

# Coalescence times for critical Galton-Watson processes with immigration\*

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## Abstract

Let  $X_n^I$  be the coalescence time of two particles picked at random from the  $n$ th generation of a critical Galton-Watson process with immigration, and let  $A_n^I$  be the coalescence time of the whole population in the  $n$ th generation. In this paper, we study the limiting behaviors of  $X_n^I$  and  $A_n^I$  as  $n \rightarrow \infty$ .

**Keywords** critical Galton-Watson process, immigration, coalescence times.

**2010 MR Subject Classification** primary 60J68; secondary 62E15; 60F10; 60J80

## 1 Introduction and Main Results

Suppose  $(Y_n)_{n \geq 0}$  is a Galton-Watson process with offspring distribution  $(p_j)_{j \geq 0}$  and initial size  $Y_0 = 1$ . For  $n \geq 1$ , conditional on  $\{Y_n \geq 2\}$ , pick 2 distinct particles uniformly from the  $n$ -th generation and trace their lines of descent backward in time. The common nodes in the two lines are called the common ancestors of the two particles. Let  $X_n$  denote the generation of their most recent common ancestor, which is called *the pairwise coalescence time*. Next, for  $n \geq 1$ , conditional on  $\{Y_n \geq 1\}$ , we trace the lines of descent of all particles in generation  $n$  backward in time. The common nodes in the  $Y_n$  lines of descent are called the common ancestors of all the particles in generation  $n$ . Define *the total coalescence time*  $A_n$  as the generation of the most recent common ancestor of all the particles in generation  $n$ . When  $m := \sum_{n=0}^{\infty} j p_j = 1$  (critical case),  $p_1 < 1$  and  $\sigma^2 := \sum_{n=0}^{\infty} j^2 p_j - 1 < \infty$ , Athreya [3] proved that for  $u \in (0, 1)$ ,

$$\lim_{n \rightarrow \infty} P \left( \frac{X_n}{n} \geq u \mid Y_n \geq 2 \right) = E \left[ \frac{\sum_{i=1}^{N_u} \eta_i^2}{(\sum_{i=1}^{N_u} \eta_i)^2} \right], \quad (1.1)$$

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\*The research of this project is supported by the National Key R&D Program of China (No. 2020YFA0712902)

†The research of R. Liu is supported in part by NSFC (Grant No. 12271374)

‡The research of Y.-X. Ren is supported in part by NSFC (Grant Nos. 12071011 and 12231002) and The Fundamental Research Funds for the Central Universities, Peking University LMEQF

where  $(\eta_i)_{i \geq 1}$  are independent and identically distributed exponential random variables with mean  $\sigma^2/2$ , and  $N_u$  is independent of  $(\eta_i)_{i \geq 1}$  and is a geometric random variable of parameter  $1 - u$  (i.e.,  $P(N_u = k) = (1 - u)u^{k-1}, k \geq 1$ ). Athreya [3] also proved the following conditional limit result:

$$\lim_{n \rightarrow \infty} P\left(\frac{A_n}{n} > u | Y_n \geq 1\right) = 1 - u, \quad \text{for } u \in (0, 1).$$

The genealogy of branching processes has been widely studied. Athreya [1, 2], Durrett [6], Zubkov [21] also investigated the distributional properties of the coalescence times for Galton-Watson processes. Kersting [12] gave the genealogy structure of branching processes in random environment. Harris, Johnston and Roberts [7], Johnston [10] and Le [14] investigated the coalescent structure of continuous time Galton-Watson processes. Hong [9] studied the corresponding results for multitype branching processes.

Suppose  $(p_j)_{j \geq 0}$  and  $(b_j)_{j \geq 0}$  are probability distributions on the set  $\mathbb{N}$  of nonnegative integers. Let  $(\xi_{n,i}; n \in \mathbb{N}, i \in \mathbb{N})$  be a doubly infinite family of independent random variables with common distribution  $(p_j)_{j \geq 0}$ , and let  $(I_n)_{n \geq 0}$  be a sequence of independent random variables with common distribution  $(b_j)_{j \geq 0}$  which are independent of  $(\xi_{n,i}; n \in \mathbb{N}, i \in \mathbb{N})$  as well. Let  $(Z_n)_{n \geq 0}$  be a Galton-Watson process with immigration (GWPI for short) defined by

$$Z_0 = I_0, \quad Z_{n+1} = \sum_{i=1}^{Z_n} \xi_{n,i} + I_{n+1}, \quad n = 0, 1, \dots$$

Here  $Z_n$  is the population size in generation  $n$ , and  $I_n$  is the number of immigrants in generation  $n$ . For each  $1 \leq i \leq Z_n$ ,  $\xi_{n,i}$  denotes the number of children of the  $i$ -th particle in generation  $n$ . We assume that all the immigrants have different ancestors. Set  $m = E\xi_{0,1} = \sum_{j=0}^{\infty} jp_j$ . Then  $(Z_n)_{n \geq 0}$  is called supercritical, critical or subcritical according to  $m > 1, m = 1$  or  $m < 1$ , respectively. GWPI was first considered by Heathcote [8] in 1965. Recently, Wang, Li and Yao [20] found that the pairwise coalescence time  $X_n$  for some supercritical GWPI converges in distribution to a  $(0, \infty]$ -valued random variable as  $n \rightarrow \infty$ .

In this paper, we consider the coalescence times for critical GWPI  $(Z_n)_{n \geq 0}$ . Unlike the case of a Galton-Watson process starting with one particle, two randomly picked distinct particles (all particles) from generation  $n$  of a GWPI may not have a common ancestor. Conditional on  $\{Z_n > 1\}$ , we pick two distinct particles, say  $v_1$  and  $v_2$ , uniformly from the  $n$ th generation and trace their lines of descent backward in time. Define the *pairwise coalescence time* for GWPI

$$X_n^I = \begin{cases} |v|, & \text{if the most recent common ancestor of } v_1 \text{ and } v_2 \text{ is } v, \\ \infty, & \text{otherwise,} \end{cases} \quad (1.2)$$

where  $|v|$  is the generation of  $v$ . Note that even if  $v_1$  and  $v_2$  are descendants of two distinct particles immigrated to the system at the same time, we do not say they have a common ancestor. Similarly, conditional on  $\{Z_n > 0\}$ , define the *total coalescence time* for GWPI

$$A_n^I = \begin{cases} |v|, & \text{if the most recent common ancestor of all particles alive at } n \text{ is } v, \\ \infty, & \text{otherwise.} \end{cases} \quad (1.3)$$

We will study the asymptotic behaviors of the distribution of  $X_n^I$  conditioned on  $\{Z_n > 1\}$  and the distribution of  $A_n^I$  conditioned on  $\{Z_n > 0\}$ . We will explore the effect of the immigrations on the coalescence times. Throughout this paper we suppose the following assumption holds.

**Assumption 1**  $0 < p_0 + p_1 < 1$ ,  $m = 1$ ,  $\sigma^2 = \sum_j (j^2 - 1)p_j < \infty$ .  $b_0 < 1$  and  $\beta = \sum_j j b_j < \infty$ .

We use  $\langle g, \mu \rangle$  to denote the integral of a function  $g$  with respect to a Radon measure  $\mu$  whenever this integral makes sense.

**Theorem 1.1** Suppose Assumption 1 holds. Let  $\gamma = 2\beta/\sigma^2$ . Define

$$\phi(j, \mu) = E \left[ \frac{\sum_{i=1}^j \omega_i^2 + \langle f^2, \mu \rangle}{(\sum_{i=1}^j \omega_i + \langle f, \mu \rangle)^2} \right], \quad (1.4)$$

where  $f(r) = r$ ,  $r > 0$ , and  $(\omega_i)_{i \geq 1}$  are independent exponential random variables with parameter  $\frac{2}{\sigma^2}$ .

(1) For  $0 < u < 1$ ,

$$\lim_{n \rightarrow \infty, k/n \rightarrow u} P(k \leq X_n^I < n | Z_n > 1) = E\phi(N_u^I, W),$$

where  $N_u^I$  is a negative binomial random variable with law

$$P(N_u^I = k) = \frac{(-\gamma)(-\gamma-1)\cdots(-\gamma-k+1)}{k!} (1-u)^\gamma (-u)^k, \quad k = 0, 1, 2, \dots, \quad (1.5)$$

with the convention  $\frac{(-\gamma)(-\gamma-1)\cdots(-\gamma-k+1)}{k!} = 1$  when  $k = 0$ ,  $W$  is a Poisson random measure on  $(0, \infty)$  with intensity  $\frac{2}{r} e^{-\frac{2}{\sigma^2}r} dr$ , and  $N_u^I$  and  $W$  are independent.

(2)

$$\lim_{n \rightarrow \infty} P(X_n^I < \infty | Z_n > 1) = E \left[ \frac{\langle f^2, W \rangle}{\langle f, W \rangle^2} \right].$$

Note that  $N_u$  in (1.1) for a critical Galton-Watson process only takes positive integer values, while  $N_u^I$  in Theorem 1.1 can take value 0 with positive probability. In the special case  $\gamma = 1$ , the random number  $N_u^I + 1$  and  $N_u$  have the same distribution.

We conclude from [16, Theorem 3] (see Lemma 2.2) that  $Z_n$  diverges to infinity in probability as  $n \rightarrow \infty$ . Our second result says that as  $n \rightarrow \infty$ , the probability that all the particles of generation  $n$  have a common ancestor goes to 0.

**Theorem 1.2** Suppose Assumption 1 holds. Then

$$\lim_{n \rightarrow \infty} P(A_n^I < \infty | Z_n > 0) = 0.$$

## 2 Some preliminary results

Recall that  $(Y_n)_{n \geq 0}$  is a critical Galton-Watson process with offspring distribution  $(p_j)_{j \geq 0}$  starting with  $Y_0 = 1$ . The following result was proved in [4].

**Lemma 2.1** When  $m = 1$ ,  $p_1 < 1$ ,  $\sigma^2 = \sum_j (j^2 - j)p_j < \infty$ ,

$$\lim_{n \rightarrow \infty} nP(Y_n > 0) = \frac{2}{\sigma^2}, \quad (2.1)$$

and for any  $t > 0$ ,

$$\lim_{n \rightarrow \infty} P\left(\frac{Y_n}{n} > t | Y_n > 0\right) = e^{-\frac{2t}{\sigma^2}}. \quad (2.2)$$

The following result for critical GWPI is from [16, Theorem 3].

**Lemma 2.2** *Suppose Assumption 1 holds. Put  $\gamma = \frac{2\beta}{\sigma^2}$ . Then, as  $n \rightarrow \infty$ ,  $\frac{Z_n}{n}$  converges in distribution to a Gamma random variable with parameters  $(2/\sigma^2, \gamma)$ , whose density function is*

$$h(t) = \frac{2}{\sigma^2 \Gamma(\gamma)} \left( \frac{2t}{\sigma^2} \right)^{\gamma-1} e^{-\frac{2t}{\sigma^2}}, \quad t > 0. \quad (2.3)$$

The above lemma implies that  $\lim_{n \rightarrow \infty} P(Z_n > 0) = 1$ . The rate that  $1 - P(Z_n > 0)$  converges to 0 was investigated in [15].

From the construction (1.2) of the GWPI  $(Z_n)_{n \geq 0}$ , for any  $0 \leq k < n$ ,  $Z_n$  can be rewritten as

$$Z_n = \sum_{i=1}^{Z_k} Y_{n,k,i} + \sum_{j=k+1}^n \sum_{l=1}^{I_j} Y_{n-j,l}^{(j)}, \quad (2.4)$$

where  $Y_{n,k,i}$ ,  $i = 1, 2, \dots$ , are independent and have the same distribution as  $Y_{n-k}$ , and for  $0 \leq j \leq n$ ,  $Y_{n-j,l}^{(j)}$ ,  $l = 1, 2, \dots$ , are independent and have the same distribution as  $Y_{n-j}$ . Note that  $Y_{n,k,i}$  represents the number of descendants in generation  $n$  of the  $i$ th particle in generation  $k$ , and  $Y_{n-j,l}^{(j)}$  represents the number of descendants in generation  $n$  of the  $l$ th particle in the  $I_j$  immigrants in generation  $j$ . For any non-negative integer  $m$ , set  $(m)_2 = m(m-1)$ . Notice that  $(m)_2 = 0$  when  $m = 0$  or  $1$ . Starting from the representation (2.4), the distribution of the pairwise coalescence time  $X_n^I$ , given  $\{Z_n > 1\}$ , has the following expression.

**Lemma 2.3** *For any  $0 \leq k < n$ ,*

$$P(k \leq X_n^I < n | Z_n > 1) = E \left[ \frac{\sum_{i=1}^{Z_k} (Y_{n,k,i})_2 + \sum_{j=1+k}^{n-1} \sum_{l=1}^{I_j} (Y_{n-j,l}^{(j)})_2}{(Z_n)_2} \middle| Z_n > 1 \right],$$

*with the convention that the second term in the numerator equals 0 when  $k > n - 2$ . In particular,*

$$P(X_n^I < \infty | Z_n > 1) = E \left[ \frac{\sum_{j=0}^{n-1} \sum_{l=1}^{I_j} (Y_{n-j,l}^{(j)})_2}{(Z_n)_2} \middle| Z_n > 1 \right].$$

**Proof.** For  $0 \leq k < n$ , the event  $\{k \leq X_n^I < n\}$  occurs if and only if either the two randomly picked particles from generation  $n$  are both descendants of a particle in the  $k$ th generation, or they are both descendants of a particle immigrated into the system between generation  $k+1$  and generation  $n-1$ . The number of choices of the two particles from the descendants of the  $i$ th particle in generation  $k$  is  $(Y_{n,k,i})_2$ , and therefore the total number is  $\sum_{i=1}^{Z_k} (Y_{n,k,i})_2$  with the convention that the sum is 0 if  $Z_k = 0$ . The number of choices of the two particles from the descendants of the  $l$ th particle immigrated into the system in generation  $j$  for  $k+1 \leq j < n$  is  $(Y_{n-j,l}^{(j)})_2$ , and the total number is  $\sum_{j=k+1}^{n-1} \sum_{l=1}^{I_j} (Y_{n-j,l}^{(j)})_2$ . Also, the total number of choices of the two particles from the  $n$ th generation is  $(Z_n)_2$ . Thus for any  $n \geq 1$  and  $0 \leq k < n$ , conditional on  $\{Z_n > 1\}$ , the probability of  $\{k \leq X_n^I < n\}$  is given by

$$P(k \leq X_n^I < n | Z_n > 1) = E \left[ \frac{\sum_{i=1}^{Z_k} (Y_{n,k,i})_2 + \sum_{j=k+1}^{n-1} \sum_{l=1}^{I_j} (Y_{n-j,l}^{(j)})_2}{(Z_n)_2} \middle| Z_n > 1 \right].$$

Since  $Z_0 = I_0$ , we have  $Y_{n,0,i} = Y_{n,i}^{(0)}$ ,  $i = 1, \dots, I_0$ . Taking  $k = 0$  in the above identity, we obtain

$$P(X_n^I < \infty | Z_n > 1) = P(X_n^I < n | Z_n > 1) = E \left[ \frac{\sum_{j=0}^{n-1} \sum_{l=1}^{I_j} (Y_{n-j,l}^{(j)})^2}{(Z_n)_2} \middle| Z_n > 1 \right].$$

□

Let  $\mathcal{M}$  be the space of finite measures on  $[0, \infty)$  equipped with the topology of weak convergence. Let  $C_b[0, \infty)(C_b^+[0, \infty))$  be the space of bounded continuous (nonnegative bounded continuous) functions on  $[0, \infty)$ . Then for any  $g \in C_b[0, \infty)$ , the map  $\pi_g : \mu \rightarrow \langle g, \mu \rangle$  on  $\mathcal{M}$  is continuous. For random measures  $\eta_n, \eta \in \mathcal{M}$ ,  $n = 1, 2, \dots$ ,  $\eta_n$  converges to  $\eta$  in distribution as  $n \rightarrow \infty$  is equivalent to  $\langle g, \eta_n \rangle \xrightarrow{d} \langle g, \eta \rangle$  for all  $g \in C_b^+[0, \infty)$ . We refer the readers to [11, p.109] for more details. Let  $\mathcal{F}_k$  be the  $\sigma$ -algebra generated by  $\xi_{i,j}, i < k, j = 1, 2, \dots$ , and  $I_j, j = 0, 1, \dots, k$ . Then  $\mathcal{F}_k$  contains all information up to generation  $k$ . For  $k \geq 0$ , given  $\mathcal{F}_k$ ,  $(Y_{n,k,i})_{n \geq k}, i = 1, 2, \dots$ , are independent critical Galton-Watson processes with initial value 1 at generation  $k$ .

**Lemma 2.4** *Suppose Assumption 1 holds. If  $\frac{k}{n} \rightarrow u$  as  $n \rightarrow \infty$  for some  $u \in (0, 1)$ , then as  $n \rightarrow \infty$ , the random measure*

$$V_{n,k}(\cdot) = \sum_{i=1}^{Z_k} \mathbf{I}_{\{Y_{n,k,i} > 0\}} \delta_{\frac{Y_{n,k,i}}{n-k}}(\cdot) \in \mathcal{M}$$

*converges in distribution to the random measure  $V_u := \sum_{i=1}^{N_u^I} \delta_{\omega_i}(\cdot) \in \mathcal{M}$  with the convention that  $V_u = 0$  when  $N_u^I = 0$ , where  $(\omega_i)_{i \geq 1}$  are independent exponential random variables with parameter  $\frac{2}{\sigma^2}$ , and  $N_u^I \in \mathbb{N}$  is independent of  $(\omega_i)_{i \geq 1}$  with the law given by (1.5).*

**Proof.** Suppose  $g \in C_b^+[0, \infty)$ . For any  $0 \leq k < n$ , let

$$L_{n,k}(g) = \exp \{ -\langle g, V_{n,k} \rangle \} = \exp \left\{ - \sum_{i=1}^{Z_k} g\left(\frac{Y_{n,k,i}}{n-k}\right) \mathbf{I}_{\{Y_{n,k,i} > 0\}} \right\},$$

and set  $S_{n,k}g = E \left( \exp \left\{ -g\left(\frac{Y_{n-k}}{n-k}\right) \mathbf{I}_{\{Y_{n-k} > 0\}} \right\} \right)$ . Then we have

$$E[L_{n,k}(g) | \mathcal{F}_k] = E[L_{n,k}(g) | Z_k] = \left[ E \left( \exp \left\{ -g\left(\frac{Y_{n-k}}{n-k}\right) \mathbf{I}_{\{Y_{n-k} > 0\}} \right\} \right) \right]^{Z_k} = (S_{n,k}g)^{Z_k}.$$

Let  $q_n = P(Y_n > 0)$  be the survival probability of the process  $(Y_k)_{k \geq 0}$  in generation  $n$ . Then we have

$$\begin{aligned} S_{n,k}g &= E \left[ \exp \left\{ -g\left(\frac{Y_{n-k}}{n-k}\right) \right\} \middle| Y_{n-k} > 0 \right] q_{n-k} + (1 - q_{n-k}) \\ &= 1 - q_{n-k} \left[ 1 - E \left( \exp \left\{ -g\left(\frac{Y_{n-k}}{n-k}\right) \right\} \middle| Y_{n-k} > 0 \right) \right]. \end{aligned}$$

It follows from (2.2) that for any  $g \in C_b^+[0, \infty)$  and  $u \in (0, 1)$ ,

$$\lim_{n \rightarrow \infty, k/n \rightarrow u} E \left[ \exp \left\{ -g\left(\frac{Y_{n-k}}{n-k}\right) \right\} \middle| Y_{n-k} > 0 \right] = \frac{2}{\sigma^2} \int_0^\infty e^{-g(r)} e^{-\frac{2r}{\sigma^2}} dr =: L(g).$$

By the dominated convergence theorem for convergence in distribution, we have that

$$\begin{aligned}
\lim_{n \rightarrow \infty, k/n \rightarrow u} E[L_{n,k}(g)] &= \lim_{n \rightarrow \infty, k/n \rightarrow u} E[E(L_{n,k}(g) | \mathcal{F}_k)] = \lim_{n \rightarrow \infty, k/n \rightarrow u} E[(S_{n,k}g)^{Z_k}] \\
&= E \lim_{n \rightarrow \infty, k/n \rightarrow u} \left[ \left( 1 - q_{n-k} \left[ 1 - E \left( \exp \left\{ -g \left( \frac{Y_{n-k}}{n-k} \right) \right\} \middle| Y_{n-k} > 0 \right) \right] \right)^{Z_k} \right] \\
&= E \left[ \exp \left\{ - \lim_{n \rightarrow \infty, k/n \rightarrow u} Z_k q_{n-k} \left[ 1 - E \left( \exp \left\{ -g \left( \frac{Y_{n-k}}{n-k} \right) \right\} \middle| Y_{n-k} > 0 \right) \right] \right\} \right].
\end{aligned}$$

Then using (2.1) and Lemma 2.2, we obtain

$$\lim_{n \rightarrow \infty, k/n \rightarrow u} E[\exp \{-\langle g, V_{n,k} \rangle\}] = \lim_{n \rightarrow \infty, k/n \rightarrow u} E[L_{n,k}(g)] = E[\exp \{-\xi_u(1 - L(g))\}], \quad (2.5)$$

where  $\xi_u$  is a random variable having Gamma distribution with parameters  $\left(\frac{1-u}{u}, \gamma\right)$ . Then the Laplace transform of  $\xi_u$  is given by (c.f. [17, Example 2.15])

$$L_{\xi_u}(\lambda) = Ee^{-\lambda\xi_u} = \left(1 + \frac{u\lambda}{1-u}\right)^{-\gamma}, \quad \lambda > 0.$$

Therefore,

$$\begin{aligned}
E[\exp \{-\xi_u(1 - L(g))\}] &= \left[1 + \frac{u}{1-u}(1 - L(g))\right]^{-\gamma} = (1-u)^\gamma [1 - uL(g)]^{-\gamma} \\
&= \sum_{k=0}^{\infty} \frac{(-\gamma)(-\gamma-1)\cdots(-\gamma-k+1)}{k!} (1-u)^\gamma (-u)^k L(g)^k \\
&= Ee^{-\sum_{j=1}^{N_u^I} g(w_j)} = E[e^{-\langle g, V_u \rangle}].
\end{aligned}$$

In conclusion,  $V_{n,k}$  converges to  $V_u$  in distribution as  $n \rightarrow \infty, k/n \rightarrow u$ .  $\square$

For  $r > 0$ , put

$$f(r) = r, \quad g_1(r) = r \wedge r^{-1}, \quad g_2(r) = 1 \wedge r^2. \quad (2.6)$$

**Remark 2.5** Using the same argument as in the proof of Lemma 2.4 for the random measure

$$\tilde{V}_{n,k}(\cdot) := \sum_{i=1}^{Z_k} \mathbf{I}_{\{Y_{n,k,i} > 0\}} \left( 1 \vee \left( \frac{Y_{n,k,i}}{n-k} \right)^2 \right) \delta_{\frac{Y_{n,k,i}}{n-k}}(\cdot),$$

and using the fact that  $h(r) := (1 \vee r^2)$  is a continuous function on  $[0, \infty)$ , we obtain that

$$\tilde{V}_{n,k}(dr) \xrightarrow{d} (1 \vee r^2)V_u(dr) =: \tilde{V}_u(dr) \quad \text{in } \mathcal{M}.$$

Since  $g_1, g_2 \in C_b^+[0, \infty)$ ,  $\langle g_1, \tilde{V}_{n,k} \rangle = \langle f, V_{n,k} \rangle$  and  $\langle g_2, \tilde{V}_{n,k} \rangle = \langle f^2, V_{n,k} \rangle$ , we have

$$\begin{aligned}
(\langle f, V_{n,k} \rangle, \langle f^2, V_{n,k} \rangle) &= (\langle g_1, \tilde{V}_{n,k} \rangle, \langle g_2, \tilde{V}_{n,k} \rangle) \\
&\xrightarrow{d} (\langle g_1, \tilde{V}_u \rangle, \langle g_2, \tilde{V}_u \rangle) = (\langle f, V_u \rangle, \langle f^2, V_u \rangle) = \left( \sum_{k=1}^{N_u^I} \omega_k, \sum_{k=1}^{N_u^I} \omega_k^2 \right), \quad (2.7)
\end{aligned}$$

as  $n \rightarrow \infty, k/n \rightarrow u$  with  $u \in (0, 1)$ .

Define the birth time  $\tau_n$  of the oldest clan in generation  $n$  by

$$\tau_n = \inf \left\{ 0 \leq j \leq n; \sum_{l=1}^{I_j} Y_{n-j,l}^{(j)} > 0 \right\}$$

with the convention  $\inf \emptyset = +\infty$ . The birth time of the oldest clan for stationary continuous state branching processes is studied in [5, Corollary 4.2]. Using Lemma 2.4, it is easy to get the limit distribution of  $\tau_n$ . Recall that  $\gamma = 2\beta/\sigma^2$ .

**Corollary 2.6** *Suppose Assumption 1 holds. We have*

$$\lim_{n \rightarrow \infty, k/n \rightarrow u} P(\tau_n > k) = P(N_u^I = 0) = (1 - u)^\gamma, \quad 0 < u < 1.$$

**Proof.** The event  $\{\tau_n > k\}$  can be written as  $\{V_{n,k}(1) = 0\}$ . Thus

$$\lim_{n \rightarrow \infty, k/n \rightarrow u} P(\tau_n > k) = \lim_{n \rightarrow \infty, k/n \rightarrow u} P(V_{n,k}(1) = 0) = P(N_u^I = 0) = (1 - u)^\gamma.$$

□

Define a function  $w$  by

$$w(r) = r \vee r^2, \quad r \in (0, \infty). \quad (2.8)$$

We next consider the following random measures related to immigrations after generation  $k$ ,

$$W_{n,k}(\cdot) := \sum_{j=k+1}^n \sum_{l=1}^{I_j} \mathbf{I}_{\{Y_{n-j,l}^{(j)} > 0\}} w\left(\frac{Y_{n-j,l}^{(j)}}{n-k}\right) \delta_{\frac{Y_{n-j,l}^{(j)}}{n-k}}(\cdot), \quad n > k.$$

For each  $(n, k)$  with  $k < n$ , thanks to (2.4), we see that  $W_{n,k}(\cdot)$  has the same distribution as the random measure

$$\widetilde{W}_{n-k}(\cdot) := \sum_{j=0}^{n-k-1} \sum_{l=1}^{I_j} \mathbf{I}_{\{Y_{j,l} > 0\}} w\left(\frac{Y_{j,l}}{n-k}\right) \delta_{\frac{Y_{j,l}}{n-k}}(\cdot), \quad (2.9)$$

where  $Y_{j,l}, j \in \mathbb{N}, l = 1, 2, \dots$ , are independent and for each  $j$ ,  $Y_{j,l}, l = 1, 2, \dots$ , are identically distributed as  $Y_j$ , and where  $(Y_{j,l})_{j \geq 0, l \geq 1}$  are independent of the immigration process  $(I_j)_{j \geq 0}$ . By an argument very similar to that used in the proof of Lemma 2.4, we get the following convergence in distribution result for the random measures  $(W_{n,k})_{n \geq k}$ .

**Lemma 2.7** *Suppose Assumption 1 holds. Let  $\zeta$  be the random measure defined by*

$$\zeta(dr) = w(r)W(dr),$$

where  $W$  is a Poisson random measure with intensity  $\frac{\gamma}{r} e^{-\frac{2r}{\sigma^2}} dr$  on  $(0, \infty)$  and  $w$  is the function defined in (2.8). Then  $W_{n,k} \xrightarrow{d} \zeta$  in  $\mathcal{M}$  as  $n - k \rightarrow \infty$ .

**Proof.** Since  $W_{n,k} \stackrel{d}{=} \widetilde{W}_{n-k}$ , we have for  $g \in C_b^+[0, \infty)$ ,

$$E[\exp\{-\langle g, W_{n,k} \rangle\}] = E[\exp\{-\langle g, \widetilde{W}_{n-k} \rangle\}], \quad (2.10)$$

which means that we only need to consider the limit of the Laplace functional of  $\widetilde{W}_n$  as  $n \rightarrow \infty$ . For any  $g \in C_b^+[0, \infty)$ , put

$$T_{n,j}(g) = E\left[\exp\left\{-w\left(\frac{Y_j}{n}\right)g\left(\frac{Y_j}{n}\right)\mathbf{I}_{\{Y_j>0\}}\right\}\right], \quad j = 0, 1, \dots, n-1.$$

Then  $0 < T_{n,j}(g) < 1$ . By the definition (2.9) of  $\widetilde{W}_n$ ,

$$\exp\{-\langle g, \widetilde{W}_n \rangle\} = \exp\left\{-\sum_{j=0}^{n-1} \sum_{l=1}^{I_j} w\left(\frac{Y_{j,l}}{n}\right)g\left(\frac{Y_{j,l}}{n}\right)\mathbf{I}_{\{Y_{j,l}>0\}}\right\}.$$

The Laplace transform of  $\widetilde{W}_n$  can be written as

$$E[\exp\{-\langle g, \widetilde{W}_n \rangle\}] = \prod_{j=0}^{n-1} E[T_{n,j}(g)^{I_j}] = \prod_{j=0}^{n-1} B(T_{n,j}(g)) = \exp\left\{\sum_{j=0}^{n-1} \ln B(T_{n,j}(g))\right\}, \quad (2.11)$$

where  $B(s) = \sum_j b_j s^j$ ,  $|s| < 1$ , is the probability generating function of  $I_k$ ,  $k \geq 0$ . We claim that

$$\lim_{n \rightarrow \infty} \sum_{j=0}^{n-1} \ln B(T_{n,j}(g)) = \gamma \int_0^\infty (e^{-w(r)g(r)} - 1) \frac{1}{r} e^{-\frac{2r}{\sigma^2}} dr. \quad (2.12)$$

Suppose for the moment the claim is true. Then by (2.11), for any  $g \in C_b^+[0, \infty)$ ,

$$\lim_{n \rightarrow \infty} E[\exp\{-\langle g, \widetilde{W}_n \rangle\}] = \exp\left\{\gamma \int_0^\infty (e^{-w(r)g(r)} - 1) \frac{1}{r} e^{-\frac{2r}{\sigma^2}} dr\right\}.$$

And then using (2.10), we have

$$\lim_{n-k \rightarrow \infty} E[\exp\{-\langle g, W_{n,k} \rangle\}] = \exp\left\{\gamma \int_0^\infty (e^{-w(r)g(r)} - 1) \frac{1}{r} e^{-\frac{2r}{\sigma^2}} dr\right\}.$$

Since  $\int_0^\infty (w(r) \wedge 1) \frac{1}{r} e^{-\frac{2r}{\sigma^2}} dr < \infty$ , it follows from [11, Theorem 3.20] that there is an infinitely divisible random measure  $\zeta \in \mathcal{M}$  represented as  $\zeta(dr) = w(r)W(dr)$ ,  $r > 0$ , where  $W$  is a Poisson random measure with intensity  $\mathbf{I}_{\{r>0\}} \frac{\gamma}{r} e^{-\frac{2r}{\sigma^2}} dr$ . The Laplace functional of  $\zeta$  is given by

$$E[\exp\{-\langle g, \zeta \rangle\}] = \exp\left\{\gamma \int_0^\infty (e^{-w(r)g(r)} - 1) \frac{1}{r} e^{-\frac{2r}{\sigma^2}} dr\right\}, \quad \forall g \in C_b^+[0, \infty).$$

Thus  $W_{n,k} \xrightarrow{d} \zeta$  as  $n-k \rightarrow \infty$ .

Now we prove the claim (2.12). By the mean value theorem, there exists  $\xi_{n,j} \in (T_{n,j}(g), 1)$  such that

$$B(T_{n,j}(g)) - 1 = B'(\xi_{n,j})(T_{n,j}(g) - 1)$$



$$= \beta(T_{n,j}(g) - 1) + (B'(\xi_{n,j}) - \beta)(T_{n,j}(g) - 1). \quad (2.13)$$

Thanks to the inequality  $0 < 1 - e^{-x} \leq x$  for  $x > 0$  and the fact that  $\text{Var}(Y_j) = j\sigma^2$  (see [4, Section I.2]), we have that for  $0 \leq j \leq n-1$ ,

$$0 \leq 1 - T_{n,j}(g) \leq \|g\|_\infty E\left[w\left(\frac{Y_j}{n}\right)\right] \leq \|g\|_\infty E\left[\frac{Y_j}{n} + \left(\frac{Y_j}{n}\right)^2\right] \leq \frac{a\|g\|_\infty}{n}, \quad (2.14)$$

for some constant  $a > 0$ . Thus  $n(1 - T_{n,j}(g))$  is bounded for  $n > 0$  and  $j \leq n$ . Moreover from (2.1) and (2.2), it follows that for any  $0 < t < 1$ ,

$$\begin{aligned} \lim_{n \rightarrow \infty} n[1 - T_{n,[nt]}(g)] &= \lim_{n \rightarrow \infty} nP(Y_{[nt]} > 0)E\left[1 - \exp\left\{-w\left(\frac{Y_{[nt]}}{n}\right)g\left(\frac{Y_{[nt]}}{n}\right)\right\} \middle| Y_{[nt]} > 0\right] \\ &= \frac{4}{(\sigma^2)^2 t} \int_0^\infty \left(1 - e^{-w(rt)g(rt)}\right) e^{-\frac{2r}{\sigma^2}} dr. \end{aligned}$$

Then by the dominated convergence theorem,

$$\begin{aligned} \lim_{n \rightarrow \infty} \sum_{j=0}^{n-1} (T_{n,j}(g) - 1) &= \lim_{n \rightarrow \infty} \int_0^1 n(T_{n,[nt]}(g) - 1) dt \\ &= \int_0^1 \frac{4}{(\sigma^2)^2 t} dt \int_0^\infty (e^{-w(rt)g(rt)} - 1) e^{-\frac{2r}{\sigma^2}} dr \\ &= \frac{2}{\sigma^2} \int_0^\infty (e^{-w(r)g(r)} - 1) \frac{1}{r} e^{-\frac{2r}{\sigma^2}} dr. \end{aligned} \quad (2.15)$$

Using (2.14) and the continuity of  $B'(s)$  on  $[0, 1]$ , we get that  $B'(\xi_{n,j}) - \beta$  converges to 0 uniformly for  $0 \leq j \leq n$ , as  $n \rightarrow \infty$ . It has been shown in (2.15) that  $\sum_{j=0}^{n-1} |T_{n,j}(g) - 1|$  converges. Therefore,  $\sum_{j=0}^{n-1} (B'(\xi_{n,j}) - \beta)(T_{n,j}(g) - 1)$  converges to 0. Thus, by (2.13),  $\sum_{j=0}^{n-1} (B(T_{n,j}(g)) - 1)$  and  $\beta \sum_{j=0}^{n-1} (T_{n,j}(g) - 1)$  have the same limit. More precisely, from (2.15), it follows that

$$\begin{aligned} \lim_{n \rightarrow \infty} \sum_{j=0}^{n-1} (B(T_{n,j}(g)) - 1) &= \lim_{n \rightarrow \infty} \beta \sum_{j=0}^{n-1} (T_{n,j}(g) - 1) \\ &= \gamma \int_0^\infty (e^{-w(r)g(r)} - 1) \frac{1}{r} e^{-\frac{2r}{\sigma^2}} dr. \end{aligned}$$

Meanwhile, since  $-x \geq \ln(1 - x) \geq -x - \frac{x^2}{1 - x}$  for  $0 < x < 1$ , if

$$\lim_{n \rightarrow \infty} \sum_{j=0}^{n-1} \frac{[B(T_{n,j}(g)) - 1]^2}{B(T_{n,j}(g))} = 0, \quad (2.16)$$

then  $\sum_{j=0}^{n-1} \ln B(T_{n,j}(g))$  and  $\beta \sum_{j=0}^{n-1} (T_{n,j}(g) - 1)$  have the same limit as  $n \rightarrow \infty$ , and thus the claim is true. Now we prove (2.16). By (2.14), for any  $1/2 < \delta < 1$ , there is  $N > 0$ , such that for any  $n > N$ ,  $0 < j \leq n$ ,  $T_{n,j}(g) > \delta$ . Since  $B(s)$  is an increasing continuous function on  $[0, 1]$  and

$B(1) = 1$ , for any  $\varepsilon > 0$ , we can choose  $\delta$  above such that when  $1 > s > \delta$ ,  $B(s) > 1 - \varepsilon$ . Therefore when  $n > N$ ,

$$0 \leq \sum_{j=0}^{n-1} \frac{[B(T_{n,j}(g)) - 1]^2}{B(T_{n,j}(g))} \leq \frac{\varepsilon}{B(\frac{1}{2})} \sum_{j=0}^{n-1} [1 - B(T_{n,j}(g))].$$

Then (2.16) follows from the convergence of  $\sum_{j=0}^{n-1} [1 - B(T_{n,j}(g))]$  and the arbitrariness of  $\varepsilon$ .  $\square$

**Remark 2.8** (1) Let  $\tilde{g}_1(r) = 1 \wedge r^{-1}$ ,  $r > 0$  and  $\tilde{g}_2(r) = 1 \wedge r$ ,  $r > 0$ . Then  $\tilde{g}_1, \tilde{g}_2 \in C_b^+[0, \infty)$ . Thanks to Lemma 2.7 and the facts  $\tilde{g}_1(r)w(r) = r = f(r)$  and  $\tilde{g}_2(r)w(r) = r^2 = f^2(r)$  for  $r > 0$ , we get that

$$(\langle \tilde{g}_1, W_{n,k} \rangle, \langle \tilde{g}_2, W_{n,k} \rangle) \xrightarrow{d} (\langle \tilde{g}_1, \zeta \rangle, \langle \tilde{g}_2, \zeta \rangle) = (\langle f, W \rangle, \langle f^2, W \rangle), \quad \text{as } n - k \rightarrow \infty.$$

(2) We observe that

$$\frac{n-k}{n} [\langle f, V_{n,k} \rangle + \langle \tilde{g}_1, W_{n,k} \rangle] = \frac{Z_n}{n},$$

where  $f$  and  $\tilde{g}_1$  are defined as above. Since  $V_{n,k}$  and  $W_{n,k}$  are independent, from Lemma 2.4 and Lemma 2.7, it follows that for any  $\lambda > 0$ .

$$\begin{aligned} & \lim_{n \rightarrow \infty} E \left[ \exp \left\{ -\lambda \frac{Z_n}{n} \right\} \right] = \lim_{n \rightarrow \infty, k/n \rightarrow u} E \exp \left\{ -\lambda \frac{n-k}{n} (\langle f, V_{n,k} \rangle + \langle \tilde{g}_1, W_{n,k} \rangle) \right\} \\ &= \lim_{n \rightarrow \infty, k/n \rightarrow u} E \left[ \exp \left\{ -\lambda \frac{n-k}{n} \langle f, V_{n,k} \rangle \right\} \right] \lim_{n \rightarrow \infty, k/n \rightarrow u} E \left[ \exp \left\{ -\lambda \frac{n-k}{n} \langle \tilde{g}_1, W_{n,k} \rangle \right\} \right] \\ &= E[\exp\{-\lambda(1-u)\langle f, V_u \rangle\}] E[\exp\{-\lambda(1-u)\langle f, W \rangle\}] \\ &= \left( \frac{\lambda + \frac{2}{\sigma^2}}{\lambda(1-u) + \frac{2}{\sigma^2}} \right)^{-\gamma} \left( \frac{\lambda(1-u) + \frac{2}{\sigma^2}}{\frac{2}{\sigma^2}} \right)^{-\gamma} = \left( 1 + \frac{\lambda}{\frac{2}{\sigma^2}} \right)^{-\gamma}, \end{aligned}$$

where the last term is the Laplace transform of the Gamma distribution with parameters  $(\frac{2}{\sigma^2}, \gamma)$ . This is consistent with Lemma 2.2.

### 3 Proofs of the main results

**Proof of Theorem 1.1:** Let  $f$  be the function defined in (2.6), and let  $\tilde{g}_1, \tilde{g}_2$  be the functions defined in Remark 2.8(1). The random variable in Lemma 2.3 can be expressed in terms of the random measures defined in Section 2, and then we have

$$\frac{\sum_{i=1}^{Z_k} (Y_{n,k,i})_2 + \sum_{j=1+k}^{n-1} \sum_{l=1}^{I_j} (Y_{n-j,l}^{(j)})_2}{(Z_n)_2} = \frac{\langle f^2, V_{n,k} \rangle - \frac{1}{n-k} \langle f, V_{n,k} \rangle + \langle \tilde{g}_2, W_{n,k} \rangle - \frac{1}{n-k} \langle \tilde{g}_1, W_{n,k} \rangle}{[\langle f, V_{n,k} \rangle + \langle \tilde{g}_1, W_{n,k} \rangle]^2 - \frac{1}{n-k} [\langle f, V_{n,k} \rangle + \langle \tilde{g}_1, W_{n,k} \rangle]}.$$

Since  $(V_{n,k})_{n>k}$  and  $(W_{n,k})_{n>k}$  are independent and  $0 < \frac{\sum_{i=1}^{Z_k} (Y_{n,k,i})_2 + \sum_{j=1+k}^{n-1} \sum_{l=1}^{I_j} (Y_{n-j,l}^{(j)})_2}{(Z_n)_2} \leq$

1 is a bounded continuous function of  $(\langle f, V_{n,k} \rangle, \langle f^2, V_{n,k} \rangle, \langle \tilde{g}_1, W_{n,k} \rangle, \langle \tilde{g}_2, W_{n,k} \rangle)$ , according to Remark 2.5 and Remark 2.8, for  $u \in (0, 1)$ ,

$$\lim_{n \rightarrow \infty, k/n \rightarrow u} \frac{\langle f^2, V_{n,k} \rangle - \frac{1}{n-k} \langle f, V_{n,k} \rangle + \langle \tilde{g}_2, W_{n,k} \rangle - \frac{1}{n-k} \langle \tilde{g}_1, W_{n,k} \rangle}{[\langle f, V_{n,k} \rangle + \langle \tilde{g}_1, W_{n,k} \rangle]^2 - \frac{1}{n-k} [\langle f, V_{n,k} \rangle + \langle \tilde{g}_1, W_{n,k} \rangle]} = \frac{\langle f^2, V_u \rangle + \langle f^2, W \rangle}{[\langle f, V_u \rangle + \langle f, W \rangle]^2}$$

in distribution. It follows from Lemma 2.2 that  $\lim_{n \rightarrow \infty} P(Z_n > 1) = 1$ . The results of this theorem follow from Lemma 2.3.

**Proof of Theorem 1.2:** If all the particles in generation  $n$  have the same ancestor, then they must be descendants of one immigrant before generation  $n$ . Thus

$$\{A_n^I < \infty, Z_n > 0\} \subset \{Y_{n-j,l}^{(j)} = 0 \text{ for all but one pair } (j, l), 0 \leq j \leq n, 1 \leq l \leq I_j\}.$$

Then we only need to prove that the probability of the event on the right hand side converges to 0. Recall that  $q_n = P(Y_n > 0)$ . Set  $a_n = 1 - q_n = P(Y_n = 0)$ . Then

$$\begin{aligned} & P\left(Y_{n-j,l}^{(j)} = 0 \text{ for all but one pair } (j, l), 0 \leq j \leq n, 1 \leq l \leq I_j\right) \\ &= E\left[\sum_{j=0}^n \prod_{k \neq j} P(Y_{n-k} = 0)^{I_k} I_j P(Y_{n-j} = 0)^{I_j-1} P(Y_{n-j} > 0)\right] \\ &= \left[\prod_{k=0}^n B(a_k)\right] \left[\sum_{j=0}^n \frac{B'(a_j)}{B(a_j)} q_j\right], \end{aligned} \quad (3.1)$$

where  $B(a_0) = B(0) = b_0$  and  $B'(a_0) = B'(0) = b_1$ . From (2.1), we know  $q_k = 1 - a_k \sim \frac{2}{\sigma^2 k}$  as  $k \rightarrow \infty$ . In addition, since  $B(s) = 1 + \beta(s-1) + o(1-s)$  as  $s \rightarrow 1-$ ,

$$\lim_{j \rightarrow \infty} j(1 - B(a_j)) = \lim_{j \rightarrow \infty} \beta j(1 - a_j) + o(j(1 - a_j)) = \gamma > 0. \quad (3.2)$$

Therefore, there exists some  $N \in \mathbb{N}$ , such that when  $k \geq N$ ,  $k(1 - B(a_k)) > \gamma/2$ , which implies that  $B(a_k) < 1 - \frac{\gamma}{2k}$  for  $k \geq N$ . Noticing that  $B(a_k) \leq 1$ , the first factor on the right-hand side of (3.1) can be estimated as follows:

$$\prod_{j=0}^n B(a_j) \leq \prod_{j=N}^n B(a_j) \leq \prod_{j=N}^n \left(1 - \frac{\gamma}{2j}\right) = \exp\left\{\sum_{j=N}^n \ln\left(1 - \frac{\gamma}{2j}\right)\right\}, \quad n > N.$$

Since  $\ln(1-x) < -x$  for  $0 < x < 1$ , we have

$$\sum_{k=N}^n \ln\left(1 - \frac{\gamma}{2k}\right) \leq -\sum_{k=N}^n \frac{\gamma}{2k} \leq -L(\ln n - \ln N),$$

for some constant  $L > 0$ . As a result, there exists  $C_1 > 0$ , such that

$$\prod_{k=0}^n B(a_k) \leq C_1 \cdot n^{-L}. \quad (3.3)$$

Since  $a_k$  is nondecreasing in  $k$  and converges to 1 as  $k \rightarrow \infty$ , and  $B'(s)$  is a continuous function on  $[0, 1]$ ,

$$\lim_{j \rightarrow \infty} \frac{B'(a_j)}{B(a_j)} = B'(1) = \beta.$$

The the second factor on the right-hand side of (3.1) has the following upper bound:

$$\sum_{j=1}^n \frac{B'(a_j)}{B(a_j)} q_j \leq C_2 \sum_{j=1}^n q_j \leq C_3 \sum_{j=1}^n \frac{1}{j} \leq C_3(1 + \ln n), \quad (3.4)$$

for some positive constants  $C_2$  and  $C_3$ . Combining (3.3) and (3.4), we obtain

$$\lim_{n \rightarrow \infty} P\left(Y_{n-j,l}^{(j)} = 0 \text{ for all but one pair } (j, l), 0 \leq j \leq n, 1 \leq l \leq I_j\right) = 0.$$

We finish the proof.  $\square$

**Acknowledgment:** We thank the referees for very helpful comments and suggestions.

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