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A note on the almost sure central limit theorem for the product of some partial sums

Yang Chen¹, Zhongquan Tan^{2*} and Kaiyong Wang¹

*Correspondence: tzq728@163.com

²College of Mathematics, Physics and Information Engineering, Jiaxing University, Jiaxing, 314001, P.R. China

Full list of author information is available at the end of the article

Abstract

Let (X_n) be a sequence of i.i.d., positive, square integrable random variables with $E(X_1) = \mu > 0$, $\text{Var}(X_1) = \sigma^2$. Denote by $S_{n,k} = \sum_{i=1}^n X_i - X_k$ and by $\gamma = \sigma/\mu$ the coefficient of variation. Our goal is to show the unbounded, measurable functions g , which satisfy the almost sure central limit theorem, i.e.,

$$\lim_{N \rightarrow \infty} \frac{1}{\log N} \sum_{n=1}^N \frac{1}{n} g\left(\left(\frac{\prod_{k=1}^n S_{n,k}}{(n-1)^n \mu^n}\right)^{\frac{1}{\gamma \sqrt{n}}}\right) = \int_0^\infty g(x) dF(x) \quad \text{a.s.,}$$

where $F(\cdot)$ is the distribution function of the random variable $e^{\mathcal{N}}$ and \mathcal{N} is a standard normal random variable.

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1 Introduction

The almost sure central limit theorem (ASCLT) has been first introduced independently by Schatte [1] and Brosamler [2]. Since then, many studies have been done to prove the ASCLT in different situations, for example, in the case of function-typed almost sure central limit theorem (FASCLT) (see Berkes *et al.* [3], Ibragimov and Lifshits [4]). The purpose of this paper is to investigate the FASCLT for the product of some partial sums.

Let (X_n) be a sequence of i.i.d. random variables and define the partial sum $S_n = \sum_{k=1}^n X_k$ for $n \geq 1$. In a recent paper of Rempala and Wesolowski [5], it is showed under the assumption $E(X^2) < \infty$ and $X > 0$ that

$$\left(\frac{\prod_{k=1}^n S_k}{n! \mu^n}\right)^{\frac{1}{\gamma \sqrt{n}}} \xrightarrow{d} e^{\sqrt{2}\mathcal{N}}, \quad (1)$$

where \mathcal{N} is a standard normal random variable, $\mu = E(X)$ and $\gamma = \sigma/\mu$ with $\sigma^2 = \text{var}(X)$. For further results in this field, we refer to Qi [6], Lu and Qi [7] and Rempala and Wesolowski [8].

Recently Gonchigdanzan and Rempala [9] obtained the almost sure limit theorem related to (1) as follows.

Theorem A Let (X_n) be a sequence of i.i.d., positive random variables with $E(X_1) = \mu > 0$ and $\text{Var}(X_1) = \sigma^2$. Denote by $\gamma = \sigma/\mu$ the coefficient of variation. Then, for any real x ,

$$\lim_{N \rightarrow \infty} \frac{1}{\log N} \sum_{n=1}^N \frac{1}{n} I \left(\left(\frac{\prod_{k=1}^n S_k}{n! \mu^n} \right)^{\frac{1}{\gamma \sqrt{n}}} \leq x \right) = G(x) \quad a.s., \quad (2)$$

where $G(x)$ is the distribution function of $e^{\sqrt{2}\mathcal{N}}$, \mathcal{N} is a standard normal random variable. Some extensions on the above result can be found in Ye and Wu [10] and the reference therein.

A similar result on the product of partial sums was provided by Miao [11], which stated the following.

Theorem B Let (X_n) be a sequence of i.i.d., positive, square integrable random variables with $E(X_1) = \mu > 0$ and $\text{Var}(X_1) = \sigma^2$. Denote by $S_{n,k} = \sum_{i=1}^n X_i - X_k$ and $\gamma = \sigma/\mu$ the coefficient of variation. Then

$$\left(\frac{\prod_{k=1}^n S_{n,k}}{(n-1)^n \mu^n} \right)^{\frac{1}{\gamma \sqrt{n}}} \xrightarrow{d} e^{\mathcal{N}}, \quad (3)$$

and for any real x ,

$$\lim_{N \rightarrow \infty} \frac{1}{\log N} \sum_{n=1}^N \frac{1}{n} I \left(\left(\frac{\prod_{k=1}^n S_{n,k}}{(n-1)^n \mu^n} \right)^{\frac{1}{\gamma \sqrt{n}}} \leq x \right) = F(x) \quad a.s., \quad (4)$$

where $F(\cdot)$ is the distribution function of the random variable $e^{\mathcal{N}}$ and \mathcal{N} is a standard normal random variable.

The purpose of this paper is to investigate the validity of (4) for some class of unbounded measurable functions g .

Throughout this article, (X_n) is a sequence of i.i.d. positive, square integrable random variables with $E(X_1) = \mu > 0$ and $\text{Var}(X_1) = \sigma^2$. We denote by $S_{n,k} = \sum_{i=1}^n X_i - X_k$ and by $\gamma = \sigma/\mu$ the coefficient of variation. Furthermore, \mathcal{N} is the standard normal random variable, Φ is the standard normal distribution function, ϕ is its density function and $a \ll b$ stands for $\limsup_{n \rightarrow \infty} |a_n/b_n| < \infty$.

2 Main result

We state our main result as follows.

Theorem 1 Let $g(x)$ be a real-valued, almost everywhere continuous function on \mathbb{R} such that $|g(e^x)\phi(x)| \leq c(1+|x|)^{-\alpha}$ with some $c > 0$ and $\alpha > 5$. Then, for any real x ,

$$\lim_{N \rightarrow \infty} \frac{1}{\log N} \sum_{n=1}^N \frac{1}{n} g \left(\left(\frac{\prod_{k=1}^n S_{n,k}}{(n-1)^n \mu^n} \right)^{\frac{1}{\gamma \sqrt{n}}} \right) = \int_0^\infty g(x) dF(x) \quad a.s., \quad (5)$$

where $F(\cdot)$ is the distribution function of the random variable $e^{\mathcal{N}}$.

Let $f(x) = g(e^x)$. By a simple calculation, we can get the following result.

Remark 1 Let $f(x)$ be a real-valued, almost everywhere continuous function on R such that $|f(x)\phi(x)| \leq c(1 + |x|)^{-\alpha}$ with some $c > 0$ and $\alpha > 5$. Then (5) is equivalent to

$$\lim_{N \rightarrow \infty} \frac{1}{\log N} \sum_{n=1}^N \frac{1}{n} f\left(\frac{1}{\gamma \sqrt{n}} \sum_{k=1}^n \log \frac{S_{n,k}}{(n-1)\mu}\right) = \int_{-\infty}^{\infty} f(x)\phi(x) dx \quad \text{a.s.} \quad (6)$$

Remark 2 Lu *et al.* [12] proved the function-typed almost sure central limit theorem for a type of random function, which can include U-statistics, Von-Mises statistics, linear processes and some other types of statistics, but their results cannot imply Theorem 1.

3 Auxiliary results

In this section, we state and prove several auxiliary results, which will be useful in the proof of Theorem 1.

Let $\tilde{S}_n = \sum_{i=1}^n \frac{X_i - \mu}{\sigma}$ and $U_i = \frac{1}{\gamma \sqrt{i}} \sum_{k=1}^i \log \frac{S_{i,k}}{(i-1)\mu}$. Observe that for $|x| < 1$ we have

$$\log(1+x) = x + \frac{\theta}{2}x^2,$$

where $\theta \in (-1, 0)$. Thus

$$\begin{aligned} U_i &= \frac{1}{\gamma \sqrt{i}} \sum_{k=1}^i \log \frac{S_{i,k}}{(i-1)\mu} \\ &= \frac{1}{\gamma \sqrt{i}} \sum_{k=1}^i \left(\frac{S_{i,k}}{(i-1)\mu} - 1 \right) + \frac{1}{\gamma \sqrt{i}} \sum_{k=1}^i \frac{\theta_k}{2} \left(\frac{S_{i,k}}{(i-1)\mu} - 1 \right)^2 \\ &= \frac{1}{\sqrt{i}} \sum_{k=1}^i \left(\frac{\sum_{j \neq k, j \leq i} (X_j - \mu)}{(i-1)\sigma} \right) + \frac{1}{\gamma \sqrt{i}} \sum_{k=1}^i \frac{\theta_k}{2} \left(\frac{S_{i,k}}{(i-1)\mu} - 1 \right)^2 \\ &= \frac{1}{\sqrt{i}} \sum_{k=1}^i \frac{X_k - \mu}{\sigma} + \frac{1}{\gamma \sqrt{i}} \sum_{k=1}^i \frac{\theta_k}{2} \left(\frac{S_{i,k}}{(i-1)\mu} - 1 \right)^2 \\ &=: \frac{1}{\sqrt{i}} \tilde{S}_i + R_i. \end{aligned} \quad (7)$$

By the law of iterated logarithm, we have for $k \rightarrow \infty$

$$\max_{1 \leq k \leq i} \left| \frac{S_{i,k}}{(i-1)\mu} - 1 \right| = O((\log \log i/i)^{1/2}) \quad \text{a.s.}$$

Therefore,

$$|R_i| = \left| \frac{1}{\gamma \sqrt{i}} \sum_{k=1}^i \frac{\theta_k}{2} \left(\frac{S_{i,k}}{(i-1)\mu} - 1 \right)^2 \right| \ll \frac{1}{\sqrt{i}} \sum_{k=1}^i \left(\frac{S_{i,k}}{(i-1)\mu} - 1 \right)^2 \ll \frac{\log \log i}{i^{1/2}} \quad \text{a.s.} \quad (8)$$

Obviously,

$$\begin{aligned} E|R_i| &= E \left| \frac{1}{\gamma \sqrt{i}} \sum_{k=1}^i \frac{\theta_k}{2} \left(\frac{S_{i,k}}{(i-1)\mu} - 1 \right)^2 \right| \\ &\ll \frac{1}{\sqrt{i}} \sum_{k=1}^i E \left(\frac{S_{i,k}}{(i-1)\mu} - 1 \right)^2 \ll \frac{1}{\sqrt{i}} \sum_{k=1}^i \frac{1}{i-1} \ll \frac{1}{i^{1/2}}. \end{aligned} \quad (9)$$

Our proof mainly relies on decomposition (7). Properties (8) and (9) will be extensively used in the following parts of this section.

Lemma 1 *Let X and Y be random variables. We write $F(x) = P(X < x)$, $G(x) = P(X + Y < x)$. Then*

$$F(x - \varepsilon) - P(|Y| \geq \varepsilon) \leq G(x) \leq F(x + \varepsilon) + P(|Y| \geq \varepsilon)$$

for every $\varepsilon > 0$ and x .

Proof It is Lemma 1.3 of Petrov [13]. \square

Lemma 2 *Let (X_n) be a sequence of i.i.d. random variables. Let $S_n = \sum_{k \leq n} X_k$, F^s denote the distribution function obtained from F by symmetrization, and choose $L > 0$ so large that $\int_{|x| \leq L} x^2 dF^s \geq 1$. Then, for any $n \geq 1$, $\lambda > 0$,*

$$\sup_a P\left(a \leq \frac{S_n}{\sqrt{n}} \leq a + \lambda\right) \leq A\lambda$$

with some absolute constant A , provided $\lambda\sqrt{n} \geq L$.

Proof It can be obtained from Berkes et al. [3]. \square

Lemma 3 *Assume that (6) is true for all indicator functions of intervals and for a fixed a.e. continuous function $f(x) = f_0(x)$. Then (6) is also true for all a.e. continuous functions f such that $|f(x)| \leq |f_0(x)|$, $x \in \mathbb{R}$, and, moreover, the exceptional set of probability 0 can be chosen universally for all such f .*

Proof See Berkes et al. [3]. \square

In view of Lemma 3 and Remark 1, in order to prove Theorem 1, it suffices to prove (6) for the case when $f(x)\phi(x) = (1 + |x|)^{-\alpha}$, $\alpha > 5$. Thus, in the following part, we put $f(x)\phi(x) = (1 + |x|)^{-\alpha}$, $\alpha > 5$ and

$$\begin{aligned}\xi_k &= \sum_{i=2^k+1}^{2^{k+1}} \frac{1}{i} f(U_i), \\ \xi_k^* &= \sum_{i=2^k+1}^{2^{k+1}} \frac{1}{i} f(U_i) I\left\{f(U_i) \leq \frac{k}{(\log k)^\beta}\right\},\end{aligned}$$

where $1 < \beta < \frac{1}{2}(\alpha - 3)$.

Lemma 4 *Under the conditions of Theorem 1, we have $P(\xi_k \neq \xi_k^* \text{ i.o.}) = 0$.*

Proof Let f^{-1} denote an inverse function of f in some interval, and let α, β satisfy $1 < \beta < \frac{1}{2}(\alpha - 3)$. It is easy to check that

$$\{\xi_k \neq \xi_k^*\} \subseteq \{|U_i| \geq f^{-1}(k/(\log k)^\beta) \text{ for some } 2^k < i \leq 2^{k+1}\}$$

and

$$\begin{aligned} f((2 \log k + (\alpha - 2\beta) \log \log k)^{1/2}) &= \frac{k}{(\log k)^\beta} \frac{\sqrt{2\pi} (\log k)^{\alpha/2}}{\{1 + (2 \log k + (\alpha - 2\beta) \log \log k)^{1/2}\}^\alpha} \\ &\leq \frac{k}{(\log k)^\beta}. \end{aligned} \quad (10)$$

Note that the function f is even and strictly increasing for $x \geq x_0$. We have

$$f^{-1}(k/(\log k)^\beta) \geq (2 \log k + (\alpha - 2\beta) \log \log k)^{1/2}. \quad (11)$$

Observing that $2^k < i \leq 2^{k+1}$ implies $k \geq \frac{1}{2} \log i$, in view of (8) we get

$$\begin{aligned} P(\xi_k \neq \xi_k^* \text{ i.o.}) &\leq P(|U_i| \geq (2 \log \log i + (\alpha - 2\beta) \log \log \log i - O(1))^{1/2} \text{ i.o.}) \\ &= P\left(\left|\frac{\tilde{S}_i}{\sqrt{i}} + R_i\right| \geq (2 \log \log i + (\alpha - 2\beta) \log \log \log i - O(1))^{1/2} \text{ i.o.}\right) \\ &\leq P\left(\left|\frac{\tilde{S}_i}{\sqrt{i}}\right| \geq (2 \log \log i + (\alpha - 2\beta) \log \log \log i - O(1))^{1/2} \text{ i.o.}\right) \\ &= 0, \end{aligned}$$

where in the last step we use the assumption $\alpha - 2\beta > 3$ and a version of the Kolmogorov-Erdős-Feller-Petrovski test (see Feller [14], Theorem 2). This completes the proof of Lemma 4. \square

Let $a_k = f^{-1}(k/(\log k)^\beta)$ and let G_i and F_i denote, respectively, the distribution function of U_i and $\frac{\tilde{S}_i}{\sqrt{i}}$. Set

$$\begin{aligned} \sigma_i^2 &= \int_{-\sqrt{i}}^{\sqrt{i}} x^2 dF_i(x) - \left(\int_{-\sqrt{i}}^{\sqrt{i}} x dF_i(x)\right)^2, \\ \eta_i &= \sup_x \left|G_i(x) - \Phi\left(\frac{x}{\sigma_i}\right)\right|, \\ \varepsilon_i &= \sup_x \left|F_i(x) - \Phi\left(\frac{x}{\sigma_i}\right)\right|. \end{aligned}$$

Clearly, $\sigma_i \leq 1$, $\lim_{i \rightarrow \infty} \sigma_i = 1$.

Lemma 5 *Under the conditions of Theorem 1, we have*

$$\sum_{k \leq N} E(\xi_k^*)^2 \ll \frac{N^2}{(\log N)^{2\beta}}.$$

Proof Observe now that the relation

$$\left| \int_{-a}^a \psi(x) d(G_1(x) - G_2(x)) \right| \leq \sup_{-a \leq x \leq a} |\psi(x)| \cdot \sup_{-a \leq x \leq a} |G_1(x) - G_2(x)| \quad (12)$$

is valid for any bounded, measurable functions ψ and distribution functions G_1, G_2 . Let, as previously, $a_k = f^{-1}(k/(\log k)^\beta)$. Thus, for any $2^k < i \leq 2^{k+1}$, we obtain that

$$\begin{aligned} Ef^2(U_i)I\left\{f(U_i) \leq \frac{k}{(\log k)^\beta}\right\} &= \int_{|x| \leq a_k} f^2(x) dG_i(x) \\ &\leq \int_{|x| \leq a_k} f^2(x) d\Phi\left(\frac{x}{\sigma_i}\right) + \eta_i \frac{k^2}{(\log k)^{2\beta}} \\ &\ll \int_{|x| \leq a_k} f^2(x) d\Phi(x) + \eta_i \frac{k^2}{(\log k)^{2\beta}}, \end{aligned}$$

where in the last step, we have used the fact that $\sigma_i \leq 1$, $\lim_{i \rightarrow \infty} \sigma_i = 1$. Hence, by the Cauchy-Schwarz inequality, we have

$$\begin{aligned} E(\xi_k^*)^2 &\ll E\left[\left(\sum_{i=2^k+1}^{2^{k+1}} \left(\frac{1}{i}\right)^2\right)^{1/2} \left(\sum_{i=2^k+1}^{2^{k+1}} f^2(U_i)I\left\{f(U_i) \leq \frac{k}{(\log k)^\beta}\right\}\right)^{1/2}\right]^2 \\ &\ll \left(\sum_{i=2^k+1}^{2^{k+1}} \frac{1}{i^2}\right) \left(\sum_{i=2^k+1}^{2^{k+1}} \left(\int_{|x| \leq a_k} f^2(x) d\Phi(x) + \eta_i \frac{k^2}{(\log k)^{2\beta}}\right)\right) \\ &\ll \frac{1}{2^k} \left(2^k \int_{|x| \leq a_k} f^2(x) d\Phi(x) + \frac{k^2}{(\log k)^{2\beta}} \sum_{i=2^k+1}^{2^{k+1}} \eta_i\right) \\ &\ll \int_{|x| \leq a_k} \frac{e^{x^2/2}}{(1+|x|)^{2\alpha}} dx + \frac{k^2}{(\log k)^{2\beta}} \sum_{i=2^k+1}^{2^{k+1}} \frac{\eta_i}{i}. \end{aligned} \quad (13)$$

Note that

$$\int_0^t \frac{e^{x^2/2}}{(1+|x|)^{2\alpha}} dx = \int_0^{t/2} + \int_{t/2}^t \ll te^{t^2/8} + \frac{1}{t^{2\alpha+1}} \int_{t/2}^t xe^{x^2/2} dx \ll \frac{e^{t^2/2}}{t^{2\alpha+1}},$$

and thus by (10) and (11), we have

$$\int_{|x| \leq a_k} \frac{e^{x^2/2}}{(1+|x|)^{2\alpha}} dx \ll \frac{e^{a_k^2/2}}{a_k^{2\alpha+1}} \ll f(a_k) \frac{1}{a_k^{\alpha+1}} \ll \frac{k}{(\log k)^{\beta+(\alpha+1)/2}}. \quad (14)$$

Now we estimate η_i . By Lemma 1, we have that for some $\varepsilon > 0$,

$$\begin{aligned} \eta_i &= \sup_x \left| G_i(x) - \Phi\left(\frac{x}{\sigma_i}\right) \right| \\ &\leq \sup_x |G_i(x) - F_i(x)| + \sup_x \left| F_i(x) - \Phi\left(\frac{x}{\sigma_i}\right) \right| \\ &= \sup_x \left| P(U_i \leq x) - P\left(\frac{\tilde{S}_i}{\sqrt{i}} \leq x\right) \right| + \varepsilon_i \\ &= \sup_x \left| P\left(\left(\frac{\tilde{S}_i}{\sqrt{i}} + R_i\right) \leq x\right) - P\left(\frac{\tilde{S}_i}{\sqrt{i}} \leq x\right) \right| + \varepsilon_i \\ &\leq P(|R_i| \geq \varepsilon) + \sup_x \left\{ P\left(\frac{\tilde{S}_i}{\sqrt{i}} \leq x + \varepsilon\right) - P\left(\frac{\tilde{S}_i}{\sqrt{i}} \leq x\right) \right\} + \varepsilon_i. \end{aligned}$$

The Markov inequality and (9) imply that

$$P(|R_i| \geq \varepsilon) \leq \frac{E|R_i|}{\varepsilon} \ll \frac{1}{i^{1/2}\varepsilon}.$$

In addition, Lemma 2 yields

$$\sup_x \left\{ P\left(\frac{\tilde{S}_i}{\sqrt{i}} \leq x + \varepsilon\right) - P\left(\frac{\tilde{S}_i}{\sqrt{i}} \leq x\right) \right\} \ll \varepsilon.$$

Setting $\varepsilon = i^{-1/3}$, we have

$$\eta_i \ll \frac{1}{i^{1/6}} + \frac{1}{i^{1/3}} + \varepsilon_i.$$

Using Theorem 1 of Friedman *et al.* [15], we get

$$\sum_{i=1}^{\infty} \frac{\varepsilon_i}{i} < \infty.$$

Hence,

$$\sum_{i=1}^{\infty} \frac{\eta_i}{i} \ll \sum_{i=1}^{\infty} \frac{\frac{1}{i^{1/6}} + \varepsilon_i}{i} < \infty, \quad (15)$$

which, coupled with (13), (14) and the fact $\frac{1}{2}(\alpha + 1) > \beta$, yields

$$\begin{aligned} \sum_{k \leq N} E(\xi_k^*)^2 &\ll \sum_{k \leq N} \frac{k}{(\log k)^{\beta + (\alpha + 1)/2}} + \sum_{k \leq N} \frac{k^2}{(\log k)^{2\beta}} \sum_{i=2^{k+1}}^{2^{k+1}} \frac{\eta_i}{i} \\ &\ll \frac{N^2}{(\log N)^{2\beta}}, \end{aligned}$$

which completes the proof. \square

Lemma 6 Let $\xi_k^* = \sum_{i=2^{k+1}}^{2^{k+1}} \frac{1}{i} f(U_i) I\{f(U_i) \leq \frac{k}{(\log k)^\beta}\}$, $\xi_l^* = \sum_{i=2^{l+1}}^{2^{l+1}} \frac{1}{i} f(U_i) I\{f(U_i) \leq \frac{l}{(\log l)^\beta}\}$. Under the conditions of Theorem 1, we have for $l \geq l_0$

$$|\text{cov}(\xi_k^*, \xi_l^*)| \ll \frac{kl}{(\log k)^\beta (\log l)^\beta} 2^{-(l-k-1)/4}.$$

Proof We first show the following result, for any $1 \leq i \leq \frac{j}{2}$ and real x, y ,

$$|P(U_i \leq x, U_j \leq y) - P(U_i \leq x)P(U_j \leq y)| \ll \left(\frac{i}{j}\right)^{1/4}. \quad (16)$$

Letting $\rho = \frac{i}{j}$, the Chebyshev inequality yields

$$P\left(\left|\frac{\tilde{S}_i}{\sqrt{j}}\right| \geq \rho^{1/4}\right) \leq \frac{1}{j} \rho^{-1/2} E|\tilde{S}_i|^2 = \rho^{1/2}. \quad (17)$$

Using the Markov inequality and (9), we have

$$P(|R_j| \geq \rho^{1/4}) \leq \frac{E|R_j|}{\rho^{1/4}} \ll \frac{1}{j^{1/2}\rho^{1/4}} = \frac{1}{j^{1/4}l^{1/4}} \leq \rho^{1/4}. \quad (18)$$

It follows from Lemma 1, Lemma 2, (17), (18) and the positivity and independence of (X_n) that

$$\begin{aligned} &P(U_i \leq x, U_j \leq y) \\ &= P\left(U_i \leq x, \frac{\tilde{S}_j}{\sqrt{j}} + R_j \leq y\right) \\ &= P\left(U_i \leq x, \frac{\tilde{S}_i}{\sqrt{j}} + \sqrt{1-\rho} \frac{\tilde{S}_j - \tilde{S}_i}{\sqrt{j-i}} + R_j \leq y\right) \\ &\geq P\left(U_i \leq x, \sqrt{1-\rho} \frac{\tilde{S}_j - \tilde{S}_i}{\sqrt{j-i}} \leq y\right) \\ &\quad - P\left(y - 2\rho^{1/4} \leq \sqrt{1-\rho} \frac{\tilde{S}_j - \tilde{S}_i}{\sqrt{j-i}} \leq y\right) - P\left(\left|\frac{\tilde{S}_i}{\sqrt{j}}\right| \geq \rho^{1/4}\right) - P(|R_j| \geq \rho^{1/4}) \\ &\geq P\left(U_i \leq x, \sqrt{1-\rho} \frac{\tilde{S}_j - \tilde{S}_i}{\sqrt{j-i}} \leq y\right) - (4A + O(1) + 1)\rho^{1/4} \\ &= P(U_i \leq x)P\left(\sqrt{1-\rho} \frac{\tilde{S}_j - \tilde{S}_i}{\sqrt{j-i}} \leq y\right) - (4A + O(1) + 1)\rho^{1/4}. \end{aligned} \quad (19)$$

We can obtain an analogous upper estimate for the first probability in (19) by the same way. Thus

$$P(U_i \leq x, U_j \leq y) = P(U_i \leq x)P\left(\sqrt{1-\rho} \frac{\tilde{S}_j - \tilde{S}_i}{\sqrt{j-i}} \leq y\right) - \theta(4A + O(1) + 1)\rho^{1/4},$$

where $|\theta| \leq 1$. A similar argument yields

$$P(U_i \leq x)P(U_j \leq y) = P(U_i \leq x)P\left(\sqrt{1-\rho} \frac{\tilde{S}_j - \tilde{S}_i}{\sqrt{j-i}} \leq y\right) - \theta'(4A + O(1) + 1)\rho^{1/4},$$

where $|\theta'| \leq 1$, and (16) follows. Letting $G_{i,j}(x, y)$ denote the joint distribution function of U_i and U_j , in view of (12), (16), we get for $l \geq l_0$

$$\begin{aligned} &\left| \text{cov}\left(f(U_i)I\left\{f(U_i) \leq \frac{k}{(\log k)^\beta}\right\}, f(U_j)I\left\{f(U_j) \leq \frac{l}{(\log l)^\beta}\right\}\right) \right| \\ &= \left| \int_{|x| \leq a_k} \int_{|y| \leq a_l} f(x)f(y) d(G_{i,j}(x, y) - G_i(x)G_j(y)) \right| \\ &\ll \frac{kl}{(\log k)^\beta (\log l)^\beta} 2^{-(l-k-1)/4}, \end{aligned}$$

where the last relation follows from the facts that: f is strictly increasing for $x \geq x_0$, $f(a_i) = \frac{i}{(\log i)^\beta}$ and $2^k < i \leq 2^{k+1}$, $2^l < j \leq 2^{l+1}$. Thus

$$|\text{cov}(\xi_k^*, \xi_l^*)| \ll \frac{kl}{(\log k)^\beta (\log l)^\beta} 2^{-(l-k-1)/4}. \quad \square$$

Lemma 7 Under the conditions of Theorem 1, letting $\zeta_k = \xi_k^* - E\xi_k^*$, we have

$$E(\zeta_1 + \cdots + \zeta_N)^2 = O\left(\frac{N^2}{(\log N)^{2\beta-1}}\right), \quad N \rightarrow \infty.$$

Proof By Lemma 6, we have

$$\left| \sum_{\substack{1 \leq k \leq l \leq N \\ l-k > 40 \log N}} E(\zeta_k \zeta_l) \right| \ll \frac{N^2}{(\log N)^{2\beta}} N^2 2^{-10 \log N} = o(1).$$

On the other hand, letting $\|\cdot\|$ denote the L_2 norm, Lemma 5 and the Cauchy-Schwarz inequality imply

$$\begin{aligned} \left| \sum_{\substack{1 \leq k \leq l \leq N \\ l-k \leq 40 \log N}} E(\zeta_k \zeta_l) \right| &\leq \sum_{\substack{1 \leq k \leq l \leq N \\ l-k \leq 40 \log N}} \|\zeta_k\| \|\zeta_l\| \\ &\leq \sum_{\substack{1 \leq k \leq l \leq N \\ l-k \leq 40 \log N}} \|\xi_k^*\| \|\xi_l^*\| \\ &= \sum_{0 \leq j \leq 40 \log N} \sum_{k=1}^{N-j} \|\xi_k^*\| \|\xi_{k+j}^*\| \\ &\leq \left(\sum_{k=1}^N \|\xi_k^*\|^2 \right)^{1/2} \left(\sum_{l=1}^N \|\xi_l^*\|^2 \right)^{1/2} 40 \log N \\ &= O\left(\frac{N^2}{(\log N)^{2\beta-1}}\right), \end{aligned}$$

and Lemma 7 is proved. \square

4 Proof of the main result

We only prove the property in (6), since, in view of Remark 1, it is sufficient for the proof of Theorem 1.

Proof of Theorem 1 By Lemma 7 we have

$$E\left(\frac{\zeta_1 + \cdots + \zeta_N}{N}\right)^2 = O((\log N)^{1-2\beta}),$$

and thus setting $N_k = [\exp(k^\lambda)]$ with $(2\beta - 1)^{-1} < \lambda < 1$, we get

$$\sum_{k=1}^{\infty} E\left(\frac{\zeta_1 + \cdots + \zeta_{N_k}}{N_k}\right)^2 < \infty,$$

and therefore

$$\lim_{k \rightarrow \infty} \frac{\xi_1 + \cdots + \xi_{N_k}}{N_k} = 0 \quad \text{a.s.} \quad (20)$$

Observe now that for $2^k < i \leq 2^{k+1}$ we have

$$\begin{aligned} Ef(U_i)I\left\{f(U_i) \leq \frac{k}{(\log k)^\beta}\right\} &= \int_{|x| \leq a_k} f(x) dG_i(x) \\ &= \int_{|x| \leq a_k} f(x) d\Phi\left(\frac{x}{\sigma_i}\right) + \int_{|x| \leq a_k} f(x) d\left(G_i(x) - \Phi\left(\frac{x}{\sigma_i}\right)\right). \end{aligned}$$

Put $m = \int_{-\infty}^{\infty} f(x) d\Phi(x)$. Since $\sigma_i \leq 1$, $\lim_{i \rightarrow \infty} \sigma_i = 1$ and $a_k \rightarrow \infty$ as $k \rightarrow \infty$, we have

$$\lim_{k \rightarrow \infty} \sup_{2^k < i \leq 2^{k+1}} \left| \int_{|x| \leq a_k} f(x) d\Phi\left(\frac{x}{\sigma_i}\right) - m \right| = 0,$$

and thus, using (12), we get

$$\left| Ef(U_i)I\left\{f(U_i) \leq \frac{k}{(\log k)^\beta}\right\} - m \right| \leq \frac{k\eta_i}{(\log k)^\beta} + o_k(1).$$

Thus we have

$$E\xi_k^* = m \sum_{i=2^{k+1}}^{2^{k+1}} \frac{1}{i} + \vartheta_k \frac{k}{(\log k)^\beta} \sum_{i=2^{k+1}}^{2^{k+1}} \frac{\eta_i}{i} + o_k(1), \quad |\vartheta_k| \leq 1.$$

Consequently, using the relation $\sum_{i \leq L} 1/i = \log L + O(1)$ and (15), we conclude

$$\begin{aligned} \left| \frac{E(\xi_1^* + \cdots + \xi_{N_k}^*)}{\log 2^{N_k+1}} - m \right| &\ll \frac{1}{N} \sum_{k \leq N} \frac{k}{(\log k)^\beta} \sum_{i=2^{k+1}}^{2^{k+1}} \frac{\eta_i}{i} + o_N(1) \\ &= O((\log N)^{-\beta}) + o_N(1) = o_N(1), \end{aligned}$$

and thus (20) gives

$$\lim_{k \rightarrow \infty} \frac{\xi_1^* + \cdots + \xi_{N_k}^*}{\log 2^{N_k+1}} = m \quad \text{a.s.}$$

By Lemma 4 this implies

$$\lim_{k \rightarrow \infty} \frac{\xi_1 + \cdots + \xi_{N_k}}{\log 2^{N_k+1}} = m \quad \text{a.s.} \quad (21)$$

The relation $\lambda < 1$ implies $\lim_{k \rightarrow \infty} N_{k+1}/N_k = 1$, and thus (21) and the positivity of ξ_k yield

$$\lim_{N \rightarrow \infty} \frac{\xi_1 + \cdots + \xi_N}{\log 2^{N+1}} = m \quad \text{a.s.}, \quad (22)$$

i.e., (6) holds for the subsequence $\{2^{N+1}\}$. Now, for each $N \geq 4$, there exists n , depending on N , such that $2^{n+1} \leq N \leq 2^{n+2}$. Then

$$\frac{\xi_1 + \xi_2 + \cdots + \xi_n}{\log 2^{n+1}} \leq \frac{\sum_{i=1}^N \frac{1}{i} f(U_i)}{\log N} \frac{\log N}{\log 2^{n+1}} \leq \frac{\xi_1 + \xi_2 + \cdots + \xi_{n+2}}{\log 2^{n+2}} \frac{\log 2^{n+2}}{\log 2^{n+1}} \quad (23)$$

by the positivity of each term of (ξ_k) . Noting that $(n+1)\log 2 \sim \log N \sim (n+2)\log 2$ as $N \rightarrow \infty$, we get (6) by (22) and (23). \square

Competing interests

The authors declare that they have no competing interests.

Authors' contributions

All authors read and approved the final manuscript.

Author details

¹School of Mathematics and Physics, Suzhou University of Science and Technology, Suzhou, 215009, P.R. China. ²College of Mathematics, Physics and Information Engineering, Jiaxing University, Jiaxing, 314001, P.R. China.

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