

**APPLICATION OF CONCOMITANTS OF ORDER STATISTICS OF
INDEPENDENT NON-IDENTICALLY DISTRIBUTED BIVARIATE
NORMAL RANDOM VARIABLES IN ESTIMATION**

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ABSTRACT

In this paper, we obtain the means, variances and covariances of order statistics arising from independent non-identically distributed bivariate normal random variables. A method of estimation of common parameters involved in several bivariate normal distributions using concomitants of order statistics is also discussed.

1. INTRODUCTION

It is well known that order statistics are very useful in the estimation of location and scale parameters of a distribution. For a survey of literature on the applications of order statistics of *iid* random variables in estimating the location and scale parameters of distributions, see David and Nagaraja (2003) and Balakrishnan and Cohen (1991). Vaughan and Venables (1972) have first discussed about the distribution theory of order statistics of *inid* random variables. For some further results on the order statistics of *inid* random variables, see Beg (1991) and Samuel and Thomas (1998). Sajeevkumar and Thomas (2005) and Thomas and Sajeevkumar (2005) have illustrated some applications of order statistics of independent non-identically distributed random variables in the estimation of common location and scale parameters of several distributions.

In a bivariate setup, study of concomitants of order statistics of *iid* bivariate random variables has gained momentum in a theoretical perspective as well as in terms of its applications. For details, see Beg and Ahsanullah (2007), Chacko (2007), David and Nagaraja (1998) and Nagaraja and David (1994). However as in the case of order statistics of *inid* random variables, not much works have been initiated on the theory and applications of concomitants of order statistics of *inid* random variables. Eryilmaz (2005) introduced the general expression for the *cdf* of concomitants of order statistics of *inid* bivariate random

variables. Veena and Thomas (2011) have obtained the general expression for the *pdf* of concomitants of order statistics of *inid* random variables and the means, variances and covariances of order statistics arising from independent non-identically distributed bivariate Pareto distributions. They have also described a method of estimation of common parameters involved in several bivariate Pareto distributions using concomitants of order statistics. Suppose $(X_1, Y_1), (X_2, Y_2), \dots, (X_n, Y_n)$ are n independent bivariate random variables with (X_i, Y_i) having an absolutely continuous bivariate distribution with *pdf* $f_i(X_i, Y_i), i = 1, 2, \dots, n$. If we order X_1, X_2, \dots, X_n involved in the above bivariate collection of random variables as $X_{1:n}, X_{2:n}, \dots, X_{n:n}$, then the accompanying Y value of $X_{r:n}$ in the ordered pair from which $X_{r:n}$ is taken is called the concomitant of the r -th order statistic and is denoted by $Y_{[r:n]}$. If we write $F_{X_i}(x)$ to denote the marginal distribution function of X_i of the bivariate distribution function of the random variable $(X_i, Y_i), i = 1, 2, \dots, n$ then from Veena and Thomas (2011), we can write the *pdf* $f_{Y_{[r:n]}}(y)$ of $Y_{[r:n]}$ as

$$f_{Y_{[r:n]}}(y) = \frac{1}{(r-1)!(n-r)!} \int_{-\infty}^{\infty} \text{Per} \begin{bmatrix} F_{X_1}(x) & 1-F_{X_1}(x) & f_1(x, y) \\ \vdots & \vdots & \vdots \\ F_{X_n}(x) & 1-F_{X_n}(x) & f_n(x, y) \end{bmatrix} dx \quad (1)$$

$\underbrace{\hspace{10em}}_{r-1} \quad \underbrace{\hspace{10em}}_{n-r} \quad \underbrace{\hspace{10em}}_1$

where $\text{per } A$ is meant to denote the permanent of a square matrix A which is just like the determinant of A except that in $\text{per } A$ all terms in its expansion are taken with positive sign and if a symbol k is marked below a column vector a in $\text{per } A$ then it means that A includes k copies of a .

For $1 \leq r < s \leq n$, the joint *pdf* of $Y_{[r:n]}$ and $Y_{[s:n]}$ has been developed by Veena and Thomas (2011) and is given by,

$$f_{Y_{[r,s:n]}}(y, z) = \frac{1}{(r-1)!(s-r-1)!(n-s)!} I$$

where

$$I = \iint_{u < v} \text{Per} \begin{bmatrix} F_{X_1}(u) & F_{X_1}(v) - F_{X_1}(u) & 1 - F_{X_1}(v) & f_1(u, y) & f_1(v, z) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ F_{X_n}(u) & F_{X_n}(v) - F_{X_n}(u) & 1 - F_{X_n}(v) & f_n(u, y) & f_n(v, z) \end{bmatrix} dudv. \quad (2)$$

In this work our main interest lies in establishing an application of the above theory of distribution of concomitants of order statistics of *inid* random variables in the estimation of common parameters involved in several bivariate normal distributions.

In section 2, we have considered the problem of estimation of the common correlation coefficient ... (ie., when ..._i = ..., i = 1, 2, ..., n) involved in several bivariate normal distributions with different †_i's using concomitants of *inid* normal random variables. In section 3, we consider concomitants of order statistics arising from several bivariate normal distributions with ~_{1i} = ~₁, †_{1i} = †₁, ~_{2i} = ~₂, †_{2i} = †₂, i = 1, 2, ..., n, but with different known values of the correlation coefficient. Further we illustrate an application of concomitants of order statistics of *inid* normal random variables in estimating the parameters ~₂ and †₂.

2. ESTIMATION OF ...

Let (X_i, Y_i), i = 1, 2, ..., n be independent bivariate random variables with (X_i, Y_i) having pdf h_i(x, y) of the form

$$\frac{(2f \dagger_1 \dagger_{2i})^{-1}}{\sqrt{1 - \dots^2}} \exp \left\{ \frac{-2^{-1}}{1 - \dots^2} \left[\frac{(x - \sim_1)^2}{\dagger_1^2} - 2 \dots \frac{(x - \sim_1)(y - \sim_{2i})}{\dagger_1 \dagger_{2i}} + \frac{(y - \sim_{2i})^2}{\dagger_{2i}^2} \right] \right\} \tag{3}$$

for i = 1, 2, ..., n.

Clearly the marginal distributions of X_i and Y_i are N(~₁, †₁) and N(~_{2i}, †_{2i}) respectively. Let f(x) and F(x) denote the marginal pdf and distribution function respectively of each of the X_i's and h_i(y|x) denote the conditional pdf of Y_i given X_i = x. Then we have,

$$E[Y_{[r:n]}] = \int_{-\infty}^{\infty} y f_{Y_{[r:n]}}(y) dy$$

$$= \frac{1}{(r-1)!(n-r)!} \int_{-\infty}^{\infty} Per \begin{bmatrix} F(x) & 1-F(x) & f(x) \int_{-\infty}^{\infty} y h_1(y|x) dy \\ \vdots & \vdots & \vdots \\ \underbrace{F(x)}_{r-1} & \underbrace{1-F(x)}_{n-r} & \underbrace{f(x) \int_{-\infty}^{\infty} y h_n(y|x) dy}_1 \end{bmatrix} dx$$

We know that

$$\int_{-\infty}^{\infty} y h_i(y | x) dy = \sim_{2i} + \dots \dagger_{2i} \left(\frac{x - \sim_1}{\dagger_1} \right).$$

Hence,

$$E[Y_{[r:n]}] = \frac{1}{n} \sum_i (\sim_{2i} + \dots \dagger_{2i} \Gamma_{r:n}) \quad (4)$$

where we write $\Gamma_{r:n}$ to denote the expected value of the r^{th} order statistic $U_{r:n}$ arising from a random sample of size n from $N(0,1)$.

$$E[Y_{[r:n]}^2] = \int_{-\infty}^{\infty} y^2 f_{Y_{[r:n]}}(y) dy$$

$$= \frac{1}{(r-1)!(n-r)!} \int_{-\infty}^{\infty} \text{Per} \begin{bmatrix} F(x) & 1-F(x) & f(x) \int_{-\infty}^{\infty} y^2 h_1(y|x) dy \\ \vdots & \vdots & \vdots \\ \underbrace{F(x)}_{r-1} & \underbrace{1-F(x)}_{n-r} & \underbrace{f(x) \int_{-\infty}^{\infty} y^2 h_n(y|x) dy}_1 \end{bmatrix} dx. \quad (5)$$

We know that

$$\int_{-\infty}^{\infty} y^2 h_i(y|x) dy = \dagger_{2i}^2 (1 - \dots^2) + \left[\sim_{2i} + \dots \dagger_{2i} \left(\frac{x - \sim_1}{\dagger_1} \right) \right]^2$$

Hence,

$$E[Y_{[r:n]}^2] = \frac{1}{n} \sum_i \sim_{2i}^2 + \frac{1}{n} \sum_i \dagger_{2i}^2 (1 - \dots^2) + 2 \dots \Gamma_{r:n} \frac{1}{n} \sum_i \sim_{2i} \dagger_{2i} + \Gamma_{r,r:n} \dots^2 \frac{1}{n} \sum_i \dagger_{2i}^2 \quad (6)$$

where we write $\Gamma_{r,r:n}$ to denote $E[U_{r:n}^2]$ and similarly we write

$$S_{r,r:n} = \text{Var}(U_{r:n}) = \Gamma_{r,r:n} - \Gamma_{r:n}^2.$$

Now,

$$\text{Var}[Y_{[r:n]}] = E[Y_{[r:n]}^2] - (E[Y_{[r:n]}])^2$$

$$= (1 - \dots^2) \frac{1}{n} \sum_i \dagger_{2i}^2 + \frac{1}{n} \dots^2 S_{r,r:n} \sum_i \dagger_{2i}^2 + \frac{1}{n^2} \sum_{i < j} [(\sim_{2i} - \sim_{2j}) + \dots (\dagger_{2i} - \dagger_{2j}) \Gamma_{r:n}]^2$$

We have, for $r < s$,

$$E[Y_{[r:n]}Y_{[s:n]}] = \frac{1}{(r-1)!(s-r-1)!(n-s)!} \int_{-\infty}^{\infty} \int_{x_1}^{\infty} Per I dx_2 dx_1,$$

where the matrix I is given by

$$\begin{bmatrix} F(x_1) & F(x_2)-F(x_1) & 1-F(x_2) & f(x_1) \int_{-\infty}^{\infty} y_1 f_1(y_1|x_1) dy_1 & f(x_2) \int_{-\infty}^{\infty} y_2 f_1(y_2|x_2) dy_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \underbrace{F(x_1)}_{r-1} & \underbrace{F(x_2)-F(x_1)}_{s-r-1} & \underbrace{1-F(x_2)}_{n-s} & \underbrace{f(x_1) \int_{-\infty}^{\infty} y_1 f_n(y_1|x_1) dy_1}_{1} & \underbrace{f(x_2) \int_{-\infty}^{\infty} y_2 f_n(y_2|x_2) dy_2}_{1} \end{bmatrix}$$

Now if we write $r_{r,s,n} = E(U_{r:n} U_{s:n})$ then,

$$\begin{aligned} E[Y_{[r:n]}Y_{[s:n]}] &= \frac{1}{n(n-1)} \sum_{i \neq j} (\sim_{2i} \sim_{2j} + \dots \sim_{2i} \dagger_{2j} r_{r,n} + \dots \sim_{2j} \dagger_{2i} r_{s,n} + \dots^2 \dagger_{2i} \dagger_{2j} r_{r,s,n}) \\ Cov[Y_{[r:n]}Y_{[s:n]}] &= E[Y_{[r:n]}Y_{[s:n]}] - E[Y_{[r:n]}]E[Y_{[s:n]}] \\ &= \frac{1}{n(n-1)} \dots^2 S_{r,s,n} \sum_{i \neq j} \dagger_{2i} \dagger_{2j} - \frac{1}{n^2(n-1)} \sum_{i < j} [(\sim_{2i} - \sim_{2j}) + \dots (\sim_{2i} - \sim_{2j}) r_{r,n}] \\ &\quad \times [(\sim_{2i} - \sim_{2j}) + \dots (\dagger_{2i} - \dagger_{2j}) r_{s,n}] \end{aligned}$$

Consider the units of bivariate sample in which measurement of the X variate can be done easily where as a measurement of Y is not so easy or economic. In this case we order the X observations and make measurements only on the concomitants $Y_{[c+1:n]}, \dots, Y_{[n-c:n]}$. Now based on this restricted sample we may use estimates based on the available concomitants of order statistics. Suppose $\sim_{2i} = \sim_2, \forall i = 1, 2, \dots, n$ and consider the transformation $Y_i^* = Y_i - \sim_2$. Then the corresponding vector of transformed concomitants of record values $Y_{[n,c]}^*$ has expectation and variance-covariance matrix which can be expressed in the form

$$E[Y_{[n,c]}^*] = \dots S, \tag{7}$$

where

$$S = \frac{1}{n} \sum_{i=1}^n \dagger_{2i} (r_{c+1:n}, r_{c+2:n}, \dots, r_{n-c:n})'$$

and

$$D[Y_{[n,c]}^*] = (1 - \dots^2) \frac{1}{n} \sum_{i=1}^n \dagger_{2i}^2 I + \dots^2 H, \tag{8}$$

where I is the identity matrix of order $(n-c) \times (n-c)$ and $H = \|h_{rs}\|$,

$$h_{rr} = \frac{1}{n} \sum_i \dagger_{2i}^2 S_{r,r;n} + \frac{1}{n^2} \sum_{i < j} (\dagger_{2i} - \dagger_{2j})^2 r_{r;n}^2$$

and for $r \neq s$,

$$h_{rs} = \frac{1}{n(n-1)} \sum_{i \neq j} \dagger_{2i} \dagger_{2j} S_{r,s;n} + \frac{1}{n^2(n-1)} \sum_{i < j} (\dagger_{2i} - \dagger_{2j})^2 r_{r;n} r_{s;n},$$

where i and j vary from 1 to n and r and s are such that $c+1 \leq r < s \leq n-c$.

Clearly (7) and (8) do not provide a general Gauss-Markov set up so as to derive the BLUE of Hence we may obtain two linear unbiased estimators of ... by minimizing the variance in a restricted sense as done in Chacko and Thomas (2008).

Theorem 2.1 Let R be a column vector of scalars of order n and $R'Y_{[n,c]}^*$ be a linear function of $Y_{[c+1;n]}, Y_{[c+2;n]}, \dots, Y_{[n-c;n]}$ with variance given by

$$\text{Var}(R'Y_{[n,c]}^*) = (1 - \dots^2) \frac{1}{n} \sum_{i=1}^n \dagger_{2i}^2 R'R + \dots^2 R'HR \quad (9)$$

Then an estimator $\hat{\dots}_1$ obtained by minimizing $R'R$ involved in (9) subject to the condition that $R'Y_{[n,c]}^*$ is unbiased for ... is given by $\hat{\dots}_1 = \frac{S'}{S'S} Y_{[n,c]}^*$ and an estimator $\hat{\dots}_2$ obtained by minimizing $R'HR$ involved in (9) subject to the condition that $R'Y_{[n,c]}^*$ is unbiased for ... is given by $\hat{\dots}_2 = \frac{S'H^{-1}}{S'H^{-1}S} Y_{[n,c]}^*$.

The variances of these estimators are given by

$$\text{Var}(\hat{\dots}_1) = (1 - \dots^2) \frac{1}{n} \sum_{i=1}^n \dagger_{2i}^2 \frac{1}{S'S} + \dots^2 \frac{S'HS}{(S'S)^2} \quad (10)$$

and

$$\text{Var}(\hat{\dots}_2) = (1 - \dots^2) \frac{1}{n} \sum_{i=1}^n \dagger_{2i}^2 \frac{S'H^{-2}S}{(S'H^{-1}S)^2} + \dots^2 \frac{1}{S'H^{-1}S} \quad (11)$$

Proof

Using (7), we have

$$E(R'Y_{[n,c]}^*) = R'S \dots$$

Hence, $R'Y_{[n,c]}^*$ will be an unbiased estimator for ... if

$$R'S = 1. \tag{12}$$

To minimize $R'R$ subject to the condition that $R'Y_{[n,c]}^*$ is unbiased for ... , we have to minimize

$$\{E_1 = R'R - 2\}_1(R'S - 1), \tag{13}$$

Where $\}_1$ is the Lagrangian multiplier. Differentiating (13) with respect to R and equating to zero, we get $2R - 2\}_1S = 0$.

That is,

$$R = \}_1S.$$

Substituting the value of R in (12), we get

$$\}_1 = \frac{1}{S'S}$$

Therefore,

$$R = \frac{S}{S'S}$$

Thus the required unbiased estimator $\hat{\dots}_1$ of ... is given by $\hat{\dots}_1 = \frac{S'}{S'S} Y_{[n,c]}^*$.

Then by using (8), the variance of $\hat{\dots}_1$ is given by

$$Var(\hat{\dots}_1) = (1 - \dots^2) \frac{1}{n} \sum_{i=1}^n \dagger^{2i} \frac{1}{S'S} + \dots^2 \frac{S'HS}{(S'S)^2}$$

Similarly, to minimize $R'HR$ subject to the condition that $R'Y_{[n,c]}^*$ is unbiased for ... , we have to minimize

$$\{E_2 = R'HR - 2\}_2(R'S - 1), \tag{14}$$

where $\}_2$ is the Lagrangian multiplier. Differentiating (14) with respect to R and equating to zero, we get

$$2HR - 2\}_2S = 0.$$

That is,

$$R = \}_2H^{-1}S.$$

Substituting the value of R in (12), we get

$$\}_2 = \frac{1}{S'H^{-1}S}.$$

Therefore,

$$R = \frac{H^{-1}S}{S'H^{-1}S}.$$

Thus the required unbiased estimator $\hat{\mu}_2$ of μ is given by $\hat{\mu}_2 = \frac{S'H^{-1}}{S'H^{-1}S} Y_{[n,c]}^*$.

Then by using (8), the variance of $\hat{\mu}_2$ is given by

$$\text{Var}(\hat{\mu}_2) = (1 - \mu^2) \frac{1}{n} \sum_{i=1}^n t_{2i}^2 \frac{S'H^{-2}S}{(S'H^{-1}S)^2} + \mu^2 \frac{1}{S'H^{-1}S}$$

Theorem 2.2 If $\hat{\mu}_1 = \frac{S'}{S'S} Y_{[n,c]}^*$ and $\hat{\mu}_2 = \frac{S'H^{-1}}{S'H^{-1}S} Y_{[n,c]}^*$ are two unbiased estimators of μ with variances given by (10) and (11) respectively, then $\hat{\mu}_1$ is more efficient than $\hat{\mu}_2$ if $|\mu| < \sqrt{\frac{K_2}{K_1 + K_2}}$ where

$$K_1 = \frac{S'HS}{(S'S)^2} - \frac{1}{S'H^{-1}S}$$

and

$$K_2 = \left[\frac{S'H^{-2}S}{(S'H^{-1}S)^2} - \frac{1}{S'S} \right] \frac{1}{n} \sum_{i=1}^n t_{2i}^2.$$

Proof

$$\text{Var}(\hat{\mu}_1) = (1 - \mu^2) \frac{1}{n} \sum_{i=1}^n t_{2i}^2 \frac{1}{S'S} + \mu^2 \frac{1}{S'H^{-1}S} + K_1 \mu^2, \quad (15)$$

$$\text{Var}(\hat{\mu}_2) = (1 - \mu^2) \frac{1}{n} \sum_{i=1}^n t_{2i}^2 \frac{1}{S'S} + \mu^2 \frac{1}{S'H^{-1}S} + K_2 (1 - \mu^2) \quad (16)$$

From (15) and (16), we have

$$\text{Var}(\hat{\mu}_1) < \text{Var}(\hat{\mu}_2) \text{ if } K_1 \mu^2 < K_2 (1 - \mu^2).$$

Thus $\hat{\mu}_1$ is more efficient than $\hat{\mu}_2$ if

$$\mu^2 < \frac{K_2}{K_1 + K_2}.$$

That is,

$$|\mu| < \sqrt{\frac{K_2}{K_1 + K_2}}.$$

3. ESTIMATION OF COMMON PARAMETERS \sim_2 AND \dagger_2

Let $(X_i, Y_i), i=1,2,\dots,n$ be independent bivariate random variables with (X_i, Y_i) having pdf $f_i(x, y)$ of the form

$$\frac{(2f\dagger_1\dagger_2)^{-1}}{\sqrt{1-\dots_i^2}} \exp\left\{\frac{-2^{-1}}{1-\dots_i^2}\left[\frac{(x-\sim_1)^2}{\dagger_1^2}-2\dots_i\frac{(x-\sim_1)(y-\sim_2)}{\dagger_1\dagger_2}+\frac{(y-\sim_2)^2}{\dagger_2^2}\right]\right\}$$

for $i=1,2,\dots,n$. In this section we estimate the common parameters \sim_2 and \dagger_2 under the assumption that $\dots_i, i=1,2,\dots,n$ are known using concomitants of order statistics of *inid* random variables.

Clearly the marginal distributions of X_i and Y_i are $N(\sim_1, \dagger_1)$ and $N(\sim_2, \dagger_2)$ respectively for $i=1,2,\dots,n$. Let $f(x)$ and $F(x)$ denote the marginal pdf and distribution function respectively of each of the X_i 's. Let $f_i(y|x)$ denote the conditional pdf of Y_i given $X_i = x, i=1,2,\dots,n$.

Then we have,

$$E[Y_{[r:n]}] = \sim_2 + \frac{1}{n} \sum_i \dots_i \dagger_2 r_{r:n} \tag{17}$$

$$\begin{aligned} E[Y_{[r:n]}^2] &= \frac{1}{n} \sum_i [\sim_2^2 + \dagger_2^2(1-\dots_i^2) + 2\dots_i\sim_2\dagger_2 r_{r:n} + \dots_i^2 \dagger_2^2 r_{r,n}] \\ &= \sim_2^2 + \dagger_2^2(1-\frac{1}{n} \sum_i \dots_i^2) + 2\sim_2\dagger_2 r_{r,n} \frac{1}{n} \sum_i \dots_i + \dagger_2^2 r_{r,n} \frac{1}{n} \sum_i \dots_i^2 \end{aligned}$$

Now,

$$Var(Y_{[r:n]}) = \dagger_2^2 + (S_{r,r:n} - 1) \frac{1}{n} \sum_i \dots_i^2 \dagger_2^2 + \frac{1}{n^2} \dagger_2^2 r_{r,n}^2 \sum_{i < j} (\dots_i - \dots_j)^2 \tag{18}$$

We have, for $r < s$,

$$\begin{aligned} E[Y_{[r:n]}Y_{[s:n]}] &= \frac{1}{n(n-1)} \sum_{i \neq j} (\sim_2^2 + \dots_i\sim_2\dagger_2 r_{r:n} + \dots_j\sim_2\dagger_2 r_{s:n} + \dots_i\dots_j \dagger_2^2 r_{r,s:n}) \\ &= \sim_2^2 + \frac{1}{n} \sum_i \dots_i \sim_2 \dagger_2 (r_{r:n} + r_{s:n}) + \frac{1}{n(n-1)} \dagger_2^2 r_{r,s:n} \sum_{i \neq j} \dots_i \dots_j \end{aligned}$$

Hence,

$$\begin{aligned} Cov[Y_{[r:n]}Y_{[s:n]}] &= E[Y_{[r:n]}Y_{[s:n]}] - E[Y_{[r:n]}]E[Y_{[s:n]}] \\ &= \frac{1}{n(n-1)} \dagger_2^2 S_{r,s:n} \sum_{i \neq j} \dots_i \dots_j - \frac{1}{n^2(n-1)} \dagger_2^2 r_{r:n} r_{s:n} \sum_{i < j} (\dots_i - \dots_j)^2. \tag{19} \end{aligned}$$

Consider the units of bivariate sample in which measurement of the X variate can be done easily where as a measurement of Y is not so easy or economic. In this case we order the X observations and make measurements only on the concomitants $Y_{[c+1:n]}, \dots, Y_{[n-c:n]}$. Now based on this restricted sample we may use estimates based on the available concomitants of order statistics.

Let

$$Y_{[n,c]} = (Y_{[c+1:n]}, Y_{[c+2:n]}, \dots, Y_{[n-c:n]})'$$

Then

$$E[Y_{[n,c]}] = \tilde{\tau}_2 \mathbf{1} + \dagger_2 \mathbf{r} \quad (20)$$

where $\mathbf{1}$ is a column vector of $n - 2c$ ones,

$$\mathbf{r} = \frac{1}{n} \sum_{i=1}^n \dots_i (\mathbf{r}_{c+1:n}, \mathbf{r}_{c+2:n}, \dots, \mathbf{r}_{n-c:n})'$$

and the variance covariance matrix of $Y_{[n,c]}$ can be written in the form

$$D[Y_{[n,c]}] = \dagger_2^2 G, \quad (21)$$

where

$G = \|g_{rs}\|$ given by

$$g_{rr} = 1 + (S_{r,r;n} - 1) \frac{1}{n} \sum_i \dots_i^2 + \frac{1}{n^2} r_{rn}^2 \sum_{i < j} (\dots_i - \dots_j)^2$$

and for $r \neq s$,

$$g_{rs} = \frac{1}{n(n-1)} S_{r,s;n} \sum_{i \neq j} \dots_i \dots_j - \frac{1}{n^2(n-1)} \sum_{i < j} (\dots_i - \dots_j)^2 r_{rn} r_{sn},$$

where i and j vary from 1 to n and r and s are such that $c+1 \leq r < s \leq n-c$.

Equations (20) and (21) together defines a generalized Gauss-Markov set up when the \dots_i 's are known and then the BLUEs $\tilde{\tau}_2$ and \dagger_2 are given by

$$\tilde{\tau}_2 = \frac{\mathbf{r}' G^{-1} (\mathbf{r}' \mathbf{1}' - \mathbf{1} \mathbf{r}') G^{-1}}{\Delta} Y_{[n,c]}$$

and

$$\dagger_2 = \frac{\mathbf{1}' G^{-1} (\mathbf{1} \mathbf{r}' - \mathbf{r}' \mathbf{1}') G^{-1}}{\Delta} Y_{[n,c]},$$

where

$$\Delta = (\mathbf{r}' G^{-1} \mathbf{r}) (\mathbf{1}' G^{-1} \mathbf{1}) - (\mathbf{r}' G^{-1} \mathbf{1})^2.$$

The variances of the above estimators are given by

$$Var(\hat{\tau}_2) = \frac{\mathbf{r}'\mathbf{G}^{-1}\mathbf{r}}{\Delta} \dagger_2^2$$

and

$$Var(\dagger_2) = \frac{\mathbf{1}'\mathbf{G}^{-1}\mathbf{1}}{\Delta} \dagger_2^2.$$

It is clear that $\hat{\tau}_2$ and \dagger_2 are linear functions of the concomitants and hence we can write

$$\hat{\tau}_2 = \sum_{r=c+1}^{n-c} a_r Y_{[r:n]}$$

and

$$\dagger_2 = \sum_{r=c+1}^{n-c} b_r Y_{[r:n]},$$

where $a_r, b_r, r = c + 1, c + 2, \dots, n - c$ are constants which can be determined.

The values of $\Gamma_{r:n}$ for different values of r and n are given in Harter (1961) and those of $S_{r,s:n}$ for different values of r, s and n are given in Sarhan and Greenberg (1956). Hence, the constants $a_r, b_r, r = c + 1, c + 2, \dots, n - c$ can be easily determined using *MATHCAD* software. For an illustration, let us assume that k of the observations are from a bivariate normal population with correlation coefficient ρ_1 and the remaining $n - k$ observations are from a bivariate normal population with correlation coefficient ρ_2 . Then we have computed the values of the constants $a_r, b_r, r = c + 1, c + 2, \dots, n - c$ and the variances of the estimators $\hat{\tau}_2$ and \dagger_2 for $(\rho_1, \rho_2) = (0.8, 0.7), (0.6, 0.5)$ for $n = 5$. The values are given in the following tables. From tables numbered 1 to 4, we observe that both $\hat{\tau}_2$ and \dagger_2 are estimated with more precision for larger values of ρ_i 's than for the cases with smaller values of ρ_i 's. Since $Var(\hat{\tau}_2)$ is always smaller than $Var(\dagger_2)$ for the concomitants of order statistics for a given collection of random variables we infer that concomitants of order statistics of *inid* n normal random variables can be more profitably used for estimating τ_2 than for estimating \dagger_2 . Very rarely in problems of estimation of common parameters of several distributions, explicit expression for the values of the proposed estimator exists. However in our method it can be explicitly expressed and hence we can determine the quality of our estimator as well.

Table 1: Coefficients a_i 's in the BLUE $\hat{\tau}_2 = \sum_{r=c+1}^{n-c} a_r Y_{[r:n]}$ and $Var(\hat{\tau}_2) / \tau_2^2$ for $\dots_1 = 0.8, \dots_2 = 0.7$

n	c	k	a_1	a_2	a_3	a_4	a_5	$Var(\hat{\tau}_2) / \tau_2^2$	
5	0	1	0.1995	0.2003	0.2004	0.2003	0.1995	0.2000	
		2	0.1991	0.2005	0.2008	0.2005	0.1991	0.2000	
		3	0.1991	0.2005	0.2008	0.2005	0.1991	0.2000	
		4	0.1994	0.2003	0.2006	0.2003	0.1994	0.2000	
	1	1			0.3370	0.3260	0.3370		0.2779
		2			0.3374	0.3253	0.3374		0.2744
		3			0.3379	0.3242	0.3379		0.2713
		4			0.3385	0.3230	0.3385		0.2685

Table 2: Coefficients b_i 's in the BLUE $\hat{\tau}_2 = \sum_{r=c+1}^{n-c} b_r Y_{[r:n]}$ and $Var(\hat{\tau}_2) / \tau_2^2$ for $\dots_1 = 0.8, \dots_2 = 0.7$.

n	c	k	b_1	b_2	b_3	b_4	b_5	$Var(\hat{\tau}_2) / \tau_2^2$	
5	0	1	-0.5064	-0.2132	0.0000	0.2132	0.5064	0.4243	
		2	-0.4927	-0.2076	0.0000	0.2076	0.4927	0.3921	
		3	-0.4798	-0.2018	0.0000	0.2018	0.4798	0.3625	
		4	-0.4678	-0.1959	0.0000	0.1959	0.4678	0.3350	
	1	1			-1.4033	0.0000	1.4033		2.2230
		2			-1.3644	0.0000	1.3644		2.0105
		3			-1.3291	0.0000	1.3291		1.8175
		4			-1.2949	0.0000	1.2949		1.6404

Table 3: Coefficients a_i 's in the BLUE $\tilde{\tau}_2 = \sum_{r=c+1}^{n-c} a_r Y_{[r:n]}$ and $Var(\tilde{\tau}_2) / \tau_2^2$ for $\dots_1 = 0.6, \dots_2 = 0.5$

n	c	k	a_1	a_2	a_3	a_4	a_5	$Var(\tilde{\tau}_2) / \tau_2^2$	
5	0	1	0.1995	0.2003	0.2004	0.2003	0.1995	0.2001	
		2	0.1994	0.2003	0.2006	0.2003	0.1994	0.2001	
		3	0.1994	0.2003	0.2006	0.2003	0.1994	0.2001	
		4	0.1996	0.2002	0.2004	0.2002	0.1996	0.2001	
	2	1			0.3351	0.3298	0.3351		0.3050
		2			0.3350	0.3300	0.3350		0.3010
		3			0.3350	0.3300	0.3350		0.2999
		4			0.3351	0.3298	0.3351		0.2975

Table 4: Coefficients b_i 's in the BLUE $\tilde{\tau}_2 = \sum_{r=c+1}^{n-c} b_r Y_{[r:n]}$ and $Var(\tilde{\tau}_2) / \tau_2^2$ for $\dots_1 = 0.6, \dots_2 = 0.5$.

n	c	k	b_1	b_2	b_3	b_4	b_5	$Var(\tilde{\tau}_2) / \tau_2^2$	
5	0	1	-0.7003	-0.2973	0.0000	0.2973	0.7003	0.9781	
		2	-0.6741	-0.2866	0.0000	0.2866	0.6741	0.8940	
		3	-0.6502	-0.2762	0.0000	0.2762	0.6502	0.8187	
		4	-0.6280	-0.2661	0.0000	0.2661	0.6280	0.7510	
	3	1			-1.9415	0.0000	1.9415		5.8262
		2			-1.8694	0.0000	1.8694		5.2755
		3			-1.8049	0.0000	1.8049		4.7905
		4			-1.7426	0.0000	1.7426		4.3519

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