On the distributional expansions of powered extremes from Maxwell distribution

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Abstract. In this paper, asymptotic expansions of the distributions and densities of powered extremes for Maxwell samples are considered. The results show that the convergence speeds of normalized partial maxima relies on the powered index. Additionally, compared with previous result, the convergence rate of the distribution of powered extreme from Maxwell samples is faster than that of its extreme. Finally, numerical analysis is conducted to illustrate our findings.

Keywords. Asymptotic expansion; density; Maxwell distribution; powered extreme.

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1 Introduction

In extreme value theory, researchers recently focus on investigating the quality of convergence of normalized \( \max \{ X_k, 1 \leq k \leq n \} := M_n \) of a sample. For the convergence rate of normalized \( M_n \), general cases were discussed by Smith \cite{Smith}, Leadbetter et al. \cite{Leadbetter}, Galambos \cite{Galambos} and de Haan and Resnick \cite{DeHaanResnick}, and specific cases were considered by Hall \cite{Hall1, Hall2}, Nair \cite{Nair}, Liao and Peng \cite{LiaoPeng}, Lin et al. \cite{Lin1, Lin2}, Du and Chen \cite{DuChen1, DuChen2}, and Huang et al. \cite{Huang1, Huang2}. Hall \cite{Hall1} derived the asymptotics of distribution of normalized \( |M_n|^t \), the powered extremes for given power index \( t > 0 \). Zhou and Ling \cite{ZhouLing} improved Hall’ results and proved that the convergence speed of distributions and densities of extremes depends on the power index. Nair \cite{Nair} established the asymptotic expansions of normalized maximum from normal samples. Liao et al. \cite{Liao3} and Jia et al. \cite{Jia} generalized Nair’s work to skew-normal distribution and general error distribution, respectively.

Since the Maxwell distribution was proposed by James Clerk Maxwell \cite{Maxwell}, a variety of applications of it in physics (in particular in statistical mechanics) have been found; see Shim and Gatignol \cite{ShimGatignol}, Tomer and Panwar \cite{TomerPanwar} and Shim \cite{Shim} and some statisticians and reliability engineers have investigated the statistical properties of it as well, see \cite{Huang1, Huang2, Huang3}.

The aim of this paper is to investigate the distributional tail representation of \(|X|^t\) with \( X \) follow-
ing Maxwell distribution and the limiting distribution of normalized \(|M_n|^t\), and obtain asymptotic expansions of distribution and density of powered maximum from Maxwell distribution.

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Let \( \{X_n, n \geq 1\} \) be a sequence of independent identically distributed (i.i.d.) random variables with marginal cumulative distribution function (cdf) \( F \) obeying the Maxwell distribution (abbreviated as \( F \sim MD \)), and as before let \( M_n = \max\{X_i, 1 \leq i \leq n\} \) denote the partial maximum of \( \{X_n, n \geq 1\} \). The probability density function (pdf) of the MD is defined by

\[
f(x) = \sqrt{\frac{2}{\pi}} \frac{x^{2}}{\sigma^{3}} \exp\left(-\frac{x^{2}}{2\sigma^2}\right), \ x > 0, \tag{1.1}\]

where \( \sigma > 0 \) is the scale parameter. Figure 1 presents the graph of pdf of Maxwell distribution. It shows that with the scale parameter increasing, the tail of pdf of MD becomes much heavier.

![Figure 1: Probability density function of Maxwell distribution](image)

Liu and Liu [21] showed that \( F \in D(\Lambda) \), i.e., the max-domain of attraction of Gumbel extreme value distribution and the normalizing constants \( a_n \) and \( b_n \) can be given by

\[
a_n = \sigma^2 b_n^{-1} \tag{1.2}\]

and

\[
\sqrt{\frac{\pi}{2}} \frac{\sigma}{b_n} \exp\left(\frac{b_n^2}{2\sigma^2}\right) = n \tag{1.3}\]

such that

\[
\lim_{n \to \infty} P(M_n \leq a_n x + b_n) = \Lambda(x) = \exp\{-\exp(-x)\}. \tag{1.4}\]

The paper is constructed as follows. Section 2 presents auxiliary lemmas with proofs. The main results are given in Section 3. Numerical studies presented in Section 4 compare the precision of the true values with its approximations. Section 5 provides the proofs of main results.

2 Auxiliary results

To prove the main results, the following auxiliary lemmas are needed.

**Lemma 2.1.** Let \( F(x) \) and \( f(x) \) respectively represent the cdf and the pdf of MD with \( \sigma > 0 \), respectively. For large \( x \), we have

\[
1 - F(x) = \sigma^2 x^{-1} f(x) \left[1 + \sigma^2 x^{-2} - \sigma^4 x^{-4} + 3\sigma^6 x^{-6} + O(x^{-8})\right]. \tag{2.1}\]
The proof of Lemma 2.1 is derived by integration by parts.

The following lemma gives the distributional tail representation of $X^t$ with $X \sim MD$.

**Lemma 2.2.** Suppose that $0 < t \neq 2$. Let $F_t(x)$ denote the cdf of $X^t$ with $X \sim MD$. Then for large $x$, we get

$$1 - F_t(x) = C_t(x) \exp \left\{ - \int_1^x \frac{g_t(u)}{f_t(u)} \, du \right\},$$

where

$$C_t(x) \rightarrow \frac{2}{\sigma} \sqrt{\frac{2}{\pi}} \exp \left( - \frac{1}{2\sigma^2} \right) \text{ as } x \rightarrow \infty,$$

$$g_t(x) = 1 - \sigma^2 x^{-2/t} \rightarrow 1 \text{ as } x \rightarrow \infty,$$

and

$$\tilde{f}_t(x) = \sigma^2 t x^{1 - \frac{2}{t}} \text{ with } \tilde{f}_t(x) \rightarrow 0 \text{ as } x \rightarrow \infty.$$  \hspace{1cm} (2.3)

**Proof.** Combining with (2.1), we get

$$1 - F_t(x) = 2 \frac{\sigma^2 f(x^{\frac{1}{t}})}{x^{\frac{1}{t}}} \left[ 1 + \sigma^2 x^{-\frac{2}{t}} - \sigma^4 x^{-\frac{4}{t}} + 3\sigma^6 x^{-\frac{6}{t}} + O(x^{-\frac{8}{t}}) \right]$$

$$= 2 \frac{\sigma}{\sqrt{2 \pi}} \exp \left( - \frac{x^{\frac{2}{t}}}{2 \sigma^2} + \frac{1}{t} \log x \right) \left[ 1 + \sigma^2 x^{-\frac{2}{t}} - \sigma^4 x^{-\frac{4}{t}} + 3\sigma^6 x^{-\frac{6}{t}} + O(x^{-\frac{8}{t}}) \right]$$

$$= C_t(x) \exp \left( - \int_1^x \frac{g_t(u)}{f_t(u)} \, du \right) \left[ 1 + \sigma^2 x^{-\frac{2}{t}} - \sigma^4 x^{-\frac{4}{t}} + 3\sigma^6 x^{-\frac{6}{t}} + O(x^{-\frac{8}{t}}) \right]$$

with $\tilde{f}_t(x) = \sigma^2 t x^{1 - \frac{2}{t}}$, $g_t(x) = 1 - \sigma^2 x^{-2/t}$ and $C_t(x) \rightarrow \frac{2}{\sigma} \sqrt{\frac{2}{\pi}} \exp \left( - \frac{1}{2\sigma^2} \right)$ as $x \rightarrow \infty$. \hfill \Box

Applying the result of Lemma 2.2 and Corollary 1.7 [28], the following result holds.

**Proposition 2.1.** Under the conditions of Lemma 2.2, we have $F_t(x) \in D(\Lambda)$, where $D(\Lambda)$ is the domain of $\Lambda(x) = \exp \{ - \exp(-x) \}$.

Then, our aim is to select the suitable normalizing constants which ensure that the distribution of maximum tends to its extreme value limit. A combination of (1.3) and (2.4), we obtain that $d_n = b_n^t$. It follows from (2.3) that

$$c_n = \tilde{f}_t(d_n) = \sigma^2 t b_n^t \left( \frac{1}{1 - \frac{2}{t}} \right) = \sigma^2 t b_n^{t-2}.$$  \hspace{1cm} (2.5)

The following work is to find the special normalizing constants $c_n$ and $d_n$ for the case of powered index $t = 2$. Similarly, it is necessary to establish the distributional tail representation of $X^2$ with $X \sim MD$.

**Lemma 2.3.** Assume that $t = 2$. Let $F_2(x)$ stand for the cdf of $X^2$ with $X \sim MD$. Then for large $x$, we get

$$1 - F_2(x) = C_2(x) \exp \left\{ - \int_1^x \frac{g_2(u)}{f_2(u)} \, du \right\},$$

where

$$C_2(x) \rightarrow \frac{2}{\sigma} \sqrt{\frac{2}{\pi}} \exp \left( - \frac{1}{2\sigma^2} \right) \text{ as } x \rightarrow \infty,$$

$$g_2(x) = 1 - \sigma^2 x^{-2} \rightarrow 1 \text{ as } x \rightarrow \infty,$$

and

$$\tilde{f}_2(x) = \sigma^2 t x^{1 - \frac{2}{2}} \text{ with } \tilde{f}_2(x) \rightarrow 0 \text{ as } x \rightarrow \infty.$$  \hspace{1cm} (2.6)
where

\[ C_2(x) \rightarrow \frac{2}{\sigma} \sqrt{\frac{2}{\pi}} \exp \left( -\frac{1}{2\sigma^2} \right) \text{ as } x \rightarrow \infty, \]

\[ g_2(x) = 1 + \frac{x^4}{4\sigma^2} \rightarrow 1 \text{ as } x \rightarrow \infty, \]

and

\[ \tilde{f}_2(x) = 2\sigma^2 \left( 1 + \frac{x^2}{\sigma^2} \right) \text{ with } \tilde{f}_2(x) \rightarrow 0 \text{ as } x \rightarrow \infty. \] (2.7)

**Proof.** Similar to the case of \( t \neq 2 \), we get

\[
1 - F_2(x) = 2\sigma^2 f(x^2) \left[ 1 + \sigma^2 x^{-1} - \sigma^4 x^{-2} + 3\sigma^6 x^{-3} + O(x^{-4}) \right]
\]

\[
= 2\sigma^2 f(x^2) \left[ 1 + \sigma^2 x^{-1} \right] \left[ 1 - \sigma^4 x^{-2}(1 + \sigma^2 x^{-1})^{-1} + 3\sigma^6 x^{-3}(1 + \sigma^2 x^{-1})^{-1} + O(x^{-4}) \right]
\]

\[
= \frac{2}{\sigma} \sqrt{\frac{2}{\pi}} \exp \left( -\frac{x}{2\sigma^2} + \frac{1}{2} \log x + \log \left( 1 + \frac{x^2}{\sigma^2} \right) \right) \left[ 1 - \sigma^4 x^{-2} + 4\sigma^6 x^{-3} + O(x^{-4}) \right]
\]

\[
= \frac{2}{\sigma} \sqrt{\frac{2}{\pi}} \exp \left( -\frac{1}{2\sigma^2} \right) \exp \left( - \int_1^{x} \frac{g_2(u)}{f_2(u)} du \right) \left[ 1 - \sigma^4 x^{-2} + 4\sigma^6 x^{-3} + O(x^{-4}) \right]
\] (2.8)

with \( g_2(x) = 1 + \sigma^4 t^{-2} \) and \( \tilde{f}_2(x) = 2\sigma^2(1 + \sigma^4 t^{-1}) \), where the third equality follows from the fact that \((1 + x)^a = 1 + ax + (a(a - 1)/2)x^2 + O(x^3)\) for all \( a \in \mathbb{R} \), as \( x \rightarrow 0 \).

\[ \square \]

Similar to the case of \( t \neq 2 \), we have the following result:

**Proposition 2.2.** Under the assumptions of Lemma 2.3, we get \( F_2(x) \in D(\Lambda) \), where \( D(\Lambda) \) is the domain of \( \Lambda(x) = \exp \{-\exp(-x)\} \).

Now we discuss how to find the constants \( c_n \), \( d_n \). Analogous to the case of \( t \neq 2 \), we may make choice of \( d_n = b_n^2 \) and \( c_n = \tilde{f}_2(d_n) = 2\sigma^2(1 + \sigma^2 b_n^{-2}) \). Inspired by \( c_n \), now change

\[
\bar{d}_n = b_n^2 + 2\sigma^2 b_n^{-2},
\]

\[
\bar{c}_n = \tilde{f}_2(\bar{d}_n) = 2\sigma^2[1 + \sigma^2 b_n^{-2} - 2\sigma^6 b_n^{-6} + O(b_n^{-10})]
\]

\[ \sim 2\sigma^2(1 + \sigma^2 b_n^{-2}). \] (2.9)

Let

\[ T_n(x, t) = F^{n-1}((c_n x + d_n)^{1/t}) - (1 - F((c_n x + d_n)^{1/t}))^{n-1}. \]

The following lemmas present the expansions of the two terms of densities of \((\lvert M_n \rvert^t - d_n)/c_n\).

**Lemma 2.4.** For normalizing constants \( c_n \) and \( d_n \) determined by (2.3) and \( 0 < t \neq 2 \), we have

\[ T_n(x, t) = \Lambda(x) \left\{ 1 - A_1(t, x)e^{-x}b_n^{-2} + \left( \frac{1}{2}A_1^2(t, x)e^{-x} - A_2(t, x) \right)e^{-x}b_n^{-4} + O(b_n^{-6}) \right\} \] (2.10)
as \( n \to \infty \), where

\[
A_1(t, x) = \sigma^2 \left( 1 + x + \frac{(t - 2)x^2}{2} \right)
\]

(2.11)

and

\[
A_2(t, x) = \sigma^4 \left( \frac{(t - 2)x^4}{8} + \frac{1}{6}(t - 2)(5 - 2t)x^3 - \frac{x^2}{2} - x - 1 \right).
\]

(2.12)

**Proof.** Let \( \delta_n(x, t) = (c_n x + d_n)^{1/t} \). One can easily see that \( c_n x + d_n > 0 \) for large \( n \) and fixed \( x \in \mathbb{R} \). By (1.3), for large \( n \), we have \( b_n^2 \sim 2\sigma^2 \log n \). Then, by (2.5), we have

\[
\delta_n^a(x, t) = b_n^a \left[ 1 + \frac{a \sigma^2 x}{b_n^2} + \frac{a(a - t)\sigma^4 x^2}{2b_n^4} + \frac{a(a - t)(a - 2t)\sigma^6 x^3}{6b_n^6} + O(b_n^{-8}) \right],
\]

(2.13)

where it follows from the fact that

\[
(1 + x)^a = 1 + ax + (a(a - 1)/2)x^2 + (a(a - 1)(a - 2)/6)x^3 + O(x^4),
\]

for \( a \in \mathbb{R} \), as \( x \to 0 \). Then, we get

\[
\frac{\sigma^2 f(\delta_n(x, t))}{\delta_n(x, t)} \stackrel{(a)}{=} \frac{1}{\sigma} \sqrt{\frac{2}{\pi}} b_n \left[ \frac{a \sigma^2 x}{b_n^2} + \frac{(1 - t)\sigma^4 x^2}{2b_n^4} + \frac{(1 - t)(1 - 2t)\sigma^6 x^3}{6b_n^6} + O(b_n^{-8}) \right] \times \exp \left\{ -\frac{b_n^2}{2\sigma^2} \left[ 1 + \frac{2a \sigma^2 x}{b_n^2} + \frac{(2 - t)\sigma^4 x^2}{b_n^4} + \frac{(2 - t)(2 - 2t)\sigma^6 x^3}{3b_n^6} + O(b_n^{-8}) \right] \right\}
\]

\[
\stackrel{(b)}{=} \frac{\sigma^2 f(b_n)}{b_n} e^{-x} \left[ 1 + \frac{a \sigma^2 x}{b_n^2} + \frac{(1 - t)\sigma^4 x^2}{2b_n^4} + O(b_n^{-8}) \right] \times \left[ 1 - \frac{(2 - t)\sigma^2 x^2}{2b_n^2} - \frac{(2 - t)(1 - t)\sigma^4 x^3}{3b_n^4} + \frac{(2 - t)^2\sigma^4 x^4}{8b_n^6} + O(b_n^{-8}) \right]
\]

\[
\stackrel{(c)}{=} n^{-1} e^{-x} \left\{ 1 + \frac{a \sigma^2 x}{b_n^2} \left( 1 + \frac{1}{2}(t - 2)x \right) + \frac{\sigma^4 x^2}{b_n^4} \left[ \frac{1}{8}(t - 2)^2 x^2 + \frac{1}{6}(t - 2)(5 - 2t)x + \frac{1 - t}{2} \right] + O(b_n^6) \right\}
\]

(2.14)

where (a) follows from (2.13) with \( a = 1 \) and 2, (b) is from the fact that \( e^x = 1 + x + x^2/2 + O(x^3) \), as \( x \to 0 \) and (c) is due to (1.3). Furthermore, we get

\[
1 + \sigma^2 \delta_n^{-2}(x, t) - \sigma^4 \delta_n^{-4}(x, t) + O(\delta_n^{-6}(x, t)) \]

\[
\stackrel{(a)}{=} 1 + \frac{\sigma^2}{b_n^2} \left[ 1 - x + O(b_n^{-4}) \right] - \frac{\sigma^4}{b_n^4} \left[ 1 + O(b_n^{-2}) \right] + O(b_n^{-6})
\]

\[
= 1 + \frac{\sigma^2}{b_n^2} - \frac{\sigma^4}{b_n^4} (1 + 2x) + O(b_n^{-6}),
\]

(2.15)

where (a) is from (2.13) with \( a = -2 \) and 4. By Lemma 2.1, we get

\[
1 - F(\delta_n(x, t)) = \frac{\sigma^2 f(\delta_n(x, t))}{\delta_n(x, t)} \left[ 1 + \sigma^2 \delta_n^{-2}(x, t) - \sigma^4 \delta_n^{-2}(x, t) + O(\delta_n^{-6}(x, t)) \right]
\]

\[
\stackrel{(a)}{=} n^{-1} e^{-x} \left\{ 1 + \frac{\sigma^2}{b_n^2} \left[ 1 + x + \frac{1}{2}(t - 2)x^2 \right] \right\}
\]
Proof.

It is not hard to check that

\[
+ \sigma^4 \left[ \frac{1}{8} (t - 2)^2 x^4 + \frac{1}{6} (t - 2)(5 - 2t)x^3 - \frac{x^2}{2} - x - 1 \right] + O(b_n^{-6})
\]

\[
= n^{-1} e^{-x} \left[ 1 + A_1(t, x)b_n^{-2} + A_2(t, x)b_n^{-4} + O(b_n^{-6}) \right], \tag{2.16}
\]

where (a) is due to (2.14) and (2.15). Accordingly,

\[
F^{n-1}(\delta_n(x, t)) = \exp \{ (n - 1) \log [1 - (1 - F(\delta_n(x, t)))] \}
\]

\[
\begin{aligned}
&\overset{(a)}{=} \Lambda(x) \exp \left[ -A_1(t, x)e^{-x}b_n^{-2} - A_2(t, x)e^{-x}b_n^{-4} + O(b_n^{-6}) \right] \\
&\overset{(b)}{=} \Lambda(x) \left\{ 1 - A_1(t, x)e^{-x}b_n^{-2} + \left( \frac{1}{2} A_1^2(t, x)e^{-x} - A_2(t, x) \right) e^{-x}b_n^{-4} + O(b_n^{-6}) \right\}, \\
&\tag{2.17}
\end{aligned}
\]

and

\[
(1 - F(\delta_n(x, t)))^{n-1} = \left\{ \frac{e^{-x}}{n} \left[ 1 + O(b_n^{-2}) \right] \right\}^{n-1} = o(b_n^{-\eta}), \ \eta \geq 6, \tag{2.18}
\]

where (a) is from the fact that \( \log(1 - x) = -x + O(x^2) \), as \( x \to 0 \), and (b) follows from that Taylor's expansion of \( e^x \). The desired result follows by (2.17) and (2.18).

\[\Box\]

Lemma 2.5. For the normalizing constants \( c_n \) and \( d_n \) determined by (2.5) and \( 0 < t \neq 2 \), we have

\[
n \frac{d}{dx} F((c_n x + d_n)^{1/t}) = e^{-x} \left\{ 1 + \sigma^2 x \right\} \left[ 1 + \frac{3(t - 2)}{6} x + \frac{1}{8} (t - 2)^2 x^2 \right] + O(b_n^{-6})
\]

as \( n \to \infty \).

Proof. It is not hard to check that

\[
n \frac{d}{dx} F((c_n x + d_n)^{1/t}) = \frac{1}{t} n c_n (c_n x + d_n)^{1/t-1} f((c_n x + d_n)^{1/t}).
\]

Therefore, we get

\[
n \frac{d}{dx} F((c_n x + d_n)^{1/t}) \overset{(a)}{=} n \frac{b_n}{\sigma} \sqrt{\frac{2}{\pi}} \left[ 1 + \frac{(3 - t) \sigma^2 x}{b_n^2} + \frac{(3 - t)(3 - 2t) \sigma^4 x^2}{2b_n^4} + O(b_n^{-6}) \right]
\]

\[
\times \exp \left\{ - \frac{b_n^2}{2 \sigma^2} \left[ 1 + \frac{2 \sigma^2 x}{b_n^2} + \frac{(2 - t) \sigma^4 x^2}{b_n^4} + \frac{(2 - t)(2 - 2t) \sigma^6 x^3}{3b_n^6} + O(b_n^{-8}) \right] \right\}
\]

\[
\overset{(b)}{=} n f(b_n) \frac{\sigma^2 b_n}{b_n} e^{-x} \left[ 1 + \frac{(3 - t) \sigma^2 x}{b_n^2} + \frac{(3 - t)(3 - 2t) \sigma^4 x^2}{2b_n^4} + O(b_n^{-6}) \right]
\]

\[
\times \left[ 1 - \frac{(2 - t) \sigma^2 x^2}{2b_n^2} - \frac{(2 - t)(1 - t) \sigma^4 x^3}{3b_n^4} + \frac{(2 - t)^2 \sigma^4 x^4}{8b_n^6} + O(b_n^{-6}) \right]
\]

\[
\overset{(c)}{=} e^{-x} \left[ 1 + \frac{\sigma^2 x}{b_n^2} [3 - t - (2 - t)x] \right]
\]
due to (1.3). The proof is complete.

where (a) follows from (2.13) with \( a = 3 - t \), (2.5) and (2.14) for the expansion of \( f(\delta_n(x, t)) \) with \( \delta_n(x, t) = (c_n x + d_n)^{1/2} \), (b) is from the fact that \( e^x = 1 + x + x^2/2 + O(x^3) \), as \( x \to 0 \) and (c) is due to (1.3). The proof is complete.

\[ \square \]

Lemma 2.6. For the normalizing constants \( c_n \) and \( d_n \) determined by (2.9) and \( t = 2 \), we have

\[ T_n(x, t) = \Lambda(x) \left[ 1 - B_1(t, x)e^{-x}b_n^{-4} - B_2(t, x)e^{-x}b_n^{-6} + O(b_n^{-8}) \right], \quad (2.20) \]
as \( n \to \infty \), where

\[ B_1(t, x) = -\sigma^4 \left( x^2 + x + \frac{1}{2} \right) \quad (2.21) \]

and

\[ B_2(t, x) = \sigma^6 \left( \frac{4}{3} x^3 + 2x^2 - 2x + \frac{7}{3} \right). \quad (2.22) \]

Proof. The proof of the case of \( t = 2 \) is similar to the case of \( 0 < t \neq 2 \). Note that \( c_n = 2\sigma^2(1 + \sigma^2 b_n^{-2}) \), \( d_n = b_n^2 + 2\sigma^4 b_n^{-2} \) for \( t = 2 \). So, we get

\[ \delta_n(x, 2) = (c_n x + d_n)^{1/2} = b_n[1 + 2\sigma^2 b_n^{-2} x + 2\sigma^4(x + 1)b_n^{-4}]^{1/2} =: \beta_n. \]

Then, we have

\[ \beta_n^a = b_n^a \left[ 1 + \frac{a\sigma^2 x}{b_n^2} + \frac{a\sigma^4}{b_n^4} \left( 1 + x - \frac{2 - a}{2} x^2 \right) - \frac{a(2 - a)\sigma^6 x}{b_n^6} \left( 1 + x - \frac{4 - a}{6} x^2 \right) + O(b_n^{-8}) \right]. \quad (2.23) \]

Further, we get

\[ \frac{\sigma^2 f(\beta_n)}{\beta_n} = \sqrt{\frac{2}{\pi \sigma^3}} \exp \left( -\frac{b_n^2}{2\sigma^2} \right) \sigma^2 b_n e^x \times \left[ 1 + \frac{\sigma^2 x}{b_n^2} + \frac{\sigma^4}{b_n^4} \left( 1 + x - \frac{1}{2} x^2 \right) - \frac{\sigma^6 x}{b_n^6} \left( 1 + x - \frac{1}{2} x^2 \right) + O(b_n^{-8}) \right] \times \left[ 1 - \frac{\sigma^2(1 + x)}{b_n^2} + \frac{\sigma^4(1 + x)^2}{2b_n^4} - \frac{\sigma^6(1 + x)^3}{6b_n^6} + O(b_n^{-8}) \right] \]

\[ \overset{(b)}{=} n^{-1} e^x \left[ 1 - \frac{\sigma^2}{b_n^2} \frac{\sigma^4}{b_n^4} \left( x^2 - x - \frac{3}{2} \right) + \frac{\sigma^6}{b_n^6} \left( \frac{4x^3}{3} - x^2 - 3x - \frac{7}{6} \right) + O(b_n^{-8}) \right], \quad (2.24) \]

where (a) is from (2.23) with \( a = 1 \) and 2 and \( e^x = 1 + x + x^2/2 + O(x^3) \), as \( x \to 0 \), and (b) is due to (1.3). Besides, applying (2.23) with \( a = -2, -4 \) and \(-6\), we get

\[ 1 + \sigma^2 \beta_n^{-2} - \sigma^4 \beta_n^{-4} + 3\sigma^6 \beta_n^{-6} + O(\beta_n^{-8}) \]

\[ = 1 + \sigma^2 b_n^{-2} \left[ 1 - \frac{2\sigma^2 x}{b_n^2} - \frac{2\sigma^4}{b_n^4} \left( 1 + x - 2x^2 \right) + O(b_n^{-6}) \right] \]
\[-\sigma^4 b_n^{-4} \left[ 1 - \frac{4\sigma^2 x}{b_n^2} + O(b_n^{-4}) \right] + 3\sigma^6 b_n^{-6} (1 + O(b_n^{-2})) + O(b_n^{-8})\]

\[= 1 + \frac{\sigma^2}{b_n^2} - \frac{\sigma^4}{b_n^4} (2x + 1) + \frac{\sigma^6}{b_n^6} (4x^2 - 2x + 1) + O(b_n^{-8}). \tag{2.25}\]

Combining with Lemma 2.1, (2.24) and (2.25), we get

\[1 - F(\beta_n) = n^{-1} e^{-x} \left[ 1 - \frac{\sigma^4}{b_n^4} \left( x^2 + x + \frac{1}{2} \right) + \frac{\sigma^6}{b_n^6} \left( \frac{4}{3} x^3 + 2x^2 - 2x + \frac{7}{3} \right) + O(b_n^{-8}) \right] \]

\[= n^{-1} e^{-x} \left[ 1 + B_1(t, x)b_n^{-4} + B_2(t, x)b_n^{-6} + O(b_n^{-8}) \right]. \tag{2.26}\]

The remainder proof is the same as the case of \(0 < t \neq 2\). We omit it. The proof is complete.

\[\Box\]

**Lemma 2.7.** For the normalizing constants \(c_n\) and \(d_n\) determined by (2.9) and \(t = 2\), we have

\[n \frac{d}{dx} F((c_n x + d_n)^{1/t}) = e^{-x} \left\{ 1 - \frac{\sigma^4}{b_n^4} \left( x^2 - x - \frac{1}{2} \right) + \frac{\sigma^6}{b_n^6} \left( \frac{4}{3} x^3 - 2x^2 - 2x + \frac{1}{3} \right) + O(b_n^{-8}) \right\},\]

as \(n \to \infty\).

**Proof.** By (2.24) and after observing that \(c_n = 2\sigma^2(1 + \sigma^2 b_n^{-2})\), we get

\[n \frac{d}{dx} F(\beta_n) = e^{-x} \left\{ 1 + \frac{\sigma^2}{b_n^2} - \frac{\sigma^4}{b_n^4} \left( x^2 - x - \frac{3}{2} \right) + \frac{\sigma^6}{b_n^6} \left( \frac{4}{3} x^3 - 3x^2 - 3x - \frac{7}{6} \right) + O(b_n^{-8}) \right\} \]

\[= e^{-x} \left\{ 1 - \frac{\sigma^4}{b_n^4} \left( x^2 - x - \frac{1}{2} \right) + \frac{\sigma^6}{b_n^6} \left( \frac{4}{3} x^3 - 2x^2 - 2x + \frac{1}{3} \right) + O(b_n^{-8}) \right\}. \tag{2.27}\]

The proof is complete.

\[\Box\]

As we mentioned in the introduction, Liu and Liu [21] obtained the pointwise convergence rate of distribution of partial maximum to its limiting distribution. Their main results are stated as follows.

**Theorem 2.1.** Suppose that \(\{X_n, n \geq 1\}\) is a sequence of i.i.d. random variables with cdf MD. Then,

\[F^n(\hat{a}_n x + \hat{b}_n) - \Lambda(x) \sim \Lambda(x) e^{-x} \frac{(\log(2 \log n))^2}{16 \log n}, \tag{2.28}\]

for large \(n\), where

\[\hat{a}_n = \frac{\sigma}{(2 \log n)^{1/2}} \text{ and } \hat{b}_n = (2\sigma^2 \log n)^{1/2} + \frac{\sigma \log(2 \log n) + \sigma \log^2 \frac{2}{\pi}}{2(2 \log n)^{1/2}}. \tag{2.29}\]

**3 Main result**

In this section, we establish the higher-order expansions of the cdf and the pdf of powered maximum from MD sample.
Theorem 3.1. 
(i) For $0 < t \neq 2$ and the normalizing constants $c_n$ and $d_n$ given by (2.5), we have
\[
\mathbb{P}(|M_n| \leq c_n x + d_n) = \Lambda(x) \left\{ 1 - e^{-x} A_1(t, x) b_n^{-2} + e^{-x} \left[ \frac{1}{2} e^{-x} A_1^2(t, x) - A_2(t, x) \right] b_n^{-4} + O(b_n^{-6}) \right\},
\]
(3.1)

where
\[
A_1(t, x) = \sigma^2 \left[ 1 + x + \frac{1}{2} (t - 2)x^2 \right]
\]
and
\[
A_2(t, x) = \sigma^4 \left\{ \frac{1}{8} (t - 2)^2 x^4 + \frac{1}{6} (t - 2)(5 - 2t)x^3 - \frac{x^2}{2} - x - 1 \right\}.
\]
(3.3)

(ii) For $t = 2$ and the normalizing constants $c_n$ and $d_n$ given by (2.9), we have
\[
\mathbb{P}(|M_n| \leq c_n x + d_n) = \Lambda(x) \left[ 1 - e^{-x} B_1(t, x) b_n^{-4} - e^{-x} B_2(t, x) b_n^{-6} + O(b_n^{-8}) \right],
\]
(3.4)

where
\[
B_1(t, x) = -\sigma^4 \left( x^2 + x + \frac{1}{2} \right)
\]
(3.5)

and
\[
B_2(t, x) = \sigma^6 \left( \frac{4}{3} x^3 + 2x^2 - 2x + \frac{7}{3} \right).
\]
(3.6)

Remark 3.1. From Theorem 3.1, one can easily see that the convergence rates of powered maximum of cdf for MD are proportional to $1/\log n$ and $1/((\log n)^2)$ for power index $0 < t \neq 2$ and $t = 2$, respectively, since $1/b_n^2 \sim 2\sigma^2 \log n$ by (1.3).

Remark 3.2. From Theorems 2.1 and 3.1 (ii), we can observe that the convergence speed of powered extreme of cdf for MD is better than that of extreme of cdf.

In the following we provide the higher-order expansions of the pdf of powered maximum.

Theorem 3.2. 
(i) For $0 < t \neq 2$ and the normalizing constants $c_n$ and $d_n$ given by (2.5), we have
\[
\frac{d}{dx} \mathbb{P}(|M_n| \leq c_n x + d_n) = \Lambda'(x) \left[ 1 + P_1(t, x) b_n^{-2} + P_2(t, x) b_n^{-4} + O(b_n^{-6}) \right],
\]
(3.7)

where
\[
P_1(t, x) = \sigma^2 \left\{ - \left[ \frac{(t - 2)x^2}{2} + x + 1 \right] e^{-x} + (t - 2)x^2 - (t - 3)x \right\}
\]
and
\[
P_2(t, x) = \sigma^4 \left\{ \frac{1}{2} \left[ \frac{(t - 2)x^2}{2} + x + 1 \right]^2 e^{-2x} \right\}
\]
where then we derive the normalizing constants for Remark 3.4. Extreme of pdf for MD are the same order of 1 as the following:

\[
\frac{(t - 2)^2 x^3}{8} - \left( t - 2 \left( \frac{5}{6} t - \frac{10}{3} \right) x^2 + \left( 2t + \frac{1}{2} \right) x^2 - 1 \right) e^{-x} + \frac{(t - 2)^2 x^3}{8} - \left( t - 2 \left( \frac{5}{6} t - \frac{11}{6} \right) x^2 + \left( t - 3 \right)(2t - 3) x \right).
\]

(ii) For \( t = 2 \) and the normalizing constants \( c_n \) and \( d_n \) given by (2.9), we have

\[
\frac{d}{dx} \mathbb{P}(|M_n|^t \leq c_n x + d_n) = \Lambda'(x) \left[ 1 + Q_1(t, x)b_n^{-4} + Q_2(t, x)b_n^{-6} + O(b_n^{-8}) \right], \quad (3.8)
\]

where

\[
Q_1(t, x) = \sigma^4 \left[ (x^2 + x + \frac{1}{2}) e^{-x} - x^2 + x + \frac{1}{2} \right]
\]

and

\[
Q_2(t, x) = -\sigma^6 \left[ \left( \frac{4}{3} x^3 + 2x^2 - 2x + \frac{7}{3} \right) e^{-x} - \frac{4}{3} x^3 + 2x^2 + 2x - \frac{1}{3} \right].
\]

Remark 3.3. From Theorem 3.2, it is not difficult to observe that the convergence speeds of powered extreme of pdf for MD are the same order of 1/\( \log n \) and 1/(\log n)^2 for power index 0 < \( t \neq 2 \) and \( t = 2 \), respectively, because of \( 1/b_n^2 \sim 2\sigma^2 \log n \) by (1.3).

Remark 3.4. For \( t = 2 \), the normalizing constants \( c_n \) and \( d_n \) are not given by (2.9), but we choose them as follows:

\[
c_n = 2\sigma^2 (1 - \sigma^2 b_n^{-2}) \quad \text{and} \quad d_n = b_n^2 - 2\sigma^4 b_n^{-2}, \quad (3.9)
\]

then we derive

\[
\mathbb{P}(|M_n|^t \leq c_n x + d_n) = \Lambda(x) \left\{ 1 - \frac{2e^{-x}\sigma^2}{b_n^2} (x + 1) + \frac{e^{-x}\sigma^4}{b_n^4} \left[ 2e^{-x}(x + 1)^2 - x^2 - x - \frac{3}{2} \right] b_n^{-4} - \frac{e^{-x}\sigma^6}{b_n^6} \left[ \frac{4}{3} e^{-2x}(x + 1)^3 - 2e^{-x}(x + 1) \left( x^2 + x + \frac{3}{2} \right) \right. \\
\left. + \frac{2}{3} x^3 + 2x^2 + 3x + \frac{14}{3} \right] + O(b_n^{-8}) \} \right. \quad (3.10)
\]

and

\[
\frac{d}{dx} \mathbb{P}(|M_n|^t \leq c_n x + d_n) = \Lambda'(x) \left\{ 1 - \frac{2\sigma^2}{b_n^2} e^{-x}(x + 1) - x \right. + \frac{\sigma^4}{b_n^4} \left[ 2e^{-2x}(x + 1)^2 - \left( 5x^2 + 5x + \frac{3}{2} \right) e^{-x} \right. \\
\left. + x^2 - x + \frac{1}{2} + \frac{\sigma^6}{b_n^6} \left[ 4x(x + 1)^2 e^{-2x} - (4x^3 + 2x^2 + 2x + 1) e^{-x} + \frac{2}{3} x^3 - x - \frac{7}{6} \right] + O(b_n^{-8}) \right\}. \quad (3.11)
\]

Obviously, the convergence rates of the cdf and the pdf of powered extreme given by (3.4) and (3.8), which are proportional to 1/(\log n)^2, are faster than that given by (3.10) and (3.11). Consequently, the normalizing constants \( c_n \) and \( d_n \) determined by (2.9) are optimal.
4 Numerical analysis

In this section, we conduct numerical studies to illustrate the accurateness of higher-order expansions for the cdf and the pdf of $|M_n|^t$. Let $T^{(i)}(x)$ and $S^{(i)}(x)$, $i = 1, 2, 3$, respectively represent the first-order, the second-order and the third-order approximations of the cdf and the pdf of $|M_n|^t$. Since the analysis of the case of $t \neq 2$ is similar to that of $t = 2$, we only consider the situation of $t = 2$. By Theorems 3.1 and 3.2 we obtain

$$T^{(1)}(x) = \Lambda(x),$$
$$T^{(2)}(x) = \Lambda(x) \left[1 - e^{-x}B_1(t, x)b_n^{-4}\right],$$
$$T^{(3)}(x) = \Lambda(x) \left[1 - e^{-x}B_1(t, x)b_n^{-4} - e^{-x}B_2(t, x)b_n^{-6}\right],$$

and

$$S^{(1)}(x) = \Lambda(x) \exp(-x),$$
$$S^{(2)}(x) = \Lambda(x) \exp(-x) \left[1 + Q_1(t, x)b_n^{-4}\right],$$
$$S^{(3)}(x) = \Lambda(x) \exp(-x) \left[1 + Q_1(t, x)b_n^{-4} + Q_2(t, x)b_n^{-6}\right].$$

Easily observe that the second-order approximation and the third-order relate to the sample size $n$.

In order to compare the precision of true values with its approximations, let

$$E^{(i)}(x) = \left|P^n(\sqrt{c_n x + d_n}) - T^{(i)}(x)\right|$$

and

$$G^{(i)}(x) = \left|\frac{nc_n}{2\sqrt{c_n x + d_n} f(\sqrt{c_n x + d_n})} F^{n-1}(\sqrt{c_n x + d_n}) f(\sqrt{c_n x + d_n}) - S^{(i)}(x)\right|$$

respectively stand for the absolute errors of the cdf and the pdf, where $i = 1, 2, 3$. We utilize MATLAB to compute the approximations and the true values of the cdf and the pdf of $M_n^2$.

First, we estimate the absolute errors of the cdf of $M_n^2$ at $x = 0.7$, where the sample size $n$ varies from 25 to 1000 with step size 25. For given $x = 0.7$, numerical analysis results of $E^{(i)}(x)$ are recorded in Table 4. The table demonstrates that the precision of all three kinds of approximations of the cdf can be refined as the sample size $n$ increases.

To order to indicate the precision of all approximations more intuitive with the change of the sample size $n$, the actual values and its approximation of the cdf of $M_n^2$ are plotted versus the values of $n$ with $x = 1.5$. Figure 2 evidences that the larger $n$, the better all asymptotics.

Secondly, we estimate the absolute errors of the pdf of $M_n^2$ at $x = 0.7$, where the value of the sample size $n$ ranges from 375 to 15000 with step length 375. Table 4 lists the numerical analysis results of $G^{(i)}(x)$, where $i = 1, 2, 3$. Table 4 reveals that the precision of all three kinds of approximations of the pdf enhances as the sample size $n$ grows.

To clear the precision of all approximations more intuitive with $n$, the actual and its approximations of the pdf of $M_n^2$ are plotted versus the values of $n$ with $x = 1.5$. Figure 3 indicates that as the sample size $n$ becomes larger, all approximations become better.
| $n$  | $E^{(1)}(x)$     | $E^{(2)}(x)$ | $E^{(3)}(x)$ |
|------|-----------------|--------------|--------------|
| 25   | 0.0169056391    | 0.00877452615| 0.00733539417|
| 50   | 0.0143357459    | 0.00869068028| 0.00785819009|
| 75   | 0.0131346277    | 0.00843346219| 0.00780078242|
| 100  | 0.0123911158    | 0.00821865868| 0.00768964941|
| 125  | 0.0118668421    | 0.00804347997| 0.00757945239|
| 150  | 0.0114683134    | 0.0078976489 | 0.00747885611|
| 175  | 0.0111502039    | 0.00777354585| 0.00738841683|
| 200  | 0.0108874336    | 0.00766594114| 0.00730705118|
| 225  | 0.0106648041    | 0.00757120115| 0.00723346892|
| 250  | 0.0104724714    | 0.00748673237| 0.00716650872|
| 275  | 0.0103037264    | 0.00741063197| 0.00710519645|
| 300  | 0.0101538089    | 0.00734146835| 0.00704873143|
| 325  | 0.0100192298    | 0.00727814037| 0.0069964575 |
| 350  | 0.00989736162   | 0.00721978455| 0.00694783483|
| 375  | 0.00978618048   | 0.00716571218| 0.00690241634|
| 400  | 0.00968409693   | 0.0071153658 | 0.00685982891|
| 425  | 0.00958984178   | 0.00706828819| 0.00681975869|
| 450  | 0.00950238672   | 0.00702409995| 0.00678193964|
| 475  | 0.00942088789   | 0.00698248302| 0.00674614548|
| 500  | 0.00934464492   | 0.00694316822| 0.00671217821|
| 525  | 0.00927307061   | 0.00690592583| 0.00667987148|
| 550  | 0.00920566819   | 0.00687055834| 0.00664907727|
| 575  | 0.00914201391   | 0.00683689469| 0.00661966674|
| 600  | 0.00908174361   | 0.00680478587| 0.00659152652|
| 625  | 0.00902454227   | 0.00677410125| 0.00656455636|
| 650  | 0.00897013561   | 0.00674472575| 0.00653866719|
| 675  | 0.00891828351   | 0.00671655745| 0.00651377957|
| 700  | 0.00886877463   | 0.00668950571| 0.00648982235|
| 725  | 0.00882142208   | 0.00666348955| 0.00646673154|
| 750  | 0.00877605982   | 0.00663843637| 0.00644444946|
| 775  | 0.00873253972   | 0.00661428081| 0.00642292387|
| 800  | 0.00869072914   | 0.00659096382| 0.00640210739|
| 825  | 0.00865050883   | 0.00656843192| 0.00638195685|
| 850  | 0.00861177127   | 0.00654663651| 0.00636243286|
| 875  | 0.00857441915   | 0.00652553326| 0.00634349935|
| 900  | 0.00853363418   | 0.00650508169| 0.00632512325|
| 925  | 0.008503526     | 0.0064852447 | 0.00630724714|
| 950  | 0.00846983127   | 0.00646598823| 0.00628992938|
| 975  | 0.0084372129    | 0.00644728091| 0.00627304687|
| 1000 | 0.00840560939   | 0.00642909381| 0.00625661887|

Table 1: Absolute errors between actual values and their asymptotics of the cdf at $x = 0.7$ with $\sigma = 2$
| n   | $G^{(1)}(x)$ | $G^{(2)}(x)$ | $G^{(3)}(x)$ |
|-----|-------------|-------------|-------------|
| 375 | 0.00825613746 | 0.00585394461 | 0.00554667797 |
| 750 | 0.00710011928 | 0.00514055207 | 0.00491416905 |
| 1125| 0.0065538405  | 0.00479753582 | 0.00460544643 |
| 1500| 0.00621014157 | 0.00457905959 | 0.00440714319 |
| 1875| 0.00596472382 | 0.00442157961 | 0.00426337709 |
| 2250| 0.00577637198 | 0.00429979382 | 0.0041517166  |
| 2625| 0.00562489953 | 0.00420122856 | 0.00406103823 |
| 3000| 0.00549902795 | 0.00411887475 | 0.0039850629  |
| 3375| 0.00539186326 | 0.00404842643 | 0.0039191863  |
| 3750| 0.00529890627 | 0.00398706069 | 0.00386305898 |
| 4125| 0.00521707021 | 0.0039328329  | 0.00381272502 |
| 4500| 0.0051411522  | 0.00388435007 | 0.0037675376  |
| 4875| 0.00507852912 | 0.00384058231 | 0.0037269095  |
| 5250| 0.00501897306 | 0.00380074803 | 0.00368978076 |
| 5625| 0.00496453429 | 0.0037624093  | 0.0036557147  |
| 6000| 0.00491446145 | 0.00373058177 | 0.00362427365 |
| 6375| 0.00486816283 | 0.00369938562 | 0.00359510557 |
| 6750| 0.00482514285 | 0.00367033886 | 0.00356792328 |
| 7125| 0.00478500308 | 0.00364318286 | 0.00354248964 |
| 7500| 0.00474740971 | 0.00361770192 | 0.00351860668 |
| 7875| 0.00471208225 | 0.00359371443 | 0.00349610752 |
| 8250| 0.00467878285 | 0.00357106611 | 0.00347485024 |
| 8625| 0.00464730824 | 0.00354962483 | 0.0034571324  |
| 9000| 0.0046174834  | 0.00352927666 | 0.0034359152  |
| 9375| 0.00458915666 | 0.00350992269 | 0.00341739387 |
| 9750| 0.00456219575 | 0.00349147652 | 0.00340004057 |
| 10125|0.00453648471 | 0.0034738623  | 0.00338346154 |
| 10500|0.00451192133 | 0.00345701305 | 0.0033675949  |
| 10875|0.00448841509 | 0.0034408694  | 0.00335238574 |
| 11250|0.00446588547 | 0.00342537844 | 0.00333778509 |
| 11625|0.00444426057 | 0.00341049288 | 0.00332374917 |
| 12000|0.00442347592 | 0.00339617026 | 0.00331023861 |
| 12375|0.00440347351 | 0.00338237231 | 0.00329721797 |
| 12750|0.00438420096 | 0.00336906445 | 0.00328465516 |
| 13125|0.00436561084 | 0.00335261534 | 0.00327252109 |
| 13500|0.00434766007 | 0.00334379647 | 0.00326078929 |
| 13875|0.00433030941 | 0.00333178183 | 0.0032494356  |
| 14250|0.0043152301  | 0.00332014766 | 0.00323843795  |
| 14625|0.00429726807 | 0.00330887219 | 0.00322777608 |
| 15000|0.00428151447 | 0.00329793539 | 0.00321743138 |

Table 2: Absolute errors between actual values and their asymptotics of the pdf at $x = 0.7$ with $\sigma = 2$
Figure 2: Actual values and its asymptotics of the cdf of $M_n^2$ with $x = 1.5$. The actual values drawn in black, the first-order approximations drawn in blue, the second-order approximations drawn in red and the third-order approximation drawn in green.

Figure 3: Actual values and its asymptotics of the pdf of $M_n^2$ with $x = 1.5$. The actual values drawn in black, the first-order approximations drawn in blue, the second-order approximations drawn in red and the third-order approximation drawn in green.

5 Proof of main result

Proof of Theorem 3.1. By some fundamental calculations, we get

$$P(\left|M_n\right|^t \leq c_n x + d_n) = F_n^n((c_n x + d_n)^{1/t}) - (1 - F((c_n x + d_n)^{1/t}))^n.$$ (5.1)

First, we consider the case of $0 < t \neq 2$. By (2.16) and similar discussions as for (2.17) and (2.18), we get

$$F_n^n(\delta_n(x,t)) = \Lambda(x) \left\{1 - A_1(t,x)e^{-x}b_n^{-2} + \left(\frac{1}{2}A_1^2(t,x)e^{-x} - A_2(t,x)\right)e^{-x}b_n^{-4} + O(b_n^{-6})\right\},$$ (5.2)

where $A_1(t,x)$ and $A_2(t,x)$ are determined by (2.11) and (2.12), and

$$\left(1 - F(\delta_n(x,t))\right)^n = \left\{\frac{e^{-x}}{n}\left[1 + O(b_n^{-2})\right]\right\}^n = o(b_n^{-\eta}), \ \eta \geq 6.$$ (5.3)
A combination of (5.2) and (5.3) implies that (3.1) holds.

For the case of $t = 2$, by similar arguments as for $0 < t \neq 2$, the desired result follows. The proof is complete.

**Proof of Theorem 3.2.** One can easily check that

$$
\frac{d}{dt}[P(|M_n|^t \leq c_n x + d_n)] - n\left(\frac{d}{dt}F((c_n x + d_n)^{1/t})\right)
$$

$$
\times \left\{F^{n-1}((c_n x + d_n)^{1/t}) + [1 - F((c_n x + d_n)^{1/t})]^{n-1}\right\}.
$$

For $0 < t \neq 2$, combining with Lemmas 2.4 and 2.5, we get

$$
\frac{1}{N'(x)} \frac{d}{dx}P(|M_n| \leq c_n x + d_n) - 1 = \left\{1 + \frac{\sigma^2 x}{b_n^4} [3 - t - (2 - t)x]ight\}
$$

$$
+ \frac{\sigma^4 x^2}{b_n^4} \left[\frac{1}{2} (3 - t)(3 - 2t) + (t - 2) \left(\frac{11}{6} - \frac{5}{6} t\right) x + \frac{1}{8} (t - 2)^2 x^2\right] + O(b_n^{-6})
$$

$$
\times \left\{1 - \sigma^2 \left[1 + x + \frac{1}{2} (t - 2)x^2\right] e^{-x} + \frac{1}{2} [1 + x + \frac{1}{2} (t - 2)x^2] e^{-x}
$$

$$
- \left[\frac{1}{8} (t - 2)^2 x^2 + \frac{1}{6} (t - 2)(5 - 2t)x^3 - \frac{x^2}{2} - 1\right] \sigma^4 e^{-x} + O(b_n^{-6})\right\} - 1
$$

$$
= \sigma^2 b_n^{-2} \left\{- \frac{1}{2} \left[\left(\frac{1}{2} - x\right) + x + 1\right] e^{-x} + (t - 2)x^2 - (t - 3)x\right\}
$$

$$
+ \frac{\sigma^4}{b_n^4} \left[\frac{1}{2} \left[\left(\frac{1}{2} - x\right) + x + 1\right]^2 e^{-x}
$$

$$
- \left[\frac{5(t - 2)x^3}{8} - (t - 2) \left(\frac{5}{6} t - \frac{10}{3}\right) x^3 + \left(\frac{2t}{1} + \frac{1}{2}\right) x^2 - 1\right] e^{-x}
$$

$$
+ \frac{1}{8} (t - 2)^2 x^3 - \frac{1}{6} (t - 2) \left(\frac{5}{6} t - \frac{11}{6}\right) x^2 + \frac{(t - 3)(2t - 3)}{2} x\right\} + O(b_n^{-6})
$$

$$
P_1(t, x)b_n^{-2} + P_2(t, x)b_n^{-4} + O(b_n^{-6}),
$$

which deduces (3.7).

The following is for the case of $t = 2$. By (5.4) and Lemmas 2.6 and 2.7, we gain

$$
\frac{1}{N'(x)} \frac{d}{dx}P(|M_n|^t \leq c_n x + d_n) - 1 = \left\{1 - \frac{\sigma^4 x}{b_n^6} \left(x^2 - x - \frac{1}{2}\right)\right\}
$$

$$
+ \frac{\sigma^6}{b_n^8} \left[\frac{4}{3} x^3 - 2x^2 - 2x + \frac{1}{3}\right] + O(b_n^{-8})\right\}
$$

$$
\times \left[1 + \frac{\sigma^4 e^{-x}}{b_n^6} \left(x^2 + x + \frac{1}{2}\right) - \frac{\sigma^6 e^{-x}}{b_n^8} \left(\frac{4}{3} x^3 + 2x^2 - 2x + \frac{7}{3}\right) + O(b_n^{-8})\right] - 1
$$

$$
= \frac{\sigma^4}{b_n^6} \left[\left(x^2 + x + \frac{1}{2}\right) e^{-x} - x^2 + x + \frac{1}{2}\right]
$$

$$
- \frac{\sigma^6}{b_n^8} \left[\left(\frac{4}{3} x^3 + 2x^2 - 2x + \frac{7}{3}\right) e^{-x} - \frac{4}{3} x^3 + 2x^2 - 2x + \frac{1}{3}\right] + O(b_n^{-8})
$$

$$
= Q_1(t, x)b_n^{-4} + Q_2(t, x)b_n^{-6} + O(b_n^{-8}),
$$
which proves (3.8). The proof of Theorem 3.2 is finished.

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