# Error bounds for asymptotic expansions of the maximums of the multivariate *t*- and *F*-variables with common denominator

Yasunori FUJIKOSHI (Received July 20, 1988)

### 1. Introduction

Let  $X = (X_1, ..., X_p)$  be a scale mixture of a *p*-dimensional random vector  $Z = (Z_1, ..., Z_p)$  with scale factor  $\sigma > 0$ , i.e.,

$$(1.1) X = \sigma Z,$$

where Z and  $\sigma$  are independent. Let  $F_p$  and  $Q_p$  denote the distribution functions of X and Z, respectively. Then

(1.2) 
$$F_{p}(\mathbf{x}) = P(X_{1} \le x_{1}, ..., X_{p} \le x_{p})$$
$$= E_{\sigma}[Q_{p}(\sigma^{-1}\mathbf{x})],$$

where  $\mathbf{x} = (x_1, ..., x_p)$ . The distribution function of  $Max\{X_j\}$  is given by  $F_p(x, ..., x)$ . We are concerned with asymptotic expansions of the distribution functions of  $Max\{X_j\}$  and their error bounds in the two important special cases:

(i)  $Z_1, \ldots, Z_p$  i.i.d. ~  $N(0, 1), \sigma = (\chi_n^2/n)^{1/2},$ 

(ii) 
$$Z_1, \ldots, Z_n$$
 i.i.d.  $\sim G(\lambda), \qquad \sigma = \chi_n^2/n,$ 

where  $G(\lambda)$  denotes the gamma distribution with the probability density function  $g(x; \lambda) = x^{\lambda-1}e^{-x}/\Gamma(\lambda)$ , if x > 0, and = 0, if  $x \le 0$ . The random vector X in the case (i) is a multivariate *t*-variable with common denominator. The random vector X in the case (ii) is essentially equivalent to a multivariate *F*-variable with common denominator. These distributions are used in simultaneous inferences about the means of normal populations. It may be noted that asymptotic expansions of the distributions of Max $\{X_j\}$  in the cases (i) and (ii) have been studied by Hartley [6], Nair [7], Dunnett and Sobel [2], Chambers [1], etc. The purpose of this paper is to give a unified derivation of the asymptotic expansions as well as their error bounds.

In Section 2 we give two types of asymptotic approximations for the distribution function of X and their error bounds. The one is newly given, but the other has been given in Fujikoshi and Shimizu [5]. In Section 3 we

consider the distribution of  $Max\{X_j\}$  in the case when  $Z_1, \ldots, Z_p$  are independent and identically distributed. The results obtained are based on further reductions of the general results in Section 2. In Section 4 we obtain asymptotic expansions of the distributions of  $Max\{X_j\}$  and their error bounds in the two cases (i) and (ii).

#### 2. The distribution of X

We assume that the support of Z is either  $\Omega = \mathbb{R}^p$  or  $\mathbb{R}^p_+$ , and  $Q_p$  is k times continuously differentialbe on  $\Omega$ . We consider the following two types of approximations for the function  $Q_p(\sigma^{-1}\mathbf{x})$  in (1.2):

(2.1) 
$$A_{p,\delta,k}(x, \sigma) = \sum_{j=0}^{k-1} \frac{1}{j!} a_{p,\delta,j}(x) (\sigma^{2\delta} - 1)^{j},$$

(2.2) 
$$B_{p,\delta,k}(\boldsymbol{x}, \sigma) = \sum_{j=0}^{k-1} \frac{1}{j!} b_{p,\delta,j}(\boldsymbol{x}) (\sigma^{\delta} - 1)^{j},$$

where  $\delta = -1$  or 1, and

(2.3) 
$$a_{p,\delta,j}(\mathbf{x}) = (d^j/ds^j)Q_p(s^{-\delta/2}\mathbf{x})\Big|_{s=1},$$

(2.4) 
$$b_{p,\delta,j}(\mathbf{x}) = (d^j/ds^j)Q_p(s^{-\delta}\mathbf{x})|_{s=1}.$$

The approximation  $A_{p,\delta,k}(\mathbf{x}, \sigma)$  is newly introduced, but  $B_{p,\delta,k}(\mathbf{x}, \sigma)$  has been given in Fujikoshi and Shimizu [5]. In Section 4 we shall see that  $A_{p,\delta,k}(\mathbf{x}, \sigma)$ in the case of p = 1 is the same as the previous one due to Fujikoshi [3] and Fujikoshi and Shimizu [5]. Under the appropriate conditions on the moments of  $\sigma$  we propose the following two types of approximations for the distribution function of X:

(2.5) 
$$A_{p,\delta,k}(\mathbf{x}) = E_{\sigma}[A_{p,\delta,k}(\mathbf{x}, \sigma)]$$
$$= Q_{p}(\mathbf{x}) + \sum_{j=1}^{k-1} \frac{1}{j!} a_{p,\delta,j}(\mathbf{x}) E\{(\sigma^{2\delta} - 1)^{j}\},$$
  
(2.6) 
$$B_{p,\delta,k}(\mathbf{x}) = E_{\sigma}[B_{p,\delta,k}(\mathbf{x}, \sigma)]$$
$$= Q_{p}(\mathbf{x}) + \sum_{j=1}^{k-1} \frac{1}{j!} b_{p,\delta,j}(\mathbf{x}) E\{(\sigma^{\delta} - 1)^{j}\}.$$

It will be seen that the approximations  $A_{p,\delta,k}(x)$  and  $B_{p,\delta,k}(x)$  are useful for the cases (i) and (ii), respectively. In the following we list all the assumptions used in this paper.

1: 
$$Q_p$$
 is k times continuously differentiable on  $\Omega = \mathbb{R}^p$  or  $\mathbb{R}^p_+$ ,  
A1( $\delta$ ):  $\bar{a}_{p,\delta,k} = \sup_x |a_{p,\delta,k}(x)| < \infty$ ,

A2: 
$$E(\sigma^{2k}) < \infty$$
,  $E(\sigma^{-2k}) < \infty$ ,  
A3( $\delta$ ):  $\bar{a}_{p,\delta,k}(\ell) = \sup_{x}(1 + ||\mathbf{x}||^{\ell})|a_{p,\delta,k}(\mathbf{x})| < \infty$ ,  
A4:  $E(\sigma^{2k+\ell}) < \infty$ ,  $E(\sigma^{-2k}) < \infty$ ,  
B1( $\delta$ ):  $\bar{b}_{p,\delta,k} = \sup_{x}|b_{p,\delta,k}(\mathbf{x})| < \infty$ ,  
B2:  $E(\sigma^{k}) < \infty$ ,  $E(\sigma^{-k}) < \infty$ ,  
B3( $\delta$ ):  $\bar{b}_{p,\delta,k}(\ell) = \sup_{x}(1 + ||\mathbf{x}||^{\ell})|b_{p,\delta,k}(\mathbf{x})| < \infty$ ,  
B4:  $E(\sigma^{k+\ell}) < \infty$ ,  $E(\sigma^{-k}) < \infty$ .

LEMMA 2.1. Suppose that  $Q_p(\mathbf{x})$  satisfies Assumption 1. (i) Under Assumption A1( $\delta$ ) it holds that

(2.7) 
$$\sup_{\mathbf{x}} |Q_{p}(\sigma^{-1}\mathbf{x}) - A_{p,\delta,k}(\mathbf{x}, \sigma)| \leq \frac{1}{k!} \bar{a}_{p,\delta,k}(\sigma^{2} \vee \sigma^{-2} - 1)^{k}$$
  
  $\leq \frac{1}{k!} \bar{a}_{p,\delta,k} \{ |\sigma^{2} - 1|^{k} + |\sigma^{-2} - 1|^{k} \}.$ 

(ii) Under Assumption  $B1(\delta)$  it holds that

(2.8) 
$$\sup_{x} |Q_{p}(\sigma^{-1}x) - B_{p,\delta,k}(x, \sigma)| \leq \frac{1}{k!} \bar{b}_{p,\delta,k}(\sigma \vee \sigma^{-1} - 1)^{k}$$
  
  $\leq \frac{1}{k!} \bar{b}_{p,\delta,k} \{ |\sigma - 1|^{k} + |\sigma^{-1} - 1|^{k} \}.$ 

PROOF. (ii) has been proved by Fujikoshi and Shimizu [5]. We shall show (i). Letting  $s = \sigma^{2\delta}$  and considering Taylor's expansion of  $Q_p(s^{-\delta/2}x)$  around s = 1, we have

(2.9) 
$$Q_p(\sigma^{-1}x) = A_{p,\sigma,k}(x, \sigma) + \Delta_{p,\delta,k}(x, \sigma),$$

where

$$\Delta_{p,\delta,k}(\mathbf{x}, \sigma) = \frac{1}{k!} (\sigma^{2\delta} - 1)^k \frac{d^k}{ds^k} Q_p(s^{-\delta/2}\mathbf{x}) \Big|_{s=1+\theta(\sigma^{2\delta}-1)}$$

and  $0 \le \theta \le 1$ . We can write

(2.10) 
$$\Delta_{p,\delta,k}(\mathbf{x}, \ \sigma) = \frac{1}{k!} a_{p,\delta,k}(t) \{1 + \theta(\sigma^{2\delta} - 1)\}^{-k} (\sigma^{2\delta} - 1)^{k},$$

where  $t = \{1 + \theta(\sigma^{2\delta} - 1)\}^{-\delta/2} x$ . Noting that  $0 \le \theta \le 1$ , we have

$$\begin{aligned} |1 + \theta(\sigma^{2\delta} - 1)|^{-k} |\sigma^{2\delta} - 1|^k &\leq (\sigma^2 \vee \sigma^{-2} - 1)^k \\ &\leq |\sigma^2 - 1|^k + |\sigma^{-2} - 1|^k \end{aligned}$$

which proves (i).

THEOREM 2.1. Suppose that  $X = \sigma Z$  is a scale mixture of Z satisfying Assumption 1.

(i) Under Assumptions  $A1(\sigma)$  and A2 it holds that

(2.11) 
$$\sup_{x} |F_{p}(x) - A_{p,\sigma,k}(x)| \leq \frac{1}{k!} \bar{a}_{p,\sigma,k} E\{ (\sigma^{2} \vee \sigma^{-2} - 1)^{k} \}$$
$$\leq \frac{2}{k!} \bar{a}_{p,\sigma,k} E\{ |\sigma^{2} - 1|^{k} + |\sigma^{-2} - 1|^{k} \}.$$

(ii) Under Assumptions  $B1(\delta)$  and B2 it holds that

(2.12) 
$$\sup_{x} |F_{p}(x) - B_{p,\sigma,k}(x)| \leq \frac{1}{k!} \bar{b}_{p,\sigma,k} E\{(\sigma \lor \sigma^{-1} - 1)^{k}\} \\ \leq \frac{1}{k!} \bar{b}_{p,\sigma,k} E\{|\sigma - 1|^{k} + |\sigma^{-1} - 1|^{k}\}$$

**PROOF.** The results (i) and (ii) follow immediately from (1.2) and Lemma 2.1. The second result (ii) was obtained by Fujikoshi and Shimizu [5].

Next we derive nonuniform error bounds in approximating  $F_p(x)$  by  $A_{p,\sigma,k}(x)$  or  $B_{p,\sigma,k}(x)$ , which are improvements on the uniform bounds in the tail part of the distribution of X. The following lemma, which is an extension of Fujikoshi [4] to the multivariate case, is fundamental in our nonuniform error bounds.

LEMMA 2.2. Suppose that  $Q_p(\mathbf{x})$  satisfies Assumption 1. (i) Under Assumption A3( $\sigma$ ) it holds that

(2.13) 
$$(1 + ||\mathbf{x}||^{\ell})|Q_{p}(\sigma^{-1}\mathbf{x}) - A_{p,\delta,k}(\mathbf{x}, \sigma)|$$
$$\leq \frac{1}{k!}\bar{a}_{p,\delta,k}(\ell)(\sigma^{\ell} \vee 1)(\sigma^{2} \vee \sigma^{-2} - 1)^{k}$$
$$\leq \frac{1}{k!}\bar{a}_{p,\delta,k}(\ell)\{\sigma^{\ell}|\sigma^{2} - 1|^{k} + |\sigma^{-2} - 1|^{k}\}.$$

(ii) Under Assumption  $B3(\sigma)$  it holds that

(2.14) 
$$(1 + ||x||^{\ell})|Q_{p}(\sigma^{-1}x) - B_{p,\delta,k}(x, \sigma)|$$
$$\leq \frac{1}{k!}\bar{b}_{p,\delta,k}(\ell)(\sigma^{\ell} \vee 1)(\sigma \vee \sigma^{-1} - 1)^{k}$$
$$\leq \frac{1}{k!}\bar{b}_{p,\delta,k}(\ell)\{\sigma^{\ell}|\sigma - 1|^{k} + |\sigma^{-1} - 1|^{k}\}.$$

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**PROOF.** Using (2.9) and (2.10), we have

(2.15) 
$$(1 + ||\mathbf{x}||^{\ell})|\Delta_{p,\sigma,k}(\mathbf{x}, \sigma)| = \{1 + |1 + \theta(\sigma^{2\delta} - 1)|^{\ell\delta/2} ||\mathbf{t}||^{\ell}\} \times \frac{1}{k!} |a_{p,\delta,k}(\mathbf{t})||(\sigma^{2\delta} - 1)|^{k}|1 + \theta(\sigma^{2\delta} - 1)|^{-k}.$$

The first factor of the right-hand side in (2.15) is bounded by

$$\begin{cases} 1 + \sigma^{\ell} \|t\|^{\ell}, & \text{if } \sigma \geq 1, \\ 1 + \|t\|^{\ell}, & \text{if } 0 < \sigma < 1, \end{cases} \leq (1 + \|t\|^{\ell})(1 \vee \sigma^{\ell}).$$

This result and Lemma 2.1(i) imply (i). Similarly we can prove (ii).

Lemma 2.2 implies the following Theorem 2.2.

THEOREM 2.2. Suppose that  $X = \sigma Z$  is a scale mixture of Z satisfying Assumption 1.

(i) Under Assumptions  $A3(\sigma)$  and A4 it holds that

(2.16) 
$$|F_{p}(\mathbf{x}) - A_{p,\delta,k}(\mathbf{x})| \leq \frac{1}{k!} (1 + ||\mathbf{x}||^{\ell})^{-1} \bar{a}_{p,\delta,k}(\ell) \\ \times E\{\sigma^{\ell} | \sigma^{2} - 1 |^{k} + |\sigma^{-2} - 1 |^{k}\}.$$

(ii) Under Assumptions  $B3(\sigma)$  and B4 it holds that

(2.17) 
$$|F_{p}(\mathbf{x}) - B_{p,\delta,k}(\mathbf{x})| \leq \frac{1}{k!} (1 + ||\mathbf{x}||^{\ell})^{-1} \bar{b}_{p,\delta,k}(\ell) \\ \times E\{\sigma^{\ell} | \sigma - 1 |^{k} + |\sigma^{-1} - 1 |^{k}\}$$

The results (2.16) and (2.17) in the special case of p = 1 were obtained by Fujikoshi [4].

## 3. The distribution of $Max \{X_1, \dots, X_p\}$

The distribution function of  $Max \{X_i\}$  can be expressed as

(3.1) 
$$P(\operatorname{Max} \{X_j\} \le x) = P(X_1 \le x, \cdots, X_p \le x)$$
$$= F_p(x, \cdots, x).$$

Therefore we can get two types of approximations for  $P(Max\{X_j\} \le x)$  and their error bounds from Theorems 2.1 and 2.2 by putting  $x_1 = \cdots = x_p$ = x. Let  $a_{p,\delta,k}^{[p]}(x)$ ,  $A_{p,\delta,k}^{[p]}(x)$ ,  $b_{p,\delta,k}^{[p]}(x)$  and  $B_{p,\delta,k}^{[p]}(x)$  denote  $a_{p,\delta,k}(x)$ ,  $A_{p,\delta,k}(x)$ ,  $b_{p,\delta,k}(x)$  and  $B_{p,\delta,k}(x)$  in the case of  $x_1 = \cdots = x_p = x$ , respectively. Then we can write two types of approximations for  $P(Max \{X_j\} \le x)$  as follows:

(3.2) 
$$A_{\delta,k}^{[p]}(x) = \sum_{j=0}^{k-1} \frac{1}{j!} a_{\delta,k}^{[p]}(x) E\{(\sigma^{2\delta} - 1)^j\},$$

(3.3) 
$$B_{\delta,k}^{[p]}(x) = \sum_{j=0}^{k-1} \frac{1}{j!} b_{\delta,k}^{[p]}(x) E\{(\sigma^{\delta} - 1)^j\}$$

The quantities appearing in the error bounds are expressed as

(3.4)  

$$\bar{a}_{\delta,k}^{[p]} = \sup |a_{\delta,k}^{[p]}(x)|, \quad \bar{b}_{\delta,k}^{[p]} = \sup |b_{\delta,k}^{[p]}(x)|,$$

$$\bar{a}_{\delta,k}^{[p]}(\ell) = \sup \{1 + (\sqrt{p}|x|)^{\ell}\} |a_{\delta,k}^{[p]}(x)|,$$

$$\bar{b}_{\delta,k}^{[p]}(\ell) = \sup \{1 + (\sqrt{p}|x|)^{\ell}\} |b_{\delta,k}^{[p]}(x)|.$$

Now we consider the case when  $Z_1, \dots, Z_p$  are independent and identically distributed. Let Q denote the distribution function of  $Z_1$ . Then

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(3.5) 
$$a_{\delta,j}^{[p]}(x) = (d^j/ds^j) \{ Q(s^{-\delta/2}x) \}^p \Big|_{s=1},$$

(3.6) 
$$b_{\delta,k}^{[p]}(x) = (d^j/ds^j) \{Q(s^{-\delta}x)\}^p \Big|_{s=1}$$

These quantities can be expressed in terms of

(3.7) 
$$a_{\delta,j}(x) = (d/ds)Q(s^{-\delta/2}x)|_{s=1},$$

(3.8) 
$$b_{\delta,j}(x) = (d/ds)Q(s^{-\delta}x)|_{s=1},$$

respectively. We denote the correspondence from  $(Q, \{a_{\delta,i}(x)\})$  to  $a_{\delta,k}^{[p]}(x)$  by  $Y_j$ , i.e.,

(3.9) 
$$a_{\delta,j}^{[p]}(x) = Y_j(Q, \{a_{\delta,i}(x)\}).$$

Then we can write

(3.10) 
$$b_{\delta,k}^{[p]}(x) = Y_j(Q, \{b_{\delta,i}(x)\}).$$

Letting  $Y_j = Y_j(Q, \{q_i\})$ , it is seen that  $Y_i = Q_i^p$ 

$$Y_{0} = Q^{p},$$

$$Y_{1} = pQ^{p-1}q_{1},$$
(3.11) 
$$Y_{2} = p(p-1)Q^{p-2}q_{1}^{2} + pQ^{p-1}q_{2},$$

$$Y_{3} = p(p-1)(p-2)Q^{p-3}q_{1}^{3} + 3p(p-1)Q^{p-2}q_{1}q_{2} + pQ^{p-1}q_{3},$$

$$Y_{4} = p(p-1)(p-2)(p-3)Q^{p-3}q_{1}^{4} + 6p(p-1)(p-2)Q^{p-3}q_{1}^{2}q_{2}$$

$$+ p(p-1)Q^{p-2}\{3q_{2}^{2} + 4q_{1}q_{3}\} + pQ^{p-1}q_{4}.$$

We note that

(3.12)  $\bar{a}_{\delta,k}^{[p]} \le \tilde{a}_{\delta,k}^{[p]} = Y_k(1, \{\bar{a}_{\delta,i}\}),$ 

(3.13) 
$$\bar{b}_{\delta,k}^{[p]} \leq \bar{b}_{\delta,k}^{[p]} = Y_k(1, \{\bar{b}_{\delta,i}\}),$$

where  $\bar{a}_{\delta,i} = \sup |a_{\delta,i}(x)|$  and  $\bar{b}_{\delta,i} = \sup |b_{\delta,i}(x)|$ . Similar bounds are also obtained for  $\bar{a}_{\delta,k}^{[p]}(\ell)$  and  $\bar{b}_{\delta,k}^{[p]}(\ell)$ .

### 4. The two special cases

4.1. The case (i). Let  $X_j = Z_j/(\chi_n^2/n)^{1/2}$ , j = 1, ..., p, where  $Z_1, ..., Z_p$  i.i.d.  $\sim N(0, 1)$  and  $(Z_1, ..., Z_p)$  and  $\sigma$  are independent. Let  $\Phi(X)$  and  $\phi(X)$  denote the distribution and the probability density functions of the standard normal variable. We use (3.1) as an approximation for  $P(Max \{X_j\} \le x)$ . We have seen that  $a_{\delta,j}^{p}(x)$ 's are determined by

(4.1) 
$$a_{\delta,j}^{[p]}(x) = Y_j(\Phi(x), \{a_{\delta,i}(x)\}),$$

where  $a_{\delta,j}(x) = (d^j/ds^j)\Phi(s^{-\delta/2}x)|_{s=1}$ . Then, by induction, it is proved that  $a_{1,j}(x) = -2^{-j}H_{2j-1}(x)\phi(x),$ (4.2)  $a_{-1,j}(x) = (-1)^{j-1}2^{-j}\{x^{2j-1} + \sum_{i=1}^{j-1} 1 \cdot 3 \cdots (2i-1) {j-1 \choose i} \times x^{2j-2i-1}\}\phi(x),$ 

where  $H_{i}(x)$  is the Hermite polynomial defined by

$$(d^{j}/dx^{j})\phi(x) = (-1)^{j}H_{j}(x)\phi(x).$$

We note that  $a_{\delta,j}(x)$ 's are the same as the previous ones due to Fujikoshi [3] and Fujikoshi and Shimizu [5], which are introduced by the other methods. For nonnegative integers j and  $\ell$ , let

(4.3)  
$$m_{1,j}(\ell) = E[(\chi_n^2/n)^{-\ell} \{ (\chi_n^2/n)^{-1} - 1 \}^j],$$
$$m_{1,j} = m_{1,j}(0), \quad m_{-1,j} = E[\{ (\chi_n^2/n) - 1 \}^j].$$

The quantities  $m_{-1,j}$ 's exist for any *j*, but the quantities  $m_{1,j}(\ell)$ 's exist only for  $n - 2\ell - 2j > 0$ . For  $m_{1,j}(\ell)$  and  $m_{-1,j}$  of j = 1, ..., 6, see Fujikoshi [4]. We can write (3.1) as

(4.4) 
$$A_{\delta,k}^{[p]}(x) = \Phi(x)^p + \sum_{j=1}^{k-1} \frac{1}{j!} a_{\delta,j}^{[p]}(x) m_{\delta,j}.$$

From Theorems 2.1 and 2.2 it holds that

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(i) if n - 2k > 0 and k is even,

(4.5) 
$$\sup_{x} |P(\max\{X_{j}\} \le x) - A_{\delta,k}^{[p]}(x)| \le \frac{1}{k!} \bar{a}_{\delta,k}^{[p]}\{m_{1,k} + m_{-1,k}\},$$

(ii) if  $n - 2\ell - 2k > 0$  and k is even,

$$(4.6) |P(\operatorname{Max}\{X_j\} \le x) - A_{\delta,k}^{[p]}(x)| \le \frac{1}{k!} \{1 + (px^2)^{\ell}\}^{-1} a_{\delta,k}^{[p]}(2\ell) \{m_{1,k}(\ell) + m_{-1,k}\}.$$

It may be noted that the order of error terms is  $O(n^{-k/2})$  and  $A_{\delta,1}^{[p]}(x)$  is an asymptotic expansion for  $P(Max\{X_j\} \le x)$  up to  $O(n^{-k/2})$  since  $m_{\delta,j}(\ell) = O(n^{-(j+1)/2})$ , if j is odd, and  $= O(n^{-j/2})$ , if j is even.

4.2. The case (ii). Let  $X_j = Z_j/(\chi_n^2/n)$ , j = 1, ..., p, where  $Z_1, ..., Z_p$  i.i.d.  $\sim G(\lambda)$  and  $(Z_1, ..., Z_p)$  and  $\sigma$  are independent. Let  $G(x; \lambda)$  and  $g(x; \lambda)$  denote the distribution and the probability density functions of the gamma distribution  $G(\lambda)$ . We use (3.2) as an approximation for  $P(\max\{X_j\} \le x)$ . Here the support of  $\max\{X_j\}$  is  $\mathbb{R}_+$  and so we consider only for x > 0. It is known (Fujikoshi [3], Fujikoshi and Shimizu [5]) that

$$b_{1,j}(x; \lambda) = (d^j/ds^j)G(s^{-1}x; \lambda)|_{s=1}$$
$$= -xL_{j-1}^{(\lambda)}(x)g(x; \lambda),$$

(4.7)

$$b_{-1,j}(x; \lambda) = (d^j/ds^j)G(sx; \lambda)\Big|_{s=1}$$
  
=  $(-1)^{j-1}x \widetilde{L}_{j-1}^{(\lambda)}(x)g(x; \lambda),$ 

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

$$L_p^{(\lambda)}(x) = (-1)^p x^{-\lambda} e^x (d^p/dx^p) (x^{p+\lambda} e^{-x})$$

and

$$\widetilde{L}_{p}^{(\lambda)}(x) = x^{p} + \sum_{i=1}^{p} (1-\lambda) \cdots (i-\lambda) \binom{p}{i} x^{p-\lambda}.$$

We can write (3.2) as

(4.8) 
$$B_{\delta,k}^{[p]}(x; \lambda) = G(x; \lambda)^p + \sum_{j=1}^{k-1} \frac{1}{j!} B_{\delta,j}^{[p]}(x; \lambda) m_{\delta,j},$$

where

(4.9) 
$$b_{\delta,j}^{[p]}(x; \lambda) = Y_j(G(x; \lambda), \{b_{\delta,i}(x; \lambda)\}).$$

From Theorems 2.1 and 2.2 it holds that

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(i) if n - 2k > 0 and k is even,

(4.10) 
$$\sup_{x} |P(\operatorname{Max}(X_{j}) \leq x) - B^{[p]}_{\delta,k}(x; \lambda)| \leq \frac{1}{k!} \bar{b}^{[p]}_{\delta,k}\{m_{1,k} + m_{-1,k}\},$$

(ii) if  $n - 2\ell - 2k > 0$  and k is even,

(4.11) 
$$|P(\operatorname{Max} \{X_{j}\} \leq x) - B_{\delta,k}^{[p]}(x; \lambda)|$$
$$\leq \frac{1}{k!} \{1 + (\sqrt{p} \ x)^{\ell}\}^{-1} \bar{b}_{\delta,k}^{[p]}(\ell; \lambda) \{m_{1,k}(\ell) + m_{-1,k}(\ell)\}$$

where  $\bar{b}_{\delta,k}^{[p]}(\ell; \lambda) = \sup_{x>0} \{1 + (\sqrt{p} x)^{\ell}\} |b_{\delta,k}^{[p]}(x; \lambda)|$ . We note that  $B_{\delta,k}^{[p]}(x; \lambda)$  is an asymptotic expansion for  $P(\max\{X_j\} \le x)$  up to  $O(n^{-k/2})$  and the order of the error terms in (4.11) and (4.12) is  $O(n^{-k/2})$ .

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Department of Mathematics, Faculty of Science, Hiroshima University