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# **RESEARCH ARTICLE**

# On The Distribution of Partial Sums of Randomly Weighted Powers of Uniform Spacings

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## Abstract:

## **Objectives:**

To study the asymptotic theory of the randomly wieghted partial sum process of powers of k-spacings from the uniform distribution.

#### Methods:

Earlier results on the distribution of the uniform incremental randomly weighted sums.

#### Methods:

Based on theorems on weak and strong approximations of partial sum processes.

#### **Results and conculsions:**

Our first contribution is to classify the multitude of earlier proofs in Section 3. The second contribution consists of a new class of proofs.

Keywords: Uniform spacings, Weak convergence, Gaussian process, Incremental asymptotic convergence, Random Sample, k spacings.

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# 1. INTRODUCTION

Let  $0 = U_{(0)} \le U_{(1)} \le U_{(2)} \le \dots \le U_{(n-1)} \le U_{(n)} = 1$  be the order statistics of a random sample of size (n-1) from the U(0,1) distribution. Let  $k=1,2, \dots$  be arbitrary but fixed and assume that n=mk. The U(0,1) k-spacings are defined as

$$R_{i,k} = U_{(ik)} - U_{((i-1)k)}, i = 1, 2, \cdots, m.$$
 (1)

Let  $X_1, X_2,...$  be *iidrv* with  $E(X_i)=\mu$ ,  $Var(X_i)=\delta^2 < \infty$  and common distribution function F(.). Assume that the Xi's are independent of the Ui's. Define

$$S_m(t,k,r,F) = \begin{cases} \sum_{i=1}^{[mt]} R_{i,k}^r X_i, & \frac{1}{m} \le t \le 1\\ 0, & 0 \le t < \frac{1}{m}, \end{cases}$$
(2)

where [s] is the integer part of s and r>0 is fixed.

Looking at  $S_m(t,k,r,F)$  of (2) as a weighted partial sum of

the X's, Van Assche [1] obtained the exact distribution of  $S_2$  (1, 1,1, *F*). Johnson and Kotz [2] studied some generalizations of Van Assche results. Soltani and Homei [3] considered the finite sample distribution of  $S_n$  (1,1,1, *F*). Soltani and Roozegar [4] considered the finite sample distribution of a case similar to  $S_m$  (1,k,1, *F*) in which the spacings (1) are not equally spaced. It is interesting to note that  $S_m$  (t,k,r, *F*) of (2) is also a randomly weighted partial sum of powers of k-spacings from the U(0,1) distribution.

Here, we will obtain the asymptotic distribution of the stochastic process

$$\alpha_{m}(t,k,r,F) = \begin{cases} m^{\frac{1}{2}} \{k^{r} m^{r-1} S_{m}(t,k,r,F) \\ 0, \\ -t \mu \mu_{r,k} \}, \ \frac{1}{m} \le t \le 1 \\ 0 \le t < \frac{1}{m}, \end{cases}$$
(3)

where

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$$\mu_{l,k} = \frac{\Gamma(k+l)}{\Gamma(k)}, k \ge 1 \ l > 0 \tag{4}$$

and  $\Gamma(.)$  is the gamma function.

The motivations and justifications of this work are given next. First, as noted by Johnson and Kotz [2],  $S_2(1,1,1, F)$  is a random mixture of distributions and as such it has numerous applications in Sociology and in Biology. Second, the asymptotic theory of  $S_m(t,k,r, F)$  is a generalization of important results of Kimball [5], Darling [6], LeCam [7], Sethuraman and Rao [8], Koziol [9], Aly [10] and Aly [11] for sums of powers of spacings from the U(0,1) distribution. Finally, we solve the open problem of proving the asymptotic normality of  $S_m(1,k,1, F)$  proposed by Soltani and Roozegar [4].

## 2. METHODS

#### 2.1. The asymptotic distribution of $\alpha$ m (., k,r, F)

Let  $Y_1, Y_2,...$  be *iidrv* with the exponential distribution with mean 1 which are independent of the *Xi's*. By Proposition 13.15 of Breiman [12] we have for each *n*,

$$\{ 0 = U_{(0)}, U_{(1)}, U_{(2)}, \cdots, U_{(n-1)}, U_{(n)} = 1 \}$$
  
$$= \left\{ 0, \frac{Y_1}{\sum_{i=1}^n Y_i}, \frac{Y_1 + Y_2}{\sum_{i=1}^n Y_i}, \cdots, \frac{Y_1 + Y_2 + \cdots + Y_{n-1}}{\sum_{i=1}^n Y_i}, 1 \right\}.$$

Hence, for each m,

$$\left\{R_{i,k}, 1 \leq i \leq m\right\} \stackrel{D}{=} \left\{\frac{Z_{i,k}}{\sum_{i=1}^{m} Z_{i,k}}, 1 \leq i \leq m\right\},$$

where for  $1 \le i \le m$ ,

$$Z_{i,k} = Y_{(i-1)k+1} + \dots + Y_{ik}$$

are *iid Gamma* (k,1) random variables. Hence, for each m

$$S_m(t,k,r,F) \stackrel{D}{=} \sum_{i=1}^{[mt]} Z_{i,k}^r X_i / \left( \sum_{i=1}^m Z_{i,k} \right)^r, 0 \le t \le 1$$
 (5)

and

$$\alpha_m(\cdot, k, r, F) \stackrel{D}{=} \beta_m(\cdot, k, r, F), \tag{6}$$

where

$$\beta_m(t,k,r,F) = \begin{cases} 0, & 0 \le t < \frac{1}{m}.\\ m^{\frac{1}{2}} \left\{ k^r m^{r-1} \sum_{i=1}^{[mt]} Z_{i,k}^r X_i \\ / \left( \sum_{i=1}^m Z_{i,k} \right)^r - t \mu \mu_{r,k} \right\}, & \frac{1}{m} \le t \le 1 \end{cases}$$
(7)

Let  $\mu_{l,k}$  be as in (4). Note that

$$E(Z_{i,k}^{l}) = \mu_{l,k},$$

$$E(Z_{i,k}^{r}X_{i}) = \mu\mu_{r,k},$$

$$\sigma_{r,k}^{2} = Var(Z_{i,k}^{r}X_{i}) = \sigma^{2}\mu_{2r,k} + \mu^{2}\{\mu_{2r,k} - \mu_{r,k}^{2}\}$$
(8)

and

$$Cov(Z_{i,k}^r X_i, Z_{i,k}) = r\mu\mu_{r,k}.$$

The following Theorem will be needed in the sequel.

**Theorem A.** There exists a probability space on which a two-dimensional Wiener process  $\{\underline{\mathbf{W}}^t(s) = (W_1(s), W_2(s)); s \ge 0\}$  is defined such that

$$\sup_{0 \le s \le 1} \left\| \left( \sum_{j=1}^{[ms]} \left( Z_{j,k}^r X_j - \mu \mu_{r,k} \right), \sum_{j=1}^{[ms]} \left( Z_{j,k} - k \right) \right)^t - \underline{\mathbf{W}}^t([ms]) \right\| \stackrel{a.s.}{=} o\left( m^{\frac{1}{4}} \right),$$
(9)

where  $E \underline{W}(s)=0$ , and

$$E\underline{\mathbf{W}}(s)\underline{\mathbf{W}}^{t}(t) = \min(s,t) \begin{bmatrix} \sigma_{r,k}^{2} & r\mu\mu_{r,k} \\ r\mu\mu_{r,k} & k \end{bmatrix}.$$
 (10)

Theorem A follows from the results of Einmahl [13], Zaitsev [14] and Götze and Zaitsev [15].

The main result of this paper is the following Theorem.

**Theorem 1.** On some probability space, there exists a sequence of mean zero Gaussian processes  $\Gamma_m(t, k, r, F)$ ,  $0 \le t \le l$  such that

$$\sup_{0 \le t \le 1} |\alpha_m(t,k,r,F) - \Gamma_m(t,k,r,F)| \stackrel{P}{=} o\left(m^{-\frac{1}{4}}\right), \quad (11)$$

where  $\Gamma_m(t,k,r,F) \stackrel{D}{=} \Gamma(t,k,r,F)$  for each m, and

$$E\{\Gamma(t,k,r,F)\Gamma(s,k,r,F)\} = (t \wedge s)\sigma_{r,k}^2 - \frac{r^2\mu^2\mu_{r,k}^2}{k}ts.$$
 (12)

Theorem 1 follows from (6) and the following Theorem. **Theorem 2.** *On the probability space of Theorem A,* 

$$\sup_{0 \le t \le 1} \left| \beta_m(t, k, r, F) - m^{-\frac{1}{2}} \Big\{ W_1(mt) - \frac{tr \mu \mu_{r,k}}{k} W_2(m) \Big\} \right| \stackrel{a.s.}{=} o\left( m^{-\frac{1}{4}} \right),$$
(13)

where  $\underline{W}(.)$  is as in (9).

**Proof of Theorem 2:** We will only prove here the case when  $E(X)=\mu\neq 0$ . The case when  $\mu=0$  is straightforward and can be looked at as a special case of the case  $\mu\neq 0$ . Note that

$$\beta_m(t,k,r,F) = \frac{m^{\frac{1}{2}k^r A_m(t)}}{\left(\frac{1}{m} \sum_{i=1}^m Z_{i,k}\right)^r},$$
 (14)

where

$$A_m(t) = \frac{1}{m} \sum_{i=1}^{[mt]} Z_{j,k}^r X_j - t\mu\mu_{r,k} \frac{1}{k^r} \left(\frac{1}{m} \sum_{i=1}^m Z_{j,k}\right)^r$$
$$= \frac{1}{m} \sum_{i=1}^{[mt]} \left(Z_{j,k}^r X_j - \mu\mu_{r,k}\right) + \mu\mu_{r,k} \frac{([mt]-mt)}{m}$$

$$+\mu\mu_{r,k}t - t\mu\mu_{r,k}\frac{1}{k^{r}}\left(\frac{1}{m}\sum_{i=1}^{m}\left(Z_{j,k}-k\right)+k\right)^{r}.$$
 (15)

It is clear that, uniformly in t,  $0 \le t \le 1$ ,

$$\frac{|[mt]-mt|}{m} < \frac{1}{m}.$$
 (16)

By (9), (15) and (16) we have, uniformly in  $t,0 \le t \le 1$ ,

$$A_{m}(t) \stackrel{a.s.}{=} \frac{1}{m} W_{1}(mt) + \frac{1}{m} (W_{1}([mt]) - W_{1}(mt)) + O\left(\frac{1}{m}\right) + \mu \mu_{r,k} t - t \mu \mu_{r,k} \left(1 + \frac{1}{mk} W_{2}(m) + o(m^{-\frac{3}{4}})\right)^{r} + o(m^{-\frac{3}{4}}).$$
(17)

By Lemma 1.1.1 of Csörgö and Révész [17] we have, uniformly in  $t,0 \le t \le 1$ ,

$$\frac{1}{m}|W_1([mt]) - W_1(mt)| \stackrel{a.s.}{=} O(\frac{1}{m}\sqrt{\log m}).$$
(18)

By (17) and (18) we have, uniformly in  $t,0 \le t \le 1$ ,

$$A_{m}(t) \stackrel{a.s.}{=} \frac{1}{m} W_{1}(mt) + O(\frac{1}{m}\sqrt{\log m}) + \mu\mu_{r,k}t$$
$$- t\mu\mu_{r,k} \left(1 + \frac{1}{mk} W_{2}(m) + o(m^{-\frac{3}{4}})\right)^{r} + o(m^{-\frac{3}{4}}) \quad (19)$$
$$\stackrel{a.s.}{=} \frac{1}{m} W_{1}(mt) - \frac{tr\mu\mu_{r,k}}{mk} W_{2}(m) + o(m^{-\frac{3}{4}}).$$

By the LIL

$$\left(\frac{1}{m}\sum_{i=1}^{m} Z_{i,k}\right)^{r} \stackrel{a.s.}{=} \left(k + O\left(m^{-\frac{1}{2}}\sqrt{\log\log m}\right)\right)^{r}$$

$$\stackrel{a.s.}{=} k^{r} + O\left(m^{-\frac{1}{2}}\sqrt{\log\log m}\right).$$
(20)

By (14), (19) and (20) we have, uniformly in  $t,0 \le t \le 1$ ,

$$\begin{split} \beta_m(t,k,r,F) &\stackrel{a.s.}{=} \frac{\frac{m^2 k^r}{k^r + o\left(m^{-\frac{1}{2}}\sqrt{\log\log m}\right)} \left\{\frac{1}{m} W_1(mt) - \frac{tr \mu \mu_{r,k}}{mk} W_2(m) + o\left(m^{-\frac{3}{4}}\right)\right\} \\ & = m^{-\frac{1}{2}} \left\{W_1(mt) - \frac{tr \mu \mu_{r,k}}{k} W_2(m)\right\} + o\left(m^{-\frac{1}{4}}\right). \end{split}$$

This proves (13).

**Corollary 1.** *By* (4), (8) *and* (12),

$$\Gamma(\cdot, k, r, F) \stackrel{D}{=} \lambda_{r,k} W(\cdot) + \frac{r \mu \Gamma(r+k)}{\sqrt{k} \Gamma(k)} B(\cdot), \qquad (21)$$

where

$$\lambda_{r,k}^2 = \frac{\Gamma(2r+k)}{\Gamma(k)} \sigma^2 + \mu^2 \left\{ \frac{\Gamma(2r+k)}{\Gamma(k)} - \frac{(r^2+k)\Gamma^2(r+k)}{k\Gamma^2(k)} \right\},$$

W(.) is a Wiener process, B(.) is a Brownian bridge and W(.) and B(.) are independent.

**Corollary 2.** *By* (11) *and* (21) *we have, as*  $m \rightarrow \infty$ ,

$$\alpha_m(\cdot,k,r,F) \xrightarrow{D} \Gamma(\cdot,k,r,F) \xrightarrow{D} \lambda_{r,k} W(\cdot) + \frac{r\mu\Gamma(r+k)}{\sqrt{k}\Gamma(k)} B(\cdot)$$
 (22)

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and, in particular,

$$\alpha_m(1,k,r,F) \xrightarrow{D} N(0,\lambda_{r,k}^2).$$
 (23)

Some special cases of (22) and (23) are given . For r=1 and  $k \ge 1$ ,

$$\Gamma(\cdot, k, 1, F) = \sigma \sqrt{k(k+1)}W(\cdot) + \mu\sqrt{k}B(\cdot)$$

and

$$\alpha_m(1,k,1,F) \xrightarrow{D} N(0,k(k+1)\sigma^2). \text{ For } r > 0 \text{ and } k = 1,$$
  
 
$$\Gamma(\cdot,1,r,F) \xrightarrow{D} \lambda_{r,1} W(\cdot) + r\mu\Gamma(r+1)B(\cdot)$$

and

$$\alpha_m(1,1,r,F) \xrightarrow{D} N(0,\lambda_{r,1}^2),$$

where

$$\lambda_{r,1}^2 = \sigma^2 \Gamma(2r+1) + \mu^2 \{ \Gamma(2r+1) - (1+r^2) \Gamma^2(r+1) \}.$$

## **3. RESULTS**

In this section, we will use the same notation of Section 1

## 3.1. The scaled sum case

Define

$$T_{m,1}(t,k,r,F) = \begin{cases} \frac{1}{\sum_{j=1}^{m} X_j} \sum_{i=1}^{[mt]} R_{i,k}^r X_i, & \frac{1}{m} \le t \le 1\\ 0, & 0 \le t < \frac{1}{m} \end{cases}$$

and

$$\gamma_{m,1}(t,k,r,F) = \begin{cases} m^{\frac{1}{2}} \left\{ \frac{k^r m^r}{\mu_{r,k}} T_{m,1}(t,k,r,F) - t \right\}, & \frac{1}{m} \le t \le 1\\ 0, & 0 \le t < \frac{1}{m} \end{cases}$$

We can prove that

$$\gamma_{m,1}(t,k,r,F) \xrightarrow{D} \gamma_1(t,k,r,F),$$

where

$$\gamma_1(t,k,r,F) = \frac{1}{\mu \mu_{r,k}} W_1(t) - \frac{r}{k} t W_2(1) - \frac{1}{\mu} t W_3(1),$$

 $(W_1(.),W_2(.),W_3(.))^t$  is a mean zero Gaussian vector with covariance (t  $\Lambda$  s)  $\sum_1$  and

$$\Sigma_{1} = \begin{bmatrix} \sigma_{r,k}^{2} & r\mu\mu_{r,k} & \sigma^{2}\mu_{r,k} \\ r\mu\mu_{r,k} & k & 0 \\ \sigma^{2}\mu_{r,k} & 0 & \sigma^{2} \end{bmatrix}$$

Let

$$\delta_{r,k}^2 = \left(\frac{\mu_{2r,k}}{\mu_{r,k}^2} - 1\right) \left(\frac{\sigma^2}{\mu^2} + 1\right) - \frac{r^2}{k}.$$

We can show that

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$$\gamma_1(t,k,r,F) \stackrel{D}{=} \delta_{r,k} W(t) + \sqrt{\frac{r^2}{k} + \frac{\sigma^2}{\mu^2}} B(t),$$

where W(.) is a Brownian Motion and B(.) is a Brownian bridge and W(.) and B(.) are independent. Consequently,

$$\gamma_{m,1}(1,k,r,F) \xrightarrow{D} N(0,\delta_{r,k}^2).$$

When  $r=1, k\geq 1$ 

$$\delta_{1,k}^2 = \frac{\sigma^2}{k\mu^2}.$$

When r > 0, k=1

$$\delta_{r,1}^2 = \left(\frac{\Gamma(2r+1)}{\Gamma^2(r+1)} - 1\right) \left(\frac{\sigma^2}{\mu^2} + 1\right) - r^2.$$

#### 3.2. The Centered Sum Process

Let 
$$\overline{X} = \frac{1}{m} \sum_{j=1}^{m} X_j$$
 and define

$$T_{m,2}(t,k,r,F) = \begin{cases} \sum_{i=1}^{[mt]} R_{i,k}^r (X_i - \overline{X}), & \frac{1}{m} \le t \le 1\\ 0, & 0 \le t < \frac{1}{m} \end{cases}$$

and

$$\gamma_{m,2}(t,k,r,F) = \begin{cases} k^r m^{r-\frac{1}{2}} T_{m,2}(t,k,r,F), & \frac{1}{m} \le t \le 1\\ 0, & 0 \le t < \frac{1}{m}. \end{cases}$$

We can prove that

$$\gamma_{m,2}(t,k,r,F) \xrightarrow{D} \gamma_2(t,k,r,F),$$

where

$$\gamma_2(t, k, r, F) = W_1(t) - \mu W_2(t) - \mu_{r,k} t W_3(1),$$

 $(W_1(.), W_2(.), W_3(.))^t$  is a mean zero Gaussian vector with covariance  $(t \land s) \sum_2$  and

$$\Sigma_2 = \begin{bmatrix} \sigma_{r,k}^2 & \mu(\mu_{2r,k} - \mu_{r,k}^2) & \sigma^2 \mu_{r,k} \\ \mu(\mu_{2r,k} - \mu_{r,k}^2) & \mu_{2r,k} - \mu_{r,k}^2 & 0 \\ \sigma^2 \mu_{r,k} & 0 & \sigma^2 \end{bmatrix}.$$

We can show that

$$\gamma_2(t, k, r, F) \stackrel{D}{=} \sigma \left\{ \sqrt{\mu_{2r,k} - \mu_{r,k}^2} W(t) + \mu_{r,k} B(t) \right\}$$

where W(.) is a Brownian Motion and B(.) is a Brownian bridge and W(.) and B(.) are independent. Consequently,

$$\gamma_{m,2}(1,k,r,F) \xrightarrow{D} N\left(0,\sigma^{2}\left(\mu_{2r,k}-\mu_{r,k}^{2}\right)\right).$$
  
When  $r=1,k\geq 1$   
$$\gamma_{m,2}(1,k,r,F) \xrightarrow{D} N(0,k\sigma^{2}).$$

When r > 0, k=1

$$\gamma_{m,2}(1,k,r,F) \xrightarrow{D} N(0,\sigma^2(\Gamma(2r+1)-\Gamma^2(r+1))).$$

# 3.3. The Renewal Process

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For simplicity, we will consider the case of r=1. Define

$$S_m^*(t) = \begin{cases} \frac{1}{\mu} \sum_{i=1}^{[mt]} R_{i,k} X_i, & \frac{1}{m} \le t \le 1\\ 0, & 0 \le t < \frac{1}{m}, \end{cases}$$

$$T_m^*(t) = \begin{cases} \frac{1}{\mu} \sum_{i=1}^{[mt]} Z_{i,k} X_i / (\sum_{i=1}^m Z_{i,k}), & \frac{1}{m} \le t \le 1\\ 0, & 0 \le t < \frac{1}{m} \end{cases}$$

$$N_m(t) = \inf\{u: S_m^*(u) > t\},$$

$$M_m(t) = \inf\{u: T_m^*(u) > t\},$$

$$\alpha_m^*(t) = \begin{cases} m^{\frac{1}{2}} k \mu \{S_m^*(t) - t\}, & \frac{1}{m} \le t \le 1\\ 0, & 0 \le t < \frac{1}{m}, \end{cases}$$

$$\beta_m^*(t) = \begin{cases} m^{\frac{1}{2}} k \mu \{T_m^*(t) - t\}, & \frac{1}{m} \le t \le 1\\ 0, & 0 \le t < \frac{1}{m}, \end{cases}$$

$$\eta_m(t) = m^{\frac{1}{2}} k \mu \{t - N_m(t)\}$$

and

$$\xi_m(t) = m^{\frac{1}{2}} k \mu \{ t - M_m(t) \}.$$

.

By (5), for each m

$$\alpha_m^*(\cdot) \stackrel{D}{=} \beta_m^*(\cdot) \text{ and } \eta_m(\cdot) \stackrel{D}{=} \xi_m(\cdot).$$
 (24)

Note that (see (3))

$$\alpha_m^*(\cdot) = \alpha_m(\cdot, k, 1, F)$$

and hence, by Theorem 1

$$\sup_{0 \le t \le 1} |\alpha_m^*(t) - \Gamma_m(t, k, 1, F)| \stackrel{P}{=} o\left(m^{-\frac{1}{4}}\right),$$

where  $\Gamma_{\rm m}(., k, 1, F)$  is as in (11).

**Theorem 3.** On the probability space of Theorem A,

$$\sup_{0\leq t\leq 1} |\eta_m(t)-\Gamma_m(t)| \stackrel{P}{=} o\left(m^{-\frac{1}{4}} (\log m \log \log m)^{\frac{1}{2}}\right),$$

where

$$\Gamma_m(t) = m^{-\frac{1}{2}} \{ W_1(mt) - t\mu W_2(m) \}$$
(25)

and  $\underline{W}(.)$  is as in (9).

Theorem 3 follows directly from (24) and the following Theorem.

**Theorem 4.** On the probability space of Theorem A,

$$\sup_{0 \le t \le 1} |\xi_m(t) - \Gamma_m(t)| \stackrel{a.s.}{=} O\left(m^{-\frac{1}{4}} (\log m \log \log m)^{\frac{1}{2}}\right),$$

where  $\Gamma_m(t)$  is as in (25).

**Proof:** By (7),

$$\beta_m^*(\cdot) = \beta_m(\cdot, k, 1, F).$$

Note that

$$\xi_m(t) = \beta_m^*(M_m(t)) - m^{\frac{1}{2}}k\mu\{T_m(M_m(t)) - t\}.$$

Hence

$$\sup_{0 \le t \le 1} |\xi_m(t) - \Gamma_m(t)| \le E_{m1} + E_{m2} + E_{m3}, \quad (26)$$

where

$$E_{m1} = \sup_{0 \le t \le 1} |\beta_m^*(M_m(t)) - \Gamma_m(M_m(t))|,$$
$$E_{m2} = m^{\frac{1}{2}} k \mu \sup_{0 \le t \le 1} |T_m(M_m(t)) - t|$$

and

$$E_{m3} = \sup_{0 \le t \le 1} |\Gamma_m(M_m(t)) - \Gamma_m(t)|.$$

By Theorem 2 and the LIL for Wiener processes,

$$E_{m1} \stackrel{a.s.}{=} o\left(m^{-\frac{1}{4}}\right).$$
 (27)

and

$$\sup_{0 \le t \le 1} |T_m(t) - t| \stackrel{a.s.}{=} O\left(\sqrt{m^{-1} \log \log m}\right)$$

By a Lemma of Horváth [18]

$$\sup_{0 \le t \le 1} |M_m(t) - t| \le \sup_{0 \le t \le 1} |T_m(t) - t|$$

and hence

$$\sup_{0 \le t \le 1} |M_m(t) - t| \stackrel{a.s.}{=} O\left(\sqrt{m^{-1} \text{loglog}m}\right).$$
(28)

By the proof of Step 5 of Horváth [18] and Theorem 2 we can show that

$$E_{m2} \stackrel{a.s.}{=} O\left(m^{-\frac{1}{4}} \log m\right).$$
 (29)

As to  $E_{m3}$ ,

$$E_{m3} \le E_{m31} + E_{m32}, \tag{30}$$

where

$$E_{m31} = \sup |W_1(M_m(t)) - W_1(t)|$$

and

$$E_{m32} = m^{-\frac{1}{2}} \mu |W_2(m)| \sup |M_m(t) - t|.$$

By (28) and Lemma 1.1.1 of Csörgö and Révész [17] we have, uniformly in  $t,0 \le t \le 1$ ,

$$E_{m31} = \sup |W_1(t + (M_m(t) - t)) - W_1(t)|$$
  
$$\stackrel{a.s.}{=} \sup_{0 \le h \le m^{-\frac{1}{2}}(\log \log m)^{\frac{1}{2}}} |W_1(t + h) - W_1(t)|$$

$$\stackrel{a.s.}{=} O\left(m^{-\frac{1}{4}}\sqrt{\log m \log \log m}\right).$$
(31)

By (28) and the LIL for Wiener processes,

$$E_{m32} \stackrel{a.s.}{=} O\left(m^{-\frac{1}{2}} \text{loglog}m\right).$$
(32)

By (30)-(32),

$$E_{m3} \stackrel{a.s.}{=} O\left(m^{-\frac{1}{4}}\sqrt{\log m \log \log m}\right).$$
(33)

By (26)-(33) we obtain Theorem 4.

# 4. THE RANDOM VECTOR CASE

Let  $\underline{X}_1$ ,  $\underline{X}_2$ ,... be *iid* random vectors with  $E(\underline{X}_i) = \underline{\mu} = (\mu_1, \mu_2, \cdots, \mu_p)^t$  and  $Var(\underline{X}_i) = \sum = [\sigma_{ij}]$ . Assume that the  $U_is$  and the  $R_{i,k}s$  are same as in Section 1 and are independent of  $\underline{X}_1, \underline{X}_2, \dots$  Define

$$\underline{S}_m(t,k,r,F) = \begin{cases} \sum_{i=1}^{[mt]} R_{i,k}^r \underline{X}_i, & \frac{1}{m} \le t \le 1\\ 0, & 0 \le t < \frac{1}{m} \end{cases}$$

and

$$\underline{\alpha}_{m}(t,k,r,F) = \begin{cases} 0, & 0 \le t < \frac{1}{m}, \\ m^{\frac{1}{2}} \left\{ k^{r} m^{r-1} \underline{S}_{m}(t,k,r,F) \\ -t \mu_{r,k} \underline{\mu} \right\}, & \frac{1}{m} \le t \le 1 \end{cases}$$

Theorem 5 is a generalization of Theorem 1.

**Theorem 5.** On some probability space, there exists a mean zero sequence of Gaussian processes  $\{\underline{\Gamma}_{m}(t,k,r,F), 0 \le t \le 1\}$  such that

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$$\sup_{0\leq t\leq 1} \left\|\underline{\alpha}_m(t,k,r,F) - \underline{\Gamma}_m(t,k,r,F)\right\| \stackrel{P}{=} o\left(m^{-\frac{1}{4}}\right),$$

where, for each m,

$$\underline{\Gamma}_{m}(\cdot,k,r,F) \stackrel{p}{=} \underline{\Gamma}(\cdot,k,r,F),$$

$$E\underline{\Gamma}(s,k,r,F)\underline{\Gamma}^{t}(t,k,r,F) = (t \wedge s) \sum_{r,k}^{(1)} - \frac{r^{2}\Gamma^{2}(r+k)}{k\Gamma^{2}(k)} ts\underline{\mu}\underline{\mu}^{t}$$

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and

$$\Sigma_{r,k}^{(1)} = \frac{\Gamma(2r+k)}{\Gamma(k)} \Sigma + \left\{ \frac{\Gamma(2r+k)}{\Gamma(k)} - \frac{\Gamma^2(r+k)}{\Gamma^2(k)} \right\} \underline{\mu} \underline{\mu}^t.$$

**Corollary 1** \*. *By* (11) *and* (21) *we have, as*  $m \rightarrow \infty$ ,

$$\underline{\alpha}_m(\cdot, k, r, F) \xrightarrow{D} \underline{\Gamma}(\cdot, k, r, F)$$

and, in particular,

$$\underline{\alpha}_m(1,k,r,F) \xrightarrow{D} MVN(\underline{0}, \sum_{r,k}^{(2)})$$

where

$$\Sigma_{r,k}^{(2)} = \frac{\Gamma(2r+k)}{\Gamma(k)} \Sigma + \left\{ \frac{\Gamma(2r+k)}{\Gamma(k)} - \frac{(k+r^2)\Gamma^2(r+k)}{k\Gamma^2(k)} \right\} \underline{\mu} \underline{\mu}^t.$$

Particular cases of Corollary 1\* are given next. For r = 1 and  $k \ge 1$ ,

$$E\underline{\Gamma}(s,k,1,F)\underline{\Gamma}^{t}(t,k,1,F) =$$

$$(t \wedge s) \sum_{1,k}^{(1)} - tsk\underline{\mu}\underline{\mu}^{t},$$

$$\sum_{1,k}^{(1)} = k(k+1) \sum + k\mu\mu^{t}$$

and

$$\Gamma(1,k,1,F) \stackrel{D}{=} MVN(0,k(k+1)\Sigma).$$

For r > 0 and k = 1,

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$$E\underline{\Gamma}(s, 1, r, F)\underline{\Gamma}^{t}(t, 1, r, F) =$$
  
(t \lambda s)  $\sum_{r,1}^{(1)} - tsr^{2}\Gamma^{2}(r+1)\underline{\mu}\mu^{t}$ ,

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$$\sum_{r,1}^{(1)} = \Gamma(2r+1)\sum +$$

$${\Gamma(2r+1) - \Gamma^2(r+1)}\mu\mu^t$$

and

$$\underline{\Gamma}(1,1,r,F) \stackrel{D}{=} MVN(\underline{0}, \underline{\Sigma}^*),$$

where

$$\begin{split} \Sigma^* &= \Gamma(2r+1) \Sigma + \{ \Gamma(2r+1) \\ &- (1+r^2) \Gamma^2(r+1) \} \mu \mu^t. \end{split}$$

#### CONCLUSION

We proved the weak convergence of a stochastic process defined in terms of partial sums of randomly weighted powers of uniform spacings. The asymptotic results of several important generalizations and special cases are given.

## CONSENT FOR PUBLICATION

Not applicable.

### AVAILABILITY OF DATA AND MATERIALS

Not applicable.

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## CONFLICT OF INTEREST

The author declare no conflict of interest, financial or otherwise.

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#### REFERENCES

- W. Van Assche, "A random variable uniformly distributed between two independent random variables", *Sankhya A*, vol. 49, no. 2, pp. 207-211, 1987.
- [2] N.L. Johnson, and S. Kotz, "Randomly weighted averages: Some aspects and extensions", *Am. Stat.*, vol. 44, no. 3, pp. 245-249, 1990.
- [3] A.R. Soltani, and H. Homei, "Weighted averages with random proportions that are jointly uniformly distributed over the unit simplex", *Stat. Probab. Lett.*, vol. 79, no. 9, pp. 1215-1218, 2009. [http://dx.doi.org/10.1016/j.spl.2009.01.009]
- [4] A.R. Soltani, and R. Roozegar, "On distribution of randomly ordered uniform incremental weighted averages: Divided difference approach", *Stat. Probab. Lett.*, vol. 82, no. 5, pp. 1012-1020, 2012. [http://dx.doi.org/10.1016/j.spl.2012.02.007]
- H.E. Kimball, "On the asymptotic distribution of the sum of powers of unit frequency differences", *Ann. Math. Stat.*, vol. 21, no. 2, pp. 263-271, 1950.
   [http://dx.doi.org/10.1214/aoms/1177729843]
- [6] D.A. Darling, "On a class of problems related to the random division of an interval", Ann. Math. Stat., vol. 24, no. 2, pp. 239-253, 1953. [http://dx.doi.org/10.1214/aoms/1177729030]
- [7] L. LeCam, "Un theoreme sur la division d'un intervalle par des points pris au hasard", *Publ. Inst. Stat. Univ. Paris*, vol. 7, no. 3/4, pp. 7-16, 1958.
- [8] J. Sethuraman, and J.S. Rao, "Weak convergence of empirical distribution functions of random variables subject to perturbations and

scale factors", Ann. Stat., vol. 3, no. 2, pp. 299-313, 1975. [http://dx.doi.org/10.1214/aos/1176343058]

- J.A. Koziol, "A note on limiting distributions for spacings statistics", Z. Wahrsch. Verw. Gebiete, vol. 51, no. 1, pp. 55-62, 1980. [http://dx.doi.org/10.1007/BF00533817]
- [10] E-E.A.A. Aly, "Some limit theorems for uniform and exponential spacings", *Canad. J. Statist.*, vol. 11, no. 1, pp. 211-219, 1983.
- [11] E-E.A.A. Aly, "Strong approximations of quadratic sums of uniform spacings", *Can. J. Stat.*, vol. 16, no. 2, pp. 201-207, 1988. [http://dx.doi.org/10.2307/3314641]
- [12] L. Breiman, *Probability.*, Addison-Wesley: Reading, Massachusetts, 1968.
- [13] U. Einmahl, "Extension of results of Komlós, Major and Tusnády to the multivariate case", J. Mult. Anal., vol. 28, no. 1, pp. 20-68, 1989.

[http://dx.doi.org/10.1016/0047-259X(89)90097-3]

- [14] A.Yu. Zaitsev, "Multidimensional version of the results of Komlós, Major and Tusnády for vectors with finite exponential moments", *ESAIM Probab. Stat.*, vol. 2, pp. 41-108, 1998. [http://dx.doi.org/10.1051/ps:1998103]
- [15] F. Götze, and A.Yu. Zaitsev, "Bounds for the rate of strong approximation in the multidimensional invariance principle", *Theory Probab. Appl.*, vol. 53, no. 1, pp. 100-123, 2008.
- [16] M. Csörgö, and L. Horváth, Weighted Approximations in Probability and Statistics., John Wiley and Sons: New York, 1993.
- [17] M. Csörgö, and P. Revesz, P. Strong Approximations in Probability and Statistics., Academic Press: New York, 1981.
- [18] L. Horváth, "Strong approximation of renewal processes", *Stochastic Process. Appl.*, vol. 18, no. 1, pp. 127-138, 1984. [http://dx.doi.org/10.1016/0304-4149(84)90166-2]

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