Complements on classical linear model *

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1. Formulas for partitioned regression

$$y = X\beta + \varepsilon$$

$$= (X_1, X_2) {\beta_1 \choose \beta_2} + \varepsilon$$

$$= X_1\beta_1 + X_2\beta_2 + \varepsilon$$
(1.1)

$$\hat{\boldsymbol{\beta}} = (X'X)^{-1}X'y = \begin{pmatrix} \hat{\beta}_1\\ \hat{\beta}_2 \end{pmatrix} \tag{1.2}$$

where

$$X : T \times k, X_1 : T \times k_1, X_2 : T \times k_2,$$

 $\beta_1 : k_1 \times 1, \beta_2 : k_2 \times 1, k = k_1 + k_2.$

$$\hat{\beta}_{1} = (X_{1}'X_{1})^{-1}X_{1}'y - (X_{1}'X_{1})^{-1}X_{1}'X_{2}D^{-1}X_{2}'M_{1}y$$

$$= b_{1} - (X_{1}'X_{1})^{-1}X_{1}'X_{2}D^{-1}X_{2}'M_{1}y$$
(1.3)

where

$$b_1 = (X_1'X_1)^{-1}X_1'y, (1.4)$$

$$M_1 = I_T - X_1 (X_1' X_1)^{-1} X_1', (1.5)$$

$$D = X_2' M_1 X_2; (1.6)$$

$$\hat{\beta}_2 = D^{-1} X_2' M_1 y = (X_2' M_1 X_2)^{-1} X_2' M_1 y; \tag{1.7}$$

$$\hat{\boldsymbol{\beta}}_1 = (X_1' M_2 X_1)^{-1} X_1' M_2 y \tag{1.8}$$

where

$$M_2 = I_T - X_2 (X_2' X_2)^{-1} X_2'. (1.9)$$

For further discussion, the reader may con consult Schmidt (1976) and Seber

(1977).

2. Updating formulas for linear regressions

$$y_t = x_t' \beta + \varepsilon_t \quad , \quad t = 1, ..., T \tag{2.1}$$

where

$$x_t: k \times 1 \,, \tag{2.2}$$

$$Y_r = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_r \end{pmatrix}$$
 , $X_r = \begin{bmatrix} x'_1 \\ x'_2 \\ \vdots \\ x'_r \end{bmatrix}$, $r = k, k+1, ..., T$. (2.3)

$$b_r = (X_r'X_r)^{-1}X_r'Y_r (2.4)$$

is the estimator of β based on the first r observations. Then the following updating formulas hold [see Brown, Durbin and Evans (1975)]:

$$b_r = b_{r-1} + (X_r'X_r)^{-1} x_r (y_r - x_r'b_{r-1}) , k+1 \le r \le T,$$
 (2.5)

$$(X_r'X_r)^{-1} = (X_{r-1}'X_{r-1})^{-1} - \frac{(X_{r-1}'X_{r-1})^{-1} x_r x_r' (X_{r-1}'X_{r-1})^{-1}}{1 + x_r' (X_{r-1}'X_{r-1})^{-1} x_r}.$$
 (2.6)

Further,

$$V(b_r) - V(b_{r-1}) = \sigma^2 (X_r' X_r)^{-1} - \sigma^2 (X_{r-1}' X_{r-1})^{-1}$$

$$= -\sigma^2 \frac{(X_{r-1}' X_{r-1})^{-1} x_r x_r' (X_{r-1}' X_{r-1})^{-1}}{1 + x_r' (X_{r-1}' X_{r-1})^{-1} x_r}$$
(2.7)

is a negative semidefinite matrix.

3. Orthogonal decompositions of least squares estimators

Consider $\hat{\beta}$ and $\hat{\beta}_0$, respectively the unrestricted estimator of β and the restricted estimator of β under the constraint $R\beta = r$:

$$\hat{\beta} = (X'X)^{-1}X'y, \tag{3.1}$$

$$\hat{\boldsymbol{\beta}}_0 = \hat{\boldsymbol{\beta}} + Q_R [r - R\hat{\boldsymbol{\beta}}] \tag{3.2}$$

where

$$Q_R = (X'X)^{-1} R' [R(X'X)^{-1} R']^{-1}. (3.3)$$

Then, we see easily that

$$R\hat{\beta} - r = R[\beta + (X'X)^{-1}X'\varepsilon] - r \tag{3.4}$$

$$= (R\beta - r) + R_X \varepsilon \tag{3.5}$$

where

$$R_X = R(X'X)^{-1}X',$$
 (3.6)

$$\hat{\beta} - \hat{\beta}_{0} = Q_{R}[R\hat{\beta} - r]$$

$$= Q_{R}[(R\beta - r) + R_{X}\varepsilon]$$

$$= Q_{R}(R\beta - r) + Q_{R}R_{X}\varepsilon$$

$$= Q_{R}(R\beta - r) + Q\varepsilon$$
(3.7)

and

$$\hat{\boldsymbol{\beta}}_{0} = \hat{\boldsymbol{\beta}} + (\hat{\boldsymbol{\beta}}_{0} - \hat{\boldsymbol{\beta}})$$

$$= \boldsymbol{\beta} + (X'X)^{-1} X' \boldsymbol{\varepsilon} - Q_{R} (R\boldsymbol{\beta} - r) - Q \boldsymbol{\varepsilon}$$

$$= \boldsymbol{\beta} + Q_{R} (r - R\boldsymbol{\beta}) + [(X'X)^{-1} X' - Q] \boldsymbol{\varepsilon}$$
(3.8)

where

$$Q = Q_R R_X = Q_R R (X'X)^{-1} X'. (3.9)$$

Since

$$R_X X (X'X)^{-1} = R (X'X)^{-1} X'X (X'X)^{-1} = R (X'X)^{-1},$$
 (3.10)

$$R_X R_X' = R(X'X)^{-1} X' X (X'X)^{-1} R' = R(X'X)^{-1} R'$$
(3.11)

and

$$R_X Q' = R_X R_X' Q_R'$$

$$= R(X'X)^{-1} R' [R(X'X)^{-1} R']^{-1} R(X'X)^{-1}$$

$$= R(X'X)^{-1},$$
(3.12)
$$= R(X'X)^{-1},$$

it follows that

$$C(R\hat{\beta} - r, \hat{\beta}_{0}) = C(R_{X}\varepsilon, [(X'X)^{-1}X' - Q]\varepsilon)$$

$$= E[R_{X}\varepsilon\varepsilon'[(X'X)^{-1}X' - Q]']$$

$$= \sigma^{2}R_{X}[(X'X)^{-1}X' - Q]'$$

$$= \sigma^{2}R_{X}[X(X'X)^{-1} - Q']$$

$$= \sigma^{2}[R(X'X)^{-1} - R(X'X)^{-1}] = 0.$$
(3.14)

and

$$C(\hat{\beta} - \hat{\beta}_0, \, \hat{\beta}_0) = C(Q_R[R\hat{\beta} - r], \, \hat{\beta}_0)$$

= $Q_RC(R\hat{\beta} - r, \, \hat{\beta}_0) = 0.$

Thus $\hat{\beta}_0$ and $R\hat{\beta} - r$ are uncorrelated under the assumptions of the classical linear model, and similarly for $\hat{\beta}_0$ and $\hat{\beta} - \hat{\beta}_0$. This holds even if the normality assumption or the restriction $R\beta = r$ do not hold. Consequently, the identity

$$\hat{\beta} = \hat{\beta}_0 + (\hat{\beta} - \hat{\beta}_0) \tag{3.15}$$

provides a decomposition of $\hat{\beta}$ as the sum of two uncorrelated random vectors, so that

$$V(\hat{\boldsymbol{\beta}}) = V(\hat{\boldsymbol{\beta}}_0) + V(\hat{\boldsymbol{\beta}} - \hat{\boldsymbol{\beta}}_0). \tag{3.16}$$

More explicitly, we have

$$\hat{\beta} = \hat{\beta}_0 + Q_R(r - R\beta) - Q\varepsilon \tag{3.17}$$

where

$$C[\hat{\boldsymbol{\beta}}_0, Qy] = C[\hat{\boldsymbol{\beta}}_0, Q\varepsilon] = 0. \tag{3.18}$$

An interesting special case of the latter results is the one where

$$y = X_1 \beta_1 + X_2 \beta_2 + \varepsilon \tag{3.19}$$

and the restrictions take the form

$$\beta_2 = 0, \tag{3.20}$$

with

$$R = [0, I_{k_2}], r = 0. (3.21)$$

Then

$$\hat{\boldsymbol{\beta}} = \begin{pmatrix} \hat{\boldsymbol{\beta}}_1 \\ \hat{\boldsymbol{\beta}}_2 \end{pmatrix}, \quad \hat{\boldsymbol{\beta}}_0 = \begin{pmatrix} \hat{\boldsymbol{\beta}}_{10} \\ \hat{\boldsymbol{\beta}}_{20} \end{pmatrix} = \begin{pmatrix} (X_1'X_1)^{-1}X_1'y \\ 0 \end{pmatrix}$$
(3.22)

and

$$\hat{\beta}_1 = \hat{\beta}_{10} - Q_{20}R\hat{\beta} = \hat{\beta}_{10} - Q_{20}\hat{\beta}_2 \tag{3.23}$$

where

$$\hat{\boldsymbol{\beta}}_2 = (X_2' M_1 X_2)^{-1} X_2' M_1 y \tag{3.24}$$

and $\hat{\beta}_2$ is independent of $\hat{\beta}_{10}$.

¹See Magnus and Durbin (1999) and Danilov and Magnus (2001) for further discussion.

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