



**HAL**  
open science

# Spread of parasites affecting death and division rates in a cell population

Aline Marguet, Charline Smadi

► **To cite this version:**

Aline Marguet, Charline Smadi. Spread of parasites affecting death and division rates in a cell population. 2023. hal-03854347v2

**HAL Id: hal-03854347**

**<https://hal.science/hal-03854347v2>**

Preprint submitted on 24 Mar 2023 (v2), last revised 30 Aug 2023 (v3)

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# SPREAD OF PARASITES AFFECTING DEATH AND DIVISION RATES IN A CELL POPULATION

ALINE MARGUET AND CHARLINE SMADI

ABSTRACT. We introduce a general class of branching Markov processes for the modelling of a parasite infection in a cell population. Each cell contains a quantity of parasites which evolves as a diffusion with positive jumps. The drift, diffusive function and positive jump rate of this quantity of parasites depend on its current value. The division rate of the cells also depends on the quantity of parasites they contain. At division, a cell gives birth to two daughter cells and shares its parasites between them. Cells may also die, at a rate which may depend on the quantity of parasites they contain. We study the long-time behaviour of the parasite infection.

KEY WORDS AND PHRASES: Continuous-time and space branching Markov processes, Structured population, Long-time behaviour, Birth and Death Processes

MSC 2000 subject classifications: 60J80, 60J85, 60H10.

## INTRODUCTION

We introduce a general class of continuous-time branching Markov processes for the study of a parasite infection in a cell population. This framework is general enough to be applied for the modelling of other structured populations, with individual traits evolving on the set of positive real numbers. Another application we can think of, similar in spirit, is the modelling of the protein aggregates in a cell population. These latter, usually eliminated by the cells, can undergo sudden increases due to cellular stress (positive jumps), and are known to be distributed unequally between daughter cells (see [28] for instance).

The dynamic of the quantity of parasites in a cell is given by a Stochastic Differential Equation (SDE) with drift, diffusion and positive jumps. Then, at a random time whose law may depend on the quantity of parasites in the cell, this latter dies or divides. At division, it shares its parasites between its two daughter cells. We are interested in the long-time behaviour of the parasite infection in the cell population. More precisely, we will focus on the quantity of parasites in the cells, including the possibility of explosion or extinction of the quantity of parasites. We will see that those quantities are very sensitive to the way cell division and death rates depend on the quantity of parasites in the cell, and to the law of the sharing of the parasites between the two daughter cells at division.

In discrete time, from the pioneer model of Kimmel [16], many studies have been conducted on branching within branching processes to study the host-parasite dynamics: on the associated quasistationary distributions [5], considering random environment and immigration events [6], on multitype branching processes [1, 2]. In continuous time, host-parasites dynamics have also been studied using two-level branching processes, in which the dynamics of the parasites is modelled by a birth-death process with interactions [23, 24] or a Feller process [9, 8] and the cell population dynamics by a structured branching process.

Some experiments, conducted in the TAMARA laboratory, have shown that cells distribute unequally their parasites between their two daughter cells [29]. This could be a mechanism aiming at concentrating the parasites in some cell lines in order to ‘save’ the remaining

lines. It is thus important to understand the effect of this unequal sharing on the long-time behaviour of the infection in the cell population. This question has been addressed by Bansaye and Tran in [9]. They introduced and studied branching Feller diffusions with a cell division rate depending on the quantity of parasites in the cell and a sharing of parasites at division between the two daughter cells according to a random variable with any symmetric distribution on  $[0, 1]$ . They provided some extinction criteria for the infection in a cell line, in the case where the cell division rate is constant or a monotone function of the quantity of parasites in the cell, as well as recovery criteria at the population level, in the constant division rate case. In [8], Bansaye *et al.* extended this study by providing the long time asymptotic of the recovery rate in the latter case. Our work further extends these results in several directions. First, we allow the drift and the diffusion coefficient of the quantity of parasites in a cell to vary with the quantity of parasites. Second, we add the possibility to have positive jumps in the parasites dynamics, with a rate which may depend on the current quantity of parasites in the cell. Third, we allow the cell division rate to depend not monotonically on the quantity of parasites. This situation is more difficult to study than the previous ones, as the genealogical tree of the cell population depends on the whole history of the quantity of parasites in the different cell lines. Finally, we add the possibility for the cells to die at a rate which may depend on the quantity of parasites they contain, which complicates the underlying population process for the cells.

For the study of structured branching populations, a classical method to obtain information on the distribution of a trait in the population is to introduce a penalized Markov process, called auxiliary process, corresponding to the dynamics of the trait of a typical individual in the population, *i.e.* an individual picked uniformly at random. The link between the auxiliary process and the population process is given by Many-to-One formulas. We refer to [13, 4, 15, 7, 12, 21, 20] for general results on these topics in the continuous-time case.

Part of our proof strategy consists thus in investigating the long-time behaviour of this auxiliary process and deduce properties on the asymptotic behaviour of the process at the population level, extending previous results derived for a smaller class of structured Markov branching processes (see [9, 7, 12] for instance). In the case of a constant growth rate for the cell population, the auxiliary process belongs to the class of continuous-state non-linear branching processes that has been studied in [18, 22]. This case will be explored in a companion paper. In the general case, the auxiliary process is time-inhomogeneous, which makes the study of its asymptotic behaviour much more involved, even out of reach. An alternative approach consists in introducing a Markov process with another penalization, corresponding to the dynamics of the trait of an individual in the population, which is chosen according to some weight, and not picked uniformly at random [12]. When this weight is a positive eigenvector of a given operator, the alternative auxiliary process that we obtain is time-homogeneous and its asymptotic study is easier. Additional work is needed to obtain properties at the population level.

The paper is structured as follows. In Section 1, we define the population process and give assumptions ensuring its existence and uniqueness as the strong solution to a SDE. In Section 2 we provide necessary conditions for the cell population to get rid of parasites or for the quantity of parasites to explode in all the cells. Then, in Section 3, we explore asymptotics of the proportion of cells with a given level of infection. In particular in Section 3.3, we investigate the case of a linear division rate. We prove that this strategy of division allows the cell population to contain the infection, and we give additional information on the asymptotic distribution of the quantity of parasites in the cells under some assumptions. Sections 4 and 5 are dedicated to the proofs.

In the sequel  $\mathbb{N} := \{0, 1, 2, \dots\}$  will denote the set of nonnegative integers,  $\mathbb{R}_+ := [0, \infty)$  the real line,  $\overline{\mathbb{R}}_+ := \mathbb{R}_+ \cup \{+\infty\}$ , and  $\mathbb{R}_+^* := (0, \infty)$ . We will denote by  $\mathcal{C}_b^2(\mathbb{R}_+)$  (resp.  $\mathcal{C}_0^2(\mathbb{R}_+)$ ) the set of bounded (resp. vanishing at 0 and infinity) twice continuously differentiable functions on  $\mathbb{R}_+$ . Finally, for any stochastic process  $X$  on  $\overline{\mathbb{R}}_+$  or  $Z$  on the set of point measures on  $\overline{\mathbb{R}}_+$ , we will denote by  $\mathbb{E}_x[f(X_t)] = \mathbb{E}[f(X_t)|X_0 = x]$  and  $\mathbb{E}_{\delta_x}[f(Z_t)] = \mathbb{E}[f(Z_t)|Z_0 = \delta_x]$ .

## 1. DEFINITION OF THE POPULATION PROCESS

**1.1. Parasites dynamics in a cell.** Each cell contains parasites whose quantity evolves as a diffusion with positive jumps. More precisely, we consider the SDE

$$\begin{aligned} \mathfrak{X}_t = x + \int_0^t g(\mathfrak{X}_s) ds + \int_0^t \sqrt{2\sigma^2(\mathfrak{X}_s)} dB_s + \int_0^t \int_0^{p(\mathfrak{X}_{s-})} \int_{\mathbb{R}_+} z \tilde{Q}(ds, dx, dz) \\ + \int_0^t \int_0^{\mathfrak{X}_{s-}} \int_{\mathbb{R}_+} z R(ds, dx, dz), \end{aligned} \quad (1.1)$$

where  $x$  is nonnegative,  $g$ ,  $\sigma$  and  $p$  are real functions on  $\overline{\mathbb{R}}_+$ ,  $B$  is a standard Brownian motion,  $\tilde{Q}$  is a compensated Poisson point measure (PPM) with intensity  $ds \otimes dx \otimes \pi(dz)$ ,  $\pi$  is a nonnegative measure on  $\mathbb{R}_+$ ,  $R$  is a PPM with intensity  $ds \otimes dx \otimes \rho(dz)$ , and  $\rho$  is a measure on  $\mathbb{R}_+$  with density:

$$\rho(dz) = \frac{c_b \mathbf{b}(\mathbf{b} + 1)}{\Gamma(1 - \mathbf{b})} \frac{1}{z^{2+\mathbf{b}}} dz,$$

where  $\mathbf{b} \in (-1, 0)$  and  $c_b < 0$  (see [17, Section 1.2.6] for details on stable distributions and processes). Finally,  $B$ ,  $Q$  and  $R$  are independent.

We will provide below conditions under which the SDE (1.1) has a unique nonnegative strong solution. In this case, it is a Markov process with infinitesimal generator  $\mathcal{G}$ , satisfying for all  $f \in C_0^2(\mathbb{R}_+)$ ,

$$\begin{aligned} \mathcal{G}f(x) = g(x)f'(x) + \sigma^2(x)f''(x) + p(x) \int_{\mathbb{R}_+} (f(x+z) - f(x) - zf'(x)) \pi(dz) \\ + x \int_{\mathbb{R}_+} (f(x+z) - f(x)) \rho(dz), \end{aligned} \quad (1.2)$$

and 0 and  $+\infty$  are two absorbing states. Following [21], we denote by  $(\Phi(x, s, t), s \leq t)$  the corresponding stochastic flow *i.e.* the unique strong solution to (1.1) satisfying  $\mathfrak{X}_s = x$  and the dynamics of the trait between division events is well-defined.

**1.2. Cell division.** A cell with a quantity of parasites  $x$  divides at rate  $r(x)$  and is replaced by two individuals with quantity of parasites at birth given by  $\Theta x$  and  $(1 - \Theta)x$ . Here  $\Theta$  is a nonnegative random variable on  $(0, 1)$  with associated symmetric distribution  $\kappa(d\theta)$  satisfying  $\int_0^1 |\ln \theta| \kappa(d\theta) < \infty$ .

**1.3. Cell death.** Cells have a death rate  $q(x)$  which depends on the quantity of parasites  $x$  they carry. The function  $q$  may be nondecreasing, because the presence of parasites may kill the cell, or nonincreasing, if parasites slow down the cellular machinery (production of proteins, division, etc.).

**1.4. Existence and uniqueness.** We use the classical Ulam-Harris-Neveu notation to identify each individual. Let us denote by

$$\mathcal{U} := \bigcup_{n \in \mathbb{N}} \{0, 1\}^n$$

the set of possible labels,  $\mathcal{M}_P(\overline{\mathbb{R}}_+)$  the set of point measures on  $\overline{\mathbb{R}}_+$ , and  $\mathbb{D}(\mathbb{R}_+, \mathcal{M}_P(\overline{\mathbb{R}}_+))$ , the set of càdlàg measure-valued processes. For any  $Z \in \mathbb{D}(\mathbb{R}_+, \mathcal{M}_P(\overline{\mathbb{R}}_+))$ ,  $t \geq 0$ , we write

$$Z_t = \sum_{u \in V_t} \delta_{X_t^u}, \quad (1.3)$$

where  $V_t \subset \mathcal{U}$  denotes the set of individuals alive at time  $t$  and  $X_t^u$  the trait at time  $t$  of the individual  $u$ . We denote by  $N_t := \text{Card}(V_t)$  the number of cells in the population at time  $t$ . Let  $E = \mathcal{U} \times (0, 1) \times \overline{\mathbb{R}}_+$  and  $M(ds, du, d\theta, dz)$  be a PPM on  $\mathbb{R}_+ \times E$  with intensity  $ds \otimes n(du) \otimes \kappa(d\theta) \otimes dz$ , where  $n(du)$  denotes the counting measure on  $\mathcal{U}$ . Let  $(\Phi^u(x, s, t), u \in \mathcal{U}, x \in \overline{\mathbb{R}}_+, s \leq t)$  be a family of independent stochastic flows satisfying (1.1) describing the individual dynamics. We assume that  $M$  and  $(\Phi^u, u \in \mathcal{U})$  are independent. We denote by  $\mathcal{F}_t$  the filtration generated by the restriction of the PPM  $M$  to  $[0, t] \times E$  and the family of stochastic processes  $(\Phi^u(x, s, t), u \in \mathcal{U}, x \in \overline{\mathbb{R}}_+, s \leq t)$  up to time  $t$ .

We now consider assumptions to ensure the strong existence and uniqueness of the process. We obtain a large class of branching Markov processes for the modelling of parasite infection in a cell population. Points *i*) to *iii*) of Assumption **EU** (Existence and Uniqueness) ensure that the dynamics in a cell line is well-defined [25] (as the unique nonnegative strong solution to the SDE (1.1) up to explosion, and with infinite value after explosion); points *iv*) and *v*) ensure the non-explosion of the cell population size in finite time, as in [21].

**Assumption EU.** *We assume that*

- i) The functions  $r$  and  $p$  are locally Lipschitz on  $\mathbb{R}_+$ ,  $p$  is non-decreasing and  $p(0) = 0$ . The function  $g$  is continuous on  $\mathbb{R}_+$ ,  $g(0) = 0$  and for any  $n \in \mathbb{N}$  there exists a finite constant  $B_n$  such that for any  $0 \leq x \leq y \leq n$*

$$|g(y) - g(x)| \leq B_n \phi(y - x), \quad \text{where } \phi(x) = \begin{cases} x(1 - \ln x) & \text{if } x \leq 1, \\ 1 & \text{if } x > 1. \end{cases}$$

- ii) The function  $\sigma$  is Hölder continuous with index  $1/2$  on compact sets and  $\sigma(0) = 0$ .  
iii) The measure  $\pi$  satisfies*

$$\int_0^\infty (z \wedge z^2) \pi(dz) < \infty.$$

- iv) There exist  $r_1, r_2 \geq 0$  and  $\gamma \geq 0$  such that for all  $x \geq 0$ ,  $r(x) - q(x) \leq r_1 x^\gamma + r_2$ .  
v) There exist  $c_1, c_2 \geq 0$  such that, for all  $x \in \mathbb{R}_+$ ,*

$$\lim_{n \rightarrow +\infty} \mathcal{G}h_{n,\gamma}(x) \leq c_1 x^\gamma + c_2,$$

where  $\mathcal{G}$  is defined in (1.2),  $\gamma$  has been defined in *iv*) and  $h_{n,\gamma} \in C_b^2(\mathbb{R}_+)$  is a sequence of functions such that  $\lim_{n \rightarrow +\infty} h_{n,\gamma}(x) = x^\gamma$  for all  $x \in \mathbb{R}_+$ .

Then the structured population process may be defined as the strong solution to a SDE.

**Proposition 1.1.** *Under Assumption **EU** there exists a strongly unique  $\mathcal{F}_t$ -adapted càdlàg process  $(Z_t, t \geq 0)$  taking values in  $\mathcal{M}_P(\overline{\mathbb{R}}_+)$  such that for all  $f \in C_0^2(\overline{\mathbb{R}}_+)$  and  $x_0, t \geq 0$ ,*

$$\begin{aligned} \langle Z_t, f \rangle = & f(x_0) + \int_0^t \int_{\mathbb{R}_+} \mathcal{G}f(x) Z_s(dx) ds + M_t^f(x_0) \\ & + \int_0^t \int_E \mathbf{1}_{\{u \in V_{s-}\}} \left( \mathbf{1}_{\{z \leq r(X_{s-}^u)\}} (f(\theta X_{s-}^u) + f((1-\theta)X_{s-}^u) - f(X_{s-}^u)) \right. \\ & \left. - \mathbf{1}_{\{0 < z - r(X_{s-}^u) \leq q(X_{s-}^u)\}} f(X_{s-}^u) \right) M(ds, du, d\theta, dz), \end{aligned}$$

where  $\mathcal{G}$  is defined in (1.2) and for all  $x \geq 0$ ,  $M_t^f(x)$  is a  $\mathcal{F}_t$ -martingale.

The proof is a combination of [25, Proposition 1] and [21, Theorem 2.1] (see Appendix A for details). Note that we replaced (1) and (3) of Assumption A in [21] by *iv*) in Assumption **EU**. A careful look at the proof of [21, Theorem 2.1] (in particular (2.5) in [21, Lemma 2.5]) shows that in our case, the growth of the population is governed by the function  $x \mapsto r(x) - q(x)$  so that our condition is sufficient. Note also that in [21] the exponent  $\gamma$  of *iv*) in Assumption **EU** is required to be greater than 1 but this condition is not necessary for conservative fragmentation processes as considered here. In what follows, we will assume that all the processes under consideration satisfy Assumption **EU**, but we will not indicate it.

## 2. CONTAINMENT OR EXPLOSION OF THE INFECTION

In this section, we consider general cell division and death rates, and we look for sufficient conditions for the quantity of parasites to become large (resp. small) in every alive cell. We exhibit a function characterizing the parasites growth rate in a typical cell and compare it to the growth rate of the cell population.

For  $a \in \mathbb{R}_+ \setminus \{1\}$ , we introduce when it is well-defined the function  $G_a$ , for  $x > 0$  via

$$G_a(x) := (a-1) \left[ \frac{g(x)}{x} - a \frac{\sigma^2(x)}{x^2} + x^{-b} C_a - p(x) I_a(x) - 2r(x) \frac{\mathbb{E}[\Theta^{1-a}] - 1}{a-1} \right], \quad (2.1)$$

where we recall that  $\Theta$  is a random variable with distribution  $\kappa$  and

$$C_a = \frac{1}{2+b} \int_0^\infty \frac{z\rho(dz)}{(1+z)^a}, \quad I_a(x) = \frac{(a + \mathbf{1}_{\{a=0\}})}{x^2} \int_0^\infty \left( \int_0^1 \frac{z^2(1-v)dv}{(1+zx^{-1}v)^{1+a}} \right) \pi(dz). \quad (2.2)$$

From [22, Lemma 7.1] (see Lemma B.1 in our case), if  $Y$  denotes the auxiliary process describing the behaviour of a ‘typical individual’, then the process

$$(Y_t^{1-a} e^{\int_0^t G_a(Y_s) ds}, t \geq 0)$$

is a local martingale, which entails that,  $Y_t^{1-a}$  roughly behaves as  $e^{-\int_0^t G_a(Y_s) ds}$  and thus,  $G_a$  contains informations on the dynamics of the quantity of parasites in a typical cell. Moreover, the growth rate of a cell population with a constant quantity  $x$  of parasites is  $r(x) - q(x)$ . The next assumptions combine conditions on those two key quantities, leading to results on the asymptotic behaviour of the infection in the entire population.

**Assumption EXPL.** *There exist  $a > 1$  such that  $\mathbb{E}[\Theta^{1-a}] < \infty$  and  $0 \leq \gamma < \gamma'$  such that*

$$r(x) - q(x) \leq \gamma < \gamma' \leq G_a(x), \quad \forall x \geq 0.$$

**Assumption EXT.** *There exist  $a < 1$  and  $0 \leq \gamma < \gamma'$  such that*

$$r(x) - q(x) \leq \gamma < \gamma' \leq G_a(x), \quad \forall x \geq 0.$$

Note that for  $a > 1$ , the condition  $G_a(x) \geq \gamma'$  in Assumption **EXPL** is equivalent to

$$\frac{g(x)}{x} - a \frac{\sigma^2(x)}{x^2} + x^{-b} C_a - p(x) I_a(x) - 2r(x) \frac{\mathbb{E}[\Theta^{1-a}] - 1}{a-1} \geq \gamma',$$

for all  $x \geq 0$ , which can be interpreted as the growth of the parasites being stronger than the growth of the cell population and the noise. On the contrary, for  $a < 1$ , the condition  $G_a(x) \geq \gamma'$  of Assumption **EXT** is equivalent to

$$\frac{g(x)}{x} - a \frac{\sigma^2(x)}{x^2} + x^{-b} C_a - p(x) I_a(x) - 2r(x) \frac{\mathbb{E}[\Theta^{1-a}] - 1}{a-1} \leq \gamma'.$$

In this case, the cell population growth and the noise outweigh the growth of the parasites.

**Proposition 2.1.** *Let  $K > 0$ . Then for every  $x > 0$ ,*

- i) *Under Assumption **EXPL**,  $\lim_{t \rightarrow \infty} \mathbb{P}_{\delta_x}(\exists u \in V_t, X_t^u \leq K) = 0$ .*

ii) Under Assumption **EXT**,  $\lim_{t \rightarrow \infty} \mathbb{P}_{\delta_x} (\exists u \in V_t, X_t^u \geq 1/K) = 0$ .

Thus in case i), the quantity of parasites goes to infinity in all the cells, and in case ii), the quantity of parasites goes to zero in all the cells with a probability close to one.

Proposition 2.1 applies to a large class of dynamics for the growth of parasites within cells, but imposes a limited cell growth (bounded  $r - q$ ). In the next two sections, we focus on more general cases for cell growth, requiring more assumptions on parasite dynamics.

### 3. ASYMPTOTICS OF THE PROPORTION OF CELLS WITH A GIVEN LEVEL OF INFECTION

**3.1. The role of noise.** We consider a simple case where the parasites follow a Geometric Brownian motion. This is a particular case of CSBP in a Lévy environment. The case of the Brownian environment, specifically studied in [11, 26], can be seen as an agitation or disturbance due to the cell environment. The cells might, for example, tune the intensity of this perturbation (quantified by the  $\sigma$  parameter) by modifying the temperature or the fluidity of the cell medium. The assumptions of this first case are summarized below.

**Assumption LGBE.** (*Linear growth, Brownian environment*) We assume that

- There are no jumps in the parasites dynamics ( $p = \mathbf{c}_b = 0$ ).
- There exist  $g, \sigma \in \mathbb{R}_+$  such that  $g(x) = gx$  and  $\sigma^2(x) = \sigma^2 x^2$ .
- There exist  $\beta \in (0, +\infty)$  and  $\mathbf{c} \geq 0$  such that  $\beta r(x) - q(x) = \mathbf{c}$  for all  $x \geq 0$ .

Under Assumption **LGBE**, we provide conditions under which the mean number of cells with a small (resp. a large) quantity of parasites is equivalent to the mean number of cells alive in the population.

**Proposition 3.1.** *Let  $\beta \in [0, +\infty)$  be such that Assumption **LGBE** holds and assume that there exists  $\alpha_\beta \in \mathbb{R}$  such that  $2\mathbb{E}[\Theta^{\alpha_\beta}] - 1 = \beta$ . Then,*

(i) *if  $\beta \in (0, 1)$  (then  $\alpha_\beta \in (0, 1)$ ) and  $\alpha_\beta < 1 - g/\sigma^2$ , for all  $K > 0$ ,*

$$\lim_{t \rightarrow +\infty} \frac{\mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} \mathbf{1}_{\{X_t^u > K\}} \right]}{\mathbb{E}_{\delta_x} [N_t]} = 0.$$

(ii) *if  $\beta \in (0, 1)$  (then  $\alpha_\beta \in (0, 1)$ ) and there exist  $x_0(\alpha_\beta) \geq 0$  and  $\eta > 0$  such that*

$$g \leq \sigma^2(1 - 2\alpha_\beta) + 2\mathbb{E}[\Theta^{\alpha_\beta} \ln(1/\Theta)] r(x) - \eta, \quad \forall x \geq x_0(\alpha_\beta), \quad (3.1)$$

*then for all  $\varepsilon, x > 0$  there exists  $K_{\varepsilon, x}$  such that  $K \geq K_{\varepsilon, x}$  implies*

$$\limsup_{t \rightarrow \infty} \frac{\mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} \mathbf{1}_{\{X_t^u \geq K\}} \right]}{\mathbb{E}_{\delta_x} [N_t]} \leq \varepsilon.$$

(iii) *if  $\beta > 1$  (then  $\alpha_\beta < 0$ ) and there exist  $x_0(\alpha_\beta) \geq 0$  and  $\eta > 0$  such that*

$$g \geq \sigma^2(1 + 2|\alpha_\beta|) + 2\mathbb{E}[\Theta^{\alpha_\beta} \ln(1/\Theta)] r(x) + \eta, \quad \forall x \leq x_0(\alpha_\beta), \quad (3.2)$$

*then for all  $\varepsilon, x > 0$  there exists  $K_{\varepsilon, x}$  such that  $K \leq K_{\varepsilon, x}$  implies*

$$\limsup_{t \rightarrow \infty} \frac{\mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} \mathbf{1}_{\{X_t^u \leq K\}} \right]}{\mathbb{E}_{\delta_x} [N_t]} \leq \varepsilon.$$

This result shows the importance of noise in the process dynamics for the long-term behaviour of the infection. It implies that if the cells induce more fluctuations in the dynamics of the parasites while maintaining the same rate of growth for the parasites, the cell population may contain the infection. The first point of Proposition 3.1 corresponds to the case of a growing cell population ( $r(x) - q(x) \geq 0$ ), with a moderate growth of the parasites compared to the noise of the environment ( $g < \sigma^2$ ). The condition  $\alpha_\beta < 1 - g/\sigma^2$  links the growth

of the population and the growth of the parasites: if  $g/\sigma^2$  is small, there is no additional restriction on the growth of the cell population (except that  $\beta \in [0, 1)$ ), but if  $g/\sigma^2$  is close to 1, then  $\beta$  has to be close to 1 for the condition to be fulfilled, which corresponds to a growth of the cell population independent of the quantity of parasites ( $(r - q)(x)$  close to  $\mathfrak{c}$ ).

**Remark 3.2.** *The case  $\beta = 1$  ( $\alpha_\beta = 0$ ) corresponds to a constant  $r - q$ , and will be studied in details and in more generality in another work. In our case, if  $r$  and  $q$  are constant, for the second and third points, it amounts to look at the sign of*

$$g - \sigma^2 - 2r\mathbb{E}[\ln(1/\Theta)],$$

and completes [8, Corollary 16] for the case of Geometric Brownian motion.

**3.2. Competition between division and parasites growth.** We consider another case where the mean growth of parasites is linked with the cell death rate (see Assumption **PGCD** below). It may be the case when parasites kill the cell to be extruded in the cell medium.

**Assumption PGCD.** (*Parasite Growth, Cell Death*) We assume that

- There are no stable jumps in the parasites dynamic ( $c_b = 0$ ).
- There exists  $\mathfrak{c} \geq 0$  such that  $g(x)/x - q(x) = \mathfrak{c}$  for all  $x \geq 0$ .

To state the next results, we introduce generalized conditions from [22] under which the quantity of parasites may not reach the state 0 (**(SN0)** for small noise at 0) or reach the state  $\infty$  (**(SN $\infty$ )** for strong noise at  $\infty$ ). Recall the definition of  $C_a$  and  $I_a$  in (2.2).

**(SN0)** There exist  $a > 1$  such that  $\mathbb{E}[\Theta^{1-a}] < \infty$  and  $f : \mathbb{R}_+ \rightarrow \mathbb{R}_+$  such that

$$\frac{g(u)}{u} - a \frac{\sigma^2(u)}{u^2} + u^{-b}C_a - p(u)I_a(u) = f(u) + o(\ln(u)), \quad u \rightarrow 0.$$

**(SN $\infty$ )** There exist  $a < 1$  and  $f : \mathbb{R}_+ \rightarrow \mathbb{R}_+$  such that

$$\frac{g(u)}{u} - a \frac{\sigma^2(u)}{u^2} + u^{-b}C_a - r(u) \frac{1 - \mathbb{E}[\Theta^{1-a}]}{1 - a} - p(u)I_a(u) = -f(u) + o(\ln(u)), \quad u \rightarrow \infty.$$

Under Assumption **PGCD**,  $C_a = 0$ , but we will use later those general conditions.

**Proposition 3.3.** *Let  $\mathfrak{c} \geq 0$  be such that Assumption **PGCD** holds. Then,*

i) if

$$\limsup_{x \rightarrow \infty} \left\{ \frac{\sigma^2(x)}{x^4} + \frac{r(x)}{x^2} + \frac{p(x)}{x^3} \right\} < \infty, \quad (3.3)$$

and there exists  $x_0 \geq 0, \eta_0 > 0$  such that

$$\frac{g(x)}{x} - \frac{\sigma^2(x)}{x^2} - \frac{p(x)}{2x^2} \int_{\mathbb{R}_+} \frac{z^2}{1 + z/x} \pi(dz) - r(x) (\mathbb{E}[1/\Theta] - 1/2) \geq \eta_0, \quad \forall x \leq x_0, \quad (3.4)$$

and  $x_1 > 0, \eta_1 > 0$  such that

$$\frac{g(x)}{x} + \frac{\sigma^2(x)}{x^2} + \frac{p(x)}{x^2} \int_{\mathbb{R}_+} z^2 \pi(dz) + 2r(x) (\mathbb{E}[\Theta^2] - 1/2) \leq -\eta_1, \quad \forall x \geq x_1, \quad (3.5)$$

then for all  $\varepsilon, x > 0$  there exists  $K_{\varepsilon, x}$  such that  $K \leq K_{\varepsilon, x}$  implies

$$\limsup_{t \rightarrow \infty} \frac{\mathbb{E}_x \left[ \sum_{u \in V_t} \mathbf{1}_{\{X_t^u \leq K\}} \right]}{\mathbb{E}_x [N_t]} \leq \varepsilon.$$

ii) if **(SN $\infty$ )** holds and if there exist  $x_0 \geq 0, \eta > 0$  such that

$$\frac{g(x)}{x} + \frac{\sigma^2(x)}{x^2} + p(x)I_0(x) + 2\mathbb{E}[\Theta \ln \Theta] r(x) \leq -\eta, \quad \forall x \geq x_0, \quad (3.6)$$

then for all  $\varepsilon, x > 0$  there exists  $K_{\varepsilon, x}$  such that  $K \geq K_{\varepsilon, x}$  implies

$$\limsup_{t \rightarrow \infty} \frac{\mathbb{E}_x \left[ \sum_{u \in V_t} \mathbf{1}_{\{X_t^u \geq K\}} \right]}{\mathbb{E}_x [N_t]} \leq \varepsilon.$$

**Remark 3.4.** *The class of processes considered here includes, in particular, the case  $q(\cdot) \equiv q$ ,  $g(x) = gx$  studied in previous works. Furthermore, assumptions on the cell division rate  $r(\cdot)$ , and on the noise  $\sigma(\cdot)$  in the parasite dynamics are only on their local behaviour (around 0 and  $\infty$ ). This constitutes a strong generalisation of previous results.*

**Remark 3.5.** *The results of Proposition 3.3 are weaker than the ones of Proposition 3.1: they concern mean numbers of cells with given amounts of parasites, and not the proportions of such cells in the population. But the assumptions of Proposition 3.3 are much more flexible than the assumptions of Proposition 3.1: they are in some way their local versions.*

A consequence of Proposition 3.3 is that if the cells are able to increase their rate of division above an explicit threshold, this is sufficient to contain the infection. In the same direction, if the parasites manage to slow down the rate of cell division sufficiently, this gives them enough time to multiply and be numerous in a large proportion of the cells.

**3.3. Linear division rate, constant death rate.** In this section, we study in details the case of a linear division rate. Let us first state the general assumptions of the section.

**Assumption LDCG.** (*Linear Division, Constant Growth*) We assume that

- There are no stable jumps ( $c_b = 0$ ).
- There exist  $\alpha, \beta > 0$ ,  $g, q \geq 0$  such that  $\max(g, \beta) > q$  and

$$g(x) = gx, \quad q(x) \equiv q, \quad r(x) = \alpha x + \beta.$$

- The measure  $\pi$  satisfies  $\int (z^2 \wedge z^3) \pi(dz) < \infty$  and for all  $x \geq 0$ ,  $x p'(x) \geq p(x)$ .

We first make three remarks on this assumption:

- If the division rate is linear in the quantity of parasites, the mean number of cells at time  $t$  depends on the expectation of the total quantity of parasites in the population, which is infinite if we consider stable jumps.
- In Lemma 5.3, we will see that the quantity  $\max(g, \beta) - q$  is the Malthusian growth rate of the population. Therefore, we only consider the case of a growing population.
- The last point is needed for the existence of an auxiliary process (see Prop. 4.1).

A linear increase of the division rate in order to get rid of the parasites is an efficient strategy for the cell population, as stated in the next proposition. Recall that  $\mathcal{G}$  has been defined in (1.2).

**Proposition 3.6.** *Under Assumption LDCG, for all  $x \geq 0$ ,*

*i) For all  $a > 0$ ,*

$$\frac{\mathbb{E}_{\delta_x} [\#\{u \in V_t : X_t^u \in [a, a + da]\}]}{\mathbb{E}_{\delta_x} [N_t]} = \frac{\mathbb{P}_x(\mathcal{Y}_t \in [a, a + da])}{a \mathbb{E}_x[\mathcal{Y}_t^{-1}]},$$

*where  $\mathcal{Y}$  has infinitesimal generator*

$$\begin{aligned} \mathcal{A}f(x) = & \mathcal{G}f(x) + p(x) \int (f(x+z) - f(x) - zf'(x)) \frac{z}{x} \pi(dz) \\ & + \left( 2 \frac{\sigma^2(x)}{x} + \frac{p(x)}{x} \int z^2 \pi(dz) \right) f'(x) + 2r(x) \left[ \int_0^1 \theta (f(\theta x) - f(x)) \kappa(d\theta) \right]. \end{aligned} \quad (3.7)$$

ii) For all  $\varepsilon > 0$ ,

$$\lim_{K \rightarrow \infty} \lim_{t \rightarrow \infty} \mathbb{P}_{\delta_x} \left( \mathbf{1}_{\{N_t \geq 1\}} \frac{\#\{u \in V_t : X_t^u > K\}}{N_t} > \varepsilon \right) = 0.$$

Point *i*) of Proposition 3.6 gives information on the distribution of the quantity of parasites in the cells in large time. Point *ii*) extends the results of [9] to a class of division rates increasing with the quantity of parasites. It is similar in spirit to [9, Conjecture 5.2] in the case of birth rates increasing with the quantity of parasites, but we relax the assumption of bounded division rates. Moreover, we consider positive jumps and various diffusive functions for the dynamics of the parasites, and add the possibility for the cells to die.

From this result, we see that the proportion of very infected cells goes to 0 as  $t$  tends to infinity so that a linear division rate is sufficient to contain the infection. Under additional technical assumptions we are able to establish a law of large numbers, linking asymptotically the behaviour of a typical individual at time  $t$ , given by the auxiliary process  $Y^{(t)}$ , with the behaviour of the whole population.

**Assumption LDCG+.** We assume that Assumption **LDCG** holds and that

$$\int_0^\infty (z \vee z^6) \pi(dz) < \infty, \quad (3.8)$$

$$\limsup_{x \rightarrow \infty} \frac{\sigma^2(x)}{x^2} < \infty \quad \text{and} \quad \limsup_{x \rightarrow \infty} \frac{p(x)}{x^2} < \infty. \quad (3.9)$$

Under this assumption, we obtain a convergence result for the branching process.

**Theorem 3.7.** Suppose that Assumptions **LDCG+** holds. Then, for all bounded measurable functions  $F : \mathbb{D}([0, T], \mathcal{X}) \rightarrow \mathbb{R}$ , for all  $x, y, T \geq 0$ ,

$$\mathbb{E}_{\delta_x} \left[ \mathbf{1}_{\{N_{t+T} \geq 1\}} \left( \frac{\sum_{u \in V_{t+T}} F(X_{t+s}^u, s \leq T)}{N_{t+T}} - \mathbb{E} \left[ F(Y_{t+s}^{(t+T)}, s \leq T) \mid Y_0^{(t+T)} = y \right] \right)^2 \right] \xrightarrow{t \rightarrow \infty} 0,$$

where  $Y$  is a time-inhomogeneous Markov process solution of a SDE given below in (4.9).

Theorem 3.7 ensures that asymptotically, the trajectory of the traits of a sampling along its ancestral lineage corresponds to the trajectory of  $Y$ . Hence, the study of the asymptotic behaviour of the proportion of individuals satisfying some properties, such as the proportion of infected individuals, is reduced to the study of the time-inhomogeneous process  $Y$ .

To state the following results, we also need to introduce conditions under which the quantity of parasites may (**LN0**) or may not (**SN0**) reach the state 0. They are almost necessary and sufficient conditions (see [22, Remark 3.2 and Theorem 3.3]). Condition (**SN0**) has already been introduced, and we notice that under Assumption **LDCG+** it reduces to  $\sigma^2(u)/u^2 = o(\ln(u^{-1}))$  close to 0. Condition (**LN0**) writes

(**LN0**) There exist  $\eta > 0$  and  $u_0 > 0$  such that for all  $u \leq u_0$

$$\frac{g(u)}{u} - \frac{\sigma^2(u)}{u^2} \leq -\ln(u^{-1}) (\ln \ln(u^{-1}))^{1+\eta}.$$

Under Assumption **LDCG+** it reduces to  $\sigma^2(u)/u^2 \geq \ln(u^{-1}) (\ln \ln(u^{-1}))^{1+\eta}$  close to 0.

The following proposition states that in the case of a division rate increasing linearly with the quantity of parasites, at least two long-time behaviours are possible for the infection at the cell population level: extinction or stabilization of the infection.

**Proposition 3.8.** Assume that Assumption **LDCG+** holds.

*i) If **(LNO)** holds, then*

$$\mathbb{E}_{\delta_0} \left[ \mathbf{1}_{\{N_t \geq 1\}} \left( \frac{\#\{u \in V_t : X_t^u > 0\}}{N_t} \right)^2 \right] \rightarrow 0, \quad (t \rightarrow \infty).$$

*ii) If **(SNO)** holds, then for any  $x_0, y_0 > 0$ ,  $0 < \mathbf{a} < \mathbf{b}$ ,*

$$\mathbb{E}_{\delta_{x_0}} \left[ \mathbf{1}_{\{N_t \geq 1\}} \left( \frac{\sum_{u \in V_t} \mathbf{1}_{\{\mathbf{a} < X_t^u < \mathbf{b}\}}}{N_t} - \mathbb{P} \left( \mathbf{a} \leq Y_t^{(t)} \leq \mathbf{b} \mid Y_0^{(t)} = y_0 \right) \right)^2 \right] \xrightarrow{t \rightarrow +\infty} 0.$$

*Moreover, there exist two processes  $(\mathfrak{Y}^{(1)}, \mathfrak{Y}^{(2)})$  satisfying*

$$\mathfrak{Y}_t^{(1)} \leq Y_t^{(t)} \leq \mathfrak{Y}_t^{(2)} \quad a.s. \quad \forall t \geq 0$$

*and admitting a proper limit (without atoms in 0 and  $\infty$ ) at infinity.*

Notice that point *i)* covers the classical diffusive function ( $\sigma^2(x) = \sigma^2 x$ ,  $\sigma > 0$ ). The cell population may thus recover if the dynamics of the parasites in a cell is such that the probability of absorption of the infection process is positive (condition **(LNO)**).

Under condition **(SNO)**, the parasites in the cell line do not get extinct, and point *ii)* gives information on the distribution of the quantity of parasites in the cells for large times. The auxiliary process  $Y$  of Theorem 3.7, describing the behavior of a typical quantity of parasites, is time-inhomogeneous. The result is thus obtained by a coupling with  $\mathfrak{Y}^{(1)}$  and  $\mathfrak{Y}^{(2)}$  such that our auxiliary process is sandwiched between the two processes  $\mathfrak{Y}^{(1)}$  and  $\mathfrak{Y}^{(2)}$ , for which we are able to prove convergence and some properties of the limit.

The rest of the paper is dedicated to the proofs of the results presented in previous sections. As mentioned before, the proofs rely on the construction of an auxiliary process, which gives information on the dynamics of the quantity of parasites in a ‘typical’ cell. But to have information on the long-time behaviour of the infection at the population level, we need to derive additional results on the number of cells alive, which is not an easy task due to both the death rate and the dependence of the cell division rate in the quantity of parasites.

#### 4. MANY-TO-ONE FORMULA

**4.1. Construction of the auxiliary process.** Recall from (1.3) that the population state at time  $t$ ,  $Z_t$ , can be represented by a sum of Dirac masses. We denote by  $(M_t, t \geq 0)$  the first-moment semi-group associated with the population process  $Z$  given for all measurable functions  $f$  and  $x, t \geq 0$  by

$$M_t f(x) = \mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} f(X_t^u) \right].$$

The trait of a typical individual in the population at time  $t$  is characterized by the so-called auxiliary process  $(Y_s^{(t)}, s \leq t)$  (see [21, Theorem 3.1] for detailed computations and proofs). Its associated time-inhomogeneous semi-group is given for  $r \leq s \leq t$ ,  $x \geq 0$  by

$$P_{r,s}^{(t)} f(x) = \frac{M_{s-r}(f M_{t-s} \mathbf{1})(x)}{M_{t-r} \mathbf{1}(x)}, \quad (4.1)$$

where  $\mathbf{1}$  is the constant function on  $\mathbb{R}_+$  equal to 1. More precisely, if we denote by  $m(x, s, t) = M_{t-s} \mathbf{1}(x)$  the mean number of cells in the population at time  $t$  starting from one individual with trait  $x$  at time  $s$  with  $s \leq t$ , then, for all measurable bounded functions  $F : \mathbb{D}([0, t], \mathbb{R}_+) \rightarrow \mathbb{R}$ , we have:

$$\mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} F(X_s^u, s \leq t) \right] = m(x, 0, t) \mathbb{E}_x \left[ F(Y_s^{(t)}, s \leq t) \right]. \quad (4.2)$$

The Markov process  $(Y_s^{(t)}, s \leq t)$  is time-inhomogeneous and its law is characterized by its associated infinitesimal generator  $(\mathcal{A}_s^{(t)}, s \leq t)$  given for  $f \in \mathcal{D}(\mathcal{A})$  and  $x \geq 0$  by:

$$\mathcal{A}_s^{(t)} f(x) = \widehat{\mathcal{G}}_s^{(t)} f(x) + 2r(x) \int_{\mathbb{R}_+} (f(\theta x) - f(x)) \frac{m(\theta x, s, t)}{m(x, s, t)} \kappa(d\theta),$$

where

$$\mathcal{D}(\mathcal{A}) = \{f \in \mathcal{C}_b^2(\mathbb{R}_+) \text{ s.t. } m(\cdot, s, t) f \in \mathcal{C}_b^2(\mathbb{R}_+), \forall t \geq 0, \forall s \leq t\}$$

and

$$\begin{aligned} \widehat{\mathcal{G}}_s^{(t)} f(x) &= \left( g(x) + 2\sigma^2(x) \frac{\partial_x m(x, s, t)}{m(x, s, t)} + p(x) \int_{\mathbb{R}_+} z \left( \frac{m(x+z, s, t) - m(x, s, t)}{m(x, s, t)} \right) \pi(dz) \right) f'(x) \\ &+ \sigma^2(x) f''(x) + p(x) \int_{\mathbb{R}_+} (f(x+z) - f(x) - z f'(x)) \frac{m(x+z, s, t)}{m(x, s, t)} \pi(dz) \\ &+ x \int_{\mathbb{R}_+} (f(x+z) - f(x)) \frac{m(x+z, s, t)}{m(x, s, t)} \rho(dz). \end{aligned}$$

Those formulas come from [21, Theorem 3.1], with  $B(x) = r(x) + q(x)$  and  $m(x, dy) = 2r(x)(r(x) + q(x))^{-1} \int_0^1 \delta_{\theta x}(dy) \kappa(d\theta)$ . Note that explicit expressions for the mean population size  $m(x, s, t)$  are usually out of range, except for particular cases (see Section 3.3).

**4.2. Role of the death rate in the auxiliary process.** In this section, we compare the auxiliary process associated to a population with or without death. More precisely, we demonstrate why the death rate does not appear in the generator of the auxiliary process.

Let  $(\tilde{Z}_t, t \geq 0)$  be the previously defined population process to which we add a trait  $D_t^u$  to each individual  $u$  in the population:  $D_t^u = 0$ , the individual is still alive,  $D_t^u = 1$ , the individual is dead. To compare the population dynamics with or without death, we consider that the trait of the dead individuals still evolves and that they can still divide but their descendants will be born with the status  $D_t = 1$ . More precisely,

$$\tilde{Z}_t := \sum_{u \in V_t} \delta_{(X_t^u, D_t^u)} = \sum_{u \in V_t^0} \delta_{(X_t^u, 0)} + \sum_{u \in V_t^1} \delta_{(X_t^u, 1)},$$

where  $V_t^0$  (respectively  $V_t^1$ ) denotes the alive (respectively dead) individuals in the population at time  $t$ . We denote by  $N_t^0$  (respectively  $N_t^1$ ) its cardinal and introduce  $\tilde{X}_t^u = (X_t^u, D_t^u)$  for all  $u \in \mathcal{U}$  and  $t \geq 0$ . Next, we consider the following dynamics:

- a death event for  $u$  leads to set  $D_t^u = 1$ . Therefore, it does not affect dead cells.
- a division event does not change the status  $D_t^u$  of an individual and its descendants inherit the status of their ancestor.
- we extend the generator  $\mathcal{G}$  to the functions  $f : \overline{\mathbb{R}}_+ \times \{0, 1\} \rightarrow \mathbb{R}_+$  such that  $f(\cdot, 0), f(\cdot, 1) \in \mathcal{C}_b^2(\overline{\mathbb{R}}_+)$ .

Then,  $(\tilde{Z}_t, t \geq 0)$  is defined as the unique strong solution in  $\mathcal{M}_P(\mathbb{R}_+ \times \{0, 1\})$  to

$$\begin{aligned} \langle \tilde{Z}_t, f \rangle &= f(x_0, 0) + \int_0^t \int_{\mathbb{R}_+} \mathcal{G} f(\tilde{x}) \tilde{Z}_s(d\tilde{x}) ds + M_t^f(x_0, 0) \\ &+ \int_0^t \int_E \mathbf{1}_{\{u \in V_{s-}\}} \left( \mathbf{1}_{\{z \leq r(X_{s-}^u)\}} (f(\theta X_{s-}^u, D_s^u) + f((1-\theta)X_{s-}^u, D_s^u) - f(X_{s-}^u, D_s^u)) \right. \\ &\quad \left. + \mathbf{1}_{\{0 < z - r(X_{s-}^u) \leq q(X_{s-}^u)\}} (f(X_{s-}^u, 1) - f(X_{s-}^u, D_{s-}^u)) \right) M(ds, du, d\theta, dz), \end{aligned}$$

for all  $f : \mathbb{R}_+ \times \{0, 1\} \rightarrow \mathbb{R}_+$  such that  $f(\cdot, 0), f(\cdot, 1) \in \mathcal{C}_b^2(\mathbb{R}_+)$ , where  $M^f$  is an  $\tilde{\mathcal{F}}_t$ -martingale ( $\tilde{\mathcal{F}}_t$  denotes the canonical extension of  $\mathcal{F}_t$ ). Let  $N_t = N_t^0 + N_t^1$ . Introduce

$$m_0(x, s, t) := \mathbb{E} \left[ N_t^0 \mid \tilde{Z}_s = \delta_{(x,0)} \right]$$

and consider the auxiliary process  $\tilde{Y}_s^{(t)} = (Y_s^{(t)}, D_s)$  for all  $0 \leq s \leq t$  and its associated generator  $\tilde{\mathcal{A}}_s^{(t)}$  given for all  $\psi : \mathbb{R}_+ \times \{0, 1\} \rightarrow \mathbb{R}_+$  such that  $\psi(\cdot, 0), \psi(\cdot, 1) \in \mathcal{D}(\mathcal{A})$ , and for all  $(x, d) \in \mathbb{R}_+ \times \{0, 1\}$ , by

$$\begin{aligned} \tilde{\mathcal{A}}_s^{(t)} \psi(x, d) = & \tilde{\mathcal{G}}_s^{(t)} \psi(\cdot, d)(x) + 2r(x) \int_{\mathbb{R}_+} (\psi(\theta x, d) - \psi(x, d)) \frac{m((y, d), s, t)}{m((x, d), s, t)} \kappa(d\theta) \\ & + q(x) (\psi(x, 1) - \psi(x, d)). \end{aligned} \quad (4.3)$$

Using the Many-to-One formula (4.2), we get

$$m_0(x, s, t) = \mathbb{E} \left[ \sum_{u \in V_t} \mathbf{1}_{\{D_t^u=0\}} \mid \tilde{Z}_s = \delta_{(x,0)} \right] = m((x, 0), s, t) \mathbb{P} \left( D_t = 0 \mid \tilde{Y}_s^{(t)} = (x, 0) \right).$$

As we can see on the expression of the generator of the auxiliary process in (4.3),  $D_s$  switches from 0 to 1 at rate  $q(x)$  and 1 is absorbing for  $D_t$ . Therefore,

$$m_0(x, s, t) = \mathbb{E} \left[ \exp \left( - \int_s^t q(Y_u^{(t)}) du \right) \mid Y_s^{(t)} = x \right] m((x, 0), s, t),$$

and in the case  $q(x) \equiv q \geq 0$  for all  $x \geq 0$ , we get

$$m_0(x, s, t) = e^{-q(t-s)} m((x, 0), s, t).$$

In particular, for all  $x, y \geq 0$

$$\frac{m_0(y, s, t)}{m_0(x, s, t)} = \frac{m((y, 0), s, t)}{m((x, 0), s, t)}. \quad (4.4)$$

The expressions appearing in the generator of the auxiliary process given page 11 are identical with or without death, but the difference is hidden in the ratios of  $m(y, s, t)/m(x, s, t)$ . From the previous computations, we obtain that in the case of a constant death rate, the auxiliary process is the same as the auxiliary process of a population process without death and

$$\mathbb{E} \left[ \sum_{u \in V_t^0} f(X_s^u) \mid Z_r = \delta_x \right] = m_0(x, r, t) \mathbb{E} \left[ f(Y_s^{(t)}) \mid Y_r^{(t)} = x \right] = e^{-q(t-r)} \mathbb{E} \left[ \sum_{u \in V_t} f(X_s^u) \mid Z_r = \delta_x \right].$$

**4.3. The case**  $r(x) = \alpha x + \beta$ ,  $q(x) \equiv q$ . Assume that  $c_b = 0$  (no stable positive jumps). Then under Assumption **LDCG**, a direct computation (see [21, Section 2.2.3] for details) shows that if  $g \neq \beta$ , the mean number of individuals can be written

$$m(x, s, t) = \frac{\alpha x}{g - \beta} e^{(g-q)(t-s)} + \left( 1 - \frac{\alpha x}{g - \beta} \right) e^{(\beta-q)(t-s)}. \quad (4.5)$$

We introduce the following functions for  $y > 0$ ,  $s, z \geq 0$ , and  $\theta \in [0, 1]$ :

$$f_1(y, s) := gy + \left( 2\sigma^2(y) + p(y) \int_{\mathbb{R}_+} z^2 \pi(dz) \right) \frac{\alpha (e^{(g-\beta)s} - 1)}{g - \beta + \alpha y (e^{(g-\beta)s} - 1)}, \quad (4.6)$$

$$f_2(y, s, \theta) := 2(\alpha y + \beta) \frac{g - \beta + \alpha \theta y (e^{(g-\beta)s} - 1)}{g - \beta + \alpha y (e^{(g-\beta)s} - 1)}, \quad (4.7)$$

and

$$f_3(y, s, z) := p(y) \left( 1 + \frac{\alpha z (e^{(g-\beta)s} - 1)}{(g - \beta) + \alpha y (e^{(g-\beta)s} - 1)} \right). \quad (4.8)$$

We obtain that  $\mathcal{A}^{(t)}$  is the infinitesimal generator of the solution to the following SDE, when existence and uniqueness in law of the solution hold. For  $0 \leq s \leq t$ ,

$$\begin{aligned} Y_s^{(t)} = & Y_0^{(t)} + \int_0^s f_1(Y_u^{(t)}, t - u) du + \int_0^s \int_0^\infty \int_0^\infty f_3(Y_{u^-}^{(t)}, t - u, z) z \tilde{Q}(du, dz, dx) \\ & + \int_0^s \sqrt{2\sigma^2(Y_u^{(t)})} dB_u + \int_0^s \int_0^1 \int_0^\infty f_2(Y_{u^-}^{(t)}, t - u, \theta) (\theta - 1) Y_{u^-}^{(t)} N(du, d\theta, dz), \end{aligned} \quad (4.9)$$

where  $\tilde{Q}$ ,  $B$  are the same as in (1.1) and  $N$  is a PPM on  $\mathbb{R}_+ \times \mathbb{R}_+ \times [0, 1]$  with intensity  $ds \otimes dx \otimes \kappa(d\theta)$ .

The auxiliary process  $Y^{(t)}$  can be realised as the unique strong solution to the SDE (4.9) under some moment conditions on the measure associated with the positive jumps. We also need an additional assumption on  $p$  that ensures that the rate of positive jumps  $f_3$  of the process  $Y$  is increasing with the quantity of parasites.

**Proposition 4.1.** *Suppose that Assumption **LDCG** holds and that  $\int z^2 \pi(dz) < \infty$ , and that  $xp'(x) \geq p(x)$  for every  $x \geq 0$ . Then, Equation (4.9) has a pathwise unique nonnegative strong solution.*

The proof of this proposition is given in Appendix C. The case  $g = \beta$  will not be considered in this work, as it entails additional computations and does not bring new insights.

## 5. PROOFS

**5.1. Proof of Proposition 2.1.** Let us introduce the SDE

$$\begin{aligned} Y_t = & x + \int_0^t g(Y_s) ds + \int_0^t \sqrt{2\sigma^2(Y_s)} dB_s + \int_0^t \int_0^{p(Y_{s^-})} \int_{\mathbb{R}_+} z \tilde{Q}(ds, dx, dz) \\ & + \int_0^t \int_0^{Y_{s^-}} \int_{\mathbb{R}_+} z R(ds, dx, dz) + \int_0^t \int_0^{2r(Y_{s^-})} \int_0^1 (\theta - 1) Y_{s^-} N(ds, dx, d\theta), \end{aligned} \quad (5.1)$$

where  $N$  is a PPM on  $\mathbb{R}_+ \times \mathbb{R}_+ \times [0, 1]$  with intensity  $ds \otimes dx \otimes \kappa(d\theta)$ . Note that  $Y$  is well-defined as the unique strong solution to (5.1) under Assumption **EU** (see [22, Proposition 2.2] and Appendix A). Then, Proposition 2.1 is a consequence of the following two lemmas.

**Lemma 5.1.** *Assume that there exists a real number  $\gamma$  such that  $r(x) - q(x) \leq \gamma$  for any  $x \in \mathbb{R}_+$ , and let  $f$  be a nonnegative measurable function on  $\mathbb{R}_+$ . Then for  $x, t \geq 0$ ,*

$$\mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} f(X_t^u) \right] \leq e^{\gamma t} \mathbb{E}_x [f(Y_t)],$$

where  $Y$  is the unique strong solution to the SDE (5.1).

**Lemma 5.2.** *Let  $\zeta > 0$ .*

*i) If Assumption **EXPL** holds for some  $a > 1$  such that  $\mathbb{E}[\Theta^{1-a}] < \infty$  then*

$$\lim_{t \rightarrow \infty} \mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} (X_t^u \vee \zeta)^{1-a} \right] = 0, \quad \forall x \geq 0.$$

ii) If Assumption **EXT** holds for some  $a < 1$  then

$$\lim_{t \rightarrow \infty} \mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} (X_t^u \wedge \zeta)^{1-a} \right] = 0, \quad \forall x \geq 0.$$

*Proof of Lemma 5.1.* Let us introduce the generator

$$\mathcal{A}f(x) = \mathcal{G}f(x) + 2r(x) \int_0^1 (f(\theta x) - f(x)) \kappa(d\theta). \quad (5.2)$$

We normalize the population process similarly as in (4.1). Let  $\gamma \in \mathbb{R}$  be such that for all  $x \geq 0$ ,  $r(x) - q(x) \leq \gamma$ . Let  $f \in \mathcal{C}_b^2$  and for  $x, t \geq 0$  let

$$\gamma_t f = e^{-\gamma t} \mathbb{E} \left[ \sum_{u \in V_t} f(X_t^u) | Z_0 = \delta_x \right]$$

be the renormalized first moment semigroup of  $Z$ . Then we have

$$\begin{aligned} \frac{\partial}{\partial t} \gamma_t f &= \int_{\mathbb{R}_+} (\mathcal{G}f(\mathbf{x}) - \gamma f(\mathbf{x})) \gamma_t(d\mathbf{x}) \\ &\quad + \int_{\mathbb{R}_+} \left( r(\mathbf{x}) \int_0^1 (f(\theta \mathbf{x}) + f((1-\theta)\mathbf{x}) - f(\mathbf{x})) \kappa(d\theta) - q(\mathbf{x})f(\mathbf{x}) \right) \gamma_t(d\mathbf{x}) \\ &= \int_{\mathbb{R}_+} (\mathcal{G}f(\mathbf{x}) - \gamma f(\mathbf{x})) \gamma_t(d\mathbf{x}) \\ &\quad + \int_{\mathbb{R}_+} \left( 2r(\mathbf{x}) \int_0^1 (f(\theta \mathbf{x}) - f(\mathbf{x})) \kappa(d\theta) + (r(\mathbf{x}) - q(\mathbf{x}))f(\mathbf{x}) \right) \gamma_t(d\mathbf{x}), \end{aligned}$$

and using that  $r(x) - q(x) \leq \gamma$  for all  $x \geq 0$ , we obtain

$$\frac{\partial}{\partial t} \gamma_t f \leq \gamma_t(\mathcal{A}f),$$

where  $\mathcal{A}$  is defined in (5.2). Finally, by unicity of the solution to the Kolmogorov's backward equation,

$$\gamma_t f = \mathbb{E} \left[ \sum_{u \in V_t} f(X_t^u) | Z_0 = \delta_x \right] e^{-\gamma t} \leq \mathbb{E}_x [f(Y_t)], \quad (5.3)$$

where  $Y$  is the unique strong solution to the SDE (5.1).  $\square$

*Proof of Lemma 5.2.* Let  $Y$  be the unique strong solution to (5.1). First, we prove using a coupling argument that under Assumption **EXPL**, for all  $y > 0$ ,  $\mathbb{P}_y(\tau^-(0) < \infty) = 0$ , where

$$\tau^-(0) = \inf \{ t \geq 0, Y_t = 0 \}. \quad (5.4)$$

Let  $K > 0$ . We consider the process  $\tilde{Y}$  defined as the unique strong solution to

$$\begin{aligned} \tilde{Y}_t &= x + \int_0^t g(\tilde{Y}_s) ds + \int_0^t \sqrt{2\sigma^2(\tilde{Y}_s)} dB_s + \int_0^t \int_{\mathbb{R}_+}^{p(\tilde{Y}_{s-})} z \tilde{Q}(ds, dx, dz) \\ &\quad + \int_0^t \int_{\mathbb{R}_+}^{\tilde{Y}_{s-}} z R(ds, dx, dz) + \int_0^t \int_0^{2\bar{r}_K} \int_0^1 (\theta - 1) \tilde{Y}_{s-} N(ds, dx, d\theta), \end{aligned}$$

where  $B, \tilde{Q}$  and  $N$  are the same as in (5.1) and  $\bar{r}_K = \sup_{x \in [0, K]} r(x)$ . Then, as  $p$  is a non-decreasing function,

$$\tilde{Y}_t \leq Y_t \quad \text{for all } t \leq \tau^+(K) := \inf \{ t \geq 0, Y_t \geq K \}. \quad (5.5)$$

Let  $\tilde{\tau}^-(0) = \inf\{t \geq 0, \tilde{Y}_t = 0\}$ . Adapting [22, Theorem 3.3] (see Appendix B.1), if **(SN0)** holds,  $\mathbb{P}_y(\tilde{\tau}^-(0) < \infty) = 0$  for all  $y > 0$ . Let  $a > 1$  be as in Assumption **EXPL**. Using that  $G_a(x) \geq \gamma'$ , we have

$$\frac{g(x)}{x} - a \frac{\sigma^2(x)}{x^2} + x^{-b} C_a - p(x) I_a(x) \geq (a-1)^{-1} \gamma' + 2r(x) \frac{\mathbb{E}[\Theta^{1-a} - 1]}{a-1},$$

so that **(SN0)** holds. We thus obtain that for all  $y > 0$ ,  $\mathbb{P}_y(\tilde{\tau}^-(0) < \infty) = 0$ . Then, from (5.5) we get  $\mathbb{P}_y(\tau^-(0) < \tau^+(K)) = 0$  and letting  $K$  tend to infinity yields

$$\mathbb{P}_y(\tau^-(0) < \infty) = 0. \quad (5.6)$$

Now, let  $\zeta > 0$  and  $\varepsilon > 0$ . Let  $T(\varepsilon) := \tau^-(\varepsilon) \wedge \tau^+(1/\varepsilon)$  where

$$\tau^-(\varepsilon) = \inf\{t \geq 0, Y_t < \varepsilon\}. \quad (5.7)$$

Then we have from (5.3), for every  $t \geq 0$ ,  $x > 0$ ,

$$\mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} (X_t^u \vee \zeta)^{1-a} \right] \leq e^{\gamma t} \mathbb{E}_x [\mathbf{1}_{\{t \leq T(\varepsilon)\}} Y_t^{1-a}] + e^{\gamma t} \mathbb{E}_x [\mathbf{1}_{\{t > T(\varepsilon)\}} (Y_t \vee \zeta)^{1-a}].$$

For the first term, using that  $G_a(x) \geq \gamma'$  for all  $x \geq 0$  and the martingale property proved in Lemma B.1, we have

$$\begin{aligned} e^{\gamma t} \mathbb{E}_x [\mathbf{1}_{\{t \leq T(\varepsilon)\}} Y_t^{1-a}] &= e^{(\gamma - \gamma')t} \mathbb{E}_x \left[ Y_{t \wedge T(\varepsilon)}^{1-a} e^{\gamma'(t \wedge T(\varepsilon))} \mathbf{1}_{\{t \leq T(\varepsilon)\}} \right] \\ &\leq e^{(\gamma - \gamma')t} \mathbb{E}_x \left[ Y_{t \wedge T(\varepsilon)}^{1-a} e^{\int_0^{t \wedge T(\varepsilon)} G_a(Y_s) ds} \right] = x e^{(\gamma - \gamma')t}. \end{aligned}$$

And for the second term,

$$\mathbb{E}_x [\mathbf{1}_{\{t > T(\varepsilon)\}} (Y_t \vee \zeta)^{1-a}] \leq \mathbb{E}_x [\mathbf{1}_{\{t > \tau^-(\varepsilon)\}} (Y_t \vee \zeta)^{1-a}] + \mathbb{E}_x [\mathbf{1}_{\{t > \tau^+(1/\varepsilon)\}} (Y_t \vee \zeta)^{1-a}].$$

For any fixed  $t \geq 0$ , as  $a > 1$ ,

$$\mathbf{1}_{\{t > \tau^-(\varepsilon)\}} (Y_t \vee \zeta)^{1-a} \leq \zeta^{1-a}$$

where  $\zeta^{1-a}$  is finite and does not depend on  $\varepsilon$ , and we know thanks to (5.6) that

$$\lim_{\varepsilon \rightarrow 0} \mathbf{1}_{\{t > \tau^-(\varepsilon)\}} = 0 \quad \text{almost surely.}$$

Hence by the dominated convergence theorem, we obtain that

$$\lim_{\varepsilon \rightarrow 0} \mathbb{E}_x [\mathbf{1}_{\{t > \tau^-(\varepsilon)\}} (Y_t \vee \zeta)^{1-a}] = 0 \quad \text{almost surely.}$$

Let us finally consider the last term. First, notice that for every  $\varepsilon > 0$

$$\mathbf{1}_{\{t > \tau^+(1/\varepsilon)\}} (Y_t \vee \zeta)^{1-a} \leq \zeta^{1-a} \quad (5.8)$$

where  $\zeta^{1-a}$  is finite and does not depend on  $\varepsilon$ . Now, let us consider the sequence of stopping times  $(\tau^+(1/\varepsilon), \varepsilon > 0)$ . This sequence increases when  $\varepsilon$  decreases, and there exists  $\tau^+(\infty)$ , which may be infinite, defined by

$$\lim_{\varepsilon \rightarrow 0} \tau^+(1/\varepsilon) =: \tau^+(\infty). \quad (5.9)$$

There are two cases:

- If  $\tau^+(\infty) \leq t$  then  $Y_t = \infty$  and

$$\mathbf{1}_{\{t > \tau^+(1/\varepsilon)\}} (Y_t \vee \zeta)^{1-a} = 0.$$

- If  $t > \tau^+(\infty)$  then there exists  $\varepsilon_0 > 0$  such that for any  $\varepsilon \leq \varepsilon_0$ ,  $\tau^+(1/\varepsilon) \geq t$ , and

$$\mathbf{1}_{\{t > \tau^+(1/\varepsilon)\}} (Y_t \vee \zeta)^{1-a} = 0, \quad \forall \varepsilon \leq \varepsilon_0.$$

We deduce that for any fixed  $t \geq 0$

$$\lim_{\varepsilon \rightarrow 0} \mathbf{1}_{\{t > \tau^+(1/\varepsilon)\}} (Y_t \vee \zeta)^{1-a} = 0 \quad \text{almost surely.}$$

From (5.8) we may apply the dominated convergence theorem and obtain

$$\lim_{\varepsilon \rightarrow 0} \mathbb{E}_x \left[ \mathbf{1}_{\{t > \tau^+(1/\varepsilon)\}} (Y_t \vee \zeta)^{1-a} \right] = 0.$$

To sum up, we proved that for any  $t \geq 0$ ,  $x > 0$ , and  $\varepsilon > 0$ ,

$$\mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} (X_t^u \vee \zeta)^{1-a} \right] \leq x e^{(\gamma - \gamma')t} + e^{\gamma t} \mathbb{E}_x \left[ \mathbf{1}_{\{t > T(\varepsilon)\}} (Y_t \vee \zeta)^{1-a} \right] \xrightarrow[\varepsilon \rightarrow 0]{} x e^{(\gamma - \gamma')t}.$$

Letting  $t$  tend to infinity ends the proof of point *i*), as  $\gamma < \gamma'$ .

Let us now turn to the proof of point *ii*). It is similar in spirit to the proof of point *i*). Let  $a < 1$  and  $\gamma' > 0$  be such that Assumption **EXT** holds. Adapting [22, Theorem 4.1i)] (see Proposition B.3), under Condition **(SN $\infty$ )**, we get for  $Y$  (defined as before as the unique strong solution to (5.1)), and for all  $y > 0$ ,

$$\mathbb{P}_y (\tau^+(\infty) < \infty) = 0, \quad (5.10)$$

where  $\tau^+(\infty)$  has been defined in (5.9). And as  $G_a(x) \geq \gamma'$  for all  $x \geq 0$ , **(SN $\infty$ )** holds.

Let  $\varepsilon > 0$ . Similar computations as for point *i*) lead to

$$\mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} (X_t^u \wedge \zeta)^{1-a} \right] \leq x e^{(\gamma - \gamma')t} + e^{\gamma t} \left( \mathbb{E}_x \left[ \mathbf{1}_{\{\tau^-(\varepsilon) < t\}} (Y_t \wedge \zeta)^{1-a} \right] + \mathbb{P}_x(\tau^+(1/\varepsilon) < t) \zeta^{1-a} \right).$$

From (5.10), the last term converges to 0 when  $\varepsilon$  goes to 0. Moreover, distinguishing between the cases  $\{\tau^-(0) \leq t\}$  and  $\{\tau^-(0) > t\}$  and applying the dominated convergence theorem, the second term also converges to 0 when  $\varepsilon$  goes to 0. This ends the proof of *ii*).  $\square$

*Proof of Proposition 2.1.* Let  $K > 0$ ,  $t \geq 0$ . Under Assumption **EXPL**, as  $a > 1$ :

$$\begin{aligned} \mathbb{P}_{\delta_x} (\exists u \in V_t, X_t^u \leq K) &= \mathbb{P}_{\delta_x} (\exists u \in V_t, (X_t^u \vee K)^{1-a} = K^{1-a}) \\ &\leq \mathbb{P}_{\delta_x} \left( \sum_{u \in V_t} (X_t^u \vee K)^{1-a} \geq K^{1-a} \right) \leq \mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} (X_t^u \vee K)^{1-a} \right] K^{a-1}, \end{aligned}$$

by Markov's inequality. The other case is similar. Proposition 2.1 follows from Lemma 5.2.  $\square$

## 5.2. Proofs of Section 3.1 and 3.2.

*Proof of Proposition 3.1.* First note that  $\alpha_\beta$  is well-defined because  $\psi : \alpha \mapsto 2\mathbb{E}[\Theta^\alpha] - 1$  is decreasing on  $\mathbb{R}$ , and  $\psi((-\infty, 1]) = [0, +\infty)$ . Let  $\mathcal{B}$  be the infinitesimal generator associated with the first moment semigroup of the branching process given for all  $f \in \mathcal{C}_b^2(\mathbb{R}_+)$  by

$$\begin{aligned} \mathcal{B}f(x) &= g(x)f'(x) + \sigma^2(x)f''(x) + p(x) \int_{\mathbb{R}_+} (f(x+z) - f(x) - zf'(x)) \pi(dz) \\ &\quad + r(x) \int_0^1 (f(\theta x) + f((1-\theta)x) - f(x)) \kappa(d\theta) - q(x)f(x). \end{aligned} \quad (5.11)$$

Let  $V_\alpha(x) = x^\alpha$ . Under Assumption **LGBE**, we have

$$\mathcal{B}V_\alpha(x) = \left( \alpha g + \alpha(\alpha - 1)\sigma^2 + r(x) \int_0^1 (2\theta^\alpha - 1) \kappa(d\theta) - q(x) \right) V_\alpha(x).$$

Then, as  $2\mathbb{E}[\Theta^{\alpha\beta}] - 1 = \beta$ , we obtain

$$\mathcal{B}V_{\alpha\beta}(x) = (\alpha_\beta g + \alpha_\beta(\alpha_\beta - 1)\sigma^2 + \mathbf{c}) V_{\alpha\beta}(x) := \lambda V_{\alpha\beta}(x).$$

Then, according to [12, Lemma 3.2], we have for all  $x \geq 0$ ,  $f \in \mathcal{C}_b^2(\mathbb{R}_+)$ ,

$$\mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} f(X_t^u) \right] = x^{\alpha_\beta} e^{\lambda t} \mathbb{E}_x \left[ f(\mathcal{Y}_t) V_{\alpha_\beta}^{-1}(\mathcal{Y}_t) \right], \quad (5.12)$$

where  $\mathcal{Y}$  is a Markov process with infinitesimal generator given by

$$\mathcal{A}_{V_{\alpha_\beta}} f(x) = (g + 2\sigma^2 \alpha_\beta) x f'(x) + \sigma^2 x^2 f''(x) + 2r(x) \left[ \int_0^1 \theta^{\alpha_\beta} (f(\theta x) - f(x)) \kappa(d\theta) \right],$$

and  $\mathcal{F}^{\mathcal{Y}}$  its natural filtration. Note that in particular, as  $2r(x)\mathbb{E}[\Theta^{\alpha_\beta}] = \beta r(x) + r(x) = \mathbf{c} + r(x) + q(x)$ , we get

$$d\mathcal{Y}_t^{-\alpha_\beta} = (r(\mathcal{Y}_t) - q(\mathcal{Y}_t) - \lambda) \mathcal{Y}_t^{-\alpha_\beta} dt + dM_t^{(1)},$$

where  $(M_t^{(1)}, t \geq 0)$  is a  $\mathcal{F}_t^{\mathcal{Y}}$ -martingale. Note also that taking  $f \equiv 1$  in (5.12), we obtain

$$\mathbb{E}_{\delta_x} [N_t] = x^{\alpha_\beta} e^{\lambda t} \mathbb{E}_x \left[ \mathcal{Y}_t^{-\alpha_\beta} \right]. \quad (5.13)$$

Next, let  $K \geq 0$  and  $f(x) = \mathbf{1}_{\{x > K\}}$ . Combining (5.12) and (5.13), we have

$$\frac{\mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} \mathbf{1}_{\{X_t^u > K\}} \right]}{\mathbb{E}_{\delta_x} [N_t]} = \frac{\mathbb{E}_x \left[ \mathbf{1}_{\{\mathcal{Y}_t > K\}} \mathcal{Y}_t^{-\alpha_\beta} \right]}{\mathbb{E}_x \left[ \mathcal{Y}_t^{-\alpha_\beta} \right]}.$$

First, we prove the point (i) of Proposition 3.1. Let  $\beta \in (0, 1)$ . Then,  $\alpha_\beta \in (0, 1)$  and

$$\frac{\mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} \mathbf{1}_{\{X_t^u > K\}} \right]}{\mathbb{E}_{\delta_x} [N_t]} \leq \frac{K^{-\alpha_\beta} \mathbb{P}_x(\mathcal{Y}_t > K)}{\mathbb{E}_x \left[ \mathcal{Y}_t^{-\alpha_\beta} \right]}. \quad (5.14)$$

Moreover, in this case

$$\frac{d}{dt} \mathbb{E}_x \left[ \mathcal{Y}_t^{-\alpha_\beta} \right] = \mathbb{E}_x \left[ ((1 - \beta)r(\mathcal{Y}_t) + \mathbf{c} - \lambda) \mathcal{Y}_t^{-\alpha_\beta} \right] \geq (\mathbf{c} - \lambda) \mathbb{E}_x \left[ \mathcal{Y}_t^{-\alpha_\beta} \right],$$

and by Grönwall's lemma we obtain

$$\mathbb{E}_x \left[ \mathcal{Y}_t^{-\alpha_\beta} \right] \geq x^{-\alpha_\beta} e^{(\mathbf{c} - \lambda)t}.$$

Combining this inequality with (5.14), we have

$$\frac{\mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} \mathbf{1}_{\{X_t^u > K\}} \right]}{\mathbb{E}_{\delta_x} [N_t]} \leq \left( \frac{x}{K} \right)^{\alpha_\beta} e^{\alpha_\beta(g + (\alpha_\beta - 1)\sigma^2)t}$$

where we used that  $\lambda - \mathbf{c} = \alpha_\beta(g + (\alpha_\beta - 1)\sigma^2)$ . This ends the proof of point (i).

For the point (iii), let  $\beta > 1$ . Then,  $\alpha_\beta < 0$ . Using Itô's formula, we have for all  $t \geq 0$ ,

$$\ln(\mathcal{Y}_t) = \ln(\mathcal{Y}_0) + (g + \sigma^2(2\alpha_\beta - 1))t + 2\mathbb{E}[\Theta^{\alpha_\beta} \ln(\Theta)] \int_0^t r(\mathcal{Y}_s) ds + M_t^{(2)},$$

where  $(M_t^{(2)}, t \geq 0)$  is a  $\mathcal{F}_t^{\mathcal{Y}}$ -martingale. By assumption, there exist  $x_0(\alpha_\beta), \eta > 0$  such that (3.2) holds. To simplify, we write  $x_0$  instead of  $x_0(\alpha_\beta)$  later in the proof. Then, for  $0 < y_0 < x_0$ ,

$$\ln(\mathcal{Y}_{t \wedge \tau^+(x_0)}) - \ln(y_0) \geq \eta(t \wedge \tau^+(x_0)) + M_{t \wedge \tau^+(x_0)}^{(2)}, \quad (5.15)$$

where  $\tau^+(x_0)$  has the same definition as in (5.5) except that it is for the process  $\mathcal{Y}$ . Note that  $\mathcal{Y}_{\tau^+(x_0)} = x_0$ . Therefore, for all  $t \geq 0$ ,  $\ln(\mathcal{Y}_{t \wedge \tau^+(x_0)}) \leq \ln(x_0)$  almost surely. Then, taking the expectation in (5.17), using this inequality and letting  $t$  tend to infinity, we obtain

$$\mathbb{E}_{y_0} [\tau^+(x_0)] \leq \eta^{-1} \ln \left( \frac{x_0}{y_0} \right) < \infty.$$

Applying [10, Theorem 7.1.4],  $\mathcal{Y}_t$  converges in law to a variable  $\mathcal{Y}_\infty$  on  $\mathbb{R}_+$ , satisfying

$$\mathbb{P}(\mathcal{Y}_\infty \leq A) = \frac{1}{\mathbb{E}_{x_0}[\tau^+(x_0)]} \mathbb{E} \left[ \int_0^{\tau^+(x_0)} \mathbf{1}_{\{\mathcal{Y}_s \leq A\}} ds \right].$$

Moreover, as **(SN0)** is satisfied thanks to (3.2), applying [22, Theorem 3.3i)], we obtain  $\mathbb{P}(\mathcal{Y}_\infty = 0) = 0$ . Recalling that as  $\alpha_\beta < 0$ , Fatou's lemma implies that for any  $x > 0$ ,

$$\liminf_{t \rightarrow \infty} \mathbb{E}_x [\mathcal{Y}_t^{-\alpha_\beta}] \geq \liminf_{t \rightarrow \infty} \mathbb{E}_x [(\mathcal{Y}_t \wedge 1)^{-\alpha_\beta}] = \mathbb{E}_x [(\mathcal{Y}_\infty \wedge 1)^{-\alpha_\beta}] > 0. \quad (5.16)$$

Finally, as before, combining (5.12) and (5.13), we obtain for any  $K \geq 0$ ,

$$\frac{\mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} \mathbf{1}_{\{X_t^u \leq K\}} \right]}{\mathbb{E}_{\delta_x} [N_t]} = \frac{\mathbb{E}_x \left[ \mathbf{1}_{\{\mathcal{Y}_t \leq K\}} \mathcal{Y}_t^{-\alpha_\beta} \right]}{\mathbb{E}_x [\mathcal{Y}_t^{-\alpha_\beta}]} \leq \frac{K^{-\alpha_\beta}}{\mathbb{E}_x [\mathcal{Y}_t^{-\alpha_\beta}]}.$$

Using (5.16) ends the proof of (iii).

The proof of point (ii) is very similar, and we only give the main ideas of the proof. Assume that there exist  $x_0(\alpha_\beta), \eta > 0$  such that (3.1) holds. Then, one can prove as before that for  $y_0 > x_0 > 0$ ,

$$\mathbb{E}_{y_0} [\tau^-(x_0)] \leq (\mathbb{E}[\ln 1/\Theta] + \ln(y_0/x_0))/\eta,$$

where  $\tau^-(x_0)$  has the same definition as in (5.7) except that it is for  $\mathcal{Y}$ . Applying again [10, Theorem 7.1.4],  $\mathcal{Y}_t$  converges in law to a variable  $\mathcal{Y}_\infty$  on  $\mathbb{R}_+$ . As **(SN $\infty$ )** is satisfied thanks to (3.1), [22, Theorem 4.1i)] implies  $\mathbb{P}(\mathcal{Y}_\infty = \infty) = 0$ . Finally, as  $\alpha_\beta \geq 0$ ,

$$\mathbb{E}_x [\mathcal{Y}_\infty^{-\alpha_\beta}] \geq \mathbb{E}_x [(\mathcal{Y}_\infty \vee 1)^{-\alpha_\beta}] > 0.$$

Combining this with (5.12) and (5.13) ends the proof as before.  $\square$

*Proof of Proposition 3.3.* The proof is very similar to the proof of Proposition 3.1, we thus only give the main ideas. Recall the definition of  $\mathcal{B}$  in (5.11). Then for  $V_1(x) = x$ , we obtain

$$\mathcal{B}V_1(x) = g(x) - q(x)V_1(x) = \left( \frac{g(x)}{x} - q(x) \right) V_1(x) = \mathfrak{c}V_1(x),$$

and (5.12) thus holds where  $\mathcal{Y}$  is the Markov process with infinitesimal generator given by

$$\begin{aligned} \mathcal{A}_{V_1} f(x) &= \left( g(x) + 2 \frac{\sigma^2(x)}{x} + \frac{p(x)}{x} \int z^2 \pi(dz) \right) f'(x) + \sigma^2(x) f''(x) \\ &+ p(x) \int (f(x+z) - f(x) - zf'(x)) \frac{(x+z)}{x} \pi(dz) + 2r(x) \left[ \int_0^1 \theta (f(\theta x) - f(x)) \kappa(d\theta) \right]. \end{aligned}$$

Let us begin with the proof of point ii). We have

$$\frac{\mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} \mathbf{1}_{\{X_t^u \geq K\}} \right]}{\mathbb{E}_{\delta_x} [N_t]} = \frac{\mathbb{E}_x \left[ \mathbf{1}_{\{\mathcal{Y}_t \geq K\}} \mathcal{Y}_t^{-1} \right]}{\mathbb{E}_x [\mathcal{Y}_t^{-1}]} \leq \frac{K^{-1}}{\mathbb{E}_x [\mathcal{Y}_t^{-1}]}.$$

Let us prove that  $\liminf_{t \rightarrow \infty} \mathbb{E}_x [\mathcal{Y}_t^{-1}] > 0$ . Using Itô's formula and Taylor's formula for the term accounting for positive jumps, we have for all  $t \geq 0$ ,

$$\ln(\mathcal{Y}_t) = \ln(\mathcal{Y}_0) + \int_0^t \left( \frac{g(\mathcal{Y}_s)}{\mathcal{Y}_s} + \frac{\sigma^2(\mathcal{Y}_s)}{\mathcal{Y}_s^2} + p(\mathcal{Y}_s) I_0(\mathcal{Y}_s) \right) ds + 2\mathbb{E}[\Theta \ln(\Theta)] \int_0^t r(\mathcal{Y}_s) ds + M_t^{(3)},$$

where  $(M_t^{(3)}, t \geq 0)$  is a  $\mathcal{F}_t^{\mathcal{Y}}$ -martingale. By assumption, there exist  $x_0, \eta > 0$  such that (3.6) holds. Then, for  $0 < x_0 < y_0$ ,

$$\ln(\mathcal{Y}_{t \wedge \tau^-(x_0)}) - \ln(y_0) \leq -\eta(t \wedge \tau^-(x_0)) + M_{t \wedge \tau^-(x_0)}^{(3)}. \quad (5.17)$$

Hence, taking the expectation in (3.6), we obtain  $\mathbb{E}_{y_0}[\tau^-(x_0)] \leq (\mathbb{E}[\ln 1/\Theta] + \ln(y_0/x_0))/\eta$ .

Applying [10, Theorem 7.1.4],  $\mathcal{Y}_t$  converges in law to a variable  $\mathcal{Y}_\infty$  on  $\mathbb{R}_+$ , satisfying

$$\mathbb{P}(\mathcal{Y}_\infty \leq A) = \frac{1}{\mathbb{E}_{x_0}[\tau^-(x_0)]} \mathbb{E} \left[ \int_0^{\tau^-(x_0)} \mathbf{1}_{\{\mathcal{Y}_s \leq A\}} ds \right].$$

As  $(\mathbf{SN}_\infty)$  is satisfied, [22, Theorem 4.1i)] ensures  $\mathbb{P}(\mathcal{Y}_\infty = \infty) = 0$ . Fatou's lemma implies that for any  $x > 0$ ,

$$\liminf_{t \rightarrow \infty} \mathbb{E}_x[\mathcal{Y}_t^{-1}] \geq \liminf_{t \rightarrow \infty} \mathbb{E}_x[(\mathcal{Y}_t \vee 1)^{-1}] = \mathbb{E}_x[(\mathcal{Y}_\infty \vee 1)^{-1}] > 0,$$

which ends the proof of point ii).

For point i), applying the generator  $\mathcal{A}_{V_1}$  to the function  $f(x) = x^{-2}$  (as  $\mathbb{P}(\mathcal{Y}_t = 0) = 0$  for all  $t \geq 0$  using (5.12) with  $f(x) = x \mathbf{1}_{\{x=0\}}$ ), we obtain:

$$d(\mathcal{Y}_t^{-2}) = -2\mathcal{Y}_t^{-2} \left( \frac{g(\mathcal{Y}_t)}{\mathcal{Y}_t} - \frac{\sigma^2(\mathcal{Y}_t)}{\mathcal{Y}_t^2} - \frac{p(\mathcal{Y}_t)}{2\mathcal{Y}_t} \int_{\mathbb{R}_+} \frac{z^2 \pi(dz)}{\mathcal{Y}_t + z} - r(\mathcal{Y}_t) \mathbb{E} \left[ \frac{1}{\Theta} - \frac{1}{2} \right] \right) dt + dM_t^{(4)},$$

where  $(M_t^{(4)}, t \geq 0)$  is a  $\mathcal{F}_t^{\mathcal{Y}}$ -martingale. From (3.3), there exists  $C_1 < \infty$  such that

$$\sup_{x \geq x_0} \left\{ 2 \frac{\sigma^2(x)}{x^4} + \frac{p(x)}{x^3} \int_{\mathbb{R}_+} \frac{z^2 \pi(dz)}{x+z} + \frac{r(x)}{x^2} \mathbb{E} \left[ \frac{2}{\Theta} - 1 \right] \right\} = C_1.$$

Adding condition (3.4), we thus obtain that

$$\frac{d}{dt} \mathbb{E}[\mathcal{Y}_t^{-2}] \leq \left( -2\eta_1 \mathbb{E}[\mathcal{Y}_t^{-2}] + \frac{2}{x_0^2} \eta_1 + C_1 \right),$$

which yields the existence of a finite constant  $C_2$  such that

$$\sup_{t \geq 0} \mathbb{E}[\mathcal{Y}_t^{-2}] = C_2.$$

Applying the generator  $\mathcal{A}_{V_1}$  to the function identity and taking the expectation, we get

$$\frac{d}{dt} \mathbb{E}[\mathcal{Y}_t] = \mathbb{E} \left[ \mathcal{Y}_t \left( \frac{g(\mathcal{Y}_t)}{\mathcal{Y}_t} + 2 \frac{\sigma^2(\mathcal{Y}_t)}{\mathcal{Y}_t^2} + \frac{p(\mathcal{Y}_t)}{\mathcal{Y}_t^2} \int_{\mathbb{R}_+} z^2 \pi(dz) + 2r(\mathcal{Y}_t) \left( \mathbb{E}[\Theta^2] - \frac{1}{2} \right) \right) \right].$$

Combining (3.5) with  $\mathbf{EU}$ , there exists  $C_3 > 0$  such that

$$\frac{d}{dt} \mathbb{E}[\mathcal{Y}_t] \leq -\eta \mathbb{E}[\mathcal{Y}_t] + C_3,$$

which yields the existence of a finite constant  $C_4$  such that  $\sup_{t \geq 0} \mathbb{E}[\mathcal{Y}_t] = C_4$ . Using Jensen's inequality, we obtain  $\mathbb{E}[\mathcal{Y}_t^{-1}]^{-1} \leq C_4$ . Next, from the definition of  $\mathcal{Y}$  we know that

$$\frac{\mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} \mathbf{1}_{\{X_t^u \leq K\}} \right]}{\mathbb{E}_{\delta_x} [N_t]} = \frac{\mathbb{E}_x [\mathbf{1}_{\{\mathcal{Y}_t \leq K\}} \mathcal{Y}_t^{-1}]}{\mathbb{E}_x [\mathcal{Y}_t^{-1}]}.$$

Using the previous computations and Cauchy-Schwarz inequality, we obtain

$$\frac{\mathbb{E}_x [\mathbf{1}_{\{\mathcal{Y}_t \leq K\}} \mathcal{Y}_t^{-1}]}{\mathbb{E}_x [\mathcal{Y}_t^{-1}]} \leq C_4 \sqrt{\mathbb{P}(\mathcal{Y}_t^{-2} \geq K^{-2})} \mathbb{E} \left[ \frac{1}{\mathcal{Y}_t^2} \right] \leq C_2 C_4 K,$$

which ends the proof of point i).  $\square$

### 5.3. Proof of Section 3.3.

5.3.1. *Proof of Proposition 3.6.* First, we need to control the value of the second moment of the population size relatively to the square of its mean.

**Lemma 5.3.** *Suppose that Assumption LDCG holds. Then for all  $x > 0$ ,*

(i) *if  $\beta > \max(g, q)$ ,*

$$\mathbb{E}_{\delta_x} [N_t^2] \underset{t \rightarrow \infty}{\sim} C_1^2(x) e^{2(\beta-q)t}, \quad \mathbb{E}_{\delta_x}^2 [N_t] \underset{t \rightarrow \infty}{\sim} \left(1 + \frac{\alpha x}{\beta - g}\right)^2 e^{2(\beta-q)t},$$

where

$$C_1^2(x) = 1 + \frac{\alpha x}{2\beta - g - q} - \frac{\alpha^2 x^2}{(\beta - g)^2} + \left(1 + \frac{\alpha x}{\beta - g}\right) \left(\frac{2\alpha x}{\beta - g} + \frac{\beta + q}{\beta - q}\right) + \frac{\alpha x}{g - \beta} \frac{(\beta + q)}{2\beta - g - q}.$$

(ii) *if  $g > \max(\beta, q)$  and  $\alpha > 0$ ,*

$$\mathbb{E}_{\delta_x} [N_t^2] \underset{t \rightarrow \infty}{\sim} \mathbb{E}_{\delta_x}^2 [N_t] \underset{t \rightarrow \infty}{\sim} \left(\frac{\alpha x}{\beta - g}\right)^2 e^{2(g-q)t},$$

*Proof.* According to Itô's formula, we have for all  $t \geq 0$  and  $x > 0$ ,

$$\begin{aligned} \frac{d}{dt} \mathbb{E}_{\delta_x} [N_t^2] &= \mathbb{E}_{\delta_x} \left[ \left( \alpha x e^{(g-q)t} + \beta N_t \right) (1 + 2N_t) \right] + \mathbb{E}_{\delta_x} [q N_t (1 - 2N_t)] \\ &= \alpha x e^{(g-q)t} + 2\alpha x e^{(g-q)t} \mathbb{E}_{\delta_x} [N_t] + (\beta + q) \mathbb{E}_{\delta_x} [N_t] + 2(\beta - q) \mathbb{E}_{\delta_x} [N_t^2]. \end{aligned}$$

Using (4.5) and variation of constants we obtain

$$\begin{aligned} \mathbb{E}_{\delta_x} [N_t^2] &= e^{2(\beta-q)t} + \alpha x \frac{(e^{(g-q)t} - e^{2(\beta-q)t})}{g - 2\beta + q} + \frac{2\alpha^2 x^2 (e^{2(g-q)t} - e^{2(\beta-q)t})}{g - \beta} \frac{1}{2(g - \beta)} \\ &\quad + 2\alpha x \left(1 - \frac{\alpha x}{g - \beta}\right) \frac{(e^{(g+\beta-2q)t} - e^{2(\beta-q)t})}{g - \beta} + (\beta + q) \frac{\alpha x}{g - \beta} \frac{(e^{(g-q)t} - e^{2(\beta-q)t})}{g - 2\beta + q} \\ &\quad - \left(1 - \frac{\alpha x}{g - \beta}\right) (\beta + q) \frac{(e^{(\beta-q)t} - e^{2(\beta-q)t})}{\beta - q}. \end{aligned}$$

Therefore,

$$\begin{aligned} \text{if } g > \max(\beta, q), \quad \mathbb{E}_{\delta_x} [N_t^2] &\underset{t \rightarrow +\infty}{\sim} \frac{\alpha^2 x^2}{(g - \beta)^2} e^{2(g-q)t} \\ \text{if } \beta > \max(g, q), \quad \mathbb{E}_{\delta_x} [N_t^2] &\underset{t \rightarrow +\infty}{\sim} C_1^2(x) e^{2(\beta-q)t}. \end{aligned}$$

Moreover,

$$\mathbb{E}_{\delta_x} [N_t]^2 = \frac{\alpha^2 x^2}{(g - \beta)^2} e^{2(g-q)t} + \left(1 - \frac{\alpha x}{g - \beta}\right)^2 e^{2(\beta-q)t} - \frac{\alpha x}{\beta - g} \left(1 - \frac{\alpha x}{g - \beta}\right) e^{g+\beta-2q},$$

so that

$$\begin{aligned} \text{if } g > \max(\beta, q), \quad \mathbb{E}_{\delta_x} [N_t]^2 &\underset{t \rightarrow +\infty}{\sim} \frac{\alpha^2 x^2}{(g - \beta)^2} e^{2(g-q)t} \\ \text{if } \beta > \max(g, q), \quad \mathbb{E}_{\delta_x} [N_t]^2 &\underset{t \rightarrow +\infty}{\sim} \left(1 + \frac{\alpha x}{\beta - g}\right)^2 e^{2(\beta-q)t}. \end{aligned}$$

□

*Proof of Proposition 3.6.* Point *i*) is a direct consequence of the point *i*) of Proposition 3.3. Let  $a > 0$ . If we consider the process  $\mathcal{Y}$  with infinitesimal generator (3.7), we get from [12, Lemma 3.2] the following Many-to-One formulas, when considering the functions  $f(x) = x \mathbf{1}_{x \in [a, a+da]}$  and  $f(x) \equiv 1$ ,

$$a \mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} \mathbf{1}_{X_t^u \in [a, a+da]} \right] = x e^{ct} \mathbb{P}_x (\mathcal{Y} \in [a, a + da]) \quad \text{and} \quad \mathbb{E}_{\delta_x} \left[ \sum_{u \in V_t} 1 \right] = x e^{ct} \mathbb{E}_x [\mathcal{Y}_t^{-1}].$$

It concludes the proof of point *i*).

We now prove point *ii*). Proposition 3.3*i*) and Markov's inequality yield for any  $\varepsilon > 0$ ,

$$\lim_{K \rightarrow \infty} \lim_{t \rightarrow \infty} \mathbb{P}_{\delta_x} \left( \mathbf{1}_{\{N_t \geq 1\}} \frac{\#\{u \in V_t : X_t^u > K\}}{\mathbb{E}_{\delta_x}[N_t]} > \varepsilon \right) = 0.$$

To prove point *ii*), it is thus enough to prove that

$$\lim_{K \rightarrow \infty} \lim_{t \rightarrow \infty} \text{Diff}(K, t, \varepsilon) = 0, \quad (5.18)$$

where

$$\text{Diff}(K, t, \varepsilon) := \mathbb{P}_{\delta_x} \left( \mathbf{1}_{\{N_t \geq 1\}} \left| \frac{\#\{u \in V_t : X_t^u > K\}}{\mathbb{E}_{\delta_x}[N_t]} - \frac{\#\{u \in V_t : X_t^u > K\}}{N_t} \right| > \varepsilon \right).$$

We use different strategies depending on whether  $g > \max(\beta, q)$  and  $\alpha > 0$  or  $\beta > \max(g, q)$ .

**Case  $g > \max(\beta, q)$  and  $\alpha > 0$ .** Applying Markov's and Cauchy-Schwarz inequalities,

$$\text{Diff}(K, t, \varepsilon) \leq \frac{1}{\varepsilon \mathbb{E}_{\delta_x}[N_t]} \mathbb{E}_{\delta_x} \left[ \mathbf{1}_{\{N_t \geq 1\}} \frac{\#\{u \in V_t : X_t^u > K\}}{N_t} |N_t - \mathbb{E}[N_t]| \right] \leq \frac{\sqrt{\text{Var}_{\delta_x}(N_t)}}{\varepsilon \mathbb{E}_{\delta_x}[N_t]}$$

which goes to 0 as  $t$  goes to  $\infty$  according to Lemma 5.3 and (5.18) holds.

**Case  $\beta > \max(g, q)$ .** Notice that in this case, from the proof of Proposition 3.3 Many-to-One formula with the function  $f(x) = x$  writes  $\mathbb{E}_{\delta_x}[P_t] = x e^{(g-q)t}$ , where  $P_t := \sum_{u \in V_t} X_t^u$ , and from Lemma 5.3,

$$\mathbb{E}_{\delta_x}[N_t] \underset{t \rightarrow \infty}{\sim} \left( 1 + \frac{\alpha x}{\beta - g} \right) e^{(\beta-q)t}.$$

Hence

$$\mathbb{E}_{\delta_x}[P_t] \ll \mathbb{E}_{\delta_x}[N_t], \quad t \rightarrow \infty.$$

Let us introduce, for  $\varepsilon, t, K > 0$ , the event

$$A_{\varepsilon, t, K} := \left\{ \mathbf{1}_{\{N_t \geq 1\}} \frac{\#\{u \in V_t : X_t^u > K\}}{N_t} > \varepsilon \right\}.$$

We will make a reductio ad absurdum and assume that point *ii*) of Proposition 3.6 does not hold. As a consequence, there exists  $\varepsilon_0, a_0 > 0$  such that

$$\limsup_{K \rightarrow \infty} \limsup_{t \rightarrow \infty} \mathbb{P}_{\delta_x}(A_{\varepsilon_0, t, K}) \geq a_0. \quad (5.19)$$

But for any  $K, t > 0$ , we have

$$\mathbb{E}_{\delta_x}[P_t] \geq K \mathbb{E}_{\delta_x} \left[ \mathbf{1}_{\{N_t \geq 1\}} \frac{\sum_{u \in V_t} \mathbf{1}_{X_t^u > K}}{N_t} N_t \right] \geq K \varepsilon_0 \mathbb{E}_{\delta_x}[N_t \mathbf{1}_{A_{\varepsilon_0, t, K}}]. \quad (5.20)$$

The process  $(N_t, t \geq 0)$  has the same law as a supercritical branching process, with individual birth and death rates  $\beta$  and  $q$ , and a time inhomogeneous immigration (with rate  $\alpha P_t$ ). Then,

- (1) either there exists  $T_0 < \infty$  such that there is no more immigration after time  $T_0$ . In this case, either  $N_t$  goes to 0 at infinity, or  $N_t e^{-(\beta-q)t}$  converges almost surely when  $t$  goes to infinity to a positive random variable  $W_0$  ([3, p.112]).
- (2) or there is an infinite number of migrants, and as every birth-death process has probability  $1 - q/\beta > 0$  to survive ([3, p.109]), there is a time  $T_1 < \infty$  such that the immigrant arriving at time  $T_1$  has an infinite line of descent, and thus  $N_{t-T_1} e^{-(\beta-q)(t-T_1)}$  is larger than a process which converges almost surely when  $t$  goes to infinity to a positive random variable  $W_0$ .

From this analysis, we deduce that  $\liminf_{t \rightarrow \infty} \mathbb{E} [N_t e^{-(\beta-q)t} \mathbf{1}_{\{N_t \geq 1\}}] > 0$ . According to (5.19), there are sequences  $(K_n, n \in \mathbb{N})$ ,  $(t_n, n \in \mathbb{N})$  going to  $\infty$  and  $n_0 \in \mathbb{N}$  such that  $n \geq n_0$  implies  $\mathbb{P}_{\delta_x}(A_{\varepsilon_0, t_n, K_n}) \geq a_0/2$ . As for all  $n \geq 0$ ,  $A_{\varepsilon_0, t_n, K_n} \subseteq \{N_t \geq 1\}$ , there exists  $C > 0$  such that for all  $n \geq n_0$

$$\mathbb{E}_{\delta_x}[N_{t_n} e^{-(\beta-q)t_n} \mathbf{1}_{A_{\varepsilon_0, t_n, K_n}}] = \mathbb{E}_{\delta_x}[N_{t_n} e^{-(\beta-q)t_n} \mathbf{1}_{\{N_{t_n} \geq 1\}}] \mathbb{P}(A_{\varepsilon_0, t_n, K_n}) \geq C a_0/2.$$

We deduce, using (5.20), that for any  $n \geq n_0$ ,

$$x e^{(g-q)t_n} = \mathbb{E}_{\delta_x}[P_{t_n}] \geq K_n \varepsilon_0 \mathbb{E}_{\delta_x}[N_{t_n} \mathbf{1}_{A_{\varepsilon_0, t_n, K_n}}] \geq C \frac{a_0}{2} K_n \varepsilon_0 e^{(\beta-q)t_n},$$

which is absurd because  $\beta > g$ . It concludes the proof.  $\square$

**5.3.2. Preliminary results on the auxiliary process.** Recall that the auxiliary process  $(Y_s^{(t)}, s \leq t)$  is well-defined as the unique strong solution to (4.9) under **LDCG**. In what follows, we set  $Y_s^{(t)} = Y_t^{(t)}$  for all  $s \geq t$  and  $f_3(x, u, z) = 0$  if  $u \leq 0$ , for all  $x, z \geq 0$ .

The next proposition is an analogue of the auxiliary process of [22, Theorem 3.3] Let

$$\tau_t^-(0) := \inf\{0 < s \leq t : Y_s^{(t)} = 0\}.$$

**Proposition 5.4.** *Suppose that Assumptions **LDCG** holds, that  $\int_0^\infty (z \vee z^2) \pi(dz) < \infty$  and that  $x p'(x) \geq p(x)$  for every  $x \geq 0$ .*

- i) *If Condition **(SNO)** holds, then  $\mathbb{P}_x(\tau_t^-(0) < \infty) = 0$  for all  $x > 0$ .*
- ii) *If Condition **(LNO)** holds, then for any  $x > 0$  and  $s > 0$ ,  $\mathbb{P}_x(\tau_t^-(0) < s) > 0$ .*

*Proof of Proposition 5.4.* This proof is very similar to the proof of [22, Theorem 3.3]. The only modifications are due to the time-inhomogeneity, and to the fact that the time interval is restricted to  $[0, t]$ . We proceed by coupling to overcome these two difficulties.

i) Introduce  $\tilde{Y}$  the unique strong solution to

$$\begin{aligned} \tilde{Y}_t = \tilde{Y}_0 + g \int_0^t \tilde{Y}_s ds + \int_0^t \sqrt{2\sigma^2(\tilde{Y}_s)} dB_s + \int_0^t \int_{\mathbb{R}_+} \int_0^{f_3(\tilde{Y}_{s-}, t-s, z)} z \tilde{Q}(ds, dz, dx) \\ + \int_0^t \int_0^{2(\alpha \tilde{Y}_{s-} + \beta)} \int_0^1 (\theta - 1) \tilde{Y}_{s-} N(ds, dz, d\theta), \end{aligned} \quad (5.21)$$

where  $B, \tilde{Q}, N$  are the same as in (4.9),  $f_3$  is defined in (4.8). Notice that

$$f_1(y, s) \geq gy, \quad f_2(y, s, \theta) \leq 2(\alpha y + \beta), \quad \forall y, z, t \geq 0, s \in [0, t], \theta \in [0, 1].$$

and  $f_3(x, t-s, z)$  is non-decreasing in  $x$  because  $x p'(x) \geq x$  for all  $x \geq 0$ . In particular this implies that if  $\tilde{Y}$  is a solution with  $\tilde{Y}_0 = Y_0^{(t)}$ , then  $\tilde{Y}_s \leq Y_s^{(t)}$  for any  $s$  smaller than  $t$ . But  $\tilde{Y}$  satisfies the assumptions of a modified version of point i) of [22, Theorem 3.3] where the rate of positive jumps depends on time (see Appendix B.3). Therefore, applying this result, we proved that  $\tilde{Y}$  does not reach 0 in finite time, so that  $Y^{(t)}$  does not reach 0 before time  $t$ .

ii) First notice that for any  $x > 0$  and  $s \leq t$ , the function  $f_1$  defined in (4.6) satisfies

$$f_1(x, s) \leq gx + \left( 2\sigma^2(x) + p(x) \int_{\mathbb{R}_+} z^2 \pi(dz) \right) \frac{A_t}{1 + x A_t} =: \bar{g}_t(x),$$

where  $A_t = \alpha(e^{(g-\beta)t} - 1)/(g - \beta)$ . Let  $(\bar{Y}_s, s \geq 0)$  be the unique strong solution to

$$\begin{aligned} \bar{Y}_s = Y_0^{(t)} + \int_0^s \bar{g}_t(\bar{Y}_u) du + \int_0^s \sqrt{2\sigma^2(\bar{Y}_u)} dB_u + \int_0^s \int_0^1 \int_0^{\bar{r}(\theta)} (\theta - 1) \bar{Y}_u N(du, d\theta, dz) \\ + \int_0^s \int_0^\infty \int_0^{f_3(\bar{Y}_{s-}, t-u, z)} z \tilde{Q}(du, dz, dx), \end{aligned} \quad (5.22)$$

where for all  $x, s \geq 0$  and  $\theta \in [0, 1]$ ,  $\bar{r}(\theta) := 2\theta\beta \leq f_2(x, s, \theta)$ , with  $f_2$  defined in (4.7),  $f_3$  in (4.8),  $B$ ,  $N$  and  $\tilde{Q}$  are the same as in (4.9). Then, for all  $0 \leq s \leq t$ ,  $\bar{Y}_s \geq Y_s^{(t)}$ . Then, for  $\bar{\tau}^-(0) := \inf\{s \geq 0 : \bar{Y}_s = 0\}$ , if we prove that

$$\mathbb{P}(\bar{\tau}^-(0) < v) > 0, \quad \forall 0 < v \leq t, \quad (5.23)$$

it will imply that  $\mathbb{P}(\tau_t^-(0) < v) \geq \mathbb{P}(\bar{\tau}^-(0) < v) > 0$  and end the proof. To prove (5.23), we apply [22, Theorem 3.3iii)] to the process  $\bar{Y}$ . Notice that here, unlike in [22, Theorem 3.3], the division rate  $\bar{r}$  depends on  $\theta$ . However, the dependence in  $\theta$  in the division rate can be removed by considering a new PPM  $N'$  with a modified fragmentation kernel so that all the results derived above still hold. We refer the reader to Appendix D for more details.  $\square$

In the case where the absorption of the auxiliary process occurs with positive probability, we prove the convergence of the auxiliary process trajectory on a time window of any size.

**Proposition 5.5.** *Let  $T \geq 0$ . Suppose that Assumption **LDCG**, Equation (3.9) and **(LN0)** hold, and that  $\int_0^\infty (z \vee z^2) \pi(dz)$  and  $xp'(x) \geq p(x)$  for every  $x \geq 0$ . Then, there exist  $C, \bar{c} > 0$  and a probability measure  $\Pi$  on the Borel  $\sigma$ -field of  $\mathbb{D}([0, T], \mathcal{X})$  endowed with the Skorokhod distance such that for all bounded measurable functions  $F : \mathbb{D}([0, T], \mathcal{X}) \rightarrow \mathbb{R}$ ,*

$$\left| \mathbb{E} \left[ F \left( Y_{t+s}^{(t+T)}, s \leq T \right) \middle| Y_0^{(t+T)} = x \right] - \Pi(F) \right| \leq Ce^{-\bar{c}t} \|F\|_\infty (1+x), \quad \forall x \geq 0.$$

We prove the convergence of the auxiliary process by verifying a Foster-Lyapunov inequality and a minoration condition, both stated in Lemma 5.6 below. Those standard conditions were exhibited in [20] as an extension of [14] to time-inhomogeneous processes. The Foster-Lyapunov inequality (Condition *i*) in Lemma 5.6) ensures that

$$\mathbb{E}_x \left[ V \left( Y_s^{(t)} \right) \right] \leq e^{-as} V(x) + \frac{d}{a} (1 - e^{-as}),$$

where  $a$  and  $d$  are positive constants, so that the process is brought back to the sublevel sets of  $V$ . The minoration condition (*i.e.* Condition *ii*) in Lemma 5.6) ensures some type of irreducibility of the process on those sublevel sets. Let  $V(x) = x$  for  $x \in \mathbb{R}_+$ .

**Lemma 5.6.** *Under the assumptions of Proposition 5.5, we have the following:*

*i) There exist  $a, d > 0$  such that for all  $0 \leq s \leq t$  and  $x \in \mathbb{R}_+^*$ ,*

$$\mathcal{A}_s^{(t)} V(x) \leq -aV(x) + d.$$

*ii) There exists  $R > 2da^{-1}$  such that for all  $r < s \leq t$ , there exist  $\alpha_{s-r} > 0$  and a probability measure  $\nu$  on  $\mathbb{R}_+$  such that for all Borel sets  $A$  of  $\mathbb{R}_+$ ,*

$$\inf_{x \leq R} \mathbb{P} \left( Y_s^{(t)} \in A \middle| Y_r^{(t)} = x \right) \geq \alpha_{s-r} \nu(A).$$

*Proof.* *i)* We have

$$\begin{aligned} \mathcal{A}_s^{(t)} V(x) &= f_1(x, t-s) - \int_0^1 f_2(x, t-s, \theta) x(1-\theta) \kappa(d\theta) \\ &\leq V(x) \left( g + 2 \frac{\sigma(x)^2}{x^2} + \frac{p(x)}{x^2} \int_{\mathbb{R}_+} z^2 \pi(dz) - 2\alpha x \mathbb{E}[\Theta(1-\Theta)] \right). \end{aligned}$$

According to (3.9), there exist  $A > 0$  and  $a > 0$  such that for all  $x > A$

$$2 \frac{\sigma(x)^2}{x^2} + \frac{p(x)}{x^2} \int_{\mathbb{R}_+} z^2 \pi(dz) - 2\alpha x \mathbb{E}[\Theta(1-\Theta)] < -(a+g).$$

Then,

$$\mathcal{A}_s^{(t)}V(x) \leq -ax + \mathbf{1}_{\{x \leq A\}} \left( 2 \frac{\sigma(x)^2}{x} + \frac{p(x)}{x} \int_{\mathbb{R}_+} z^2 \pi(dz) - 2\alpha x^2 \mathbb{E}[\Theta(1 - \Theta)] \right),$$

and according to Assumption **EU**, there exists  $d > 0$  such that for every  $x \geq 0$ ,

$$\mathcal{A}_s^{(t)}V(x) \leq -ax + d.$$

*ii)* Let  $R > 2da^{-1}$ , where  $a, d$  are given in *i*). We will prove the minoration condition with  $\nu = \delta_0$ , where  $\delta_0$  is the Dirac measure at 0. Consider again  $\bar{Y}$ , defined as the unique strong solution to the SDE (5.22). We recall that  $\bar{Y}_s \geq Y_s^{(t)}$ , for all  $s \leq t$ . Therefore for all  $r < s \leq t$  and all Borel sets  $A$  of  $\mathbb{R}_+$ ,

$$\mathbb{P}\left(Y_s^{(t)} \in A | Y_r^{(t)} = x\right) \geq \mathbb{P}\left(Y_s^{(t)} = 0 | Y_r^{(t)} = x\right) \delta_0(A) \geq \mathbb{P}\left(\bar{Y}_s = 0 | \bar{Y}_r = x\right) \delta_0(A).$$

Next, notice that if  $\bar{Y}^1, \bar{Y}^2$  are two solutions to (5.22) with respective initial conditions at time  $r$  satisfying  $\bar{Y}_r^1 \leq \bar{Y}_r^2$ , then  $\bar{Y}_s^1 \leq \bar{Y}_s^2$  for all  $r \leq s \leq t$ . Hence, for all  $x \leq R$ ,

$$\mathbb{P}\left(\bar{Y}_s = 0 | \bar{Y}_r = x\right) = \mathbb{P}\left(\bar{Y}_{s-r} = 0 | \bar{Y}_0 = x\right) \geq \mathbb{P}\left(\bar{Y}_{s-r} = 0 | \bar{Y}_0 = R\right).$$

Finally, as **(LNO)** holds, using [22, Theorem 3.3iii] on  $\bar{Y}$ , there exists  $\alpha_{s-r} > 0$  such that

$$\mathbb{P}\left(\bar{Y}_{s-r} = 0 | \bar{Y}_0 = R\right) > \alpha_{s-r},$$

which ends the proof.  $\square$

*Proof of Proposition 5.5.* This result is a direct application of [20, Proposition 3.3]. The main assumptions are satisfied thanks to Lemma 5.6. Note that using the expression of  $m$  given in (4.5), [20, Assumption 2.4] is satisfied because

$$\int_0^1 \frac{m(\theta x, s, t)}{m(x, s, t)} \kappa(d\theta) \leq 1/2.$$

$\square$

This convergence result allows us to establish a law of large numbers, linking asymptotically the behaviour of a typical individual with the behaviour of the whole population.

**5.3.3. Proof of Theorem 3.7.** It is a direct application of [20, Corollary 3.7]. Assumptions 2.1, 2.3 and 2.4 in [20] are satisfied thanks to Assumption **EU**, using (4.4) and (4.5), and the fact that  $\beta > 0$ . We proved that Assumption 3.1 in [20] is verified in Lemma 5.6. It remains to check that Assumptions 3.4 and 3.6 in [20] are satisfied. Note that in our case, the function  $c(x)$  defined in [20, Equation 3.3] is equal to  $\max(g, \beta) - q$  and the first point of Assumption 3.4 in [20] is satisfied.

Next, we set some notations, introduced in [20]. For all  $x, y \geq 0$  and  $s \geq 0$ , we define

$$\varphi_s(x, y) = \sup_{t \geq s} \frac{m(x, 0, s)m(y, s, t)}{m(x, 0, t)},$$

(which does not depend on  $q$ ) and for all measurable functions  $f : \mathbb{R}_+ \rightarrow \mathbb{R}$  and  $x \geq 0$ ,

$$Jf(x) = 2 \int_0^1 f(\theta x) f((1 - \theta)x) \kappa(d\theta).$$

The next lemma amounts to check the second point of Assumption 3.4 in [20].

**Lemma 5.7.** *Under Condition **LDCG+**, then for all  $x \geq 0$ ,*

$$\sup_{t \geq 0} \mathbb{E}_x \left[ r \left( Y_t^{(t)} \right) J \left( (1 \vee V(\cdot)) \varphi_t(x, \cdot) \right) \left( Y_t^{(t)} \right) \right] < \infty.$$

*Proof.* Note that if  $x = 0$ ,  $Y_t^{(t)} = 0$  almost surely for all  $t \geq 0$ . Therefore, we only need to consider  $x > 0$ . First assume that  $\alpha > 0$ . Notice that for all  $t \geq 0$   $x > 0$ , and  $y \geq 0$ ,

$$\varphi_t(x, y) \leq \left(1 + \frac{\alpha x}{|g - \beta|}\right) \left(1 + \frac{\alpha y}{|g - \beta|}\right) \left(\min\left(\frac{\alpha x}{|g - \beta|}, 1\right)\right)^{-1},$$

where we simplified by  $e^{\max(g, \beta)t}$  in the fraction in the definition of  $\varphi_s$ . Next, for all  $x > 0$ ,

$$\begin{aligned} & \mathbb{E}_x \left[ r \left( Y_t^{(t)} \right) J \left( (1 \vee V(\cdot)) \varphi_t(x, \cdot) \right) \left( Y_t^{(t)} \right) \right] \\ & \leq \left( \frac{|g - \beta| + \alpha x}{\min(\alpha x, |g - \beta|)} \right)^2 \mathbb{E}_x \left[ \left( \alpha Y_t^{(t)} + \beta \right) 2 \int_0^1 \left( 1 \vee \theta Y_t^{(t)} \right) \left( 1 \vee (1 - \theta) Y_t^{(t)} \right) \left( 1 + \frac{\alpha Y_t^{(t)}}{|g - \beta|} \right)^2 \kappa(d\theta) \right]. \end{aligned}$$

For all  $k \geq 0$ , we define

$$f_k^{(t)}(x, s) = \mathbb{E}_x \left[ \left( Y_s^{(t)} \right)^k \right]$$

and we end the proof of the lemma by showing that,  $\sup_{t \geq 0} \sup_{s \leq t} f_5^{(t)}(x, s) < \infty$ . According to Itô's formula, we have for  $k \geq 2$ ,

$$\begin{aligned} f_k^{(t)}(x, s) &= k \int_0^s \mathbb{E}_x \left[ \left( Y_u^{(t)} \right)^{k-1} f_1 \left( Y_u^{(t)}, t - u \right) \right] du + k(k-1) \int_0^s \mathbb{E}_x \left[ \sigma^2 \left( Y_u^{(t)} \right) \left( Y_u^{(t)} \right)^{k-2} \right] du \\ &+ \int_0^s \int_{\mathbb{R}_+} \mathbb{E}_x \left[ f_2 \left( Y_u^{(t)}, t - u, \theta \right) \left( Y_u^{(t)} \right)^k \left( \theta^k - 1 \right) \right] \kappa(d\theta) du \\ &+ \int_0^s \int_{\mathbb{R}_+} \mathbb{E}_x \left[ f_3 \left( Y_u^{(t)}, t - u, z \right) \left( \left( Y_u^{(t)} + z \right)^k - \left( Y_u^{(t)} \right)^k - kz \left( Y_u^{(t)} \right)^{k-1} \right) \right] \pi(dz) du. \end{aligned}$$

Differentiating with respect to  $s$  and using that for all  $x, s, z \geq 0$  and  $\theta \in [0, 1]$ ,  $f_2(x, s, \theta) \geq 2\theta\alpha x$ ,  $f_3(x, s, z) \leq (x+z)p(x)/x$ , and  $x^{k-1}f_1(x, s) \leq gx^k + 2\sigma(x)^2x^{k-2} + p(x)x^{k-2} \int_{\mathbb{R}_+} z^2\pi(dz)$ .

Let  $H(k, y) = (k+1)\sigma^2(y)y^{-2} + kp(y)y^{-2} \int_{\mathbb{R}_+} z^2\pi(dz)$ . Applying Taylor's formula with integral remainder, we obtain

$$\begin{aligned} \partial_s f_k^{(t)}(x, s) &\leq gk \mathbb{E}_x \left[ \left( Y_s^{(t)} \right)^k \right] + k \mathbb{E}_x \left[ H(k, Y_s^{(t)}) \left( Y_s^{(t)} \right)^k \right] - \int_{\mathbb{R}_+} \mathbb{E}_x \left[ 2\alpha \left( Y_s^{(t)} \right)^{k+1} \theta(1 - \theta^k) \right] \kappa(d\theta) \\ &+ k(k-1) \int_{\mathbb{R}_+} \int_0^z (z-u) \mathbb{E}_x \left[ \frac{p \left( Y_s^{(t)} \right)}{Y_s^{(t)}} \left( Y_s^{(t)} + u \right)^{k-2} \left( Y_s^{(t)} + z \right) \right] du \pi(dz). \end{aligned}$$

Moreover, for all  $y > 0$ ,

$$\begin{aligned} & \int_{\mathbb{R}_+} \int_0^z (z-u) \frac{p(y)}{y} (y+u)^{k-2} (y+z) du \pi(dz) \\ & \leq \int_{\mathbb{R}_+} z^2 \frac{p(y)}{y} (y+z)^{k-1} \pi(dz) = \frac{p(y)}{y} \int_{\mathbb{R}_+} z^2 \sum_{l=0}^{k-1} \binom{k-1}{l} y^l z^{k-1-l} \pi(dz) \\ & = \frac{p(y)}{y} \int_{\mathbb{R}_+} z^2 \sum_{l=0}^{k-2} \binom{k-1}{l} y^l z^{k-1-l} \pi(dz) + \frac{p(y)}{y^2} \left( \int_{\mathbb{R}_+} z^2 \pi(dz) \right) y^k. \end{aligned}$$

Combining the last two inequalities, we get

$$\partial_s f_k^{(t)}(x, s) \leq k \left( A_t^{(k)} + B_t^{(k)} - C_t^{(k)} + D_t^{(k)} \right),$$

with

$$A_t^{(k)} = g f_k^{(t)}(x, s), \quad B_t^{(k)} = \mathbb{E}_x \left[ H(k, Y_s^{(t)}) (Y_s^{(t)})^k \right], \quad C_t^{(k)} = \frac{2\alpha}{k} \mathbb{E} \left[ \Theta(1 - \Theta^k) \right] f_{k+1}^{(t)}(x, s),$$

$$D_t^{(k)} = (k-1) \int_{\mathbb{R}_+} \mathbb{E}_x \left[ \frac{p(Y_s^{(t)})}{(Y_s^{(t)})^2} \sum_{l=0}^{k-2} \binom{k-1}{l} (Y_s^{(t)})^{l+1} z^{k+1-l} \right] \pi(dz).$$

To end the proof we consider the case  $k = 5$ . According to (3.9) and using that  $\sigma$  and  $p$  are continuous (Assumption **EU**), there exist  $C_1, C_2, A > 0$  such that for all  $y \geq 0$ ,

$$H(5, y)y^5 = H(5, y)y^5 \mathbf{1}_{\{y > A\}} + H(5, y)y^5 \mathbf{1}_{\{y \leq A\}} \leq C_1 y^5 \mathbf{1}_{\{y > A\}} + C_2 \mathbf{1}_{\{y \leq A\}} \leq C_1 y^5 + C_2.$$

Moreover,  $\limsup_{0+} p(x)/x < \infty$  as  $p(0) = 0$  and  $p$  is locally Lipschitz,  $\limsup_{\infty} p(x)/x^2 < \infty$  thanks to (3.9) and  $\int_{\mathbb{R}_+} z^6 \pi(dz) < \infty$ , which yields

$$D_t^{(5)} \leq C_3 (f_5^{(t)}(x, s) + 1),$$

for some  $C_3 \geq 0$ . Combining the last two inequalities, there exists  $D_1 > 0$  such that

$$\partial_s f_5^{(t)}(x, s) \leq D_1 (f_5^{(t)}(x, s) + 1) - D_2 f_6^{(t)}(x, s),$$

where  $D_2 = \frac{2\alpha}{5} \mathbb{E} [\Theta(1 - \Theta^5)]$ . Applying Jensen inequality, we have  $f_6^{(t)}(x, s) \geq f_5^{(t)}(x, s)^{6/5}$ . Finally, we obtain

$$\partial_s f_5^{(t)}(x, s) \leq F \left( f_5^{(t)}(x, s) \right),$$

with  $F(y) = D_1(y + 1) - D_2 y^{1+1/5}$ . Any solution to the equation  $y' = F(y)$  is bounded by  $y(0) \vee x_0$ , where  $x_0 = (5D_1/6D_2)^5$  and so is  $f_5^{(t)}(x, \cdot)$ . It ends the proof for this case.  $\square$

Adding Lemma 5.3 (which corresponds to Assumption 3.6 in [20].) we have all required assumptions to apply [20, Corollary 3.4]. This ends the proof of Theorem 3.7.

5.3.4. *Proof of Proposition 3.8.* *i)* The first step consists in proving that for every  $x \geq 0$ ,

$$\mathbb{P}_x(\exists t < \infty, Y_t^{(t)} = 0) = 1. \quad (5.24)$$

A direct application of [22, Theorem 6.2] is not possible because of the time-inhomogeneity of  $Y^{(t)}$ . Therefore, we couple  $Y^{(t)}$  with a process  $\hat{Y}$  defined as the unique strong solution to

$$\begin{aligned} \hat{Y}_s = & Y_0^{(t)} + \int_0^s \hat{g}(\hat{Y}_u) du + \int_0^s \sqrt{2\sigma^2(\hat{Y}_u)} dB_u + \int_0^s \int_0^1 (\theta - 1) \int_0^{\hat{r}(\hat{Y}_u, \theta)} \hat{Y}_u N(du, d\theta, dx) \\ & + \int_0^s \int_0^\infty \int_0^{f_3(\hat{Y}_u, t-s, z)} z \tilde{Q}(du, dz, dx), \end{aligned} \quad (5.25)$$

where  $B$ ,  $N$  and  $\tilde{Q}$  are the same as in (4.9) and for  $x, s \geq 0$ ,  $0 \leq \theta \leq 1$ ,

$$\begin{aligned} f_1(x, s) & \leq \hat{g}(x) := gx + \left( \frac{\alpha \mathbf{1}_{\{\beta > g\}}}{\beta - g + \alpha x} + \frac{\mathbf{1}_{\{g > \beta\}}}{x} \right) \left( 2\sigma^2(x) + p(x) \int_{\mathbb{R}_+} z^2 \pi(dz) \right) \\ f_2(x, s, \theta) & \geq \hat{r}(x, \theta) := 2\theta(\alpha x + \beta). \end{aligned}$$

Then, for all  $t \geq 0$  and  $0 \leq s \leq t$ ,  $Y_s^{(t)} \leq \hat{Y}_s$ . In particular, for all  $t \geq 0$ ,

$$Y_t^{(t)} \leq \hat{Y}_t. \quad (5.26)$$

According to Lemma D.1, there exists a PPM  $N'$  on  $\mathbb{R}_+ \times [0, 1] \times \mathbb{R}_+$  with intensity  $du \otimes \hat{\kappa}(d\theta) \otimes dx$  where  $\hat{\kappa}(d\theta) = 2\theta\kappa(d\theta)$ , such that  $\hat{Y}$  is also a strong pathwise solution to

$$\begin{aligned} \hat{Y}_s = Y_0^{(t)} + \int_0^s \hat{g}(\hat{Y}_u) du + \int_0^s \sqrt{2\sigma^2(\hat{Y}_u)} dB_u + \int_0^s \int_0^{r(\hat{Y}_u)} \int_0^1 (\theta - 1) \hat{Y}_u N'(du, dx, d\theta) \\ + \int_0^s \int_0^\infty \int_0^{f_3(\hat{Y}_u, t-s, z)} z \tilde{Q}(du, dz, dx), \end{aligned}$$

where we used that  $\int_0^1 2\theta\kappa(d\theta) = 1$  as  $\kappa$  is symmetrical with respect to  $1/2$ . The jump rate  $f_3$  depends on jump size and time, but we have

$$f_3(x, s, z) \leq p(x) \left( 1 + \alpha z \frac{(e^{(g-\beta)s} - 1)}{g - \beta} \right)$$

so that (6.3) in [22, Theorem 6.2] holds for  $\hat{Y}$  (see Appendix B.5) if **(SN $\infty$ )**, **(LN0)** and **(LSG)** are satisfied, where

**(LSG)** There exist  $\eta_1, x_1 > 0$  such that for all  $x > x_1$

$$\hat{H}(x) := \frac{\hat{g}(x)}{x} - \frac{\sigma^2(x)}{x^2} + \hat{r}(x) \mathbb{E}[\ln \Theta] < -\eta_1.$$

First, **(LN0)** is satisfied by assumption. Let us check that **(LSG)** holds. We have

$$\hat{H}(x) \leq g + \left( \frac{\mathbf{1}_{\{\beta > g\}} \alpha x}{\beta - g + \alpha x} + \mathbf{1}_{\{g \geq \beta\}} \right) \left( 2 \frac{\sigma^2(x)}{x^2} + \frac{p(x)}{x^2} \int_{\mathbb{R}_+} z^2 \pi(dz) \right) + 2(\alpha x + \beta) \mathbb{E}[\Theta \ln \Theta].$$

According to Assumptions **EU** and (3.9), there exist  $x_1, C > 0$  such that for all  $x > x_1$

$$\hat{H}(x) \leq g + C \left( \frac{\mathbf{1}_{\{\beta > g\}} \alpha x}{\beta - g + \alpha x} + \mathbf{1}_{\{g \geq \beta\}} \right) + 2(\alpha x + \beta) \mathbb{E}[\Theta \ln \Theta],$$

and as  $\mathbb{E}[\Theta \ln \Theta] < 0$ , condition **(LSG)** is satisfied. Finally, we check that **(SN $\infty$ )** is satisfied for  $\hat{Y}$ . And it is the case according to (3.9) as

$$\frac{\hat{g}(x)}{x} = g + \left( \mathbf{1}_{\{\beta > g\}} \frac{\alpha x}{\beta - g + \alpha x} + \mathbf{1}_{\{g > \beta\}} \right) \left( 2 \frac{\sigma^2(x)}{x^2} + \frac{p(x)}{x^2} \int_{\mathbb{R}_+} z^2 \pi(dz) \right).$$

Hence [22, Eq. (6.3)] holds for  $\hat{Y}$ , and (5.26) gives (5.24). Applying Theorem 3.7 to the function  $F(X_{t+s}^u, s \leq T) = \mathbf{1}_{\{X_{t+T}^u > 0\}}$  concludes the proof of point *i*).

Let us now prove point *ii*). The convergence result stems directly from Theorem 3.7. For the bounds on the process  $(Y_t^{(t)}, t \geq 0)$ , the idea is to use the same couplings as before, and apply the generalization of [22, Theorem 6.2(i)] proved in Appendix B.5.

First, we consider again  $\hat{Y}$  defined as the unique strong solution to (5.25). Recall that for all  $t \geq 0$  and all  $0 \leq s \leq t$ ,  $Y_s^{(t)} \leq \hat{Y}_s$ . To apply [22, Theorem 6.2(i)], we have to check that **(SN0)**, **(SN $\infty$ )** and **(LSG)** are satisfied. By assumption, **(SN0)** holds for  $\hat{Y}$ . We refer the reader to the proof of *i*) for the two other conditions. According to [22, Theorem 6.2(i)],  $\hat{Y}$  converges in law to  $\hat{Y}_\infty$  as  $t$  goes to infinity.

Next, we consider again  $\tilde{Y}$ , defined as the unique strong solution to (5.21). Recall that for all  $t \geq 0$  and  $0 \leq s \leq t$ ,  $\tilde{Y}_s \leq Y_s^{(t)}$ . Let us check that **(SN0)**, **(SN $\infty$ )** and **(LSG)** of [22] holds for  $\tilde{Y}$ . Again, **(SN0)** holds by assumption. Then, **(SN $\infty$ )** holds combining (3.9) with the fact that the division rate of  $\tilde{Y}$  is linear in  $x$ . Finally, let

$$\tilde{H}(x) := g - \frac{\sigma^2(x)}{x^2} + 2(\alpha x + \beta) \mathbb{E}[\ln \Theta].$$

According to (3.9), there exist  $\eta, x_1 > 0$  such that for all  $x > x_1$ ,  $\tilde{H}(x) \leq -\eta$  so that **(LSG)** of [22] holds for  $\tilde{Y}$ . Then, according to [22, Theorem 6.2(i)],  $\tilde{Y}$  converges in law to  $\tilde{Y}_\infty$  as  $t$  goes to infinity.

Finally, we have for all  $t \geq 0$   $\mathfrak{Y}_t^{(1)} := \tilde{Y}_t \leq Y_t^{(t)} \leq \mathfrak{Y}_t^{(2)} := \hat{Y}_t$ , which yields the result.

#### APPENDIX A. PROOF OF PROPOSITION 1.1

To prove that the SDE (1.1) admits a unique nonnegative strong solution with generator given by  $\mathcal{G}$  defined in (1.2), we apply [25, Proposition 1]. The proof is the same as the proof of [22, Proposition 2.1], except that we have to take into account the extra stable term. To prove that we still have a unique nonnegative strong solution with the addition of this term, it is enough to check that for any  $n \in \mathbb{N}$ , there exists a finite constant  $A_n$  such that for any  $0 \leq x, y \leq n$ ,

$$\int_{\mathbb{R}_+} |\mathbf{1}_{\{x \leq u\}} z \wedge n - \mathbf{1}_{\{y \leq u\}} z \wedge n| \frac{dz}{z^{2+\beta}} du \leq A_n |x - y|,$$

where we recall that  $\beta \in (-1, 0)$ . This is a consequence of the following series of equalities:

$$\int |(\mathbf{1}_{\{x \leq u\}} - \mathbf{1}_{\{y \leq u\}}) z \wedge n| \frac{dz du}{z^{2+\beta}} = \int |x - y| z \wedge n \frac{dz du}{z^{2+\beta}} = |x - y| \left( \int_0^n \frac{dz}{z^{1+\beta}} + n \int_n^\infty \frac{dz}{z^{2+\beta}} \right).$$

To prove that it gives the existence and uniqueness of the process at the cell population level, we apply [21, Theorem 2.1].

#### APPENDIX B. EXTENSION OF RESULTS OF [22]

**B.1. Proof of [22, Theorem 3.3] with stable jumps.** In this section we give the proof of the generalization of [22, Theorem 3.3i)] to processes with stable jumps defined as the unique solution (see [25, Proposition 1]) to (5.1). Recall that  $G_a$  is defined in (2.1), and  $\tau^+, \tau^-$  in (5.4), (5.5) and (5.7).

**Lemma B.1.** [22, Lemma 7.1] *Suppose that Assumption **EU** holds. For all  $b > c > 0$ , let  $T = \tau^-(c) \wedge \tau^+(b)$ . Then, for all  $a \in (0, 1)$  or  $a > 1$  such that  $\mathbb{E}[\Theta^{1-a}] < \infty$ , the process*

$$Z_{t \wedge T}^{(a)} := (Y_{t \wedge T})^{1-a} \exp \left( \int_0^{t \wedge T} G_a(Y_s) ds \right)$$

is a  $\mathcal{F}_t$ -martingale, where  $Y$  is the unique solution of (5.1).

*Proof of Lemma B.1.* First notice that using Taylor's formula, we have

$$C_a = (2 + \mathfrak{b})^{-1} \int_{\mathbb{R}_+} z(1+z)^{-a} \rho(dz) = (1-a)^{-1} \int_{\mathbb{R}_+} \left( (1+z)^{(1-a)} - 1 \right) \rho(dz), \quad (\text{B.1})$$

and

$$(1-a)I_a(x) = \int_{\mathbb{R}_+} \left( (1+zx^{-1})^{(1-a)} - 1 - (1-a)zx^{-1} \right) \pi(dz). \quad (\text{B.2})$$

We follow the proof of [22, Lemma 7.1]. Let  $a \in (0, 1) \cup \{a > 1, \mathbb{E}[\Theta^{1-a}] < \infty\}$ . Combining Itô's formula with jumps, (B.1), (B.2), we have for all  $t \geq 0$

$$Y_t^{1-a} = Y_0^{1-a} - \int_0^t Y_s^{1-a} G_a(X_s) ds + M_t,$$

where  $(M_t, t \geq 0)$  is a local martingale. Next, using integration by parts we obtain that  $(Z_{t \wedge T}^{(a)}, t \geq 0)$  is a local martingale. Similarly to [18], combining Assumptions **EU** and [27, Theorem 51 p.38] ends the proof.  $\square$

**Proposition B.2.** *Suppose that Assumption **EU** holds and let  $Y$  be the pathwise unique solution to (5.1). If **(SN0)** holds then  $\mathbb{P}_x(\tau^-(0) < \infty) = 0$  for all  $x > 0$ .*

*Proof.* ([22, Theorem 3.3i]) Let  $n \in \mathbb{N}$  be such that  $n \geq 2$  and let  $0 < \varepsilon < b < 1$  and  $a > 1$  such that  $\mathbb{E}[\Theta^{1-a}] < \infty$  be such that **(SNO)** holds for all  $u \leq b$ . Let  $T_n = \tau^-(\varepsilon^n) \wedge \tau^+(b)$ . As in [22, Theorem 3.3i)], combining Lemma B.1 and **(SNO)**, we have that for all  $0 < \varepsilon < b$ ,

$$\mathbb{P}_\varepsilon(\tau^-(0) = \infty \text{ or } \tau^+(b) < \tau^-(0)) = 1. \quad (\text{B.3})$$

We use a coupling to show that  $\mathbb{P}_\varepsilon(\tau^-(0) < \infty) = 0$ . Let for  $N \in \mathbb{N}$ ,  $r_{[0,N]} := \sup_{0 \leq x \leq N} 2r(x)$ , which is finite as  $r$  is a continuous function. Let  $\tilde{Y}$  be the unique strong solution to

$$\begin{aligned} \tilde{Y}_t = \tilde{Y}_0 + \int_0^t g(\tilde{Y}_s) ds + \int_0^t \sqrt{2\sigma^2(\tilde{Y}_s)} dB_s + \int_0^t \int_0^{p(\tilde{Y}_{s-})} \int_{\mathbb{R}_+} z \tilde{Q}(ds, dx, dz) \\ \int_0^t \int_0^{\tilde{Y}_{s-}} \int_{\mathbb{R}_+} z R(ds, dx, dz) + \int_0^t \int_0^{r_{[0,N]}} \int_0^1 (\theta - 1) \tilde{Y}_{s-} N(ds, dx, d\theta), \end{aligned}$$

where the Brownian motion  $B$  and the Poisson random measures  $\tilde{Q}$  and  $N$  are the same as in (5.1). We will use four properties of this equation.

- It has a unique strong solution (see [25, Proposition 1] and Assumptions **EU**).
- If  $\tilde{Y}^{(1)}$  and  $\tilde{Y}^{(2)}$  are two solutions with  $\tilde{Y}_0^{(1)} \leq \tilde{Y}_0^{(2)}$ , then  $\tilde{Y}_t^{(1)} \leq \tilde{Y}_t^{(2)}$  for any  $t \geq 0$ .
- If  $\tilde{Y}$  is a solution with  $\tilde{Y}_0 = Y_0$ , then  $\tilde{Y}_t \leq Y_t$  for any  $t$  smaller than  $\tau^-(0) \wedge \tau^+(N)$ .
- Equation (B.3) holds for both  $Y$  and  $\tilde{Y}$ .

Following the proof of [22, Theorem 3.3i)], we obtain that  $\mathbb{P}_\varepsilon(\tilde{\tau}^-(0) < \infty) = 0$ , where the  $\tilde{\tau}$ 's are defined as the  $\tau$ 's in (5.7) and (5.4) but for the process  $\tilde{Y}$ . Using the coupling described in point c), it implies that  $\mathbb{P}_\varepsilon(\tau^+(N) \leq \tau^-(0)) = 1$ , and letting  $N$  tend to infinity, we get  $\mathbb{P}_\varepsilon(\tau^-(0) = \infty) = 1$ .  $\square$

**B.2. Proof of [22, Theorem 4.1] with stable jumps.** We consider again  $Y$  being a solution (5.1) and define  $\tau^+(\infty) = \lim_{n \rightarrow +\infty} \tau^+(n)$ , where  $\tau^+(n) = \inf\{t \geq 0, Y_t \geq n\}$ .

**Proposition B.3.** *Suppose that Assumption **EU** holds and let  $Y$  be the pathwise unique solution to (5.1). If **(SNO)** holds, then  $\mathbb{P}_x(\tau^+(\infty) < \infty) = 0$  for all  $x > 0$ .*

*Proof.* ([22, Theorem 4.1i)]) Similarly as in the proof of [22, Theorem 4.1i)], for  $b^{-1}$  small enough and  $\varepsilon$  satisfying  $0 < b < \varepsilon^{-1}$ , we have for any  $\varepsilon^{-1} \leq y \leq 2\varepsilon^{-1}$ ,

$$\mathbb{P}_y(\tau^+(\infty) = \infty \text{ or } \tau^-(b) < \tau^+(\infty) < \infty) = 1. \quad (\text{B.4})$$

Now, we have to take into account that  $Y$  has two different types of positive jumps, from the PPMs  $\tilde{Q}$  or  $R$ . Let

$$\begin{aligned} J_\pi(\varepsilon) &= \{\text{A jump associated to } \tilde{Q} \text{ occurs at } \tau^+(\varepsilon^{-1})\}, \\ J_\rho(\varepsilon) &= \{\text{A jump associated to } R \text{ occurs at } \tau^+(\varepsilon^{-1})\}. \end{aligned}$$

Let us fix  $\lambda > 0$  and introduce the following real number:

$$\mathcal{A}(\varepsilon) := \sup_{\varepsilon^{-1} \leq y \leq 2\varepsilon^{-1}} \mathbb{E}_y \left[ e^{-\lambda \tau^+(\infty)}; \tau^+(\infty) < \infty \right].$$

Let  $\Delta X_{\tau^+(\varepsilon^{-1})} = X_{\tau^+(\varepsilon^{-1})} - X_{\tau^+(\varepsilon^{-1})-}$ . For any  $\varepsilon < 1$ ,  $y \leq \varepsilon^{-1}$ , we have

$$\mathbb{P}_y(X_{\tau^+(\varepsilon^{-1})} > 2\varepsilon^{-1}) \leq \mathbb{P}_y(\Delta X_{\tau^+(\varepsilon^{-1})} > \varepsilon^{-1}) = A_\pi + A_\rho,$$

where

$$\begin{aligned} A_\pi &:= \mathbb{P}_y(J_\pi(\varepsilon), \Delta X_{\tau^+(\varepsilon^{-1})} > \varepsilon^{-1}) = \mathbb{P}_y \left( J_\pi(\varepsilon), (\Delta X_{\tau^+(\varepsilon^{-1})})^2 \wedge \Delta X_{\tau^+(\varepsilon^{-1})} > \varepsilon^{-1} \right) \\ &\leq \varepsilon \int_0^\infty (z \wedge z^2) \pi(dz), \end{aligned}$$

and for  $\alpha > 0$  such that  $\alpha < 1 + \mathbf{b} < 1$ ,

$$\begin{aligned} A_\rho &:= \mathbb{P}_y(J_\rho(\varepsilon), \Delta X_{\tau^+(\varepsilon-1)} > \varepsilon^{-1}) = \mathbb{P}_y(J_\rho(\varepsilon), (\Delta X_{\tau^+(\varepsilon-1)})^\alpha \wedge \Delta X_{\tau^+(\varepsilon-1)} > \varepsilon^{-\alpha}) \\ &\leq \varepsilon^\alpha \int_0^\infty (z^\alpha \wedge z) \rho(dz) \end{aligned}$$

where we used the Markov inequality.

Using Equation (B.4) and the strong Markov property, we get, for any  $\varepsilon^{-1} \leq y \leq 2\varepsilon^{-1}$ :

$$\begin{aligned} \mathbb{E}_y \left[ e^{-\lambda\tau^+(\infty)}; \tau^+(\infty) < \infty \right] &= \mathbb{E}_y \left[ e^{-\lambda\tau^+(\infty)}; \tau^-(b) < \tau^+(\infty) < \infty \right] \\ &\leq \mathbb{E}_y \left[ e^{-\lambda\tau^-(b)} \mathbb{E}_{X_{\tau^-(b)}} \left[ e^{-\lambda\tau^+(\infty)}; \tau^+(\infty) < \infty \right]; \tau^-(b) < \infty \right]. \end{aligned}$$

Using again the strong Markov property, we get for all  $x \leq b \leq \varepsilon^{-1}$

$$\begin{aligned} \mathbb{E}_x \left[ e^{-\lambda\tau^+(\infty)}; \tau^+(\infty) < \infty \right] &= \mathbb{E}_y \left[ e^{-\lambda\tau^+(\infty)}; \tau^-(b) < \tau^+(\infty) < \infty \right] \\ &= \mathbb{E}_y \left[ e^{-\lambda\tau^+(\infty)}; \tau^-(b) < \tau^+(\varepsilon^{-1}) < \tau^+(\infty) < \infty \right] \\ &= \mathbb{E}_x \left[ e^{-\lambda\tau^+(\varepsilon^{-1})} \mathbb{E}_{X_{\tau^+(\varepsilon^{-1})}} \left[ e^{-\lambda\tau^+(\infty)}; \tau^+(\infty) < \infty \right]; \tau^+(\varepsilon^{-1}) < \infty \right] \\ &\leq \mathcal{A}(\varepsilon) + \varepsilon^\alpha \underbrace{\left( \varepsilon^{1-\alpha} \int_0^\infty (z \wedge z^2) \pi(dz) + \int_0^\infty (z^\alpha \wedge z) \rho(dz) \right)}_{C_{\pi, \rho}}, \end{aligned}$$

where the last inequality is obtained by considering the event  $\{\varepsilon^{-1} \leq X_{\tau^+(\varepsilon^{-1})} \leq 2\varepsilon^{-1}\}$  and its complement. Finally, combining the last two inequalities, we obtain

$$\mathbb{E}_y \left[ e^{-\lambda\tau^+(\infty)}; \tau^+(\infty) < \infty \right] \leq \mathbb{E}_y \left[ e^{-\lambda\tau^-(b)}; \tau^-(b) < \infty \right] (\mathcal{A}(\varepsilon) + \varepsilon^\alpha C_{\pi, \rho}).$$

But there exists  $C(b) < 1$  such that for  $2b \leq y$ ,

$$\mathbb{E}_y \left[ e^{-\lambda\tau^-(b)}; \tau^-(b) < \infty \right] < C(b).$$

Otherwise we would have

$$\lim_{y \rightarrow \infty} \mathbb{E}_y \left[ e^{-\lambda\tau^-(b)}; \tau^-(b) < \infty \right] = 1,$$

and thus  $\tau^-(b)$  would converge to 0 when the initial condition of the process goes to  $\infty$  which would contradict our assumptions on the regularity of the negative jumps. Hence, as for  $\varepsilon$  small enough,  $2b \leq \varepsilon^{-1}$ , we obtain for such an  $\varepsilon$  that  $\mathcal{A}(\varepsilon) \leq \frac{C(b)C_{\pi, \rho}\varepsilon^\alpha}{1-C(b)}$ . We thus deduce that

$$\lim_{y \rightarrow \infty} \mathbb{E}_y \left[ e^{-\lambda\tau^+(\infty)}; \tau^+(\infty) < \infty \right] = 0.$$

Now, let us take  $x, \mu > 0$ . Then, there exists  $N_0$  such that for any  $N \geq N_0$ ,

$$\mathbb{E}_N \left[ e^{-\lambda\tau^+(\infty)}; \tau^+(\infty) < \infty \right] \leq \mu.$$

Hence,

$$\mathbb{E}_x \left[ e^{-\lambda\tau^+(\infty)}; \tau^+(\infty) < \infty \right] \leq \mathbb{E}_x \left[ \mathbb{E}_{X_{\tau^+(N_0)}} \left[ e^{-\lambda\tau^+(\infty)}; \tau^+(\infty) < \infty \right] \right] \leq \mu$$

and thus for all  $x > 0$

$$\mathbb{E}_x \left[ e^{-\lambda\tau^+(\infty)}; \tau^+(\infty) < \infty \right] = 0,$$

which completes the proof.  $\square$

**B.3. Proof of [22, Theorem 3.3] with time dependent positive jump rate.** Let  $t > 0$  and consider the process  $Y$  solution to

$$Y_t = Y_0 + \int_0^t g(Y_s) ds + \int_0^t \sqrt{2\sigma^2(Y_s)} dB_s + \int_0^t \int_{\mathbb{R}_+} \int_0^{p_t(Y_{s-}, s, z)} z \tilde{Q}(ds, dz, dx) \quad (\text{B.5})$$

$$+ \int_0^t \int_0^{r(Y_{s-})} \int_0^1 (\theta - 1) Y_{s-} N(ds, dx, d\theta),$$

where  $\tilde{Q}$ ,  $B$  are the same as in (1.1),  $N$  is a PPM on  $\mathbb{R}_+ \times \mathbb{R}_+ \times [0, 1]$  with intensity  $ds \otimes dx \otimes \kappa(d\theta)$ , and for  $x, z \geq 0$  and  $s \leq t$ , we assume that  $p_t(\cdot, s, z)$  is non-decreasing on  $\mathbb{R}_+$  and that there exists a finite and positive constant  $\mathfrak{c}_t$  depending on  $t$  such that

$$p_t(x, s, z) \leq p(x)(1 + \mathfrak{c}_t z). \quad (\text{B.6})$$

For the existence of a unique pathwise solution to (B.5), we refer to Appendix C.

**Theorem B.4.** [22, Theorem 3.3i)] *Suppose that  $\int (z \vee z^2) \pi(dz) < \infty$  and that **LDCG** holds. Let  $Y$  be a pathwise unique solution to (B.5). Then, if there exist  $a > 1$  such that  $\mathbb{E}[\Theta^{1-a}] < \infty$  and a non-negative function  $f$  on  $\mathbb{R}_+$  such that*

$$\frac{g(x)}{x} - a \frac{\sigma^2(x)}{x^2} = f(x) + o(\ln(x)), \quad (x \rightarrow 0), \quad (\text{B.7})$$

then  $\mathbb{P}_x(\tau^-(0) < \infty) = 0$  for all  $x > 0$ .

*Proof.* [22, Theorem 3.3i)] Let us define for  $a > 1$

$$G_a^{(s)}(x) := (a-1) \frac{g(x)}{x} - a(a-1) \frac{\sigma^2(x)}{x^2} - r(x) \mathbb{E}[\Theta^{1-a} - 1]$$

$$- \int_{\mathbb{R}_+} p_t(x, s, z) ((zx^{-1} + 1)^{1-a} - 1 - (1-a)zx^{-1}) \pi(dz). \quad (\text{B.8})$$

First, applying Itô's formula with jumps, we can check that Lemma B.1 ([22, Lemma 7.1 and Equation (7.1)]) holds for  $Y$ , replacing  $G_a$  by  $G_a^{(s)}$ . Next, Using (B.6) we can show (see the proof of [22, Remark 3.2]) that under (3.8)

$$\limsup_{x \rightarrow 0^+} \left( x^{-2} \int_0^\infty p_t(x, s, z) z^2 \left( \int_0^1 (1 + zx^{-1}v)^{-1-a} (1-v) dv \right) \pi(dz) \right)$$

$$\leq C_t \left( \limsup_{x \rightarrow 0^+} p(x)x^{-1} \right) \left( \int_0^\infty (z + z^2) \pi(dz) \right) < \infty$$

where  $C_t$  is a finite constant. Therefore, the integral corresponding to the positive jumps is bounded in the neighborhood of 0, and Condition (B.7) is enough to control the behaviour of the process around 0. The proof of [22, Theorem 3.3] is thus unchanged and the results hold also for processes whose rate of positive jumps satisfy (B.6).  $\square$

**B.4. Proof of [22, Theorem 4.1.i)] with time dependent positive jump rate.** Let  $t > 0$  and consider again the process  $Y$  solution to (B.5) under condition (B.6).

**Theorem B.5.** [22, Theorem 4.1.i)] *Suppose that Assumption **LDCG** and (3.9) hold and that  $\int (z^2 \vee z^3) \pi(dz) < \infty$  and let  $Y$  be a pathwise unique solution to (B.5). If **(SN $\infty$ )** holds, then  $\mathbb{P}_x(\tau^+(\infty) < \infty) = 0$  for all  $x > 0$ .*

*Proof.* [22, Theorem 4.1.i)] Let us recall the definition of  $G_a^{(s)}$  in (B.8). We have using Taylor's formula and (B.6) that

$$\begin{aligned} & \limsup_{x \rightarrow \infty} \int_{\mathbb{R}_+} p_t(x, s, z) \left( (zx^{-1} + 1)^{1-a} - 1 - (1-a)zx^{-1} \right) \pi(dz) \\ &= a(1-a) \limsup_{x \rightarrow \infty} x^{-2} \int_{\mathbb{R}_+} p_t(x, s, z) z^2 \left( \int_0^1 (1 + zx^{-1}v)^{-1-a} (1-v) dv \right) \pi(dz) \\ &\leq C_t \limsup_{x \rightarrow \infty} \frac{p(x)}{x^2} \int_{\mathbb{R}_+} (z^2 + z^3) \pi(dz) < \infty \end{aligned}$$

for some  $C_t > 0$ , combining **LDCG**, (3.9) and the fact that  $\int_{\mathbb{R}_+} (z^2 \vee z^3) \pi(dz) < \infty$ . Therefore, the integral corresponding to the positive jumps is bounded for large values of  $x$ , and Condition **(SN $\infty$ )** is enough to control the behaviour of the process near infinity. The proof of [22, Theorem 4.1.i)] is thus unchanged and the results hold also for processes whose rate of positive jumps satisfies (B.6).  $\square$

**B.5. Proof of [22, Theorem 6.2] with time dependent positive jump rate.** Let  $t > 0$  and consider again the process  $Y$  solution to (B.5) where for  $x > 0$ ,  $z \geq 0$  and  $s \leq t$ ,  $p_t(x, s, z) \leq p(x)(1 + \mathbf{c}_t z)$  and  $p_t(x, s, z) \leq p(x)(1 + zx^{-1})$  with  $\mathbf{c}_t$  a finite and positive constant depending on  $t$ .

**Theorem B.6.** [22, Theorem 6.2.ii)] *Suppose that Assumption **LDCG**, (3.9) and **(SN $\infty$ )** hold and that  $\int (z^2 \vee z^3) \pi(dz) < \infty$  and let  $Y$  be a pathwise unique solution to (B.5). Assume also that **(LSG)** holds (with  $g, r$  instead of  $\hat{g}, \hat{r}$ ).*

(i) *If **(SN0)** holds, then  $Y$  converges in law as  $t$  tends to infinity to  $Y_\infty$  and for every bounded and measurable function  $f$ , almost surely*

$$\lim_{t \rightarrow +\infty} \frac{1}{t} \int_0^t f(X_s) ds = \mathbb{E}[f(X_\infty)].$$

(ii) *If **(LN0)** holds, then  $\mathbb{P}_x(\exists t < \infty, Y_t = 0) = 1$ .*

We first prove a lemma, as in [22]. Let  $x_0, t_0 > 0$ . For all  $i \geq 0$ , we consider the stopping times  $T_i(x_0)$ , given by  $T_0 = 0$  and for all  $i \geq 1$ ,  $T_i(x_0) = \inf\{t \geq T_{i-1}(x_0) + t_0, Y_t \leq x_0\}$ .

**Lemma B.7.** [22, Lemma 7.2.] *Suppose that Assumption **LDCG** and (3.9) hold and that  $\int (z^2 \vee z^3) \pi(dz) < \infty$ . Then, if **(SN $\infty$ )** and **(LSG)** hold, then  $\mathbb{E}[T_i(x_0)] < \infty$  for all  $i \geq 0$ .*

*Proof.* ([22, Lemma 7.2]) Let us choose  $0 < x_0 < x_1$  and let  $\tau = \tau^-(x_0) \wedge \tau^+(x_1)$ , where  $\tau^+, \tau^-$  are defined in (5.5) and (5.7). Following the same steps as in the proof of [22, Lemma 7.2] we have,

$$\ln Y_{t \wedge \tau} \leq \ln Y_0 + \int_0^{t \wedge \tau} \frac{g(Y_s)}{Y_s} ds - \int_0^{t \wedge \tau} \frac{\sigma^2(Y_s)}{Y_s^2} ds + \mathbb{E}[\ln \Theta] \int_0^{t \wedge \tau} r(Y_s) ds + M_{t \wedge \tau}$$

where  $(M_{s \wedge \tau}, s \geq 0)$  is a martingale. According to **(LSG)**, we have

$$\ln(Y_{t \wedge \tau}) - \ln(Y_0) \leq -\eta(t \wedge \tau) + M_{t \wedge \tau},$$

and following the proof of [22, Lemma 7.2], we obtain

$$\mathbb{E}_x(\tau) \leq \frac{1}{\eta} \ln \left( \frac{x}{\Theta x_0} \right).$$

For the end of the proof, we follow exactly [22, Lemma 7.2], using the generalization of [22, Theorem 4.1.i)] proved in Appendix B.4.  $\square$

*Proof of Theorem B.6.* [22, Theorem 6.2.] The first point follows directly from Lemma B.7 and [10, Theorem 7.1.4] as in [22]. For the second point, let  $a < 1$  be such that Condition **(LN0)** is satisfied, and let  $\delta < (3 - 2a)^{-1}$ . Following the proof of [22, Theorem 3.3.ii)], replacing  $G_a$  by  $G_a^{(s)}$  defined in (B.8), and using that for  $a < 1$ , under **(LN0)**,

$$G_a^{(s)}(x) \geq (a - 1) \frac{g(x)}{x} - a(a - 1) \frac{\sigma^2(x)}{x^2} \geq (1 - a) \ln(x^{-1}) (\ln(\ln(x^{-1})))^{1+\eta_2},$$

we get that there exist  $\mathbf{t}$  and  $\mathbf{p}$  such that for all  $\varepsilon$  small enough, and  $z \in (\varepsilon^{1+\delta}, \varepsilon^{1-\delta})$ ,

$$\mathbb{P}_z(\tau^-(0) \leq \mathbf{t}(\varepsilon)) \geq \mathbf{p}(\varepsilon).$$

From this result, we can prove [22, Eq. (7.29)]. Next, the proof of [22, Eq. (6.3)] requires [22, Eq.(7.18)]. To prove [22, Eq.(7.18)] in our case, we have to deal with the dependence on the jump size of the jump rate  $p_t$  to obtain a lower bound on the probability to have no positive jump during a time interval of the form  $[0, t \wedge \tau^+(y) \wedge \tau^-(x)]$  with  $0 < x < y$ . Hence the idea is to bound the expectation of the sum of positive jumps on  $[0, t \wedge \tau^+(y) \wedge \tau^-(x)]$  and use Markov inequality. Let  $T = \tau^+(y) \wedge \tau^-(x)$ . Then, for any  $y_0 \in (x, y)$ ,

$$\mathbb{P}_{y_0}(Y_{t \wedge T} \geq y) \leq \mathbb{P}_{y_0} \left( \int_0^{t \wedge T} g(Y_s) ds + I_Q(t \wedge T) + \int_0^{t \wedge T} \sqrt{2\sigma^2(Y_s)} dB_s \geq y - y_0 \right),$$

where

$$\begin{aligned} I_Q(t \wedge T) &:= \int_0^{t \wedge T} \int_{\mathbb{R}_+} \int_0^{p_t(Y_s, s, z)} z Q(ds, dz, dx) \\ &\leq \int_0^{t \wedge T} \int_0^{Y_s} \int_0^{2p(Y_s)} z Q(ds, dz, dx) + \int_0^{t \wedge T} \int_{Y_s}^{\infty} \int_0^{2zp(Y_s)/Y_s} z Q(ds, dz, dx) \\ &\leq \int_0^{t \wedge T} \int_{\mathbb{R}_+} \int_0^{2p(Y_s)} z Q(ds, dz, dx) + \int_0^{t \wedge T} \int_{\mathbb{R}_+} \int_0^{2zp(Y_s)/\hat{Y}_s} z Q(ds, dz, dx). \end{aligned} \quad (\text{B.9})$$

Then, as in [22] p.19, if we denote by  $J(t, x, y)$  the event of having no positive jumps due to the first integral in (B.9), we have for all  $y_0 \in (x, y)$ ,

$$\mathbb{P}_{y_0}(J(t, x, y)) \geq e^{-2tp(y)},$$

because  $p$  is non-decreasing according to Assumption **EU**. Next,

$$\mathbb{P}_{y_0}(Y_{t \wedge T} \geq y, J(t, x, y))$$

$$\leq \mathbb{P}_{y_0} \left( \int_0^{t \wedge T} g(Y_s) ds + \int_0^{t \wedge T} \int_0^{2p(Y_s)/Y_s} \int_{\mathbb{R}_+} z \bar{Q}(ds, dx, dz) + \int_0^{t \wedge T} \sqrt{2\sigma^2(Y_s)} dB_s \geq y - y_0 \right),$$

where  $\bar{Q}$  is a PPM with intensity  $ds \otimes dx \otimes z\pi(dz)$  (see Appendix D). Considering as before the event that there is no positive jumps associated to  $\bar{Q}$ , we get

$$\mathbb{P}_{y_0}(Y_{t \wedge T} \geq y) \leq 2 - e^{-2tp(y)} - e^{-2tp(y)/y} + \mathbb{P}_{y_0} \left( \int_0^{t \wedge T} g(Y_s) ds + \int_0^{t \wedge T} \sqrt{2\sigma^2(Y_s)} dB_s \geq y - y_0 \right).$$

We conclude as in [22], that  $\sup_{x \leq v \leq z} g(v) < \infty$  according to Assumption **EU** and that  $\inf_{x \leq v \leq y} r(v) > 0$  holds under Assumption **LDCG**.  $\square$

#### APPENDIX C. PROOF OF PROPOSITION 4.1

We provide the proof of the proposition in the case  $g \neq \beta$ . The proof is very similar in the case  $g = \beta$  and does not bring new insight. We thus skip it. The proof is a direct application of [25, Proposition 1]. Notice that in the statement of [25, Proposition 1], the functions  $b$ ,  $g$  and  $h$  do not depend on time, unlike the present case of our process. However this additional dependence does not bring any modification to the proofs (which are mostly derived in the

earlier paper [19]). First according to their conditions (i) to (iv) on page 60, our parameters are admissible. Second, we need to check that conditions (a), (b) and (c) are fulfilled. It follows directly from Assumption **EU**.

#### APPENDIX D. GENERALIZATION TO A DIVISION RATE DEPENDING ON THE FRAGMENTATION PARAMETER $\theta$

In some proofs, we need to consider a slight generalization of the SDE (5.1) where an individual with trait  $x$  dies and transmits a proportion  $\theta \in [0, 1]$  of its trait to its left offspring at a rate  $r(x)l(\theta)$ , that depends on  $\theta$ , where  $l : [0, 1] \rightarrow \mathbb{R}_+$  is a nonnegative function. However, using the properties of Poisson random measures we can prove that a solution to such an SDE can be rewritten as the solution to (5.1) by modifying the death rate  $r$  and the fragmentation kernel  $\kappa$ .

**Lemma D.1.** *Assume that  $\int_0^1 l(\theta)\kappa(d\theta) < \infty$ . Let*

$$\hat{\kappa}(d\theta) = l(\theta) \left( \int_0^1 l(\theta)\kappa(d\theta) \right)^{-1} \kappa(d\theta), \quad \hat{r}(x) = r(x) \int_0^1 l(\theta)\kappa(d\theta),$$

and  $\tilde{Q}$ ,  $B$  and  $N$  be defined as in (5.1). Then, there exists a Poisson random measure  $N'$  with intensity  $ds \otimes dz \otimes \hat{\kappa}(d\theta)$  such that  $X$  is the pathwise unique solution to

$$\begin{aligned} X_t = X_0 + \int_0^t g(X_s)ds + \int_0^t \sqrt{2\sigma^2(X_s)}dB_s + \int_0^t \int_0^{p(X_{s-})} \int_{\mathbb{R}_+} z\tilde{Q}(ds, dx, dz) \\ + \int_0^t \int_0^{\hat{r}(X_{s-})} \int_0^1 (\theta - 1)X_{s-}N'(ds, dz, d\theta), \end{aligned}$$

if and only if  $X$  is the pathwise unique nonnegative strong solution to

$$\begin{aligned} X_t = X_0 + \int_0^t g(X_s)ds + \int_0^t \sqrt{2\sigma^2(X_s)}dB_s + \int_0^t \int_0^{p(X_{s-})} \int_{\mathbb{R}_+} z\tilde{Q}(ds, dx, dz) \\ + \int_0^t \int_0^1 \int_0^{r(X_{s-})l(\theta)} (\theta - 1)X_{s-}N(ds, dz, d\theta). \end{aligned}$$

#### ACKNOWLEDGMENTS

The authors are grateful to V. Bansaye for his advice and comments and to B. Cloez for fruitful discussions. This work was partially funded by the Chair ‘Modélisation Mathématique et Biodiversité’ of VEOLIA-Ecole Polytechnique-MNHN-F.X., by the French national research agency (ANR) via project ANR NOLO (ANR-20-CE40-0015) and in the framework of the ‘France 2030’ program (ANR-15-IDEX-0002) and by the LabEx PERSYVAL-Lab (ANR-11-LABX-0025-01).

#### REFERENCES

- [1] G. Alsmeyer and S. Gröttrup. A host-parasite model for a two-type cell population. *Adv. in Appl. Probab.*, 45(3):719–741, 09 2013.
- [2] G. Alsmeyer and S. Gröttrup. Branching within branching: A model for host–parasite co-evolution. *Stoch. Proc. Appl.*, 126(6):1839 – 1883, 2016.
- [3] K. B. Athreya and P. E. Ney. *Branching processes*. Springer-Verlag Berlin, Mineola, NY, 1972. Reprint of the 1972 original [Springer, New York; MR0373040].
- [4] E. Baake and H.-O. Georgii. Mutation, selection, and ancestry in branching models: a variational approach. *J. Math. Biol.*, 54(2):257–303, 2007.
- [5] V. Bansaye. Proliferating parasites in dividing cells: Kimmel’s branching model revisited. *Ann. Appl. Probab.*, 18(3):967–996, 2008.
- [6] V. Bansaye. Cell contamination and branching processes in a random environment with immigration. *Adv. Appl. Probab.*, 41(4):1059–1081, 2009.

- [7] V. Bansaye, J.-F. Delmas, L. Marsalle, V. C. Tran, et al. Limit theorems for Markov processes indexed by continuous time Galton–Watson trees. *Ann. Appl. Probab.*, 21(6):2263–2314, 2011.
- [8] V. Bansaye, J. C. Pardo, and C. Smadi. On the extinction of continuous state branching processes with catastrophes. *Electron. J. Probab.*, 18:no. 106, 31, 2013.
- [9] V. Bansaye and V. Tran. Branching feller diffusion for cell division with parasite infection. *ALEA, Lat. Am. J. Probab. Math. Stat.*, 2011.
- [10] M. Bladt and B. F. Nielsen. *Matrix-exponential distributions in applied probability*, volume 81 of *Probability Theory and Stochastic Modelling*. Springer, New York, 2017.
- [11] C. Boeinghoff and M. Hutzenthaler. Branching diffusions in random environment. *Markov Proc. Rel. Fields*, 2012.
- [12] B. Cloez. Limit theorems for some branching measure-valued processes. *Adv. Appl. Probab.*, 49(2):549–580, 2017.
- [13] H.-O. Georgii and E. Baake. Supercritical multitype branching processes: the ancestral types of typical individuals. *Adv. Appl. Probab.*, 35(4):1090–1110, 2003.
- [14] M. Hairer and J. C. Mattingly. Yet another look at Harris’ ergodic theorem for Markov chains. In *Seminar on Stochastic Analysis, Random Fields and Applications VI*, pages 109–117. Springer, 2011.
- [15] R. Hardy and S. C. Harris. A spine approach to branching diffusions with applications to  $L_p$ -convergence of martingales. In *Séminaire de probabilités XLII*, pages 281–330. Springer, 2009.
- [16] M. Kimmel. Quasistationarity in a branching model of division-within-division. In *Classical and modern branching processes (Minneapolis, MN, 1994)*, volume 84 of *IMA Vol. Math. Appl.*, pages 157–164. Springer, New York, 1997.
- [17] A. E. Kyprianou. *Introductory lectures on fluctuations of Lévy processes with applications*. Springer Science & Business Media, 2006.
- [18] P.-S. Li, X. Yang, and X. Zhou. A general continuous-state nonlinear branching process. *Ann. Appl. Probab.*, 29(4):2523–2555, 2019.
- [19] Z. Li and F. Pu. Strong solutions of jump-type stochastic equations. *Electron. Commun. Probab.*, 17(2011):1–13, 2012.
- [20] A. Marguet. A law of large numbers for branching markov processes by the ergodicity of ancestral lineages. *ESAIM: PS*, 23:638–661, 2019.
- [21] A. Marguet. Uniform sampling in a structured branching population. *Bernoulli*, 25, 2019.
- [22] A. Marguet and C. Smadi. Long time behaviour of continuous-state nonlinear branching processes with catastrophes. *Electron. J. Probab.*, 26:1–32, 2021.
- [23] S. Méléard and S. Roelly. Evolutionary two-level population process and large population approximations. *Ann. Univ. Bucharest, Mathematical ser.*, 4 (LXII):37–70, 2013.
- [24] L. Osorio and A. Winter. Two level branching model for virus population under cell division. Preprint, arXiv:2004.14352, 2020.
- [25] S. Palau and J. Pardo. Branching processes in a Lévy random environment. *Acta Appl. Math.*, 153(1):55–79, 2018.
- [26] S. Palau and J. C. Pardo. Continuous state branching processes in random environment: The Brownian case. *Stoch. Proc. Appl.*, 127(3):957–994, 2017.
- [27] P. E. Protter. Stochastic differential equations. In *Stochastic integration and differential equations*, pages 249–361. Springer, 2005.
- [28] M. A. Rujano, F. Bosveld, F. A. Salomons, F. Dijk, M. A. Van Waarde, J. J. Van Der Want, R. A. De Vos, E. R. Brunt, O. C. Sibon, and H. H. Kampinga. Polarised asymmetric inheritance of accumulated protein damage in higher eukaryotes. *PLoS Biol.*, 4(12):e417, 2006.
- [29] E. J. Stewart, R. Madden, G. Paul, and F. Taddei. Aging and death in an organism that reproduces by morphologically symmetric division. *PLoS Biol.*, 3(2):e45, 2005.

ALINE MARGUET, UNIV. GRENOBLE ALPES, INRIA, 38000 GRENOBLE, FRANCE  
*Email address:* [aline.marguet@inria.fr](mailto:aline.marguet@inria.fr)

CHARLINE SMADI, UNIV. GRENOBLE ALPES, INRAE, LESSEM, 38000 GRENOBLE, FRANCE AND UNIV. GRENOBLE ALPES, CNRS, INSTITUT FOURIER, 38000 GRENOBLE, FRANCE  
*Email address:* [charline.smadi@inrae.fr](mailto:charline.smadi@inrae.fr)