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Mehrdad, B.; Sen, S.; Zhu, L.

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The speed of a biased walk on a Galton–Watson tree without leaves is monotonic with respect to progeny distributions for high values of bias

Behzad Mehrdad, Sanchayan Sen and Lingjiong Zhu

Courant Institute of Mathematical Sciences, New York University, 251 Mercer Street, New York, NY 10012, USA.
E-mail: mehrdad@cims.nyu.edu; sen@cims.nyu.edu; ling@cims.nyu.edu

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Abstract. Consider biased random walks on two Galton–Watson trees without leaves having progeny distributions $P_1$ and $P_2$ ($\text{GW}(P_1)$ and $\text{GW}(P_2)$) where $P_1$ and $P_2$ are supported on positive integers and $P_1$ dominates $P_2$ stochastically. We prove that the speed of the walk on $\text{GW}(P_1)$ is bigger than the same on $\text{GW}(P_2)$ when the bias is larger than a threshold depending on $P_1$ and $P_2$. This partially answers a question raised by Ben Arous, Fribergh and Sidoravicius (Comm. Pure Appl. Math. 67 (2014) 519–530).

MSC: 60K37; 60J80; 60G50

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1. Introduction and main results

1.1. Introduction

Consider a supercritical Galton–Watson tree, i.e., a random rooted tree, where the offspring size of all individuals are i.i.d. copies of an integer random variable $Z$, which satisfies $P(Z = k) = p_k$, $k = 0, 1, \ldots$ and $\sum_{k=1}^{\infty} kp_k > 1$. The tree has no leaves if $p_0 = 0$. We shall use $|x|$ to denote the distance of a vertex $x$ from the root. Moreover $x_0$ will denote the ancestor of $x$ for any vertex $x$ different from the root and $x_i$ will denote the $i$th child of $x$. Given a tree $T$ and $\beta > 0$, we define $\beta$-biased random walk $(X_n)_{n\geq 0}$ on $T$ as follows. Transitions to each of the children of the root are equally likely. If the vertex $x$ has $k$ children and $x$ is not the root then the transition probabilities are given by

$$P(X_{n+1} = x_0 | X_n = x) = \frac{1}{1 + \beta k},$$

$$P(X_{n+1} = x_i | X_n = x) = \frac{\beta}{1 + \beta k}, \quad i = 1, 2, \ldots, k.$$
We start the walk from the root of the tree and denote by $P^\omega$ the law of $(X_n)_{n \geq 0}$ on a tree $\omega$. We define the averaged law as the semi-direct product $\mathbb{P} = \overline{P} \times P^\omega$ where $\overline{P}$ is the Galton–Watson measure (associated with offspring distribution $P$) on the space of rooted trees conditioned on non-extinction.

Lyons [6] proved that if $\beta > \frac{1}{\mathbb{E}[Z]}$, then the random walk is transient, i.e., $\lim_{n \to \infty} |X_n| = \infty$. Lyons, Pemantle and Peres [7] showed that $\mathbb{P}$ almost surely, the speed

$$v(\beta, P) := \lim_{n \to \infty} \frac{|X_n|}{n}$$

exists and is a non-random constant. A lot of work has been done on the behavior of the speed as a function of $\beta$. It was conjectured in [7] that $v(\beta, P)$ increases in $\beta$ on $\left(\frac{1}{\mathbb{E}[Z]}, \infty\right)$ when the tree has no leaves, i.e., $P\{0\} = 0$. The conjecture has been open for a long time until proven recently in [3] for large values of $\beta$.

**Theorem (3).** The speed $v(\beta, P)$ of a $\beta$-biased random walk on a Galton–Watson tree without leaves is increasing for $\beta > \beta_c$ for some $\beta_c > 0$ very large when $P\{0\} = 0$.

Very recently, Aïdékon obtained an expression for the speed $v$.

**Theorem (1).**

$$v(\beta, P) = \frac{\mathbb{E}[(\beta Z - 1)Y_0/(1 - \beta + \beta \sum_{i=0}^{Z} Y_i)]}{\mathbb{E}[(\beta Z + 1)Y_0/(1 - \beta + \beta \sum_{i=0}^{Z} Y_i)]},$$

where $Y_i$ are i.i.d. copies distributed as $P_1(\tau_{x_0} = \infty)$ and $\tau_y$ is the first hitting time of $y$.

Using his own formula, Aïdékon (private communications) can prove the monotonicity for $\beta \geq 2$ when $P\{0\} = 0$. However, the original conjecture is still open in the sense that it is not known if the monotonicity holds for every $\beta > 1/\mathbb{E}[Z]$.

In this paper we shall investigate how the speed changes when one changes the progeny distribution keeping the bias fixed.

The paper is organized as the following. In Section 1.2, we shall introduce our main results. In Section 2, we shall describe in details our coupling method. Finally, in Section 3, we shall provide the proofs of all the results in Section 1.2.

### 1.2. Main results

In [3], the authors raised the following interesting question, if $P_1$ stochastically dominates $P_2$, does it imply that $v(\beta, P_1) \geq v(\beta, P_2)$? We show that this is indeed the case at least when the bias is large.

Throughout this paper, when we say $P_1$ dominates $P_2$ stochastically, we also mean that $P_1 \neq P_2$. We also recall that if $P_1$ dominates $P_2$ stochastically then there is a coupling of the random variables $Z_1$ and $Z_2$ having distributions $P_1$ and $P_2$ respectively such that $Z_2 \leq Z_1$.

We have the following result.

**Theorem 1.** Assume that $P_1$ and $P_2$ are two probability measures on positive integers such that $P_1$ dominates $P_2$ stochastically. Consider $\beta$-biased random walks on $GW(P_1)$ and $GW(P_2)$. Then for every $\delta > 0$, there exists a $\beta_0 := \beta_0(P_1, P_2, \delta) > 0$ such that for any $\beta > \beta_0$, we have $v(\beta, P_1) > v(\beta, P_2)$. The constant $\beta_0$ equals $\max\{\beta_1, \frac{25}{\delta} + \delta\}$ where

$$\beta_1 := c_5 \cdot \min\left\{ \frac{E[(1/Z_1 - 1/Z_2)1_{Z_1 < Z_2}]}{E[1/Z_1 - 1/Z_1]}, \frac{E[Z_2(1/Z_2 - 1/Z_1)]}{E[1/Z_1 - 1/Z_1]} + 1 \right\},$$

and $c_5$ is a universal constant depending only on $\delta$. Here, $Z_1$, $Z_2$ are independent and are distributed according to $P_1$ and $P_2$ respectively, $Z_1'$ and $Z_2'$ are jointly distributed so that $Z_1' \geq Z_2'$ almost surely and their marginal distributions are $P_1$ and $P_2$. 


Remark 2. There is a universal cut-off $\beta_1 = \beta_1(M)$ which works for all $P_2$ supported on $\{1, 2, \ldots, M\}$ since we have
\[
E\left[Z'_2\left(\frac{1}{Z'_2} - \frac{1}{Z'_1}\right)\right] \leq M \cdot E\left[\frac{1}{Z'_2} - \frac{1}{Z'_1}\right].
\]
The other expression inside the parentheses in the definition of $\beta_1$ in Theorem 1 is more useful when “the distribution of $Z_1$ is much larger than that of $Z'_2$”, we shall illustrate this in Corollary 5.

Remark 3. Suppose $P_1$ dominates $P_2$ and are both supported on positive integers. Then $v(\beta, P_1) \geq v(\beta, P_2)$ follows trivially in the following cases.

(i) It is easy to see (via a coupling argument) that if the maximum of the support of $P_2$ is not larger than the minimum of the support of $P_1$, then for any $\beta > 0$, we have $v(\beta, P_1) \geq v(\beta, P_2)$.

(ii) We have $v(1, P_1) \geq v(1, P_2)$ just by considering the expression
\[
v(1, P) = E_P\left[\frac{Z - 1}{Z + 1}\right]
\]
obtained in [7].

(iii) Note that $v(1/E_{P_1}[Z], P_1) = 0$, $v(1/E_{P_2}[Z], P_1) > 0$, and $v(\beta, P_1)$ is continuous in $\beta$ for $j = 1, 2$. Thus, for some small $\varepsilon > 0$ we have $v(\beta, P_1) \geq v(\beta, P_2)$ for $0 < \beta < \varepsilon + 1/E_{P_1}[Z]$.

Further (ii) and (iii) hold even when the offspring distributions are supported on non-negative integers as long as we define the speed as in (1.1) conditional on non-extinction of the trees.

We can improve the threshold $\beta_0$ of Theorem 1 by making stronger assumptions.

Theorem 4. Suppose $P_1$ and $P_2$ are two probability measures on positive integers such that for some $\ell > 1$, there exists a coupling of $Z^{(1)}_1, Z^{(2)}_1, \ldots, Z^{(\ell)}_1$ and $Z^{(1)}_2, Z^{(2)}_2, \ldots, Z^{(\ell)}_2$ for which $\min\{Z^{(1)}_1, Z^{(2)}_1, \ldots, Z^{(\ell)}_1\} \geq \max\{Z^{(1)}_2, Z^{(2)}_2, \ldots, Z^{(\ell)}_2\}$ almost surely, where $Z^{(j)}_1, \ldots, Z^{(j)}_2$ are i.i.d. distributed according to $P_j$ for $j = 1, 2$. Then for any $\delta > 0$, we have $v(\beta, P_1) \geq v(\beta, P_2)$ for any $\beta > \max\{K \cdot \beta_1^{1/\ell}, 23/4 + \delta\}$ where the constant $K$ equals $27/4 \cdot 3^{5/3}$.

Corollary 5. Assume that $P_1$ and $P_2$ are two probability measures on positive integers such that $P_1$ stochastically dominates $P_2$. Let $m_i := E_{P_i}[Z]$ and $Z^{(n)}_i$ be the number of children in the $n$th generation in $GW(P_i)$, denote the law of $Z^{(n)}_i$ by $P^{(n)}_i$ for $i = 1, 2$. Assume that there exists some $\theta > 0$ such that $E[e^{\theta Z^{(n)}_1}] < \infty$. Let $f$ be the generating function for $P_1$ and $\alpha := -\log f'(0)/\log f'(1)$. Further assume that $m_1 > m_2^{\max[2/\alpha, 1/(\alpha + 1)]}$ (if $P_1[1] = 0$, then $\alpha = \infty$ and this condition is automatically satisfied). Then, for any $\beta > 23/4$, there exists some $k = k(P_1, P_2, \beta)$ such that $v(\beta, P_1^{(k)}) > v(\beta, P_2^{(k)})$. (We emphasize that $v(\beta, P_1^{(k)})$ is the speed of a $\beta$-biased random walk on a Galton–Watson tree having $P_1^{(k)}$ as its offspring distribution.)

The following corollary is the counterpart to Theorem 1.2 in [3].

Corollary 6. Assume all the assumptions in Theorem 1 and recall the definition of $\beta_0$ from there. Moreover, assume that the minimum degrees of both $P_1$ and $P_2$ are bigger than $d$ (for some $d \geq 2$), i.e., $d_i := \min\{k \geq 1, P_i(Z = k) > 0\} \geq d$, for $i \in \{1, 2\}$.

Then we have, $v(\beta, P_1) > v(\beta, P_2)$ for any $\beta > \beta_0/d$.

2. Constructing the walks

Let us describe precisely the coupling we use. Let $U_i$ have uniform distribution on $(1/(\beta + 1), 1)$. Let $(U_i)_{i \geq 2}$ be i.i.d. uniformly distributed random variables on $[0, 1]$ independent of $U_1$. Let $(Z'_{1,k}, Z'_{2,k})_{k \geq 1}$ be i.i.d. random vectors such that for each $k$, $Z'_{1,k}$ has the marginal distribution $P_1$ and $Z'_{2,k}$ has the marginal distribution.
Consider the random walk \( X_n \) then we assign \( X(i) \). Figure 1 gives an illustration.

In our proof we shall work conditional on an event which ensures that the roots are only visited once, for this reason we only need one copy of \( U_1 \). Note that our definition of \( U_1 \) is slightly different from the one in [3].

We construct two random walks \( X_n^{(1)} \) and \( X_n^{(2)} \) (on \( GW(P_1) \) and \( GW(P_2) \)) and another walk \( Y_n \) on \( \mathbb{Z}_{\geq 0} \) in the following way. Define \( Y_0 := 0 \) and for \( n \geq 1 \),

\[
Y_n := \sum_{i=1}^{n} \{1_{U_i > 1/(\beta+1)} - 1_{U_i \leq 1/(\beta+1)}\}, \quad n \in \mathbb{N}.
\]

We start \( X^{(1)} \) and \( X^{(2)} \) at the roots and grow the trees \( GW(P_1) \) and \( GW(P_2) \) dynamically. For simplicity we drop the time parameter \( n \) and denote the position of \( X_n^{(i)} \) by \( x(i) \).

Now, if at time \( n \geq 0 \), \( X_n^{(1)} \) and \( X_n^{(2)} \) are at two sites \( x^{(1)} \) and \( x^{(2)} \), neither of them visited before by the corresponding walks, then we assign \( Z_{1,n+1}' \) and \( Z_{2,n+1}' \) many children to \( x^{(1)} \) and \( x^{(2)} \) respectively (recall that \( Z_{1,n+1}' \geq Z_{2,n+1}' \)).

If at time \( n \), one of the walks, say \( X^{(1)} \) is at a site \( x^{(1)} \) previously visited by the walk while the other walk \( X^{(2)} \) is at a new site \( x^{(2)} \) then we assign \( Z_{2,n+1}' \) many children to \( x^{(2)} \).

Let us now explain the rules for transition. Denote the number of offsprings of \( x^{(i)} \) by \( Z_i \) and let \( x_k^{(i)} \) be the \( k \)th child of \( x^{(i)} \) \((i = 1, 2)\).

Define

\[
\eta_1 := \frac{\beta}{(\beta+1)} Z_1, \quad \eta_2 := (\frac{\beta}{\beta+1}) \left( \frac{1}{Z_2} - \frac{1}{Z_1} \right), \quad \eta_3 := \left( \frac{1}{\beta+1} - \frac{1}{Z_2 \beta + 1} \right) \frac{1}{Z_2},
\]

\[
\eta_4 := \left( \frac{1}{\beta+1} - \frac{1}{Z_1 \beta + 1} \right) \frac{1}{Z_1}, \quad \eta_5 := |\eta_3 - \eta_4|.
\]

Then whenever \( Z_1' \geq Z_2 \), we move according to the rule explained below.

When \( U_{n+1} \in (1/(\beta+1), 1) \) we have the following cases.

1. Consider the random walk \( X^{(1)} \).
   - If \( U_{n+1} \in (\frac{1}{\beta+1} + (i-1)\eta_1, \frac{1}{\beta+1} + i \eta_1) \), then \( X_{n+1}^{(1)} = x_{Z_{1,n+1}'-i}^{(1)} \) for \( i = 1, 2, \ldots, Z_1 \).

2. Consider the random walk \( X^{(2)} \).
   - If \( U_{n+1} \in (\frac{1}{\beta+1} + (i-1)\eta_2, \frac{1}{\beta+1} + i \eta_2) \), then we have \( X_{n+1}^{(2)} = x_{Z_{2,n+1}'-i}^{(2)} \), where \( i = 1, 2, \ldots, Z_2 \).
   - If \( U_{n+1} \in (\frac{1}{\beta+1} + Z_2 \eta_2 + (i-1)\eta_1, \frac{1}{\beta+1} + Z_2 \eta_2 + i \eta_1) \), then we have \( X_{n+1}^{(2)} = x_{Z_{2,n+1}'-i}^{(2)} \), where \( i = 1, 2, \ldots, Z_2 \).

When \( U_{n+1} \in (0, 1/(\beta+1)) \) we have to consider two cases. If \( \eta_3 \geq \eta_4 \), then we use the following coupling. Figure 1 gives an illustration.

1. Consider the random walk \( X^{(1)} \).
   - If \( U_{n+1} \in [0, \frac{1}{Z_i \beta + 1}] \), then we have \( X_{n+1}^{(1)} = x_{s}^{(1)} \).
   - If \( U_{n+1} \in (\frac{1}{Z_i \beta + 1} + (i-1)\eta_4, \frac{1}{Z_i \beta + 1} + i \eta_4) \), then we have \( X_{n+1}^{(1)} = x_{Z_{1,n+1}'-i}^{(1)} \), where \( i = 1, 2, \ldots, Z_1 \).

2. Consider the random walk \( X^{(2)} \).
   - If \( U_{n+1} \in [0, \frac{1}{Z_2 \beta + 1}] \), then we have \( X_{n+1}^{(2)} = x_{s}^{(2)} \).
   - If \( U_{n+1} \in (\frac{1}{Z_2 \beta + 1} + (i-1)\eta_5, \frac{1}{Z_2 \beta + 1} + i \eta_5) \), then we have \( X_{n+1}^{(2)} = x_{Z_{2,n+1}'-i}^{(2)} \), where \( i = 1, 2, \ldots, Z_2 \).
   - If \( U_{n+1} \in (\frac{1}{Z_2 \beta + 1} + Z_2 \eta_5 + (i-1)\eta_4, \frac{1}{Z_2 \beta + 1} + Z_2 \eta_5 + i \eta_4) \), then we have \( X_{n+1}^{(2)} = x_{Z_{2,n+1}'-i}^{(2)} \), where \( i = 1, 2, \ldots, Z_2 \).

If \( \eta_3 < \eta_4 \), then we use the following coupling. Figure 2 is an illustration of the following coupling.

1. Consider the random walk \( X^{(1)} \).
Fig. 1. The coupling for $\eta_3 \geq \eta_4$. In the illustration, we use $Z_2; \eta_4$ etc. to denote $Z_2$ many subintervals with each subinterval of length $\eta_4$ etc.

If $U_{n+1} \in [0, \frac{1}{Z_1 \beta+1}]$, then we have $X_{n+1}^{(1)} = x_{x}^{(1)}$

If $U_{n+1} \in (\frac{1}{Z_1 \beta+1} + (i - 1) \eta_4, \frac{1}{Z_1 \beta+1} + i \eta_4)$, then we have $X_{n+1}^{(1)} = x_{Z_1+1-i}^{(1)}$, where $i = 1, 2, \ldots, Z_1 - Z_2$.

If $U_{n+1} \in (\frac{1}{Z_1 \beta+1} + (Z_1 - Z_2) \eta_4 + (i - 1) \eta_5, \frac{1}{Z_1 \beta+1} + (Z_1 - Z_2) \eta_4 + i \eta_5)$, then $X_{n+1}^{(1)} = x_{Z_2+1-i}^{(1)}$, where $i = 1, 2, \ldots, Z_2$.

If $U_{n+1} \in (\frac{1}{Z_1 \beta+1} + (i - 1) \eta_3, \frac{1}{Z_2 \beta+1} + i \eta_3)$, then we have $X_{n+1}^{(1)} = x_{Z_2+1-i}^{(1)}$, where $i = 1, 2, \ldots, Z_2$.

Finally if $Z_1 < Z_2$ we move according to the following rule.

(1) For $i = 1, 2$:
If \( U_{n+1} \in [0, \frac{1}{Z_{\beta+1}}] \), then we have \( X_{n+1}^{(i)} = x_{n+1}^{(i)} \).

If \( U_{n+1} \in (\frac{1}{Z_{\beta+1}} + (j - 1) \frac{\beta}{Z_{\beta+1}}, \frac{1}{Z_{\beta+1}} + j \frac{\beta}{Z_{\beta+1}}] \), then we have \( X_{n+1}^{(i)} = x_{n+1}^{(i)} \), where \( j = 1, 2, \ldots, Z_i \).

It is routine to check that \( X^{(i)} \) is a \( \beta \)-biased random walk on \( GW(P_i) \) for \( i = 1, 2 \).

3. Proofs

The main idea in our proof is to use a technique originally used in [3], to couple the walks on the Galton–Watson trees with a random walk on \( \mathbb{Z} \). We shall use a super-regeneration time which is a regeneration time for all the three walks \( Y, GW(P_1) \) and \( GW(P_2) \). Regeneration time is an often-used technique in the study of random walks in random media. (See, e.g., [10].) Informally, a regeneration time is a maximum of a random walk which is also a minimum of the future of the random walk. A time \( \tau \) is a regeneration time for the \( \beta \)-biased random walk \( (Y_n)_{n \geq 0} \) on \( \mathbb{Z} \) if we have

\[
Y_\tau > \max_{n < \tau} Y_n \quad \text{and} \quad Y_\tau < \min_{n > \tau} Y_n.
\]

Consider the regeneration time for walks on \( GW(P_1) \) and \( GW(P_2) \) in the sense that is usually defined on trees (see [8]). As in [3] if \( \tau \) is a regeneration time for \( (Y_n)_{n \geq 0} \), then it is also a regeneration time for \( GW(P_1) \) and \( GW(P_2) \). In this respect, \( \tau \) is called a super-regeneration time.

Let us consider the event that 0 is a regeneration time for \( (Y_n)_{n \geq 0} \). Following the notation in [3], we denote this event by \( \{0 - SR\} \). Then, we have

\[
p_\infty := P(0 - SR) = \frac{\beta - 1}{\beta}.
\]

Let us define the probability measure \( \tilde{P} \) as

\[
\tilde{P}(\cdot) := P(\cdot|0 - SR).
\]

Under \( \tilde{P} \), 0 is a regeneration time and let \( \tau_i \) be \( i \)th non-zero regeneration time.

Then, \( (|X_{\tau_i+1}^{(1)} - X_{\tau_i}^{(1)}|, |\tau_{i+1} - \tau_i|)_{i \geq 1} \) is a sequence of i.i.d. random vectors having the same distribution as \( (|X_{\tau_1}^{(1)}|, \tau_1) \) under \( \tilde{P} \) and as in [3], we have, for any \( \beta > 1 

\[
\nu(\beta, P_1) = \frac{\tilde{E}[|X_{\tau_1}^{(1)}|]}{\tilde{E}[\tau_1]} \quad \text{and} \quad \nu(\beta, P_2) = \frac{\tilde{E}[|X_{\tau_1}^{(2)}|]}{\tilde{E}[\tau_1]}.
\]

Hence, \( \nu(\beta, P_1) > \nu(\beta, P_2) \) is equivalent to \( \tilde{E}[|X_{\tau_1}^{(1)}|] > \tilde{E}[|X_{\tau_1}^{(2)}|] \).

Let us denote by \( B \) the set of times before \( \tau_1 \) when the random walk on \( \mathbb{Z}_{\geq 0} \) takes a step back, i.e., \( B = \{ j \leq \tau_1 | U_j \leq 1/(\beta + 1) \} \).

We quote the following lemma from [3].

**Lemma 7 (Lemma 4.1, [3]).** If \( |B| = k \), then \( \tau_1 \leq 3k + 2 \).

**Proof of Theorem 1.** Consider \( |B| = k \), i.e., \( B = \{ i_1 < \cdots < i_k \} \), where \( k \geq 1 \) and \( \tau_1 = n \). Let us make two simple observations.

(i) \( |X_{\tau_1}^{(1)}| - |X_{\tau_1}^{(2)}| = 2 \) or 0 when \( k = 1 \).

(ii) \( |X_{\tau_1}^{(1)}| - |X_{\tau_1}^{(2)}| \geq -2(k - 1) \) when \( k \geq 2 \).

We have

\[
\tilde{E}[|X_{\tau_1}^{(1)}| - |X_{\tau_1}^{(2)}|] = \tilde{E}[|X_{\tau_1}^{(1)}| - |X_{\tau_1}^{(2)}|; |B| = 1] + \sum_{i_1 < \cdots < i_k, \tau_1 = n} \tilde{E}[|X_{\tau_1}^{(1)}| - |X_{\tau_1}^{(2)}|; B = \{ i_1 < \cdots < i_k \}]
\]
\[ \geq \hat{E}[|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}|; |B| = 1] - \sum_{k} 2(k - 1) \tilde{P}(|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}| < 0; B = \{i_1 < \cdots < i_k\}, \tau_1 = n), \]

where \( \sum_{k} \) stands for summation over all \( n \geq 2, k \geq 2 \) and \( \{i_1, \ldots, i_k\} \subseteq \{1, \ldots, n\} \) for which the walk \( Y_k \) does not come back to the origin.

For the first term, we have

\[ \hat{E}[|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}|; |B| = 1] \geq 2 \left( \frac{\beta}{\beta + 1} \right)^4 E \left[ \frac{1}{Z_2 \beta + 1} - \frac{1}{Z_1 \beta + 1} \right]. \tag{3.1} \]

Let us explain the inequality in (3.1). Let \( \epsilon_i = I(U_i \geq 1/(\beta + 1)) - I(U_i < 1/(\beta + 1)) \). When \( |B| = 1, |X_{t_1}^{(1)}| - |X_{t_1}^{(2)}| = 2 \) or 0, hence we have

\[ \hat{E}[|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}|; |B| = 1] = \frac{2}{\rho_\infty} P(|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}| = 2; |B| = 1; 0 - SR) \]

and thus we get the lower bound in (3.1) by considering the event

\[ A = \{\epsilon_1 = \epsilon_2 = 1, \epsilon_3 = -1 \text{ and } |X_3^{(1)}| - |X_3^{(2)}| = 2, \epsilon_4 = \epsilon_5 = 1, \tau_1 = 5\}. \]

For the second term, we have

\[ \tilde{P}(|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}| < 0; B = \{i_1 < \cdots < i_k\}, \tau_1 = n) \]

\[ \leq \frac{1}{\rho_\infty} P(|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}| < 0; B = \{i_1 < \cdots < i_k\}, \tau_1 = n). \]

On \(|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}| < 0\), let \( \sigma \) be the first time when the walk on \( GW(P_1) \) goes up but the walk on \( GW(P_2) \) goes down, necessarily \( \sigma \in B \). (When \(|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}| \geq 0\), define \( \sigma = \infty \).) We introduce some notation here. Given a sequence \( \theta = (\theta_i)_{i \geq 1} \) where \( \theta_n = \pm 1 \) we denote by \( \tau(\theta) \), the first non-zero regeneration time for the walk \( Z_n = \sum_{i=1}^{n} \theta_i \); e.g., the first non-zero regeneration time for \( Y_n \), \( \tau_1 \) equals \( \tau(\epsilon) \) where \( \epsilon = (\epsilon_n)_{n \geq 1} \) and \( \epsilon_n = I(U_n \geq 1/(\beta + 1)) - I(U_n < 1/(\beta + 1)) \). Define

\[ \tau_{1,i}^{(j)} = \tau(\epsilon^{(j)}) \quad \text{where } \epsilon^{(j)} := (\epsilon_1, \ldots, \epsilon_{j-1}, -1, \epsilon_{j+1}, \ldots). \]

Let \( B^{(j)} := \{i \leq \tau_{1,i}^{(j)} : \epsilon_i^{(j)} = -1\} \). Also define

\[ \tau_{1,i}^{(j)} = \tau(\epsilon^{(j)}) \quad \text{where } \epsilon^{(j)} := (\epsilon_1, \ldots, \epsilon_{j-1}, +1, \epsilon_{j+1}, \ldots). \]

Let \( B^{(j)} := \{i \leq \tau_{1,i}^{(j)} : \epsilon_i^{(j)} = -1\} \). Note that, for fixed \( j \), \( \epsilon^{(j)} \) and \( \epsilon^{(j)}_i \) are functions of \( \{U_j : i \neq j\} \), and are hence independent of \( \epsilon^{(j)}_i \).

Also note that if \(|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}| < 0\) then the event

\[ \mathcal{E} = \bigcup_{i,j \leq \tau_1} \{Z_{1,i} < Z_{2,j}^\prime\} \bigcup_{i,j \leq \tau_1} \{Z_{1,i}^\prime < Z_{2,j}\} \bigcup_{i,j \leq \tau_1} \{Z_{1,i} < Z_{2,j} \} \bigcup_{i \neq j} \{Z_{1,i}^\prime < Z_{2,j}^\prime\} \]

is true. For every \( n \geq 2 \), let \( \mathcal{E}_{i \ell}^n := \bigcup_{j=1}^d \mathcal{E}_{j \ell,i}^n \) where

\[ \mathcal{E}_{i \ell,i}^n := \bigcup_{i,j \leq n} \left[ \{Z_{1,i} < Z_{2,j}^\prime\} \cap \left\{ U_{i \ell} \in \left[ \frac{1}{Z_{2,j}^\prime \beta + 1}, \frac{1}{Z_{1,i} \beta + 1} \right] \right\} \right] \]
and $\mathcal{E}_{2,i}^n$, $\mathcal{E}_{3,i}^n$, $\mathcal{E}_{4,i}^n$ are defined similarly (i.e., use the random variables $Z_{1,i}, Z_{2,j}$ in the definition of $\mathcal{E}_{2,i}^n$ etc.).

\[
P\left( |X_{11}^{(1)}| - |X_{11}^{(2)}| < 0; B = \{i_1 < \cdots < i_k\}, \tau_1 = n \right)
\leq \sum_{\ell=1}^k P\left( B = \{i_1 < \cdots < i_k\}, \tau_1 = n, \sigma = i_\ell \right)
\leq \sum_{\ell=1}^k P\left( B^{(i_\ell)} = \{i_1 < \cdots < i_k\}, \tau_1^{(i_\ell)} = n, \sigma = i_\ell \right)
\leq \sum_{\ell=1}^k \sum_{i=1}^k 4n^2 P\left( B^{(i_\ell)} = \{i_1 < \cdots < i_k\}, \tau_1^{(i_\ell)} = n \right) E\left[ \frac{1}{Z_1 \beta + 1} - \frac{1}{Z_2 \beta + 1}; 1_{Z_1 < Z_2} \right],
\]

where we used independence of $\varepsilon^{(i_\ell)}$ and $U_{i_\ell}$. Then, by Lemma 7,

\[
P\left( |X_{11}^{(1)}| - |X_{11}^{(2)}| < 0; B = \{i_1 < \cdots < i_k\}, \tau_1 = n \right)
\leq 4(3k + 2)^2 \sum_{\ell=1}^k P\left( B^{(i_\ell)} = \{i_1 < \cdots < i_k\}, \tau_1^{(i_\ell)} = n, U_{i_\ell} \leq \frac{1}{\beta + 1} \right)
\cdot (\beta + 1) \cdot E\left[ \frac{1}{Z_1 \beta + 1} - \frac{1}{Z_2 \beta + 1}; 1_{Z_1 < Z_2} \right]
\]

\[
= 4(\beta + 1)(3k + 2)^2 E\left[ \frac{1}{Z_1 \beta + 1} - \frac{1}{Z_2 \beta + 1}; 1_{Z_1 < Z_2} \right] \sum_{\ell=1}^k P\left( B = \{i_1 < \cdots < i_k\}, \tau_1 = n \right)
\leq 8\beta k(3k + 2)^2 E\left[ \frac{(Z_2 - Z_1)\beta}{(Z_1 \beta + 1)(Z_2 \beta + 1)}; 1_{Z_1 < Z_2} \right] P\left( B = \{i_1 < \cdots < i_k\}, \tau_1 = n \right)
\leq 8k(3k + 2)^2 E\left[ \frac{1}{Z_1} - \frac{1}{Z_2}; 1_{Z_1 < Z_2} \right] P\left( B = \{i_1 < \cdots < i_k\}, \tau_1 = n \right).
\]

Therefore, by using the simple upper bound $P(|B| = k) \leq c\left(\frac{27}{4(1+\beta)}\right)^k$ (Lemma 6.1 in [3]) for a universal constant $c$ and the fact that $p_\infty = (\beta - 1)/\beta$, we get

\[
\tilde{E}\left[ |X_{11}^{(1)}| - |X_{11}^{(2)}| \right] \geq 2\left( \frac{\beta}{\beta + 1} \right)^4 E\left[ \frac{1}{Z_2 \beta + 1} - \frac{1}{Z_1 \beta + 1}; 1_{Z_1 < Z_2} \right] - \sum_{k=2}^\infty \frac{16}{p_\infty} k(k - 1)(3k + 2)^2 E\left[ \frac{1}{Z_1} - \frac{1}{Z_2}; 1_{Z_1 < Z_2} \right] P(|B| = k)
\geq 2\left( \frac{\beta}{\beta + 1} \right)^4 E\left[ \frac{(Z_1' - Z_2')\beta}{(Z_1' \beta + 1)(Z_2' \beta + 1)} \right]
\]

\[
- \frac{c}{p_\infty} E\left[ \frac{1}{Z_1} - \frac{1}{Z_2}; 1_{Z_1 < Z_2} \right] \sum_{k=2}^\infty 16k(k - 1)(3k + 2)^2 \left( \frac{27}{4(1+\beta)} \right)^k
\geq 2\left( \frac{\beta}{\beta + 1} \right)^4 E\left[ \frac{(Z_1' - Z_2')\beta}{4Z_2' Z_1' \beta^2} \right] - \frac{c\beta}{(\beta - 1)} E\left[ \frac{1}{Z_1} - \frac{1}{Z_2}; 1_{Z_1 < Z_2} \right] \sum_{k=2}^\infty 16k(k - 1)(3k + 2)^2 \left( \frac{27}{4(1+\beta)} \right)^k
\]
\[
\geq 2 \left( \frac{\beta}{\beta + 1} \right)^4 E \left[ \frac{(Z'_1 - Z'_2)}{4Z'_2 Z'_4 \beta} \right] - \frac{c \cdot 27^2 \beta}{4^2(\beta - 1)(\beta + 1)^2} E \left[ \left( \frac{1}{Z_1} - \frac{1}{Z_2} \right) \mathbb{1}_{Z_1 < Z_2} \right] \\
\sum_{k=2}^{\infty} 16k(k - 1)(3k + 2)^2 \left( \frac{27}{4(1 + \beta)} \right)^{k-2},
\]

(3.2)

where we used the fact that \(Z'_1 \geq Z'_2 \geq 1\) and \(\beta > 1\). Hence we conclude that for any \(\delta > 0\), \(\bar{E}[|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}|] > 0\) if we have

\[
\beta > \max \left\{ c_3 \cdot \frac{E[((1/Z_1) - (1/Z_2))\mathbb{1}_{Z_1 < Z_2}]}{E[(1/Z'_2) - (1/Z'_1)]}, \frac{23}{4} + \delta \right\},
\]

(3.3)

for some universal constant \(c_3 > 0\) that depends only on \(\delta\).

Now we derive the other lower bound in (1.3). On \(\{|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}| < 0\}\), let us define the events \(E\) and \(F\) as

\[
E := \{\text{for some } \sigma_1 \leq t_1, |X_{\sigma_1+1}^{(1)}| \neq |X_{\sigma_1+1}^{(2)}| \text{ and } X_j^{(1)} = X_j^{(2)} \text{ for any } j \leq \sigma_1\},
\]

\[
F := \{\text{for some } \sigma_2 \leq t_1, X_j^{(1)} = X_j^{(2)} \text{ for any } j \leq \sigma_2, \text{ and } X_{\sigma_2+1}^{(1)} \neq X_{\sigma_2+1}^{(2)}, \text{ but } |X_{\sigma_2+1}^{(1)}| = |X_{\sigma_2+1}^{(2)}|\}.
\]

In other words, \(E\) is the event that the first time the walks on \(GW(P_1)\) and \(GW(P_2)\) decouple, the walk on \(GW(P_2)\) goes up and the walk on \(GW(P_1)\) goes down. Clearly this happens at time \(\sigma_1 \in \mathcal{B}\). \(F\) is the event that the first time the walks on \(GW(P_1)\) and \(GW(P_2)\) decouple, they both go downwards but to different offsprings. This happens at time \(\sigma_2\) which may or may not be in \(\mathcal{B}\).

Next,

\[
P\left(|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}| < 0; \mathcal{B} = \{i_1, \ldots, i_k\}, t_1 = n\right) = P\left(|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}| < 0; \mathcal{B} = \{i_1, \ldots, i_k\}, t_1 = n; E \right) + P\left(|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}| < 0; \mathcal{B} = \{i_1, \ldots, i_k\}, t_1 = n; F \right).
\]

(3.4)

Let us get an upper bound for the second term in (3.4).

\[
P\left(|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}| < 0; \mathcal{B} = \{i_1, \ldots, i_k\}, t_1 = n; F \right) = \sum_{\ell=1}^{n} P\left(|X_{t_1}^{(1)}| - |X_{t_1}^{(2)}| < 0; \mathcal{B} = \{i_1, \ldots, i_k\}, t_1 = n, \sigma_2 = \ell; F \right)
\]

\[
\leq \sum_{\ell=1}^{n} P\left(\mathcal{B} = \{i_1, \ldots, i_k\}, t_1 = n, \sigma_2 = \ell; F \right).
\]

(3.5)

If \(\ell \notin \{i_1, \ldots, i_k\}\), then we have

\[
P\left(\mathcal{B} = \{i_1, \ldots, i_k\}, t_1 = n, \sigma_2 = \ell; F \right) \leq P\left(\mathcal{B} = \{i_1, \ldots, i_k\}, t_1 = n; U_{t_1} \in \bigcup_{m=1}^{n} \left( \frac{1}{\beta + 1}, \frac{Z'_1 - Z'_2}{(\beta + 1)Z'_1} + \frac{1}{\beta + 1} \right) \right)
\]

\[
= P\left(\mathcal{B}_{(\ell)} = \{i_1, \ldots, i_k\}, t_{1(\ell)} = n, U_{t_1} \in \bigcup_{m=1}^{n} \left( \frac{1}{\beta + 1}, \frac{Z'_1 - Z'_2}{(\beta + 1)Z'_1} + \frac{1}{\beta + 1} \right) \right)
\]

\[
= P\left(\mathcal{B}_{(\ell)} = \{i_1, \ldots, i_k\}, t_{1(\ell)} = n\right) P\left(U_{t_1} \in \bigcup_{m=1}^{n} \left( \frac{1}{\beta + 1}, \frac{Z'_1 - Z'_2}{(\beta + 1)Z'_1} + \frac{1}{\beta + 1} \right) \right)
\]

(3.6)
For a coupled $(Z'_1, Z'_2)$, we have (after a little computation)

\[
\left(\frac{1}{\beta + 1} - \frac{1}{Z'_2 \beta + 1}\right) - \left(\frac{1}{\beta + 1} - \frac{1}{Z'_1 \beta + 1}\right) \frac{Z'_2}{Z'_1} = \left(\frac{1}{\beta + 1}\right) \left[1 - \frac{(Z'_1 - 1)\beta}{Z'_1 \beta + 1} \right] - \frac{\beta + 1}{Z'_1 \beta + 1} + \left(\frac{(Z'_1 - 1)\beta}{Z'_1 \beta + 1}\right) \left(1 - \frac{Z'_2}{Z'_1}\right).
\]

It is easy to check that

\[
1 - \frac{(Z'_1 - 1)\beta}{Z'_1 \beta + 1} - \frac{\beta + 1}{Z'_1 \beta + 1} = \frac{(Z'_2 - Z'_1)\beta + (Z'_2 - Z'_1)\beta^2}{(Z'_1 \beta + 1)(Z'_2 \beta + 1)} \leq 0,
\]

and

\[
0 \leq \frac{(Z'_1 - 1)\beta}{Z'_1 \beta + 1} \left(1 - \frac{Z'_2}{Z'_1}\right) \leq 1 - \frac{Z'_2}{Z'_1}.
\]

Hence $E[G_m] \leq (\frac{1}{\beta + 1})E[(1 - \frac{Z'_2}{Z'_1})]$ and therefore

\[
(\beta + 1) P(\mathcal{B} = \{i_1, \ldots, i_k\}, \tau_1 = n) \cdot n \cdot E[G_m] \leq (\beta + 1) P(\mathcal{B} = \{i_1, \ldots, i_k\}, \tau_1 = n) \cdot n \cdot \frac{1}{\beta + 1} E\left[1 - \frac{Z'_2}{Z'_1}\right]
\]

\[
= n P(\mathcal{B} = \{i_1, \ldots, i_k\}, \tau_1 = n) E\left[1 - \frac{Z'_2}{Z'_1}\right].
\]

(3.7)
So plugging (3.6) and (3.7) back into (3.5), we get

\[
P\left(\left|X^{(1)}_{\tau_1}\right| - \left|X^{(2)}_{\tau_1}\right| < 0; B = \{i_1, \ldots, i_k\}, \tau_1 = n; F\right)
\leq 2n^2 P\left(B = \{i_1, \ldots, i_k\}, \tau_1 = n\right) E\left[1 - \frac{Z'_2}{Z'_1}\right]
\leq 2(3k + 2)^2 P\left(B = \{i_1, \ldots, i_k\}, \tau_1 = n\right) E\left[1 - \frac{Z'_2}{Z'_1}\right].
\]

This takes care of the second term in (3.4). Finally, let us give an upper bound for the first term in (3.4). We omit some of the steps since they are similar. In the following computations, remember that \(\sigma_1 \in B\).

\[
P\left(\left|X^{(1)}_{\tau_1}\right| - \left|X^{(2)}_{\tau_1}\right| < 0; B = \{i_1, \ldots, i_k\}, \tau_1 = n; E\right)
\leq \sum_{m=1}^{k} P\left(B = \{i_1, \ldots, i_k\}, \tau_1 = n; \sigma_1 = i_m; E\right)
\leq kn P\left(B = \{i_1, \ldots, i_k\}, \tau_1 = n\right) \cdot (\beta + 1) \cdot E\left[\frac{1}{Z'_2\beta + 1} - \frac{1}{Z'_1\beta + 1}\right]
\leq k(3k + 2) P\left(B = \{i_1, \ldots, i_k\}, \tau_1 = n\right) \cdot (\beta + 1) \cdot E\left[\frac{1}{Z'_2} - \frac{1}{Z'_1}\right].
\]

Similar to our arguments in (3.2), we get

\[
\begin{align*}
\bar{E}\left[\left|X^{(1)}_{\tau_1}\right| - \left|X^{(2)}_{\tau_1}\right|\right] \\
&\geq 2\left(\frac{\beta}{\beta + 1}\right)^4 E\left[\frac{1}{Z'_2\beta + 1} - \frac{1}{Z'_1\beta + 1}\right]
- \frac{1}{p_{\infty}} \sum_{k=2}^{\infty} 2(3k + 2)^2 P\left(|B| = k\right) E\left[1 - \frac{Z'_2}{Z'_1}\right]
- \frac{1}{p_{\infty}} \sum_{k=2}^{\infty} 2k(3k + 2) P\left(|B| = k\right) \cdot E\left[\frac{1}{Z'_2} - \frac{1}{Z'_1}\right]
\geq \left(\frac{1}{2\beta}\right)\left(\frac{\beta}{\beta + 1}\right)^4 E\left[\frac{1}{Z'_2} - \frac{1}{Z'_1}\right]
- \frac{c}{p_{\infty}} E\left[1 - \frac{Z'_2}{Z'_1}\right] \sum_{k=2}^{\infty} 2(3k + 2)^2 \left(\frac{27}{4(1 + \beta)}\right)^k
- \frac{c}{p_{\infty}} E\left[\frac{1}{Z'_2} - \frac{1}{Z'_1}\right] \sum_{k=2}^{\infty} 2k(3k + 2) \left(\frac{27}{4(1 + \beta)}\right)^k.
\end{align*}
\]

(3.8)

As earlier, we conclude that for any \(\delta > 0\) there is a universal constant \(c'_\delta\) such that

\[
\bar{E}\left[\left|X^{(1)}_{\tau_1}\right| - \left|X^{(2)}_{\tau_1}\right|\right] > 0,
\]

such that
whenever
\[ \beta > \max \left\{ c_0 \left( \frac{E[Z_2(1/Z_2) - (1/Z_1)]}{E[(1/Z_2) - (1/Z_1)]} + 1 \right), \frac{23}{4} + \delta \right\}. \]

\[ \square \]

**Proof of Corollary 5.** We shall write \( Z_i \) for \( Z_i^{(1)} \), for \( i = 1, 2 \) and \( p_j \) for \( P_1(j) \). Let us first prove that \( E[m^k_2/Z_{1}^{(k)}] \to 0 \) as \( k \to \infty \). Pick up some \( m_3 \) satisfying \( m_2 < m_3 < m_1 \). Then, we have

\[
m^k_2 E \left[ \frac{1}{Z_{1}^{(k)}} \right] = m^k_2 \sum_{n \leq m_3} \frac{1}{n} P(Z_{1}^{(k)} = n) + m^k_2 \sum_{n > m_3} \frac{1}{n} P(Z_{1}^{(k)} = n)
\]

\[
\leq m^k_2 P(Z_{1}^{(k)} \leq m_3^k) + \frac{m^k_2}{m_3^k}.
\]

Therefore, it is sufficient to prove that \( m^k_2 P(Z_{1}^{(k)} \leq m_3^k) \to 0 \) as \( k \to \infty \).

If \( W_i \) denotes the almost sure limit of the martingale \( Z_i^{(k)}/m_2^k \), then under the assumption \( E[Z_i \log^+ Z_i] < \infty \), \( W_i \) is a positive random variable for \( i = 1, 2 \) (see, e.g., [5] and [9]). Several other properties of \( W_i \) have been well studied in the literature. Recall that \( f \) is the generating function of \( Z_1 \), then \( 0 < \alpha = -\log f'(0)/\log f'(1) \). Let us first consider the case \( p_1 > 0 \). Note that \( \alpha < \infty \) when \( p_1 > 0 \). From [4] and the references therein, if \( p_1 > 0 \), then, there exists a positive constant \( D \) such that \( P(W_1 \leq \varepsilon) \leq De^\varepsilon \) as \( \varepsilon \downarrow 0 \).

Moreover, [2] proved that if there exists some \( \theta > 0 \) such that \( E[e^{\theta Z_1}] < \infty \) and \( p_j \neq 1 \) for any \( j \geq 1 \), then there exist some constants \( C_1, C_2 \) such that

\[
P \left( \left| \frac{Z_1^{(k)}}{m_1^k} - W_1 \right| \geq \varepsilon \right) \leq C_1 e^{-C_2 \varepsilon^{2/3} m_1^{k/3}}.
\]

Now, splitting \( P(Z_{1}^{(k)} \leq m_3^k) \) into two terms, we get

\[
P \left( Z_{1}^{(k)} \leq m_3^k \right) = P \left( Z_{1}^{(k)} \leq m_3^k, \left| \frac{Z_1^{(k)}}{m_1^k} - W_1 \right| > \varepsilon \right) + P \left( Z_{1}^{(k)} \leq m_3^k, \left| \frac{Z_1^{(k)}}{m_1^k} - W_1 \right| \leq \varepsilon \right)
\]

\[
\leq P \left( \left| \frac{Z_1^{(k)}}{m_1^k} - W_1 \right| > \varepsilon \right) + P \left( W_1 \leq \varepsilon + \frac{m_3^k}{m_1^k} \right).
\]

Let us choose \( \varepsilon = m_2^{-(k/\alpha) - k\delta} \) for some \( \delta > 0 \).

Using the results stated before from [4],

\[
m_2^k P \left( W_1 \leq \varepsilon + \frac{m_3^k}{m_1^k} \right) \leq Dm_2^k \left( \varepsilon + \frac{m_3^k}{m_1^k} \right)^{\alpha}
\]

\[
= D \left( m_2^{k\delta} + \left( \frac{m_3^{1/\alpha}}{m_1} \right)^k \right)^{\alpha} \to 0,
\]

as \( k \to \infty \) if we have \( m_1 > m_3^{1/\alpha} m_3 \). Since it is valid for any \( m_2 < m_3 < m_1 \), the condition \( m_1 > m_2^{(1/\alpha)+1} \) is enough.

Using the results stated before from [2],

\[
m_2^k P \left( \left| \frac{Z_1^{(k)}}{m_1^k} - W_1 \right| > \varepsilon \right) \leq m_2^k C_1 e^{-C_2 (\varepsilon)^{2/3} m_1^{k/3}} = m_2^k C_1 e^{-C_2 m_2^{-(2k/3\alpha) - (2/3)\delta} m_1^{k/3}} \to 0,
\]
as \( k \to \infty \) if \( m_1 > m_2^{(2/\alpha^2 + 2\delta)} \). Since we can pick up any \( \delta > 0 \), the condition \( m_1 > m_2^{2/\alpha} \) is enough. This proves that 
\[
E[m_k^2/Z_1^{(k)}] \to 0 \text{ as } k \to \infty.
\]

If \( p_1 = 0 \), then \( k := \min\{k > 0: p_k > 0\} \geq 2 \) and from [4], we have \( \log P(W_1 \leq \varepsilon) \sim -C \varepsilon^{-\beta/(1-\beta)} \), for some positive constant \( C \) and \( \beta := \log k/\log m_1 \). In other words, \( P(W_1 \leq \varepsilon) \) is exponentially small. Since \( m_1 > m_2 \), we can pick up some \( \alpha' \) large enough such that \( m_1 > m_2^{\max[2/\alpha', (1/\alpha') + 1]} \) holds. Since \( P(W_1 \leq \varepsilon) \) is exponentially small, we can find a positive constant \( D' \) such that \( P(W_1 \leq \varepsilon) \leq D'e^{\alpha'} \). Repeat the arguments as in the case \( p_1 > 0 \) replacing \( \alpha \) by \( \alpha' \) and \( D \) by \( D' \). This proves that 
\[
E[m_k^2/Z_1^{(k)}] \to 0 \text{ as } k \to \infty.
\]

Now, let us go back to the proof of the corollary. From (1.3), it suffices to show that 
\[
\frac{E[(1/Z_1^{(k)}) - (1/Z_2^{(k)})]1_{Z_1^{(k)} < Z_2^{(k)}}}{E[(1/Z_1^{(k)}) - (1/Z_2^{(k)})]} \to 0, \text{ as } k \to \infty. \tag{3.9}
\]

Since, \( E(\exp(\theta Z_1)) < \infty \) (in particular \( E[Z_1 \log^+ Z_1] < \infty \)), we have \( \lim Z_i^{(k)}/m_i^k > 0 \) a.s. and hence 
\[
\frac{Z_2^{(k)}}{Z_1^{(k)}} = \frac{m_k^2}{m_1^k} \cdot \frac{Z_2^{(k)}/m_k^2}{Z_1^{(k)}/m_1^k} \to 0,
\]
as \( k \to \infty \), which implies that 
\[
\liminf_{k \to \infty} E\left(\frac{m_k^2}{Z_1^{(k)}} - \frac{1}{Z_1^{(k)}}\right) \leq \liminf_{k \to \infty} E\left(\frac{m_k^2}{Z_2^{(k)}} \cdot \frac{1}{Z_2^{(k)}}\right) = E\left(\frac{1}{W_2}\right) > 0.
\]

Finally, notice that 
\[
m_k^2 E\left(\frac{1}{Z_1^{(k)}} - \frac{1}{Z_2^{(k)}}\right)1_{Z_1^{(k)} < Z_2^{(k)}} = E\left(\frac{m_k^2}{Z_1^{(k)}} \cdot \frac{1}{Z_1^{(k)}}\right)1_{Z_1^{(k)} < Z_2^{(k)}} \leq E\left(\frac{m_k^2}{Z_2^{(k)}}\right).
\]

Therefore, we proved (3.9). Given any \( \beta > 23/4 \) we can choose \( \delta > 0 \) such that \( 23/4 + \delta < \beta \) and then choose \( k = k(P_1, P_2) \) large enough so that the maximum in (3.3) equals \( 23/4 + \delta \). \( \Box \)

We now sketch a proof of Theorem 4.

**Proof of Theorem 4.** We begin with the independent sequences \( \{U_i\}_{i \geq 1}, \{Z_{1,k}\}_{k \geq 1}, \{Z_{2,k}\}_{k \geq 1} \) and \( \{\tilde{Z}_{1,k}, \tilde{Z}_{2,k}\}_{k \geq 1} \) where the first three have the same meaning as in Section 2 and \( \{\tilde{Z}_{1,k}, \tilde{Z}_{2,k}\}_{k \geq 1} \) are i.i.d. copies of \( \{(Z_{1,1}^{(i)}, \ldots, Z_{1,\ell}^{(i)}), (Z_{2,1}^{(i)}, \ldots, Z_{2,\ell}^{(i)})\} \), the latter having the same meaning as in the statement of Theorem 4. We shall write \( \tilde{Z}_{i,k} = (Z_{1,i,k}, \ldots, Z_{\ell,k}) \) for \( i = 1, 2 \).

We start both walks at the roots and when \( X_{(i)} \) visits the \( j \)th distinct site at level \( k \) for the first time, we assign \( Z_{i,k}^{(j)} \) many children to that site for \( i = 1, 2 \) and \( j \leq \ell \). If one of the walks, say \( X_{(1)} \) is visiting the \( j \)th distinct site at level \( k \) for the first time where \( j > \ell \), then we assign \( Z_{1,i} \) many children to that site for some \( i \) for which \( Z_{1,i} \) has not been used before. At time \( n \), we make the transition using the two rules explained in Section 2 according as the number of children of \( X_{(n)}^{(1)} \) is larger or smaller than the number of children of \( X_{(n)}^{(2)} \).

If \( |B| = k \), we have

(i) \( 0 \leq |X_{(1)}^{(i)}| - |X_{(2)}^{(i)}| \leq 2\ell \) when \( k \leq \ell \).

(ii) \( |X_{(1)}^{(i)}| - |X_{(2)}^{(i)}| \geq 2(k - \ell) \) when \( k \geq \ell + 1 \).

This can be argued as follows. Assume that \( B = \{i_1, \ldots, i_k\} \) where \( k \geq \ell \). If \( |X_{(1)}^{(i)}| < |X_{(2)}^{(i)}| \) for some \( j \leq i_\ell \), define \( j_\ell := \min\{i: |X_{(1)}^{(i)}| < |X_{(2)}^{(i)}|\} \). Then \( |X_{(1)}^{(j_\ell)}| = |X_{(2)}^{(j_\ell)}| \). Since \( j_\ell - 1 < i_\ell \), none of the walks has visited any of the levels more than \( \ell \) times up till time \( j_\ell - 1 \). We also have \( \min\{|Z_{1,K}, \ldots, Z_{\ell,K}| \geq \max\{|Z_{2,K}, \ldots, Z_{2,K}| \} \) and hence the
number of offsprings of $X^{(1)}_{j_{k-1}}$ is not smaller than the number of offsprings of $X^{(2)}_{j_k}$. But then $|X^{(1)}_{j_k}| \geq |X^{(2)}_{j_k}|$, a contradiction. Hence $|X^{(1)}_{j_k}| \geq |X^{(2)}_{j_k}|$ whenever $j \leq i_\ell$, this implies the claims in (i) and (ii) stated above. A similar argument can be given for the case $|B| < \ell$.

So if we carry out an analysis similar to the one given in the proof of Theorem 1, then instead of (3.2), we shall get

$$
\tilde{E}[X^{(1)}_{t_1}] - |X^{(2)}_{t_1}| \geq 2 \left( \frac{\beta}{\beta + 1} \right)^4 E \left[ \frac{1}{Z_2} - \frac{1}{Z_1} \right] \cdot \sum_{k=\ell+1}^{\infty} 16k(k-\ell)(3k+2)^2 \left( \frac{27}{4(1 + \beta)} \right)^{k-\ell-1},
$$

and (3.8) can be modified similarly.

Proof of Corollary 6. The proof is an extension and almost the same as the proof of Theorem 1. One needs to couple the two random walks on $GW(P_1)$ and $GW(P_2)$, with a $d\beta$-random walk on $\mathbb{Z}_{\geq 0}$. Formally we re-define the walk $Y_n$ as $Y_0 := 0$ and for $n \geq 1$,

$$
Y_n := \sum_{i=1}^{n} \{ 1_{U_i > 1/(d\beta + 1)} - 1_{U_i \leq 1/(d\beta + 1)} \}, \quad n \in \mathbb{N}.
$$

The walk on $GW(P_1)$ and $GW(P_2)$ should also be changed accordingly. Similar arguments, as in the proof of Theorem 1, give the counterparts to (3.2) and (3.8). Let us only present the latter, which is

$$
\tilde{E}[X^{(1)}_{t_1}] - |X^{(2)}_{t_1}| \geq \left( \frac{1}{2\beta} \right) \left( \frac{d \cdot \beta}{d \cdot \beta + 1} \right)^4 E \left[ \frac{1}{Z_2'} - \frac{1}{Z_1'} \right] \cdot \sum_{k=2}^{\infty} 2(3k+2)^2 \left( \frac{27}{4(1 + d \cdot \beta)} \right)^k
$$

$$
- \frac{c}{p_\infty} E \left[ \frac{1}{Z_2'} - \frac{1}{Z_1'} \right] \sum_{k=2}^{\infty} 2k(3k+2) \left( \frac{27}{4(1 + d \cdot \beta)} \right)^k,
$$

Now, note that this gives the same constant as in (3.8). Therefore, as long as $d \cdot \beta > \beta_0$ we have $\tilde{E}[X^{(1)}_{t_1}] - |X^{(2)}_{t_1}| > 0$ which completes the proof.

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