# Some Large Deviation Results for Generalized Compound Binomial Risk Models 

KONG Fan Chao, ZHAO Peng<br>(School of Mathematics, Anhui University, Anhui 230039, China)<br>(E-mail: zhaopeng7885@sohu.com)


#### Abstract

This paper is a further investigation of large deviation for partial and random sums of random variables, where $\left\{X_{n}, n \geq 1\right\}$ is non-negative independent identically distributed random variables with a common heavy-tailed distribution function $F$ on the real line $R$ and finite mean $\mu \in R$. $\{N(n), n \geq 0\}$ is a binomial process with a parameter $p \in(0,1)$ and independent of $\left\{X_{n}, n \geq 1\right\} ;\{M(n), n \geq 0\}$ is a Poisson process with intensity $\lambda>0, S_{n}=\sum_{i=1}^{N(n)} X_{i}-c M(n)$. Suppose $F \in C$, we futher extend and improve some large deviation results. These results can apply to certain problems in insurance and finance.


Keywords generalized compound binomial risk model; large deviations; heavy-tailed distribution; ruin probability.

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## 1. Introduction and main results

$\mathrm{Hu}^{[1]}$ introduced a generalized compound binomial risk model, which is based on the following independent objects:
(i) A binomial process $\{N(n) ; n=0,1,2, \ldots\}$ with a parameter $p, 0<p<1$, corresponding to the claim number process, $N(0)=0$;
(ii) A sequence $\left\{X_{n} ; n \geq 1\right\}$ of non-negative i.i.d random variables with common distribution function (df for short) $F$, corresponding to the claim size process, $0<\mu=E X_{1}<\infty$;
(iii) A Poisson process $\{M(n) ; n=0,1,2, \ldots\}$ with intensity $\lambda>0$, where $M(n)$ is corresponding to the number of customers who buy the insurance portfolios in the time interval $(0, n]$, $M(0)=0$;
(iv) $\{N(n) ; n=0,1,2, \ldots\} ;\left\{X_{n} ; n \geq 1\right\}$ and $\{M(n) ; n=0,1,2, \ldots\}$ are mutually independent.
For the GCBRM, the risk reserve process $\{R(n) ; n=0,1,2, \ldots\}$ is then given by

$$
\begin{equation*}
R(n)=u+c M(n)-\sum_{i=1}^{N(n)} X_{i}, \quad n=0,1,2, \ldots \tag{1}
\end{equation*}
$$

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while the net total claim amount process $\{S(n) ; n=0,1,2, \ldots\}$ is

$$
\begin{equation*}
S(n)=\sum_{i=1}^{N(n)} X_{i}-c M(n), \quad n=0,1,2, \ldots \tag{2}
\end{equation*}
$$

where $c>0$ is the premium of a single insurance portfolio (i.e., the price of the insurance portfolio), and $u>0$ is the initial capital of the company. For the GCBRM, the net profit condition becomes $c \lambda>p E X_{1}$.

The time of ruin for the GCBRM is described by

$$
\begin{equation*}
T(u)=\inf \{n ; R(n)<0\}=\inf \{n ; S(n)>u\} \tag{3}
\end{equation*}
$$

In [1], Hu investigated the GCBRM with heavy-tailed claim sizes, namely in
(i) The probabilities of large deviations of $\{S(n)\}$;
(ii) The Lundberg type limiting results for the finite time ruin probabilities.

He obtained the following results.
Theorem A For the GCBRM, let $\{S(n)\}$ be as in (2) and suppose that $\bar{F} \in E R V(-\alpha,-\beta)$ for some $1<\alpha \leq \beta<\infty$. Then $P(S(n)-E S(n)>x) \sim p n \bar{F}(x)$ holds uniformly for $x \geq \gamma p n$ for any fixed $\gamma>0$ satisfying $\gamma p>c \lambda$, i.e.,

$$
\begin{equation*}
\lim _{n \rightarrow \infty} \sup _{x \geq \gamma p n}\left|\frac{P(S(n)-E S(n)>x)}{p n \bar{F}(x)}-1\right|=0 \tag{4}
\end{equation*}
$$

Theorem B For the GCBRM, suppose that $\bar{F} \in E R V(-\alpha,-\beta)$ for some $1<\alpha \leq \beta<\infty$. Then
(i) For every $x>0$ and $y>0$,

$$
\begin{equation*}
\liminf _{u \rightarrow \infty} \frac{1}{\log u} \log P\left(T(u) \leq y u^{x}\right) \geq x-\beta \cdot \max \{1, x\} \tag{5}
\end{equation*}
$$

(ii) For either $x=1$ and $0<y<(p \mu)^{-1}$ or $0<x<1$ and $y>0$,

$$
\begin{equation*}
\limsup _{u \rightarrow \infty} \frac{1}{\log u} \log P\left(T(u) \leq y u^{x}\right) \leq x-\alpha \tag{6}
\end{equation*}
$$

where $\mu=E X_{1}<\infty$.
In this paper, we will extend $\bar{F} \in E R V(-\alpha,-\beta)$ to $\bar{F} \in C$, and give some counterparts of (4), (5) and (6). First we give some definitions.

Definition 1 The random variable $X$ (or its d.f.F) is called heavy-tailed, if $E e^{t X}=\infty$ holds for any fixed $t>0$. The two important subclasses of heavy-tailed df are $C$ and ERV.
(i) We call $\bar{F} \in C$, if $\lim _{l \downarrow 1} \liminf _{x \rightarrow \infty} \frac{\bar{F}(l x)}{\bar{F}(x)}=1$.
(ii) We call $\bar{F} \in E R V(-\alpha,-\beta)$, if there exist constants $1<\alpha \leq \beta<\infty$ such that

$$
y^{-\beta} \leq \liminf _{x \rightarrow \infty} \frac{\bar{F}(x y)}{\bar{F}(x)} \leq \limsup _{x \rightarrow \infty} \frac{\bar{F}(x y)}{\bar{F}(x)} \leq y^{-\alpha}, \quad \forall y>1
$$

Remark 1 Let $N$ be a random variable with the geometric distribution, i.e., $P(N=k)=$ $p(1-p)^{k-1}, k>1,0<p<1 ; U$ is another r.v. with uniform distribution $U(0,1)$ and it is independent of $N$. Write $X:=2^{2^{N}(1+U)}$. F denotes distribution of r.v.X, then $\bar{F} \in C$, but
$\bar{F} \notin E R V$. From Lemma 7 in [2], we have $E R V \subset C$. Thereby, $C$ is a larger subclass than ERV.

Corresponding to the Proposition 2.1 in [1], we have the following result.
Theorem 1 For the GCBRM, if $\bar{F} \in C$, then for every fixed $\gamma>0, P(Y(n)-E Y(n)>x) \sim$ $p n \bar{F}(x)$ holds uniformly for $x \geq \gamma p n$, that is,

$$
\lim _{n \rightarrow \infty} \sup _{x \geq \gamma p n}\left|\frac{P(Y(n)-E Y(n)>x)}{p n \bar{F}(x)}-1\right|=0
$$

where $Y(n)=\sum_{i=1}^{N(n)} X_{i}, n=0,1,2, \ldots$.
About the large deviations of $\{S(n)\}$ in (2), we have the following theorem.
Theorem 2 For the GCBRM, let $\{S(n)\}$ be as in (2) and suppose that $\bar{F} \in C$. Then for any fixed $\gamma>0, P(S(n)-E S(n)>x) \sim p n \bar{F}(x)$ holds uniformly for $x \geq \gamma p n$, where $\gamma p>c \lambda$, i.e.,

$$
\begin{equation*}
\lim _{n \rightarrow \infty} \sup _{x \geq \gamma p n}\left|\frac{P(S(n)-E S(n)>x)}{p n \bar{F}(x)}-1\right|=0 \tag{7}
\end{equation*}
$$

Remark 2 Obviously, (7) is equivalent to the following properties: for any fixed $\gamma>0$, where $\gamma p>c \lambda$,

$$
\liminf _{n \rightarrow \infty} \inf _{x \geq \gamma p n} \frac{P(S(n)-E S(n)>x)}{p n \bar{F}(x)} \geq 1, \quad \limsup _{n \rightarrow \infty} \sup _{x \geq \gamma p n} \frac{P(S(n)-E S(n)>x)}{p n \bar{F}(x)} \leq 1
$$

Before giving Theorem 3, we first see Lemma 1.
Lemma 1 Let $X$ be a non-negative random variable with its tail $\bar{F} \in C$ and $0<\mu=E X_{1}<\infty$. There exists some $1<\beta<\infty$, such that $K_{1} x^{-\beta} \leq \bar{F}(x) \leq \mu x^{-1}$ for all $x \geq x_{0}(\beta)$, where the constant $K_{1}=K_{1}(\beta)$ is independent of $x$.

Proof By Lemma 3.1 in [3], if $\bar{F} \in C$, then there exists $\beta>1, K>0$ and $x_{0}>0$, such that $\bar{F}(x) \geq K x^{-\beta}$. For all $x>x_{0}$, where $K>0$ is a constant and independent of $x$. Since $\infty>\mu=E X \geq E X I_{(X>x)} \geq x \bar{F}(x), \bar{F}(x) \leq \mu x^{-1}$.

Recall that $T(u)$ as in (3) is time of ruin for the GCBRM. By the corresponding Lundberg type limiting result, we have

Theorem 3 For the GCBRM, suppose that $\bar{F} \in C$. Then
(i) For every $0<x \leq 1$ and $y>0, \beta_{0}=\inf \{\beta\}$, $\beta$ satisfying Lemma 1, we have

$$
\begin{equation*}
\liminf _{u \rightarrow \infty} \frac{1}{\log u} \log P\left(T(u) \leq y u^{x}\right) \geq x-\beta_{0} \tag{8}
\end{equation*}
$$

(ii) For $0<x<1$ and $y>0$, we get

$$
\begin{equation*}
\limsup _{u \rightarrow \infty} \frac{1}{\log u} \log P\left(T(u) \leq y u^{x}\right) \leq x-1 \tag{9}
\end{equation*}
$$

## 2. Proofs of main results

We first prove Theorem 1.

Proof of Theorem 1 For the GCBRM and $\bar{F} \in C$, from Lemma 9 in [2] we have

$$
\lim _{n \rightarrow \infty} \sup _{x \geq \gamma n}\left|\frac{P\left(S_{n}-E S_{n}>x\right)}{n \bar{F}(x)}-1\right|=0
$$

where $S_{n}=\sum_{i=0}^{n} X_{i}, n=1,2, \ldots$
Since $\{N(n) ; n \geq 0\}$ is a binomial process with a parameter $p \in(0,1)$, there exists a sequence $\left\{Y_{i} ; i \geq 1\right\}$ which are i.i.d.r.v, independent of $\left\{X_{n} ; n \geq 1\right\}$, and $P\left(Y_{1}=1\right)=p=1-P\left(Y_{1}=0\right)$, such that $N(n)=\sum_{i=1}^{n} Y_{i}$. Then

$$
Y(n)=\sum_{i=1}^{N(n)} X_{i}=\sum_{i=1}^{Y_{1}} X_{i}+\sum_{i=Y_{1}+1}^{Y_{1}+Y_{2}} X_{i}+\cdots+\sum_{i=\sum_{k=1}^{n-1} Y_{k}+1}^{\sum_{k=1}^{n} Y_{k}} X_{i}:=\sum_{j=1}^{n} Z_{j}
$$

where $\sum_{i=1}^{0} X_{i}:=0$ and $N(0):=0$. Obviously, $\left\{Z_{j}, j=1, \ldots, n\right\}$ are independent.

$$
\begin{aligned}
E \exp \left(r \sum_{i=\sum_{k=1}^{j} Y_{k}+1}^{\sum_{k=1}^{j+1} Y_{k}} X_{i}\right) & =\sum_{n_{1}=0}^{1} \cdots \sum_{n_{j}=0}^{1} E \exp \left(r \sum_{i=n_{1}+\cdots+n_{j}+1}^{n_{1}+\cdots+n_{j}+Y_{j+1}} X_{i}\right) I_{\left(Y_{1}=n_{1}, \ldots, Y_{j}=n_{j}\right)} \\
& =E \exp \left(r \sum_{i=1}^{Y_{j+1}} X_{i}\right)=E \exp \left(r \sum_{i=1}^{Y_{1}} X_{i}\right)
\end{aligned}
$$

Thus $\left\{Z_{j}, j \geq 1\right\}$ are i.i.d and $E Z_{1}=E Y_{1} \cdot E X_{1}=p \mu>0$.
Since $P\left(Z_{1}>x\right)=P\left(X_{1}>x, Y_{1}=1\right)=p \bar{F}(x), x>0$, for any $y>1$, we have

$$
\frac{P\left(Z_{1}>x y\right)}{P\left(Z_{1}>x\right)}=\frac{p \bar{F}(x y)}{p \bar{F}(x)}=\frac{\bar{F}(x y)}{\bar{F}(x)}
$$

By $\bar{F} \in C$, we obtain $\bar{Z}_{1} \in C$. Then

$$
\lim _{n \rightarrow \infty} \sup _{x \geq \gamma n}\left|\frac{P\left(\sum_{i=1}^{n} Z_{i}-E\left(\sum_{i=1}^{n} Z_{i}\right)>x\right)}{n P\left(Z_{1}>x\right)}-1\right|=0,
$$

thereby

$$
\lim _{n \rightarrow \infty} \sup _{x \geq \gamma n}\left|\frac{P(Y(n)-E(Y(n))>x)}{n p \bar{F}(x)}-1\right|=0
$$

Thus the proof of Theorem 1 is completed.
Proof of Theorem 2 Observe that $\{M(n) ; n=0,1,2, \ldots\}$ is a Poisson process with intensity $\lambda>0$, by [1], there exist a positive sequence $\{\varepsilon(n) \downarrow 0\}$ as $n \rightarrow \infty$ and

$$
\begin{equation*}
P(|M(n)-\lambda n|>\varepsilon(n) \lambda n)=o(1) \tag{10}
\end{equation*}
$$

Noting that $Y(n)=\sum_{i=1}^{N(n)} X_{i}, n=0,1,2, \ldots$, we have

$$
\begin{aligned}
P(S(n)-E S(n)>x) & =P(Y(n)-E Y(n)>x-c \lambda n+c M(n)) \\
& =\sum_{k=0}^{\infty} P(Y(n)-E Y(n)>x-c \lambda n+c k) P(M(n)=k) .
\end{aligned}
$$

Therefore, Theorem 2 will be proved from the following three Lemmas 2-4.
Lemma 2 Let $\{\varepsilon(n)\}$ be as in (10). Then for any fixed $\gamma>0$

$$
\sum_{|k-\lambda n| \leq \varepsilon(n) \lambda n} P(M(n)=k) P(Y(n)-E Y(n)>x-c \lambda n+c k) \sim p n \bar{F}(x)
$$

holds uniformly for $x \geq \gamma p n$.
Lemma 3 Let $\{\varepsilon(n)\}$ be as in (10). Then for any fixed $\gamma>0$ satisfying $\gamma p>c \lambda$

$$
\sum_{k-\lambda n<-\varepsilon(n) \lambda n} P(M(n)=k) P(Y(n)-E Y(n)>x-c \lambda n+c k)=o(p n \bar{F}(x))
$$

holds uniformly for $x \geq \gamma p n$.
Lemma 4 Let $\{\varepsilon(n)\}$ be as in (10). Then for any fixed $\gamma>0$

$$
\sum_{k-\lambda n>\varepsilon(n) \lambda n} P(M(n)=k) P(Y(n)-E Y(n)>x-c \lambda n+c k)=o(p n \bar{F}(x))
$$

holds uniformly for $x \geq \gamma p n$.
Proof of Lemma 2 In view of Theorem 1, for fixed $\gamma>0$, we have

$$
P(Y(n)-E Y(n)>x) \sim p n \bar{F}(x)
$$

as $n \rightarrow \infty$, holds uniformly for $x \geq \gamma p n$.
Moreover, for $|k-\lambda n| \leq \varepsilon(n) \lambda n$ with $\varepsilon(n)$ as in (10), and $x \geq \gamma p n$,

$$
x-c \lambda n+c k=x+c(k-\lambda n)=x+o(x), \quad n \rightarrow \infty
$$

Then

$$
\frac{\bar{F}(x-c \lambda n+c k)}{\bar{F}(x)}=\frac{\bar{F}(x+o(x))}{\bar{F}(x)}
$$

By Lemma 8 in [2], for any $\gamma>0$, we have

$$
\lim _{n \rightarrow \infty} \sup _{x \geq \gamma p n}\left|\frac{\bar{F}(x+o(x))}{\bar{F}(x)}-1\right|=0
$$

Thereby

$$
P(Y(n)-E(Y(n))>x-c \lambda n+c k) \sim p n \bar{F}(x-c \lambda n+c k)
$$

as $n \rightarrow \infty$, holds uniformly for $|k-\lambda n| \leq \varepsilon(n) \lambda n$ and $x \geq \gamma p n$. Hence

$$
\begin{aligned}
& \sum_{|k-\lambda n| \leq \varepsilon(n) \lambda n} P(M(n)=k) P(Y(n)-E Y(n)>x-c \lambda n+c k) \\
& \sim p n \bar{F}(x) \sum_{|k-\lambda n| \leq \varepsilon(n) \lambda n} P(M(n)=k) \frac{\bar{F}(x-c \lambda n+c k)}{\bar{F}(x)} \\
& \sim p n \bar{F}(x) P(|M(n)-\lambda n| \leq \varepsilon(n) \lambda n) \sim p n \bar{F}(x)
\end{aligned}
$$

holds uniformly for $x \geq \gamma p n$. Lemma 2 is proved.

Proof of Lemma 3 For $x \geq \gamma p n$, we have

$$
x-c \lambda n=x\left(1-\frac{c \lambda n}{x}\right) \geq x\left(1-\frac{c \lambda}{\gamma p}\right):=\gamma^{\prime} x .
$$

Since $\bar{F} \in C \subset D=\left\{\limsup _{x \rightarrow \infty} \frac{\bar{F}\left(\gamma^{\prime} x\right)}{\bar{F}(x)}<\infty\right\}$ for any fixed $0<\gamma^{\prime}<1$, again using Theorem 1 and choosing $\varepsilon(n)$ as $\operatorname{in}(10)$, we obtain that

$$
\begin{aligned}
& \sum_{k-\lambda n<-\varepsilon(n) \lambda n} P(M(n)=k) P(Y(n)-E Y(n)>x-c \lambda n+c k) \\
& \leq \sum_{k-\lambda n<-\varepsilon(n) \lambda n} P(M(n)=k) P(Y(n)-E Y(n)>x-c \lambda n) \\
& \sim p n \bar{F}(x) \sum_{k-\lambda n<-\varepsilon(n) \lambda n} P(M(n)=k) \frac{\bar{F}(x-c \lambda n)}{\bar{F}(x)} \\
& \leq p n \bar{F}(x) \sum_{k-\lambda n<-\varepsilon(n) \lambda n} P(M(n)=k) \frac{\bar{F}\left(\gamma^{\prime} x\right)}{\bar{F}(x)} \\
& \leq c_{1} p n \bar{F}(x) P(M(n)-\lambda n \leq-\varepsilon(n) \lambda n)=o(1) p n \bar{F}(x)=o(p n \bar{F}(x))
\end{aligned}
$$

uniformly for $x \geq \gamma p n$, where $\gamma>0$ is a fixed constant, satisfying $\gamma p>c \lambda$ and $c_{1}>0$ is also a constant. Lemma 3 is proved.

Proof of Lemma 4 Using Theorem 1 once more and choosing $\varepsilon(n)$ as in(10), we have

$$
\begin{aligned}
& \sum_{k-\lambda n>\varepsilon(n) \lambda n} P(M(n)=k) P(Y(n)-E Y(n)>x-c \lambda n+c k) \\
\leq & \sum_{k-\lambda n>\varepsilon(n) \lambda n} P(M(n)=k) P(Y(n)-E Y(n)>x) \\
\sim & p n \bar{F}(x) \sum_{k-\lambda n>\varepsilon(n) \lambda n} P(M(n)=k) \\
= & p n \bar{F}(x) P(M(n)-\lambda n>\varepsilon(n) \lambda n)=o(1) p n \bar{F}(x)=o(p n \bar{F}(x))
\end{aligned}
$$

uniformly for $x \geq \gamma \lambda n$ where $\gamma>0$ is a fixed constant. Lemma 4 is proved.
By Lemmas 2, 3 and 4, the proof of Theorem 2 is completed.
Proof of Theorem 3 (i) Proof of (8). Let $0<x \leq 1$ and $y>0$, in view of Remark 2, for any $0<\theta<1$ we have uniformly for $u$ large enough that

$$
\begin{aligned}
& P\left(T(u) \leq y u^{x}\right) \geq P\left(S\left(\left[y u^{x}\right]\right)>u\right)=P\left(S\left(\left[y u^{x}\right]\right)-E S\left(\left[y u^{x}\right]\right)>u-(p u-c \lambda)\left[y u^{x}\right]\right) \\
& \quad \geq P\left(S\left(\left[y u^{x}\right]\right)-E S\left(\left[y u^{x}\right]\right)>u+c \lambda\left[y u^{x}\right]\right) \geq(1-\theta) p\left[y u^{x}\right] \bar{F}\left(u+c \lambda\left[y u^{x}\right]\right)
\end{aligned}
$$

where $[y]$ stands for the integer part of $y \in R$. Consequently, let $1<\beta<\infty$, by Lemma 1

$$
\liminf _{u \rightarrow \infty} \frac{1}{\log u} \log P\left(T(u) \leq\left[y u^{x}\right]\right) \geq x+\liminf _{u \rightarrow \infty} \frac{1}{\log u}(-\beta) \log \left(u+c \lambda\left[y u^{x}\right]\right) \geq x-\beta_{0}
$$

thus (8) is proved.
(ii) Proof of (9). Let $0<x<1$ and $y>0$. By Theorem 1, for every $0<\theta<1$, we have
uniformly for $u$ large enough that

$$
\begin{aligned}
P\left(T(u) \leq\left[y u^{x}\right]\right) \leq P\left(Y\left(\left[y u^{x}\right]>u\right)\right. & =P\left(Y\left(\left[y u^{x}\right]\right)-E Y\left(\left[y u^{x}\right]\right)>u-p\left[y u^{x}\right] \mu\right) \\
& \leq(1+\theta) p\left[y u^{x}\right] \bar{F}\left(u-p \mu\left[y u^{x}\right]\right) .
\end{aligned}
$$

Consequently, by Lemma 4

$$
\limsup _{u \rightarrow \infty} \frac{1}{\log u} \log P\left(T(u) \leq y u^{x}\right) \leq x+\limsup _{u \rightarrow \infty} \frac{1}{\log u}(-1) \log \left(u-p \mu\left[y u^{x}\right]\right)=x-1
$$

The proof of Theorem 3 is completed.

## References

[1] HU Yijun. Finite time ruin probabilities and large deviations for generalized compound binomial risk models [J]. Acta Math. Sin. (Engl. Ser.), 2005, 21(5): 1099-1106.
[2] KONG Fanchao. Large deviations of heavy-tailed random sums in the risk models [J]. Southeast Asian Bull. Math., 2004, 28(6): 1049-1062.
[3] SU Chun, TANG Qihe, JIANG Tao. A contribution to large deviations for heavy-tailed random sums [J]. Sci. China Ser. A, 2001, 44(4): 438-444.
[4] JIANG Tao. Improvement on: "Large deviations for heavy-tailed random sums in compound renewal model" [J]. Statist. Probab. Lett., 2001, 52(1): 91-100.
[5] WILLMOT G E. Ruin probabilities in the compound binomial model [J]. Insurance Math. Econom., 1993, 12(2): 133-142.
[6] GERBER H U. An Introduction to Mathematical Risk Theory [M]. Homewood, Ill., 1979.

