

THE DAVIS–GUT LAW AND LAI LAW FOR FINITELY INHOMOGENEOUS WALKS

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Abstract. Let $\{X_n, n \geq 1\}$ be a sequence of independent and identically distributed random variables with partial sums $S_n = \sum_{k=1}^n X_k$, $n \geq 1$. Davis-Gut law states that

$$\sum_{n=1}^{\infty} \frac{1}{n} P\left\{|S_n| > (1 + \varepsilon)\sqrt{2n \log \log n}\right\} \begin{cases} < \infty, & \text{if } \varepsilon > 0, \\ = \infty, & \text{if } \varepsilon < 0 \end{cases}$$

if and only if $EX_1 = 0$ and $EX_1^2 = 1$. Lai law states that

$$\sum_{n=1}^{\infty} n^{r-1} P\left\{|S_n| > (1 + \varepsilon)\sqrt{2rn \log n}\right\} \begin{cases} < \infty, & \text{if } \varepsilon > 0, \\ = \infty, & \text{if } \varepsilon < 0 \end{cases}$$

if and only if $EX_1 = 0$, $EX_1^2 = 1$ and $E(X_1^2 / \log |X_1|)^{r+1} < \infty$, where $r > 0$. The paper will extend those results to the case where $\{X_n, n \geq 1\}$ are no longer identically distributed, but rather their distributions come from a finite set of distributions.

1. Introduction and the main result

The classical Hartman-Wintner law of the iterated logarithm (see Hartman and Wintner [6]) states that for $\{X_n, n \geq 1\}$, a sequence of independent and identically distributed random variables, if

$$EX_1 = 0 \text{ and } EX_1^2 = 1, \tag{1.1}$$

then

$$\limsup_{n \rightarrow \infty} \frac{S_n}{\sqrt{2n \log \log n}} = 1 \text{ a.s. and } \liminf_{n \rightarrow \infty} \frac{S_n}{\sqrt{2n \log \log n}} = -1 \text{ a.s.}, \tag{1.2}$$

where $S_n = \sum_{k=1}^n X_k$, $n \geq 1$, $\log x = \log_e \max\{x, e\}$ for $x > 0$. The converse, the implication (1.2) \Rightarrow (1.1), was proved by Strassen [15].

The following theorem, related to the Hartman-Wintner law of the iterated logarithm, is well-known.

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THEOREM A. *Let $\{X_n, n \geq 1\}$ be a sequence of independent and identically distributed random variables with partial sums $S_n = \sum_{k=1}^n X_k, n \geq 1$. The following statements are equivalent*

(1.1) holds,

$$\sum_{n=1}^{\infty} \frac{1}{n} P\left\{|S_n| > (1 + \varepsilon)\sqrt{2n \log \log n}\right\} \begin{cases} < \infty, & \text{if } \varepsilon > 0, \\ = \infty, & \text{if } \varepsilon < 0. \end{cases} \tag{1.3}$$

One can call this result the Davis-Gut law. The implication (1.1) \Rightarrow (1.3) should be due to Theorem 4 of Davis [4] which was remedied by Corollary 2.3 of Li et al. [10]. For the implication (1.3) \Rightarrow (1.1), see Theorem 6.2 of Gut [5]. The sufficient part of Theorem A for the moving processes, i.e. (1.1) \Rightarrow (1.3), is obtained by Chen and Wang [2].

The following theorem, related to the law of single logarithm, is also well-known.

THEOREM B. *Let $r > 0$ and $\{X_n, n \geq 1\}$ be a sequence of independent and identically distributed random variables with partial sums $S_n = \sum_{k=1}^n X_k, n \geq 1$. Suppose that*

$$EX_1 = 0, \quad EX_1^2 = 1 \text{ and } E(X_1^2 / \log |X_1|)^{r+1} < \infty. \tag{1.4}$$

Then

$$\sum_{n=1}^{\infty} n^{r-1} P\{|S_n| > (1 + \varepsilon)\sqrt{2rn \log n}\} < \infty, \text{ for all } \varepsilon > 0. \tag{1.5}$$

Conversely, if (1.5) holds for some $\varepsilon > -1$, then $EX_1 = 0$ and $E(X_1^2 / \log |X_1|)^{r+1} < \infty$.

One can label this result as the Lai law which first established by Lai [9]. Chen and Wang [2] extended it to the moving processes partly, and furthermore showed that

$$\sum_{n=1}^{\infty} n^{r-1} P\{|S_n| > (1 + \varepsilon)\sqrt{2rn \log n}\} = \infty, \text{ for all } \varepsilon < 0.$$

Combining the results of Lai [9] and Chen and Wang [2], we have

$$\sum_{n=1}^{\infty} n^{r-1} P\{|S_n| > (1 + \varepsilon)\sqrt{2rn \log n}\} \begin{cases} < \infty, & \text{if } \varepsilon > 0, \\ = \infty, & \text{if } \varepsilon < 0 \end{cases} \tag{1.6}$$

if and only if (1.4) holds.

When $r = 0$, an analog of (1.6) is discussed by Chen and Qi [1].

Recently, Spătaru [14] obtained the classical Hartman-Winter law of the iterated logarithm for finitely inhomogeneous walks. The term *finitely inhomogeneous walk* designs a sequence of sums $S_n = \sum_{k=1}^n X_k, n \geq 1$, where the steps $X_n, n \geq 1$, are independent random variables having a finite number of possible distributions. This setting arises naturally in the study of some type Galton-Watson process, and was proposed by Kesten and Lawler [8]. Due to the work of Spătaru [14], the purpose of this paper is to generalize Theorem A and Theorem B to the finitely inhomogeneous walks.

In the following, we always assume that $\{X_n, n \geq 1\}$ is a sequence of independent random variables having a finite number of possible distributions as $Y_1, \dots, Y_p, p \geq 1$, set $S_n = \sum_{k=1}^n X_k, n \geq 1$. Some lemmas and the proofs of the main results will be presented in the next section.

THEOREM 1.1. Assume that $EY_i = 0$ and $EY_i^2 = 1$ for $1 \leq i \leq p$. Then (1.3) holds.

THEOREM 1.2. Let $r > 0$. Assume that $EY_i = 0$, $EY_i^2 = 1$ and $E(Y_i^2 / \log |Y_i|)^{r+1} < \infty$ for $1 \leq i \leq p$. Then (1.6) holds.

THEOREM 1.3. Let $\{X_{nk}, 1 \leq k \leq n \geq 1\}$ be an array of independent random variables having a finite number of possible distributions as Y_1, \dots, Y_p , $p \geq 1$, set $S_{nn} = \sum_{k=1}^n X_{nk}$, $n \geq 1$. Assume that $EY_i = 0$, $EY_i^2 = 1$ and $E(Y_i^2 / \log |Y_i|)^2 < \infty$ for $1 \leq i \leq p$. Then

$$\limsup_{n \rightarrow \infty} \frac{|S_{nn}|}{\sqrt{2n \log n}} = 1 \text{ a.s.} \tag{1.7}$$

Throughout this paper, C always stands for a positive constant which may differ from one place to another and $I(A)$ denotes the indicator function of the event A .

2. Lemmas and proofs of main results

The main idea in the proof of the main result is from the invariance principle' way to estimate the rate of convergence (see Sakhanenko [11, 12, 13]), which is a powerful tool in the field of limit theory (for example, see Csörgo, Szyszkowicz and Wu [3], Jiang and Zhang [7], Chen and Wang [2], etc.) and is listed as the following lemma.

LEMMA 2.1. For any $q > 2$, there exists $B = B(q) > 0$ satisfying that for any sequence of independent random variables $\{\xi_k, 1 \leq k \leq n\}$ with mean zero and $E|\xi_k|^q < \infty, 1 \leq k \leq n$, there is a sequence of independent normal random variables $\{\eta_k, 1 \leq k \leq n\}$ with $E\eta_k = 0, E\eta_k^2 = E\xi_k^2$ and for all $y > 0$,

$$P \left\{ \max_{1 \leq m \leq n} \left| \sum_{k=1}^m \xi_k - \sum_{k=1}^m \eta_k \right| > y \right\} \leq B y^{-q} \sum_{k=1}^n E|\xi_k|^q. \tag{2.1}$$

The following two lemmas are well-known.

LEMMA 2.2. Let Y be a random variable with $EY^2 < \infty$. Then

$$\sum_{n=1}^{\infty} P\{|Y| > \sqrt{n}\} \leq CEY^2 < \infty$$

and

$$\sum_{n=1}^{\infty} n^{-q/2} E|Y|^q I(|Y| \leq \sqrt{n}) \leq CE|Y|^2 < \infty,$$

for any $q > 2$.

LEMMA 2.3. Let Y be a random variable with $E(Y^2 / \log |Y|)^{r+1} < \infty$ for some $r > 0$. Then

$$\sum_{n=1}^{\infty} n^r P\{|Y| > \sqrt{n \log n}\} \leq CE(Y^2 / \log |Y|)^{r+1} < \infty$$

and

$$\sum_{n=1}^{\infty} n^r (n \log n)^{-q/2} E|Y|^q I(|Y| \leq \sqrt{n \log n}) \leq CE(Y^2 / \log |Y|)^{r+1} < \infty$$

for any $q > 2(r + 1)$.

Proof of Theorem 1.1. Set $a_n = \sqrt{2n \log \log n}$, $X_{nk} = X_k I(|X_k| \leq \sqrt{n})$ and $T_n = \sum_{k=1}^n X_{nk}$. We first prove that

$$\sum_{n=1}^{\infty} \frac{1}{n} P\{|S_n| > (1 + \varepsilon)a_n\} < \infty, \quad \forall \varepsilon > 0. \tag{2.2}$$

Note that

$$\{|S_n| > (1 + \varepsilon)a_n\} \subset \left\{ \max_{1 \leq k \leq n} |X_k| > \sqrt{n} \right\} \cup \{|T_n| > (1 + \varepsilon)a_n\}$$

and by Lemma 2.2,

$$\sum_{n=1}^{\infty} \frac{1}{n} P\left\{ \max_{1 \leq k \leq n} |X_k| > \sqrt{n} \right\} \leq \sum_{i=1}^p \sum_{n=1}^{\infty} P\{|Y_i| > \sqrt{n}\} \leq C \sum_{i=1}^p EY_i^2 < \infty \tag{2.3}$$

and

$$\frac{1}{a_n} |ET_n| \leq \frac{1}{a_n} \sum_{k=1}^n E|X_k| I(|X_k| > \sqrt{n}) \leq \frac{1}{\sqrt{2 \log \log n}} \rightarrow 0 \tag{2.4}$$

as $n \rightarrow \infty$. Hence to prove (2.2), it is enough to prove that

$$\sum_{n=1}^{\infty} \frac{1}{n} P\{|T_n - ET_n| > (1 + \varepsilon)a_n\} < \infty, \quad \forall \varepsilon > 0. \tag{2.5}$$

We can get from Lemma 2.1 that for any $n \geq 1$, there exists normal random variables Z_{nk} with $EZ_{nk} = 0$ and $EZ_{nk}^2 = E(X_{nk} - EX_{nk})^2$, $1 \leq k \leq n$, such that for any $q > 2$ and all $y > 0$

$$P\left\{ \left| (T_n - ET_n) - \sum_{k=1}^n Z_{nk} \right| > y \right\} \leq Ay^{-q} \sum_{k=1}^n E|X_{nk} - EX_{nk}|^q. \tag{2.6}$$

Note that

$$\begin{aligned} \{|T_n - ET_n| > (1 + \varepsilon)a_n\} &\subset \left\{ \left| (T_n - ET_n) - \sum_{k=1}^k Z_{nk} \right| > \varepsilon_1 a_n \right\} \\ &\cup \left\{ \left| \sum_{k=1}^n Z_{nk} \right| > (1 + \varepsilon_2)a_n \right\} \end{aligned}$$

where $\varepsilon_1 > 0, \varepsilon_2 > 0$ with $\varepsilon = \varepsilon_1 + \varepsilon_2$. Hence

$$\begin{aligned} & \sum_{n=1}^{\infty} \frac{1}{n} P\{|T_n - ET_n| > (1 + \varepsilon)a_n\} \\ & \leq \sum_{n=1}^{\infty} \frac{1}{n} P\left\{|(T_n - ET_n) - \sum_{k=1}^n Z_{nk}| > \varepsilon_1 a_n\right\} + \sum_{n=1}^{\infty} \frac{1}{n} P\left\{|\sum_{k=1}^n Z_{nk}| > (1 + \varepsilon_2)a_n\right\} \\ & = I_1 + I_2. \end{aligned}$$

By (2.6) and Lemma 2.2 we can derive that for $q > 2$

$$\begin{aligned} I_1 & \leq C \sum_{n=1}^{\infty} \frac{1}{na_n^q} \sum_{k=1}^n E|X_{nk} - EX_{nk}|^q \\ & \leq C \sum_{n=1}^{\infty} \frac{1}{na_n^q} \sum_{k=1}^n E|X_k|^q I(|X_k| \leq \sqrt{n}) \\ & \leq C \sum_{i=1}^p \sum_{n=1}^{\infty} \frac{1}{a_n^q} E|Y_i|^q I(|Y_i| \leq \sqrt{n}) \\ & \leq C \sum_{i=1}^p EY_i^2 < \infty. \end{aligned}$$

Let N be a standard normal random variable. Note that $E(X_{nk} - EX_{nk})^2 \leq 1$ for all $1 \leq k \leq n$ and $n \geq 1$, and $P\{|N| > x\} \sim \sqrt{2/\pi} x^{-1} e^{-x^2/2}$. Hence for large enough n ,

$$\begin{aligned} P\left\{|\sum_{k=1}^n Z_{nk}| > (1 + \varepsilon_2)a_n\right\} & = P\left\{|N| > \frac{(1 + \varepsilon_2)a_n}{\sqrt{\sum_{k=1}^n E(X_{nk} - EX_{nk})^2}}\right\} \\ & \leq C \exp\left\{-\frac{(1 + \varepsilon_2)^2 n \log \log n}{\sum_{k=1}^n E(X_{nk} - EX_{nk})^2}\right\} \\ & \leq C \exp\{- (1 + \varepsilon_2)^2 \log \log n\} \\ & = C(\log n)^{-t_1}, \end{aligned}$$

where $t_1 = (1 + \varepsilon_2)^2 > 1$. Then $I_2 < \infty$.

Now we prove that

$$\sum_{n=1}^{\infty} \frac{1}{n} P\{|S_n| > (1 + \varepsilon)a_n\} = \infty, \quad \forall \varepsilon < 0. \tag{2.7}$$

By (2.3) and (2.4), (2.7) is equivalent to

$$\sum_{n=1}^{\infty} \frac{1}{n} P\{|T_n - ET_n| > (1 + \varepsilon)a_n\} = \infty, \quad \forall \varepsilon < 0. \tag{2.8}$$

Note that for any $\varepsilon < 0$, if we take $\varepsilon_3 > 0$ and $\varepsilon_4 < 0$ with $\varepsilon_4 = \varepsilon_3 + \varepsilon$, then

$$\begin{aligned} \left\{|\sum_{k=1}^n Z_{nk}| > (1 + \varepsilon_4)a_n\right\} & \subset \left\{|(T_n - ET_n) - \sum_{k=1}^n Z_{nk}| > \varepsilon_3 a_n\right\} \\ & \cup \{|T_n - ET_n| > (1 + \varepsilon)a_n\}, \end{aligned}$$

Then by $I_1 < \infty$, it is enough to show that

$$\sum_{n=1}^{\infty} \frac{1}{n} P \left\{ \left| \sum_{k=1}^n Z_{nk} \right| > (1 + \varepsilon_4) a_n \right\} = \infty. \tag{2.9}$$

Since $n^{-1} \sum_{k=1}^n E(X_{nk} - EX_{nk})^2 \rightarrow 1$ as $n \rightarrow \infty$, then there exists $\delta < 1$ close to 1 enough with $t_2 = (1 + \varepsilon_4)^2 / \delta < 1$ such that $\sum_{k=1}^n E(X_{nk} - EX_{nk})^2 \geq \delta n$ for n large enough. Using $P\{|N| > x\} \sim \sqrt{2/\pi} x^{-1} e^{-x^2/2}$ again,

$$\begin{aligned} P \left\{ \left| \sum_{k=1}^n Z_{nk} \right| > (1 + \varepsilon_4) a_n \right\} &= P \left\{ |N| > \frac{(1 + \varepsilon_4) a_n}{\sqrt{\sum_{k=1}^n E(X_{nk} - EX_{nk})^2}} \right\} \\ &\geq P \left\{ |N| > \frac{(1 + \varepsilon_4) a_n}{\sqrt{\delta n}} \right\} \sim \frac{C}{(\log n)^{t_2} (\log \log n)^{1/2}}. \end{aligned}$$

Therefore (2.9) holds by the fact that the series $\sum_{n=1}^{\infty} n^{-1} (\log n)^{-t_2} (\log \log n)^{-1/2} = \infty$. The proof is completed. \square

Proof of Theorem 1.2. For all $1 \leq k \leq n$ and $n \geq 1$, set

$$X_{nk} = X_k I(|X_{nk}| \leq \sqrt{n \log n}), \quad T_n = \sum_{k=1}^n X_{nk}.$$

We first prove that

$$\sum_{n=1}^{\infty} n^{r-1} P\{|S_n| > (1 + \varepsilon) \sqrt{2rn \log n}\} < \infty, \quad \forall \varepsilon > 0. \tag{2.10}$$

Note that

$$P\{|S_n| > (1 + \varepsilon) \sqrt{2rn \log n}\} \subset \left\{ \max_{1 \leq k \leq n} |X_k| > \sqrt{n \log n} \right\} \cup \left\{ |T_n| > (1 + \varepsilon) \sqrt{2rn \log n} \right\}$$

and by Lemma 2.3,

$$\begin{aligned} \sum_{n=1}^{\infty} n^{r-1} P\left\{ \max_{1 \leq k \leq n} |X_k| > \sqrt{n \log n} \right\} &\leq \sum_{i=1}^p \sum_{n=1}^{\infty} n^r P\{|Y_i| > \sqrt{n \log n}\} \\ &\leq C \sum_{i=1}^p E(Y_i^2 / \log |Y_i|)^{r+1} < \infty \end{aligned} \tag{2.11}$$

and

$$\frac{1}{\sqrt{n \log n}} |ET_n| \leq \frac{1}{\sqrt{n \log n}} \sum_{k=1}^n E|X_k| I(|X_k| \leq \sqrt{n \log n}) \leq \frac{1}{\log n} \rightarrow 0 \tag{2.12}$$

as $n \rightarrow \infty$. Hence to prove (2.10), it is enough to prove that

$$\sum_{n=1}^{\infty} n^{r-1} P\{|T_n - ET_n| > (1 + \varepsilon) \sqrt{2rn \log n}\} < \infty, \quad \forall \varepsilon > 0. \tag{2.13}$$

We can get from Lemma 2.1 that for any $n \geq 1$, there exists normal random variables Z_{nk} with $EZ_{nk} = 0$ and $EZ_{nk}^2 = E(X_{nk} - EX_{nk})^2$, $1 \leq k \leq n$, such that for any $q > 2$ and all $y > 0$

$$P \left\{ |(T_n - ET_n) - \sum_{k=1}^n Z_{nk}| > y \right\} \leq Ay^{-q} \sum_{k=1}^n E|X_{nk} - EX_{nk}|^q. \tag{2.14}$$

Note that

$$\begin{aligned} \left\{ |T_n - ET_n| > (1 + \varepsilon)\sqrt{2rn \log n} \right\} &\subset \left\{ |(T_n - ET_n) - \sum_{k=1}^k Z_{nk}| > \varepsilon_1 \sqrt{2rn \log n} \right\} \\ &\cup \left\{ \left| \sum_{k=1}^n Z_{nk} \right| > (1 + \varepsilon_2)\sqrt{2rn \log n} \right\} \end{aligned}$$

where $\varepsilon_1 > 0, \varepsilon_2 > 0$ with $\varepsilon = \varepsilon_1 + \varepsilon_2$. Hence

$$\begin{aligned} &\sum_{n=1}^{\infty} n^{r-1} P \left\{ |T_n - ET_n| > (1 + \varepsilon)\sqrt{2rn \log n} \right\} \\ &\leq \sum_{n=1}^{\infty} n^{r-1} P \left\{ |(T_n - ET_n) - \sum_{k=1}^n Z_{nk}| > \varepsilon_1 \sqrt{2rn \log n} \right\} \\ &\quad + \sum_{n=1}^{\infty} n^{r-1} P \left\{ \left| \sum_{k=1}^n Z_{nk} \right| > (1 + \varepsilon_2)\sqrt{2rn \log n} \right\} = J_1 + J_2. \end{aligned}$$

By (2.14) and Lemma 2.3 we can derive that for any $q > 2(r + 1)$,

$$\begin{aligned} J_1 &\leq C \sum_{n=1}^{\infty} n^{r-1-q/2} (\log n)^{-q/2} \sum_{k=1}^n E|X_{nk} - EX_{nk}|^q \\ &\leq C \sum_{n=1}^{\infty} n^{r-1-q/2} (\log n)^{-q/2} \sum_{k=1}^n E|X_k|^q I(|X_k| \leq \sqrt{n \log n}) \\ &\leq C \sum_{i=1}^p \sum_{n=1}^{\infty} n^{r-q/2} (\log n)^{-q/2} E|Y_i|^q I(|Y_i| \leq \sqrt{n \log n}) \\ &\leq C \sum_{i=1}^p E(Y_i^2 / \log |Y_i|)^{r+1} < \infty. \end{aligned}$$

Let N be a standard normal random variable. Note that $E(X_{nk} - EX_{nk})^2 \leq 1$ for all $1 \leq k \leq n$ and $n \geq 1$, and $P\{|N| > x\} \sim \sqrt{2/\pi} x^{-1} e^{-x^2/2}$. Hence for large enough n ,

$$\begin{aligned} P \left\{ \left| \sum_{k=1}^n Z_{nk} \right| > (1 + \varepsilon_2)\sqrt{2rn \log n} \right\} &= P \left\{ |N| > \frac{(1 + \varepsilon_2)\sqrt{2rn \log n}}{\sqrt{\sum_{k=1}^n E(X_{nk} - EX_{nk})^2}} \right\} \\ &\leq C \exp \left\{ -\frac{r(1 + \varepsilon_2)^2 n \log n}{\sum_{k=1}^n E(X_{nk} - EX_{nk})^2} \right\} \\ &\leq C \exp \{-r(1 + \varepsilon_2)^2 \log n\} = Cn^{-t_1}, \end{aligned}$$

where $t_1 = r(1 + \varepsilon_2)^2 > r$. Then $J_2 < \infty$.

Now we prove that

$$\sum_{n=1}^{\infty} n^{r-1} P\left\{|S_n| > (1 + \varepsilon)\sqrt{2rn \log n}\right\} = \infty, \quad \forall \varepsilon < 0. \tag{2.15}$$

By (2.11) and (2.12), (2.15) is equivalent to

$$\sum_{n=1}^{\infty} n^{r-1} P\left\{|T_n - ET_n| > (1 + \varepsilon)\sqrt{2rn \log n}\right\} = \infty, \quad \forall \varepsilon < 0. \tag{2.16}$$

Note that for any $\varepsilon < 0$, if we take $\varepsilon_3 > 0$ and $\varepsilon_4 < 0$ with $\varepsilon_4 = \varepsilon_3 + \varepsilon$, then

$$\begin{aligned} \left\{ \left| \sum_{k=1}^n Z_{nk} \right| > (1 + \varepsilon_4)\sqrt{2rn \log n} \right\} &\subset \left\{ |(T_n - ET_n) - \sum_{k=1}^n Z_{nk}| > \varepsilon_3\sqrt{2rn \log n} \right\} \\ &\cup \left\{ |T_n - ET_n| > (1 + \varepsilon)\sqrt{2rn \log n} \right\}, \end{aligned}$$

Then by $J_1 < \infty$, it is enough to show that

$$\sum_{n=1}^{\infty} n^{r-1} P\left\{ \left| \sum_{k=1}^n Z_{nk} \right| > (1 + \varepsilon_4)\sqrt{2rn \log n} \right\} = \infty. \tag{2.17}$$

Since $n^{-1} \sum_{k=1}^n E(X_{nk} - EX_{nk})^2 \rightarrow 1$ as $n \rightarrow \infty$, then there exists $\delta < 1$ close to 1 enough with $t_2 = r(1 + \varepsilon_4)^2/\delta < r$ such that $\sum_{k=1}^n E(X_{nk} - EX_{nk})^2 \geq \delta n$ for n large enough. Using $P\{|N| > x\} \sim \sqrt{2/\pi} x^{-1} e^{-x^2/2}$ again,

$$\begin{aligned} P\left\{ \left| \sum_{k=1}^n Z_{nk} \right| > (1 + \varepsilon_4)\sqrt{2rn \log n} \right\} &= P\left\{ |N| > \frac{(1 + \varepsilon_4)\sqrt{2rn \log n}}{\sqrt{\sum_{k=1}^n E(X_{nk} - EX_{nk})^2}} \right\} \\ &\geq P\left\{ |N| > \frac{(1 + \varepsilon_4)\sqrt{2rn \log n}}{\sqrt{\delta n}} \right\} \\ &\sim \frac{C}{n^{t_2}(\log n)^{1/2}}. \end{aligned}$$

Therefore (2.17) holds by the fact that the series $\sum_{n=1}^{\infty} n^{r-1-t_2}(\log n)^{-1/2} = \infty$. The proof is completed. \square

Proof of Theorem 1.3. By the same argument as Theorem 1.2, we have

$$\sum_{n=1}^{\infty} P\{|S_{nn}| > (1 + \varepsilon)\sqrt{2n \log n}\} \begin{cases} < \infty, & \text{if } \varepsilon > 0, \\ = \infty, & \text{if } \varepsilon < 0. \end{cases}$$

Then by the Borel-Cantelli lemma, (1.7) holds at once. \square

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REFERENCES

- [1] P. CHEN, Y. QI, *Generalized law of the iterated logarithm and its convergence rate*, Stoch. Anal. Appl. **25** (2007), 89–103.
- [2] P. CHEN, Q. WANG, *Convergence rates for probabilities of moderate deviations for moving average processes*, Acta Math. Sinica, English Series **24** (2008), 611–622.
- [3] M. CSÖRGO, B. SZYSZKOWICZ, Q. Y. WU, *Donsker's theorem for self-normalized partial sums processes*, Ann. Probab. **31** (2003), 1228–1240.
- [4] J. A. DAVIS, *Convergence rates for the law of the iterated logarithm*, Ann. Math. Statist. **39** (1968), 1479–1485.
- [5] A. GUT, *Convergence rates for probabilities of moderate deviations for sums of random variables with multidimensional indices*, Ann. Probab. **8** (1980), 298–313.
- [6] P. HARTMAN, A. WINTNER, *On the law of the iterated logarithm*, Amer. J. Math. **63** (1941), 169–176.
- [7] Y. JIANG, L. ZHANG, *Precise rates in the law of iterated logarithm for the moment of I. I. D. random variables*, Acta Math. Sinica **22** (2006), 781–792.
- [8] M. KESTEN, G. LAWLER, *A necessary condition for making money from fair games*, Ann. Probab. **20** (1992), 855–882.
- [9] T. L. LAI, *Limit theorems for delayed sums*, Ann. Probab. **2** (1974) 432–440.
- [10] D. L. LI, X. WANG, M. B. RAO, *Some results on convergence rates for probabilities of moderate deviations for sums of random variables*, Internat. J. Math. Math. Sci. **15** (1992), 481–497.
- [11] A. I. SAKHANENKO, *On unimprovable estimates of the rate of convergence in the invariance principle*, In Colloquia Math. Soci. János Bolyai **32** (1980), 779–783, Nonparametric Statistical Inference, Budapest (Hungary).
- [12] A. I. SAKHANENKO, *On estimates of the rate of convergence in the invariance principle*, In Advances in Probab. Theory: Limit Theorems and Related Problems (A. A. Borovkov, Ed.), Springer, New York, 1984, 124–135.
- [13] A. I. SAKHANENKO, *Convergence rate in the invariance principle for non-identically distributed variables with exponential moments*, In Advances in Probab. Theory: Limit Theorems for Sums of Random Variables (A. A. Borovkov, Ed.), Springer, New York, 1985, 2–73.
- [14] A. SPĂTARU, *The law of the iterated logarithm for finitely inhomogeneous random walks*, J. Theor. Probab. **23** (2010), 417–427.
- [15] V. STRASSEN, *A converse to the law of the iterated logarithm*, Z. Wahrsch. Verw. Gebiete **4** (1966), 265–268.

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