

# Rank order probabilities for the dispersion problem

Subhash C. Kochar

*Indian Statistical Institute, New Delhi 110 016, India*

George Woodworth

*University of Iowa, Iowa City, IA 52242, USA*

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*Abstract:* First we consider the two-sample dispersion problem. Let  $X$  and  $Y$  be independent random variables of continuous type with distribution functions  $F$  and  $G$ , respectively, satisfying  $G(x) = F(\sigma x)$  for all  $x$  where  $\sigma > 0$  and  $F(x) = 1 - F(-x)$ , for all  $x$ . Let  $X_1, X_2$  ( $Y_1, Y_2$ ) be two independent copies of  $X$  ( $Y$ ) and define  $p(\sigma) = P[X_1 \leq Y_1 \leq Y_2 \leq X_2]$ . It is shown that  $p(\sigma)$  is nondecreasing in  $\sigma$  implying  $P[X_1 \leq Y_1 \leq Y_2 \leq X_2] \geq P[Y_1 \leq X_1 \leq X_2 \leq Y_2]$  for  $\sigma \geq 1$ . Next, we consider the bivariate scale problem where  $(X, Y)$  has joint c.d.f.  $F(x, y)$  satisfying  $F(x, y) = H(x, \sigma y)$ , where  $H(x, y)$  is bivariate symmetric and also  $H(x, y) = \bar{H}(-x, -y)$  for every  $(x, y)$ . Sufficient conditions are given under which  $p(\sigma)$  is nondecreasing in  $\sigma$ . These results have been applied to study the properties of some nonparametric tests for the two-sample dispersion and paired-sample problems.

*Keywords:* Mood's test for dispersion, U-statistic, bivariate symmetry.

## 1. Introduction

Let  $X = (X_1, \dots, X_m)$  and  $Y = (Y_1, \dots, Y_n)$  be two independent random samples drawn from absolutely continuous populations with densities  $f(\cdot)$  and  $g(\cdot)$ , respectively.  $F(\cdot)$  and  $G(\cdot)$  denote the corresponding distribution functions. We use the notation  $\bar{F}$  for  $1 - F$ ,  $W = (W_1, \dots, W_{m+n})$  denotes the order statistics of the combined sample  $(X, Y) = (X_1, \dots, X_m, Y_1, \dots, Y_n)$ , and  $Z = (Z_1, \dots, Z_{m+n})$  is a random vector of zeros and ones whose  $i$ th component,  $Z_i$ , is 0 if  $W_i$  comes from  $f(\cdot)$  and 1 if  $W_i$  comes from  $g(\cdot)$ .

Let  $z = (z_1, \dots, z_{m+n})$  be a fixed vector of zeros and ones; we define the transpose of  $z$  by  $z^t = (z_1^t, \dots, z_{m+n}^t)$ , where  $z_i^t = z_{m+n+1-i}$ .  $P(z) = P[Z = z]$  denotes the probability of the rank order  $z$ .

In a series of papers Savage (1956, 1957) and Savage, Sobel and Woodworth (1966) gave many interesting results on rank order probabilities for the two-sample problem. They mainly considered cases when the two distributions are ordered by monotone likelihood ratio property or when the distributions are symmetric differing only in their location parameters.

In Section 2, we consider the two-sample scale problem when both the distributions are symmetric about the origin. Some monotonicity results are obtained for the rank order probabilities and applications of these results to some testing problems are considered. In the last section, the bivariate scale problem has been considered.

**2. The two-sample scale problem**

**Lemma 2.1.** *Let  $f$  and  $g$  be symmetric about the origin, then  $P[z] = P[z^t]$ .*

**Proof.** Proof is simple and hence omitted.  $\square$

In particular, if  $G(x) = F(\sigma x)$ ,  $\sigma > 0$ , and  $f$  is symmetric about zero, then  $P[0011] = P[1100]$  and  $P[0101] = P[1010]$ , when  $m = n = 2$ . The only information about  $\sigma$  is contained in the arrangements [0110] and [1001].

Kochar and Gupta (1986) have shown that when  $m = n$ , the Mood's statistic for the two-sample-scale problem is a linear function of the U-statistic

$$S_{22} = \left[ \binom{m}{2} \binom{n}{2} \right]^{-1} \sum \phi(X_i, X_j; Y_k, Y_l), \tag{2.1}$$

where the summation is over  $1 \leq i < j \leq m, 1 \leq k < l \leq n$  and where

$$\phi(x_i, x_j; y_k, y_l) = \begin{cases} 1 & \text{if } z = [0110], \\ -1 & \text{if } z = [1001], \\ 0 & \text{otherwise.} \end{cases} \tag{2.2}$$

As a result,  $E[S_{2,2}] = P[0110] - P[1001]$ . To study the power properties of the Mood's test, we discuss the monotonicity properties of the functional  $p(\sigma) = P[0110]$  in the following theorem.

**Theorem 2.2.** *Let  $G(x) = F(\sigma x)$ ,  $\sigma > 0$ , where  $f$  is symmetric about the origin. Then  $p(\sigma) = P[0110]$  is nondecreasing in  $\sigma$ .*

**Proof.**

$$\begin{aligned} p(\sigma) &= 2P[X_1 \leq (Y_1, Y_2) \leq X_2] \\ &= 2 \int_{x \leq y} \int [G(y) - G(x)]^2 dF(x) dF(y) \end{aligned} \tag{2.3}$$

$$= 2 \int_{y \leq x} \int [G(x) - G(y)]^2 dF(x) dF(y). \tag{2.4}$$

From (2.3) and (2.4), we get

$$\begin{aligned} p(\sigma) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} [G(x) - G(y)]^2 dF(x) dF(y) \\ &= 2 \int_{-\infty}^{\infty} G^2(x) dF(x) - 2 \left[ \int_{-\infty}^{\infty} G(x) dF(x) \right]^2 \\ &= 2P[YYX] - 2P^2[YX] \\ &= 2P[YYX] - \frac{1}{2} \quad (\text{from Lemma 2.1}). \end{aligned}$$

Now

$$\begin{aligned}
 P[YYX] &= \int_{-\infty}^{\infty} F^2(\sigma x) \, dF(x) \\
 &= \int_{-\infty}^0 F^2(\sigma y) \, dF(y) + \int_0^{\infty} F^2(\sigma x) \, dF(x) \\
 &\quad \text{(making the transformation } x = -y, \text{ in the first integral and using symmetry)} \\
 &= \int_0^{\infty} [\bar{F}^2(\sigma x) + F^2(\sigma x)] \, dF(x).
 \end{aligned}$$

Since for  $x \geq 0$ , the integrand  $[F^2(\sigma x) + \bar{F}^2(\sigma x)]$  is nondecreasing in  $\sigma$ , the required result follows. □

**Corollary 2.3.** *Under the conditions of the above theorem,  $P[0110] - P[1001]$  is nondecreasing in  $\sigma$ . This implies:*

- (i)  $P[0110] > P[1001]$  for  $\sigma > 1$ . (2.5)
- (ii)  $\phi(X_1, X_2; Y_1, Y_2)$  is stochastically increasing in  $\sigma$ .

**Proof.** As  $G(x) = F(\sigma x)$ ,  $X \stackrel{\text{dist}}{=} \sigma Y$ . Hence

$$p(\sigma) = P[0110] = 2P[\sigma Y_1 \leq (Y_2, Y_3) \leq \sigma Y_4]$$

and

$$p[1001] = 2P[Y_1 \leq (\sigma Y_2, \sigma Y_3) \leq Y_4] = 2P\left[\frac{Y_1}{\sigma} \leq (Y_2, Y_3) \leq \frac{Y_4}{\sigma}\right] = p\left(\frac{1}{\sigma}\right).$$

Since  $p(\sigma)$  is nondecreasing in  $\sigma$ , it follows that  $p(\sigma) - p(1/\sigma) = P[0110] - P[1001]$  is nondecreasing in  $\sigma$ . (i) follows from this since for  $\sigma > 1$ ,  $p(\sigma) > p(1/\sigma)$ , (ii) follows from the fact that statistic  $\phi$  takes only three values  $+1, 0$  and  $-1$  with the property that for  $\sigma_1 < \sigma_2$ ,  $P_{\sigma_1}[\phi = 1] \leq P_{\sigma_2}[\phi = 1]$  and  $P_{\sigma_1}[\phi = -1] \geq P_{\sigma_2}[\phi = -1]$ . □

It follows from the properties of U-statistics and this corollary that the test based on large values of  $S_{2,2}$  (or equivalently on the Mood's statistic in case  $m = n$ ) is consistent for testing  $H_0: \sigma = 1$  against the alternative  $H_1: \sigma > 1$  when both the distributions are symmetric about the same point. It will be a virtue if one can extend the result (ii) of this corollary to prove the monotonicity property of the power function of the Mood's test for  $m, n > 2$ . However, we are unable to establish this result.

**Remark.** It can be shown that a sufficient condition for (2.5) to hold for non-symmetric distributions on  $[0, \infty)$  is that  $\log f$  is convex.

Kochar and Gupta (1986) generalized the Mood's test as follows. Let  $c$  and  $d$  be fixed integers such that  $2 \leq c \leq m, 2 \leq d \leq n$  and define

$$Q_{c,d}(x_1, \dots, x_c, y_1, \dots, y_d) = \begin{cases} 1 & \text{if } z_1 = z_{c+d} = 0, \\ -1 & \text{if } z_1 = z_{c+d} = 1, \\ 0 & \text{otherwise.} \end{cases}$$

Let  $S_{c,d}$  be the corresponding U-statistic. We have the following desirable property for the measure of dispersion  $q_{c,d}(\sigma) = E[S_{c,d}]$ .

**Theorem 2.4.** *Let  $G(x) = F(\sigma x)$ , where  $f$  is symmetric about the origin. Then*

$$q_{c,d}(\sigma) = E[S_{c,d}] = P[z_1 = z_{c+d} = 0] - P[z_1 = z_{c+d} = 1]$$

*is nondecreasing in  $\sigma > 0$ . In particular,  $q_{c,c}(\sigma) > 0$  for  $\sigma > 1$ .*

**Proof.** It is easy to see that

$$\begin{aligned} q_{c,d} &= P[\max(Y_1, \dots, Y_d) \leq \max(X_1, \dots, X_c)] - P[\min(Y_1, \dots, Y_d) \leq \min(X_1, \dots, X_c)] \\ &= c \int_{-\infty}^{\infty} [G^d(x)F^{c-1}(x) + \bar{G}^d(x)\bar{F}^{c-1}(x)] dF(x) - 1 \end{aligned} \tag{2.6}$$

$$= 2c \int_0^{\infty} [F^d(\sigma x)F^{c-1}(x) + \bar{F}^d(\sigma x)\bar{F}^{c-1}(x)] dF(x) - 1 \tag{2.7}$$

as the integrand in (2.6) is symmetric about zero. The required result follows since for  $x \geq 0$ , the integrand in (2.7) is a nondecreasing function of  $\sigma$ .

For  $\sigma > 1$ ,  $q_{c,c}(\sigma) > q_{c,c}(1/\sigma) = -q_{c,c}(\sigma)$ . Hence the result.  $\square$

This result establishes the consistency of the test  $S_{c,c}$  for the one-sided two-sample scale problem in case of symmetric distributions.

### 3. The bivariate scale model

We extend the two-sample scale model to the bivariate situation, allowing for dependence between  $X$  and  $Y$ . The joint c.d.f.  $F(x, y)$  of  $X$  and  $Y$  is of the form

$$F(x, y) = H(x, \sigma y) \tag{3.1}$$

where  $H(x, y)$  is a bivariate c.d.f. satisfying

$$H(x, y) = H(y, x) \quad \forall(x, y) \tag{3.2}$$

and  $\sigma > 0$ , is a constant.

In case of independence, this model reduces to the two-sample scale problem as considered earlier. We give some sufficient conditions under which  $p(\sigma) = P_{\sigma}[X_1 < (Y_1, Y_2) < X_2]$  is nondecreasing in  $\sigma$ , where  $(X_i, Y_i)$ ,  $i = 1, 2$ , are independent observations from  $F$ . The following lemmas are easy to prove, hence the proofs are omitted.

**Lemma 3.1.** *Let  $(X_1, Y_1)$  and  $(X_2, Y_2)$  be independent and identically distributed. Then*

$$P[0110] = 2P[(Y_1, Y_2) \leq X_1] - P[Y_2 \leq X_1, Y_1 \leq X_2] - P^2[Y_1 \leq X_1]. \quad \square$$

**Lemma 3.2.** *Let  $(X_1, Y_1)$  and  $(X_2, Y_2)$  be independent and identically distributed according to a distribution which is symmetric about  $(0, 0)$ , that is,*

$$P[X \leq x, Y \leq y] = P[X \geq -x, Y \geq -y] \quad \forall(x, y). \tag{3.3}$$

*Then the following are true:*

- (a)  $P[Y_2 \leq X_1, Y_1 \leq X_2] = P[X_2 \leq Y_1, X_1 \leq Y_2]$ .
- (b)  $P[Y \leq X] = P[X \leq Y] = \frac{1}{2}$ .
- (c)  $P[0110] - P[1001] = 2[P[(Y_1, Y_2) \leq X_1] - P[(X_1, X_2) \leq Y_1]]$ .  $\square$

**Lemma 3.3.** Let  $(X_1, Y_1)$  and  $(X_2, Y_2)$  be i.i.d. observations from a distribution  $F$  satisfying (3.1) and (3.2). Then

$$P_\sigma[(X_1, X_2) \leq Y_1] = \eta(1/\sigma)$$

where

$$\eta(\sigma) = P_\sigma[(Y_1, Y_2) \leq X_1]. \quad \square \tag{3.4}$$

**Theorem 3.4.** Let  $(X_1, Y_1)$  and  $(X_2, Y_2)$  be i.i.d. observations from a distribution  $F$  satisfying (3.1) and (3.3). Then a sufficient condition for  $\eta(\sigma)$  to be nondecreasing in  $\sigma$  is

$$P[Y \leq 0 | X = x] \geq \frac{1}{2} \quad \text{for } x \geq 0. \tag{3.5}$$

**Proof.** Let  $H_1(x) = H(x, \infty)$ ,  $H_2(x) = H(\infty, x)$  and  $h_i = H_i'$ ,  $i = 1, 2$ .

$$\begin{aligned} \eta(\sigma) &= P_\sigma[Y_1 \leq X_2, Y_2 \leq X_2] \\ &= \sigma \int_{-\infty}^{\infty} \left[ \int_{-\infty}^{x_2} h(x_2, \sigma y) dy \right] H_2(\sigma x_2) dx_2 \\ &= \sigma \left[ \int_{-\infty}^0 \left\{ \int_{-\infty}^{x_2} h(x_2, \sigma y) dy \right\} H_2(\sigma x_2) dx_2 + \int_0^{\infty} \left\{ \int_{-\infty}^{x_2} h(x_2, \sigma y) dy \right\} H_2(\sigma x_2) dx_2 \right]. \end{aligned}$$

Making the substitution  $x = -x_2^*$  and  $y = -y^*$  in the first integral; and using (3.3), we get

$$\eta(\sigma) = \int_0^{\infty} \left[ \int_{-\infty}^{\sigma x} h(x, y) dy \right] H_2(\sigma x) + \left[ \int_{\sigma x}^{\infty} h(x, y) dy \right] \bar{H}_2(\sigma x) dx. \tag{3.6}$$

Differentiating (3.6) with respect to  $\sigma$  and assuming that differentiation under the integral sign is permissible, we get

$$\begin{aligned} \eta'(\sigma) &= \int_0^{\infty} x [H_2(\sigma x) - \bar{H}_2(\sigma x)] h(x, \sigma x) dx \\ &\quad + \int_0^{\infty} x h_2(\sigma x) \left\{ \int_{-\infty}^{\sigma x} h(x, y) dy - \int_{\sigma x}^{\infty} h(x, y) dy \right\} dx. \end{aligned}$$

For  $x \geq 0$ , the integrand in the first integral is nonnegative.

A sufficient condition for the second integral to be nonnegative for all  $x \geq 0, \sigma > 0$  is

$$\int_{-\infty}^{\sigma x} h(x, y) dy - \int_{\sigma x}^{\infty} h(x, y) dy \geq 0 \quad \text{for } x \geq 0,$$

That is,

$$\int_{-\infty}^{\sigma x} \frac{h(x, y)}{h_1(x)} dy \geq \frac{1}{2} \quad \text{for } x \geq 0. \tag{3.7}$$

This will hold for all  $x \geq 0$  and  $\sigma > 0$  if (3.5) holds.  $\square$

**Corollary 3.5.** If  $H$  satisfies (3.2), then under the conditions of Theorem 3.4,

$$P[0110] - P[1001] = 2[\eta(\sigma) - \eta(1/\sigma)]$$

is nondecreasing in  $\sigma$ . In particular,  $P[0110] \geq P[1001]$ .  $\square$

Proof follows from Lemmas 3.2, 3.3 and Theorem 3.4.

**Remark.** If  $F$  is such that  $P[Y \leq y | X = x]$  is nondecreasing in  $x$  for each fixed  $y$ , we say  $Y$  is stochastically decreasing in  $X$  (see Barlow and Proschan, 1981). Since  $P[Y \leq 0 | X = 0] = \frac{1}{2}$  if  $(X, Y)$  is symmetric about  $(0, 0)$ , (3.5) will hold if  $Y$  is stochastically decreasing in  $X$ .

**Example.** Bivariate normal distribution with  $E(X) = E(Y)$ ,  $\text{Var}(X) = \sigma^2 \text{Var}(Y)$ , and  $\text{Cov}(X, Y) \leq 0$  satisfies the conditions of Theorem 3.4 and Corollary 3.5.

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