

## WHEN ARE GAUSS-MARKOV AND LEAST SQUARES ESTIMATORS IDENTICAL? A COORDINATE-FREE APPROACH<sup>1</sup>

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**1. Introduction.** In the framework of the general linear hypothesis, it is well known that the Gauss-Markov (minimum variance linear unbiased) and least squares estimators may be the same even when the underlying covariance structure is not a multiple of the identity. The main purpose of this note is to develop a (known) condition for this phenomenon simply in terms of the coordinate-free approach to the subject.

For general background and bibliography see Zyskind (1967) and Watson (1967). Much of the present paper is effectively a simpler form of part of the material in the Zyskind and Watson papers. For discussion of the coordinate-free approach see Kruskal (1961). Two very simple examples may be useful at the outset.

**EXAMPLE 1.** *One-way layout with unequal variances in known ratios.* The observations correspond to uncorrelated random variables  $Y_{ij}$  ( $i = 1, \dots, I$ ;  $j = 1, \dots, J_i$ ),  $EY_{ij} = \beta_i$ , and  $\text{Var } Y_{ij} = \lambda_i^2 \sigma^2$ . Here the  $\beta_i$  are unrestricted, unknown numbers;  $\sigma^2$  is an unknown positive number; and the  $\lambda_i^2$  are known positive numbers. It is readily seen that the Gauss-Markov and least square estimators of  $\beta_i$  are both  $\bar{Y}_{i.} = J_i^{-1} \sum_j Y_{ij}$ . The corresponding conventional estimators of  $\sigma^2$  are, however, not the same, unless all the  $\lambda_i^2$  are one. These conventional estimators are  $[\sum (J_i - 1)]^{-1}$  times

$$\begin{aligned} \sum_{ij} (Y_{ij} - \bar{Y}_{i.})^2 & \quad (\text{for Least Squares}), \\ \sum_{ij} (Y_{ij} - \bar{Y}_{i.})^2 / \lambda_i^2 & \quad (\text{for Gauss-Markov}). \end{aligned}$$

(Of course if the  $\lambda_i^2$  are equal, the two expressions are proportional, and if all  $\lambda_i^2 = 1$ , the expressions are identical. To obtain unbiased estimators of  $\sigma^2$ , the first expression must be divided by  $\sum [(J_i - 1)\lambda_i^2]$  and the second by  $\sum (J_i - 1)$ .)

**EXAMPLE 2.** *Single sample with permutation-invariant covariance structure.* The observations correspond to random variables  $Y_i$  ( $i = 1, \dots, n$ ),  $EY_i = \beta$ ,  $\text{Var } Y_i = \sigma^2$ , and  $\text{Cov}(Y_i, Y_{i'}) = \sigma^2 \gamma$  for  $i \neq i'$ . Here  $\beta$  is an unrestricted unknown number,  $\sigma^2$  is an unknown positive number, and  $\gamma$  is a known number

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