

Estimable Functions and Their Least Squares Estimators in Reparameterized Models

Once again consider the linear models

$$\mathbf{y} = \mathbf{W}\boldsymbol{\alpha} + \boldsymbol{\varepsilon} \quad \text{and} \quad \mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon},$$

where $E(\boldsymbol{\varepsilon}) = \mathbf{0}$ and $\mathcal{C}(\mathbf{W}) = \mathcal{C}(\mathbf{X})$.

Suppose $\mathbf{W} = \mathbf{X}\mathbf{T}$ and $\mathbf{X} = \mathbf{W}\mathbf{S}$.

We have

$$\begin{aligned} E(\mathbf{y}) &= \mathbf{X}\boldsymbol{\beta} = \mathbf{W}\boldsymbol{\alpha} \\ &= \mathbf{WS}\boldsymbol{\beta} = \mathbf{XT}\boldsymbol{\alpha}. \end{aligned}$$

Note the correspondence between

$$\boldsymbol{\beta} \quad \text{and} \quad \mathbf{T}\boldsymbol{\alpha}$$

$$\boldsymbol{\alpha} \quad \text{and} \quad \mathbf{S}\boldsymbol{\beta}.$$

Result 3.4:

Suppose $c'\beta$ is estimable and $W'W\hat{\alpha} = W'y$. Then $c'T\hat{\alpha}$ is the least squares estimator of $c'\beta$.

Example:

Consider again the case where

$$\mathbf{X} = \begin{bmatrix} \mathbf{1}_{n_1} & \mathbf{1}_{n_1} & \mathbf{0}_{n_1} \\ \mathbf{1}_{n_2} & \mathbf{0}_{n_2} & \mathbf{1}_{n_2} \end{bmatrix} \quad \mathbf{T} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix}$$
$$\mathbf{W} = \begin{bmatrix} \mathbf{1}_{n_1} & \mathbf{0}_{n_1} \\ \mathbf{1}_{n_2} & \mathbf{1}_{n_2} \end{bmatrix} \quad \mathbf{S} = \begin{bmatrix} 1 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix}.$$

Recall that the unique solution to the NE

$$\mathbf{W}'\mathbf{W}\hat{\boldsymbol{\alpha}} = \mathbf{W}'\mathbf{y}$$

is

$$\hat{\boldsymbol{\alpha}} = \begin{bmatrix} \bar{y}_{1\cdot} \\ \bar{y}_{2\cdot} - \bar{y}_{1\cdot} \end{bmatrix}.$$

Suppose we denote the components of β by μ, τ_1, τ_2 so that

$$\beta = \begin{bmatrix} \mu \\ \tau_1 \\ \tau_2 \end{bmatrix} \quad \text{and} \quad E(\mathbf{y}) = \begin{bmatrix} (\mu + \tau_1)\mathbf{1}_{n_1} \\ (\mu + \tau_2)\mathbf{1}_{n_2} \end{bmatrix}.$$

$\tau_1 - \tau_2 = (\mu + \tau_1) - (\mu + \tau_2)$ is estimable \because it is a LC of elements of $E(\mathbf{y})$.

$\tau_1 - \tau_2 = \mathbf{c}'\boldsymbol{\beta}$ where

$$\mathbf{c}' = [0, 1, -1].$$

Result 3.4 implies that

$$\begin{aligned} \mathbf{c}'\mathbf{T}\hat{\boldsymbol{\alpha}} &= [0, 1, -1] \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \bar{y}_{1\cdot} \\ \bar{y}_{2\cdot} - \bar{y}_{1\cdot} \end{bmatrix} \\ &= [0, -1] \begin{bmatrix} \bar{y}_{1\cdot} \\ \bar{y}_{2\cdot} - \bar{y}_{1\cdot} \end{bmatrix} \\ &= \bar{y}_{1\cdot} - \bar{y}_{2\cdot}. \end{aligned}$$

is LSE of $\mathbf{c}'\boldsymbol{\beta} = \tau_1 - \tau_2$.

Result 3.5:

If $\mathbf{d}'\boldsymbol{\alpha}$ is estimable in the model $\mathbf{y} = \mathbf{W}\boldsymbol{\alpha} + \boldsymbol{\varepsilon}$, then $\mathbf{d}'\mathbf{S}\boldsymbol{\beta}$ is estimable in the model $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$, and its LSE is $\mathbf{d}'\hat{\boldsymbol{\alpha}} = \mathbf{d}'\mathbf{S}\hat{\boldsymbol{\beta}}$, where $\hat{\boldsymbol{\alpha}}$ and $\hat{\boldsymbol{\beta}}$ are solutions to

$$\mathbf{W}'\mathbf{W}\mathbf{a} = \mathbf{W}'\mathbf{y} \quad \text{and} \quad \mathbf{X}'\mathbf{X}\mathbf{b} = \mathbf{X}'\mathbf{y}, \quad \text{respectively.}$$

Returning to our example, $\text{rank}(\mathbf{W}) = 2 \Rightarrow \mathbf{d}'\boldsymbol{\alpha}$ is estimable $\forall \mathbf{d} \in \mathbb{R}^2$.

For example, $\mathbf{d}'\boldsymbol{\alpha}$ is estimable for $\mathbf{d}' = [1, 0]$, and the LSE is

$$\mathbf{d}'\hat{\boldsymbol{\alpha}} = [1, 0] \begin{bmatrix} \bar{y}_{1\cdot} \\ \bar{y}_{2\cdot} - \bar{y}_{1\cdot} \end{bmatrix} = \bar{y}_{1\cdot} \quad .$$

According to Result 3.5,

$$\begin{aligned} \mathbf{d}'\mathbf{S}\boldsymbol{\beta} &= [1, 0] \begin{bmatrix} 1 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix} \begin{bmatrix} \mu \\ \tau_1 \\ \tau_2 \end{bmatrix} \\ &= [1, 1, 0] \begin{bmatrix} \mu \\ \tau_1 \\ \tau_2 \end{bmatrix} \\ &= \mu + \tau_1 \quad \text{is also estimable.} \end{aligned}$$

The LSE is

$$\begin{aligned}d'S\hat{\beta} &= [1, 0] \begin{bmatrix} 1 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ \bar{y}_{1\cdot} \\ \bar{y}_{2\cdot} \end{bmatrix} \\ &= [1, 1, 0] \begin{bmatrix} 0 \\ \bar{y}_{1\cdot} \\ \bar{y}_{2\cdot} \end{bmatrix} \\ &= \bar{y}_{1\cdot} \quad .\end{aligned}$$