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## A necessary and sufficient condition for the non-trivial limit of the derivative martingale in a branching random walk

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**Summary.** We consider a branching random walk on the line. Biggins and Kyprianou [6] proved that, in the boundary case, the associated derivative martingale converges almost surly to a finite nonnegative limit, whose law serves as a fixed point of a smoothing transformation (Mandelbrot's cascade). In the present paper, we give a necessary and sufficient condition for the non-triviality of this limit and establish a Kesten-Stigum-like result.

*Keywords.* Branching random walk; derivative martingale; Mandelbrot's cascade; random walk conditioned to stay positive.

## 1 Introduction

We consider a discrete-time branching random walk (BRW) on the real line, which can be described in the following way. An initial ancestor, called the root and denoted by  $\emptyset$ , is created at the origin. It gives birth to some children which form the first generation and whose positions are given by a point process  $\mathcal{L}$  on  $\mathbb{R}$ . For any integer  $n \geq 1$ , each individual in the *n*th generation gives birth independently of all others to its own children in the (n+1)th generation, and the displacements of its children from this individual's position is given by an independent copy of  $\mathcal{L}$ . The system goes on if there is no extinction. We thus obtain a genealogical tree, denoted by  $\mathbb{T}$ . For each vertex (individual)  $u \in \mathbb{T}$ , we denote its generation by |u| and its position by V(u). In particular,  $V(\emptyset) = 0$  and  $(V(u); |u| = 1) = \mathcal{L}$ .

Note that the point process  $\mathcal{L}$  plays the same role in the BRW as the offspring distribution in a Galton-Watson process. We introduce the Laplace-Stieltjes transform of  $\mathcal{L}$  as follows:

(1.1) 
$$\Phi(t) := \mathbf{E} \Big[ \int_{\mathbb{R}} e^{-tx} \mathcal{L}(dx) \Big] = \mathbf{E} \Big[ \sum_{|u|=1} e^{-tV(u)} \Big], \text{ for } \forall t \in \mathbb{R}.$$

Let  $\Psi(t) := \log \Phi(t)$ . We always assume in this paper  $\Psi(0) > 0$  so that  $\mathbf{E}\left[\sum_{|u|=1} 1\right] > 1$ . This yields that with strictly positive probability, the system survives. Let q be the probability of extinction. Clearly, q < 1.

Let  $(\mathcal{F}_n; n \ge 0)$  be the natural filtration of this branching random walk, i.e. let  $\mathcal{F}_n := \sigma\{(u, V(u)); |u| \le n\}$ . We introduce the additive martingale for any  $t \in \mathbb{R}$ ,

(1.2) 
$$W_n(t) := \sum_{|u|=n} e^{-tV(u) - n\Psi(t)}.$$

It is a nonnegative martingale with respect to  $(\mathcal{F}_n; n \ge 0)$ , which converges almost surely to a finite nonnegative limit. Biggins [3] established a necessary and sufficient condition for the mean convergence of  $W_n(t)$ , and generalized Kesten-Stigum theorem for the Galton-Watson processes. A simpler proof based on a change of measures was given later by Lyons [14].

More generally, Biggins and Kyprianou [6] studied the martingales produced by the socalled mean-harmonic functions. Given suitable conditions on the offspring distribution  $\mathcal{L}$ of the branching random walk, like the  $X \log X$  condition of the Kesten-Stigum theorem, they gave a general treatment to obtain the mean convergence of these martingales. In this paper, following their ideas, we work on one special example and give a Kesten-Stigum-like theorem.

Throughout this paper, we consider the boundary case (in the sense of [7]) where  $\Psi(1) = \Psi'(1) = 0$ , i.e.,

(1.3) 
$$\mathbf{E}\Big[\sum_{|u|=1} e^{-V(u)}\Big] = 1, \quad \mathbf{E}\Big[\sum_{|u|=1} V(u)e^{-V(u)}\Big] = 0.$$

In addition, we assume that

(1.4) 
$$\sigma^2 := \mathbf{E} \Big[ \sum_{|u|=1} V(u)^2 \mathrm{e}^{-V(u)} \Big] \in (0,\infty).$$

We are interested in the derivative martingale, which is defined as follows:

(1.5) 
$$D_n := \sum_{|u|=n} V(u) \mathrm{e}^{-V(u)}, \quad \forall n \ge 0$$

It is a signed martingale with respect to  $(\mathcal{F}_n)$ , of mean zero. By Theorem 5.1 of [6], under (1.3) and (1.4),  $D_n$  converges almost surely to a finite nonnegative limit, denoted by  $D_{\infty}$ . Moreover,  $D_{\infty}$  satisfies the following equation (Mandelbrot's cascade):

(1.6) 
$$D_{\infty} = \sum_{|u|=1} e^{-V(u)} D_{\infty}^{(u)},$$

where  $D_{\infty}^{(u)}$  are copies of  $D_{\infty}$  independent of each other and of  $\mathcal{F}_1$ . Note that  $D_{\infty}$  serves as a nonnegative fixed point of a smoothing transformation. From this point of view, the questions concerning the existence, uniqueness and asymptotic behavior of such fixed points have been much studied in the literature ([5, 7, 12, 13]). We are interested in the existence of a non-trivial fixed point, and we are going to determine when  $\mathbf{P}(D_{\infty} > 0) > 0$ .

It is known that  $\mathbf{P}(D_{\infty} = 0)$  is equal to either the extinction probability q or 1 (see [1], for example). We say that the limit  $D_{\infty}$  is non-trivial if  $\mathbf{P}(D_{\infty} > 0) > 0$ , which means that  $\mathbf{P}(D_{\infty} = 0) = q$ . Otherwise, it is trivially zero. In this paper, we give a sufficient and necessary condition for the non-triviality of  $D_{\infty}$ . The main result is stated as follows.

For any  $y \in \mathbb{R}$ , let  $y_+ := \max\{y, 0\}$  and let  $\log_+ y := \log(\max\{y, 1\})$ . We introduce the following random variables:

(1.7) 
$$Y := \sum_{|u|=1} e^{-V(u)}, \quad Z := \sum_{|u|=1} V(u)_{+} e^{-V(u)}.$$

**Theorem 1.1.** The limit of the derivative martingale  $D_n$  is non-trivial, namely  $\mathbf{P}(D_{\infty} > 0) > 0$ , if and only if the following condition holds:

(1.8) 
$$\mathbf{E}\left(Z\log_{+}Z + Y(\log_{+}Y)^{2}\right) < \infty$$

**Remark 1.2.** In [6], the authors studied the optimal condition for the non-triviality of  $D_{\infty}$ . However, there is a small gap between the necessary condition and the sufficient condition for  $\mathbf{P}(D_{\infty} > 0) > 0$  in their Theorem 5.2. Our result fills this gap and gives the analogue of the result of [15] in the case of branching Brownian motion.

**Remark 1.3.** Aidékon proved that the condition (1.8) is sufficient for  $\mathbf{P}(D_{\infty} > 0) > 0$  (see Proposition A.3 in the Appendix of [1]).

The paper is organized as follows. Section 2 introduces a change of measures based on a truncated martingale which is closely related to the derivative martingale. We also prove a proposition concerning certain behaviors of a centered random walk conditioned to stay positive at the end of Section 2. Then, by using this proposition, we prove Theorem 1.1 in Section 3.

Throughout the paper,  $(c_i)_{i\geq 0}$  denote positive constants. We write  $\mathbf{E}[f; A]$  for  $\mathbf{E}[f_{1_A}]$ and set  $\sum_{\emptyset} := 0$ .

## 2 Lyons' change of measures via truncated martingales

#### 2.1 Truncated martingales

We begin with the well-known many-to-one lemma. For any  $a \in \mathbb{R}$ , let  $\mathbf{P}_a$  be the probability measure such that  $\mathbf{P}_a((V(u), u \in \mathbb{T}) \in \cdot) = \mathbf{P}((V(u) + a, u \in \mathbb{T}) \in \cdot)$ . The corresponding expectation is denoted by  $\mathbf{E}_a$ . We write  $\mathbf{P}$ ,  $\mathbf{E}$  instead of  $\mathbf{P}_0$ ,  $\mathbf{E}_0$  for brevity. For any particle  $u \in \mathbb{T}$ , we denote by  $u_i$  its ancestor at the *i*th generation, for  $0 \leq i < |u|$ . In addition, we write  $u_{|u|} := u$ . We thus denote its ancestral line by  $[[\emptyset, u]] := \{u_0, u_1, \cdots, u_{|u|}\}$ .

**Lemma 2.1** (Many-to-one). There exists a sequence of i.i.d centered random variables  $(S_{k+1} - S_k), k \ge 0$  such that for any  $n \ge 1$  and any measurable function  $g : \mathbb{R}^n \to \mathbb{R}_+$ , we have

(2.1) 
$$\mathbf{E}_{a}\left[\sum_{|u|=n}g(V(u_{1}),\cdots,V(u_{n}))\right] = \mathbf{E}_{a}\left[e^{S_{n}-a}g(S_{1},\cdots,S_{n})\right],$$

with  $\mathbf{P}_{a}[S_{0}=a]=1.$ 

In view of (1.4),  $S_1 - S_0$  has a finite variance  $\sigma^2 = \mathbf{E}[S_1^2] = \mathbf{E}[\sum_{|u|=1} V(u)^2 e^{-V(u)}].$ 

Let  $U^{-}(dy)$  be the renewal measure associated with the weak descending ladder height process of  $(S_n, n \ge 0)$ . Following the arguments in Section 2 of [4], we obtain that for any measurable function  $f : \mathbb{R} \to \mathbb{R}_+$ ,

(2.2) 
$$\mathbf{E}\Big[\sum_{j=0}^{\tau-1} f(-S_j)\Big] = \int_0^\infty f(y) U^-(\mathrm{d}y),$$

where  $\tau$  be the first time that  $(S_n)$  enters  $(0, \infty)$ , namely  $\tau := \inf\{k > 0, S_k \in (0, \infty)\}$ which is proper here. We define  $R(x) := U^-([0, x))$  for all x > 0 and define R(0) := 1. Note that R(x) equals the renewal function  $U^-([0, x])$  at points of continuity. We collect the following properties of this function R(x) which are consequences of the renewal theorem (see [4, 2, 17]).

**Fact 2.2.** (i) There exists a positive constant  $c_0 > 0$  such that

(2.3) 
$$\lim_{x \to \infty} \frac{R(x)}{x} = c_0$$

(ii) There exist two constants  $0 < c_1 < c_2 < \infty$  such that

(2.4) 
$$c_1(1+x) \le R(x) \le c_2(1+x), \quad \forall x \ge 0.$$

(*iii*) For any  $x \ge 0$ , we have  $\mathbf{E}[R(S_1 + x)\mathbf{1}_{(S_1 + x > 0)}] = R(x)$ .

Let  $\beta \geq 0$ . Started from  $V(\emptyset) = a$ , we add a barrier at  $-\beta$  to the branching random walk. Now, we define the following truncated random variables:

(2.5) 
$$D_n^{(\beta)} := \sum_{|x|=n} R(V(x) + \beta) e^{-V(x)} \mathbb{1}_{(\min_{1 \le k \le n} V(x_k) > -\beta)}, \quad \forall n \ge 1$$

and  $D_0^{(\beta)} := R(a+\beta)e^{-a}1_{(a \ge -\beta)}.$ 

**Lemma 2.3.** For any  $a \ge 0$  and  $\beta \ge 0$ , under  $\mathbf{P}_a$ , the process  $(D_n^{(\beta)}, n \ge 0)$  is a nonnegative martingale with respect to  $(\mathcal{F}_n, n \ge 0)$ .

This lemma follows immediately from (iii) of Fact 2.2 and the branching property. We feel free to omit its proof and call  $(D_n^{(\beta)})$  the truncated martingale. It also tells us that under  $\mathbf{P}_a$ ,  $(D_n^{(\beta)}, n \ge 0)$  converges almost surely to a finite nonnegative limit, which we denote by  $D_{\infty}^{(\beta)}$ .

The connection between the limits of the derivative martingale and truncated martingales is recorded in the following Lemma, the proof of which can be referred to [6] and [1].

- **Lemma 2.4.** (1) If  $D_{\infty}$  is trivial, i.e.,  $\mathbf{P}(D_{\infty} = 0) = 1$ , then for any  $\beta \ge 0$ ,  $D_{\infty}^{(\beta)}$  is trivially zero under  $\mathbf{P}$ .
  - (2) Under **P**, if there exists some  $\beta \geq 0$  such that  $D_{\infty}^{(\beta)}$  is trivially zero, so is  $D_{\infty}$ .

Thanks to Lemma 2.4, we only need to investigate the truncated martingale  $(D_n^{(0)}; n \ge 0)$ and determine when its limit is non-trivial.

### 2.2 Lyons' change of probabilities and spinal decomposition

Let  $\beta = 0$ . With this nonnegative martingale  $(D_n^{(0)}, n \ge 0)$ , we define for any  $a \ge 0$  a new probability measure  $\mathbf{Q}_a$  such that for any  $n \ge 1$ ,

(2.6) 
$$\frac{d\mathbf{Q}_a}{d\mathbf{P}_a}\Big|_{\mathcal{F}_n} = \frac{D_n^{(0)}}{R(a)e^{-a}}$$

 $\mathbf{Q}_a$  is defined on  $\mathcal{F}_{\infty} := \bigvee_{n \geq 0} \mathcal{F}_n$ . Let us give an intuitive description of the branching random walk under  $\mathbf{Q}_a$ , which is known as the spinal decomposition. We start from one single particle  $\omega_0$ , located at the position  $V(\omega_0) = a$ . At time 1, it dies and produces a point process distributed as (V(u); |u| = 1) under  $\mathbf{Q}_a$ . Among the children of  $\omega_0, \omega_1$  is chosen to be u with probability proportional to  $R(V(u))e^{-V(u)}1_{(V(u)>0)}$ . At each time n + 1, each particle v in the nth generation dies and produces independently a point process distributed as (V(u); |u| = 1) under  $\mathbf{P}_{V(v)}$  except  $\omega_n$ , which dies and generates independently a point process distributed as (V(u); |u| = 1) under  $\mathbf{Q}_{V(\omega_n)}$ . And then  $\omega_{n+1}$  is chosen to be u among the children of  $\omega_n$ , with probability proportional to  $R(V(u))e^{-V(u)}1_{(\min_{1\leq k\leq n+1}V(u_k)>0)}$ . We still use  $\mathbb{T}$  to denote the genealogical tree. Then  $(\omega_n; n \geq 0)$  is an infinite ray in  $\mathbb{T}$ , which is called the spine. The rigorous proof was given in Appendix A of [1]. Indeed, this type of measures' change and the establishment of a spinal decomposition have been developed in various cases of the branching framework; see, for example [14, 11, 8, 10].

We state the following fact about the distribution of the spine process  $(V(\omega_n); n \ge 0)$ under  $\mathbf{Q}_a$ .

Fact 2.5. Let  $a \ge 0$ . For any  $n \ge 0$  and any measurable function  $g : \mathbb{R}^{n+1} \to \mathbb{R}_+$ , we have (2.7)  $\mathbf{E}_{\mathbf{Q}_a} \Big[ g(V(\omega_0), \cdots, V(\omega_n)) \Big] = \frac{1}{R(a)} \mathbf{E}_a \Big[ g(S_0, \cdots, S_n) R(S_n); \min_{1 \le k \le n} S_i > 0 \Big],$ 

where  $(S_n)$  is the same as that in Lemma 2.1.

For convenience, let  $(\zeta_n; n \ge 0)$  be a stochastic process under  $\mathbf{P}_a$  such that

(2.8) 
$$\mathbf{P}_{a}[\left(\zeta_{n}; n \geq 0\right) \in \cdot] = \mathbf{Q}_{a}[\left(V(\omega_{n}); n \geq 0\right) \in \cdot].$$

Obviously, under  $\mathbf{P}_a$ ,  $(\zeta_n; n \ge 0)$  is a Markov chain with transition probabilities P so that, for any  $x \ge 0$ ,  $P(x, dy) = \frac{R(y)}{R(x)} \mathbf{1}_{(y>0)} \mathbf{P}_x(S_1 \in dy)$ . This process  $(\zeta_n)$  is usually called a random walk conditioned to stay positive. It has been arisen and studied in, for instance, [17, 2, 4, 18]. In what follows, we state some results about  $(\zeta_n)$ , which will be useful later in Section 3.

#### 2.3 Random walk conditioned to stay positive

Recall that  $(S_n)$  is a centered random walk on  $\mathbb{R}$  with finite variance  $\sigma^2$ . Let  $\tau_-$  be the first time that  $(S_n)$  hits  $(-\infty, 0]$ , namely,  $\tau_- := \inf\{k \ge 1 : S_k \le 0\}$ . Let  $(T_k, H_k; k \ge 0)$  be the strict ascending ladder epochs and heights of  $(S_n; n \ge 0)$ , i.e.,  $T_0 = 0$ ,  $H_0 := S_0$  and for any  $k \ge 1$ ,  $T_k := \inf\{j > T_{k-1} : S_j > H_{k-1}\}$ ,  $H_k := S_{T_k}$ . We denote by U(dx) the corresponding renewal measure (see Chapter XII in [9], for example). Then, similarly to (2.2), for any measurable function  $f : \mathbb{R} \to \mathbb{R}_+$ ,

(2.9) 
$$\mathbf{E}\Big[\sum_{n=0}^{\tau_{-}-1} f(S_n)\Big] = \mathbf{E}\Big[\sum_{k\geq 0} f(H_k)\Big] = \int_0^{\infty} f(x)U(\,\mathrm{d} x).$$

We deduce from (2.7) and (2.9) that

(2.10) 
$$\mathbf{E}\left[\sum_{n\geq 0} f(\zeta_n)\right] = \mathbf{E}_{\mathbf{Q}_0}\left[\sum_{n\geq 0} f(V(\omega_n))\right] = \sum_{n\geq 0} \mathbf{E}\left[f(S_n)R(S_n)\mathbf{1}_{(\min_{1\leq k\leq n}S_k>0)}\right]$$
$$= \mathbf{E}\left[\sum_{n=0}^{\tau_--1} f(S_n)R(S_n)\right] = \int_0^\infty f(x)R(x)U(\,\mathrm{d} x).$$

Recall also that  $U^{-}(dx)$  is the renewal measure associated with the weak descending ladder height process of  $(S_n)$ . By the renewal theorem (see P.360 in [9]), there exist two constants  $c_3$ ,  $c_4 > 0$  such that for  $\forall x, y \ge 0$ ,

(2.11) 
$$c_3(1+x) \le U([0,x]) \le c_4(1+x), \qquad 0 \le U([x,x+y]) \le c_4(1+y);$$

(2.12) 
$$c_3(1+x) \le U^-([0,x]) \le c_4(1+x), \qquad 0 \le U^-([x,x+y]) \le c_4(1+y)$$

Given a non-increasing function  $F \ge 0$ , we present the following proposition, which gives a necessary and sufficient condition for the infinity of the series  $\sum_{n} F(\zeta_n)$ .

**Proposition 2.6.** Let  $F : [0, \infty) \to [0, \infty)$  be non-increasing. Then

(2.13) 
$$\int_0^\infty F(y)y\,\mathrm{d}y = \infty \Longleftrightarrow \sum_{n\geq 0} F(\zeta_n) = \infty, \quad \mathbf{P}\text{-}a.s.$$

Note that  $(\zeta_n)$  can be viewed as a discrete-time counterpart of the 3-dimensional Bessel process, for which a similar result holds (see, for instance, Ex 2.5, Chapter XI of [16]). And we will prove (2.13) in a similar way as for the Bessel process.

*Proof.* Observe that  $0 \le F(x) \le F(0) < \infty$  for any  $x \ge 0$ . So there is no difference between the two events  $\{\sum_{n\ge 0} F(\zeta_n) = \infty\}$  and  $\{\sum_{n\ge 1} F(\zeta_n) = \infty\}$ .

We first prove " $\Leftarrow$ " in (2.13). It follows from (2.4) and (2.11) that

(2.14) 
$$\int_0^\infty F(y)y\,\mathrm{d}y = \infty \Longleftrightarrow \int_0^\infty F(y)R(y)U(\,\mathrm{d}y) = \infty.$$

Actually, by (2.10),

$$\mathbf{E}\Big[\sum_{n\geq 0}F(\zeta_n)\Big] = \int_0^\infty F(y)R(y)U(\,\mathrm{d} y).$$

Clearly,  $\mathbf{P}\left[\sum_{n\geq 0} F(\zeta_n) = \infty\right] = 1$  yields  $\int_0^\infty F(y)R(y)U(dy) = \infty$ . The " $\Leftarrow$ " in (2.13) is hence proved.

To prove " $\Longrightarrow$ " in (2.13), we only need to show that if  $\mathbf{P}\left[\sum_{n\geq 0} F(\zeta_n) = \infty\right] < 1$ , then  $\int_0^\infty F(y)y \, dy < \infty$ . From now on, we suppose that  $\mathbf{P}\left[\sum_{n\geq 0} F(\zeta_n) = \infty\right] < 1$ , which is equivalent to say that,

(2.15) 
$$\mathbf{P}\bigg[\sum_{n\geq 1}F(\zeta_n)<\infty\bigg]>0.$$

We draw support from Tanaka's construction for the random walk conditioned to stay positive ([17, 4]). Recall that  $\tau = \inf\{k \ge 1 : S_k \in (0, \infty)\}$ . We hence obtain an excursion  $(S_j; \ 0 \le j \le \tau)$ , which is denoted by  $\xi = (\xi(j), \ 0 \le j \le \tau)$ . Let  $\{\xi_k = (\xi_k(j), \ 0 \le j \le \tau_k); \ k \ge 1\}$  be a sequence of independent copies of  $\xi$ . For any  $k \ge 1$ , let

(2.16) 
$$\nu_k(j) := \xi_k(\tau_k) - \xi_k(\tau_k - j), \ \forall 0 \le j \le \tau_k.$$

This brings out another sequence of i.i.d. excursions  $\{\nu_k = (\nu_k(j), 0 \le j \le \tau_k); k \ge 1\}$ , based on which we reconstruct the random walk conditioned to stay position  $(\zeta_n)$  in the following way. Define for any  $k \ge 1$ ,

(2.17) 
$$T_k^+ := \tau_1 + \dots + \tau_k;$$

(2.18) 
$$H_k^+ := \nu_1(\tau_1) + \dots + \nu_k(\tau_k) = \xi_1(\tau_1) + \dots + \xi_k(\tau_k),$$

and let  $T_0^+ = H_0^+ = 0$ . Then the process

(2.19) 
$$\zeta_n = H_k^+ + \nu_{k+1}(n - T_k^+), \quad \text{for } T_k^+ < n \le T_{k+1}^+,$$

with  $\zeta_0 = 0$ , is what we need.

We actually establish un process distributed as  $(\zeta_n)$ . For brevity, we still denote it by  $(\zeta_n)$  without changing any conclusion in this proof. For any  $k \ge 1$ , let

(2.20) 
$$\chi_k(F) := \sum_{n=T_{k-1}^++1}^{T_k^+} F(\zeta_n) = \sum_{j=1}^{\tau_k} F\Big(H_{k-1}^+ + \nu_k(j)\Big),$$

so that  $\sum_{n\geq 1} F(\zeta_n) = \sum_{k\geq 1} \chi_k(F)$ . By (2.16), we get that

$$\chi_k(F) = \sum_{j=1}^{\tau_k} F\Big(H_{k-1}^+ + \xi_k(\tau_k) - \xi_k(\tau_k - j)\Big)$$
$$= \sum_{j=0}^{\tau_k-1} F\Big(H_k^+ - \xi_k(j)\Big).$$

(2.15) hence becomes that

(2.21) 
$$\mathbf{P}\left[\sum_{k\geq 1}\chi_k(F)<\infty\right] = \mathbf{P}\left[\sum_{k\geq 1}\sum_{j=0}^{\tau_k-1}F\left(H_k^+-\xi_k(j)\right)<\infty\right] > 0.$$

By Theorem 1 in Chapter XVIII.5 of [9], as  $(S_n)$  is of finite variance, we have  $b^+ := \mathbf{E}[H_1^+] = \mathbf{E}[S_{\tau}] < \infty$ . It follows from Strong Law of Large Numbers that **P**-a.s.,

(2.22) 
$$\lim_{k \to \infty} \frac{H_k^+}{k} = b^+.$$

Let  $A > \max\{1, b^+\}$ . This tells us that **P**-a.s., for all large  $k, H_k^+ \leq Ak$ . As F is non-increasing, one sees that

(2.23) 
$$\mathbf{P}\left[\sum_{k\geq 1}\sum_{j=0}^{\tau_k-1}F\left(Ak-\xi_k(j)\right) < \infty\right] \ge \mathbf{P}\left[\sum_{k\geq 1}\sum_{j=0}^{\tau_k-1}F\left(H_k^+-\xi_k(j)\right) < \infty\right] > 0.$$

For any  $k \ge 1$  let

(2.24) 
$$\widetilde{\chi}_k := \sum_{j=0}^{\tau_k - 1} F\left(Ak - \xi_k(j)\right)$$

So,  $\mathbf{P}\left[\sum_{k\geq 1} \widetilde{\chi}_k < \infty\right] > 0$ . Recall that  $\{\xi_k, k \geq 1\}$  is a sequence of independent copies of  $(S_j; 0 \leq j \leq \tau)$ . This yields the independence of the sequence  $\{\widetilde{\chi}_k, k \geq 1\}$ . It follows from Kolmogorov's 0-1 law that

(2.25) 
$$\mathbf{P}\left[\sum_{k\geq 1}\sum_{j=0}^{\tau_k-1}F(Ak-\xi_k(j))<\infty\right] = \mathbf{P}\left[\sum_{k\geq 1}\widetilde{\chi}_k<\infty\right] = 1.$$

Moreover, let  $E_M := \left\{ \sum_{k \ge 1} \tilde{\chi}_k < M \right\}$  for any M > 0. Either there exists some  $M_0 < \infty$  such that  $\mathbf{P}[E_{M_0}] = 1$ , or  $\mathbf{P}[E_M] < 1$  for all  $M \in (0, \infty)$ . On the one hand, if  $\mathbf{P}[E_{M_0}] = 1$  for some  $M_0 < \infty$ , then

$$M_{0} \geq \mathbf{E}\left[\sum_{k\geq 1}\widetilde{\chi}_{k}\right] = \mathbf{E}\left[\sum_{k\geq 1}\sum_{j=0}^{\tau_{k}-1}F\left(Ak - \xi_{k}(j)\right)\right]$$
$$= \sum_{k\geq 1}\mathbf{E}\left[\sum_{j=0}^{\tau-1}F(Ak - S_{j})\right]$$
$$= \sum_{k\geq 1}\int_{0}^{\infty}F(Ak + y)U^{-}(dy),$$

where the last equality follows from (2.9). One sees that  $\sum_{k\geq 1} \int_0^\infty F(Ak+y)U^-(dy) < \infty$ . It follows from the renewal theorem that there exists B > 0 such that  $U^-([jB, jB+B)) > \delta > 0$  for any  $j \geq 0$ . As F is non-increasing,

(2.26) 
$$\sum_{k\geq 1}\sum_{j\geq 1}F(Ak+Bj)\delta \leq \sum_{k\geq 1}\int_0^\infty F(Ak+y)U^-(\mathrm{d}y) < \infty.$$

We hence observe that  $\int_A^\infty dz \int_B^\infty F(y+z) dy \leq \sum_{k\geq 1} \sum_{j\geq 1} F(Ak+Bj)AB < \infty$ . This implies that

$$\int_0^\infty F(x)x\,\mathrm{d}x = \int_0^\infty dz \int_0^\infty F(z+y)\,\mathrm{d}y \le F(0)AB + \int_A^\infty \mathrm{d}z \int_B^\infty F(y+z)\,\mathrm{d}y < \infty,$$

which is what we need.

On the other hand, if  $\mathbf{P}[E_M] < 1$  for all  $M \in (0, \infty)$ , we have  $\lim_{M \uparrow \infty} \mathbf{P}[E_M] = 1$  because of (2.25). For any  $k \ge 1$  and any  $\ell \ge 1$ , define:

(2.27) 
$$\Lambda_{\ell}^{(k)} := \sum_{j=0}^{\tau_k - 1} \mathbb{1}_{\{A(\ell-1) \le -\xi_k(j) < A\ell\}}.$$

As  $\sum_{\ell \ge 1} \mathbb{1}_{\{A(\ell-1) \le -\xi_k(j) < A\ell\}} = 1$ , we get that for any  $k \ge 1$ ,

$$\widetilde{\chi}_{k} = \sum_{j=0}^{\tau_{k}-1} F\left(Ak - \xi_{k}(j)\right) \sum_{\ell \geq 1} \mathbb{1}_{\{A(\ell-1) \leq -\xi_{k}(j) < A\ell\}}$$
$$= \sum_{\ell \geq 1} \sum_{j=0}^{\tau_{k}-1} F\left(Ak - \xi_{k}(j)\right) \mathbb{1}_{\{A(\ell-1) \leq -\xi_{k}(j) < A\ell\}}$$
$$\geq \sum_{\ell \geq 1} F(Ak + A\ell) \Lambda_{\ell}^{(k)},$$

where the last inequality holds because F is non-increasing. It follows that

(2.28) 
$$\sum_{k\geq 1} \widetilde{\chi}_k \geq \sum_{k\geq 1} \sum_{\ell\geq 1} F(Ak+A\ell)\Lambda_\ell^{(k)} = \sum_{n=2}^\infty F(An) \sum_{k=1}^{n-1} \Lambda_{n-k}^{(k)}$$
$$= \sum_{m=1}^\infty F(Am+A)mY_m,$$

where

(2.29) 
$$Y_m := \frac{\sum_{k=1}^m \Lambda_{m+1-k}^{(k)}}{m}, \ \forall m \ge 1.$$

We claim that there exists a  $M_1 > 0$  sufficiently large such that for any  $m \ge 1$ ,

(2.30) 
$$c_6 \ge \mathbf{E} \Big[ Y_m \mathbf{1}_{E_{M_1}} \Big] \ge c_5 > 0,$$

where  $c_5$ ,  $c_6$  are positive constants. We postpone the proof of (2.30) and go back to (2.28). It follows that

(2.31) 
$$M_{1} \geq \mathbf{E}\left[\mathbf{1}_{E_{M_{1}}}\sum_{k\geq 1}\widetilde{\chi}_{k}\right] \geq \mathbf{E}\left[\mathbf{1}_{E_{M_{1}}}\sum_{m=1}^{\infty}F(Am+A)mY_{m}\right]$$
$$\geq \sum_{m\geq 1}F(Am+A)m\mathbf{E}\left[Y_{m}\mathbf{1}_{E_{M_{1}}}\right].$$

By (2.30), we obtain that

(2.32) 
$$\sum_{m\geq 1} F(Am+A)m \leq M_1/c_5 < \infty.$$

This implies that  $\int_0^\infty F(y)y\,\mathrm{d}y < \infty$  thus completes the proof of Proposition 2.6.

It remains to prove (2.30).

We begin with the first and second moments of  $Y_m$ . Since  $\{\omega_k; k \ge 1\}$  are i.i.d. copies of  $(S_j, 0 \le j \le \tau), (\Lambda_{\ell}^{(k)}; \ell \ge 1), k \ge 1$  are i.i.d. This yields that

(2.33) 
$$\mathbf{E}[Y_m] = \frac{1}{m} \sum_{k=1}^m \mathbf{E}[\Lambda_{m+1-k}^{(k)}] = \frac{1}{m} \sum_{k=1}^m \mathbf{E}[\Lambda_{m+1-k}^{(1)}] \\ = \frac{1}{m} \mathbf{E}\left[\sum_{k=1}^m \Lambda_k^{(1)}\right] = \frac{1}{m} \mathbf{E}\left[\sum_{j=0}^{\tau-1} \mathbb{1}_{\{-S_j < Am\}}\right] \\ = \frac{R(Am)}{m}.$$

where the last equality comes from (2.2). By (2.4), for any  $m \ge 1$ ,

(2.34) 
$$c_1 A \leq \mathbf{E}[Y_m] \leq c_2(A+1) =: c_6.$$

Obviously, we have  $\mathbf{E}[Y_m 1_{E_M}] \leq c_6$  for any  $m \geq 1$  and any M > 0. The fact that  $\Lambda^{(k)}, k \geq 1$ , are i.i.d. yields also that

(2.35) 
$$\operatorname{Var}(Y_m) = \frac{1}{m^2} \sum_{k=1}^m \operatorname{Var}(\Lambda_k^{(1)}) \le \frac{1}{m^2} \sum_{k=1}^m \mathbf{E}[(\Lambda_k^{(1)})^2].$$

Note that  $\Lambda_1^{(1)}$  is distributed as  $\sum_{j=0}^{\tau-1} \mathbb{1}_{\{-S_j < A\}}$  with  $\tau = \inf\{k > 0 : S_k > 0\}$ . We see that

$$\mathbf{E}\left[\left(\Lambda_{1}^{(1)}\right)^{2}\right] = \mathbf{E}\left[\left(\sum_{j=0}^{\tau-1} 1_{\{-S_{j} < A\}}\right)^{2}\right] \\
\leq 2\mathbf{E}\left[\sum_{j=0}^{\tau-1} 1_{\{-S_{j} < A\}} \sum_{k=j}^{\tau-1} 1_{\{-S_{k} < A\}}\right]$$

By Markov property, we obtain that

(2.36) 
$$\mathbf{E}\left[\left(\Lambda_{1}^{(1)}\right)^{2}\right] \leq 2\mathbf{E}\left[\sum_{j=0}^{\tau-1} 1_{\{-S_{j} < A\}} R(A, -S_{j})\right],$$

where

(2.37) 
$$R(x,y) := \mathbf{E}\Big[\sum_{i=0}^{\tau_y-1} \mathbb{1}_{\{S_i > y-x\}}\Big] \text{ with } \tau_y := \inf\{k > 0 : S_k > y\} \text{ for } x, y \ge 0.$$

It follows from (2.2) that

(2.38) 
$$\mathbf{E}\left[\left(\Lambda_{1}^{(1)}\right)^{2}\right] \leq 2\int_{0}^{A} R(A, y)U^{-}(\mathrm{d}y).$$

Consider now the strict ascending ladder epochs and heights  $(T_k, H_k)$  of  $(S_n)$ . We get that

$$R(x,y) = \mathbf{E} \bigg[ \sum_{k=0}^{\infty} \mathbb{1}_{\{y \ge H_k > y - x\}} \sum_{n=T_k}^{T_{k+1}-1} \mathbb{1}_{\{S_n > y - x\}} \bigg].$$

By applying the Markov property at the times  $(T_k; k \ge 1)$  and (2.2), we have for  $x, y \ge 0$ ,

(2.39) 
$$R(x,y) = \mathbf{E}\Big[\sum_{k\geq 0} R(H_k + x - y) \mathbf{1}_{\{y\geq H_k > y - x\}}\Big] = \int_{(y-x)_+}^{y} R(x - y + z) U(\mathrm{d}z).$$

Plugging it into (2.38) then using (2.4), (2.12) and (2.11) implies that

(2.40) 
$$\mathbf{E}\left[\left(\Lambda_{1}^{(1)}\right)^{2}\right] \leq c_{7}(1+A)^{3} \leq c_{8}A^{3},$$

(see also Lemma 2 in [4]).

Moreover, for any  $\ell \geq 2$ ,  $\Lambda_{\ell}^{(1)}$  has the same law as  $\sum_{j=0}^{\tau-1} \mathbb{1}_{\{\ell A - A \leq -S_j < \ell A\}}$ . Similarly, we get that

$$\begin{aligned} \mathbf{E}\Big[\left(\Lambda_{\ell}^{(1)}\right)^{2}\Big] &= \mathbf{E}\Big[\left(\sum_{j=0}^{\tau-1}\mathbf{1}_{\{\ell A-A\leq -S_{j}<\ell A\}}\right)^{2}\Big] \\ &\leq 2\mathbf{E}\Big[\sum_{j=0}^{\tau-1}\mathbf{1}_{\{\ell A-A\leq -S_{j}<\ell A\}}\sum_{k=j}^{\tau-1}\mathbf{1}_{\{\ell A-A\leq -S_{k}<\ell A\}}\Big].\end{aligned}$$

Once again, by Markov property then by (2.2),

$$\begin{split} \mathbf{E}\Big[\left(\Lambda_{\ell}^{(1)}\right)^{2}\Big] &\leq 2\mathbf{E}\Big[\sum_{j=0}^{\tau-1}\mathbf{1}_{\{\ell A-A\leq -S_{j}<\ell A\}}\Big(R(\ell A,-S_{j})-R(\ell A-A,-S_{j})\Big)\Big]\\ &= 2\int_{\ell A-A}^{\ell A}\Big(R(\ell A,y)-R(\ell A-A,y)\Big)U^{-}(\,\mathrm{d} y). \end{split}$$

Plugging (2.39) into it yields that for  $\ell \geq 2$ ,

$$\begin{split} \mathbf{E}\Big[\Big(\Lambda_{\ell}^{(1)}\Big)^{2}\Big] &\leq 2\int_{\ell A-A}^{\ell A}\Big(\int_{0}^{y}R(\ell A-y+z)U(\,\mathrm{d} z) - \int_{y-\ell A+A}^{y}R(\ell A-A-y+z)U(\,\mathrm{d} z)\Big)U^{-}(\,\mathrm{d} y)\\ &= 2\int_{\ell A-A}^{\ell A}\Big(\int_{0}^{y-\ell A+A}R(\ell A-y+z)U(\,\mathrm{d} z)\\ &\quad + \int_{y-\ell A+A}^{y}U^{-}([\ell A-A-y+z,\ell A-y+z))U(\,\mathrm{d} z)\Big)U^{-}(\,\mathrm{d} y), \end{split}$$

where the last equality holds because  $R(x) = U^{-}([0, x))$ . Observe that  $R(\ell A - y + z) \leq R(A)$ for  $0 \leq z \leq y - \ell A + A$  and  $\ell A - A \leq y \leq \ell A$ . Recall that  $A \geq 1$ . By (2.4), (2.11) and (2.12),

$$\begin{split} \mathbf{E}\Big[\Big(\Lambda_{\ell}^{(1)}\Big)^{2}\Big] &\leq c_{9} \int_{\ell A-A}^{\ell A} \Big(\int_{0}^{y-\ell A+A} (A+1)U(\,\mathrm{d} z) + \int_{y-\ell A+A}^{y} (1+A)U(\,\mathrm{d} z)\Big)U^{-}(\,\mathrm{d} y) \\ &\leq c_{10}(A+1) \int_{\ell A-A}^{\ell A} \Big(y+1\Big)U^{-}(\,\mathrm{d} y) \\ &\leq c_{11}\ell A^{3}, \end{split}$$

with  $c_{11} \ge c_8$ . Going back to (2.35), for any  $m \ge 1$ ,

(2.41) 
$$\operatorname{Var}(Y_m) \le \frac{\sum_{\ell=1}^m c_{11}\ell A^3}{m^2} \le c_{12}A^3$$

Combining this with (2.34) implies that  $\mathbf{E}[Y_m^2] = \operatorname{Var}(Y_m) + \mathbf{E}[Y_m]^2 \leq c_2^2(1+A)^2 + c_{12}A^3$ . We then use Paley-Zygmund inequality to obtain that

(2.42) 
$$\mathbf{P}\Big[Y_m > \frac{1}{2}\mathbf{E}[Y_m]\Big] \ge \frac{\mathbf{E}[Y_m]^2}{4\mathbf{E}[Y_m^2]} \ge \frac{c_1^2 A^2}{4(c_2^2(1+A)^2 + c_{12}A^3)} := c_{13} > 0.$$

So for any  $0 \le u \le c_1 A/2 \le \mathbf{E}[Y_m]/2$ , we have

(2.43) 
$$\mathbf{P}\Big(Y_m \le u\Big) \le \mathbf{P}\Big(Y_m \le \mathbf{E}[Y_m]/2\Big) \le 1 - c_{13}$$

There exists  $M_1 > 0$  such that  $\mathbf{P}(E_{M_1}) \ge 1 - c_{13}/2$ , since  $\lim_{M \uparrow \infty} \mathbf{P}[E_M] = 1$ . For such  $M_1 > 0$ ,

(2.44) 
$$\mathbf{E}[Y_m \mathbf{1}_{E_{M_1}}] = \mathbf{E}\Big[\int_0^{Y_m} \mathbf{1}_{E_{M_1}} du\Big] = \int_0^\infty \mathbf{P}[\{Y_m > u\} \cap E_{M_1}] du.$$

Notice that  $\mathbf{P}[\{Y_m > u\} \cap E_{M_1}] \ge (\mathbf{P}[E_{M_1}] - \mathbf{P}[Y_m \le u])_+$ , which is larger than  $c_{13}/2$  when  $0 \le u \le c_1 A/2$ . As a consequence,

(2.45) 
$$\mathbf{E}[Y_m \mathbf{1}_{E_{M_1}}] = \int_0^\infty \mathbf{P}[\{Y_m > u\} \cap E_{M_1}] du \ge \int_0^{c_1 A/2} \frac{c_{13}}{2} du = \frac{c_1 c_{13} A}{4} =: c_5 > 0.$$

This completes the proof of (2.30), hence completes the proof of " $\Longrightarrow$ " in (2.13). Proposition 2.6 is proved.

## **3** Proof of the main theorem

Recall that we are in the regime that

(3.1) 
$$\mathbf{E}\left[\sum_{|u|=1} e^{-V(u)}\right] = 1, \quad \mathbf{E}\left[\sum_{|u|=1} V(u)e^{-V(u)}\right] = 0, \quad \sigma^2 = \mathbf{E}\left[\sum_{|u|=1} V(u)^2 e^{-V(u)}\right] < \infty.$$

Recall also that equivalence in Theorem 1.1 is as follows:

(3.2) 
$$\mathbf{E}\left[Y\left(\log_{+}Y\right)^{2}\right] + \mathbf{E}\left[Z\log_{+}Z\right] < \infty \iff \mathbf{P}[D_{\infty} > 0] > 0$$

with  $Y = \sum_{|u|=1} e^{-V(u)}$  and  $Z = \sum_{|u|=1} V(u)_+ e^{-V(u)}$ . This section is devoted to previou that the condi-

This section is devoted to proving that the condition on the left-hand side of (3.2) (i.e. (1.8)) is necessary and sufficient for mean convergence of the truncated martingale  $\left\{D_n^{(0)} = \sum_{|u|=n} R(V(u)) e^{-V(u)} \mathbb{1}_{\{V(u_k)>0, \forall 1 \le k \le n\}}; n \ge 0\right\}$ . In view of Lemma 2.4, this follows the non-triviality of  $D_{\infty}$ , hence proves Theorem 1.1.

In what follows, we state a result about the mean convergence of the truncated martingale  $\left\{D_n^{(0)}; n \ge 0\right\}$ , which is one special case of Theorem 2.1 in Biggins and Kyprianou [6]. Define

(3.3) 
$$X := \frac{D_1^{(0)}}{D_0^{(0)}} \mathbf{1}_{(D_0^{(0)} > 0)} + \mathbf{1}_{(D_0^{(0)} = 0)}.$$

Then for any  $a \ge 0$ , under  $\mathbf{P}_a$ ,  $X = \frac{\sum_{|u|=1} R(V(u)) e^{-V(u)} \mathbf{1}_{(V(u)>0)}}{R(a) e^{-a}}$ .

**Theorem 3.1** (Biggins and Kyprianou [6]).  $(\zeta_n)$  is a random walk conditioned to stay positive, whose law was given in (2.8).

(i) If

(3.4) 
$$\mathbf{P}\text{-}a.s. \ \sum_{n\geq 1} \mathbf{E}_{\zeta_n} \Big[ X \Big( R(\zeta_n) \mathrm{e}^{-\zeta_n} X \wedge 1 \Big) \Big] < \infty,$$

then  $\mathbf{E}[D_{\infty}^{(0)}] = R(0).$ 

(ii) If for all y > 0,

(3.5) 
$$\mathbf{P}\text{-}a.s. \ \sum_{n=1}^{\infty} \mathbf{E}_{\zeta_n} \Big[ X; \ R(\zeta_n) \mathrm{e}^{-\zeta_n} X \ge y \Big] = \infty,$$

then  $\mathbf{E}[D_{\infty}^{(0)}] = 0.$ 

Our proof relies on this theorem. First, in Subsection 3.1, we give a short proof for the sufficient part to accomplish our arguments even though it has already been proved in [1]. In Subsection 3.2, we prove that (1.8) is also the necessary condition by using Proposition 2.6.

#### 3.1 (1.8) is a sufficient condition

This subsection is devoted to proving that

(3.6) 
$$\mathbf{E}\left[Y\left(\log_{+}Y\right)^{2}\right] + \mathbf{E}\left[Z\log_{+}Z\right] < \infty \Longrightarrow \mathbf{E}[D_{\infty}^{(0)}] = R(0) = 1.$$

*Proof of (3.6).* According to (i) of Theorem 3.1, it suffices to show that

(3.7) 
$$\mathbf{E}\left[Y\left(\log_{+}Y\right)^{2}\right] + \mathbf{E}\left[Z\log_{+}Z\right] < \infty \Longrightarrow \mathbf{P}\text{-a.s.} \sum_{n\geq 0} \mathbf{E}_{\zeta_{n}}\left[X\left(R(\zeta_{n})e^{-\zeta_{n}}X\wedge 1\right)\right] < \infty.$$

For any particle  $x \in \mathbb{T} \setminus \{\emptyset\}$ , we denote its parent by  $\overleftarrow{u}$  and define its relative displacement by

(3.8) 
$$\Delta V(u) := V(u) - V(\overleftarrow{u}).$$

Then for any  $a \in \mathbb{R}$ , under  $\mathbf{P}_a$ ,  $(\Delta V(u); |u| = 1)$  is distributed as  $\mathcal{L}$ . Let  $\widetilde{Y} := \sum_{|u|=1} e^{-\Delta V(u)}$ and  $\widetilde{Z} := \sum_{|u|=1} \left( \Delta V(u) \right)_+ e^{-\Delta V(u)}$  so that  $\mathbf{P}_a \left[ \left( \widetilde{Y}, \widetilde{Z} \right) \in \cdot \right] = \mathbf{P}[(Y, Z) \in \cdot].$  Note that under  $\mathbf{P}_{\zeta_n}$ ,

(3.9) 
$$X = \frac{\sum_{|u|=1} R(V(u)) e^{-V(u)} \mathbf{1}_{(V(u)>0)}}{R(\zeta_n) e^{-\zeta_n}} = \frac{\sum_{|u|=1} R(\zeta_n + \Delta V(u)) e^{-\Delta V(u)} \mathbf{1}_{(\Delta V(u)>-\zeta_n)}}{R(\zeta_n)}$$

where  $(\Delta V(u); |u| = 1)$  is independent of  $\zeta_n$ . By (2.4), it follows that

$$X \leq \frac{\sum_{|u|=1} c_2(\zeta_n+1) \mathrm{e}^{-\Delta V(u)} \mathbf{1}_{(\Delta V(u)>-\zeta_n)}}{R(\zeta_n)} + \frac{\sum_{|u|=1} c_2 \Delta V(u) \mathrm{e}^{-\Delta V(u)} \mathbf{1}_{(\Delta V(u)>-\zeta_n)}}{R(\zeta_n)}$$
  
$$\leq \frac{c_2}{c_1} \sum_{|u|=1} \mathrm{e}^{-\Delta V(u)} + c_2 \frac{\sum_{|u|=1} \Delta V(u)_+ \mathrm{e}^{-\Delta V(u)}}{R(\zeta_n)}$$
  
$$\leq c_{14} \left( \widetilde{Y} + \frac{\widetilde{Z}}{R(\zeta_n)} \right) \leq 2c_{14} \max \left\{ \widetilde{Y}, \frac{\widetilde{Z}}{R(\zeta_n)} \right\},$$

where  $\left(\widetilde{Y}, \widetilde{Z}\right)$  is independent of  $\zeta_n$ . This implies that

$$\sum_{n\geq 1} \mathbf{E}_{\zeta_n} \Big[ X \Big( R(\zeta_n) \mathrm{e}^{-\zeta_n} X \wedge 1 \Big) \Big]$$
  

$$\leq c_{15} \Big( \sum_{n\geq 0} \mathbf{E} \Big[ \widetilde{Y} \Big( R(\zeta_n) \mathrm{e}^{-\zeta_n} \widetilde{Y} \wedge 1 \Big) \Big| \zeta_n \Big] + \sum_{n\geq 0} \frac{1}{R(\zeta_n)} \mathbf{E} \Big[ \widetilde{Z} \Big( \mathrm{e}^{-\zeta_n} \widetilde{Z} \wedge 1 \Big) \Big| \zeta_n \Big] \Big)$$
(3.10) =:  $c_{15} \Big( \Sigma_1 + \Sigma_2 \Big).$ 

Hence we only need to prove that

(3.11) 
$$\mathbf{E}\left[Y\left(\log_{+}Y\right)^{2}\right] + \mathbf{E}\left[Z\log_{+}Z\right] < \infty \Longrightarrow \mathbf{E}\left[\Sigma_{1}\right] + \mathbf{E}\left[\Sigma_{2}\right] < \infty,$$

which leads to (3.7). On the one hand, as (2.4) gives that  $R(x) \leq c_{16}e^{x/2}$  for all  $x \geq 0$ , we see that

$$\begin{aligned} \mathbf{E}\Big[\Sigma_1\Big] &\leq c_{17}\mathbf{E}\Big[\sum_{n\geq 0}\mathbf{E}\Big[\widetilde{Y}\Big(\mathrm{e}^{-\zeta_n/2}\widetilde{Y}\wedge 1\Big)\Big|\zeta_n\Big]\Big] \\ &= c_{17}\sum_{n\geq 0}\mathbf{E}\Big[\Big(\widetilde{Y}\Big)^2\mathrm{e}^{-\zeta_n}\mathbf{1}_{\{\widetilde{Y}\leq \mathrm{e}^{\zeta_n/2}\}} + \widetilde{Y}\mathbf{1}_{\{\widetilde{Y}>\mathrm{e}^{\zeta_n/2}\}}\Big] \\ &= c_{17}\mathbf{E}\Big\{\Big(\widetilde{Y}\Big)^2\mathbf{E}\Big[\sum_{n\geq 0}\mathrm{e}^{-\zeta_n}\mathbf{1}_{\{\zeta_n\geq 2\log\widetilde{Y}\}}\Big|\widetilde{Y}\Big] + \widetilde{Y}\mathbf{E}\Big[\sum_{n\geq 0}\mathbf{1}_{\{\zeta_n<2\log\widetilde{Y}\}}\Big|\widetilde{Y}\Big]\Big\},\end{aligned}$$

where  $\widetilde{Y}$  and  $(\zeta_n)$  are independent. By (2.10),

(3.12) 
$$\mathbf{E}\left[\Sigma_{1}\right] \leq c_{17}\mathbf{E}\left[\left(\widetilde{Y}\right)^{2}\int_{2\log_{+}\widetilde{Y}}^{\infty}e^{-x}R(x)U(\,\mathrm{d}x) + \widetilde{Y}\int_{0}^{2\log_{+}\widetilde{Y}}R(x)U(\,\mathrm{d}x)\right],$$

which by (2.4) and (2.11) implies that

$$(3.13) \mathbf{E} \Big[ \Sigma_1 \Big] \leq c_{17} c_2 \mathbf{E} \Big[ \Big( \widetilde{Y} \Big)^2 \int_{2\log_+ \widetilde{Y}}^{\infty} e^{-x} (x+1) U(dx) + \widetilde{Y} \int_{0}^{2\log_+ \widetilde{Y}} (x+1) U(dx) \Big]$$

$$(3.14) \leq c_{18} \mathbf{E} \Big[ \widetilde{Y} \Big( 1 + \log_+ \widetilde{Y} \Big)^2 \Big] = c_{18} \mathbf{E} \Big[ Y \Big( 1 + \log_+ Y \Big)^2 \Big]$$

On the other hand, in the same way, we obtain that

(3.15) 
$$\mathbf{E}\left[\Sigma_{2}\right] \leq c_{19}\mathbf{E}\left[Z\left(1 + \log_{+} Z\right)\right]$$

Consequently,

(3.16) 
$$\mathbf{E}\left[\Sigma_{1}\right] + \mathbf{E}\left[\Sigma_{2}\right] \leq c_{20}\left(\mathbf{E}\left[Y+Z\right] + \mathbf{E}\left[Y\left(\log_{+}Y\right)^{2}\right] + \mathbf{E}\left[Z\log_{+}Z\right]\right).$$

Note that (3.1) ensures that  $\mathbf{E}[Y+Z] < \infty$ . The (3.11) is thus proved and we completes the proof of (3.6).

## 3.2 (1.8) is a necessary condition

This subsection is devoted to proving that

(3.17) 
$$\max\left\{\mathbf{E}\left[Z\log_{+}Z\right], \ \mathbf{E}\left[Y\left(\log_{+}Y\right)^{2}\right]\right\} = \infty \Longrightarrow \mathbf{E}[D_{\infty}^{(0)}] = 0.$$

Proof of (3.17). According to (ii) of Theorem 3.1, we only need to show that

(3.18) 
$$\forall y > 0, \mathbf{P}\text{-a.s. } \sum_{n=1}^{\infty} \mathbf{E}_{\zeta_n} \Big[ X; \ R(\zeta_n) \mathrm{e}^{-\zeta_n} X \ge y \Big] = \infty.$$

We break the assumption on the left-hand side of (3.17) up into three cases. In each case, we find out a different lower bound for X to establish (3.18). It hence follows that  $D_{\infty}^{(0)}$  is trivial as  $\mathbf{E}[D_{\infty}^{(0)}] = 0$ . The three cases are stated as follows:

(3.19a)  $\mathbf{E}[Y(\log_+ Y)^2] = \infty, \qquad \mathbf{E}[Y(\log_+ Y)] < \infty;$ 

$$(3.19b) E[Y(\log_+ Y)] = \infty$$

(3.19c)  $\mathbf{E}[Z(\log_+ Z)] = \infty.$ 

Proof of (3.18) under (3.19a) Recall that for any particle  $x \in \mathbb{T} \setminus \{\emptyset\}$ ,  $\Delta V(u) = V(u) - V(\overleftarrow{u})$ , and that under  $\mathbf{P}_a$ ,  $(\Delta V(u); |u| = 1)$  is distributed as  $\mathcal{L}$ . For any  $s \in \mathbb{R}$ , we define a pair of random variables:

(3.20) 
$$Y_{+}(s) := \sum_{|u|=1} e^{-\Delta V(u)} \mathbf{1}_{(\Delta V(u) > -s)}, \qquad Y_{-}(s) := \sum_{|u|=1} e^{-\Delta V(u)} \mathbf{1}_{(\Delta V(u) \le -s)}.$$

Clearly,  $\widetilde{Y} = Y_+(s) + Y_-(s)$ .

It follows from (3.9) and (2.4) that under  $\mathbf{P}_{\zeta_n}$ ,

$$X \geq \frac{\sum_{|u|=1} c_1 (1 + \zeta_n + \Delta V(u)) e^{-\Delta V(u)} \mathbf{1}_{(\Delta V(u) > -\zeta_n/2)}}{c_2 (1 + \zeta_n)},$$
  
$$\geq \frac{\sum_{|u|=1} c_1 (1/2 + \zeta_n/2) e^{-\Delta V(u)} \mathbf{1}_{(\Delta V(u) > -\zeta_n/2)}}{c_2 (1 + \zeta_n)} \geq c_{21} Y_+ (\zeta_n/2).$$

where  $\left\{\left(Y_+(s), Y_-(s)\right); s \in \mathbb{R}\right\}$  is independent of  $\zeta_n$  and  $c_{21} := \frac{c_1}{2c_2} > 0$ . We thus see that the assertion that for any y > 0,

(3.21) 
$$\sum_{n=1}^{\infty} \mathbf{E} \Big[ Y_+(\zeta_n/2); \ R(\zeta_n/2) \mathrm{e}^{-\zeta_n} Y_+(\zeta_n/2) \ge y \Big| \zeta_n \Big] = \infty, \qquad \mathbf{P}\text{-a.s.},$$

yields (3.18). It is known that  $\zeta_n \to \infty$  as n goes to infinity (see, for example, [4]). It suffices that

(3.22) 
$$\sum_{n=1}^{\infty} F(\zeta_n/2, \zeta_n) = \infty, \quad \mathbf{P}\text{-a.s.}$$

where

(3.23) 
$$F(s,z) := \mathbf{E}\Big[Y_+(s); \log Y_+(s) \ge z\Big], \quad s, z \in \mathbb{R}.$$

Let  $F_1(z) := \mathbf{E}[Y; \log Y \ge z]$  which is positive and non-increasing. It follows from Lemma 2.1 and (3.1) that  $\mathbf{E}[Y] = 1$ . Therefore, for any  $s, z \in \mathbb{R}$ ,

(3.24) 
$$0 \le F(s, z) \le F_1(z) \le \mathbf{E}[Y] = 1.$$

On the one hand, we deduce from (3.19a) that

$$\int_0^\infty F_1(y) y \, \mathrm{d}y = \int_0^\infty \mathbf{E} \Big[ Y \mathbf{1}_{(\log Y \ge y)} \Big] y \, \mathrm{d}y = \mathbf{E} \Big[ Y \int_0^{(\log_+ Y)} y \, \mathrm{d}y; \ Y \ge 1 \Big]$$
$$= \mathbf{E} \Big[ Y (\log_+ Y)^2 \Big] / 2 = \infty.$$

According to Proposition 2.6, P-almost surely,

(3.25) 
$$\sum_{n=1}^{\infty} F_1(\zeta_n) = \infty.$$

On the other hand, we can prove that  $\sum_{n=1}^{\infty} \left[ F_1(\zeta_n) - F(\zeta_n/2, \zeta_n) \right] < \infty$ , **P**-a.s. In fact, as  $Y = Y_+(s) + Y_-(s)$  under **P**, for any  $s, y \in \mathbb{R}$ ,

$$F_{1}(y) - F(s, y) = \mathbf{E} \Big[ Y \mathbf{1}_{(\log Y \ge y)} - Y_{+}(s) \mathbf{1}_{(\log Y_{+}(s) \ge y)} \Big] \\ = \mathbf{E} \Big[ Y \mathbf{1}_{(\log Y \ge y > \log Y_{+}(s))} + Y \mathbf{1}_{(\log Y_{+}(s) \ge y)} - Y_{+}(s) \mathbf{1}_{(\log Y_{+}(s) \ge y)} \Big] \\ = \mathbf{E} \Big[ Y \mathbf{1}_{(\log Y \ge y > \log Y_{+}(s))} + Y_{-}(s) \mathbf{1}_{(\log Y_{+}(s) \ge y)} \Big].$$

Note that  $Y \leq 2 \max\{Y_+(s), Y_-(s)\}$  under **P**. It follows that

$$\begin{split} F_{1}(y) - F(s,y) &\leq \mathbf{E} \Big[ 2Y_{-}(s) \mathbf{1}_{(\log Y \geq y > \log Y_{+}(s), Y_{+}(s) \leq Y_{-}(s))} + Y \mathbf{1}_{(\log Y \geq y > \log Y_{+}(s), Y_{+}(s) > Y_{-}(s)))} \Big] \\ &\quad + \mathbf{E} \Big[ Y_{-}(s) \mathbf{1}_{(\log Y_{-}(s) \geq y)} \Big] \\ &\leq 3\mathbf{E} \Big[ Y_{-}(s) \Big] + \mathbf{E} \Big[ Y \mathbf{1}_{(\log Y \geq y > \log Y_{+}(s), Y_{+}(s) > Y_{-}(s))} \Big] \\ &\leq 3\mathbf{E} \Big[ Y_{-}(s) \Big] + \mathbf{E} \Big[ Y \mathbf{1}_{(\log Y \geq y > \log(Y/2))} \Big] =: d_{1}(s) + d_{2}(y). \end{split}$$

As a consequence,

(3.26) 
$$\sum_{n=1}^{\infty} \left[ F_1(\zeta_n) - F(\zeta_n/2, \zeta_n) \right] \le \sum_{n \ge 0} d_1(\zeta_n/2) + \sum_{n \ge 0} d_2(\zeta_n).$$

Taking expectation on both sides yields that

$$\mathbf{E}\left[\sum_{n=1}^{\infty} \left(F_1(\zeta_n) - F(\zeta_n/2, \zeta_n)\right)\right] \leq \mathbf{E}\left[\sum_{n\geq 0} d_1(\zeta_n/2)\right] + \mathbf{E}\left[\sum_{n\geq 0} d_2(\zeta_n)\right]$$

$$(3.27) \qquad \qquad = \int_0^{\infty} d_1(x/2)R(x)U(\,\mathrm{d}x) + \int_0^{\infty} d_2(x)R(x)U(\,\mathrm{d}x),$$

where the last equality comes from (2.10).

For the first integration, we deduce from Lemma 2.1 that

(3.28) 
$$d_1(s) = 3\mathbf{E}\Big[Y_-(s)\Big] = 3\mathbf{E}\Big[\sum_{|x|=1} e^{-V(x)} \mathbf{1}_{(V(x) \le -s)}\Big] = 3\mathbf{P}(-S_1 \ge s).$$

By (2.4), (2.11) and (3.1),

$$\int_{0}^{\infty} d_{1}(x/2)R(x)U(dx) = 3\int_{0}^{\infty} \mathbf{P}(-2S_{1} \ge x)R(x)U(dx)$$
$$= 3\mathbf{E} \Big[ \int_{0}^{-2S_{1}} R(x)U(dx); -2S_{1} \ge 0 \Big]$$
$$\leq \leq c_{22}\mathbf{E} \Big[ \Big( 1 + (-2S_{1})_{+} \Big)^{2} \Big] < \infty.$$

For the second integration on the right-hand side of (3.27), as  $d_2(y) = \mathbf{E} \Big[ Y \mathbf{1}_{(\log Y \ge y > \log(Y/2)} \Big]$ , we use (2.4), (2.11) and (3.19a) to obtain that

$$\int_0^\infty d_2(x) R(x) U(\mathrm{d}x) = \int_0^\infty \mathbf{E} \Big[ Y \mathbf{1}_{(\log Y \ge x > \log(Y/2))} \Big] R(x) U(\mathrm{d}x)$$
$$= \mathbf{E} \Big[ Y \int_{(\log Y - \log 2)_+}^{\log_+ Y} R(x) U(\mathrm{d}x) \Big]$$
$$\leq c_{23} \mathbf{E} \Big[ Y (1 + \log_+ Y) \Big] < \infty.$$

Going back to (3.27), we conclude that

(3.29) 
$$\mathbf{E}\left[\sum_{n=1}^{\infty} \left(F_1(\zeta_n) - F(\zeta_n/2, \zeta_n)\right)\right] \le \mathbf{E}\left[\sum_{n\geq 0} d_1(\zeta_n/2)\right] + \mathbf{E}\left[\sum_{n\geq 0} d_2(\zeta_n)\right] < \infty.$$

Therefore, **P**-a.s.,

(3.30) 
$$\sum_{n=1}^{\infty} \left[ F_1(\zeta_n) - F(\zeta_n/2, \zeta_n) \right] < \infty,$$

which, combined with (3.25), implies (3.22). Thus (3.18) is proved under (3.19a).

Proof of (3.18) under (3.19b) Now we suppose that  $\mathbf{E}[Y \log_+ Y] = \infty$ . By (2.4), we observe that under  $\mathbf{P}_{\zeta_n}$ ,

(3.31) 
$$X = \frac{\sum_{|u|=1} R(\Delta V(u) + \zeta_n) e^{-\Delta V(u)} \mathbf{1}_{(\Delta V(u) > -\zeta_n)}}{R(\zeta_n)}$$
$$\geq c_1 \frac{Y_+(\zeta_n)}{R(\zeta_n)},$$

where  $\{Y_+(s); s \in \mathbb{R}\}$  and  $\zeta_n$  are independent.

To establish (3.18), we only need to show that for any  $y \ge 1$ ,

(3.32) 
$$\sum_{n\geq 1} \mathbf{E}\Big[\frac{Y_+(\zeta_n)}{R(\zeta_n)}; \ Y_+(\zeta_n) \geq y e^{\zeta_n} \Big| \zeta_n \Big] = \sum_{n\geq 1} \frac{F(\zeta_n, \log y + \zeta_n)}{R(\zeta_n)} = \infty, \qquad \mathbf{P}\text{-a.s.}$$

For any  $y \ge 1$  fixed, let

(3.33) 
$$F_2(x) := \frac{F_1(\log y + x)}{R(x)}, \ \forall x \ge 0,$$

which is non-increasing as  $R(x) = U^{-}([0, x))$  is non-decreasing and  $F_1$  is non-increasing. One sees that

(3.34) 
$$\sum_{n\geq 1} F_2(\zeta_n) = \sum_{n\geq 1} \frac{F(\zeta_n, \log y + \zeta_n)}{R(\zeta_n)} + \sum_{n\geq 1} \frac{F_1(\log y + \zeta_n) - F(\zeta_n, \log y + \zeta_n)}{R(\zeta_n)}$$

By (2.4),  $\frac{F_1(\log y + x)}{c_2(1+x)} \le F_2(x) \le \frac{1}{c_1}$ . It then follows from (3.19b) that

$$\int_0^\infty F_2(x) x \, \mathrm{d}x \geq \int_0^\infty F_1(\log y + x) \frac{x}{c_2(1+x)} \, \mathrm{d}x$$
$$\geq \int_1^\infty c_{24} \mathbf{E} \Big[ Y \mathbf{1}_{(\log Y \ge \log y + x)} \Big] \, \mathrm{d}x$$
$$\geq c_{24} \mathbf{E} [Y (\log Y - \log y - 1)_+] = \infty.$$

By Proposition 2.6,

(3.35) 
$$\sum_{n \ge 0} F_2(\zeta_n) = \sum_{n \ge 0} \frac{F_1(\log y + \zeta_n)}{R(\zeta_n)} = \infty, \ \mathbf{P}\text{-a.s.}$$

In view of (3.34) and (3.35), it suffices to show that **P**-a.s.,

(3.36) 
$$\sum_{n\geq 0} \frac{F_1(\log y + \zeta_n) - F(\zeta_n, \log y + \zeta_n)}{R(\zeta_n)} < \infty.$$

Recall that  $F_1(z) - F(s, z) \le d_1(s) + d_2(z)$ . By (2.10),

$$(3.37) \qquad \mathbf{E}\Big[\sum_{n\geq 0} \frac{F_1(\log y + \zeta_n) - F(\zeta_n, \log y + \zeta_n)}{R(\zeta_n)}\Big]$$
$$\leq \mathbf{E}\Big[\sum_{n\geq 0} \frac{d_1(\zeta_n) + d_2(\log y + \zeta_n)}{R(\zeta_n)}\Big] = \int_0^\infty \Big[d_1(x) + d_2(\log y + x)\Big]U(\,\mathrm{d}x).$$

On the one hand, recalling that  $d_1(x) = 3\mathbf{P}(-S_1 \ge x)$ , we deduce from (2.11) that

(3.38) 
$$\int_0^\infty d_1(x)U(dx) = \int_0^\infty 3\mathbf{P}(-S_1 \ge x)U(dx)$$
$$= 3\mathbf{E}\Big[\int_0^{(-S_1)_+} U(dx)\Big]$$
$$\leq 3c_4\mathbf{E}\Big[1 + (-S_1)_+\Big] < \infty.$$

On the other hand, recalling that  $d_2(x) = \mathbf{E}[Y; \log Y \ge x > \log Y - \log 2]$ , by (2.11) again, we obtain that

(3.39) 
$$\int_{0}^{\infty} d_{2}(\log y + x)U(dx) = \int_{0}^{\infty} \mathbf{E}[Y1_{(\log Y \ge \log y + x > \log Y - \log 2)}]U(dx)$$
$$= \mathbf{E}\Big[Y\int_{(\log Y - \log y) - \log 2)_{+}}^{(\log Y - \log y)_{+}}U(dx)\Big]$$
$$\leq c_{4}(1 + \log 2)\mathbf{E}[Y] < \infty.$$

Combined with (3.38) and (3.39), (3.37) becomes that

(3.40) 
$$\mathbf{E}\left[\sum_{n\geq 1}\frac{F_1(\log y+\zeta_n)-F(\zeta_n,\log y+\zeta_n)}{R(\zeta_n)}\right]<\infty$$

We thus get (3.36), and completes the proof of (3.18) given (3.19b).

Proof of (3.18) under (3.19c) In this part we assume that  $\mathbf{E}[Z \log_+ Z] = \infty$  with  $Z = \sum_{|u|=1} V(u)_+ e^{-V(x)} \ge 0$ . We observe that under  $\mathbf{P}_{\zeta_n}$ ,

(3.41) 
$$X \geq \frac{\sum_{|u|=1} R(\Delta V(u) + \zeta_n) e^{-\Delta V(u)} \mathbf{1}_{(\Delta V(u)>0)}}{R(\zeta_n)}$$
$$\geq \frac{c_1}{R(\zeta_n)} \widetilde{Z},$$

where  $\widetilde{Z} = \sum_{|x|=1} \left( \Delta V(x) \right)_+ e^{-\Delta V(x)}$  is independent of  $\zeta_n$ . As a consequence, for any y > 0,

(3.42) 
$$\sum_{n\geq 1} \mathbf{E}_{\zeta_n} \Big[ X; \ R(\zeta_n) \mathrm{e}^{-\zeta_n} X \geq y \Big] \geq \sum_{n\geq 1} \frac{c_1}{R(\zeta_n)} \mathbf{E} \Big[ \widetilde{Z}; \ c_1 \widetilde{Z} \geq y \mathrm{e}^{\zeta_n} \Big| \zeta_n \Big].$$

Recall that  $\widetilde{Z}$  is distributed as Z under **P**. Therefore, it is sufficient to prove that for any y > 0,

(3.43) 
$$\sum_{n\geq 1} \frac{1}{R(\zeta_n)} \mathbf{E}\Big[\widetilde{Z}; \ \widetilde{Z} \geq y \mathrm{e}^{\zeta_n} \Big| \zeta_n\Big] = \sum_{n\geq 1} F_3(\zeta_n) = \infty, \qquad \mathbf{P}\text{-a.s}$$

where

(3.44) 
$$F_3(z) := \frac{\mathbf{E}[Z; \log Z \ge z + \log y]}{R(z)}, \ \forall z \ge 0.$$

Since R is non-decreasing, the function  $F_3$  is non-increasing. By Lemma 2.1 and (2.4),

(3.45) 
$$0 \le F_3(z) \le \frac{\mathbf{E}[Z]}{R(z)} \le \frac{\mathbf{E}[(S_1)_+]}{c_1} < \infty$$

Moreover, by (2.11) and (3.19c),

(3.46) 
$$\int_0^\infty F_3(x) x \, \mathrm{d}x \geq \int_1^\infty c_{25} \mathbf{E} \Big[ Z; \, \log Z - \log y \geq x \Big] \, \mathrm{d}x$$
$$\geq c_{25} \mathbf{E} \Big[ Z (\log Z - \log y - 1)_+ \Big] = \infty.$$

Because of Proposition 2.6, we obtain that for any y > 0,

(3.47) 
$$\sum_{n\geq 1} \frac{1}{R(\zeta_n)} \mathbf{E} \Big[ \widetilde{Z}; \ \widetilde{Z} \geq y \mathrm{e}^{\zeta_n} \Big| \zeta_n \Big] = \sum_{n\geq 1} F_3(\zeta_n) = \infty, \qquad \mathbf{P}\text{-a.s.}$$

which completes the proof of (3.18) under (3.19c).

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