L log L CRITERION FOR A CLASS OF SUPERDIFFUSIONS

RONG-LI LIU*** AND
YAN-XIA REN,**** Perking University
RENMING SONG,**** University of Illinois

Abstract

In Lyons, Pemantle and Peres (1995), a martingale change of measure method was developed in order to give an alternative proof of the Kesten–Stigum $L \log L$ theorem for single-type branching processes. Later, this method was extended to prove the $L \log L$ theorem for multiple- and general multiple-type branching processes in Biggins and Kyprianou (2004), Kurtz *et al.* (1997), and Lyons (1997). In this paper we extend this method to a class of superdiffusions and establish a Kesten–Stigum $L \log L$ type theorem for superdiffusions. One of our main tools is a spine decomposition of superdiffusions, which is a modification of the one in Englander and Kyprianou (2004).

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1. Introduction and main result

Suppose that $\{Z_n, n \geq 1\}$ is a Galton–Watson branching process with each particle having probability p_n of giving birth to n children. Let L stand for a random variable with this offspring distribution. Let $m := \sum_{n=1}^{\infty} np_n$ be the mean number of children per particle. Then Z_n/m^n is a nonnegative martingale. Let W be the limit of Z_n/m^n as $n \to \infty$. Kesten and Stigum [8] proved that if $1 < m < \infty$ (that is, in the supercritical case) then W is nondegenerate (i.e. not almost surely zero) if and only if

$$E(L\log^+ L) = \sum_{n=1}^{\infty} p_n n \log n < \infty.$$

This result is usually referred to as the Kesten–Stigum $L \log L$ theorem. In [1], Asmussen and Hering generalized this result to the case of branching Markov processes under some conditions.

Lyons et al. [14] developed a martingale change of measure method in order to give an alternative proof of the Kesten–Stigum $L \log L$ theorem for single-type branching processes.

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**** Postal address: Department of Mathematics, University of Illinois, Urbana, IL 61801, USA.

Email address: rsong@math.uiuc.edu

^{*} Postal address: LMAM School of Mathematical Sciences, Peking University, Beijing, 100871, P. R. China.

^{**} Email address: lrl@math.pku.edu.cn

^{***} Email address: yxren@math.pku.edu.cn

Later, this method was extended to prove the $L \log L$ theorem for multiple- and general multiple-type branching processes in [2], [12], and [13].

In this paper we will extend this method to a class of superdiffusions and establish an $L \log L$ criterion for superdiffusions. To state our main result, we need to introduce the setup we are going to work with first.

Let a_{ij} , i, j = 1, ..., d, be bounded functions in $C^1(\mathbb{R}^d)$ such that all their first partial derivatives are bounded. We assume that the matrix (a_{ij}) is symmetric and satisfies

$$0 < a|v|^2 \le \sum_{i,j} a_{ij} v_i v_j$$
 for all $x \in \mathbb{R}^d$ and $v \in \mathbb{R}^d$

for some positive constant a. Let b_i , i = 1, ..., d, be bounded Borel functions on \mathbb{R}^d .

We will use $(Y, \Pi_x, x \in \mathbb{R}^d)$ to denote a diffusion process on \mathbb{R}^d corresponding to the operator

$$L = \frac{1}{2}\nabla \cdot a\nabla + b \cdot \nabla.$$

In this paper we will always assume that β is a bounded Borel function on \mathbb{R}^d and that D is a bounded domain in \mathbb{R}^d . We will use $(Y^D, \Pi_x, x \in D)$ to denote the process obtained by killing Y upon exiting from D, that is,

$$Y_t^D = \begin{cases} Y_t & \text{if } t < \tau, \\ \partial & \text{if } t \ge \tau, \end{cases}$$

where $\tau = \inf\{t \ge 0 : Y_t \notin D\}$ is the first exit time of D and ∂ is a cemetery point. Any function f on D is automatically extended to $D \cup \{\partial\}$ by setting $f(\partial) = 0$. For convenience, we use the following convention throughout this paper. For any probability measure P, we also use P to denote the expectation with respect to P. When there is only one probability measure involved, we sometimes also use P to denote the expectation with respect to that measure.

We will use $\{P_t\}_{t>0}$ to denote the following Feynman–Kac semigroup:

$$P_t f(x) = \Pi_x \left(\exp \left\{ \int_0^t \beta(Y_s^D) \, \mathrm{d}s \right\} f(Y_t^D) \right), \qquad x \in D.$$

It is well known that the semigroup $\{P_t\}_{t\geq 0}$ is strongly continuous in $L^2(D)$ and, for any t>0, P_t has a bounded, continuous, and strictly positive density p(t, x, y).

Let $\{\widehat{P}_t\}_{t\geq 0}$ be the dual semigroup of $\{P_t\}_{t\geq 0}$ defined by

$$\widehat{P}_t f(x) = \int_D p(t, y, x) f(y) \, \mathrm{d}y, \qquad x \in D.$$

It is well known that $\{\widehat{P}_t\}_{t\geq 0}$ is also strongly continuous on $L^2(D)$.

Let A and \widehat{A} be the generators of the semigroups $\{P_t\}_{t\geq 0}$ and $\{\widehat{P}_t\}_{t\geq 0}$ on $L^2(D)$, respectively. We can formally write A as $L|_D+\beta$, where $L|_D$ is the restriction of L to D with Dirichlet boundary condition. Let $\sigma(A)$ and $\sigma(\widehat{A})$ respectively denote the spectrum of A and \widehat{A} . It follows from Jentzsch's theorem [16, Theorem V.6.6, p. 337] and the strong continuity of $\{P_t\}_{t\geq 0}$ and $\{\widehat{P}_t\}_{t\geq 0}$ that the common value $\lambda_1:=\sup \operatorname{Re}(\sigma(A))=\sup \operatorname{Re}(\sigma(\widehat{A}))$ is an eigenvalue of multiplicity 1 for both A and \widehat{A} , and that an eigenfunction ϕ of A associated with λ_1 can be chosen to be strictly positive almost everywhere (a.e.) on D and an eigenfunction $\widehat{\phi}$ of \widehat{A} associated with λ_1 can be chosen to be strictly positive a.e. on D. We assume that ϕ and $\widehat{\phi}$

are strictly positive a.e. on D. By [9, Proposition 2.3] we know that ϕ and $\widetilde{\phi}$ are bounded and continuous on D, and they are in fact strictly positive everywhere on D. We choose ϕ and $\widetilde{\phi}$ so that $\int_D \phi(x)\widetilde{\phi}(x) \, \mathrm{d}x = 1$.

Throughout this paper, we make the following assumptions.

Assumption 1.1. $\lambda_1 > 0$.

Assumption 1.2. The semigroups $\{P_t\}_{t\geq 0}$ and $\{\widehat{P}_t\}_{t\geq 0}$ are intrinsic ultracontractive, that is, for any t>0, there exists a constant $c_t>0$ such that

$$p(t, x, y) \le c_t \phi(x) \widetilde{\phi}(y)$$
 for all $(x, y) \in D \times D$.

Assumption 1.2 is a very weak regularity assumption on D. It follows from [9] and [10] that Assumption 1.2 is satisfied when D is a bounded Lipshitz domain. For other, more general, examples of domain D for which Assumption 1.2 is satisfied, we refer the reader to [10] and the references therein.

Let $\mathcal{E}_t = \sigma(Y_s^D, s \leq t)$. For any $x \in D$, we define a probability measure Π_x^{ϕ} by the martingale change of measure:

$$\frac{\mathrm{d}\Pi_x^{\phi}}{\mathrm{d}\Pi_x}\bigg|_{\mathcal{E}} = \frac{\phi(Y_t^D)}{\phi(x)} \exp\bigg\{-\int_0^{t\wedge\tau} (\lambda_1 - \beta(Y_s)) \,\mathrm{d}s\bigg\}.$$

The process (Y^D, Π_x^{ϕ}) is an ergodic Markov process and its transition density is given by

$$p^{\phi}(t, x, y) = \frac{\exp\{-\lambda_1 t\}}{\phi(x)} p(t, x, y)\phi(y).$$

The function $\phi \widetilde{\phi}$ is the unique invariant density for the process (Y^D, Π_x^{ϕ}) .

By our choices for ϕ and $\widetilde{\phi}$, $\int_D \phi(x)\widetilde{\phi}(x) dx = 1$. Thus, it follows from [9, Theorem 2.8] that

$$\left| \frac{\exp\{-\lambda_1 t\} p(t, x, y)}{\phi(x)\widetilde{\phi}(y)} - 1 \right| \le c e^{-\nu t}, \qquad x \in D,$$

for some positive constants c and v, which is equivalent to

$$\sup_{x \in D} \left| \frac{p^{\phi}(t, x, y)}{\phi(y)\widetilde{\phi}(y)} - 1 \right| \le c e^{-\nu t}.$$

Thus, for any $f \in L^{\infty}_{+}(D)$, we have

$$\sup_{x \in D} \left| \int_{D} p^{\phi}(t, x, y) f(y) \, \mathrm{d}y - \int_{D} \phi(y) \widetilde{\phi}(y) f(y) \, \mathrm{d}y \right| \le c \mathrm{e}^{-\nu t} \int_{D} \phi(y) \widetilde{\phi}(y) f(y) \, \mathrm{d}y.$$

Consequently, we have

$$\lim_{t \to \infty} \sup_{x \in D} \sup_{f \in L_{+}^{\infty}(D)} \left(\int_{D} \phi(y) \widetilde{\phi}(y) f(y) \, \mathrm{d}y \right)^{-1}$$

$$\times \left| \int_{D} p^{\phi}(t, x, y) f(y) \, \mathrm{d}y - \int_{D} \phi(y) \widetilde{\phi}(y) f(y) \, \mathrm{d}y \right|$$

$$= 0,$$

which is equivalent to

$$\lim_{t \to \infty} \frac{\int_D p^{\phi}(t, x, y) f(y) \, \mathrm{d}y}{\int_D \phi(y) \widetilde{\phi}(y) f(y) \, \mathrm{d}y} = 1 \quad \text{uniformly for } f \in L^{\infty}(D)_+ \text{ and } x \in D.$$
 (1.1)

For any finite Borel measure μ on D, we define a probability measure $\Pi^{\phi}_{\phi\mu}$ as follows:

$$\Pi_{\phi\mu}^{\phi} = \int_{D} \mu(\mathrm{d}x) \frac{\phi(x)}{\langle \phi, \mu \rangle} \Pi_{x}^{\phi}.$$

Note that, for any $A \in \mathcal{E}_t$,

$$\Pi^{\phi}_{\phi\mu}(A) = \frac{1}{\langle \phi, \mu \rangle} \Pi_{\mu} \bigg(\phi(Y_t^D) \exp \bigg\{ - \int_0^{t \wedge \tau} (\lambda_1 - \beta(Y_s)) \, \mathrm{d}s \bigg\} \, \mathbf{1}_A \bigg).$$

The superdiffusion X we are going to study is a $(Y, \psi(\lambda) - \beta\lambda)$ -superprocess, which is a measure-valued Markov process with underlying spatial motion Y, branching rate dt, and branching mechanism $\psi(\lambda) - \beta\lambda$, where

$$\psi(x,\lambda) = \int_0^\infty (e^{-r\lambda} - 1 + \lambda r) n(x, dr)$$

for some σ -finite kernel n from $(\mathbb{R}^d, \mathcal{B}(\mathbb{R}^d))$ to $(\mathbb{R}_+, \mathcal{B}(\mathbb{R}_+))$, that is, n(x, dr) is a σ -finite measure on \mathbb{R}_+ for each fixed x, and $n(\cdot, A)$ is a measurable function for each Borel set $A \subset \mathbb{R}_+$. In this paper we will always assume that $\sup_{x \in D} \int_0^\infty (r \wedge r^2) n(x, dr) < \infty$. Note that this assumption implies that, for fixed $\lambda > 0$, $\psi(\cdot, \lambda)$ is bounded on D.

Let $(Y, \Pi_{r,x})$ denote a diffusion with generator L, birth time r, and starting point x. For any $\mu \in M_F(D)$, the family of all finite Borel measures on D, we will use $(X, P_{r,\mu})$ to denote a $(Y, \psi(\lambda) - \beta\lambda)$ -superprocess with starting time r such that $P_{r,\mu}(X_r = \mu) = 1$. We will simply denote $(X, P_{0,\mu})$ as (X, P_{μ}) . Let $X^{t,D}$ be the exit measure from $[0, t) \times D$, and let $\partial^{t,D}$ be the union of $(0, t) \times \partial D$ and $\{t\} \times D$.

Define $\phi^t : [0, t] \times \overline{D} \to [0, \infty)$ for each fixed $t \ge 0$, such that $\phi^t(u, x) = \phi(x)$ for $(u, x) \in [0, t] \times D$ and $\phi^t(u, x) = 0$ for $(u, x) \in [0, t] \times \partial D$. In particular, we extend ϕ to \overline{D} by setting it to be 0 on the boundary. Then

$$\{M_t(\phi) := \exp\{-\lambda_1 t\} \langle \phi^t, X^{t,D} \rangle, \ t \ge 0\}$$
(1.2)

is a P_{μ} -martingale with respect to $\mathcal{F}_t := \sigma(X^{s,D}, s \leq t)$ (see Lemma 2.1, below) and $P_{\mu}(M_t(\phi)) = \langle \phi, \mu \rangle, t \geq 0$. It is easy to check that $\{M_t(\phi), t \geq 0\}$ is a multiplicative functional of $X^{t,D}$.

To state our main result, we first define a new kernel $n^{\phi}(x, dr)$ from $(D, \mathcal{B}(D))$ to $(\mathbb{R}_+, \mathcal{B}(\mathbb{R}_+))$ such that, for any nonnegative measurable function f on \mathbb{R}_+ ,

$$\int_0^\infty f(r)n^{\phi}(x,\mathrm{d}r) = \int_0^\infty f(r\phi(x))n(x,\mathrm{d}r), \qquad x \in D.$$

The following theorem is the main result of the paper.

Theorem 1.1. Suppose that (X_t) is a $(Y, \psi(\lambda) - \beta\lambda)$ -superdiffusion starting from time 0 and with initial value μ . Set

$$l(y) := \int_{1}^{\infty} r \log r n^{\phi}(y, dr).$$

- 1. If $\int_D \widetilde{\phi}(y) l(y) dy < \infty$ then $M_{\infty}(\phi)$ is nondegenerate under P_{μ} for any $\mu \in M_F(D)$.
- 2. If $\int_D \widetilde{\phi}(y) l(y) dy = \infty$ then $M_{\infty}(\phi)$ is degenerate for any $\mu \in M_F(D)$.

The proof of this theorem is accomplished by combining the ideas from [14] with the 'spine decomposition' of [5]. The new feature here is that we consider a different branching mechanism. The new branching mechanism considered here is essential. With this branching mechanism, we can establish a strong (that is, almost-sure) version of the spine decomposition, as opposed to the weak (that is, in distribution) version in [5]. The reason is that the branching mechanism we consider here results in *discrete* immigration points, as opposed to the quadratic branching case where immigration is continuous in time.

In the next section we first give a spine decomposition of the superdiffusion *X* under a martingale change of measure with the help of Poisson point processes. Then, in Section 3 we use this decomposition to give a proof of Theorem 1.1.

2. Decomposition of superdiffusions under the martingale change of measure

Let $\mathcal{F}_t = \sigma(X^{s,D}, \ s \le t)$. We define a probability measure \widetilde{P}_{μ} by the martingale change of measure:

$$\left. \frac{\mathrm{d}\widetilde{\mathrm{P}}_{\mu}}{\mathrm{d}\mathrm{P}_{\mu}} \right|_{\mathcal{F}_t} = \frac{1}{\langle \phi, \mu \rangle} M_t(\phi).$$

The purpose of this section is to give a spine decomposition of X under \widetilde{P}_{μ} .

The most important step in proving Theorem 1.1 is a decomposition of X under \widetilde{P}_{μ} . We could decompose X under \widetilde{P}_{μ} as the sum of two independent measure-valued processes. The first process is a copy of X under P_{μ} . The second process is, roughly speaking, obtained by taking an 'immortal particle' that moves according to the law of Y under $\Pi^{\phi}_{\phi\mu}$ and spins off pieces of mass that continue to evolve according to the dynamics of X.

To give a rigorous description of this decomposition of X under \widetilde{P}_{μ} , let us first recall some results on Poisson point processes. Let (S, \mathcal{S}) be a measurable space. We will use \mathcal{M} to denote the family of σ -finite counting measures on (S, \mathcal{S}) and $\mathcal{B}(\mathcal{M})$ to denote the smallest σ -field on \mathcal{M} with respect to which all $\nu \in \mathcal{M} \mapsto \nu(B) \in \mathbb{Z}^+ \cup \{\infty\}$, $B \in \mathcal{S}$, are measurable. For any σ -finite measure $\widehat{\mathcal{N}}$ on \mathcal{S} , we call an $(\mathcal{M}, \mathcal{B}(\mathcal{M}))$ -valued random variable ξ a Poisson random measure with intensity $\widehat{\mathcal{N}}$ if

- (a) for each $B \in \mathcal{S}$ with $\widehat{N}(B) < \infty, \xi(B)$ has a Poisson distribution with parameter $\widehat{N}(B)$;
- (b) for $B_1, \ldots, B_n \in \mathcal{S}$ disjoint, the variables $\xi(B_1), \ldots, \xi(B_n)$ are independent.

Suppose that \widehat{N} is a σ -finite measure on $(0, \infty) \times S$, if $e = (e(t), t \ge 0)$ is a process taking values in $S \cup \{\Upsilon\}$, where Υ is an isolated additional point and $e(0) = \Upsilon$, such that the random counting measure $\xi = \sum_{t \ge 0} \delta_{(t,e(t))}$ is a Poisson random measure on $(0, \infty) \times S$ with intensity \widehat{N} , then e is called a Poisson point process with compensator \widehat{N} . If, for every t > 0, $\widehat{N}((0,t] \times S) < \infty$ then e can also be expressed as $e = (((\sigma_i,e_i), i=1,\ldots,N_t), t \ge 0)$, where $e_i = e(\sigma_i)$ and N_t is a Poisson process with instant intensity $\widehat{N}(\mathrm{d}t \times S)$. The following proposition follows easily from [15, Proposition 19.5].

Proposition 2.1. Suppose that $e = (e(t), t \ge 0)$ is a Poisson point process with compensator \widehat{N} . Let f be a nonnegative Borel function on $(S \cup \{\Upsilon\}) \times [0, \infty)$ with $f(\Upsilon, t) = 0$ for

all t > 0. If $\int_{(0,t)} \int_{S} |1 - e^{-f(x,s)}| \widehat{N}(ds, dx) < \infty$ for all t > 0 then

$$\mathbb{E}\bigg(\exp\bigg\{-\sum_{0\leq s\leq t}f(e(s),s)\bigg\}\bigg)=\exp\bigg\{-\int_0^t\int_S(1-\mathrm{e}^{-f(x,s)})\widehat{N}(\mathrm{d} s,\mathrm{d} x)\bigg\}.$$

Moreover, if $\int_0^\infty \int_S f(s, x) \widehat{N}(ds, dx) < \infty$ then

$$E\left(\int_0^\infty \int_{\mathcal{S}} f(x,s)N(\mathrm{d}s,\mathrm{d}x)\right) = \int_0^\infty \int_{\mathcal{S}} f(x,s)\widehat{N}(\mathrm{d}s,\mathrm{d}x). \tag{2.1}$$

To give a formula for the one-dimensional distribution of the exit measure process under \widetilde{P}_{μ} , we recall some results from [4] first.

According to [4], for any nonnegative bounded continuous function $f: \partial^{t,D} \to \mathbb{R}$, we have

$$P_{r,\mu}(\exp\langle -f, X^{t,D} \rangle) = \exp\langle -U^t(f)(r, \cdot), \mu \rangle, \tag{2.2}$$

where $U^{t}(f)$ denotes the unique nonnegative solution to

$$-\frac{\partial U(s,x)}{\partial s} = LU + \beta U(s,x) - \psi(U(s,x)), \qquad x \in D, \ s \in (0, t),$$

$$U = f \quad \text{on } \partial^{t,D}.$$
(2.3)

More precisely, $U^{t}(f)$ satisfies the following integral equation:

$$U^{t}(f)(r,x) + \Pi_{r,x} \int_{r}^{t \wedge \tau_{r}} [\psi(U^{t}(f))(s, Y_{s}) - \beta(Y_{s})U^{t}(f)(s, Y_{s})] ds$$

$$= \Pi_{r,x} f(t \wedge \tau_{r}, Y_{t \wedge \tau_{r}}), \qquad r \leq t, x \in D,$$
(2.4)

where $\tau_r = \inf\{t \ge r \colon X_t \notin D\}$. Since Y is a time-homogeneous process, we find that $X^{t,D}$ under $P_{r,\mu}$ has the same distribution as $X^{t-r,D}$ under P_{μ} . The first moment of $\langle f, X^{t,D} \rangle$ is given by

$$P_{r,x}\langle f, X^{t,D}\rangle = \Pi_{r,x}\bigg(f(t \wedge \tau_r, Y_{t \wedge \tau_r}) \exp\bigg\{\int_r^{t \wedge \tau_r} \beta(Y_s) \,\mathrm{d}s\bigg\}\bigg). \tag{2.5}$$

Lemma 2.1. $\{M_t(\phi), t \geq 0\}$ is a P_{μ} -martingale with respect to \mathcal{F}_t .

Proof. It follows from the first moment formula (2.5) that

$$P_{r,x}\langle \phi^t, X^{t,D} \rangle = \Pi_{r,x} \left(\phi(Y_t) \exp \left\{ \int_r^t \beta(Y_s) \, \mathrm{d}s \right\}, \ t < \tau_r \right)$$
$$= P_{t-r} \phi(x) \quad \text{for } r \le t, \ x \in D.$$

It is obvious that $P_{r,x}\langle \phi^t, X^{t,D}\rangle = 0$ for $x \in \partial D$. By the special Markov property of X and the invariance of ϕ under $\exp\{-\lambda_1 t\} P_t$,

$$\begin{aligned} P_{\mu}(M_{t}(\phi) \mid \mathcal{F}_{s}) &= \exp\{-\lambda_{1}s\} P_{X^{s,D}}(\exp\{-\lambda_{1}(t-s)\}\langle \phi^{t}, X^{t,D}\rangle) \\ &= \exp\{-\lambda_{1}s\}\langle \exp\{-\lambda_{1}(t-s)\} P_{t-s} \phi, X^{s,D}|_{D}\rangle \\ &= \exp\{-\lambda_{1}s\}\langle \phi^{s}, X^{s,D}\rangle \\ &= M_{s}(\phi) \quad \text{for } s \leq t, \end{aligned}$$

where $X^{s,D}|_D$ is the restriction of the measure $X^{s,D}$ on $\{s\} \times D$.

Now we give a formula for the one-dimensional distribution of X under \widetilde{P}_{μ} .

Theorem 2.1. Suppose that μ is a finite measure on D and that $g \in C_h^+(\partial^{t,D})$. Then

$$\widetilde{P}_{\mu}(\exp\langle -g, X^{t,D} \rangle) = P_{\mu}(\exp\langle -g, X^{t,D} \rangle)
\times \Pi^{\phi}_{\phi\mu} \left(\exp\left\{ -\int_{0}^{t \wedge \tau} \psi'(Y_{s}, U^{t}(g)(s, Y_{s})) \, \mathrm{d}s \right\} \right),$$
(2.6)

where $U^{t}(g)$ is the unique solution of (2.3) or, equivalently, (2.4) with f replaced by g.

Proof. This theorem can be proved using the same argument as that given in [5] to obtain Theorem 5 therein, with some obvious modifications. We omit the details.

From (2.6) we can see that the superprocess $(X^{t,D}, \widetilde{P}_{\mu})$ can be decomposed into two independent parts in the sense of distributions. The first part is a copy of the original superprocess and the second part is an immigration process. To explain the second part more precisely, we need to introduce another measure-valued process (\widehat{X}_t) . Now we construct the measure-valued process (\widehat{X}_t) as follows.

- (a) Suppose that $\widetilde{Y}=(\widetilde{Y}_t,\ t\geq 0)$ is defined on some probability space $(\Omega, P_{\mu,\phi})$ and that $\widetilde{Y}=(\widetilde{Y}_t,\ t\geq 0)$ has the same law as $(Y,\Pi^\phi_{\phi\mu})$. Here \widetilde{Y} serves as the spine or the immortal particle, which visits every part of D for large times since it is an ergodic diffusion.
- (b) Suppose that $m = \{m_t, t \geq 0\}$ is a point process taking values in $(0, \infty) \cup \{\Upsilon\}$ such that, conditional on $\sigma(\widetilde{Y}_t, t \geq 0)$, m is a Poisson point process with intensity $rn(\widetilde{Y}_t, dr)$. Now $(0, \infty)$ is the 'space of mass' and $m_t = \Upsilon$ simply means that there is no immigration at t. We suppose that $\{m_t, t \geq 0\}$ is also defined on $(\Omega, P_{\mu,\phi})$. Set $\mathcal{D}_m = \{t : m_t(\omega) \neq \Upsilon\}$. Note that \mathcal{D}_m is almost surely (a.s.) countable. The process m describes the immigration mechanism: along the path of \widetilde{Y} , at the moment $t \in \mathcal{D}_m$, a particle with mass m_t is immigrated into the system at the position \widetilde{Y}_t .
- (c) Once the particles are in the system, they begin to move and branch according to a $(Y, \psi(\lambda) \beta\lambda)$ -superprocess independently.

We use $(X_t^{\sigma}, t \geq \sigma)$ to denote the measure-valued process generated by the mass immigrated at time σ and position \widetilde{Y}_{σ} . Conditional on $\{\widetilde{Y}_t, m_t, t \geq 0\}$, $\{X^{\sigma}, \sigma \in \mathcal{D}_m\}$ are independent $(Y, \psi - \beta \lambda)$ -superprocesses. The birth time of X^{σ} is σ and the initial value of X^{σ} is $m_{\sigma} \delta_{\widetilde{Y}_{-}}$. Set

$$\widehat{X}^{t,D} = \sum_{\sigma \in (0,t] \cap \mathcal{D}_m} X^{\sigma,(t,D)},$$

where, for each $\sigma \in \mathcal{D}_m$, $X^{\sigma,(t,D)}$ is the exit measure of the superprocess X^{σ} from $[0,t) \times D$. The Laplace functional of $\widehat{X}^{t,D}$ is described in the following proposition.

Proposition 2.2. The Laplace functional of $\widehat{X}^{t,D}$ under $P_{\mu,\phi}$ is

$$\Pi_{\phi\mu}^{\phi}\left(\exp\left\{-\int_{0}^{t}\psi'(Y_{s},U^{t}(g)(Y_{s},s))\,\mathrm{d}s\right\}\right).$$

Proof. For any $g \in C_h^+(\partial^{t,D})$, using (2.2), we have

$$\begin{split} \mathbf{P}_{\mu,\phi}(\exp\{-\langle g,\widehat{X}^{t,D}\rangle\}) &= \mathbf{P}_{\mu,\phi}\bigg(\mathbf{P}_{\mu,\phi}\bigg(\exp\Big\{-\sum_{\sigma\in(0,t]\cap\mathcal{D}_m}\langle g,X^{\sigma,(t,D)}\rangle\Big\}\ \bigg|\ \widetilde{Y},\sigma,m\bigg)\bigg) \\ &= \mathbf{P}_{\mu,\phi}\bigg(\prod_{\sigma\in(0,t]\cap\mathcal{D}_m}\exp\{-m_\sigma U^t(g)(\widetilde{Y}_\sigma,\sigma)\}\bigg) \\ &= \mathbf{P}_{\mu,\phi}\bigg(\mathbf{P}_{\mu,\phi}\bigg(\exp\Big\{-\sum_{\sigma\in[0,t]\cap\mathcal{D}_m}m_\sigma U^t(g)(\widetilde{Y}_\sigma,\sigma)\Big\}\ \bigg|\ \widetilde{Y}\bigg)\bigg). \end{split}$$

Using Proposition 2.1, we obtain

$$\begin{split} & P_{\mu,\phi}(\exp\{-\langle g,\widehat{X}^{t,D}\rangle\}) \\ & = \Pi_{\phi\mu}^{\phi} \exp\left\{-\int_{0}^{t} \int_{0}^{\infty} (1 - \exp\{-rU^{t}(g)(Y_{s},s)\}) rn(Y_{s},\mathrm{d}r) \,\mathrm{d}s\right\} \\ & = \Pi_{\phi\mu}^{\phi} \bigg(\exp\left\{-\int_{0}^{t} \psi'(Y_{s},U^{t}(g)(s,Y_{s})) \,\mathrm{d}s\right\} \bigg). \end{split}$$

Without loss of generality, we suppose that $(X_t, t \ge 0; P_{\mu,\phi})$ is a superdiffusion defined on $(\Omega, P_{\mu,\phi})$, equivalent to $(X_t, t \ge 0; P_{\mu})$ and independent of \widehat{X} . Proposition 2.2 says that we have the following decomposition of $X^{t,D}$ under \widehat{P}_{μ} : for any t > 0,

$$(X^{t,D}, \widetilde{\mathbf{P}}_{\mu}) = (X^{t,D} + \widehat{X}^{t,D}, \mathbf{P}_{\mu,\phi})$$
 in distribution, (2.7)

where $X^{t,D}$ is the exit measure of X from $[0,t)\times D$. Since $(X_t,\,t\geq0;\,\widetilde{P}_\mu)$ is generated from the time-homogeneous Markov process $(X_t,\,t\geq0;\,P_\mu)$ via a nonnegative martingale multiplicative functional, $(X_t,\,t\geq0;\,\widetilde{P}_\mu)$ is also a time-homogeneous Markov process (see [17, Section 62]). From the construction of $(\widehat{X}^{t,D},\,t\geq0;\,P_{\mu,\phi})$ we see that $(\widehat{X}^{t,D},\,t\geq0;\,P_{\mu,\phi})$ is a time-homogeneous Markov process. For a rigorous proof of $(\widehat{X}^{t,D},\,t\geq0;\,P_{\mu,\phi})$ being a time-homogeneous Markov process, we refer the reader to [6]. Although [6] dealt with the representation of the superprocess conditioned to stay alive forever, we can check that the arguments there work in our case. Therefore, (2.7) implies that

$$(X^{t,D}, t \ge 0; \widetilde{P}_{\mu}) = (X^{t,D} + \widehat{X}^{t,D}, t \ge 0; P_{\mu,\phi})$$
 in distribution.

3. Proof of Theorem 1.1

To prove Theorem 1.1, we need some preparations. The following elementary result is taken from [3].

Lemma 3.1. ([3, Exercise 1.3.8].) Let $Y \ge 0$ with $E(Y) < \infty$, and let $0 \le a < E(Y)$. Then

$$P(Y > a) \ge \frac{(E(Y) - a)^2}{E(Y^2)}.$$

Proposition 3.1. Set $h(x) = P_{\delta_x}(M_{\infty}(\phi))/\phi(x)$.

- 1. h is nonnegative and invariant for the process (Y^D, Π_x^{ϕ}) .
- 2. Either M_{∞} is nondegenerate under P_{μ} for all $\mu \in M_F(D)$ or M_{∞} is degenerate under P_{μ} for all $\mu \in M_F(D)$.

Proof. 1. Since $\phi^t(\cdot, u) = \phi(\cdot)$ for each $u \in [0, t]$ and ϕ is identically 0 on ∂D , we have, by the special Markov property of X,

$$\begin{split} h(x) &= \frac{1}{\phi(x)} \operatorname{P}_{\delta_{x}} \left(\lim_{s \to \infty} \langle \exp\{-\lambda_{1}(t+s)\} \phi^{t+s}, X^{t+s,D} \rangle \right) \\ &= \frac{\exp\{-\lambda_{1}t\}}{\phi(x)} \operatorname{P}_{\delta_{x}} \left(\operatorname{P}_{X^{t,D}} \left(\lim_{s \to \infty} \langle \exp\{-\lambda_{1}s\} \phi^{s}, X^{s,D} \rangle \right) \right) \\ &= \frac{\exp\{-\lambda_{1}t\}}{\phi(x)} \operatorname{P}_{\delta_{x}} (\operatorname{P}_{X^{t,D}} (M_{\infty})) \\ &= \frac{\exp\{-\lambda_{1}t\}}{\phi(x)} \operatorname{P}_{\delta_{x}} (\langle (h\phi)^{t}, X^{t,D} \rangle) \\ &= \frac{\exp\{-\lambda_{1}t\}}{\phi(x)} \Pi_{x} \left(\exp\left\{ \int_{0}^{t} \beta(Y_{s}) \, \mathrm{d}s \right\} (h\phi)(Y_{t}), \ t < \tau \right) \\ &= \frac{1}{\phi(x)} \Pi_{x} \left(\exp\left\{ \int_{0}^{t \wedge \tau} (\beta - \lambda_{1})(Y_{s}) \, \mathrm{d}s \right\} (h\phi)(Y_{t}^{D}) \right), \qquad x \in D. \end{split}$$

By the definition of Π_x^{ϕ} we obtain $h(x) = \Pi_x^{\phi}(h(Y_t^D))$. So, h is an invariant function of the process (Y^D, Π_x^{ϕ}) . The nonnegativity of h is obvious.

2. Since h is nonnegative and invariant, if there exists an $x_0 \in D$ such that $h(x_0) = 0$, then $h \equiv 0$ on D. Since $P_{\mu}(M_{\infty}(\phi)) = \langle h\phi, \mu \rangle$, we then have $P_{\mu}(M_{\infty}(\phi)) = 0$ for any $\mu \in M_F(D)$. If h > 0 on D then $P_{\mu}(M_{\infty}(\phi)) > 0$ for any $\mu \in M_F(D)$.

Using Proposition 3.1, we see that, to prove Theorem 1.1, we only need to consider the case $\mu(dx) = \widetilde{\phi}(x) dx$. So, in the remaining part of this paper we will always suppose that $\mu(dx) = \widetilde{\phi}(x) dx$.

Lemma 3.2. Let $(m_t, t \ge 0)$ be the Poisson point process constructed in Section 2. Define

$$\sigma_0 = 0,$$
 $\sigma_i = \inf\{s \in \mathcal{D}_m : s > \sigma_{i-1}, m_s \phi(\widetilde{Y}_s) > 1\},$ $\eta_i = m_{\sigma_i},$ $i = 1, 2, \ldots$

If $\int_D \widetilde{\phi}(y) l(y) \, dy < \infty$ then

$$\sum_{s\in\mathcal{D}_m}\exp\{-\lambda_1 s\}m_s\phi(\widetilde{Y}_s)<\infty\quad \mathrm{P}_{\mu,\phi}\text{-}a.s.$$

If $\int_D \widetilde{\phi}(y) l(y) dy = \infty$ then

$$\limsup_{i \to \infty} \exp\{-\lambda_1 \sigma_i\} \eta_i \phi(\widetilde{Y}_{\sigma_i}) = \infty \quad P_{\mu,\phi} -a.s.$$

Proof. Since ϕ is bounded from above, σ_i is strictly increasing with respect to i. We first prove that if $\int_D \widetilde{\phi}(y) l(y) dy < \infty$ then

$$\sum_{s \in \mathcal{D}_m} \exp\{-\lambda_1 s\} m_s \phi(\widetilde{Y}_s) < \infty \quad P_{\mu,\phi} \text{-a.s.}$$

For any $\varepsilon > 0$, we write the sum above as

$$\sum_{s \in \mathcal{D}_{m}} \exp\{-\lambda_{1} s\} m_{s} \phi(\widetilde{Y}_{s})$$

$$= \sum_{s \in \mathcal{D}_{m}} \exp\{-\lambda_{1} s\} m_{s} \phi(\widetilde{Y}_{s}) \mathbf{1}_{\{\phi(\widetilde{Y}_{s}) m_{s} \leq e^{\varepsilon s}\}} + \sum_{s \in \mathcal{D}_{m}} \exp\{-\lambda_{1} s\} m_{s} \phi(\widetilde{Y}_{s}) \mathbf{1}_{\{m_{s} \phi(\widetilde{Y}_{s}) > e^{\varepsilon s}\}}$$

$$= \sum_{s \in \mathcal{D}_{m}} \exp\{-\lambda_{1} s\} m_{s} \phi(\widetilde{Y}_{s}) \mathbf{1}_{\{\phi(\widetilde{Y}_{s}) m_{s} \leq e^{\varepsilon s}\}} + \sum_{i=1}^{\infty} \exp\{-\lambda_{1} \sigma_{i}\} \eta_{i} \phi(\widetilde{Y}_{\sigma_{i}}) \mathbf{1}_{\{\eta_{i} \phi(\widetilde{Y}_{\sigma_{i}}) > \exp\{\varepsilon \sigma_{i}\}\}}$$

$$=: I + II. \tag{3.1}$$

By (2.1) we have

$$\begin{split} \sum_{i=1}^{\infty} \mathrm{P}_{\mu,\phi}(\eta_{i}\phi(\widetilde{Y}_{\sigma_{i}}) > \exp\{\varepsilon\sigma_{i}\}) &= \sum_{i=1}^{\infty} \mathrm{P}_{\mu,\phi}(\mathrm{P}_{\mu,\phi}(\eta_{i}\phi(\widetilde{Y}_{\sigma_{i}}) > \exp\{\varepsilon\sigma_{i}\} \mid \sigma(\widetilde{Y}))) \\ &= \mathrm{P}_{\mu,\phi}\bigg(\mathrm{P}_{\mu,\phi}\bigg(\sum_{i=1}^{\infty} \mathbf{1}_{\{\eta_{i} > \exp\{\varepsilon\sigma_{i}\}\phi(\widetilde{Y}_{\sigma_{i}})^{-1}\}} \mid \sigma(\widetilde{Y})\bigg)\bigg) \\ &= \Pi_{\phi\mu}^{\phi}\bigg(\int_{0}^{\infty} \bigg(\int_{\phi(Y_{s})^{-1}e^{\varepsilon s}}^{\infty} rn(Y_{s},\mathrm{d}r)\bigg)\,\mathrm{d}s\bigg). \end{split}$$

Recall that, under $\Pi_{\phi\mu}^{\phi}$, Y starts at the invariant measure $\phi(x)\mu(\mathrm{d}x)=\phi(x)\widetilde{\phi}(x)\,\mathrm{d}x$. So we have

$$\begin{split} \sum_{i=1}^{\infty} \mathrm{P}_{\mu,\phi}(\eta_i \phi(\widetilde{Y}_{\sigma_i}) > \exp\{\varepsilon \sigma_i\}) &= \int_0^{\infty} \mathrm{d}s \int_D \mathrm{d}y \phi(y) \widetilde{\phi}(y) \int_{\phi(y)^{-1} e^{\varepsilon s}}^{\infty} rn(y,\mathrm{d}r) \\ &= \int_D \phi(y) \widetilde{\phi}(y) \, \mathrm{d}y \int_{\phi(y)^{-1}}^{\infty} rn(y,\mathrm{d}r) \int_0^{\ln(r\phi(y))/\varepsilon} \mathrm{d}s \\ &= \varepsilon^{-1} \int_D \widetilde{\phi}(y) l(y) \, \mathrm{d}y. \end{split}$$

By the assumption that $\int_D \widetilde{\phi}(y) l(y) \, \mathrm{d}y < \infty$ and the Borel–Cantelli lemma, we obtain

$$P_{\mu,\phi}(\eta_i\phi(\widetilde{Y}_{\sigma_i})>\exp\{\varepsilon\sigma_i\} \text{ infinitely often})=0 \quad \text{for all } \varepsilon>0,$$

which implies that

$$II < \infty \quad P_{\mu,\phi}$$
 -a.s. (3.2)

Meanwhile, for $\varepsilon < \lambda_1$,

$$\begin{split} \mathbf{P}_{\mu,\phi} I &= \mathbf{P}_{\mu,\phi} \bigg(\sum_{s \in \mathcal{D}_m} \exp\{-\lambda_1 s\} m_s \phi(\widetilde{Y}_s) \, \mathbf{1}_{\{m_s \le \mathbf{e}^{\varepsilon s} \phi(\widetilde{Y}_s)^{-1}\}} \bigg) \\ &= \Pi_{\phi\mu}^{\phi} \int_0^{\infty} \mathrm{d}t \exp\{-\lambda_1 t\} \int_0^{\phi(Y_t)^{-1} \mathbf{e}^{\varepsilon t}} \phi(Y_t) r^2 n(Y_t, \mathrm{d}r) \\ &\le \|\phi\|_{\infty} \Pi_{\phi\mu}^{\phi} \int_0^{\infty} \mathrm{d}t \exp\{-\lambda_1 t\} \int_0^1 r^2 n(Y_t, \mathrm{d}r) \\ &+ \Pi_{\phi\mu}^{\phi} \int_0^{\infty} \mathrm{d}t \exp\{-(\lambda_1 - \varepsilon)t\} \int_1^{\infty} r n(Y_t, \mathrm{d}r), \end{split}$$

where for the second term of the last inequality we used the fact that $r \le \phi(Y_t)^{-1} e^{\varepsilon t}$ implies that $r\phi(Y_t) \le e^{\varepsilon t}$. By the assumption that $\sup_{x \in D} \int_0^\infty (r \wedge r^2) n(x, dr) < \infty$ we have $P_{\mu, \phi} I < \infty$, which implies that

$$I < \infty \quad P_{\mu,\phi}$$
 -a.s. (3.3)

Combining (3.1), (3.2), and (3.3), we see that $\sum_{s \in \mathcal{D}_m} \exp\{-\lambda_1 s\} m_s \phi(\widetilde{Y}_s) < \infty$, $P_{\mu,\phi}$ -a.s. Next we prove that if $\int_D \widetilde{\phi}(y) l(y) dy = \infty$ then

$$\limsup_{i \to \infty} \exp\{-\lambda_1 \sigma_i\} \eta_i \phi(\widetilde{Y}_{\sigma_i}) = \infty \quad P_{\mu,\phi} \text{-a.s.}$$

It suffices to prove that, for any K > 0,

$$\limsup_{i \to \infty} \exp\{-\lambda_1 \sigma_i\} \eta_i \phi(\widetilde{Y}_{\sigma_i}) > K \quad P_{\mu,\phi} \text{-a.s.}$$
 (3.4)

Set $K_0 := 1 \vee (\max_{x \in D} \phi(x))$. Then, for $K \geq K_0$,

$$K \inf_{x \in D} \phi(x)^{-1} \ge 1.$$

Note that, for any $T \in (0, \infty)$, conditional on $\sigma(\widetilde{Y})$,

$$\sharp\{i:\sigma_i\in(0,T];\eta_i>K\phi(\widetilde{Y}_{\sigma_i})^{-1}\exp\{\lambda_1\sigma_i\}\}$$

is a Poisson random variable with parameter $\int_0^T \mathrm{d}t \int_{K\phi(\widetilde{Y}_t)^{-1}\exp\{\lambda_1t\}}^\infty rn(\widetilde{Y}_t,\mathrm{d}r)$ a.s. Since $(\widetilde{Y},\mathrm{P}_{\mu,\phi})$ has the same distribution as $(Y,\Pi^\phi_{\mu\phi})$, we have

$$\begin{aligned} \mathbf{P}_{\mu,\phi} & \int_{0}^{T} \mathrm{d}t \int_{K\phi(\widetilde{Y}_{t})^{-1} \exp\{\lambda_{1}t\}}^{\infty} rn(\widetilde{Y}_{t}, \mathrm{d}r) \\ & = \int_{0}^{T} \mathrm{d}t \int_{D} \mathrm{d}y \phi(y) \widetilde{\phi}(y) \int_{K\phi(y)^{-1} \exp\{\lambda_{1}t\}}^{\infty} rn(y, \mathrm{d}r) \\ & < \infty; \end{aligned}$$

thus,

$$\int_0^T \mathrm{d}t \int_{K\phi(\widetilde{Y}_t)^{-1}\exp\{\lambda_1 t\}}^\infty rn(\widetilde{Y}_t,\mathrm{d}r) < \infty \quad \mathrm{P}_{\mu,\phi} \text{ -a.s.}$$

Consequently, we have

$$\sharp\{i:\sigma_i\in(0,T];\eta_i>K\phi(\widetilde{Y}_{\sigma_i})^{-1}\exp\{\lambda_1\sigma_i\}\}<\infty\quad \mathrm{P}_{\mu,\phi}\text{-a.s.}$$

So, to prove (3.4), we need to prove that

$$\int_0^\infty \mathrm{d}t \int_{K\phi(\widetilde{Y}_t)^{-1}\exp\{\lambda_1 t\}}^\infty rn(\widetilde{Y}_t,\mathrm{d}r) = \infty \quad \mathrm{P}_{\mu,\phi} \text{ -a.s.},$$

which is equivalent to

$$\int_0^\infty dt \int_{K\phi(Y_t)^{-1} \exp\{\lambda_1 t\}}^\infty rn(Y_t, dr) = \infty \quad \Pi_{\phi\mu}^{\phi} \text{-a.s.}$$
 (3.5)

For this purpose, we first prove that

$$\Pi_{\phi\mu}^{\phi}\left(\int_{0}^{\infty} dt \int_{K\phi(Y_{t})^{-1}\exp\{\lambda_{1}t\}}^{\infty} rn(Y_{t}, dr)\right) = \infty.$$
(3.6)

Applying Fubini's theorem, we obtain

$$\begin{split} &\Pi^{\phi}_{\phi\mu} \Biggl(\int_{0}^{\infty} \mathrm{d}t \int_{K\phi(Y_{t})^{-1} \exp\{\lambda_{1}t\}}^{\infty} rn(Y_{t}, \mathrm{d}r) \Biggr) \\ &= \int_{D} \phi(y) \widetilde{\phi}(y) \, \mathrm{d}y \int_{0}^{\infty} \mathrm{d}t \int_{K\phi(y)^{-1} \exp\{\lambda_{1}t\}}^{\infty} rn(y, \mathrm{d}r) \\ &= \int_{D} \phi(y) \widetilde{\phi}(y) \, \mathrm{d}y \int_{K\phi(y)^{-1}}^{\infty} rn(y, \mathrm{d}r) \int_{0}^{(1/\lambda_{1}) \ln(r\phi(y)/K)} \, \mathrm{d}t \\ &= \frac{1}{\lambda_{1}} \int_{D} \phi(y) \widetilde{\phi}(y) \, \mathrm{d}y \int_{K\phi(y)^{-1}}^{\infty} (\ln[r\phi(y)] - \ln K) rn(y, \mathrm{d}r) \\ &\geq \frac{1}{\lambda_{1}} \int_{D} \phi(y) \widetilde{\phi}(y) \, \mathrm{d}y \Biggl(\int_{K\phi(y)^{-1}}^{\infty} r \ln[r\phi(y)] n(y, \mathrm{d}r) - A \Biggr) \\ &= \frac{1}{\lambda_{1}} \int_{D} \widetilde{\phi}(y) \, \mathrm{d}y \int_{K}^{\infty} r \ln rn^{\phi}(y, \mathrm{d}r) - \frac{A}{\lambda_{1}} \int_{D} \widetilde{\phi}(y) \phi(y) \, \mathrm{d}y \end{split}$$

for some positive constant A, where in the inequality we used the facts that $K\phi(y)^{-1} > 1$ for any $y \in D$ and $\sup_{y \in D} \int_1^\infty rn(y, dr) < \infty$. Since

$$\int_{D} \widetilde{\phi}(y) \, \mathrm{d}y \int_{1}^{\infty} r \ln r \, n^{\phi}(y, \mathrm{d}r) = \infty$$

and

$$\int_{D} \widetilde{\phi}(y) \, \mathrm{d}y \int_{1}^{K} r \ln r n^{\phi}(y, \mathrm{d}r) \leq K \log K \int_{D} \widetilde{\phi}(y) n(y, [\|\phi\|_{\infty}^{-1}, \infty)) \, \mathrm{d}y < \infty,$$

we obtain

$$\int_{D} \widetilde{\phi}(y) \, \mathrm{d}y \int_{K}^{\infty} r \ln r n^{\phi}(y, \mathrm{d}r) = \infty,$$

and, therefore, (3.6) holds.

By (1.1), there exists a constant c > 0 such that, for any t > c and any $f \in L^{\infty}_{+}(D)$,

$$\frac{1}{2} \int_{D} \phi(y) \widetilde{\phi}(y) f(y) \, \mathrm{d}y \le \int_{D} p^{\phi}(t, x, y) f(y) \, \mathrm{d}y \le 2 \int_{D} \phi(y) \widetilde{\phi}(y) f(y) \, \mathrm{d}y, \qquad x \in D.$$
(3.7)

For T > c, we define

$$\xi_T = \int_0^T \mathrm{d}t \int_{K\phi(Y_t)^{-1} \exp\{\lambda_1 t\}}^\infty rn(Y_t, \mathrm{d}r), \qquad A_T = \int_c^T \mathrm{d}t \int_D \widetilde{\phi}(y) \, \mathrm{d}y \int_{K \exp\{\lambda_1 t\}}^\infty rn^{\phi}(y, \mathrm{d}r).$$

Our goal is to prove (3.5), which is equivalent to

$$\xi_{\infty} := \int_0^{\infty} \mathrm{d}t \int_{K\phi(Y_t)^{-1} \exp\{\lambda_1 t\}}^{\infty} rn(Y_t, \mathrm{d}r) = \infty \quad \Pi_{\phi\mu}^{\phi} \text{-a.s.}$$

Since $\{\xi_{\infty} = \infty\}$ is an invariant event, by the ergodic property of Y under $\Pi_{\phi\mu}^{\phi}$, it is enough to prove that

$$\Pi_{\phi\mu}^{\phi}(\xi_{\infty} = \infty) > 0. \tag{3.8}$$

Note that

$$\Pi_{\phi\mu}^{\phi}\xi_{T} = \int_{0}^{T} dt \int_{D} \widetilde{\phi}(y) dy \int_{K \exp\{\lambda_{1}t\}}^{\infty} rn^{\phi}(y, dr) \ge A_{T}$$
(3.9)

and

$$\lim_{T \to \infty} \Pi_{\phi\mu}^{\phi} \xi_T \ge A_{\infty}$$

$$= \int_c^{\infty} dt \int_D \widetilde{\phi}(y) dy \int_{K \exp\{\lambda_1 t\}}^{\infty} r n^{\phi}(y, dr)$$

$$= \int_D \widetilde{\phi}(y) dy \int_{K \exp\{\lambda_1 c\}}^{\infty} \left(\frac{1}{\lambda_1} (\log r - \log K) - c\right) r n^{\phi}(y, dr)$$

$$\ge C \int_D \widetilde{\phi}(y) l(y) dy$$

$$= \infty, \tag{3.10}$$

where *C* is a positive constant. By Lemma 3.1,

$$\Pi_{\phi\mu}^{\phi} \left(\xi_T \ge \frac{1}{2} \Pi_{\phi\mu}^{\phi} \xi_T \right) \ge \frac{(\Pi_{\phi\mu}^{\phi} \xi_T)^2}{4 \Pi_{\phi\mu}^{\phi} (\xi_T^2)}.$$
 (3.11)

If we can prove that there exists a constant $\widehat{C} > 0$ such that, for all T > c,

$$\frac{(\Pi^{\phi}_{\phi\mu}\xi_T)^2}{4\Pi^{\phi}_{\phi\mu}(\xi_T^2)} \ge \widehat{C},\tag{3.12}$$

then by (3.11) we would obtain

$$\Pi_{\phi\mu}^{\phi}(\xi_T \geq \frac{1}{2}\Pi_{\phi\mu}^{\phi}\xi_T) \geq \widehat{C},$$

and, therefore,

$$\Pi_{\phi\mu}^{\phi}(\xi_{\infty} \ge \frac{1}{2}\Pi_{\phi\mu}^{\phi}\xi_{T}) \ge \Pi_{\phi\mu}^{\phi}(\xi_{T} \ge \frac{1}{2}\Pi_{\phi\mu}^{\phi}\xi_{T}) \ge \widehat{C} > 0.$$

Since $\lim_{T\to\infty} \Pi^{\phi}_{\phi\mu} \xi_T = \infty$ (see (3.10)), the above inequality implies (3.8). Now we only need to prove (3.12). For this purpose, we first estimate $\Pi^{\phi}_{\phi\mu}(\xi_T^2)$:

$$\Pi_{\phi\mu}^{\phi} \xi_{T}^{2} = \Pi_{\phi\mu}^{\phi} \int_{0}^{T} dt \int_{K\phi(Y_{t})^{-1} \exp\{\lambda_{1}t\}}^{\infty} rn(Y_{t}, dr) \int_{0}^{T} ds \int_{K\phi(Y_{s})^{-1} \exp\{\lambda_{1}s\}}^{\infty} un(Y_{s}, du)$$

$$= 2\Pi_{\phi\mu}^{\phi} \int_{0}^{T} dt \int_{K\phi(Y_{t})^{-1} \exp\{\lambda_{1}t\}}^{\infty} rn(Y_{t}, dr) \int_{t}^{T} ds \int_{K\phi(Y_{s})^{-1} \exp\{\lambda_{1}s\}}^{\infty} un(Y_{s}, du)$$

$$= 2\Pi_{\phi\mu}^{\phi} \int_{0}^{T} dt \int_{K\phi(Y_{t})^{-1} \exp\{\lambda_{1}t\}}^{\infty} rn(Y_{t}, dr) \int_{t}^{(t+c)\wedge T} ds \int_{K\phi(Y_{s})^{-1} \exp\{\lambda_{1}s\}}^{\infty} un(Y_{s}, du)$$

$$+ 2\Pi_{\phi\mu}^{\phi} \int_{0}^{T} dt \int_{K\phi(Y_{t})^{-1} \exp\{\lambda_{1}t\}}^{\infty} rn(Y_{t}, dr) \int_{(t+c)\wedge T}^{T} ds \int_{K\phi(Y_{s})^{-1} \exp\{\lambda_{1}s\}}^{\infty} un(Y_{s}, du)$$

$$= III + IV.$$

where

$$III = 2\Pi_{\phi\mu}^{\phi} \int_{0}^{T} dt \int_{K\phi(Y_{t})^{-1} \exp\{\lambda_{1}t\}}^{\infty} rn(Y_{t}, dr) \int_{t}^{(t+c)\wedge T} ds \int_{K\phi(Y_{s})^{-1} \exp\{\lambda_{1}s\}}^{\infty} un(Y_{s}, du)$$

and

$$IV = 2\Pi_{\phi\mu}^{\phi} \int_{0}^{T} dt \int_{K\phi(Y_{t})^{-1} \exp\{\lambda_{1}t\}}^{\infty} rn(Y_{t}, dr) \int_{(t+c)\wedge T}^{T} ds \int_{K\phi(Y_{s})^{-1} \exp\{\lambda_{1}s\}}^{\infty} un(Y_{s}, du)$$

$$= 2\int_{0}^{T} dt \int_{D} \phi(y)\widetilde{\phi}(y) dy \int_{K\phi(y)^{-1} \exp\{\lambda_{1}t\}}^{\infty} rn(y, dr)$$

$$\times \int_{(t+c)\wedge T}^{T} ds \int_{D} p^{\phi}(s-t, y, z) dz \int_{K\phi(z)^{-1} \exp\{\lambda_{1}s\}}^{\infty} un(z, du).$$

By our assumption on the kernel n we have $\|\int_1^\infty rn(\cdot, dr)\|_\infty < \infty$. Since $K \inf_{x \in B} \phi(x)^{-1} \ge 1$, we have

$$III \leq C_1 \Pi_{\phi\mu}^{\phi} \xi_T$$

for some positive constant C_1 which does not depend on T. Using (3.7) and the definition of n^{ϕ} , we obtain

$$\int_{(t+c)\wedge T}^{T} \mathrm{d}s \int_{D} p^{\phi}(s-t, y, z) \, \mathrm{d}z \int_{K\phi(z)^{-1} \exp\{\lambda_{1}s\}}^{\infty} un(z, \mathrm{d}u)$$

$$\leq 2 \int_{(t+c)\wedge T}^{T} \mathrm{d}s \int_{D} \phi(z) \widetilde{\phi}(z) \, \mathrm{d}z \int_{K\phi(z)^{-1} \exp\{\lambda_{1}s\}}^{\infty} un(z, \mathrm{d}u)$$

$$\leq 2 \int_{c}^{T} \mathrm{d}s \int_{D} \widetilde{\phi}(z) \, \mathrm{d}z \int_{0}^{\infty} (\phi(z)u) \, \mathbf{1}_{\{\phi(z)u > k \exp\{\lambda_{1}s\}\}} n(z, \mathrm{d}u)$$

$$= 2 \int_{c}^{T} \mathrm{d}s \int_{D} \widetilde{\phi}(z) \, \mathrm{d}z \int_{k \exp\{\lambda_{1}s\}}^{\infty} rn^{\phi}(z, \mathrm{d}r)$$

$$= 2A_{T}.$$

Then, using (3.9), we have

$$IV \le 4A_T \Pi_{\phi\mu}^{\phi} \xi_T \le 4(\Pi_{\phi\mu}^{\phi} \xi_T)^2.$$

Combining the above estimates for III and IV, we find that there exists a $C_2 > 0$ independent of T such that, for T > c,

$$\Pi_{\phi u}^{\phi}(\xi_T^2) \le 4(\Pi_{\phi u}^{\phi}\xi_T)^2 + C_1\Pi_{\phi u}^{\phi}\xi_T \le C_2(\Pi_{\phi u}^{\phi}\xi_T)^2.$$

Then we have (3.12) with $\widehat{C} = 1/C_2$, and the proof of the theorem is now complete.

Definition 3.1. Suppose that (Ω, \mathcal{F}, P) is a probability space, that $\{\mathcal{F}_t, t \geq 0\}$ is a filtration on (Ω, \mathcal{F}) , and that \mathcal{G} is a sub- σ -field of \mathcal{F} . A real-valued process U_t on (Ω, \mathcal{F}, P) is called a $P(\cdot \mid \mathcal{G})$ -martingale with respect to $\{\mathcal{F}_t, t \geq 0\}$ if

- (i) it is adapted to $\{\mathcal{F}_t \vee \mathcal{G}, t \geq 0\}$;
- (ii) for any t > 0, $E(|U_t| | \mathcal{G}) < \infty$; and

(iii) for any t > s,

$$E(U_t \mid \mathcal{F}_s \vee \mathcal{G}) = U_s$$
 a.s.

We say that U_t on (Ω, \mathcal{F}, P) is a $P(\cdot \mid \mathcal{G})$ -submartingale or a $P(\cdot \mid \mathcal{G})$ -supermartingale with respect to $\{\mathcal{F}_t, t \geq 0\}$ if, in addition to (i) and (ii), for any t > s,

$$E(U_t \mid \mathcal{F}_s \vee \mathcal{G}) \geq U_s$$
 a.s.

or, respectively,

$$E(U_t \mid \mathcal{F}_s \vee \mathcal{G}) \leq U_s$$
 a.s.

The following result is a folklore. Since we could not find a reference for this result, we provide a proof for completeness.

Lemma 3.3. Suppose that (Ω, \mathcal{F}, P) is a probability space, that $\{\mathcal{F}_t, t \geq 0\}$ is a filtration on (Ω, \mathcal{F}) , and that \mathcal{G} is a σ -field of \mathcal{F} . If U_t is a $P(\cdot \mid \mathcal{G})$ -submartingale with respect to $\{\mathcal{F}_t, t \geq 0\}$ satisfying

$$\sup_{t\geq 0} \mathsf{E}(|U_t| \mid \mathcal{G}) < \infty \quad \text{a.s.},\tag{3.13}$$

then there exists a finite random variable U_{∞} such that U_t converges a.s. to U_{∞} .

Proof. By Definition 3.1, U_t is a submartingale with respect to $\{\mathcal{F}_t \vee \mathcal{G}, t \geq 0\}$. Let $\Omega_n = \{\sup_{t \geq 0} \mathrm{E}(|U_t| \mid \mathcal{G}) \leq n\}$. Assumption (3.13) implies that $\mathrm{P}(\Omega_n) \uparrow 1$. Note that, for each fixed n, $\mathbf{1}_{\Omega_n} U_t$ is a submartingale with respect to $\{\mathcal{F}_t \vee \mathcal{G}, t \geq 0\}$ with

$$\sup_{t\geq 0} E(\mathbf{1}_{\Omega_n} | U_t |) = \sup_{t\geq 0} E(E(\mathbf{1}_{\Omega_n} | U_t | | \mathcal{G}))$$

$$= \sup_{t\geq 0} E(\mathbf{1}_{\Omega_n} E(|U_t| | \mathcal{G}))$$

$$\leq E\left(\sup_{t\geq 0} E(|U_t| | \mathcal{G}); \Omega_n\right)$$

The martingale convergence theorem says that there exists a finite random variable U_{∞} defined on Ω_n such that U_t converges to U_{∞} on Ω_n as $t \to \infty$. Therefore, there exists a finite U_{∞} on the whole space Ω such that U_t converges to U_{∞} a.s.

The next result is basically [3, Theorem 4.3.3].

Lemma 3.4. Suppose that (Ω, \mathcal{F}) is a measurable space and that $(\mathcal{F}_t)_{t\geq 0}$ is a filtration on (Ω, \mathcal{F}) with $\mathcal{F}_t \uparrow \mathcal{F}$. If P and Q are two probability measures on (Ω, \mathcal{F}) such that, for some nonnegative P-martingale Z_t with respect to $(\mathcal{F}_t)_{t\geq 0}$,

$$\frac{\mathrm{dQ}}{\mathrm{dP}}\Big|_{\mathcal{F}_t} = Z_t.$$

Then the limit $Z_{\infty} := \limsup_{t \to \infty} Z_t$ exists and is finite a.s. under P. Furthermore, for any $F \in \mathcal{F}$,

$$Q(F) = \int_{F} Z_{\infty} dP + Q(F \cap \{Z_{\infty} = \infty\}),$$

and, consequently,

$$P(Z_{\infty} = 0) = 1 \iff Q(Z_{\infty} = \infty) = 1,$$

$$\int_{\Omega} Z_{\infty} dP = \int_{\Omega} Z_{0} dP \iff Q(Z_{\infty} < \infty) = 1.$$

Proof of Theorem 1.1. We first prove that if $\int_D \widetilde{\phi}(y) l(y) \, \mathrm{d}y < \infty$ then M_∞ is nondegenerate under P_μ . Since $M_t^{-1}(\phi)$ is a positive supermartingale under $\widetilde{\mathrm{P}}_\mu$, $M_t(\phi)$ converges to some nonnegative random variable $M_\infty(\phi) \in (0, \infty]$ under $\widetilde{\mathrm{P}}_\mu$. By Lemma 3.4, we only need to prove that

$$\widetilde{P}_{\mu}(M_{\infty}(\phi) < \infty) = 1. \tag{3.14}$$

By (2.7), $(X^{t,D}, \widetilde{P}_{\mu})$ has the same law as $(X^{t,D} + \hat{X}^{t,D}, P_{\mu,\phi})$, where $X^{t,D}$ is the first exit measure of the superprocess X from $(0,t) \times D$ and $\hat{X}^{t,D} = \sum_{\sigma \in (0,t] \cap \mathcal{D}_m} X^{\sigma,(t,D)}$. Define

$$W_t(\phi) := \sum_{\sigma \in (0,t] \cap \mathcal{D}_m} \langle \phi^t, X^{\sigma,(t,D)} \rangle \exp\{-\lambda_1 t\}.$$

Then,

$$(M_t(\phi), t \ge 0; \widetilde{P}_{\mu}) = (M_t(\phi) + W_t(\phi), t \ge 0; P_{\mu,\phi})$$
 in distribution, (3.15)

where $\{M_t(\phi), t \geq 0\}$ is copy of the martingale defined in (1.2) and is independent of $W_t(\phi)$. Let \mathcal{G} be the σ -field generated by $\{\widetilde{Y}_t, m_t, t \geq 0\}$. Then, conditional on \mathcal{G} , $(X_t^{\sigma}, t \geq \sigma; P_{\mu,\phi})$ has the same distribution as $(X_{t-\sigma}, t \geq \sigma; P_{m_{\sigma}\delta_{\widetilde{Y}_{\sigma}}})$ and the $(X_t^{\sigma}, t \geq \sigma; P_{\mu,\phi})$ are independent for $\sigma \in \mathcal{D}_m$. Then we have

$$W_t(\phi) \stackrel{\mathrm{D}}{=} \sum_{\sigma \in (0,t] \cap \mathcal{D}_m} \exp\{-\lambda_1 \sigma\} M_{t-\sigma}^{\sigma}(\phi), \tag{3.16}$$

where, for each $\sigma \in \mathcal{D}_m$, $M_t^{\sigma}(\phi)$ is a copy of the martingale defined by (1.2) with $\mu = m_{\sigma} \delta_{\widetilde{Y}_{\sigma}}$ and, conditional on \mathcal{G} , the $\{M_t^{\sigma}(\phi), \sigma \in \mathcal{D}_m\}$ are independent. Here ' $\stackrel{\square}{=}$ ' denotes equality in distribution. To prove (3.14), by (3.15), it suffices to show that

$$P_{\mu,\phi}\left(\lim_{t\to\infty}[M_t(\phi)+W_t(\phi)]<\infty\right)=1.$$

Since $(M_t(\phi), t \ge 0)$ is a nonnegative martingale under the probability $P_{\mu,\phi}$, it converges $P_{\mu,\phi}$ -a.s. to a finite random variable $M_{\infty}(\phi)$ as $t \to \infty$. So we only need to prove that

$$P_{\mu,\phi}\left(\lim_{t\to\infty}W_t(\phi)<\infty\right)=1. \tag{3.17}$$

Define $\mathcal{H}_t := \mathcal{G} \vee \sigma(X^{\sigma,(s-\sigma,B)}; \sigma \in [0,t] \cap \mathcal{D}_m$, $s \in [\sigma,t]$). Then $(W_t(\phi))$ is a $P_{\mu,\phi}(\cdot \mid \mathcal{G})$ -nonnegative submartingale with respect to (\mathcal{H}_t) . By (3.16) and Lemma 3.2,

$$\sup_{t\geq 0} P_{\mu,\phi}(W_t(\phi) \mid \mathcal{G}) = \sup_{t\geq 0} \sum_{s\in[0,\ t]\cap\mathcal{D}_m} \exp\{-\lambda_1 s\} m_s \phi(\widetilde{Y}_s)$$

$$\leq \sum_{s\in\mathcal{D}_m} \exp\{-\lambda_1 s\} m_s \phi(\widetilde{Y}_s)$$

$$< \infty \quad P_{\mu,\phi} \text{-a.s.}$$

Then, by Lemma 3.3, $W_t(\phi)$ converges $P_{\mu,\phi}$ -a.s. to $W_{\infty}(\phi)$ as $t \to \infty$ and $P_{\mu,\phi}(W_{\infty}(\phi) < \infty) = 1$; therefore, (3.17) holds.

Now we turn to the proof of the second part of the theorem. Assume that $\int_D \widetilde{\phi}(y) l(y) dy = \infty$. We are going to prove that $M_{\infty}(\phi) := \lim_{t \to \infty} M_t(\phi)$ is degenerate with respect to P_{μ} .

By [7, Proposition 2], $1/M_t(\phi)$ is a supermartingale under \widetilde{P}_{μ} , and, thus, $1/(M_t(\phi)+W_t(\phi))$ is a nonnegative supermartingale under $P_{\mu,\phi}$. Recall that $M_t(\phi)$ is a nonnegative martingale under $P_{\mu,\phi}$. Then the limits $\lim_{t\to\infty} M_t(\phi)$ and $1/\lim_{t\to\infty} (M_t(\phi)+W_t(\phi))$ exist and are finite $P_{\mu,\phi}$ -a.s. Therefore, $\lim_{t\to\infty} W_t(\phi)$ exists in $[0,\infty]$ $P_{\mu,\phi}$ -a.s. Recall the definition of $(\eta_i,\sigma_i,\ i=1,2,\ldots)$ in Lemma 3.2, and note that $\lim_{t\to\infty} \sigma_i=\infty$. By Lemma 3.2,

$$\limsup_{t\to\infty}W_t(\phi)\geq \limsup_{i\to\infty}W_{\sigma_i}(\phi)\geq \limsup_{i\to\infty}\exp\{-\lambda_1\sigma_i\}\eta_i\phi(\widetilde{Y}_{\sigma_i})=\infty \quad \mathrm{P}_{\mu,\phi}\text{-a.s.}$$

So we have

$$\lim_{t\to\infty}W_t(\phi)=\infty\quad P_{\mu,\phi}\text{ -a.s.}$$

By (3.15),

$$\widetilde{P}_{\mu}(M_{\infty}(\phi) = \infty) = 1.$$

It follows from Lemma 3.4 that $P_{\mu}(M_{\infty} = 0) = 1$.

Remark 3.1. The argument of this paper actually works for general superprocesses. Our main result remains valid for any general $(Y, \psi(\lambda) - \beta\lambda)$ -superprocess with Y being a reasonable Markov process such that Assumptions 1.1 and 1.2 are satisfied. For examples of discontinuous Markov processes satisfying Assumption 1.2, we refer the reader to [11] and the references therein.

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