

*NONUNIFORM CENTRAL LIMIT BOUNDS
AND THEIR APPLICATIONS*

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1. Introduction. Let \mathcal{G} be a set of functions $g(x)$, defined on the set of real numbers \mathbf{R} and satisfying the following conditions:

$g(x)$ is nonnegative, even, and nondecreasing on $[0, \infty)$,

$x/g(x)$ is defined for all $x \in \mathbf{R}$ and nondecreasing on $[0, \infty)$.

We consider a sequence $\{X_k, k \geq 1\}$ of independent random variables with $EX_k = 0$, $EX_k^2 = \sigma_k^2$, $EX_k^2 g^s(X_k) < \infty$, $k \geq 1$, where $s > 0$ is some fixed number.

Let

$$S_n = \sum_{k=1}^n X_k, \quad B_n^2 = \sum_{k=1}^n \sigma_k^2, \quad F_n(t) = P[S_n < tB_n],$$

and

$$L_n^s(g) = \left[\sum_{k=1}^n E[X_k^2 \cdot g^s(X_k)] \right] / B_n^2 g^s(B_n).$$

The aim of this note is to give some nonuniform rates of convergence to normality. The results obtained strengthen the analogous ones of Bikelis [3], Michel [9], Maejima [8] as well as of Ghosh and Dasgupta [6].

2. Nonuniform central limit bounds. We begin with a lemma, which generalizes Lemma 2 of [10], p. 139.

LEMMA. Let $X_1, X_2, \dots, X_n; Y_1, Y_2, \dots, Y_n$ be random variables and let $g_1, g_2, \dots, g_n; f_1, f_2, \dots, f_n$ be nonnegative measurable functions such that for all $s \geq 0$, $r \geq 0$ and $k = 1, 2, \dots, n$,

$$E[g_k^s(X_k) f_k^r(Y_k)] < \infty.$$

Then for every $s < s'$ we have

$$L_n^s(g, f) \leq [L_n^{s'}(g, f)]^{s/s'},$$

where

$$L_n^s(g, f) = \sum_{k=1}^n E[g_k^s(X_k) f_k^s(Y_k)] / \sum_{k=1}^n E[g_k^s(X_k)].$$

Proof. First, let us note that the function

$$h(s) = \log \sum_{k=1}^n E [g_k^r(X_k) f_k^s(Y_k)], \quad s > 0,$$

is convex from below. Indeed, by Hölder's inequality applied twice, for $s < s'$ we obtain

$$\left(\sum_{k=1}^n E [g_k^r(X_k) f_k^{s'}(Y_k)] \right)^2 \leq \sum_{k=1}^n E [g_k^r(X_k) f_k^{s'-s}(Y_k)] \sum_{k=1}^n E [g_k^r(X_k) f_k^{s+s'}(Y_k)].$$

Taking logarithms, we have

$$h(s') \leq \frac{1}{2}(h(s'-s) + h(s'+s)).$$

Consequently, $h(s)$ is convex from below.

Note that

$$h(0^+) = \log \sum_{k=1}^n E [g_k^r(X_k)].$$

Now, we prove that the function $(h(s') - h(0^+))/s'$ is nondecreasing for $s' > 0$.

Let us put $p_1 = 1 - s/s'$ and $p_2 = s/s'$, where $s < s'$. Since the function $h(s) - h(0^+)$ is convex from below, we have

$$h(p_1 x_1 + p_2 x_2) - h(0^+) \leq p_1 [h(x_1) - h(0^+)] + p_2 [h(x_2) - h(0^+)].$$

Putting $x_2 = s'$ and $x_1 \rightarrow 0^+$, we obtain

$$h(s') - h(0^+) \geq s' [h(s) - h(0^+)]/s.$$

Thus the Lemma is proved.

All theorems in this paper are proved under the same conditions given above; therefore we do not repeat them explicitly in the formulations.

Let us put

$$\Delta_n(t) = |F_n(t) - \Phi(t)|, \quad t \in \mathbf{R}, \quad n \geq 1,$$

where Φ denotes the standard normal distribution function.

THEOREM 1. *There exist constants $b, r > 0$ (depending on s) such that for all $n \geq 1$ and every t with*

$$t^2 \geq 2s^{-1}(1+s) \log_+(1/L_n^s(g))$$

we have

$$\Delta_n(t) \leq bt^{-2(2+s)} L_n^s(g) + T_n(r),$$

where

$$T_n(r) = \sum_{k=1}^n P[|X_k| > r | t | B_n]$$

and

$$\log_+ x = \max \{0, \log x\}.$$

Proof. Without loss of generality we may and do assume that $t > 0$ (if not, replace the random variables X_k by $-X_k$, $1 \leq k \leq n$). Define

$$X_k^* = X_k \cdot I(|X_k| \leq r|t|B_n), \quad 1 \leq k \leq n, \quad S_n^* = \sum_{k=1}^n X_k^*,$$

where $r = [2(1+s)(2+s)]^{-1}$. Then

$$P[S_n \geq tB_n] \leq P[S_n^* \geq tB_n] + T_n(r).$$

Furthermore, by Lemma 2 of [5], p. 166, for

$$t^2 \geq 2s^{-1}(1+s) \log_+ (1/L_n^s(g)),$$

we get

$$\Phi(-t) \leq (2\pi)^{-1/2} t^{-1} \exp(-t^2/2(1+s)) L_n^s(g) \leq b_1 t^{-2(2+s)} L_n^s(g),$$

where (and in the sequel) b, b_1, b_2, \dots denote positive constants which may depend only on s and the same symbols may be used for different constants. Thus

$$(2.1) \quad \Delta_n(t) \leq b_1 t^{-2(2+s)} L_n^s(g) + P[S_n^* \geq tB_n] + T_n(r).$$

Let

$$h = t^{-1} B_n^{-1} [2 \log_+ (1/L_n^s(g)) + r^{-1} \log t].$$

Then

$$(2.2) \quad \begin{aligned} P[S_n^* \geq tB_n] &\leq \exp(-htB_n) E[\exp(hS_n^*)] \\ &= t^{-1/r} [L_n^s(g)]^2 E[\exp(hS_n^*)]. \end{aligned}$$

But, by our assumptions, we have

$$E[\exp(hS_n^*)] = \prod_{k=1}^n E[\exp(hX_k^*)]$$

and for $1 \leq k \leq n$ one can obtain the following inequalities:

$$h E|X_k^*| \leq h\sigma_k^2/rtB_n \leq b_2 \sigma_k^2/B_n^2, \quad E(X_k^*)^2 \leq \sigma_k^2,$$

$$h^3 E|X_k^*|^3 \exp(hrtB_n) \leq h^3 t^2 [L_n^s(g)]^{-2r} E[X_k^2 g^{s^*}(X_k)] rB_n/g^{s^*}(rtB_n),$$

where $s^* = \max \{s \geq z > 0: x/g^z(x) \text{ is nondecreasing}\}$. Putting in our Lemma $Y_k = X_k$, $f_k(x) = x$, $r = 2$, $1 \leq k \leq n$, we have

$$L_n^{s^*}(g) \leq [L_n^s(g)]^{s^*/s}.$$

Therefore

$$h^3 E|X_k^*|^3 \exp(hrtB_n) \leq b_3 E[X_k^2 g^{s^*}(X_k)] / \sum_{k=1}^n E[X_k^2 g^{s^*}(X_k)],$$

where b_3 is an appropriately chosen constant. Taking into account the inequalities given above, we get

$$E[\exp(hX_k^*)] \leq \exp[h^2 \sigma_k^2/2 + b_2 \sigma_k^2/B_n^2 + b_3 E[X_k^2 g^{s^*}(X_k)] / \sum_{k=1}^n E[X_k^2 g^{s^*}(X_k)],$$

and therefore

$$\prod_{k=1}^n E[\exp(hX_k^*)] \leq \exp[(h^2 B_n^2/2) + b_4].$$

Since $t \geq [2s^{-1}(1+s) \log_+(1/L_n^s(g))]^{1/2}$, we have

$$B_n^2 h^2/2 \leq \log_+(1/L_n^s(g)) + 2s(2+s) \log t + b_5.$$

Thus

$$E[\exp(hS_n^*)] \leq b_6 t^{2s(2+s)} [L_n^s(g)]^{-1},$$

and the desired estimation follows from (2.1) and (2.2).

THEOREM 2. *There exist positive constants b and r (depending on s) such that for all $n \geq 1$ and every t with*

$$t^2 \leq 2s^{-1}(1+s) \log_+(1/L_n^s(g))$$

we have

$$\Delta_n(t) \leq b \exp[(\sigma - 1)t^2/2] L_n^{s^*}(g) + T_n(r),$$

where $\sigma = s^*/2(1+s)$ and $s^* = \max\{s \geq z > 0: x/g^z(x) \text{ is nondecreasing}\}$.

Proof. We prove the theorem only for $t > 0$, as the proof for $t < 0$ is analogous. For $0 < t \leq 1$ the theorem follows immediately from Theorem 5 in [10], p. 112. Let $t > 1$ and let $d > 0$ be a real number to be determined later. Then

$$|P[S_n < tB_n] - \Phi(t)| \leq |P[S_n^* < tB_n] - \Phi(t)| + T_n(d),$$

where

$$S_n^* = \sum_{k=1}^n X_k I(|X_k| \leq dtB_n)$$

and

$$T_n(d) = \sum_{k=1}^n P[|X_k| > dtB_n].$$

Thus it is enough to show that

$$|P[S_n^* \leq tB_n] - \Phi(t)| \leq b \exp[(\sigma - 1)t^2/2] L_n^{s^*}(g).$$

To this aim let us put $X_k^* = X_k I(|X_k| \leq dtB_n)$, $k = 1, 2, \dots, n$, and for $1 \leq k \leq n$

$$h_k(t) = E[\exp(tX_k^*/B_n)],$$

$$m_k(t) = h_k^{-1}(t) E[X_k^* \exp(tX_k^*/B_n)],$$

$$M_n'(t) = \sum_{k=1}^n m_k(t), \quad D_n^2(t) = \sum_{k=1}^n d_k^2(t),$$

where

$$[m_k^2(t) + d_k^2(t)] h_k(t) = E[(X_k^*)^2 \exp(tX_k^*/B_n)].$$

Furthermore, let

$$G_k(x) = \int_{-\infty}^x h_k^{-1}(t) \exp(tu/B_n) dP[X_k^* < u].$$

Then standard methods (see e.g. [4]) yield

$$P[S_n^* \geq tB_n] = A_n(t) \int_{[\dots]} \exp(-ztM_n(t)B_n^{-1}) dG_n^*(z),$$

where $[\dots]$ denotes $[z > (tB_n - M_n(t))D_n^{-1}(t)]$ and

$$A_n(t) = \prod_{k=1}^n h_k(t) \exp(-tM_n(t)B_n^{-1}),$$

and

$$G_n^*(z) = G_1 * G_2 * \dots * G_n(zD_n(t) + M_n(t))$$

is the convolution of the distribution functions G_k , $1 \leq k \leq n$.

Note now that for every $k = 1, 2, \dots, n$ the following inequalities are true:

$$(2.3) \quad |E X_k^*| \leq b_1 E[X_k^2 g^{s^*}(X_k)]/tB_n g^{s^*}(B_n),$$

$$(2.4) \quad \exp(-dt^2) \leq h_k(t) \leq \exp(dt^2),$$

$$(2.5) \quad 0 \leq \sigma_k^2 - E(X_k^*)^2 \leq b_2 E[X_k^2 g^{s^*}(X_k)]/g^{s^*}(B_n),$$

$$(2.6) \quad E[|X_k^*|^3 \exp(tX_k^*/B_n)] \leq b_3 \exp(dt^2) E[X_k^2 g^{s^*}(X_k)] tB_n/g^{s^*}(B_n).$$

Now, using (2.3)–(2.6), we have

$$(2.7) \quad |h_k(t) - 1 - \sigma_k^2 t^2/2B_n^2| \leq b_4 \exp(dt^2) E X_k^2 g^{s^*}(X_k)/B_n^2 g^{s^*}(B_n),$$

$$(2.8) \quad |h_k(t) m_k(t) - \sigma_k^2 t/B_n| \leq b_5 \exp(dt^2) E X_k^2 g^{s^*}(X_k)/B_n g^{s^*}(B_n),$$

$$(2.9) \quad |E(X_k^*)^2 \exp(tX_k/B_n) - \sigma_k^2| \leq b_6 \exp(dt^2) E X_k^2 g^{s^*}(X_k)/g^{s^*}(B_n).$$

Furthermore, by the Berry–Essen inequality, Theorem 3 in [10] (p. 111), formulas (2.3), (2.4) and (2.6), we get

$$(2.10) \quad \sup_{z \in \mathbb{R}} |G_n^*(z) - \Phi(z)| \leq b_7 \exp(3dt^2) B_n g^{-s^*}(B_n) D_n^{-3}(t) \sum_{k=1}^n E X_k^2 g^{s^*}(X_k).$$

But using (2.7)–(2.9) and (2.3)–(2.5), we have

$$(2.11) \quad B_n^{-2} |D_n^2(t) - B_n^2| \leq b_8 \exp(3dt^2) L_n^*(g).$$

Furthermore, taking into account (2.7)–(2.9) and the identity (38) in [11], p. 446, we can obtain the following inequalities:

$$(2.12) \quad |A_n(t) - \exp(-t^2/2)| \leq b_9 \exp(3dt^2) L_n^*(g),$$

$$(2.13) \quad |M_n(t) B_n^{-1} - t| \leq b_{10} \exp(3dt^2) L_n^*(g).$$

On the other hand, by (2.10) and (2.13), we have

$$(2.14) \quad \left| \int_{[\dots]} \exp(-tz M_n(t) B_n^{-1}) d(G_n^*(z) - \Phi(z)) \right| \leq b_{11} \exp(3dt^2) L_n^{s^*}(g)$$

and

$$(2.15) \quad \left| \int_{[\dots]} \exp(-tz M_n(t) B_n^{-1}) d\Phi(z) - \exp(t^2/2) \Phi(-t) \right| \leq b_{12} \exp(3dt^2) L_n^{s^*}(g),$$

where $[\dots]$ denotes $[z > (tB_n - M_n(t))D_n^{-1}(t)]$. Thus, by (2.12), (2.14) and (2.15), we get

$$|P[S_n^* < tB_n] - \Phi(t)| \leq b \exp[(\sigma - 1)t^2/2] \exp[(6d - \sigma)t^2/2] L_n^{s^*}(g).$$

The last inequality completes the proof of Theorem 2.

From Theorems 1 and 2 we can easily obtain a generalization of the Berry–Essen inequality obtained in Theorem 6 of [10], p. 115, and [3], [8], [9] and [6].

THEOREM 3. *There exists a constant b depending on s such that for all $n \geq 1$ and $t \in \mathbf{R}$*

$$\Delta_n(t) \leq bg^s(B_n)(L_n^s(g) + L_n^{s^*}(g))/(1 + t^2 g^s(tB_n)).$$

Proof. For $|t| \leq 1$ the assertion follows from Theorem 5 of [10], p. 112. For $|t| > 1$ the proof of this theorem follows from Theorems 1 and 2.

From Theorems 1 and 2 we can also obtain the approximation of the moments of S_n/B_n of order greater than 2 by the corresponding moments of a standard normal distribution. This problem has been studied in [1], [2], [7], and [6].

THEOREM 4. *Suppose the function g is differentiable. Then there exists a constant $b > 0$ depending on s such that for all $n \geq 1$*

$$|E[S_n^2 g^s(S_n)/B_n^2 g^s(B_n)] - E[N^2 g^s(NB_n)/g^s(B_n)]| \leq b(L_n^s(g) + L_n^{s^*}(g)),$$

where N is a random variable with the standard normal distribution.

Proof. Since $S_n^2 g^s(S_n)/B_n^2 g^s(B_n) > 0$ implies

$$E[S_n^2 g^s(S_n)/B_n^2 g^s(B_n)] = \left(\int_0^\infty P[|S_n| > h^{-1}(t) B_n] dt \right) / g^s(B_n),$$

where $h(t) = t^2 g^s(tB_n)$, $t \in \mathbf{R}$, and $s > 0$, we obtain

$$\begin{aligned} |E[S_n^2 g^s(S_n)/B_n^2 g^s(B_n)] - E[N^2 g^s(NB_n)/g^s(B_n)]| \\ \leq \int_0^\infty |P[|S_n| > h^{-1}(t) B_n] - 2\Phi(h^{-1}(t))| dt / g^s(B_n). \end{aligned}$$

Thus putting $a_n = 2s^{-1}(1+s)\log_+(1/L_n^s(g))$, from Theorems 1 and 2 we get

$$\begin{aligned} \int_0^\infty |P[|S_n| > h^{-1}(t)B_n] - 2\Phi(h^{-1}(t))| dt \\ \leq b_1 L_n^{s^*}(g) \int_0^{a_n} \exp[-(1-\sigma)[h^{-1}(t)]^2/2] dt \\ + b_2 L_n^s(g) \int_{a_n}^x [h^{-1}(t)]^{-2(2+s)} dt \\ + \sum_{k=1}^n \int_0^x \{P[|X_k| \geq h^{-1}(t)rB_n]\} dt. \end{aligned}$$

Since the integrals in the first two terms of this inequality are finite, the conclusion of Theorem 4 is proved, as

$$\sum_{k=1}^n \int_0^\infty \{P[|X_k| \geq h^{-1}(t)rB_n]\} dt \leq bL_n^s(g).$$

Now let us consider the speed of convergence to zero of $1 - F_n(t_n)$ under the assumption that $t_n \rightarrow \infty$ as $n \rightarrow \infty$.

THEOREM 5. *Let $\{t_n, n \geq 1\}$ be a sequence of real numbers such that $t_n \rightarrow \infty$ and*

$$(2.16) \quad t_n^2 \leq 2\log_+(1/L_n^s(g)) + \log_+ \log_+(1/L_n^s(g)) + M,$$

where M is a positive constant. If

$$(2.17) \quad L_n^s(t_n, g) = \sum_{k=1}^n E[X_k^2 g^s(X_k) I(|X_k| > t_n B_n)] / \sum_{k=1}^n E[X_k^2 g^s(X_k)] \rightarrow 0$$

as $n \rightarrow \infty$, then

$$1 - F_n(t_n) \sim (2\pi)^{-1/2} t_n^{-1} \exp(-t_n^2/2).$$

Proof. Without loss of generality we may and do assume that

$$t_n^2 \leq 2s^{-1}(1+s)\log_+(1/L_n^s(g)).$$

From Theorem 2 we get

$$\begin{aligned} t_n \exp(t_n^2/2) |P[S_n \geq t_n B_n] - \Phi(-t_n)| \leq b t_n \exp(t_n^2 \sigma/2) L_n^{s^*}(g) \\ + g^s(B_n)/g^s(t_n B_n) [\exp(t_n^2/2) L_n^s(g) L_n^s(t_n, g)] (1/t_n). \end{aligned}$$

Since $t_n^2 \leq 2s^{-1}(1+s)\log_+(1/L_n^s(g))$, we have

$$t_n \exp(t_n^2 \sigma/2) L_n^s(g) = o(1).$$

It is easy to show that, for $t > 1$, $g(B_n)/g(tB_n) < 1$ and the function $t \rightarrow t^{-1} \exp(t^2/2)$ is nondecreasing. Then

$$(g(B_n)/t_n g(t_n B_n)) \exp(t_n^2/2) L_n^s(g) = O(1).$$

Thus, taking into account (2.17) and Lemma 2 of [5], p. 166, we obtain the proof of Theorem 5.

Let us observe that from Theorem 5 we can easily obtain the main results of Rubin and Sethuraman [12] on probabilities of moderate deviations under the much less restrictive moment conditions. Namely, if

$$B_n^2/n > 1 \quad \text{and} \quad \sup_n \left((1/n) \sum_{k=1}^n E X_k^2 g^s(X_k) \right) < \infty,$$

then there exists a constant $M > 0$ such that

$$s \log_+ g^2(\sqrt{n}) \leq 2 \log_+ (1/L_n^s(g)) + M.$$

Therefore, if (2.17) holds, then from Theorem 5 with $t_n^2 = s \log_+ g^2(\sqrt{n})$ we get

$$P[|S_n| \geq B_n (s \log_+ g^2(\sqrt{n}))^{1/2}] \sim 2 (g(\sqrt{n}))^{-s} (2\pi s \log_+ g^2(\sqrt{n}))^{-1/2}.$$

For sequences $\{t_n, n \geq 1\}$ with $t_n \rightarrow \infty$ which do not satisfy the assumptions of Theorem 5 we have the following

THEOREM 6. *Let $\{t_n, n \geq 1\}$ be a sequence of real numbers such that $t_n \rightarrow \infty$ and*

$$t_n^2 - 2 \log_+ (1/L_n^s(g)) - \log_+ \log_+ (1/L_n^s(g)) \rightarrow \infty \quad \text{as } n \rightarrow \infty.$$

If (2.17) holds, then

$$(t_n^2 g^s(t_n B_n)/g^s(B_n))(1 - F_n(t_n)) = o(L_n^s(g)).$$

Proof. Let

$$t_n^2 = 2 \log_+ (1/L_n^s(g)) + \log_+ \log_+ (1/L_n^s(g)) + a_n,$$

where $a_n \rightarrow \infty$ as $n \rightarrow \infty$. From Theorem 1 for all $n \geq 1$ such that $t_n^2 \geq 2s^{-1}(1+s) \log_+ (1/L_n^s(g))$ we get

$$\begin{aligned} P[S_n \geq t_n B_n] \\ \leq \Phi(-t_n) + b_1 L_n^s(g) t_n^{-2(2+s)} + t_n^{-2} g^s(B_n)/g^s(t_n B_n) L_n^s(g) L_n^s(t_n, g), \end{aligned}$$

where

$$\Phi(-t_n) \leq b_2 t_n^{-2(2+s)} L_n^s(g), \quad g^s(t_n B_n)/g^s(B_n) \leq t_n^s.$$

On the other hand, by Theorem 2, for all $n \geq 1$ such that

$$t_n^2 \leq 2s^{-1}(1+s) \log_+ (1/L_n^s(g)),$$

we have

$$\begin{aligned} P[S_n \geq t_n B_n] \leq \Phi(-t_n) + b L_n^{s^*}(g) \exp[(\sigma - 1)t_n^2/2] \\ + t_n^{-2} g^s(B_n)/g^s(t_n B_n) L_n^s(g) L_n^s(t_n, g). \end{aligned}$$

But, taking into account Lemma 2 of [5], p. 166, we get

$$(2.18) \quad (t_n^2 g^s(t_n B_n)/g^s(B_n)) \Phi(-t_n) \leq b L_n^s(g) \exp(-a_n/2).$$

Furthermore

$$\begin{aligned} & (t_n^2 g^s(t_n B_n)/g^s(B_n)) L_n^{s^*}(g) \exp[(\sigma-1)t_n^2/2] \\ & \leq (b t_n g^s(t_n B_n)/g^s(B_n)) \exp(-t_n^2/2) (L_n^s(g))^{s^*/2s} (\log_+(1/L_n^s(g)))^{1/2}. \end{aligned}$$

Thus using (2.18) we obtain the desired assertion.

Let us observe that under the assumed moment conditions and the assumption (2.17) the property

$$t_n^2 - 2 \log_+(1/L_n^s(g)) - \log_+ \log_+(1/L_n^s(g)) \rightarrow \infty$$

characterizes the sequence $\{t_n, n \geq 1\}$ for which the assertion of Theorem 6 holds. The proof of this fact is an obvious modification of the proof of Remark 2 in [9].

Let us denote the L_p -norm ($1 \leq p \leq \infty$) of any function f with respect to the Lebesgue measure by

$$\|f\|_p = \left(\int_{\mathbf{R}} |f|^p d\mu \right)^{1/p} \quad \text{and} \quad \|f\|_\infty = \sup_{x \in \mathbf{R}} |f(x)|.$$

THEOREM 7. *Assume the function g is differentiable. Then there exists a constant b (depending on s) such that for all $n \geq 1$ and every p ($1 \leq p \leq \infty$)*

$$(2.19) \quad \|\Delta_n(t) [(h(t))^{p-1} h'(t)]^{1/p}\|_p \leq b (L_n^s(g) + L_n^{s^*}(g)),$$

where $h(t) = g^s(tB_n)t^2/g^s(B_n)$ and $h'(t)$ is the derivative of the function $h(t)$.

Proof. Let us observe that, by Theorem 3, (2.19) holds for $p = \infty$. On the other hand, if $1 < p < \infty$, then

$$\|\Delta_n(t) [(h(t))^{p-1} h'(t)]^{1/p}\|_p \leq \|\Delta_n(t) h(t)\|_\infty^{p-1/p} \|\Delta_n(t) h'(t)\|_1^{1/p}.$$

Thus the proof will be completed if we show that

$$\|\Delta_n(t) h'(t)\|_1 \leq b (L_n^s(g) + L_n^{s^*}(g)).$$

Let $a_n(s) = 2s^{-1}(1+s) \log_+(1/L_n^s(g))$. Then using Theorems 1 and 2 for $t \geq a_n(s)$ and $t \leq a_n(s)$, respectively, we get

$$\|\Delta_n(t) h'(t)\|_1 \leq b (L_n^s(g) + L_n^{s^*}(g)) + 2 \sum_{k=1}^n \int_0^\infty \{h'(t) P[|X_k| > rtB_n]\} dt.$$

Now we observe that

$$\sum_{k=1}^n \int_0^\infty \{h'(t) P[|X_k| > rtB_n]\} dt \leq b L_n^s(g).$$

The proof is completed.

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