

## Error bounds for asymptotic expansions of some distributions in a multivariate two-stage procedure

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### 1. Introduction

In this paper we obtain error bounds for asymptotic expansions of the distributions of test statistics in a multivariate two-stage procedure. These statistics can be expressed as a scale mixture of a chi-square variable  $\chi_p^2$  with  $p$  degrees of freedom, i.e.

$$(1.1) \quad X = \sigma \chi_p^2,$$

where  $\sigma$  is a positive-valued random variable and is independent of  $\chi_p^2$ . The scale factor  $\sigma$  is defined by  $\sigma = \frac{1}{p} \text{tr}(S^{-1})$  for the case of a multivariate population, where  $nS$  is distributed as a Wishart distribution  $W_p(I_p, n)$ . For the case of two multivariate populations,  $\sigma = \frac{1}{2}(\sigma_1 + \sigma_2)$ , where  $\sigma_i = \frac{1}{p} \text{tr}(S_i^{-1})$ ,  $i = 1, 2$ , and  $n_i S_i$  are independently distributed as  $W_p(I_p, n_i)$ . Hyakutake and Siotani [6] obtained asymptotic expansions of the distribution of  $X$  in the two cases. Our purpose of this paper is to obtain explicit bounds for the approximations based on these asymptotic expansions. The method used is based on a general result (see, e.g., Fujikoshi and Shimizu [5]) for scale mixtures of the gamma distribution.

In the use of the result it is necessary that we evaluate the exact moments of  $\sigma^{\pm 1}$ . But it is generally difficult to obtain the exact ones in these cases. In this paper we derive appropriate approximations for their moments with error bounds. Using these results, we will obtain error bounds for asymptotic expansions of the distribution of  $X$ .

### 2. Scale mixture of a chi-square distribution

Here, we consider a scale mixture of a chi-square variable with  $p$  degrees of freedom, i.e.

$$(2.1) \quad X = \sigma \chi_p^2.$$

Let  $G(x; p)$  and  $g(x; p)$  be the distribution and the probability density function of  $\chi_p^2$ , respectively. Then the distribution function  $F(x)$  of  $X$  can be expressed as

$$F(x) = E_\sigma[G(x/\sigma; p)] .$$

The following two types of approximations have been proposed (cf. Fujikoshi and Shimizu [5]): For  $\delta = -1, 1$ ,

$$(2.2) \quad G_{\delta,k}(x; p) = E_\sigma[G_{\delta,k}(x, \sigma; p)]$$

where

$$G_{\delta,k}(x, \sigma; p) = G(x; p) + \sum_{j=1}^{k-1} \frac{1}{j!} b_{\delta,j}(x; p) g(x; p) (\sigma^\delta - 1)^j .$$

Here the coefficients  $b_{\delta,j}(x; p)$  are defined by

$$b_{\delta,j}(x; p) = \left( \frac{d}{ds} \right)^j G(xs^{-\delta}; p) \Big|_{s=1} / g(x; p)$$

or equivalently

$$b_{1,j}(x; p) = -xL_{j-1}^{(p/2)}(x/2) ,$$

$$b_{-1,j}(x; p) = (-1)^{j-1} xL_{j-1}^{(p/2-j)}(x/2) ,$$

where  $L_j^{(\lambda)}(x)$  is the Laguerre polynomial defined by

$$L_j^{(\lambda)}(x) = (-1)^j e^x x^{-\lambda} (d/dx)^j (x^{\lambda+j} e^{-x}) .$$

When the exact moments of  $\sigma^\delta$  are not available, we cannot use the approximation  $G_{\delta,k}(x; p)$ . Therefore, we consider to approximate  $(\sigma^\delta - 1)^j$  by a simple variable,  $m_{\delta,j}^*(\sigma)$ , whose exact moments are available. Namely, suppose that for  $j = 1, \dots, k - 1$ ,

$$(2.3) \quad (\sigma^\delta - 1)^j = m_{\delta,j}^*(\sigma) + R_{\delta,j}(\sigma)$$

and  $E_\sigma[m_{\delta,j}^*(\sigma)]$  can be evaluated. Then, we have the following result:

**THEOREM 2.1.** *Let  $X = \sigma\chi_p^2$  be a scale mixture of a chi-square variable. Suppose that for a given positive integer  $k$ ,  $E[\sigma^k] < \infty$ ,  $E[\sigma^{-k}] < \infty$  and  $E_\sigma[m_{\delta,j}^*(\sigma)] < \infty$ ,  $j = 1, \dots, k - 1$ . Then, letting*

$$(2.4) \quad G_{\delta,k}^*(x; p) = G(x; p) + \sum_{j=1}^{k-1} \frac{1}{j!} b_{\delta,j}(x; p) g(x; p) E_\sigma[m_{\delta,j}^*(\sigma)] ,$$

*it holds that*

$$\begin{aligned} \sup_x |F(x) - G_{\delta,k}^*(x; p)| &\leq \frac{1}{k!} \bar{b}_{\delta,k}(p) E_\sigma[(\sigma \vee \sigma^{-1} - 1)^k] \\ &\quad + \sum_{j=1}^{k-1} \frac{1}{j!} \bar{b}_{\delta,j}(p) |E_\sigma[R_{\delta,j}(\sigma)]| \\ &\leq \frac{1}{k!} \bar{b}_{\delta,k}(p) E_\sigma[|\sigma - 1|^k + |\sigma^{-1} - 1|^k] \\ &\quad + \sum_{j=1}^{k-1} \frac{1}{j!} \bar{b}_{\delta,j}(p) E_\sigma[|R_{\delta,j}(\sigma)|], \end{aligned}$$

where  $\bar{b}_{\delta,j}(p) = \sup_{x>0} |b_{\delta,j}(x; p)g(x; p)|$ ,  $j = 1, \dots, k$ .

PROOF. It is known (cf. Fujikoshi and Shimizu [5]) that

$$(2.5) \quad \sup_x |F(x) - G_{\delta,k}(x; p)| \leq \frac{1}{k!} \bar{b}_{\delta,k}(p) E_\sigma[(\sigma \vee \sigma^{-1} - 1)^k].$$

Therefore, the result follows from that

$$G_{\delta,k}(x; p) = G_{\delta,k}^*(x; p) + \sum_{j=1}^{k-1} \frac{1}{j!} b_{\delta,j}(x; p)g(x; p)E_\sigma[R_{\delta,j}(\sigma)].$$

We note that if the first  $k - 1$  moments of  $\sigma^\delta$  in Theorem 2.1 can be obtained, we can take  $R_{\delta,j} = 0$  for  $j = 1, \dots, k - 1$ .

### 3. Test statistics in a multivariate two-stage procedure

Some multivariate two-stage procedures have been proposed (see, e.g., Chatterjee [1], Dudewicz and Bishop [2]) for the purpose of overcoming the complexity which arises in statistical analysis of a normal population or several normal populations with different covariance matrices. For a summary, see Siotani, Hayakawa and Fujikoshi [7, Sections 5.6.3 and 6.4.3]. Here we consider test procedures for hypotheses

$$(i) \quad H_0: \mu = \mathbf{0} \quad \text{in } N_p(\mu, \Sigma)$$

and

$$(ii) \quad H_0: \mu_1 = \mu_2 \quad \text{in } N_p(\mu_1, \Sigma_1) \text{ and } N_p(\mu_2, \Sigma_2),$$

under a two-stage sampling scheme. For the test of (i), Chatterjee [1] proposed a statistic whose null distribution can be expressed as

$$(3.1) \quad X = \sigma \chi_p^2,$$

where  $\sigma = \frac{1}{p} \text{tr}(S^{-1})$ ,  $nS \sim W_p(I_p, n)$  and  $S$  is independent of  $\chi_p^2$ . The two-stage procedure for the test of (ii) is based on a statistic whose null distribution can be expressed as

$$(3.2) \quad \tilde{X} = \tilde{\sigma} \chi_p^2,$$

where  $\tilde{\sigma} = \frac{1}{2}(\sigma_1 + \sigma_2)$ ,  $\sigma_i = \frac{1}{p} \text{tr}(S_i^{-1})$ ,  $i = 1, 2$ , and  $S_i$ 's are independent of  $\chi_p^2$ .

Here  $n_1 S_1$  and  $n_2 S_2$  are independently distributed as Wishart distributions  $W_p(I_p, n_1)$  and  $W_p(I_p, n_2)$ , respectively, with  $n_1 = n_2 = n$ .

The exact distributions of  $X$  and  $\tilde{X}$  are known only when  $p = 1, 2$  and  $p = 1$ , respectively (see, e.g., Hyakutake and Siotani [6]). On the other hand, Hyakutake and Siotani [6] obtained asymptotic expansions of the distributions of  $X$  and  $\tilde{X}$  with respect to  $n^{-1}$ . Our purpose is to obtain error bounds for their asymptotic expansions. For the distribution of  $\tilde{X}$ , we shall treat the case where  $n_1$  and  $n_2$  may be different.

### 3.1. The distribution of $X$

It is known (see, e.g., Watamori [8]) that the first four moments of

$$(3.3) \quad \sigma = \frac{1}{p} \text{tr}(S^{-1}), \quad \text{where } nS \sim W_p(I_p, n)$$

are given as follows:

LEMMA 3.1. *Suppose that  $nS \sim W_p(I_p, n)$ . Then the  $k$ -th moment of  $\sigma = \frac{1}{p} \text{tr}(S^{-1})$  exists for  $q = n - p \geq 2k$ , and*

$$E(\sigma) = d_1^{-1} n,$$

$$E(\sigma^2) = d_2^{-1} n^2 \{p(q-2) + 2\},$$

$$E(\sigma^3) = d_3^{-1} n^3 \{p^2(q^2 - 5q + 2) + 6p(q-3) + 16\},$$

$$E(\sigma^4) = d_4^{-1} n^4 \{p^3(q^4 - 11q^3 + 28q^2 + 8q - 32) + 12p^2(q^3 - 9q^2 + 18q - 4) + 4p(19q^2 - 117q + 152) + 48(5q - 11)\},$$

where

$$d_1 = q - 1, \quad d_2 = pq(q-1)(q-3),$$

$$d_3 = p^2 q(q+1)(q-1)(q-3)(q-5)$$

and

$$d_4 = p^3q(q + 1)(q + 2)(q - 1)(q - 2)(q - 3)(q - 5)(q - 7).$$

Let

$$(3.4) \quad m_{\delta,j} = E_\sigma[(\sigma^\delta - 1)^j]$$

for  $\delta = 1, -1$ . Then, from Lemma 3.1 we obtain that

$$\begin{aligned} m_{1,1} &= d_1^{-1}(p + 1), & m_{1,2} &= d_2^{-1}[2q^2 + p\{(p^2 + 2p + 7)q - 2p(p - 1)\}], \\ m_{1,3} &= d_3^{-1}[2(3p^2 + 3p + 8)q^3 + p\{(p^4 + 3p^3 + 21p^2 + p + 78)q^2 \\ &\quad - p(5p^3 - 3p^2 + 45p - 123)q + 2p^2(p - 1)(p - 23)\}], \\ (3.5) \quad m_{1,4} &= d_4^{-1}[12pq^6 + 4(3p^4 + 6p^3 + 37p^2 - 5p + 60)q^5 + (p^7 + 4p^6 \\ &\quad + 42p^5 - 32p^4 + 385p^3 - 588p^2 + 1824p - 528)q^4 \\ &\quad - p\{(11p^6 + 8p^5 + 306p^4 - 504p^3 + 2679p^2 - 5552p \\ &\quad + 3904)q^3 - 4p(7p^5 - 53p^4 + 153p^3 - 1083p^2 + 2375p \\ &\quad - 2556)q^2 - 4p^2(2p^4 + 170p^3 - 507p^2 + 2388p - 2817)q \\ &\quad + 16p^3(p - 1)(2p^2 + 19p - 250)\}]. \end{aligned}$$

On the other hand, it seems that the exact moments of  $\sigma^{-1}$  are very complicated. However, we can obtain the following result:

LEMMA 3.2. *Under the same notation as in Lemma 3.1, it holds that*

$$E_\sigma[|\sigma^{-1} - 1|^j] \leq E_\sigma[|\sigma - 1|^j] + E[|n^{-1}\chi_{n-p+1}^2 - 1|^j]$$

for  $j \geq 1$ .

PROOF. First for  $\sigma \geq 1$ , we have

$$0 \leq 1 - \sigma^{-1} = \sigma^{-1}(\sigma - 1) \leq \sigma - 1,$$

which implies

$$(3.6) \quad |\sigma^{-1} - 1|^j \leq |\sigma - 1|^j, \quad j = 1, 2, \dots$$

Next, assume  $0 < \sigma \leq 1$  and let  $H = [\mathbf{h}_1, \dots, \mathbf{h}_p]$  be a  $p \times p$  orthogonal matrix. Then

$$\begin{aligned} 0 \leq \sigma^{-1} - 1 &= \left(\frac{1}{p} \sum_{i=1}^p \mathbf{h}_i' S^{-1} \mathbf{h}_i\right)^{-1} - 1 \\ &\leq \frac{1}{p} \sum_{i=1}^p (\mathbf{h}_i' S^{-1} \mathbf{h}_i)^{-1} - 1 \\ &= \frac{1}{p} \sum_{i=1}^p \{(\mathbf{h}_i' S^{-1} \mathbf{h}_i)^{-1} - 1\}. \end{aligned}$$

Here we note that  $\{\mathbf{h}'_i(n\mathbf{S})^{-1}\mathbf{h}_i\}^{-1}$  ( $i = 1, \dots, p$ ) are identically distributed as  $\chi_{n-p+1}^2$  (see, e.g., Siotani, Hayakawa and Fujikoshi [7]), but they are not necessarily independent. Hence

$$\begin{aligned}
 (3.7) \quad E_S \left[ \left| \frac{1}{p} \sum_{i=1}^p \{(\mathbf{h}'_i \mathbf{S}^{-1} \mathbf{h}_i)^{-1} - 1\} \right|^j \right] \\
 &= \frac{1}{p^j} E_S \left[ \left| \sum_{i_1, \dots, i_j=1}^p \{(\mathbf{h}'_{i_1} \mathbf{S}^{-1} \mathbf{h}_{i_1})^{-1} - 1\} \dots \{(\mathbf{h}'_{i_j} \mathbf{S}^{-1} \mathbf{h}_{i_j})^{-1} - 1\} \right|^j \right] \\
 &\leq \frac{1}{p^j} \sum_{i_1, \dots, i_j=1}^p E_S \left[ \{ |(\mathbf{h}'_{i_1} \mathbf{S}^{-1} \mathbf{h}_{i_1})^{-1} - 1|^j \times \dots \times |(\mathbf{h}'_{i_j} \mathbf{S}^{-1} \mathbf{h}_{i_j})^{-1} - 1|^j \}^{1/j} \right] \\
 &\leq \frac{1}{p^j} \sum_{i_1, \dots, i_j=1}^p E_S \left[ \frac{1}{j} \{ |(\mathbf{h}'_{i_1} \mathbf{S}^{-1} \mathbf{h}_{i_1})^{-1} - 1|^j + \dots + |(\mathbf{h}'_{i_j} \mathbf{S}^{-1} \mathbf{h}_{i_j})^{-1} - 1|^j \} \right] \\
 &= E[|n^{-1}\chi_{n-p+1}^2 - 1|^j].
 \end{aligned}$$

Using (3.6) and (3.7), we obtain the desired result.

Let

$$(3.8) \quad l_{2j} = E[(n^{-1}\chi_{n-p+1}^2 - 1)^{2j}].$$

Then for  $j = 1, 2$ ,

$$\begin{aligned}
 (3.9) \quad l_2 &= \frac{2}{n} + \frac{(p-1)(p-3)}{n^2}, \\
 l_4 &= \frac{4}{n^2} \left( 3 + \frac{3p^2 - 20p + 29}{n} \right) + \frac{(p-1)(p-3)(p-5)(p-7)}{n^4}.
 \end{aligned}$$

Using the above results, we obtain the following results:

**THEOREM 3.1.** *Let  $F(x)$  be the distribution function of  $X$  defined by (3.1). Then for the (non-modified) approximation  $G_{1,k}(x; p)$  defined by (2.7) and its error*

$$\varepsilon_{1,k} = \varepsilon_{1,k}(p) = \sup_{x>0} |F(x) - G_{1,k}(x; p)|,$$

it holds that

$$\begin{aligned}
 \varepsilon_{1,1} &\leq \bar{b}_{1,1}(p) \{m_{1,2}^{1/2} + (m_{1,2} + l_2)^{1/2}\}, \\
 \varepsilon_{1,k} &\leq \frac{1}{k!} \bar{b}_{1,k}(p) \{m_{1,k} + (m_{1,k} + l_k)\} \quad (k = 2, 4),
 \end{aligned}$$

where  $\bar{b}_{1,j}(p)$ 's are given in Theorem 2.2, and  $m_{1,j}$  and  $l_{2,j}$  are given by (3.5) and (3.9), respectively.

PROOF. These inequalities are immediately obtained from Lemma 3.2 and Theorem 2.2.

Next, we consider the modified approximation  $G_{\delta,k}^*(x; p)$  with  $\delta = -1$  for  $F(x)$ . Since

$$(3.10) \quad \frac{1}{\sigma} - 1 = -(\sigma - 1) + \frac{(\sigma - 1)^2}{\sigma},$$

we can approximate  $(\sigma^{-1} - 1)$  by  $-(\sigma - 1)$ . Further, its error is bounded by

$$(3.11) \quad 0 \leq E \left\{ \frac{(\sigma - 1)^2}{\sigma} \right\} \leq /E\{(1 - \sigma^{-1})^2\} E\{(\sigma - 1)^2\}]^{1/2} \\ \leq \frac{1}{2} \{E(\sigma - 1)^2 + E(\sigma^{-1} - 1)^2\}.$$

Using these results, we obtain the following result:

THEOREM 3.2. Let  $G_{\pm 1,2}^*(x; p)$  be the modified approximation defined by (2.9) with  $m_{-1,1}^*(\sigma) = -(\sigma - 1)$ . Then it holds that

$$\sup_{x>0} |F(x) - G_{\pm 1,2}^*(x; p)| \leq \frac{1}{2} \{\bar{b}_{-1,1}(p) + \bar{b}_{-1,2}(p)\} \{m_{1,2} + (m_{1,2} + l_2)\}.$$

### 3.2. The distribution of $\tilde{X}$

First, we consider the case when  $p$  is arbitrary. The following lemma is useful to obtain error bounds for asymptotic expansions of the distribution of  $\tilde{X}$ :

LEMMA 3.3. Let  $\sigma_1$  and  $\sigma_2$  are positive and mutually independent, and let

$$(3.12) \quad \tilde{\sigma} = \frac{1}{2}(\sigma_1 + \sigma_2).$$

Then for  $j = 1, 2, \dots$

$$(i) \quad E_{\tilde{\sigma}}[(\tilde{\sigma} - 1)^j] = 2^{-j} \sum_{i=0}^j \binom{j}{i} E_{\sigma_1}[(\sigma_1 - 1)^{j-i}] E_{\sigma_2}[(\sigma_2 - 1)^i],$$

$$(ii) \quad E_{\tilde{\sigma}}[|\tilde{\sigma}^{-1} - 1|^j] \leq E_{\sigma_1}[|\sigma_1^{-1} - 1|^j] + E_{\sigma_2}[|\sigma_2^{-1} - 1|^j].$$

PROOF. (i) is obvious from (3.12). Next, if  $0 < \tilde{\sigma} \leq 1$ ,

$$0 \leq \tilde{\sigma}^{-1} - 1 \leq (\sigma_1 \wedge \sigma_2)^{-1} - 1 = \sigma_1^{-1} \vee \sigma_2^{-1} - 1.$$

Similarly, if  $\tilde{\sigma} > 1$ ,

$$0 \geq \tilde{\sigma}^{-1} - 1 \geq (\sigma_1 \vee \sigma_2)^{-1} - 1 = \sigma_1^{-1} \wedge \sigma_2^{-1} - 1.$$

Therefore

$$\begin{aligned} |\tilde{\sigma}^{-1} - 1|^j &\leq \max\{ |(\sigma_1^{-1} - 1) \vee (\sigma_2^{-1} - 1)|^j, |(\sigma_1^{-1} - 1) \wedge (\sigma_2^{-1} - 1)|^j \} \\ &\leq |\sigma_1^{-1} - 1|^j + |\sigma_2^{-1} - 1|^j, \end{aligned}$$

which implies (ii).

Using the above results, we obtain the following results:

**THEOREM 3.3.** *Let  $\tilde{F}(x)$  be the distribution function of  $\tilde{X}$  defined by (3.2). Then for the approximation  $\tilde{G}_{1,k}(x; p)$  defined by (2.7) with  $\sigma$  replaced by  $\tilde{\sigma}$  and its error*

$$\tilde{\varepsilon}_{1,k} = \sup_{x>0} |\tilde{F}(x) - \tilde{G}_{1,k}(x; p)|,$$

it holds that

$$\begin{aligned} \tilde{\varepsilon}_{1,1} &\leq \bar{b}_{1,1}(p) \left[ \tilde{m}_{1,2}^{1/2} + \left\{ \sum_{i=1}^2 (m_{1,2}^{(i)} + l_2^{(i)}) \right\}^{1/2} \right], \\ \tilde{\varepsilon}_{1,k} &\leq \frac{1}{k!} \bar{b}_{1,k}(p) \left[ \tilde{m}_{1,k} + \sum_{i=1}^2 \{m_{1,k}^{(i)} + l_k^{(i)}\} \right] \quad (k = 2, 4), \end{aligned}$$

where

$$(3.13) \quad \tilde{m}_{1,j} = E_{\tilde{\sigma}}[(\tilde{\sigma} - 1)^j], \quad m_{1,j}^{(i)} = E_{\sigma_i}[(\sigma_i - 1)^j]$$

and

$$(3.14) \quad l_j^{(i)} = E[(n_i^{-1} \chi_{n_i-p+1}^2 - 1)^j], \quad i = 1, 2.$$

**PROOF.** These inequalities are immediately obtained from Lemmas 3.2, 3.3, and Theorem 2.2.

Next, we consider the modified approximation  $\tilde{G}_{\delta,k}^*(x; p)$  with  $\delta = -1$  for  $\tilde{F}(x)$ . Using (3.10) and (3.11) with  $\sigma$  replaced by  $\tilde{\sigma}$ , we obtain the following result:

**THEOREM 3.4.** *Let  $\tilde{G}_{1,2}^*(x; p)$  be the modified approximation defined by (2.9) with  $m_{-1,1}^*(\sigma)$  replaced by  $-(\tilde{\sigma} - 1)$ . Then, it holds that*



$$\sup_{x>0} |\tilde{F}(x) - \tilde{G}^*_{-1,2}(x; p)| \leq \frac{1}{2} \{ \bar{b}_{-1,1}(p) + \bar{b}_{-1,2}(p) \} \left[ \tilde{m}_{1,2} + \sum_{i=1}^2 \{ m_{1,2}^{(i)} + l_2^{(i)} \} \right].$$

Now, in the following we consider the case  $p = 2$ . For this special case, we can easily evaluate the exact moments of both  $\sigma = \frac{1}{p} \text{tr}(S^{-1})$  and  $\sigma^{-1}$  as follows:

LEMMA 3.4. Let  $\sigma = \frac{1}{p} \text{tr}(S^{-1})$ , where  $nS \sim W_p(I_p, n)$ . When  $p = 2$ , it holds that

(i) if  $n - 2j - 1 > 0$ ,

$$E(\sigma^j) = \frac{n - 1}{n - 2j - 1} \cdot \frac{n^j}{\prod_{i=1}^j (n - i)},$$

(ii) for  $j \geq 1$ ,

$$E(\sigma^{-j}) = \frac{n - 1}{n + 2j - 1} \cdot \frac{\prod_{i=0}^{j-1} (n + i)}{n^j}.$$

PROOF. When  $p = 2$ , we can write  $nS$  as

$$nS = \begin{pmatrix} t_{11} & t_{12} \\ 0 & t_{22} \end{pmatrix}' \begin{pmatrix} t_{11} & t_{12} \\ 0 & t_{22} \end{pmatrix},$$

where  $t_{ii}^2 \sim \chi_{n-i+1}^2$ ,  $i = 1, 2$ ,  $t_{12} \sim N(0, 1)$  and  $t_{11}$ ,  $t_{12}$  and  $t_{22}$  are mutually independent. This implies

$$\begin{aligned} \sigma &= \frac{n}{2} (t_{11}^2 + t_{12}^2 + t_{22}^2) / (t_{11}^2 t_{22}^2) \\ &= (4T_1 T_2)^{-1} \left( \frac{1}{2n} T_3 \right)^{-1}, \end{aligned}$$

where  $T_i = t_{ii}^2 T_3^{-1}$ ,  $i = 1, 2$  and  $T_3 = t_{11}^2 + t_{12}^2 + t_{22}^2$ . It is easily seen that (i)  $(T_1, T_2, 1 - T_1 - T_2) \sim D_3(n/2, (n - 1)/2, 1/2)$ , a three dimensional Dirichlet distribution with degrees of freedom  $n/2$ ,  $(n - 1)/2$  and  $1/2$ , and therefore  $4T_1 T_2 \sim B((n - 1)/2, 1)$ , a beta distribution with degrees of freedom  $(n - 1)/2$  and 1, (ii)  $T_3 \sim \chi_{2n}^2$  and (iii)  $(T_1, T_2)$  and  $T_3$  are mutually independent. Using these properties, we can easily obtain the desired results.

From Lemma 3.4 we obtain that for  $p = 2$ ,

$$m_{1,1} = \frac{3}{n - 3}, \quad m_{1,2} = \frac{n^2 + 11n - 30}{(n - 2)(n - 3)(n - 5)},$$

$$(3.15) \quad m_{1,3} = \frac{13n^2 + 37n - 210}{(n-2)(n-3)(n-5)(n-7)},$$

$$m_{1,4} = \frac{3(n^4 + 38n^3 - 181n^2 - 514n + 2520)}{(n-2)(n-4)(n-3)(n-5)(n-7)(n-9)},$$

$$m_{-1,1} = -\frac{2}{n+1}, \quad m_{-1,2} = \frac{n^2 + 8n - 1}{n(n+1)(n+3)},$$

$$(3.16) \quad m_{-1,3} = -\frac{2(2n^3 + 21n^2 - 2n + 3)}{n^2(n+1)(n+3)(n+5)},$$

$$m_{-1,4} = \frac{3n^5 + 62n^4 + 426n^3 + 28n^2 - 45n - 90}{n^3(n+1)(n+3)(n+5)(n+7)}.$$

Using (3.15) and (3.16), we can improve Theorems 3.3 and 3.4 (in the case  $p = 2$ ) as follows:

**THEOREM 3.3'.** *With the same notations as in Theorem 3.3 it holds that for the case  $p = 2$ ,*

$$\tilde{\varepsilon}_{1,1} \leq 0.36788[\tilde{m}_{1,2}^{1/2} + \{m_{-1,2}^{(1)} + m_{-1,2}^{(2)}\}^{1/2}],$$

$$\tilde{\varepsilon}_{1,2} \leq 0.23058[\tilde{m}_{1,2} + m_{-1,2}^{(1)} + m_{-1,2}^{(2)}],$$

$$\tilde{\varepsilon}_{1,4} \leq 0.13242[\tilde{m}_{1,4} + m_{-1,4}^{(1)} + m_{-1,4}^{(2)}],$$

where  $m_{\delta,j}^{(i)}$  are the ones obtained from  $m_{\delta,j}$  by replacing  $n$  by  $n_i$ .

**THEOREM 3.4'.** *With the same notations as in Theorem 3.4 it holds that*

$$\sup_{x>0} |\tilde{F}(x) - \tilde{G}_{-1,2}^*(x; 2)| \leq 0.31929\{\tilde{m}_{1,2} + m_{-1,2}^{(1)} + m_{-1,2}^{(2)}\}.$$

**REMARK.** For the numerical values of  $\bar{b}_{-1,j}(p)$  and  $\bar{b}_{1,j}(p)$ , see Fujikoshi [3] and Fujikoshi and Shimizu [4], respectively.

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