

SMALL DEVIATION PROBABILITIES FOR SUMS OF INDEPENDENT POSITIVE RANDOM VARIABLES

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In this note, we give estimates of small deviation probabilities of the sum $\sum_{j \geq 1} \lambda_j X_j$, where $\{\lambda_j\}$ are nonnegative numbers and $\{X_j\}$ are i.i.d. positive random variables that satisfy mild assumptions at zero and infinity. Bibliography: 10 titles.

1. INTRODUCTION

In this paper, we prove results announced in [1].

Let $S = \sum_{j \geq 1} \lambda_j X_j$, where $\lambda_1 \geq \lambda_2 \geq \dots$ are nonnegative numbers such that

$$1 \leq n = \#\{j | \lambda_j > 0\} \leq \infty \tag{1.1}$$

(if $n = \infty$, we assume that the series S converges a.s.) and $\{X_i\}$ are independent copies of a positive random variable X with distribution function $V(x)$ that satisfies the following condition: there exist constants $b \in (0, 1)$, $c_1, c_2 > 1$, and $r_0 > 0$ such that

$$c_1 V(br) \leq V(r) \leq c_2 V(br) \tag{L}$$

for any $r \leq r_0$. Here and below, c_1, c_2, \dots denote positive constants depending only on the distribution V and on parameters from conditions (L), (1.2), etc which are connected with V .

Condition (L) introduced in [2] is obviously satisfied if the function $V(r)$ is regularly varying at zero. In particular, this is so in the important Gaussian case, i.e., when $X = |\xi|^p$, $p > 0$, where ξ is the standard normal variable.

Condition (L) also implies that

$$c_1 u^\beta \geq V(ur)/V(r) \geq u^\alpha/c_2, \quad u \leq 1, \quad r \leq r_0, \tag{1.2}$$

$$u^\beta/c_1 \leq V(ur)/V(r) \leq c_2 u^\alpha, \quad u \geq 1, \quad r \leq r_0, \tag{1.3}$$

$$c_3 r^\alpha \leq V(r) \leq c_4 r^\beta, \quad r \leq r_0,$$

for some constants α, β such that $\log c_1 / |\log b| \leq \beta \leq \alpha \leq \log c_2 / |\log b|$.

We are mostly interested in the behavior of the probabilities $\mathbf{P}(r - s < S \leq r)$ for $r, s > 0$. Similar problems (mostly, for the Gaussian case) were considered by many authors (see references in [2] and [3]). The most general and exact statements (in the context of the present work) were obtained in [2]. Let us formulate the basic result of this note. For this purpose, we introduce some notation.

For $\gamma \geq 0$, set

$$\begin{aligned} \Lambda(\gamma) &= \mathbf{E} e^{-\gamma S}, \quad m(\gamma) = -(\log \Lambda(\gamma))', \quad \sigma^2(\gamma) = (\log \Lambda(\gamma))'', \\ Q(\gamma) &= -\gamma m(\gamma) - \log \Lambda(\gamma). \end{aligned} \tag{1.4}$$

Theorem 1.1. Assume that a random variable X has

(a) finite variance

and

(b) absolutely continuous distribution

and satisfies condition (L). If $\{\lambda_j\}$ is a nonincreasing positive sequence such that $\sum_{j \geq 1} \lambda_j < \infty$, then

$$\mathbf{P}(S \leq r) = (2\pi)^{-1/2} (\gamma \sigma(\gamma))^{-1} e^{-Q(\gamma)} (1 + o(1)), \quad r \searrow 0,$$

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where the parameter $\gamma = \gamma(r)$ is a solution of the equation $m(\gamma) = r$.
 Moreover, if $\mathbf{E} X^3 < \infty$ and α satisfies condition (1.3), then

$$\mathbf{P}(S \leq r) = (2\pi)^{-1/2} (\gamma\sigma(\gamma))^{-1} e^{-Q(\gamma)} \left(1 + O\left((\gamma\sigma(\gamma))^{-1} + (\gamma\sigma(\gamma))^{-(2-\kappa)/\alpha} \right) \right), \quad r \searrow 0, \quad (1.5)$$

for any $\kappa \in (0, 2)$.

Note that assumptions (a) and (b) of Theorem 1.1 are essentially used in the proofs.

Our main purpose is to show that relations of the type (1.5) are still valid without assumption (b) and under an essential relaxation of condition (a).

2. RESULTS

First we state an assertion which holds under condition (L) only.

Theorem 2.1. *Assume that the distribution function V satisfies condition (L). Then*

$$e^{-Q(\gamma)} \geq \mathbf{P}(S \leq r) \geq e^{-Q(\gamma) - c_5 \sqrt{1+Q(\gamma)}}, \quad 0 < r < \mathbf{E} S, \quad (2.1)$$

where γ is the unique solution of the equation $m(\gamma) = r$.

Remark 1. Since the function $m(u)$ monotonically decreases on $(0, \infty)$, $m(0) = \mathbf{E} S \leq \infty$, and $m(\infty) = 0$, relation (2.1) is equivalent to the following relations:

$$e^{-Q(\gamma)} \geq \mathbf{P}(S \leq m(\gamma)) \geq e^{-Q(\gamma) - c_5 \sqrt{1+Q(\gamma)}}, \quad 0 < \gamma < \infty.$$

Relation (2.1) allows us to find asymptotics of the logarithm of the probability $\mathbf{P}(S \leq r)$.

To formulate a more sharp result, we require an additional information on the behavior of V at infinity.

Introduce the following condition:

$$\limsup_{r \rightarrow \infty} \frac{r^2 \mathbf{P}(X \geq r)}{\mathbf{E} X^2 \mathbf{I}[X < r]} < \infty. \quad (F)$$

This condition, the so-called condition of Feller's stochastic compactness, is satisfied if X belongs to the domain of attraction of a stable law, including the normal case. It is also possible to show that condition (F) is equivalent to the following condition: there exists $\omega \in (0, 1)$ such that

$$r^{-\omega} \mathbf{E}(1 \wedge r X^2) \nearrow, \quad r > 0, \quad (2.2)$$

which implies, in particular, that there exists $\delta > 0$ such that $\mathbf{E} X^\delta < \infty$.

In fact, take $\xi \in (0, 2)$ and $g(x) = x^{-\xi} \mathbf{E}(x^2 \wedge X^2)$, $x \geq x_0$. In this case, $g(x) = x^{-\xi} \int_0^x \bar{V}(u) du^2$, where $\bar{V}(u) = 1 - V(u)$. Next,

$$g'(x) = -\xi g(x)/x + 2x^{1-\xi} \bar{V}(x) = x^{-1-\xi} (2x^2 \bar{V}(x) - \xi x^2 \bar{V}(x) - \xi \mathbf{E} X^2 \mathbf{I}[X \leq x]).$$

We note that $g'(x) < 0$ if and only if $\frac{x^2 \bar{V}(x)}{\mathbf{E} X^2 \mathbf{I}[X < x]} < \xi/(2 - \xi)$, which proves the equivalence of conditions (F) and (2.2).

Theorem 2.2. *Let the distribution function V satisfy conditions (L) and (F). Then*

$$\mathbf{P}(r - s < S \leq r) = e^{-Q(\gamma)} \frac{1 - e^{-\gamma s}}{\tau \sqrt{2\pi}} \left(1 + \theta \left(\tau^{-1} + \left(\frac{\log(1 + \tau)}{\tau^2} \right)^{1/\alpha} (1 + (\gamma s)^{-1}) \right) \right) \quad (2.3)$$

for all r , $0 < r < \mathbf{E} S$, and all positive s , where γ is a solution of the equation $m(\gamma) = r$, $\tau = \gamma\sigma(\gamma)$ (see (1.4)), the constant α is taken from conditions (1.3), and $|\theta| \leq c_6$.

Theorem 2.2 is a corollary of the following more general statement.

Theorem 2.3. Let conditions (L) and (F) be satisfied. Then

$$\mathbf{P}(r-s < S \leq r) = \Lambda(\gamma) e^{\gamma r} \frac{1 - e^{-\gamma s}}{\tau \sqrt{2\pi}} \left(e^{-(r-m(\gamma))^2/2\sigma^2(\gamma)} + \theta \left(\tau^{-1} + \left(\frac{\log(1+\tau)}{\tau^2} \right)^{1/\alpha} (1 + (\gamma s)^{-1}) \right) \right) \quad (2.4)$$

for all positive r, s and γ , where $\tau = \gamma \sigma(\gamma)$ and $|\theta| \leq c_7$.

Remark 2. If $n < \infty$ (see (1.1)), then, under the conditions of Theorems 2.2 and 2.3, relations (2.3) for $0 < r < m(\delta/\lambda_n)$ and (2.4) for $\gamma > \delta/\lambda_n$ remain valid for $|\theta| \leq c(V, \delta)$ and for any positive δ without condition (F).

Next, we formulate a local version of Theorem 2.3.

By analogy with [2, (3.6) and (3.7)], let us assume that a random variable X has an absolutely continuous distribution with density f such that

$$|df(x)| \leq CV(x) x^{-2} dx, \quad 0 < x \leq x_0, \quad dx > 0, \quad (2.5)$$

and

$$\int_{x_0}^{\infty} (e^{-\delta x} f(x))^p dx < \infty \quad (2.6)$$

for some positive C, x_0, δ , and $p > 1$.

Theorem 2.4. Let the distribution function V satisfy conditions (L) and (F) and let its density f satisfy conditions (2.5) and (2.6). Assume also that $n \geq n_0$, where n_0 is an integer such that $n_0 > (1 + \alpha)(1 \vee 1/\beta)$ and $n_0 \geq 2 \vee p/(p-1)$ (see the notation in (1.1), (1.2), and (2.6)). Then

$$\mathbf{P}(r-s < S \leq r) = \Lambda(\gamma) e^{\gamma r} \frac{1 - e^{-\gamma s}}{\gamma \sigma(\gamma) \sqrt{2\pi}} \left(e^{-(r-m(\gamma))^2/2\sigma^2(\gamma)} + \theta(\gamma \sigma(\gamma))^{-1} \right) \quad (2.7)$$

with

$$|\theta| \leq c_8 \left(1 + \lambda_{n_0}^{-1} \sum_{j \geq 1} \mathbf{E}(1 \wedge \lambda_j X) \right) \quad (2.8)$$

for all positive r and s and all $\gamma \geq \delta/\lambda_{n_0}$. In particular, if $0 < r \leq m(\delta/\lambda_{n_0})$ and $m(\gamma) = r$, then

$$\mathbf{P}(r-s < S \leq r) = e^{-Q(\gamma)} \frac{1 - e^{-\gamma s}}{\tau \sqrt{2\pi}} (1 + \theta(\gamma \sigma(\gamma))^{-1}).$$

We note that, in contrast to (2.4), equality (2.7) is nontrivial for arbitrarily small values of parameter s as well. Thus, one can divide both parts of (2.7) by s and, letting s tend to zero, find an appropriate asymptotic of the density $q(r)$ of the random variable S .

Thus, under the conditions of Theorem 2.4,

$$q(r) = (\sigma(\gamma) \sqrt{2\pi})^{-1} \Lambda(\gamma) e^{\gamma r} \left(e^{-(r-m(\gamma))^2/2\sigma^2(\gamma)} + \theta(\gamma \sigma(\gamma))^{-1} \right);$$

in addition, if $0 < r \leq m(\delta/\lambda_{n_0})$ and $m(\gamma) = r$, then

$$q(r) = (\sigma(\gamma) \sqrt{2\pi})^{-1} e^{-Q(\gamma)} (1 + \theta(\gamma \sigma(\gamma))^{-1}),$$

where θ satisfies condition (2.8).

Remark 3. If we replace condition (2.6) in the conditions of Theorem 2.4 by a more restrictive assumption that

$$\int_{x_0}^{\infty} e^{-\delta x} |d(x)| < \infty \quad (2.9)$$

(and omit the assumption that $n_0 \geq 2 \vee p/(p-1)$), then relation (2.7) holds for $|\theta| \leq c_8$.

Recall that the constants c_6, \dots, c_8, \dots depend only on the distribution V and on parameters which are connected with the distribution conditions (2.5) and (2.6)).

Remark 4. If $n_0 = n < \infty$ in Theorem 2.4, then its statement remains valid without condition (F).

3. COROLLARIES

Let $n = \infty$ in (1.1), i.e., let $\{\lambda_j\}$ be a nonincreasing sequence of *positive* numbers such that the series S converges, or (by the three series theorem)

$$\sum_{j \geq 1} \mathbf{E}(1 \wedge \lambda_j X) < \infty. \tag{3.1}$$

Note that if $\mathbf{E}X < \infty$, then condition (3.1) implies the convergence of the series $\sum_j \lambda_j$ and vice versa. In addition, condition (3.1) imposes some moment restrictions on the random variable X . For example, if $\lambda_j = j^{-\omega}$, $\omega > 1$, then (3.1) $\iff \mathbf{E}X^{1/\omega} < \infty$, and if $\lambda_j = q^j$, $0 < q < 1$, then (3.1) $\iff \mathbf{E} \log(1 + X) < \infty$, and the last condition follows from (F).

Theorem 3.1. *If condition (L) holds, then*

$$-\log \mathbf{P}(S \leq r) \sim Q(\gamma), \quad r \rightarrow 0, \tag{3.2}$$

where $m(\gamma) = r$, or, equivalently,

$$-\log \mathbf{P}(S \leq m(\gamma)) \sim Q(\gamma), \quad \gamma \rightarrow \infty.$$

If conditions (L) and (F) are satisfied, then

$$\mathbf{P}(S \leq r) = \Lambda(\gamma) e^{\gamma r} (\tau \sqrt{2\pi})^{-1} \left(e^{-((r-m(\gamma))/\sigma(\gamma))^2/2} + O(1/\tau + (1/\tau)^{2/\alpha} \log o f^{1/\alpha} \tau) \right), \quad \gamma \rightarrow \infty, \tag{3.3}$$

uniformly in r . In particular, if $m(\gamma) = r$, then

$$\mathbf{P}(S \leq r) = e^{-Q(\gamma)} (\tau \sqrt{2\pi})^{-1} \left(1 + O(1/\tau + (1/\tau)^{2/\alpha} \log^{1/\alpha} \tau) \right), \quad r \rightarrow 0. \tag{3.4}$$

Here we use the same notation as in Theorems 2.1–2.3, and the case $s = \infty$ is considered for simplicity.

Theorem 3.2. *Let the distribution function V satisfy conditions (L) and (F) and let its density f satisfy conditions (2.5) and (2.6). Then*

$$Q(r) = (\sigma(\gamma) \sqrt{2\pi})^{-1} e^{-Q(\gamma)} \left(1 + O((\gamma \sigma(\gamma))^{-1}) \right), \quad r \rightarrow 0, \tag{3.5}$$

where $m(\gamma) = r$.

Theorems 3.1 and 3.2 follow from Theorems 2.1–2.4 (see (4.4a), (4.4b), and the proof of relation (4.8) in [2]) since $\tau = \gamma \sigma(\gamma) \rightarrow \infty$ as γ grows, and, in addition, $Q(\gamma) \nearrow \infty$ and $m(\gamma) \searrow 0$ if and only if $\gamma \nearrow \infty$.

Note that relations (3.3)–(3.5) generalize and refine the corresponding results of [2, Theorems 2 and 3 and (6.19)].

Concerning the case of finite n , we only point out that Theorems 1 and 2 of [6] follow from Theorems 2.2 and 2.3 and Remark 2 of the present paper.

Remark. In [7] and [8], conditions for the validity of relation (3.2) were independently obtained under much weaker, compared to (L), restrictions on the behavior of the distribution V at zero. Moreover, the right-hand side of asymptotic (3.2) in these papers is given in an explicit form. But the authors of the above-mentioned papers examined cases of *polynomial* (and some other) weights, while our result holds for *any* admissible $\{\lambda_j\}$. Within the framework of the present paper, we prove the following statement.

Theorem 3.3. *Assume that*

$$\lim_{\gamma \rightarrow \infty} \sup_{u \geq \gamma} u \sigma(u) / Q(u) = 0. \tag{3.6}$$

Then relation (3.2) is valid.

Note that condition (3.6) follows from condition (L); the former condition is also carried out if the coefficients λ_j are roughly equivalent to $\lambda(j)$ as $j \rightarrow \infty$, where a function $\lambda(x)$ is regularly varying at infinity with index not exceeding -1 (see (3.1)), and $\lim_{u \rightarrow \infty} |\log V(\lambda(u))|/u = 0$.

4. LEMMAS

Lemma 1. Let γ be the unique solution of the equation $m(\gamma) = r$, $0 < r < \mathbf{E}S$. Then

$$e^{-Q(\gamma)} \geq \mathbf{P}(S \leq r) \geq \frac{1}{2} e^{-2a(1+\sqrt{1+2Q(\gamma)/a})} e^{-Q(\gamma)}$$

and

$$\mathbf{P}(S \leq r) \geq \frac{1}{2} e^{-Q(\gamma)(1+b\sqrt{2})/(1-b\sqrt{2})^+}, \tag{4.1}$$

where $a = \sup_{u \geq \gamma} \frac{u^2 \sigma^2(u)}{Q(u)}$ and $b = \sup_{u \geq \gamma} \frac{u \sigma(u)}{Q(u)}$.

Lemma 1 can be proved similarly to Lemma 1 of [4] (see also [5]).

Assume that a random variable $S(h)$, $h \geq 0$, has distribution

$$\mathbf{P}(S(h) \leq r) = \int_0^r e^{-hy} d\mathbf{P}(S \leq y)/\Lambda(h), \quad r \geq 0.$$

Note (see (1.4)) that $m(h) = \mathbf{E}S(h)$ and $\sigma^2(h) = \mathbf{Var}S(h)$.

Denote

$$G_h(t) = \mathbf{E} \exp\left(it \frac{S(h) - m(h)}{\sigma(h)}\right), \quad \tau = h\sigma(h) \quad (h > 0),$$

$$\delta_\varepsilon(h) = \int_0^{1/\varepsilon} |g_h(t) - e^{-t^2/2}| dt \quad (\varepsilon > 0). \tag{4.2}$$

Lemma 2. For any positive r , h , s , and ε ,

$$\mathbf{P}(r - s < S \leq r) = \Lambda(h) e^{hr} \frac{1 - e^{-hs}}{\tau \sqrt{2\pi}} \left(e^{-\beta^2/2} + \theta (\beta e^{-\beta^2/2}/\tau + 1/\tau^2 + \rho_\varepsilon(h, s)) \right).$$

Here

$$\beta = \frac{r - m(h)}{\sigma(h)}, \quad \rho_\varepsilon(h, s) = \delta_\varepsilon(h) + (1 + \delta_\varepsilon(h))(1 + \frac{1}{hs}) \tau \varepsilon,$$

and $|\theta| \leq c$, where c is an absolute constant. In particular, if $m(h) = r$, then $\beta = 0$ and

$$\mathbf{P}(r - s < S \leq r) = e^{-Q(h)} \frac{1 - e^{-hs}}{\tau \sqrt{2\pi}} (1 + \theta (1/\tau^2 + \rho_\varepsilon(h, s))).$$

Lemma 2 is a special case of Lemma 2 of [4]. We point out that we do not assume conditions (L) or (F) to be fulfilled in Lemmas 1 and 2.

Let a random variable $X(h)$, $h \geq 0$, have distribution $E^{-hr} V(dr)/L(h)$, where $L(h) = \mathbf{E}e^{-hX}$. Denote $G(h) = \mathbf{E}(1 \wedge (hX)^2)$ and $G_1(h) = \mathbf{E}(1 \wedge hX)$.

Lemma 3. (1) If condition (F) holds, then

$$c_9 \leq h \mathbf{E}X(h)/G_1(h) \leq c_{10}, \tag{4.3a}$$

$$c_9 \leq h^2 \mathbf{Var}X(h)/G(h) \leq c_{10}, \tag{4.3b}$$

and

$$h \mathbf{E}X^3(h)/\mathbf{Var}X(h) \leq c_{11} \tag{4.3c}$$

for all $0 < h \leq 1$.

(2) If condition (L) holds, then

$$c_9 \leq h \mathbf{E}X(h) \leq c_{10}, \tag{4.4a}$$

$$c_9 \leq h^2 \mathbf{Var}X(h) \leq c_{10}, \tag{4.4b}$$

and

$$h^3 \mathbf{E}X^3(h) \leq c_{11} \tag{4.4c}$$

for all $h \geq 1$.

The first statement of Lemma 3 was established in [9, Lemma 4.1] and can be proved by the same reasoning; the second statement coincides with [6, Lemma 1].

Lemma 4. Denote $f_h(v) = \mathbf{E} e^{ivX(h)}$. If condition (L) holds, then

$$1 - |f_h(v)| \geq c_{15} e^{-(2\pi+b)h/v} V(1/v)/V(1/h), \quad V \geq (2\pi + b)/r_0, \quad h > 0. \quad (4.5)$$

If condition (F) holds, then

$$|f_h(v)| \leq e^{-\delta G(h)(v/h)^\omega}, \quad \varepsilon h \leq v \leq v_0, \quad (4.6)$$

for any sufficiently small positive v_0 and for any $\varepsilon \in (0, 1)$, where $\delta = \delta(V, \varepsilon, v_0) > 0$ and $\omega = \omega(V) \in (0, 2)$.

Proof of Lemma 4. Relation (4.5) was obtained in [6, Lemma 1]. Let us check estimate (4.6). We assume that $\mathbf{E} X^2 = \infty$ (the opposite case is considered similarly with simplifications). Obviously,

$$\begin{aligned} L(h)|f_h(v) - 1| &\leq \left| \int_{1/v}^{\infty} e^{-hy} (e^{ivy} - 1) V(dy) \right| + \left| \int_0^{1/v} e^{-hy} (e^{ivy} - 1) V(dy) \right| = I + J, \\ I &\leq 2 \int_{1/v}^{\infty} e^{-hy} V(dy) \leq 2(1 - V(1/v)), \end{aligned}$$

and

$$\begin{aligned} J &= \left| \int_{0 \leq y < 1/v} (e^{ivy} - 1 - ivy) V(dy) + \int_{0 \leq y < 1/v} ivy V(dy) \right. \\ &\quad \left. + \int_{0 \leq y < 1/v} (e^{hy} - 1)(e^{ivy} - 1) V(dy) \right| \\ &\leq 0.5v^2 \int_{0 \leq y < 1/v} y^2 V(dy) + v \int_{0 \leq y < 1/v} y V(dy) + vhe^{h/v} \int_{0 \leq y < 1/v} y^2 V(dy). \end{aligned}$$

The reasoning above implies that

$$|f_h(v) - 1| \leq c_{12} e^{1/\varepsilon} / \varepsilon (G(v) + v \mathbf{E} X \mathbf{I}[0 \leq X \leq 1/v]) \quad (4.7)$$

for any positive v_0 that is small enough and for all h and v such that $\varepsilon h \leq v \leq v_0$. Now, if condition (F) holds, then

$$\begin{aligned} L(h) \mathbf{Re}(f_h(v) - 1) &= \int_0^{\infty} (\cos vy - 1) e^{-hy} V(dy) \leq \int_{0 \leq y < 1/v} \frac{\cos vy - 1}{(vy)^2} (vy)^2 e^{-hy} V(dy) \\ &\leq (\cos 1 - 1) e^{-h/v} v^2 \int_{0 \leq y < 1/v} y^2 V(dy) \leq -c_{13} e^{-1/\varepsilon} G(v) \end{aligned} \quad (4.8)$$

under the same restrictions on h and v (we use condition (F) in the last inequality only).

Since

$$\mathbf{E}^2 X \mathbf{I}[|X| \leq z] = o(z^2 G(1/z)), \quad z \rightarrow \infty,$$

if $\mathbf{E} X^2 = \infty$ (see [9, (4.9)]), we deduce from inequalities (4.7) and (4.8) and the estimate

$$L(h) \geq \int_0^{1/h} e^{-th} V(dt) \geq e^{-1} V(1/h)$$

that

$$|f_h(v)| \leq e^{\mathbf{Re}(f_h(v)-1) + |f_h(v)-1|^2} \leq e^{-\delta_1 G(v)}, \quad \varepsilon h \leq v \leq v_0, \quad (4.9)$$

for v_0 small enough.

Further, under condition (F) (see (2.2)) there exists an $\omega \in (0, 2)$ such that $v^{-\omega} G(v) \nearrow$ for all sufficiently small v . Thus, if $\varepsilon h \leq v$ and $\varepsilon \in (0, 1)$, then

$$G(v) = v^\omega v^{-\omega} G(v) \geq v^\omega (\varepsilon h)^{-\omega} G(\varepsilon h) \geq \varepsilon^{2-\omega} v^\omega h^{-\omega} G(h).$$

These inequalities and (4.9) imply estimate (4.6).

Lemma 4 is proved.

Lemma 5. *If condition (L) holds, then (see the notation in (1.4))*

$$Q(u) \geq c_{14} u^2 \sigma^2(u)$$

and

$$um(u) \geq c_{15} u^2 \sigma^2(u) \quad (4.10)$$

for any positive u .

Proof of Lemma 5. Set $\bar{Q}(u) = -u \mathbf{E} X(u) - \log L(u)$ and $\sigma_j^2(u) = \lambda_j^2 \mathbf{Var} X(u\lambda_j)$, $j \geq 1$.

Let k satisfy the condition $u\lambda_k > 1 \geq u\lambda_{k+1}$. Then

$$Q(u) = \sum_{j=1}^k \bar{Q}(u\lambda_j) + \sum_{j>k} \bar{Q}(u\lambda_j) = Q_1 + Q_2 \quad (4.11)$$

and (see (4.4b))

$$Q_1 \geq k \bar{Q}(u\lambda_k) \geq k \bar{Q}(1) \geq c_{16} \sum_{j=1}^k \sigma_j^2(u). \quad (4.12)$$

Further, by [9, Lemma 2.2] (without assumption (L)),

$$\bar{Q}(\gamma) \geq c_{17} \gamma^2 G(1/\gamma) \geq c_{18} \gamma^2 \mathbf{Var} X(\gamma), \quad 0 < \gamma \leq 1;$$

hence,

$$Q_2 \geq c_{19} u^2 \sum_{j>k} \sigma_j^2(u). \quad (4.13)$$

The first statement of Lemma 5 follows from inequalities (4.11)–(4.13). Relation (4.10) is checked similarly. It is enough to note (see Lemma 3) that $uG_1(1/u) \geq u^2 G(1/u)$.

Lemma 5 is proved.

Lemma 6. *Let conditions (L) and (F) be satisfied. Then (see (4.2))*

$$\int_0^{\tau\rho} |g_h(t) - e^{-t^2/2}| dt \leq c_{20} (1 \wedge 1/\tau) \quad (4.14)$$

for any $h > 0$, where $\rho = \delta_0 (\tau / \sqrt{\log(1+\tau)})^{2/\alpha}$, $\delta_0 = \delta_0(V)$ is a sufficiently small positive constant depending on V only, and α is defined in (1.2) and (1.3).

Remark. Assume that $n < \infty$ in condition (3.1). If $h > \delta/\lambda_n$ for some positive δ , then inequality (4.14) is valid without assumption (F) with constants c_{20} and δ_0 depending, in addition, on δ .

Proof of Lemma 6. Estimate (4.14) for $\tau \leq \tau_0$ is obvious. Thus, in what follows, we assume that τ is large enough and $\rho > 1$.

It is known (see [10, Chap. 5, Lemma 1]) that

$$|g_h(t) - e^{-t^2/2}| \leq 16\mu e^{-t^2/3}, \quad |t| \leq 1/4\mu,$$

where

$$\mu = \frac{1}{\sigma^3(h)} \sum_{j \geq 1} \lambda_j^3 \mathbf{E} |X(h\lambda_j) - \mathbf{E} X(h\lambda_j)|^3.$$

By Lemma 3 (see (4.3c) and (4.4c)),

$$\mu \leq \frac{8}{h\sigma^3(h)} \sum_{j \geq 1} \sigma_j^2(h) \frac{h\lambda_j \mathbf{E} X^3(h\lambda_j)}{\mathbf{Var} X(h\lambda_j)} \leq \frac{8}{\tau} \sup_{\gamma \geq h\lambda_n} \frac{\gamma \mathbf{E} X^3(\gamma)}{\mathbf{Var} X(\gamma)} \leq 8c_{11}/\tau. \quad (4.15)$$

For $\varepsilon = (32c_{11})^{-1}$, inequalities (4.15) imply that

$$\int_0^{\varepsilon\tau} |g_h(t) - e^{-t^2/2}| dt \leq c_{21}/\tau. \quad (4.16)$$

If $\rho \leq \varepsilon$, estimate (4.14) follows from (4.16). Let $\rho > \varepsilon$. Consider $I(h) = \int_{\varepsilon\tau}^{\tau\rho} |g_h(t)| dt$. In the notation of (4.2) and Lemma 4 (see (4.5)), we have the equality

$$|g_h(t)| = \prod_j |f_{h\lambda_j}(t/\sigma(h))|. \quad (4.17)$$

Let k be chosen from the condition that

$$\sum_{j=1}^k \sigma_j^2(h) \geq \sigma^2(h)/2 > \sum_{j=1}^{k-1} \sigma_j^2(h). \quad (4.18)$$

Set $\nu = v_0/\lambda_k$, where the constant v_0 is the same as in (4.6). If $\rho \leq \nu/h$, then

$$\varepsilon h \lambda_j \leq t \lambda_j / \sigma(h) \leq \tau \rho \lambda_j / \sigma(h) \leq \tau \nu \lambda_j / (h \sigma(h)) \leq v_0 \lambda_j / \lambda_k \leq v_0$$

for any $j \geq k$ and all $t \in [\varepsilon\tau, \tau\rho]$. These inequalities combined with (4.17), (4.18), and (4.6) imply by virtue of (4.3b) that

$$I(h) \leq \int_{\varepsilon\tau}^{\tau\nu/h} \prod_{j \geq k} |f_{h\lambda_j}(t\lambda_j/\sigma(h))| dt \leq \tau \int_{\varepsilon}^{\nu/h} \prod_{j \geq k} \exp(-\delta_2 \sigma_j^2(h) h^2 t^\omega) dt \leq \tau \int_{\varepsilon}^{\infty} \exp(-\delta_2 \tau^2 t^\omega) dt \leq \delta_3/\tau, \quad (4.19)$$

where $\delta_i = \delta_i(V, v_0)$. The statement of Lemma 6 for $\varepsilon < \rho \leq \nu/h$ follows from (4.16) and (4.19).

Taking into consideration equality (4.17), we see that to complete the proof of Lemma 6, it is enough to derive the estimate

$$J(h) = \tau \int_{\varepsilon\nu/h}^{\rho} \prod_{1 \leq j \leq k} |f_{h\lambda_j}(th\lambda_j)| dt \leq c_{22}/\tau. \quad (4.20)$$

For this purpose, we show that

$$|f_{h\lambda_j}(th\lambda_j)| \leq e^{-c_{23} t^{-\alpha}}, \quad t \geq \varepsilon \vee \nu/h, \quad j \leq k. \quad (4.21)$$

For brevity, denote $h\lambda_j$ ($1 \leq j \leq k$) by γ and set (see (4.5)) $\xi(t) = |f_\gamma(t\gamma)|$, $H_0 = (2\pi + b)/r_0$, and $\bar{\gamma} = H_0/\varepsilon$. At first let $\varepsilon \leq \nu/h$. If $\gamma < \bar{\gamma}$, then for $t \geq \varepsilon$ we derive from (4.5) and (1.2) that

$$\xi(t) \leq 1 - c_{24} V(1/t\gamma) \leq 1 - c_{25} t^{-\alpha}, \quad t\gamma \geq H_0, \quad (4.22)$$

for $t \geq \varepsilon$, and, moreover,

$$\xi(t) \leq e^{-\delta}, \quad \delta = \delta(V, v_0), \quad t\gamma \in [v_0, H_0], \quad (4.23)$$

since the random variable X is nonlattice and the mapping between the distributions X and $X(h)$ is continuous in h .

Since $t\gamma \geq v_0 \lambda_j / \lambda_k \geq v_0$ for $t \geq \nu/h$, estimates (4.22) and (4.23) imply (4.21).

Let now $\gamma \geq \bar{\gamma}$. Then we deduce from (1.2) that

$$V(1/t\gamma)/V(1/\gamma) \geq \frac{1}{c_2} (t^{-\alpha} \wedge 1) \geq \left(\frac{1}{c_2} \wedge \varepsilon^\alpha\right) t^{-\alpha}, \quad t \geq \varepsilon, \quad \gamma \geq 1/r_0, \quad (4.24)$$

for $t \geq \varepsilon$, where $t\gamma \geq \varepsilon\gamma \geq \varepsilon\bar{\gamma} = H_0$, i.e., inequalities (4.24) and (4.5) imply estimate (4.21). Thus, the case $\varepsilon \leq \nu/h$ is analyzed completely.

Let $\varepsilon > \nu/h$ and $t \geq \varepsilon$. In this case, $\gamma \geq \bar{\gamma} = \nu_0/\varepsilon$ and $t\gamma \geq \varepsilon\bar{\gamma} = \nu_0$. If $t\gamma \geq H_0$ and $\gamma < \bar{\gamma}$, we use estimate (4.22); if $t\gamma < H_0$, we apply (4.23). If $\gamma \geq \bar{\gamma}$, then $t\gamma \geq H_0$, and one can apply (4.24) to prove relation (4.21).

Now we use estimate (4.21) to obtain the required estimate (4.20). It follows from (4.3b), (4.4b) and (4.18) that

$$k \geq c_{26} \sum_{j=1}^k h^2 \sigma_j^2(h) \geq c_{24} h^2 \sigma^2(h)/2 = c_{27} \tau^2;$$

therefore,

$$J(h) \leq \tau \int_{\varepsilon \vee \nu/h}^{\rho} e^{-c_{23} k t^{-\alpha}} dt \leq \tau \rho e^{-c_{28} \tau^2 \rho^{-\alpha}} \leq \delta_0 \tau^{1+2/\alpha} e^{-c_{29} \delta_0^{-\alpha} \log(1+\tau)}.$$

It remains to make the constant δ_0 small enough. Lemma 6 is proved.

The remark to Lemma 6 is proved similarly; we refer to the fact that in the case $\varepsilon > \nu/h$, condition (F) is not applied (see also (4.15)).

5. PROOFS

Theorem 2.1 follows from Lemmas 1 and 5.

Theorem 2.3 for $\tau < 1$ is obvious; for $\tau \geq 1$, this theorem follows from Lemmas 6 and 2 with $\varepsilon = 1/\tau\rho$.

To establish Theorem 2.4, one can use Lemma 2 with $\varepsilon = \infty$; we only have to prove that

$$\int_{\tau\rho}^{\infty} |g_h(t)| dt \leq c_{30}/\tau \tag{5.1}$$

for all τ large enough. For any integer $m \geq 1$,

$$\int_{\tau\rho}^{\infty} |g_h(t)| dt \leq \int_{\rho}^{\infty} \prod_{j=1}^m |f_{h\lambda_j}(th\lambda_j)| dt \leq 2^{m-1} \max_{1 \leq j \leq m} \left(\int_{\rho}^{\infty} |f_{1j}|^m dt + 2^{-1} \int_{-\infty}^{\infty} |f_{2j}|^m dt \right), \tag{5.2}$$

where

$$f_{1j} = \frac{1}{L(s)} \int_0^{x_0} e^{(it-1)sx} f(x) dx, \quad f_{2j} = \frac{1}{L(s)} \int_{x_0}^{\infty} e^{(it-1)sx} f(x) dx, \quad s = h\lambda_j. \tag{5.3}$$

Integrating by parts for $tsx_0 > 1$, we see that

$$\begin{aligned} -itsL(s) f_{1j} &= (1 - e^{itsx_0}) e^{-sx_0} f(x_0) + (-s) \int_0^{x_0} (e^{itsx} - 1) e^{-sx} f(x) dx \\ &+ \left(\int_0^{1/ts} + \int_{1/ts}^{x_0} \right) (e^{itsx} - 1) e^{-sx} df(x) = I_1 + I_2 + I_3. \end{aligned}$$

In this case, we deduce from (1.2) and (2.5) that

$$\begin{aligned}
 |I_1| &\leq 2sL(s), \quad |I_2| \leq Cts \int_0^{1/ts} V(x)/x dx \leq Cts c_1 V(1/s)t^{-\beta}/\beta, \\
 |I_3| &\leq 2\left(\int_{1/ts}^{1/s} e^{-sx} |df(x)| + \int_{1/s}^{x_0} e^{-sx} |df(x)|\right) \\
 &\leq 2Cs\left(\int_{1/t}^1 V(u/s)du/u^2 + \int_1^{sx_0} V(u/s)e^{-u}du/u^2\right) = 2Cs(J_1 + J_2), \\
 J_2 &\leq V(1/s)c_2 \int_1^\infty u^{\alpha-2}e^{-u}du, \quad \text{and} \quad J_1 \leq V(1/s)c_1 \kappa(t),
 \end{aligned}$$

where $\kappa(t) = (\beta - 1)^{-1}$ if $\beta > 1$, $\kappa(t) = \log t$ if $\beta = 1$, and $\kappa(t) = t^{1-\beta}/(1 - \beta)$ if $\beta < 1$. Since

$$L(s) \geq e^{-1}V(1/s) \leq e^{-1}c_3s^{-\alpha}, \tag{5.4}$$

$$|f_{1j}| \leq c_{31} (t^{-\beta} + \log(1+t)/t), \quad s \geq \delta, \quad ts \geq 1/x_0. \tag{5.5}$$

Thus,

$$\int_\rho^\infty |f_{1j}|^m dt \leq c_{32}/\tau^2, \quad m > (1 + \alpha)/\min(1, \beta), \quad h\lambda_m \geq \delta. \tag{5.6}$$

Assume that condition (2.6) holds with some $p > 1$ and $m \geq \max(2, p/(p - 1))$. Then (see also (5.3) and (5.4))

$$\begin{aligned}
 \int_{-\infty}^\infty |f_{2j}|^m dt &\leq c_{33} \left(\int_{x_0}^\infty (s^\alpha e^{-sx} f(x))^{m/m-1} dx \right)^{m-1} \\
 &\leq s^{\alpha m/m-1} \left(\int_{x_0}^\infty e^{-sx} f(x) dx + \int_{x_0}^\infty (e^{-sx} f(x))^p dx \right).
 \end{aligned}$$

The above estimate, inequality (5.6), and the estimate $\tau^2 = h^2\sigma^2(h) \leq c_{34} \max(1, h) \sum_{j \geq 1} \mathbf{E}(1 \wedge \lambda_j X)$ (which is valid by virtue of Lemma 3) imply (5.1).

To check Remark 3, we use an inequality similar to (5.2) and the fact that an estimate similar to (5.5) holds for $|f_{h\lambda_j}(t)|$.

Finally, Theorem 3.3 follows from Lemma 1 (see (4.1)).

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