

Inference in k -Exchangeable Multivariate Models

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Model

Formulation

$$\mathbf{Y}_i = \mathbf{B} \mathbf{X}' + \mathbf{E}_i,$$

$p \times r$ $p \times m \times r$ $p \times r$

where \mathbf{X} is the design matrix

$$\begin{aligned} \text{Vec}(\mathbf{Y}_i) &= \text{Vec}(\mathbf{B} \mathbf{X}') + \text{Vec}(\mathbf{E}_i), \\ \mathbf{y}_i &= (\mathbf{X} \otimes \mathbf{I}_p) \text{Vec}(\mathbf{B}) + \mathbf{e}_i, \\ \mathbf{y}_i &= (\mathbf{X} \otimes \mathbf{I}_p) \boldsymbol{\beta} + \mathbf{e}_i, \end{aligned}$$

$p \times r$ $r \times m$ $p \times m$ $pr \times 1$

$pr \times 1$ $r \times m$ $pm \times 1$ $pr \times 1$

where $\mathbf{e}_i \sim \mathcal{N}(\mathbf{0}, \mathbf{V})$ for $i = 1, \dots, n$

Model

Parameters

Expectation

$$\begin{aligned}\mathbb{E}[\mathbf{Y}_i] &= \mathbf{B}\mathbf{X}', \\ \mathbb{E}[\text{Vec}\mathbf{Y}_i] &= \text{Vec}(\mathbf{B}\mathbf{X}'), \\ \mathbb{E}[\mathbf{y}_i] &= (\mathbf{X} \otimes \mathbf{I}_p)\text{Vec}(\mathbf{B}), \\ \mathbb{E}[\mathbf{y}_i] &= (\mathbf{X} \otimes \mathbf{I}_p)\boldsymbol{\beta},\end{aligned}$$

Model

Parameters

Covariance Matrix

$$\mathbb{V}[\mathbf{y}_i] = \mathbf{V} = \sum_{j=0}^w \mathbf{Q}_j \otimes \mathbf{\Gamma}_j,$$

with $\mathbf{\Gamma}_j$ positive definite matrices.

Orthogonality

Covariance Structure Conditions

- $\mathbf{Q}_j, j = 0, \dots, j = w$, are orthogonal projection matrices
- $\mathbf{Q}_{j_1} \mathbf{Q}_{j_2} = \mathbf{0}$, for $j_1 \neq j_2$

Mean Vector Structure Conditions

- $\mathbf{P}_X \mathbf{Q}_j = \mathbf{Q}_j \mathbf{P}_X$, where $\mathbf{P}_X = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$.

Model Properties

- Multivariate Commutative Orthogonal Block Structure – **COBS**
- $\mathbf{V}^{-1} = \sum_{j=1}^w \mathbf{Q}_j \otimes \mathbf{\Gamma}_j^{-1}$
- $|\mathbf{V}| = \prod_{j=1}^w |\mathbf{\Gamma}_j|^{g_j}$, where $g_j = \text{rank}(\mathbf{Q}_j)$

Lemma

$(\mathbf{I} - \mathbf{P}_X)$ and \mathbf{Q}_j are commutative, i.e.,

$$(\mathbf{I} - \mathbf{P}_X)\mathbf{Q}_j = \mathbf{Q}_j(\mathbf{I} - \mathbf{P}_X),$$

Doubly Exchangeable Structure

$$\mathbf{y} = \begin{pmatrix} \mathbf{y}_1 \\ \vdots \\ \mathbf{y}_v \end{pmatrix}, \quad \text{where } \mathbf{y}_t = \begin{pmatrix} \mathbf{y}_{t1} \\ \vdots \\ \mathbf{y}_{tu} \end{pmatrix}, \quad \text{with } \mathbf{y}_{ts} = \begin{pmatrix} \mathbf{y}_{ts1} \\ \vdots \\ \mathbf{y}_{tsm} \end{pmatrix}$$

for $s = 1, \dots, u$, $t = 1, \dots, v$.

$$\Gamma_{\mathbf{y}} = \mathbf{I}_{vu} \otimes (\mathbf{U}_0 - \mathbf{U}_1) + \mathbf{I}_v \otimes \mathbf{J}_u \otimes (\mathbf{U}_1 - \mathbf{W}) + \mathbf{J}_{vu} \otimes \mathbf{W},$$

$$\text{Cov}[\mathbf{y}_{ts}; \mathbf{y}_{t^*s^*}] = \begin{cases} \mathbf{U}_0 & \text{if } t = t^* \text{ and } s = s^*, \\ \mathbf{U}_1 & \text{if } t = t^* \text{ and } s \neq s^*, \\ \mathbf{W} & \text{if } t \neq t^*, \end{cases}$$

Definition

Let \mathbf{y}_r be an muv -variate partitioned real-valued random vector $\mathbf{y}_r = (\mathbf{y}'_{r,1}, \dots, \mathbf{y}'_{r,v})'$, where $\mathbf{y}_{r,t} = (\mathbf{y}'_{r,t1}, \dots, \mathbf{y}'_{r,tu})'$ for $t = 1, \dots, v$, and $\mathbf{y}'_{r,ts} = (y_{r,ts,1}, \dots, y_{r,ts,m})'$ for $s = 1, \dots, u$. Let $\boldsymbol{\mu}_x \in \mathfrak{R}^{puv}$ be the mean vector, and \mathbf{V} be the $(puv \times puv)$ -dimensional partitioned covariance matrix $\mathbf{V} = \text{Cov}[\mathbf{y}] = (\boldsymbol{\Gamma}_{\mathbf{y}_{r,t}, \mathbf{y}_{r,t^*}}) = (\boldsymbol{\Gamma}_{r,tt^*})$, where $\boldsymbol{\Gamma}_{r,tt^*} = \text{Cov}[\mathbf{y}_{r,t}, \mathbf{y}_{r,t^*}]$ for $t, t^* = 1, \dots, v$, is given by

$$\mathbf{V} = \begin{bmatrix} \mathbf{U}_0 & \mathbf{U}_1 & \dots & \mathbf{U}_1 & \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} & \dots & \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} \\ \mathbf{U}_1 & \mathbf{U}_0 & \dots & \mathbf{U}_1 & \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} & \dots & \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{U}_1 & \mathbf{U}_1 & \dots & \mathbf{U}_0 & \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} & \dots & \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} \\ \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} & \mathbf{U}_0 & \mathbf{U}_1 & \dots & \mathbf{U}_1 & \dots & \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} \\ \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} & \mathbf{U}_1 & \mathbf{U}_0 & \dots & \mathbf{U}_1 & \dots & \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} & \mathbf{U}_1 & \mathbf{U}_1 & \dots & \mathbf{U}_0 & \dots & \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} & \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} & \dots & \mathbf{U}_0 & \mathbf{U}_1 & \dots & \mathbf{U}_1 \\ \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} & \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} & \dots & \mathbf{U}_1 & \mathbf{U}_0 & \dots & \mathbf{U}_1 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} & \mathbf{W} & \mathbf{W} & \dots & \mathbf{W} & \dots & \mathbf{U}_1 & \mathbf{U}_1 & \dots & \mathbf{U}_0 \end{bmatrix},$$

where \mathbf{U}_0 is a positive definite symmetric $p \times p$ matrix, and \mathbf{U}_1 and \mathbf{W} are symmetric $p \times p$ matrices. The variance-covariance matrix $\boldsymbol{\Gamma}_{\mathbf{y}}$ is then said to have a jointly equicorrelated covariance structure with equicorrelation parameters \mathbf{U}_0 , \mathbf{U}_1 and \mathbf{W} . The matrices \mathbf{U}_0 , \mathbf{U}_1 and \mathbf{W} are all unstructured.

Model

$$\mathbf{Y}_{m \times u(v)} = \boldsymbol{\alpha}_{m \times 1} \mathbf{1}'_{1 \times u(v)} + \boldsymbol{\gamma}'_{m \times r-1} \mathbf{T}_{r-1 \times u(v)} + \mathbf{E}_{m \times u(v)},$$

$$\mathbf{Y}'_{u(v) \times m} = \mathbf{1}_{u(v) \times 1} \boldsymbol{\alpha}'_{1 \times m} + \mathbf{T}'_{u(v) \times r-1} \boldsymbol{\gamma}_{r-1 \times m} + \mathbf{E}'_{u(v) \times m},$$

Lemma

Let $\Gamma = \mathbf{C}'_{v \times v} \otimes \mathbf{I}_{mu}$ and $\Gamma^\bullet = \mathbf{I}_v \otimes (\mathbf{C}^{*'}_{u \times u} \otimes \mathbf{I}_m)$ where \mathbf{C} and \mathbf{C}^* are orthogonal matrices whose first columns are proportional to $\mathbf{1}$'s. Let $\Gamma_{\mathbf{y}}$ be a jointly equicorrelated covariance matrix as in equation (1) of Def. 1, then $\Gamma^\bullet \Gamma(\Gamma_{\mathbf{y}}) \Gamma' \Gamma^{\bullet'}$ is a diagonal matrix as follows:

$$\Gamma^\bullet \Gamma(\Gamma_{\mathbf{y}}) \Gamma' \Gamma^{\bullet'} = \begin{bmatrix} \Delta_3 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & \mathbf{I}_{u-1} \otimes \Delta_1 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & \Delta_2 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \mathbf{I}_{u-1} \otimes \Delta_1 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & \Delta_2 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & \mathbf{I}_{u-1} \otimes \Delta_1 \end{bmatrix},$$

where

$$\Delta_1 = \mathbf{U}_0 - \mathbf{U}_1,$$

$$\Delta_2 = \mathbf{U}_0 + (u-1)\mathbf{U}_1 - u\mathbf{W} = (\mathbf{U}_0 - \mathbf{U}_1) + u(\mathbf{U}_1 - \mathbf{W}), \text{ and}$$

$$\Delta_3 = \mathbf{U}_0 + (u-1)\mathbf{U}_1 + u(v-1)\mathbf{W} = (\mathbf{U}_0 - \mathbf{U}_1) + u(\mathbf{U}_1 - \mathbf{W}) + uv\mathbf{W}.$$

Corollary

If $\mathbf{W} = \mathbf{0}$, then

$$\mathbf{\Delta}_1 = \mathbf{U}_0 - \mathbf{U}_1,$$

$$\mathbf{\Delta}_2 = \mathbf{U}_0 + (u - 1) \mathbf{U}_1 = (\mathbf{U}_0 - \mathbf{U}_1) + u \mathbf{U}_1, \quad \text{and}$$

$$\mathbf{\Delta}_3 = \mathbf{U}_0 + (u - 1) \mathbf{U}_1 = (\mathbf{U}_0 - \mathbf{U}_1) + u \mathbf{U}_1.$$

Thus, we see that $\mathbf{\Delta}_3 = \mathbf{\Delta}_2$.

Covariance Structure

General Setup

$$\mathbf{V} = \sum_{j=1}^{\kappa} \mathbf{Q}_j \otimes \mathbf{\Gamma}_j = \mathbf{Q}_1 \otimes \mathbf{\Gamma}_1 + \cdots + \mathbf{Q}_{\kappa} \otimes \mathbf{\Gamma}_{\kappa},$$

where the matrices \mathbf{Q}_j are symmetric and idempotent and

$$\mathbf{Q}_j \mathbf{Q}_l = \mathbf{0}, \quad j \neq l, j, l = 1, \dots, \kappa,$$

and
$$\sum_{j=1}^{\kappa} \mathbf{Q}_j = \mathbf{I}_{uv}.$$

Covariance Structure

$$\mathbf{V}_\kappa = \sum_{i=1}^{\kappa} \left(\bigotimes_{j=i+2}^{\kappa} \mathbf{I}_{a_{\kappa-j+i+2}} \right) \otimes \mathbf{K}_{a_{i+1}} \otimes \left(\bigotimes_{l=1}^i \left(\frac{1}{a_{i-l+1}} \mathbf{J}_{a_{i-l+1}} \right) \right) \otimes \boldsymbol{\Gamma}_i^{(\kappa)}$$

Parametrization

$$\boldsymbol{\Gamma}_i^{(\kappa)} = \sum_{j=1}^i (a_j - 1) b_{j-1} \mathbf{U}_j - b_j \mathbf{U}_{i+1}, \quad i = 1, \dots, \kappa - 1.$$

$$\mathbf{Q}_i = \left(\bigotimes_{j=i+2}^{\kappa} \mathbf{I}_{a_{\kappa-j+i+2}} \right) \otimes \mathbf{K}_{a_{i+1}} \otimes \left(\bigotimes_{l=1}^i \left(\frac{1}{a_{i-l+1}} \mathbf{J}_{a_{i-l+1}} \right) \right)$$

Lemma

Let \mathbf{V} be a (κ) -exchangeable covariance structure.

- 1 If $\mathbf{\Gamma}_j, j = 1, \dots, \kappa$ are non singular matrices, the matrix \mathbf{V} is non singular, and its inverse is given by

$$\mathbf{V}^{-1} = \sum_{j=1}^{\kappa} \mathbf{Q}_j \otimes \mathbf{\Gamma}_j^{-1}. \quad (1)$$

- 2 The determinant of \mathbf{V} is given by

$$|\mathbf{V}| = \prod_{j=1}^{\kappa} |\mathbf{\Gamma}_j|^{g_j}, \quad (2)$$

The quantities g_j are rank of \mathbf{Q}_j .

Auxiliary Results

- \mathbf{Z}_{t1} and \mathbf{Z}_{t2} , $t = 1, \dots, v$ represent the m response variables at the first and the rest of $u - 1$ locations respectively at the t^{th} time point in the doubly transformed domain
- \mathbf{U}_{t1} and \mathbf{U}_{t2} are the $r - 1$ values of predictor variables at the first and the rest of $u - 1$ locations respectively at the t^{th} time point in the doubly transformed domain

Theorem

Let \mathbf{Y} represent the random matrix of three-level multivariate response variables. If

$$\Gamma \circ \Gamma(\text{Vec}_{m \times (u)v} \mathbf{Y}) = \begin{bmatrix} \text{Vec}(\mathbf{Z}_{11} : \mathbf{Z}_{12}) \\ \text{Vec}(\mathbf{Z}_{21} : \mathbf{Z}_{22}) \\ \vdots \\ \text{Vec}(\mathbf{Z}_{v1} : \mathbf{Z}_{v2}) \end{bmatrix},$$

then all the components $\mathbf{Z}_{11}, \mathbf{Z}_{12}, \mathbf{Z}_{21}, \dots, \mathbf{Z}_{v2}$ are independently normally distributed such that

$$\mathbf{Z}_{11} \sim N_{m,1}(\sqrt{uv}\alpha + \gamma' \mathbf{U}_{11}, \mathbf{\Delta}_3, 1),$$

$$\mathbf{Z}_{t1} \sim N_{m,1}(\gamma' \mathbf{U}_{t1}, \mathbf{\Delta}_2, 1) \quad t = 2, 3, \dots, v,$$

and $\mathbf{Z}_{t2} \sim N_{m,u-1}(\gamma' \mathbf{U}_{t2}, \mathbf{\Delta}_1, \mathbf{I}_{u-1}) \quad t = 1, 2, \dots, v.$

Corollary

If $\mathbf{W} = \mathbf{0}$, then

$$\mathbf{Z}_{11} \sim N_{m,1}(\sqrt{uv}\alpha + \gamma' \mathbf{U}_{11}, \mathbf{\Delta}_2, 1),$$

$$\mathbf{Z}_{t1} \sim N_{m,1}(\gamma' \mathbf{U}_{t1}, \mathbf{\Delta}_2, 1) \quad t = 2, 3, \dots, v,$$

and $\mathbf{Z}_{t2} \sim N_{m,u-1}(\gamma' \mathbf{U}_{t2}, \mathbf{\Delta}_1, \mathbf{I}_{u-1}) \quad t = 1, 2, \dots, v.$

Corollary

If $v = 1$, the DEGLM reduces to EGLM. For $v = 1$, we have

$$\mathbf{Z}_{11} \sim N_{m,1}(\sqrt{u}\alpha + \gamma' \mathbf{U}_{11}, \mathbf{U}_0 - (u-1)\mathbf{U}_1, 1),$$

and $\mathbf{Z}_{12} \sim N_{m,u-1}(\gamma' \mathbf{U}_{12}, \mathbf{U}_0 - \mathbf{U}_1, \mathbf{I}_{u-1}).$

Fixed Effects

Estimators

$$\hat{\alpha}' = (uv)^{-1/2}(\mathbf{Z}'_{11} - \mathbf{U}'_{11}\hat{\gamma})$$

$$\hat{\gamma} = \left(\sum_{j=1}^2 \sum_{t=1}^v \mathbf{U}_{tj} \mathbf{U}'_{tj} - \mathbf{U}_{11} \mathbf{U}'_{11} \right)^{-1} \left(\sum_{j=1}^2 \sum_{t=1}^v \mathbf{U}_{tj} \mathbf{Z}'_{tj} - \mathbf{U}_{11} \mathbf{Z}'_{11} \right)$$

Fixed Effects

Estimators: $\nu = 1$

$$\hat{\alpha}' = (u)^{-1/2}(\mathbf{Z}'_{11} - \mathbf{U}'_{11}\hat{\gamma}),$$

$$\begin{aligned}\hat{\gamma} &= \left(\sum_{j=1}^2 \mathbf{U}_{1j}\mathbf{U}'_{1j} - \mathbf{U}_{11}\mathbf{U}'_{11} \right)^{-1} \left(\sum_{j=1}^2 \mathbf{U}_{1j}\mathbf{Z}'_{1j} - \mathbf{U}_{11}\mathbf{Z}'_{11} \right) \\ &= \left(\mathbf{U}_{12}\mathbf{U}'_{12} \right)^{-1} \left(\begin{array}{c} \mathbf{U}_{12} \\ \mathbf{Z}'_{12} \end{array} \right),\end{aligned}$$

Fixed Effects

Estimators: $v = 1$

$$\hat{\alpha}' \sim N_{1,m} \left(\alpha', 1, \right. \\ \left. \frac{1}{uv} \left[\Delta_3 + \mathbf{U}'_{11} \mathbf{A}^{-1} \sum_{t=2}^v [\mathbf{U}_{t1} \mathbf{U}'_{t1}] \mathbf{A}^{-1} \mathbf{U}_{11} \Delta_2 \right. \right. \\ \left. \left. + \mathbf{U}'_{11} \mathbf{A}^{-1} \sum_{t=1}^v [\mathbf{U}_{t2} \mathbf{U}'_{t2}] \mathbf{A}^{-1} \mathbf{U}_{11} \Delta_1 \right] \right),$$

$$\text{Vec} \hat{\gamma}' \sim N_{(r-1)m} \left(\text{Vec} \gamma', \right. \\ \left. \mathbf{A}^{-1} \sum_{t=1}^v [\mathbf{U}_{t1} \mathbf{U}'_{t1}] \mathbf{A}^{-1} \otimes \Delta_2 + \mathbf{A}^{-1} \sum_{t=1}^v [\mathbf{U}_{t2} \mathbf{U}'_{t2}] \mathbf{A}^{-1} \otimes \Delta_1 \right),$$

where $\mathbf{A} = \sum_{j=1}^2 \sum_{t=1}^v \mathbf{U}_{tj} \mathbf{U}'_{tj} - \mathbf{U}_{11} \mathbf{U}'_{11}$

Fixed Effects

Estimator Distribution: $\mathbf{W} = \mathbf{0}$

$$\begin{aligned} \hat{\boldsymbol{\alpha}}' &\sim N_{1,m} \left(\boldsymbol{\alpha}', 1, \right. \\ &\quad \frac{1}{UV} \left[\boldsymbol{\Delta}_2 + \mathbf{U}'_{11} \mathbf{A}^{-1} \sum_{t=2}^v [\mathbf{U}_{t1} \mathbf{U}'_{t1}] \mathbf{A}^{-1} \mathbf{U}_{11} \boldsymbol{\Delta}_2 \right. \\ &\quad \left. \left. + \mathbf{U}'_{11} \mathbf{A}^{-1} \sum_{t=1}^v [\mathbf{U}_{t2} \mathbf{U}'_{t2}] \mathbf{A}^{-1} \mathbf{U}_{11} \boldsymbol{\Delta}_1 \right] \right), \\ \hat{\boldsymbol{\gamma}} &= \mathbf{A}^{-1} \left(\sum_{t=1}^v \mathbf{U}_{t1} \mathbf{Z}'_{t1} + \sum_{t=1}^v \mathbf{U}_{t2} \mathbf{Z}'_{t2} \right) \sim N_{(r-1),m} \left(\boldsymbol{\gamma}, \right. \\ &\quad \left. \mathbf{A}^{-1} \sum_{i=2}^v [\mathbf{U}_{t1} \mathbf{U}'_{t1}] \mathbf{A}^{-1} \otimes \boldsymbol{\Delta}_2 + \mathbf{A}^{-1} \sum_{t=1}^v [\mathbf{U}_{t2} \mathbf{U}'_{t2}] \mathbf{A}^{-1} \otimes \boldsymbol{\Delta}_1 \right). \end{aligned}$$

where $\mathbf{A} = \sum_{j=1}^2 \sum_{t=1}^v \mathbf{U}_{tj} \mathbf{U}'_{tj} - \mathbf{U}_{11} \mathbf{U}'_{11}$

Fixed Effects

Estimator Distribution: $\mathbf{W} = \mathbf{0}$

$$\begin{aligned}\hat{\alpha}' &\sim N_{1,m}\left(\alpha', 1, \frac{1}{u} \left[\mathbf{\Delta}_3 + \mathbf{U}'_{11} \mathbf{A}^{-1} (\mathbf{U}_{12} \mathbf{U}'_{12}) \mathbf{A}^{-1} \mathbf{U}_{11} \mathbf{\Delta}_1 \right]\right) \\ &\sim N_{1,m}\left(\alpha', 1, + \frac{1}{u} (1 + \mathbf{U}'_{11} (\mathbf{U}_{12} \mathbf{U}'_{12})^{-1} \mathbf{U}_{11}) (\mathbf{U}_0 - \mathbf{U}_1)\right)\end{aligned}$$

$$\begin{aligned}\text{Vec} \hat{\gamma}' &\sim N_{(r-1)m} \text{Vec}\left(\gamma', (\mathbf{U}_{12} \mathbf{U}'_{12})^{-1} \mathbf{U}_{12} \mathbf{U}'_{12} (\mathbf{U}_{12} \mathbf{U}'_{12})^{-1} \otimes \mathbf{\Delta}_1\right) \\ &\sim N_{(r-1)m}\left(\text{Vec} \gamma', (\mathbf{U}_{12} \mathbf{U}'_{12})^{-1} \otimes \mathbf{\Delta}_1\right), \\ \hat{\gamma} &\sim N_{(r-1),m}\left(\gamma, (\mathbf{U}_{12} \mathbf{U}'_{12})^{-1}, (\mathbf{U}_0 - \mathbf{U}_1)\right)\end{aligned}$$

Covariance Components

Estimators

Estimates for $\hat{\Delta}_1$ and $\hat{\Delta}_2$

- $\hat{\Delta}_1 = \frac{1}{v(u-r)} \mathbf{S}_1$
- $\hat{\Delta}_2 = \frac{1}{(v-r)} \mathbf{S}_2$

with

- $\mathbf{S}_1 = \sum_{t=1}^v \mathbf{S}_{t2} = \sum_{t=2}^v \left[\mathbf{z}_{t1} - (\mathbf{U}'_{t1} \hat{\gamma})' \right] \left[\mathbf{z}'_{t1} - (\mathbf{U}'_{t1} \hat{\gamma}) \right]$
- $\mathbf{S}_2 = \sum_{t=2}^v \mathbf{S}_{t1} = \sum_{t=2}^v \left[\mathbf{z}_{t2} - (\mathbf{U}'_{t2} \hat{\gamma})' \right] \left[\mathbf{z}'_{t2} - (\mathbf{U}'_{t2} \hat{\gamma}) \right]$

Covariance Components

Estimators Distribution

$$\sum_{t=2}^v \mathbf{S}_{t1} \sim W_m(\mathbf{\Delta}_2, (v - r))$$
$$\mathbf{S}_{t2} \sim W_m(\mathbf{\Delta}_1, u - r)$$

Distributions

- $\mathbf{S}_1 \sim W_m(\mathbf{\Delta}_1, v(u - r))$
- $\mathbf{S}_2 \sim W_m(\mathbf{\Delta}_2, (v - r))$

Maximum Likelihood

Log-likelihood

$$\ell(\mathbf{y}) = \log(|\mathbf{V}|) + \sum_{j=1}^{\kappa} (\mathbf{y} - (\mathbf{X} \otimes \mathbf{I}_p)\boldsymbol{\beta})' (\mathbf{Q}_j \otimes \boldsymbol{\Gamma}_j^{-1}) (\mathbf{y} - (\mathbf{X} \otimes \mathbf{I}_p)\boldsymbol{\beta})$$

$$= \underbrace{\sum_{j=1}^{\kappa} g_j \log(|\boldsymbol{\Gamma}_j|) + (\mathbf{y} - (\mathbf{X} \otimes \mathbf{I}_p)\hat{\boldsymbol{\beta}})' \left(\sum_{j=1}^{\kappa} \mathbf{Q}_j \otimes \boldsymbol{\Gamma}_j^{-1} \right) (\mathbf{y} - (\mathbf{X} \otimes \mathbf{I}_p)\hat{\boldsymbol{\beta}})}_{\text{random effects}}$$

$$+ \underbrace{(\boldsymbol{\beta} - \hat{\boldsymbol{\beta}})' \left(\sum_{j=1}^{\kappa} (\mathbf{X}' \mathbf{Q}_j \mathbf{X}) \otimes \boldsymbol{\Gamma}_j^{-1} \right) (\boldsymbol{\beta} - \hat{\boldsymbol{\beta}})}_{\text{fixed effects}}$$

Estimators

Fixed Effects

$$\begin{aligned} \hat{\boldsymbol{\beta}}_{pm \times 1} &= \left((\mathbf{X}' \mathbf{X})_{m \times r r \times m}^{-1} \mathbf{X}' \otimes \mathbf{I}_p \right)_{pr \times 1} \mathbf{y} \\ \text{Vec}(\hat{\mathbf{B}})_{p \times m} &= \text{Vec}(\mathbf{Y}_{p \times r} (\mathbf{X}_{m \times r} (\mathbf{X}'_{r \times m} \mathbf{X})^{-1})) \\ \hat{\mathbf{B}}_{p \times m} &= \mathbf{Y}_{p \times r} (\mathbf{X}_{m \times r} (\mathbf{X}'_{r \times m} \mathbf{X})^{-1}) \end{aligned}$$

Theorem

The $h_j p$ -dimensional random variable $\mathbf{z}_j = \mathbf{B}'_j \mathbf{y}$ for $j = 1, \dots, \kappa$, is normally distributed with mean vector $\mathbf{0}$ and variance-covariance matrix $(\mathbf{I}_{h_j} \otimes \boldsymbol{\Gamma}_j)$, with $\mathbf{B}_j \mathbf{B}'_j = \mathbf{I} - \mathbf{P}_X \mathbf{Q}_j$ and $h_j = \text{rank}(\mathbf{B}_j)$.

Estimators

Covariance Components

$$\hat{\Gamma}_j = \frac{1}{g_j} \mathbf{Z}_j' \mathbf{Z}_j, \quad j = 1, \dots, \kappa.$$

Note that $\frac{g_j}{h_j} \hat{\Gamma}_j$ is an unbiased estimator of Γ_j .

Estimators Distributions

- $\hat{\beta} \sim \mathcal{N}(\beta, \sum_{j=1}^k \left((\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}' \mathbf{Q}_j \mathbf{X} (\mathbf{X}'\mathbf{X})^{-1} \otimes \Gamma_j \right))$
- $g_j \hat{\Gamma}_j \sim W_{h_j}(\Gamma_j)$

Parametric Bootstrap

Definition

Let x_0 be the observed value of the random variable x with density $f(x_0; \zeta)$. $T = T(x; x_0, \zeta)$ is said to be a generalized test statistic if the following three properties hold:

- For fixed x_0 and $\zeta = (\theta_0, \eta)$, the distribution of $T(x; x_0, \zeta)$ is independent of nuisance parameter η .
- $t_{\text{obs}} = T(x; x_0, \zeta)$ does not depend on unknown parameters.
- For fixed x_0 and η , $P[T(x; x_0, \zeta) \geq t]$ is either stochastically increasing or decreasing in θ for any given t .

The **generalized p -value** for hypothesis $H_0 : \theta \leq \theta_0$ vs. $H_1 : \theta > \theta_0$ is then defined by

$$p = \sup_{\theta \leq \theta_0} P[T(x; x_0, \theta, \eta) \geq t] = P[T(x; x_0, \theta_0, \eta) \geq t].$$

Parametric Bootstrap

Auxiliary Results

$$\mathbf{Z}_{\bullet 1} = [\mathbf{Z}_{21} : \cdots : \mathbf{Z}_{v1}]$$
$$\mathbf{Z}_{\bullet 2} = [\mathbf{Z}_{12} : \cdots : \mathbf{Z}_{v2}]$$

$$\mathbf{Z}_{\bullet 1} \sim N(\gamma' \mathbf{U}_{\bullet 1}, \mathbf{\Delta}_2, I_{v-1})$$
$$\mathbf{Z}_{\bullet 2} \sim N(\gamma' \mathbf{U}_{\bullet 2}, \mathbf{\Delta}_1, I_{v(u-1)}),$$

with

$$\mathbf{U}_{\bullet 1} = [\mathbf{U}_{21} : \cdots : \mathbf{U}_{v1}]$$
$$\mathbf{U}_{\bullet 2} = [\mathbf{U}_{12} : \cdots : \mathbf{U}_{v2}].$$

Parametric Bootstrap

Pivotal Quantities

$$D_i = \widehat{\Omega}_i \mathbf{T}_i^{-1} (\mathbf{T}_i^{-1})' \widehat{\Omega}_i'$$

is a pivotal quantity for $\mathbf{\Delta}_i$, $i = 1, 2$

- $\Omega_i^{-1} \mathbf{S}_i (\Omega_i')^{-1} \sim \mathbf{T}_i \mathbf{T}_i'$
 - $\mathbf{R}_i^{-1} \widehat{\Omega}_i \sim \mathbf{T}_i$
- Ω_i is the lower triangular matrix on the Cholesky decomposition of $\mathbf{\Delta}_i$ for $i = 1, 2$
- \mathbf{R}_i as the lower triangular matrix in the Cholesky decomposition of $\widehat{\mathbf{\Delta}}_i$ for $i = 1, 2$
- \mathbf{T}_i is a lower triangular matrix, deriving from the Bartlett decomposition of the Wishart distribution \mathbf{S}_i $i = 1, 2$

Parametric Bootstrap

Slope Parameter γ

$$T_\gamma = \frac{(\text{Vec}\hat{\gamma} - \text{Vec}\gamma_0)' \mathbf{V}_\gamma^{-1} (\text{Vec}\hat{\gamma} - \text{Vec}\gamma_0)}{U_{r-1}},$$

with

$$\mathbf{V}_\gamma = \mathbf{B} \otimes \mathbf{D}_1 + \mathbf{C} \otimes \mathbf{D}_2,$$

where

- $\mathbf{B} = \mathbf{A}^{-1} \sum_{t=1}^v [\mathbf{U}_{t2} \mathbf{U}'_{t2}] \mathbf{A}^{-1}$
- $\mathbf{C} = \mathbf{A}^{-1} \sum_{t=1}^v [\mathbf{U}_{t1} \mathbf{U}'_{t1}] \mathbf{A}^{-1}$
- $U_{r-1} \sim \chi_{r-1}^2$

Parametric Bootstrap

Slope Parameter γ

Under the null hypothesis $H_0 : \text{Vec}\gamma = \mathbf{0}$, which is equivalent to

$$H_0 : H_0 : \text{Vec}\gamma = \mathbf{0} \Leftrightarrow (\text{Vec}\gamma)' \text{Vec}\gamma = \mathbf{0},$$

the variable

Generalized Test Variable

$$T_\gamma = \frac{(\text{vec}\hat{\gamma})' \mathbf{V}_\gamma^{-1} \text{vec}\hat{\gamma}}{U_{r-1}}$$

Parametric Bootstrap

Intercept parameter α

$$H_0 = \alpha = \mathbf{0} \Leftrightarrow \alpha' \alpha = 0$$

Generalized Test Variable

$$T_\alpha = \frac{(\hat{\alpha} - \alpha)' \mathbf{V}_\alpha^{-1} (\hat{\alpha} - \alpha)}{U_m}$$

with

$$\mathbf{V}_\alpha = \frac{1}{uv} (\mathbf{U}_{11} \mathbf{B} \mathbf{U}'_{11} \mathbf{D}_1 + (\mathbf{I} + \mathbf{U}_{11} \mathbf{C} \mathbf{U}'_{11}) \mathbf{D}_2),$$

where $U_m \sim \chi_m^2$

Multivariate Satterthwaite Approximation

Slope Parameter γ

$$\mathbf{Z}_{\bullet 1} = [\mathbf{Z}_{21} : \cdots : \mathbf{Z}_{v1}]$$

$$\mathbf{Z}_{\bullet 2} = [\mathbf{Z}_{12} : \cdots : \mathbf{Z}_{v2}],$$

under the null hypothesis $H_0 : \gamma = \mathbf{0}$,

$$\mathbf{Z}_{\bullet 1} \mathbf{Z}'_{\bullet 1} \sim W_m(\mathbf{\Delta}_2, v - 1)$$

$$\mathbf{Z}_{\bullet 2} \mathbf{Z}'_{\bullet 2} \sim W_m(\mathbf{\Delta}_1, v(u - 1)),$$

Multivariate Satterthwaite Approximation

Slope Parameter γ

$$\mathbf{S}_\gamma = \mathbf{Z}_{\bullet 1} \mathbf{Z}'_{\bullet 1} + \mathbf{Z}_{\bullet 2} \mathbf{Z}'_{\bullet 2}$$

has an approximate Wishart distribution with parameters

$$\begin{aligned} \mathbf{\Delta} &= \frac{1}{g} (\mathbf{\Delta}_1 + \mathbf{\Delta}_2) \\ g &= \left(\frac{|\mathbf{\Delta}_1 + \mathbf{\Delta}_2|^{m+1}}{|\mathbf{V}_\gamma|} \right)^{\frac{1}{m^*}}, \end{aligned}$$

where

$$\mathbf{V}_\gamma = \mathbf{K} \left(\frac{1}{v(u-1)} \mathbf{\Delta}_1 \otimes \mathbf{\Delta}_1 + \frac{1}{v-1} \mathbf{\Delta}_2 \otimes \mathbf{\Delta}_2 \right) \mathbf{K}^+.$$

$m^* = \frac{m(m+1)}{2}$ and \mathbf{K} is a $m^2 \times m^*$, with generic element $[k]_{ij,gh} = \frac{1}{2}(\delta_{ig}\delta_{jh} + \delta_{ih}\delta_{jg})$, $i, j \leq m, g \leq h \leq m$, $\delta_{a,b}$ is the Kronecker delta, with lexicographical ordering on the indexes

Multivariate Satterthwaite Approximation

Intercept Parameter α

$$Y_{\alpha} = Z_{11} - \gamma' U_{11} \sim N(\sqrt{uv}\alpha, \Lambda),$$

with

$$\Lambda = U'_{11} B U_{11} \Delta_1 + (1 + U'_{11} C U_{11}) \Delta_2,$$

$$c_1 = U'_{11} B U_{11}$$

$$c_2 = 1 + U'_{11} C U_{11},$$

Multivariate Satterthwaite Approximation

Intercept Parameter α

$$\mathbf{S}_\alpha = c_1 \mathbf{S}_1 + c_2 \mathbf{S}_2.$$

is approximately distributed as $W_m(\frac{1}{h}\mathbf{\Lambda}, h)$, where

$$h = \left(\frac{|\mathbf{\Lambda}|^{m+1}}{|\mathbf{V}_\alpha|} \right),$$

$$\mathbf{V}_\alpha = \mathbf{K} \left(\frac{c_1^2}{v(u-1)} \mathbf{\Delta}_1 \otimes \mathbf{\Delta}_1 + \frac{c_2^2}{v-1} \mathbf{\Delta}_2 \otimes \mathbf{\Delta}_2 \right) \mathbf{K}^+,$$

Test Variable

$\mathbf{Y}'_\alpha \mathbf{S}_\alpha^{-1} \mathbf{Y}_\alpha$, under the null hypothesis $H_0 : \alpha = \mathbf{0}$, has an approximate $F_{m,h}$ distribution.

Hypothesis Formulation

$$\mathbf{C}'\mathbf{B} = \mathbf{B}_* \Leftrightarrow \mathbf{C}'(\mathbf{B} - \mathbf{B}_0) = \mathbf{0},$$

$$(\mathbf{C} \otimes \mathbf{I}_p)'(\boldsymbol{\beta} - \boldsymbol{\beta}_0) = \mathbf{0}$$

Admit that $\mathbf{C} = \mathbf{X}'\mathbf{D}$ and, consequently, that $\mathbf{D} = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{C}$

$$(\mathbf{D}'\mathbf{X} \otimes \mathbf{I}_p)(\boldsymbol{\beta} - \boldsymbol{\beta}_0) = \mathbf{0}$$

- $\boldsymbol{\beta} - \boldsymbol{\beta}_0$ is in the kernel of $\mathbf{D}'\mathbf{X} \otimes \mathbf{I}_p = \mathbf{C}' \otimes \mathbf{I}_p$, or equivalently, in the kernel of $(\mathbf{C}'\mathbf{C}) \otimes \mathbf{I}_p$
- $\mathbf{X}(\boldsymbol{\beta} - \boldsymbol{\beta}_0)$ is in the kernel of $\mathbf{D}' \otimes \mathbf{I}_p$ or $\mathbf{D}'\mathbf{D} \otimes \mathbf{I}_p$

Log-likelihood under H_0

- $\mathbf{P}_{\mathbf{D}'}$ is the orthogonal projection matrix on the $\ker(\mathbf{D}')$
- $\mathbf{P}_{\mathbf{D}'^\perp}$ is the orthogonal projection matrix on the orthogonal complement of $\ker(\mathbf{D}')$, with $\dim(\ker(\mathbf{D}')) = c$
- $\mathbf{B}_{\mathbf{D}'}$ and $\mathbf{B}_{\mathbf{D}'^\perp}$ be matrices whose columns are orthonormal basis for $\ker(\mathbf{D}')$ and $\ker(\mathbf{D}')^\perp$, respectively

$$\ell = \sum_{j=1}^{\kappa} g_j \log(|\Gamma_j|) + \left(\mathbf{y}_0 - ((\mathbf{P}_{\mathbf{D}'^\perp} \mathbf{X}) \otimes \mathbf{I}_p)(\boldsymbol{\beta} - \boldsymbol{\beta}_0) \right)' \left(\sum_{j=1}^{\kappa} \mathbf{Q}_j \otimes \Gamma_j^{-1} \right) \left(\mathbf{y}_0 - ((\mathbf{P}_{\mathbf{D}'^\perp} \mathbf{X}) \otimes \mathbf{I}_p)(\boldsymbol{\beta} - \boldsymbol{\beta}_0) \right),$$

$$\mathbf{y}_0 = \mathbf{y} - ((\mathbf{P}_{\mathbf{D}'^\perp} \mathbf{X}) \otimes \mathbf{I}_p)\boldsymbol{\beta}_0, \quad c_j = \text{rank}((\mathbf{I} - \mathbf{P}_0)\mathbf{Q}_j) \geq \text{rank}((\mathbf{I} - \mathbf{P}_\mathbf{X})\mathbf{Q}_j) = h_j.$$

Hypothesis Test

Estimators under H_0

$$\hat{\mathbf{B}}_0 = \mathbf{Y} \mathbf{P}_{\mathbf{D}'}^\perp \mathbf{X}' (\mathbf{X}' \mathbf{P}_{\mathbf{D}'}^\perp \mathbf{X})^{-1}$$
$$\hat{\mathbf{r}}_{0,j} = \frac{1}{g_j} \mathbf{Y}' (\mathbf{I} - \mathbf{P}_0) \mathbf{Q}_j \mathbf{Y}; j = 1, \dots, \kappa$$

Test Variable

$$LRT = \frac{\prod_{j=1}^{\kappa} |\hat{\mathbf{r}}_{0,j}|^{\frac{g_j}{2}}}{\prod_{j=1}^{\kappa} |\hat{\mathbf{r}}_j|^{\frac{g_j}{2}}}$$

Hypothesis Test

Special Case

$$H_0 : \mathbf{BC} = 0$$

- $\mathbf{B}_* = \mathbf{0}$
- $\mathbf{C} = [1 \ 0 \ \dots \ 0]'$
- $\mathbf{P}_{D'} = \mathbf{I} - \frac{1}{n} \mathbf{J}_n$

Test Variable

$$LRT = \frac{|\hat{\mathbf{\Gamma}}_{0,1}|^{\frac{g_1}{2}}}{|\hat{\mathbf{\Gamma}}_1|^{\frac{g_1}{2}}}$$

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