

$$y_i = \beta_0 + \beta_1 x_{i1} + \dots + \beta_{p-1} x_{i,p-1} + e_i$$

$$X = \begin{bmatrix} J & X_* \end{bmatrix}, \quad X_* \text{ is } n \times (p-1)$$

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_* \end{bmatrix}, \quad \beta_* \text{ is } (p-1) \times 1$$

Mean-centered

$$y_i = \gamma_0 + \gamma_1 (x_{i1} - \bar{x}_{.1}) + \dots + \gamma_{p-1} (x_{i,p-1} - \bar{x}_{.p-1}) + e_i$$

$$X = \begin{bmatrix} J & (I - M_J)z \end{bmatrix}, \quad (I - M_J)z \text{ is } n \times (p-1)$$

$$\gamma = \begin{bmatrix} \gamma_0 \\ \gamma_* \end{bmatrix}, \quad \gamma_* \text{ is } (p-1) \times 1$$

$$\beta_0 + X_* \beta_* = E[Y] = \gamma_0 + [(I - M_J)z] \gamma_* \quad \star$$

Average over observations:

$$\beta_0 + \beta_1 \bar{x}_{.1} + \dots + \beta_{p-1} \bar{x}_{.p-1} = \gamma_0 + \underbrace{\gamma_1 (\bar{x}_{.1} - \bar{x}_{.1}) + \dots + \gamma_{p-1} (\bar{x}_{.p-1} - \bar{x}_{.p-1})}_{0} \quad \text{Let } \bar{X}_* = [\bar{x}_{.1}, \dots, \bar{x}_{.p-1}]'$$

$(p-1) \times 1$

$$\beta_0 + \bar{X}_*' \beta_* = \gamma_0$$

$$\beta_0 = \gamma_0 - \bar{X}_*' \beta_*$$

Substitute β_0 into \star : $\gamma_0 - \bar{X}_*' \beta_* + X_* \beta_* = \gamma_0 + [(I - M_J)z] \gamma_*$

$$\begin{bmatrix} X_* - \mathbf{1}_n \bar{X}_*' \end{bmatrix} \beta_* = [(I - M_J)z] \gamma_*$$

$n \times (p-1) \quad n \times (p-1)$

$$\text{For each } i, [x_{i1} - \bar{x}_{.1}, \dots, x_{i,p-1} - \bar{x}_{.p-1}] \beta_* \equiv [(I - M_J)z] \beta_*$$

Therefore $\beta_* = \gamma_*$, and $\beta_0 = \gamma_0 - \bar{X}_*' \gamma_*$

Book denotes $\bar{X}_*' as $(\frac{1}{n}) J_n' z$, so $\beta_0 = \gamma_0 - (\frac{1}{n}) J_n' z \gamma_*$$

From above, in the mean-centered version, $C((I - M_J)z) = C(J)_{(n)}^{\perp} = C(M - M_J)$

Normal equation $X'X\gamma = X'Y$: $X'X = \begin{bmatrix} -J & \\ -(I - M_J)z & \end{bmatrix} \begin{bmatrix} J & (I - M_J)z \\ \end{bmatrix} = \begin{bmatrix} n & 0 \\ 0 & [(I - M_J)z]'[(I - M_J)z] \end{bmatrix}$

$p \times n \quad n \times p \quad p \times p$

$$[X'X]^{-1} = \begin{bmatrix} \frac{1}{n} & 0 \\ 0 & \frac{1}{[(I - M_J)z]'[(I - M_J)z]} \end{bmatrix}$$

$p \times p$

is invertible because
X is full rank

$$X'Y = \begin{bmatrix} \sum y_i \\ [(I - M_J)z]'Y \end{bmatrix}$$

$p \times 1$

The LS. estimate of δ is $\hat{\delta} = (X'X)^{-1}X'Y = \begin{bmatrix} \frac{\sum y_i}{n} \\ \frac{[(I-M_J)z]'Y}{[(I-M_J)z]'[(I-M_J)z]} \end{bmatrix} = \begin{bmatrix} \bar{y} \\ \frac{[(I-M_J)z]'Y}{[(I-M_J)z]'[(I-M_J)z]} \end{bmatrix} = \begin{bmatrix} \hat{\delta}_0 \\ \hat{\delta}_* \end{bmatrix}$

From previous result, know that $X_* = \beta_*$, so $\hat{X}_* = \hat{\beta}_*$. This is useful in that we can relate Y under the reduced model, with $X = [J' | (I-M_J)z]'$, to the Least Squares estimate $\hat{\beta}_*$.

For LS., generally $MY = X\hat{\beta}$. Here $M_{(I-M_J)z} Y = X\hat{\beta}_*$. $M_{(I-M_J)z}$ is defined below.

$SS_{Reg} = Y'(I-M_J)Y$. Since $C(M-M_J) = C((I-M_J)z)$, can write ppm onto $(I-M_J)z$ as

$$(I-M_J)z \left[z'(I-M_J)'(I-M_J)z \right]^{-1} z'(I-M_J)' = M_{(I-M_J)z}$$

$$= Y'(I-M_J)z \left[z'(I-M_J)'(I-M_J)z \right]^{-1} z'(I-M_J)' Y$$

$$= \hat{\beta}_*' z' (I-M_J)z \left[z'(I-M_J)'(I-M_J)z \right]^{-1} z'(I-M_J)' z \hat{\beta}_*$$

$$= \hat{\beta}_*' z' (I-M_J)z \left[z'(I-M_J)z \right]^{-1} z'(I-M_J)' z \hat{\beta}_*$$

$$= \hat{\beta}_*' z' (I-M_J)z \hat{\beta}_*$$

Replacing $M-M_J$ with $M_{(I-M_J)z}$

Use normal equations to get $\hat{\beta}_*$, then $E[Y] = z\hat{\beta}_*$

Collapse ppm's, since they are idempotent.

Allow generalized inverse to cancel out.