

## INFINITE DIVISIBILITY AND RANDOM SUMS OF RANDOM VECTORS

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**ABSTRACT** In the first part of this paper we prove a theorem relating the asymptotic behavior of a multivariate infinitely divisible d.f. to that of its Lévy measure.

The second part of the paper is devoted to subordination and more generally to random sums of random vectors. Using a sequence of first passage times we then apply our results to obtain a multivariate limit theorem for the partial maxima of normed sums of random vectors.

### 1. Introduction.

Although there is an extensive literature on one-dimensional infinitely divisible (i. d.) probability distributions, there is much less available on the multivariate case. For an investigation of i. d. distributions in  $\mathbf{R}_+^n$  we refer to [6].

Now suppose  $F$  is a d.f. in  $\mathbf{R}_+^n$  such that  $F(\bar{x}) > 0$  for all  $\bar{x}$  in the interior of  $\mathbf{R}_+^n$ . Then [6, Th. 2.4]  $F$  is i. d. if and only if there is a nonnegative measure  $\nu$  on  $\mathbf{R}_+^n$  such that for  $i=1, \dots, n$  and all  $\bar{x} \in \mathbf{R}_+^n$ ,

$$\int_{\vec{y}, \vec{x}-\vec{y} \in \mathbf{R}_+^n} y_i F(dy) = \int_{\vec{y}, \vec{x}-\vec{y} \in \mathbf{R}_+^n} F(\bar{x}-y) y_i \nu(dy).$$

Moreover under these conditions we have  $\nu\{y \mid y-\bar{x} \in \mathbf{R}_+^n\} < \infty$  for all  $\bar{x}$  in the interior of  $\mathbf{R}_+^n$ .

We will call  $\nu$  the Lévy measure of  $F$ . In the first part of this paper we want to compare the asymptotic behavior of  $F$  with that of  $\nu$ . A typical example of an i. d. d.f.  $F$  is the compound Poisson distribution, i. e. for a d.f.  $G$  on  $\mathbf{R}_+^n$  and  $\lambda > 0$  we have

$$(1.1) \quad F(\cdot) = e^{-\lambda} \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} G^{*k}(\cdot)$$

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where  $G^{*k}$  denotes the  $k$ -th convolution of  $G$ . Then  $F$  is i. d. with Lévy measure  $\nu(\cdot) = \lambda G(\cdot)$ .

The second part of the paper will be devoted to generalizations of (1.1). Among others we will examine asymptotics between  $F$  and  $G$  where

$$(1.2) \quad F(\cdot) = \sum_{k=0}^{\infty} a_k G^{*k}(\cdot)$$

for some discrete probability distribution  $\{a_k\}_N$ .

Basic in our study are the papers of Stam [8] and Embrechts et al. [2]. In section 4 finally we apply our results to obtain a multidimensional limit theorem for maxima of normed sums.

## 2. Asymptotics for I. D. Distributions.

We start from the following one-dimensional result obtained in [2].

**Lemma 2.1.** *Suppose  $F$  is i. d. on  $\mathbf{R}_+^1$  with Lévy measure  $\nu$ , then for  $\alpha > 0$  the following statements are equivalent:*

- (i)  $1 - F(x) \in RV_{-\alpha}$
- (ii)  $\nu([x, \infty)) \in RV_{-\alpha}$

Both imply

- (iii)  $1 - F(x) \sim \nu([x, \infty)) \quad (x \rightarrow \infty)$ . ■

Recall that a measurable and positive function  $f: \mathbf{R}_+^1 \rightarrow \mathbf{R}_+^1$  is regularly varying with index  $\alpha \in \mathbf{R}$  ( $f \in RV_\alpha$ ) if for each  $x > 0$ ,  $\lim_{t \rightarrow \infty} f(tx)/f(t) = x^\alpha$ . A sequence of positive numbers  $\{a_n\}_N$  belongs to  $RV_\alpha$  if  $f(x) := a_{[x]} \in RV_\alpha$ . For i. d. distributions in  $\mathbf{R}_+^n$ , lemma 2.1 generalises as follows:

**Theorem 2.2.** *Suppose  $F$  is i. d. on  $\mathbf{R}_+^n$  with Lévy measure  $\nu$ . For  $\alpha > 0$ , let  $h(x) \in RV_{-\alpha}$  and for  $\bar{x} > 0$ , define  $A(\bar{x}) = \{\bar{u} \in \mathbf{R}_+^n \mid \bar{u} \leq \bar{x}\}$  and  $A^c(\bar{x}) = \mathbf{R}_+^n \setminus A(\bar{x})$ . Then the following statements are equivalent: for a measure  $\lambda$  on  $\mathbf{R}_+^n$ ,*

- (i) for all  $\bar{x} > 0$ ,  $\lim_{t \rightarrow \infty} \frac{F(tA^c(\bar{x}))}{h(t)} = \lambda(A^c(\bar{x}))$ ,
- (ii) for all  $\bar{x} > 0$ ,  $\lim_{t \rightarrow \infty} \frac{\nu(tA^c(\bar{x}))}{h(t)} = \lambda(A^c(\bar{x}))$ .

**Remark.** The measure  $\lambda$  in the theorem then satisfies

$$t^{-\alpha} \lambda(A^c(\bar{x})) = \lambda(tA^c(\bar{x}))$$

for all  $t > 0$  and  $\bar{x} > 0$ . This follows from the regular variation of  $h$ .

Before proving the theorem we first state

**Corollary 2.3.** Suppose (1.1) holds. If  $h \in RV_{-\alpha}$ ,  $\alpha > 0$ , the followings statements are equivalent: for a measure  $\mu$  on  $\mathbf{R}_+^n$

$$(i) \text{ for all } \bar{x} > 0, \lim_{t \rightarrow \infty} \frac{F(tA^c(\bar{x}))}{h(t)} = \mu(A^c(\bar{x}))$$

$$(ii) \text{ for all } \bar{x} > 0, \lim_{t \rightarrow \infty} \frac{G(tA^c(\bar{x}))}{h(t)} = \frac{1}{\lambda} \mu(A^c(\bar{x})). \quad \blacksquare$$

**Proof of Theorem 2.2.** For a measure  $M$  on  $\mathbf{R}_+^n$  and for  $a \in \mathbf{R}_+^n$ ,  $x \in \mathbf{R}_+^n$  define

$$M_{\bar{a}}(x) = M(\{\bar{u} \in \mathbf{R}_+^n \mid 0 \leq a \cdot \bar{u} \leq x\})$$

where  $a \cdot \bar{u} = \sum_{i=1}^n a_i \cdot u_i$ . Then it follows that if  $F$  is i.d. in  $\mathbf{R}_+^n$  with Lévy measure  $\nu$ , then also  $F_{\bar{a}}(x)$  is i.d. in  $\mathbf{R}_+^1$  with Lévy measure  $\nu_{\bar{a}}(\cdot)$ . To prove the theorem it is sufficient to show that (i) (or (ii)) is equivalent to regular variation of  $1 - F_{\bar{a}}(x)$  (or to regular variation of  $\nu_{\bar{a}}([x, \infty))$ ). An application of Lemma 2.1 then yields the desired result. W.l.o.g. we may and do assume  $h(x)$  decreases with  $x$ . Now define the sequence  $\{c_m\}_N$  such that  $mh(c_m) = 1$ . Then (i) is equivalent to

$$(2.1) \quad m(1 - F(c_m \bar{x})) \rightarrow \mu(\bar{x}), \text{ say.}$$

Hence if  $\{X_i, i \in N_0\} = \{(X_i^1, \dots, X_i^n), i \in N_0\}$  is a sequence of i.i.d. random vectors with d.f.  $F$ , with  $M_m := (\text{Max}(X_1^1, \dots, X_m^1), \dots, \text{Max}(X_1^n, \dots, X_m^n))$  it follows from [4] that (2.1) holds if and only if  $M_m/c_m$  converges in distribution as  $m \rightarrow \infty$ . Using Cramer-Wold device [1] this is equivalent to convergence in distribution of  $a \cdot M_m/c_m$  for all  $a \in \mathbf{R}_+^n$ , which in turn is equivalent to regular variation of  $1 - F_{\bar{a}}(x)$ .  $\blacksquare$

### 3. Subordinated distributions and random sums

Let  $G$  be a d.f. on  $\mathbf{R}_+^n$  and  $\{a_k\}_N$  a probability measure on  $N$  with  $a_0 < 1$ . The d.f.  $F$  where

$$(3.1) \quad F(\cdot) = \sum_{k=0}^{\infty} a_k G^{*k}(\cdot)$$

is called subordinate to  $G$  with respect to  $\{a_k\}_N$ . It admits the following probabilistic interpretation. Let  $\{X_i, i \in N_0\}$  be i.i.d. random vectors with d.f.  $G$  and let  $N$ , independent of  $X_1$ , be an integer valued r.v. with  $P\{N=m\} = a_m$  ( $m \in N$ ). With  $S(0) = 0$  and  $S(m) = X_1 + \dots + X_m$ , the random vector  $S(N)$  has d.f.  $F$ . In Theorems 3.1 and 3.2 below we relate an asymptotic behavior of  $G$  to that of  $F$ .

In this section we will also consider the following generalization of the previous situation. Let  $S(m) = (S^1(m), \dots, S^n(m))$  be defined as before and let

$N=(N_1, \dots, N_n)$  be an  $N^n$ -valued random vector. In Theorems 3.3 and 3.4 we will examine the asymptotic behavior of the vector  $(S^1(N_1), \dots, S^n(N_n))$ . For results in dimension  $n=1$  we refer to Kimbleton [7] and Stam [8]. See also Teicher [9] and Hagwood and Teicher [5].

We start with the following generalization of [8, Th. 1.4].

**Theorem 3.1.** *Suppose  $h \in RV_{-\alpha}$ ,  $\alpha > 1$ ,  $\sum_{k=m+1}^{\infty} a_k = o(h(m))$  and suppose that  $G$ , a d.f. on  $\mathbb{R}_+^n$ , and  $F$  are related by (3.1). Then for some measure  $\lambda$  and all  $\bar{x} > 0$ ,  $G$  satisfies*

$$(3.2) \quad \lim_{t \rightarrow \infty} \frac{G(tA^c(\bar{x}))}{h(t)} = \lambda(A^c(\bar{x}))$$

if and only if  $F$  satisfies

$$(3.3) \quad \lim_{t \rightarrow \infty} \frac{F(tA^c(\bar{x}))}{h(t)} = \eta \lambda(A^c(\bar{x})).$$

Here  $\eta = \sum_{k=0}^{\infty} k a_k$ .

**Proof.** The d.f.  $G$  satisfies (3.2) iff  $G_{\bar{a}}(x)$  satisfies, for all  $x > 0$ ,

$$(3.4) \quad \lim_{t \rightarrow \infty} \frac{1 - G_{\bar{a}}(tx)}{h(t)} = \mu(x), \quad \text{say}$$

Using [8, Th. 1.4] and (3.1), (3.4) holds iff (3.4) holds with  $G_{\bar{a}}$  (and  $\mu(x)$ ) replaced by  $F_{\bar{a}}$  (and  $\eta\mu(x)$ ). This in turn is equivalent to (3.3). ■

If in Th. 3.1,  $a_m = 1$  and  $a_k = 0$ ,  $k \neq m$  it follows that (3.2) is equivalent to (3.3) with  $F = G^{*m}$  and  $\eta = m$ . The assumption that  $\alpha > 1$  can also be dropped in this case.

**Proposition 3.2.** *Let  $h \in RV_{-\alpha}$ ,  $\alpha > 0$ . Then  $G$  satisfies (3.2) iff for all  $m \geq 2$ ,*

$$(3.5) \quad \lim_{t \rightarrow \infty} \frac{G^{*m}(tA^c(\bar{x}))}{h(t)} = m\lambda(A^c(\bar{x})).$$

**Proof.** Since (3.2) holds iff (3.4) holds it follows that  $1 - G_{\bar{a}}(x)$  is regularly varying. This in turn is equivalent to regular variation of  $1 - G_{\bar{a}}^{*m}(x)$  for all  $m \geq 2$  [2, Cor. 2]. Since in this case also  $1 - G_{\bar{a}}^{*m}(x) \sim m(1 - G_{\bar{a}}(x))$  ( $x \rightarrow \infty$ ), the result follows. ■

Our next theorem is devoted to the case where  $\sum_{k=0}^{\infty} k a_k$  is not necessarily finite, in which case Theorem 3.1 is not applicable. We shall prove the following general result.

**Theorem 3.3.** *Suppose  $N=(N_1, \dots, N_n)$  is an  $N^n$ -valued random vector, belonging to the domain of attraction of a random vector  $U=(U_1, \dots, U_n)$ , stable with indices  $(\alpha_1, \dots, \alpha_n)$ ,  $0 < \alpha_i \leq 1$ . Assume  $X_1=(X_1^1, \dots, X_1^n)$  is independent of*

$N$  and has values in  $\mathbf{R}_+^n$ . Suppose there exist constants  $\rho_i > 1$ ,  $L_i > 0$  such that for  $x_i > 0$ ,  $i=1, \dots, n$ ,

$$(3.6) \quad x_i^{\rho_i} P\{X_i^1 > x_i\} \leq L_i < \infty.$$

Then if  $X_1, X_2, \dots$  are i.i.d. and if we set  $S(0)=0$  and  $S(m) = \sum_{i=1}^m X_i = (S^1(m), \dots, S^n(m))$ , it follows that  $(S(N_1), \dots, S(N_n))$  belongs to the domain of attraction of a stable random vector  $V$ . Moreover  $V \stackrel{d}{=} (\mu_1 U_1, \dots, \mu_n U_n)$  where  $\mu_i = EX_i^1$  ( $i=1, \dots, n$ ).

**Proof.** Let  $Y_i = (Y_i^1, \dots, Y_i^n)$ ,  $i \geq 1$  be i.i.d. random vectors with  $Y_1 \stackrel{d}{=} (N_1, \dots, N_n)$  and let  $M(0)=0$ ,  $M(m) = Y_1 + \dots + Y_m$ . From the conditions of the theorem it follows that for some sequences of numbers  $A^i(m)$ ,  $B^i(m)$  with  $A^i(m) \in RV_{1/\alpha_i}$ ,

$$(3.7) \quad \left( \frac{M^1(m)}{A^1(m)} - B^1(m), \dots, \frac{M^n(m)}{A^n(m)} - B^n(m) \right) \Rightarrow U \quad (m \rightarrow \infty).$$

Now choose  $\theta_i$  such that  $\max(1/2, 1/\rho_i) < \theta_i < 1$ ,  $i=1, \dots, n$ . From (3.6) it follows that  $EX_i^1 = \mu_i$  is finite and that

$$\frac{S^i(m) - \mu_i^m}{m^{\theta_i}} \xrightarrow{P} 0 \quad (m \rightarrow \infty).$$

Since  $M^i(m) \rightarrow \infty$  and since  $X_1$  is independent of  $M(1)$  it follows that

$$(3.8) \quad \frac{S^i(M^i(m)) - \mu_i M^i(m)}{(M^i(m))^{\theta_i}} \xrightarrow{P} 0 \quad (m \rightarrow \infty).$$

Also

$$(3.9) \quad \frac{(M^i(m))^{\theta_i}}{A^i(m)} \xrightarrow{P} 0 \quad (m \rightarrow \infty).$$

From (3.7), (3.8), (3.9) and Cramer-Wold-device it follows that for  $a \in \mathbf{R}^n$ ,

$$\begin{aligned} & \sum_{i=1}^n a_i \left( \frac{S^i(M^i(m))}{A^i(m)} - \mu_i B^i(m) \right) \\ &= \sum_{i=1}^n a_i \left( \frac{S^i(M^i(m)) - \mu_i M^i(m)}{(M^i(m))^{\theta_i}} \right) \frac{(M^i(m))^{\theta_i}}{A^i(m)} + \sum_{i=1}^n a_i \mu_i \left( \frac{M^i(m)}{A^i(m)} - B^i(m) \right) \\ &\Rightarrow 0 + \sum_{i=1}^n a_i \mu_i U_i \quad (m \rightarrow \infty). \end{aligned}$$

Again using Cramer-Wold device it follows that as  $m \rightarrow \infty$ ,

$$\left( \frac{S^1(M^1(m))}{A^1(m)} - \mu_1 B^1(m), \dots, \frac{S^n(M^n(m))}{A^n(m)} - \mu_n B^n(m) \right) \Rightarrow V = (\mu_1 U_1, \dots, \mu_n U_n)$$

which proves the theorem. ■

If in Th. 3.3,  $EN_i < \infty$  ( $i=1, \dots, n$ ) (i.e.  $M^i(m)/m \xrightarrow{P} EN_i$  ( $m \rightarrow \infty$ )) and if

$X_1$  belongs to the domain of attraction of a stable r. v.  $U$ , we shall prove the following Theorem 3.4. To state the theorem, let us assume that  $X_1, X_2, \dots$  are i. i. d. random vectors such that  $X_1$  belongs to the domain of attraction of a stable law  $U$  i. e.

$$(3.10) \quad \left( \frac{\sum_{i=1}^m (X_i^1 - B^1(m))}{A^1(m)}, \dots, \frac{\sum_{i=1}^m (X_i^n - B^n(m))}{A^n(m)} \right) \Rightarrow U$$

for some sequences  $A^i(m), B^i(m)$  with  $A^i(m) > 0, i=1, \dots, n$ , where  $U$  is stable with indices  $(\alpha_1, \dots, \alpha_n), 0 < \alpha_i \leq 2 (i=1, \dots, n)$ .

Now let  $\{R^i(m), m \geq 1, i=1, \dots, n\}$  be any  $n$  sequences of  $\mathbb{N}$ -valued r. v. for which there exist a sequence  $\{c_m\}_{\mathbb{N}}$  and constants  $r_i, 0 < r_i < \infty, i=1, \dots, n$ , such that as  $m \rightarrow \infty$ ,

$$\frac{R^i(m)}{c(m)} \xrightarrow{P} r_i \quad (i=1, \dots, n).$$

Set  $b^i(m) = B^i([r_i c(m)])$  and  $a^i(m) = A^i([r_i c(m)]) (i=1, \dots, n)$ . We shall prove

**Theorem 3.4.** *Under the conditions stated above, we have*

$$(3.11) \quad \left( \frac{\sum_{j=1}^{R^1(m)} (X_j^1 - b^1(m))}{a^1(m)}, \dots, \frac{\sum_{j=1}^{R^n(m)} (X_j^n - b^n(m))}{a^n(m)} \right) \Rightarrow V$$

where  $V$  is an  $n$ -dimensional stable r. v., related to  $U$  and  $r_i (i=1, \dots, n)$ .

To prove the theorem we first need the following result of Kimbleton [7].

**Lemma 3.5.** *Under the conditions of the theorem, for  $i=1, \dots, n$*

$$(3.12) \quad \frac{\sum_{j=1}^{R^i(m)} (X_j^i - b^i(m)) - \sum_{j=1}^{[r_i c(m)]} (X_j^i - b^i(m))}{a^i(m)} \xrightarrow{P} 0. \quad \blacksquare$$

It follows from (3.12) and Cramer-Wold device that if all  $r_i = 1 (i=1, \dots, n)$ , then (3.11) holds with  $V \stackrel{d}{=} U$ . If the  $r_i$  are different for different  $i$ , we need the following lemma. For simplicity we only state and prove a result in  $\mathbb{R}^2$ .

**Lemma 3.6.** *Suppose (3.10) holds for  $n=2$  and with  $U=(U_1, U_2)$  stable with indices  $(\alpha_1, \alpha_2)$  with  $0 < \alpha_1, \alpha_2 \leq 2$ . If  $k_i = k_i(n)$  is such that  $k_i(m) \sim c_i m (m \rightarrow \infty, 0 < c_1, c_2 < \infty)$ , then*

$$(3.13) \quad \left( \frac{\sum_{i=1}^{k_1(m)} (X_i^1 - B^1(m))}{A^1(m)}, \frac{\sum_{i=1}^{k_2(m)} (X_i^2 - B^2(m))}{A^2(m)} \right) \Rightarrow V = (V_1, V_2),$$

with  $E(e^{i\xi V_1 + i\eta V_2}) = \varphi(c^{1/\alpha_1} \xi, c^{1/\alpha_2} \eta) \varphi((c_1 - c)^{1/\alpha_1} \xi, (c_2 - c)^{1/\alpha_2} \eta) e^{i\xi p_1(c, c_1) + i\eta p_2(c, c_2)}$  where  $c = \min(c_1, c_2)$ ,  $\varphi(\xi, \eta) = E(e^{i\xi U_1 + i\eta U_2})$  and  $p_1(x, y), p_2(x, y)$  are defined below.

**Proof.** From (3.10) as is well known it follow that for  $i=1, 2, A^i(m) \in RV_{1/\alpha_i}$

and that

$$(3.14) \quad \frac{B^i([xt]) - B^i([x])}{A^i([x])/x} \rightarrow \begin{cases} K^i(t^{(1/\alpha_i)-1} - 1) & \text{if } \alpha_i \neq 1 \\ K^i \log t & \text{if } \alpha_i = 1 \end{cases}$$

for some real constants  $K^i$ .

If we set  $S^i(m) = \sum_{j=1}^m X_j^i$ ,  $b^i(m) = mB^i(m)$ ,  $k(m) = \min(k_1(m), k_2(m))$  it follows that the l. h. s. of (3.13) equals

$$\begin{aligned} I &= \left( \frac{S^1(k) - b^1(k)}{A^1(m)}, \frac{S^2(k) - b^2(k)}{A^2(m)} \right) + \left( \frac{\sum_{j=k+1}^{k_1} (X_j^1 - B^1(k_1 - k))}{A^1(m)}, \frac{\sum_{j=k+1}^{k_2} (X_j^2 - B^2(k_2 - k))}{A^2(m)} \right) \\ &+ \left( \frac{b^1(k_1 - k) + b^1(k) - b^1(k_1)}{A^1(m)}, \frac{b^2(k_2 - k) + b^2(k) - b^2(k_2)}{A^2(m)} \right) \\ &=: I_1 + I_2 + I_3 \end{aligned}$$

where if e. g.  $k = k_1$  the first term in  $I_2$  and  $I_3$  should be interpreted as zero. From (3.10) it follows that

$$I_1 \Rightarrow (c^{1/\alpha_1} \tilde{U}_1, c^{1/\alpha_2} \tilde{U}_2)$$

where  $c = \min(c_1, c_2)$  and  $\tilde{U} = (\tilde{U}_1, \tilde{U}_2) \stackrel{\mathcal{D}}{=} U$ .

Now suppose  $c_1 < c_2$  so that  $k = k_1$  for large  $m$ . Then from (3.10) and independency we obtain

$$I_2 \Rightarrow (0, (c_2 - c)^{1/\alpha_2} U'_2)$$

where  $U'_2 \stackrel{\mathcal{D}}{=} U_2$  and  $U'_2$  is independent of  $\tilde{U}$ . As to  $I_3$  from (3.14) it follows that

$$I_3 \rightarrow (0, p_2(c, c_2)) = \begin{cases} (0, K^2((c_2 - c)^{1/\alpha_2} - c_2^{1/\alpha_2} - c^{1/\alpha_2})) & \text{if } \alpha_2 \neq 1 \\ (0, K^2((c_2 - c) \log(c_2 - c) - c_2 \log c_2 + c \log c)) & \text{if } \alpha_2 = 1. \end{cases}$$

Hence

$$I \Rightarrow V$$

and the characteristic function of  $V$  has the desired form.

In case  $c_2 < c_1$  the result follows in a similar way. Next consider the case  $c_1 = c_2 = c$ . For those  $m$  such that  $k_1 < k_2$  as before we have  $I = I_1 + I_2 + I_3$  and

$$I_1 \Rightarrow (c^{1/\alpha_1} \tilde{U}_1, c^{1/\alpha_2} \tilde{U}_2).$$

As to  $I_2 + I_3$  with  $\phi(\eta) = \varphi(0, \eta)$  we have

$$\begin{aligned} & E \left( \exp \left\{ i\eta \left[ \frac{\sum_{j=k+1}^{k_2} (X_j^2 - B^2(k_2 - k))}{A^2(m)} + \frac{b^2(k_2 - k) + b^2(k) - b^2(k_2)}{A^2(m)} \right] \right\} \right) \\ &= \left( \phi^m \left( \frac{\eta}{A^2(m)} \right) e^{-i\eta (b^2(m)/A^2(m))} \right)^{(k_2 - k)/m} \cdot \exp \left\{ i\eta \frac{b^2(m) \frac{k_2 - k}{m} + b^2(k) - b^2(k_2)}{A^2(m)} \right\} \\ &= (i) \cdot (ii). \end{aligned}$$

From (3.10) and  $k_2 - k = o(m)$  it follows that (i)  $\rightarrow 1$  ( $m \rightarrow \infty$ ). Finally from (3.14) we obtain also (ii)  $\rightarrow 1$ . This proves the lemma. ■

**Remark.** The functions  $p_i(x, y)$  are defined as

$$p_i(x, y) = \begin{cases} 0 & x = y \\ K^i((y-x)^{1/\alpha_i} - y^{1/\alpha_i} + x^{1/\alpha_i}) & \text{if } \alpha_i \neq 1, x \neq y \\ K^i((y-x)\log(y-x) - y\log y + x\log x) & \text{if } \alpha_i = 1, x \neq y. \end{cases}$$

**Proof of Theorem 3.4.** It follows from (3.12) that for all  $a \in \mathbb{R}^n$ ,

$$(3.15) \quad \sum_{i=1}^n a_i \frac{\sum_{j=1}^{R^i(m)} (X_j^i - b^i(m)) - \sum_{j=1}^{[r_i c(m)]} (X_j^i - b^i(m))}{a^i(m)} \xrightarrow{P} 0.$$

Also, using (3.10), lemma 3.6 and Cramer-Wold device it follows that

$$(3.16) \quad \sum_{i=1}^n a_i \frac{\sum_{j=1}^{[r_i c(m)]} (X_j^i - b^i(m))}{a^i(m)} \Rightarrow V.$$

Combining (3.15) and (3.16) proves the theorem. ■

#### 4. A multivariate limit theorem for maxima of normed sums

In this section we prove a limit theorem for the maxima of normed sums of i. i. d. random vectors, with finite mean, that belong to the domain of attraction of a multivariate stable law  $U$ , hereby extending results of Teicher and Hagwood [10], [5] and Gut [3].

**Theorem 4.1.** Let  $S_{(m)} = (S_{(m)}^1, \dots, S_{(m)}^n) = \sum_{j=1}^m X_j$  where  $X_j = (X_j^1, \dots, X_j^n)$ ,  $j \geq 1$  are i. i. d. random vectors with positive mean vector  $\mu = (\mu_1, \dots, \mu_n)$  and such that  $X_1$  belongs to the domain of attraction of a stable law  $U = (U_1, \dots, U_n)$  stable with indices  $\beta = (\beta_1, \dots, \beta_n)$ ,  $1 < \beta_i \leq 2$  ( $i = 1, \dots, n$ ). Then there exist functions  $A^i(x) \in RV_{1/\beta_i}$  ( $i = 1, \dots, n$ ) such that for any constant vector  $\alpha = (\alpha_1, \dots, \alpha_n)$  in  $[0, 1]^n$  there holds

$$P \left\{ \bigcap_{j=1}^n \left[ \max_{1 \leq k \leq m} \frac{S_{(k)}^j}{k^{\alpha_j}} - \mu_j m^{1-\alpha_j} \leq x_j A^j(m) m^{-\alpha_j} \right] \right\} \rightarrow P \left\{ \bigcap_{j=1}^n [U_j \leq -x_j] \right\}.$$

**Proof.** For each  $j = 1, \dots, n$  and  $c > 0$  define the stopping rules

$$T_j(c) = \inf \{ m \geq 1 : S^j(m) > cm^{\alpha_j} \}.$$

From [3, Th. 3.3], it then follows that with  $\lambda_j = (c/\mu_j)^{1/(1-\alpha_j)}$

$$(4.1) \quad \frac{T_j(c)}{\lambda_j} \xrightarrow{\text{a.s.}} 1 \quad \text{as } c \rightarrow \infty, 1 \leq j \leq n.$$



Also under the hypothesis of the theorem it follows that for some  $A^j(x) \in RV_{1/\beta_j}$  we have

$$\left( \frac{S^1(m) - m\mu_1}{A^1(m)}, \dots, \frac{S^n(m) - m\mu_n}{A^n(m)} \right) \Rightarrow U$$

and hence, using (4.1) and Th. 3.4 we obtain

$$(4.2) \quad \left( \frac{S^1(T_1(c_1)) - \mu_1 T_1(c_1)}{A^1(\lambda_1)}, \dots, \frac{S^n(T_n(c_n)) - \mu_n T_n(c_n)}{A^n(\lambda_n)} \right) \Rightarrow V$$

as  $c = \min_{1 \leq j \leq n} c_j \rightarrow \infty$  such that  $\lambda_j \sim \lambda_k$  ( $1 \leq j < k \leq n$ ). Moreover from  $\lambda_1 \sim \lambda_k$  ( $1 \leq k \leq n$ ),

(4.1) and the remark following lemma 3.5 we have  $V \stackrel{d}{=} U$ . Now for  $j=1, \dots, n$

$$0 \leq \frac{S^j(T_j(c_j)) - c_j(T_j(c_j))^{\alpha_j}}{A^j(\lambda_j)} \leq \frac{X_{T_j(c_j)}^j}{A^j(\lambda_j)}$$

which converges to zero in probability [3, Lemma 3.5] as  $c \rightarrow \infty$ . Hence (4.2) can be replaced by

$$(4.3) \quad P\left\{ \bigcap_{j=1}^n \left[ \frac{c_j(T_j(c_j))^{\alpha_j} - \mu_j T_j(c_j)}{A^j(\lambda_j)} \leq x_j \right] \right\} \rightarrow P\left\{ \bigcap_{j=1}^n [U_j \leq x_j] \right\}.$$

Now using (4.1) we have

$$(4.4) \quad \begin{aligned} c_j(T_j(c_j))^{\alpha_j} - \mu_j T_j(c_j) &= \mu_j T_j(c_j) \left\{ \left( \frac{T_j(c_j)}{j} \right)^{\alpha_j - 1} - 1 \right\} \\ &= -\mu_j(1 - \alpha_j)(T_j(c_j) - \lambda_j)(1 + o(1)). \end{aligned}$$

Using (4.4), (4.3) and [3, Th. 3.8] it follows that

$$(4.5) \quad P\left\{ \bigcap_{j=1}^n \left[ \frac{-\mu_j(1 - \alpha_j)(T_j(c_j) - \lambda_j)}{A^j(\lambda_j)} \leq x_j \right] \right\} \rightarrow P\left\{ \bigcap_{j=1}^n [U_j \leq x_j] \right\}.$$

To conclude the proof of the theorem, for  $x_1, \dots, x_n \in \mathbf{R}$ , define  $c_i = c_i(m) = \mu_i m^{1 - \alpha_j} + x_j A^j(m) m^{-\alpha_j}$ . Then  $\lambda_i \sim m$  ( $m \rightarrow \infty$ ) and

$$\frac{\lambda_i - m}{q_i} \sim x_i \quad (m \rightarrow \infty) \quad \text{where} \quad q_i = \frac{A^i(\lambda_j)}{\mu_j(1 - \alpha_i)}.$$

But then from (4.5) it follows that

$$\begin{aligned} &P\left\{ \bigcap_{j=1}^n \left[ \max_{1 \leq k \leq m} \frac{S^j(k)}{k^{\alpha_j}} - \mu_j m^{1 - \alpha_j} \leq x_j A^j(m) m^{-\alpha_j} \right] \right\} \\ &= P\left\{ \bigcap_{j=1}^n \left[ \max_{1 \leq k \leq m} \frac{S^j(k)}{k^{\alpha_j}} \leq c_j \right] \right\} = P\left\{ \bigcap_{j=1}^n [T_j(c_j) > m] \right\} \\ &= P\left\{ \bigcap_{j=1}^n \left[ \frac{T_j(c_j) - \lambda_j}{q_j} > \frac{m - \lambda_j}{q_j} \right] \right\} \rightarrow P\left\{ \bigcap_{j=1}^n [U_j \leq -x_j] \right\}. \end{aligned}$$

This proves the theorem. ■

The following corollary is interesting in its own right. Cf. [3, Th. 3.8].

**Corollary 4.2.** Under the conditions of Th. 4.1., if  $\min_{1 \leq j \leq n} (c_j) \rightarrow \infty$  and

$$\lambda_j := \left( \frac{j}{\mu_j} \right)^{1/(1-\alpha_j)} \sim \left( \frac{c_k}{\mu_k} \right)^{1/(1-\alpha_k)} \quad (1 \leq j < k \leq n)$$

then

$$P \left\{ \bigcap_{j=1}^n \left[ \frac{T_j(c_j) - \lambda_j}{A^j(\lambda_j)/\mu_j(1-\alpha_j)} \geq -x_j \right] \right\} \rightarrow P \left\{ \bigcap_{j=1}^n [U_j \leq x_j] \right\}. \quad \blacksquare$$

**Corollary 4.3.** If in Th. 4.1.,  $X_1$  belongs to the normal domain of attraction of an  $n$ -dimensional normal random vector with mean vector zero and covariance matrix  $\Sigma$ , then for any  $\alpha = (\alpha_1, \dots, \alpha_n)$  in  $[0, 1]^n$ ,

$$P \left\{ \bigcap_{j=1}^n \left[ m^{\alpha_j - (1/2)} \left( \max_{1 \leq k \leq m} \frac{S_k^j}{k^{\alpha_j}} - \mu_j m^{1-\alpha_j} \right) \leq x_j \right] \right\} \rightarrow P \left\{ \bigcap_{j=1}^n [U_j \leq x_j] \right\}$$

where  $U = (U_1, \dots, U_n)$  is an  $n$ -dimensional normal random vector with mean vector zero and covariance matrix  $\Sigma$ .  $\blacksquare$

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