{\alpha}$, a a a a

$$\hat{\alpha} = M_* \hat{\alpha}_1 + (I - M_*) \hat{\alpha}_2$$

$$M_* = (X_1' X_1 + X_2' (I - P_{X_3}) X_2)^{-1} X_1' X_1$$

() S a $\hat{\alpha}$, a $(\hat{\alpha}_1 - \hat{\alpha}_2)$. U , a , a $\hat{\alpha}$ a a ,
a a (fi) a a ,

$$\bar{\alpha} = M \hat{\alpha}_1 + (I - M) \hat{\alpha}_2$$

(N a $\bar{\alpha} = \hat{\alpha} + (M - M_*)(\hat{\alpha}_1 - \hat{\alpha}_2)$).

3. Fixed Effects Models

3.1 The Model

Let

$$y_{it} = \pi + \mu_i + \nu_t + x'_{it}\beta + \varepsilon_{it}$$

for $i = 1, \dots, a, t = 1, \dots, b$. The error term ε_{it} is assumed to be independent across i and t , with $E(\varepsilon_{it}) = 0$ and $\text{Var}(\varepsilon_{it}) = \sigma_\varepsilon^2$. We assume $n = ab$.

Let I_a and I_b be the identity matrices of order a and b , respectively.

$$y = \iota_n \pi + (I_a \otimes \iota_b) \mu + (\iota_a \otimes I_b) \nu + X\beta + \varepsilon$$

where $y = (y_{11}, y_{12}, \dots, y_{1b}, \dots, y_{a1}, y_{a2}, \dots, y_{ab})'$, $X = (x_{it})$, and $\varepsilon = (\varepsilon_{it})$. Let $\mu = (\mu_1, \dots, \mu_a)'$ and $\nu = (\nu_1, \dots, \nu_b)'$. The model is often written as $y_{it} = \bar{y}_i + \bar{y}_t + \bar{y} + \mu_i + \nu_t + x_{it}\beta + \varepsilon_{it}$.

Let μ and ν be fixed effects. The model is often written as *dummy variables model*. Let $\mu = \iota_a \mu$ and $\nu = \iota_b \nu$. Then

$$\sum_{i=1}^a \mu_i = \sum_{t=1}^b \nu_t = 0 \tag{5}$$

where μ and ν are fixed effects.

3.2 Estimation

We fit

$$I - \frac{\iota_a \iota_a'}{a} = H_a H_a' \quad I - \frac{\iota_b \iota_b'}{b} = H_b H_b'$$

$$H_a = I_a - \frac{\iota_a \iota_a'}{a}, \quad H_b = I_b - \frac{\iota_b \iota_b'}{b}, \quad H_a' H_a = I_{a-1}, \quad H_b' H_b = I_{b-1}$$

$$H_a' \mu = \mu^* \quad H_b' \nu = \nu^*$$

Then $H_a H_a' \mu = \mu^*$ and $H_b H_b' \nu = \nu^*$. We

$$y = \iota_n \pi + (H_a \otimes \iota_b) \mu^* + (\iota_a \otimes H_b) \nu^* + X\beta + \varepsilon$$

T

$$P = \frac{\iota_n \iota_n'}{n} + \left(I_a - \frac{\iota_a \iota_a'}{a} \right) \otimes \frac{\iota_b \iota_b'}{b} + \frac{\iota_a \iota_a'}{a} \otimes \left(I_b - \frac{\iota_b \iota_b'}{b} \right)$$

$$= I_a \otimes \frac{\iota_b \iota_b'}{b} + \frac{\iota_a \iota_a'}{a} \otimes I_b - \frac{\iota_n \iota_n'}{n}$$

L

$$Q = I - P$$

OLS

$$\hat{\beta} = (X'QX)^{-1}X'Qy \tag{6}$$

N

$$I_a \otimes \frac{\iota_b \iota_b'}{b}, \frac{\iota_a \iota_a'}{a} \otimes I_b, \frac{\iota_n \iota_n'}{n}$$

a

$$y_{it} - \bar{y}_i - \bar{y}_t + \bar{y} = (x_{it} - \bar{x}_i - \bar{x}_t + \bar{x})'\beta + e_{it}$$

a

T OLS

$$y - X\hat{\beta} = \iota_n \pi + (H_a \otimes \iota_b)\mu^* + (\iota_a \otimes H_b)\nu^* + \varepsilon$$

S

$$\mu = H_a \mu^* \quad \nu = H_b \nu^*$$

W

$$\hat{\pi} = \bar{y} - \bar{x}'\hat{\beta}, \quad \hat{\mu}_i = (\bar{y}_i - \bar{y}) - (\bar{x}_i - \bar{x})'\hat{\beta}, \quad \hat{\nu}_t = (\bar{y}_t - \bar{y}) - (\bar{x}_t - \bar{x})'\hat{\beta}$$

3.3 Exercises

1. C

$$y_{it} = \mu_i + x'_{it}\beta_i + \varepsilon_{it}$$

, $i = 1, \dots, a$ a $t = 1, \dots, b$. A $\{x_{it}\}$ a m - a a a , a $\{\varepsilon_{it}\}$ a $\dots \mathbf{N}(0, \sigma^2)$. C F- a $\beta_1 = \dots = \beta_a$.

2. C

$$y_{ij} = \pi + \mu_j + x'_{ij}\beta + \varepsilon_{ij},$$

$$y_{ij} = \nu_j + x'_{ij}\beta + \varepsilon_{ij}$$

$$\sum_j \mu_j = 0.$$

4.2 Estimation of Regression Coefficients

Т а а β GLS а , β а π , fi , .. а
 а а I :

$$\begin{aligned} P_1 &= \left(I_a - \frac{\iota_a \iota_a'}{a} \right) \otimes \left(I_b - \frac{\iota_b \iota_b'}{b} \right) \\ P_2 &= \left(I_a - \frac{\iota_a \iota_a'}{a} \right) \otimes \frac{\iota_b \iota_b'}{b} \\ P_3 &= \frac{\iota_a \iota_a'}{a} \otimes \left(I_b - \frac{\iota_b \iota_b'}{b} \right) \\ P_4 &= \frac{\iota_a \iota_a'}{a} \otimes \frac{\iota_b \iota_b'}{b} \end{aligned}$$

Т а

$$\Sigma = \sigma_\varepsilon^2 P_1 + (b\sigma_\mu^2 + \sigma_\varepsilon^2) P_2 + (a\sigma_\nu^2 + \sigma_\varepsilon^2) P_3 + (b\sigma_\mu^2 + a\sigma_\nu^2 + \sigma_\varepsilon^2) P_4$$

W $\Sigma = \sigma_\varepsilon^2 \Sigma_0$ а $\Sigma_0^{-1} = \sum_{k=1}^4 \lambda_k P_k$, λ_k а fi а а , .

C , а , а

$$\hat{\beta} = (X' Q X)^{-1} X' Q y \tag{7}$$

Q

$$\begin{aligned} Q &= \Sigma_0^{-1} - \lambda_4 \frac{\iota_n \iota_n'}{n} \\ &= I_n - \varphi_1 \left(I_a \otimes \frac{\iota_b \iota_b'}{b} \right) - \varphi_2 \left(\frac{\iota_a \iota_a'}{a} \otimes I_b \right) + \varphi_3 \frac{\iota_n \iota_n'}{n} \end{aligned}$$

$\varphi_1 = \lambda_1 - \lambda_2$, $\varphi_2 = \lambda_1 - \lambda_3$, $\varphi_3 = \lambda_1 - \lambda_2 - \lambda_3$, а а , .

$$\varphi_1 = \frac{b\sigma_\mu^2}{b\sigma_\mu^2 + \sigma_\varepsilon^2}, \varphi_2 = \frac{a\sigma_\nu^2}{a\sigma_\nu^2 + \sigma_\varepsilon^2}, \varphi_3 = \frac{ab\sigma_\mu^2\sigma_\nu^2 - \sigma_\varepsilon^4}{(a\sigma_\nu^2 + \sigma_\varepsilon^2)(b\sigma_\mu^2 + \sigma_\varepsilon^2)}$$

M , GLS а , π а а , GLS $y - X\hat{\beta} = \iota_n \pi + u$,
 а OLS а ι_n а , Σ . I ,

$$\hat{\pi} = \bar{y} - \bar{x}' \hat{\beta} \tag{8}$$

A $a, b \rightarrow \infty$, $\varphi_1, \varphi_2, \varphi_3 \rightarrow 1$ а Q
 fi ff а (6) . I а , fi ff а
 а ff , а а , β а π а а .

4.3 Estimation of Error Components

T a a, a a . W ,

$$\sigma_1^2 = \sigma_\varepsilon^2, \sigma_2^2 = b\sigma_\mu^2 + \sigma_\varepsilon^2, \sigma_3^2 = a\sigma_\nu^2 + \sigma_\varepsilon^2$$

a fi

$$\hat{\sigma}_k^2 = \frac{(y - X\beta)' P_k (y - X\beta)}{d_k} \tag{9}$$

, $k = 1, 2, 3$, d_k a P_k a $\mathbf{E}\hat{\sigma}_k^2 = \sigma_k^2$.
 N a π a (9) a P_k a

F a a $\hat{\sigma}_k^2$ (9), a β a .
 T a OLS a a a , a a
 β , a $\hat{\sigma}_k^2$ a

$$y_{it} - \bar{y}_i - \bar{y}_t + \bar{y} = (x_{it} - \bar{x}_i - \bar{x}_t + \bar{x})'\beta + e_{it} \tag{10}$$

$$\bar{y}_i - \bar{y} = (\bar{x}_i - \bar{x})'\beta + e_i \tag{11}$$

$$\bar{y}_t - \bar{y} = (\bar{x}_t - \bar{x})'\beta + e_t \tag{12}$$

a $(y - X\beta)' P_k (y - X\beta)$ a RSS . I
 a β (10) a a
 RSS' (11) a (12). T a (11) a
 (12) a a a b a , , a fi a
 n a .

I ML a a ,
 fi a

$$\Sigma = \sigma_1^{2d_1} \sigma_2^{2d_2} \sigma_3^{2d_3} (\sigma_2^2 + \sigma_3^2 - \sigma_1^2)$$

a fi a . M ML a $\hat{\beta}$ a $\hat{\pi}$, β a π , a
 a GLS a (7) a (8), a

$$(y - \iota_n \hat{\pi} - X\hat{\beta})' \Sigma^{-1} (y - \iota_n \hat{\pi} - X\hat{\beta}) = \sum_{k=1}^3 \frac{(y - X\hat{\beta})' P_k (y - X\hat{\beta})}{\sigma_k^2}$$

N a $P_4(y - \iota_n \hat{\pi} - X\hat{\beta}) = \bar{y} - \hat{\pi} - \bar{x}'\hat{\beta} = 0$. T
 $\sigma_2^2 + \sigma_3^2 - \sigma_1^2$ Σ a ML a a
 . W a fi (9) .
 a ML a . F , a
 a . N a a σ_μ^2 a σ_ν^2 a a , σ_k^2
 a a a . T , a .

4.4 Exercises

1. Consider a fixed effects model,

$$y_{it} = \pi + x'_{it}\beta + u_{it}$$

for $i = 1, \dots, a$ and $t = 1, \dots, b$, where

$$u_{it} = \mu_i + \nu_t + \varepsilon_{it}$$

and (μ_i) and (ν_t) are independent of (ε_{it}) . Assume $(\mu_i) \sim (0, \sigma_\mu^2)$, $(\nu_t) \sim (0, \sigma_\nu^2)$, and $(\varepsilon_{it}) \sim (0, \sigma_\varepsilon^2)$.

- (a) Obtain GLS estimates of π and β .
- (b) Compute the variance-covariance matrix of the GLS estimator.
- (c) Explain the relationship between the GLS estimator and the OLS estimator.

2. Suppose a fixed effects model with $\nu_t = 0$. Define within and between components

$$y_{it} - \bar{y}_i = (x_{it} - \bar{x}_i)' \beta + \varepsilon_{it}$$

$$\bar{y}_i - \bar{y} = (\bar{x}_i - \bar{x})' \beta + \varepsilon_i$$

- (a) Transform the within equation into a standard OLS form and obtain the within OLS estimator $\hat{\beta}_w$.
- (b) Show that $(A_1 + A_2)^{-1}(B_1 + B_2) = ((A_1 + A_2)^{-1}A_1)A_1^{-1}B_1 + ((A_1 + A_2)^{-1}A_2)A_2^{-1}B_2$ and use this to show that $\hat{\beta} = \Delta \hat{\beta}_w + (I - \Delta) \hat{\beta}_b$, where $\Delta = \frac{A_1}{A_1 + A_2}$.

3. Consider a random effects model,

$$y_{it} = \pi + \mu_i + x'_{it}\beta + \varepsilon_{it}$$

$$\mu_i = \bar{x}'_i \alpha + \eta_i$$

for $i = 1, \dots, a$ and $t = 1, \dots, b$, where $(\varepsilon_{it}) \sim (0, \sigma_\varepsilon^2)$, $(\eta_i) \sim (0, \sigma_\eta^2)$, and (μ_i) and (ε_{it}) are independent.

$$y_{it} = \pi + \bar{x}'_i \alpha + x'_{it}\beta + u_{it}$$

where $u_{it} = \eta_i + \varepsilon_{it}$. Show that the GLS estimator of β is the same as the OLS estimator of β in the following equation:

$$\hat{\pi} = \bar{y} - \bar{x}' \hat{\beta}_b, \quad \hat{\alpha} = \hat{\beta}_b - \hat{\beta}_w, \quad \hat{\beta} = \hat{\beta}_w$$

where $\hat{\beta}_w$ and $\hat{\beta}_b$ are the within and between OLS estimators, respectively.

4. Derive the ML estimator of β in the random effects model. Show that the ML estimator is the same as the GLS estimator.