

**LINEAR UNBIASED ESTIMATORS AS A GLS CLASS  
AND THE GENERALIZED AITKEN THEOREM  
AS A COROLLARY**

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THE GENERALIZED AITKEN THEOREM AS A COROLLARY

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## 1. INTRODUCTION.

This paper introduces two new theorems: one establishes that all linear unbiased estimators are of the GLS class; the other derives the optimal matrix solution of the covariance matrix function. One important consequence is that the Generalized Aitken Theorem is a corollary of the two theorems.

## 2. THEOREMS.

*THEOREM 1:*

Let

$$(1) \quad \underset{n \times 1}{y} = \underset{n \times k}{X} \underset{k \times 1}{\beta} + \underset{n \times 1}{u}, \quad 0 < k \leq n$$

be the linear model with all the classical assumptions except  $E(uu') = \Omega$ , where  $\Omega$  is an  $n \times n$  p.s.d. matrix with  $\rho(\Omega) \geq k$ . Then all linear unbiased estimators can be expressed as a GLS-class estimator:

$$(2) \quad b_g = b_g(\Sigma) = (X' \Sigma X)^{-1} X' \Sigma y,$$

where  $\Sigma$  is any  $n \times n$  matrix with  $\rho(\Sigma) \geq k$ .

Proof:

Since  $b_{ols} = (X'X)^{-1} X'y$  is an unbiased estimator of  $\beta$  in (1), any other linear unbiased estimator,  $b_{nols}$ , can be expressed as  $b_{nols} = b_{nols}(A) = [(X'X)^{-1} X' + A]y$  where  $A$  can be any  $k \times n$  non-null matrix such that  $AX = 0_{k \times k}$  (Theil, 1971, p.120). Combining  $b_{ols}$  and  $b_{nols}$ , we can write any linear unbiased estimator as

$$(3) \quad b_a = b_a(A) = [(X'X)^{-1} X' + A]y$$

where  $A$ , such that  $AX=0_{k \times k}$ , now can be a null matrix.

Since  $A=(X'X)^{-1}X'XA$ , and also since  $X'XAX=0_{k \times k}$  directly follows from  $AX=0_{k \times k}$ , we can rewrite  $b_a$  as:

$$\begin{aligned}
 b_a &= [(X'X)^{-1}X' + A]y \\
 &= [(X'X)^{-1}X' + (X'X)^{-1}X'XA]y \\
 &= (X'X)^{-1}X'[I_n + XA]y \\
 &= (X'X + X'XAX)^{-1}X'[I_n + XA]y \\
 &= [X'(I_n + XA)X]^{-1}X'(I_n + XA)y \\
 &= (X'\Sigma)^{-1}X'\Sigma y = b_g,
 \end{aligned}$$

where

$$(4) \quad \Sigma \equiv I_n + XA.$$

Noting that  $AX=0$ ,  $\rho(\Sigma) \geq k$  easily follows from post-multiplying (4) by  $X$ :  $\Sigma X = X + XAX = X$  so that  $\rho(\Sigma X) = \rho(X)$ ; since  $\rho(X) = k$  and  $\rho(\Sigma X) = \min(\rho(\Sigma), \rho(X))$ ,  $\min(\rho(\Sigma), k) = k$  which immediately implies that  $\rho(\Sigma) \geq k$ .

Let  $S_g$  a set of linear unbiased estimators in the form of  $b_g$ , and  $S_a$  the set of all linear unbiased estimators in the form of  $b_a$ . Since any linear unbiased estimators can be expressed in the form of  $b_a$ ,  $S_a$  is the complete set of all linear unbiased estimators; therefore

$$S_g \subset S_a.$$

However, since any linear unbiased estimator in the form of  $b_a$  can be transformed into  $b_g$ , as shown above,

$$S_g \supset S_a.$$

Therefore

$$S_g = S_a.$$

Q.E.D.

Then,  $\text{Var}(b_g) = (X' \Sigma X)^{-1} X' \Sigma \Omega \Sigma' X (X' \Sigma X)^{-1}$  can be optimized with respect to the variable matrix  $\Sigma$ , which is discussed as a separate theorem which may well be useful in some other contexts in econometric theory:

*THEOREM 2:*

Define  $V = V(\Sigma) = (X' \Sigma X)^{-1} X' \Sigma \Omega \Sigma' X (X' \Sigma X)^{-1}$  where  $\Sigma$ ,  $X$ , and  $\Omega$  are all as defined in Theorem 1. Then, under  $dV(\Sigma) = 0_{k \times k}$ , and  $d^2V(\Sigma) \geq 0_{k \times k}$  (i.e., p.s.d.); and  $\Sigma = \Omega^+$ , with  $\Omega^+$  denoting

the Moor-Penrose inverse, is a unique solution for  $\Sigma$  of the first derivative.

Proof:

Let the differential operator  $d$  operate only on the immediately following matrix. Then, using  $d(AB) = dAB + AdB$  and  $dA^{-1} = -A^{-1}dAA^{-1}$  (Graham, 1980, p.79),

$$(7) \quad dV = Q^{-1}X' \phi X Q^{-1} + Q^{-1}X' \phi' X Q^{-1} \\ = Q^{-1}[X' \phi X + (X' \phi X)'] Q^{-1}.$$

with the matrices defined as:

$$(8) \quad Q = Q(\Sigma) = X' \Sigma X \\ \phi = \phi(\Sigma) = d \Sigma M \Omega \Sigma' \\ M = M(\Sigma) = I - X Q^{-1} X' \Sigma.$$

For  $V$  in (7),  $dV = 0_{k \times k}$  obviously requires

$$(9) \quad X' \phi X = 0_{k \times k}.$$

Differentiating  $dV$  in (7) with respect to  $\Sigma$ ,

$$\begin{aligned}
(10) \quad d^2V &= d(dV) \\
&= dQ^{-1}[X' \phi X + (X' \phi X)'] Q'^{-1} \\
&\quad + Q^{-1}[X' d\phi X + (X' d\phi X)'] Q'^{-1} \\
&\quad + Q^{-1}[X' \phi X + (X' \phi X)'] dQ'^{-1}.
\end{aligned}$$

Substituting  $d\phi = -d\Sigma X Q^{-1} X' \phi + d\Sigma M \Omega d\Sigma'$  (Appendix A) into (10), then reflecting (9), we can show that  $d^2V(\Sigma)$  is p.s.d.:

$$\begin{aligned}
(11) \quad d^2V &= Q^{-1} X' d\Sigma [M \Omega + \Omega' M'] d\Sigma' X Q'^{-1} \\
&= (Q^{-1} X' d\Sigma) (M \Omega + \Omega' M') (Q^{-1} X' d\Sigma)' \\
&\geq 0_{k \times k},
\end{aligned}$$

noting that both  $M$ , idempotent, and  $\Omega$  are p.s.d. for all  $\Sigma$ .

Substituting  $\phi$  defined in (8) into (9),

$$(12) \quad X' d\Sigma M \Omega \Sigma' X = 0_{k \times k}.$$

Since  $d\Sigma$  is a non-null arbitrary matrix, it can not be that  $X' d\Sigma \neq 0_{k \times n}$ . Hence, (12) requires

$$(13) \quad d\Sigma M \Omega \Sigma' X = 0_{n \times k}.$$



Substituting  $d\Sigma = d(\Sigma G)\Sigma + \Sigma G d\Sigma$ ,  $G$  denoting a generalized inverse of  $\Sigma$ , into (13) yields (Appendix B)

$$(14) \quad d(\Sigma G)\dot{M}\Sigma\Omega\Sigma'X = 0_{n \times k}$$

where  $\dot{M} \equiv I - \Sigma X(X'\Sigma X)^{-1}X'$ .

Since  $\dot{M}\Sigma X = (I - \Sigma X(X'\Sigma X)^{-1}X')\Sigma X = 0_{n \times k}$ ,

(14) is satisfied if  $\Sigma\Omega\Sigma' = \Sigma$  of which  $\Sigma = \Omega^*$  is a unique solution for  $\Sigma$  (Appendix C).

Q.E.D.

*GENERALIZED AITKEN THEOREM AS A COROLLARY:*

For  $c'b_g$  a linear combination of  $b_g$  in Theorem I where  $c$  is an arbitrary  $k \times 1$  column vector, we can easily show that

$$(15) \quad q \equiv \text{var}(c'b_g) = c'V(\Sigma)c.$$

Then, the first- and second-order conditions for minimization of  $q$  will be

$$(16) \quad dq = c' dV(\Sigma) c = 0, \text{ and}$$

$$d^2q = c' d^2V(\Sigma) c \geq 0.$$

Both the first- and second-order conditions require  $dV(\Sigma) = 0_{k \times k}$  and  $d^2V(\Sigma) \geq 0_{k \times k}$ , respectively, which in turn are satisfied uniquely by  $\Sigma = \Omega^*$  as established in Theorem 2.

Substituting  $\Sigma = \Omega^*$  into  $b_a$  in (2) yields

$$(17) \quad b_{gls} = (X' \Omega^* X)^{-1} X' \Omega^* y$$

as the BLUE of  $\beta$  in (1), which proves the Generalized Aitken Theorem (Aitken, 1935; Theil, 1971, pp.278-280).

APPENDIX A:

Differentiating M defined in (8) with respect to  $\Sigma$ ,

$$\begin{aligned}
 \text{(A.1)} \quad dM &= -X dQ^{-1} X' \Sigma - X Q^{-1} X' d\Sigma \\
 &= X Q^{-1} X' d\Sigma X Q^{-1} X' \Sigma - X Q^{-1} X' d\Sigma \\
 &= -X Q^{-1} X' d\Sigma M.
 \end{aligned}$$

Differentiating  $\phi$  defined in (8), using (A.1), with respect to  $\Sigma$ ,

$$\begin{aligned}
 \text{(A.2)} \quad d\phi &= d(d\Sigma M \Omega \Sigma') \\
 &= d^2 \Sigma M \Omega \Sigma' + d\Sigma dM \Omega \Sigma' + d\Sigma M \Omega d\Sigma' \\
 &= -d\Sigma (X Q^{-1} X' d\Sigma M) \Omega \Sigma' + d\Sigma M \Omega d\Sigma' \\
 &= -d\Sigma X Q^{-1} X' \phi + d\Sigma M \Omega d\Sigma',
 \end{aligned}$$

noting that  $d^2 \Sigma = 0_{n \times n}$  since  $d\Sigma$  is arbitrary.

APPENDIX B:

Denoting a generalized inverse of  $\Sigma$  by  $G$ , we can express  $\Sigma$  as  $\Sigma = \Sigma G \Sigma$ . Then,  $d\Sigma$  easily follows:

$$\begin{aligned}
 \text{(B.1)} \quad d\Sigma &= d(\Sigma G \Sigma) \\
 &= d((\Sigma G) \Sigma) \\
 &= d(\Sigma G) \Sigma + \Sigma G d\Sigma.
 \end{aligned}$$

Substituting (B.1) into (13),

$$\begin{aligned}
 \text{(B.2)} \quad d\Sigma M \Omega \Sigma' X &= [d(\Sigma G) \Sigma + \Sigma G d\Sigma] M \Omega \Sigma' X \\
 &= d(\Sigma G) \Sigma M \Omega \Sigma' X + \Sigma G (d\Sigma M \Omega \Sigma' X) \\
 &= d(\Sigma G) \dot{M} \Sigma \Omega \Sigma' X \\
 &= 0_{n \times k}
 \end{aligned}$$

noting that the third equality is based on  $\Sigma M = \dot{M} \Sigma$  in which  $M$  and  $\dot{M}$  are as defined in (8) and (14), respectively, and also equation (13) itself.

APPENDIX C:

Since  $\Omega$  is p.s.d., so is  $\Sigma\Omega\Sigma'=\Sigma$ . Therefore,  $\Sigma$  and  $\Sigma^+$  can be decomposed (Theil, 1971, p. 276) as

$$(C.1) \quad \begin{aligned} \Sigma &= F\Lambda F'; \\ \Sigma^+ &= FD^{-1}F' \end{aligned}$$

where  $F$  is a  $n \times r$  full-column matrix whose columns consisting of eigenvectors corresponding to the non-zero eigenvalues of  $\Sigma$ , so that  $F'F=I_r$ , where  $r=\rho(\Sigma) \geq k$ ; and  $D$  is a  $r \times r$  diagonal matrix consisting of the  $r$  non-zero eigenvalues of  $\Omega$ . Hence, substituting (C.1) into  $\Sigma\Omega\Sigma'=\Sigma$ ,

$$(C.2) \quad FDF'\Omega FDF' = FDF'.$$

Pre- and post-multiplying  $FD^{-1}F'$  to (C.2),

$$(C.3) \quad \Omega = FD^{-1}F' = \Sigma^+;$$

subsequently

$$(C.4) \quad \Sigma = (\Sigma^{\dagger})^{\dagger} = \Omega^{\dagger}.$$

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