UNCORRELATED LINEAR TRANSFORMATIONS OF RESIDUALS IN MULTIPLE REGRESSION

BU-216-M

D. S. Robson

April, 1966

Abstract

If G is a generalized inverse of $X^{\dagger}X = (X_{1}^{\dagger}X_{1} + X_{2}^{\dagger}X_{2})$ and $\mathcal J$ is a generalized inverse of $X_{1}^{\dagger}X_{1}$ then

$$Y_1 - X_1^2 X_1^{\dagger} Y_1 = Y_1 - X_1^{\dagger} G X_1^{\dagger} Y + X_1^{\dagger} G X_2^{\dagger} K (Y_2 - X_2^{\dagger} G X_1^{\dagger} Y)$$

where K is a generalized inverse of I - $X_2GX_2^{\bullet}$. Further, if Y = X β + ϵ and $E(\epsilon\epsilon^{\bullet}) = \sigma^2 I$ then $E(Y_1 - X_1 \mathcal{B}X_1^{\bullet}Y)(Y_2 - X_2 GX^{\bullet}Y) = \phi$.

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In an earlier note (BU-210-M) it was shown that if the regression model

is fitted separately to the first k observations Y_1 and to all n observations Y then the least squares residuals in the first instance

$$f_1 = Y_1 - X_1 X_1 Y_1 , X_1 X_1 X_1 = X_1 X_1$$
 $k X_1 k X_1$

are uncorrelated with the n-k least squares residuals

$$e_2 = Y_2 - X_2GX^{\dagger}Y$$
, $X^{\dagger}XGX^{\dagger}X = X^{\dagger}X$

obtained after fitting the model to all n observations. The purpose of the present note is to show that

(1)
$$f_1 = e_1 + X_1 G X_2 K e_2$$

for all K such that

(2)
$$(I - X_2GX_2^{\dagger})K(I - X_2GX_2^{\dagger}) = I - X_2GX_2^{\dagger}$$

Rewriting (1) in terms of Y_1 and Y_2 werget

(3)
$$e_{1} + X_{1}GX_{2}^{i}Ke_{2} = (I - X_{1}GX_{1}^{i})Y_{1} - X_{1}GX_{2}^{i}Y_{2}$$
$$+ X_{1}GX_{2}^{i}K(I - X_{2}GX_{2}^{i})Y_{2} - X_{1}GX_{2}^{i}KX_{2}GX_{1}^{i}Y_{1}$$

The coefficient of Y_2 in (3) is null since

and from the relation XGX'X = X we have

(5)
$$X_2G'X_1'X_1 = (I - X_2G'X_2')X_2$$

and from the invariance of XGX' then

$$X_2G'X_1'X_1 = (I - X_2GX_2')X_2$$

Upon substituting this experssion into (4) and utilizing the relation (2) we see that the right hand side of (4) is null, and hence

$$X_1GX_2^{\dagger}K(I - X_2GX_2^{\dagger}) = X_1GX_2^{\dagger}$$
...

Equation (3) thus reduces to

$$e_1 + X_1GX_2^*Ke_2 = [I - X_1(G + GX_2^*KX_2G)X_1^*]Y_1$$

and since

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$$f_1 = (I - X_1 X_1^*) Y_1$$

then to establish (1) we must show that $G + GX_2^{\bullet}KX_2G$ is a generalized inverse of $X_1^{\bullet}X_1^{\bullet}$; i.e., that

(6)
$$X_{1}^{i}X_{1}(G + GX_{2}^{i}KX_{2}G)X_{1}^{i}X_{1} = X_{1}^{i}X_{1}$$

As in (5) we may write

$$X_{1}^{\dagger}X_{1}GX_{1}^{\dagger}X_{1} = X_{1}^{\dagger}X_{1} - X_{2}^{\dagger}X_{2}GX_{1}^{\dagger}X_{1}$$

so that (6) reduces to

$$(7) X_{1}^{i}X_{1}GX_{2}^{i}KX_{2}GX_{1}^{i}X_{1} = X_{2}^{i}X_{2}GX_{1}^{i}X_{1}$$

From (5), the left hand side of (7) may be written as

$$X_{2}^{*}(I - X_{2}GX_{2}^{*})K(I - X_{2}GX_{2}^{*})X_{2} = X_{2}^{*}(I - X_{2}GX_{2}^{*})X_{2}$$

and applying (5) to the right hand side of (7) gives the same result, thus confirming (6) and hence also (1).