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- SM1. Supplemental proofs. 6

SM1.1. Deterministic model. 7

- Proof of corollary 2.10. According to hypothesis 2.9, 8
- $\exists A > 0, \epsilon > 0$ such that $\forall a \ge A, b_i(a) + \lambda_i > \epsilon$. (SM1)9
- Let $k \in \mathbb{N}$. Using hypothesis 2.2, for all $t \ge A$, we have: 10

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$$0 \le t^k b_j(t) e^{-\int_0^t [b_j(s) + \lambda_j] \, ds} \le \overline{b}_j t^k e^{-\int_0^A [b_j(s) + \lambda_j] \, ds} e^{-\int_A^t [b_j(s) + \lambda_j] \, ds}.$$

- Then, using (SM1) we obtain: 12

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$$0 \le t^k b_j(t) e^{-\int_0^t \left[b_j(s) + \lambda_j\right] ds} \le t^k K_{A,\epsilon} e^{-\epsilon t},$$

where $K_{A,\epsilon}$ is a constant given by $K_{A,\epsilon} := \overline{b}_j e^{-\int_0^{-1} [b_j(s) + \lambda_j - \epsilon] ds}$. As $\epsilon > 0$, the 14function $t \mapsto t^k e^{-\epsilon t}$ is integrable on \mathbb{R}_+ , and we deduce that $\int_A^{+\infty} t^k e^{-\lambda_j t} d\mathcal{B}_j(t) dt < 0$ 15 ∞ . Using the continuity of b_j (hypothesis 2.2), we conclude that $t \mapsto e^{-\lambda_j t} d\mathcal{B}_j(t) dt$ 1617 is integrable on \mathbb{R}_+ .

Proof of corollary 3.1. According to (16), we obtain: 18

19 (SM2)
$$\forall j \in [\![1, \lambda_c]\!], \frac{\phi^{(j)}(a)}{2[p_S^{(j)}\phi^{(j)}(0) + p_L^{(j)}\phi^{(j+1)}(0)]} = \int_a^{+\infty} b_j(s)e^{-\int_a^s \lambda_c + b_j(u)du}ds$$

According to remark 2.5 and hypothesis 2.7, we deduce that $\lambda_c > -\overline{b}_j, \forall j \in [\![1, J]\!]$. 20Hence, using also hypothesis 2.2, we have: 21

$$\frac{\phi^{(j)}(a)}{2[p_S^{(j)}\phi^{(j)}(0) + p_L^{(j)}\phi^{(j+1)}(0)]} \ge \underline{b}_j \int_a^{+\infty} e^{-(\lambda_c + \overline{b}_j)(s-a)} ds = \frac{\underline{b}_j}{\lambda_c + \overline{b}_j},$$

and reminding that $\lambda_c > 0$ (see remark 2.5), we also obtain the right-side of (17): 23

24
$$\frac{\phi^{(j)}(a)}{2[p_S^{(j)}\phi^{(j)}(0) + p_L^{(j)}\phi^{(j+1)}(0)]} \leq \int_a^{+\infty} b_j(s)e^{-\int_a^s b_j(u)du}ds$$

25
$$= [-e^{-\int_a^s b_j(u)du}]_a^{+\infty} = 1.$$

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SM1

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Proof of lemma 3.2. For $j \in [\![1, J]\!]$, any solution of (4) in $\mathbf{L}^1(\mathbb{R}_+)$ is given by: 27

28
$$\hat{\phi}^{(j)}(a) = \hat{\phi}^{(j)}(0)e^{\int_0^a [\lambda_j + b_j(s)]ds} [1 - 2p_S^{(j)} \int_0^a b_j(s)e^{-\int_0^s [\lambda_j + b_j(u)]du}ds]$$

According to hypothesis 2.4, $1 = 2p_S^{(j)} \int_0^{+\infty} b_j(s) e^{-\int_0^s [\lambda_j + b_j(u)] du} ds$, thus 29

30
$$\hat{\phi}^{(j)}(a) = 2p_S^{(j)}\hat{\phi}^{(j)}(0)\int_a^{+\infty} b_j(s)e^{-\int_a^s [\lambda_j + b_j(u)]du}ds$$

Finally, according to remark 2.5, $\lambda_j > -\overline{b}_j$ and we obtain, using hypothesis 2.2, 31

$$\begin{array}{l} {}_{33} \qquad \frac{\hat{\phi}^{(j)}(a)}{\hat{\phi}^{(j)}(0)} = 2p_S^{(j)} \int_a^{+\infty} b_j(s) e^{-\int_a^s [\lambda_j + b_j(u)] du} ds \\ \\ {}_{34} \qquad \qquad \geq \quad 2p_S^{(j)} \underline{b}_j \int_a^{+\infty} e^{-(\lambda_j + \overline{b}_j)(s-a)} ds = 2p_S^{(j)} \frac{\underline{b}_j}{\lambda_j + \overline{b}_j} \end{array}$$

Then, we want to show that $\hat{\phi}^{(j)}(a) < \infty$ for all $a \in \mathbb{R}_+ \cup \{\infty\}$. Let 36

37
$$I(a) := \int_{a}^{+\infty} b_j(s) e^{-\int_0^s [\lambda_j + b_j(u)] du} ds$$

Applying an integration by part to I(a), we obtain that, for all $a \ge 0$, 38

$$I(a) = \left[e^{-\int_0^s [\lambda_j + b_j(u)] du}\right]_a^\infty - \lambda_j \int_a^\infty e^{-\int_0^s [\lambda_j + b_j(u)] du} ds.$$

Hypotheses 2.4 and 2.2 imply that, for all $a \ge 0$, $\int_a^{\infty} e^{-\int_0^s [\lambda_j + b_j(s)] ds} < \infty$ and so, $\lim_{s \to 0} e^{-\int_0^s [\lambda_j + b_j(u)] du} = 0$. Thus, we have: 40 41

42 (SM3)
$$I(a) = e^{-\int_0^a [\lambda_j + b_j(u)] du} - \lambda_j \int_a^\infty e^{-\int_0^s [\lambda_j + b_j(u)] du} ds.$$

Multiplying (SM3) by $e^{\int_0^a [\lambda_j + b_j(u)] du}$, we deduce: 43

44 (SM4)
$$\frac{\hat{\phi}^{(j)}(a)}{2p_S^{(j)}\hat{\phi}^{(j)}(0)} = 1 - \lambda_j \int_a^\infty e^{-\int_a^s [\lambda_j + b_j(u)] du} ds \,.$$

If $\lambda_j \geq 0$, we deduce directly from (SM4) that, for all $a \in \mathbb{R}_+ \cup \{\infty\}$, $\frac{\hat{\phi}^{(j)}(a)}{2p_{\varsigma}^{(j)}\hat{\phi}^{(j)}(0)} \leq 1$. 45We assume that $\lambda_j < 0$. Using hypothesis 2.9, we deduce that there exists constants 46

47
$$A > 0$$
 and $\epsilon > 0$ such that

$$\forall a \ge A, \quad \lambda_j + b_j(a) > \epsilon > 0$$

Hence, with $C = \frac{-\lambda_j}{\epsilon} > 0$, we have: 49

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$$\forall a \ge A, \quad -\lambda_j \le C(\lambda_j + b_j(a)).$$

Applying this inequality to (SM4), we obtain:

52
$$\forall a \ge A, \quad \frac{\hat{\phi}^{(j)}(a)}{2p_S^{(j)}\hat{\phi}^{(j)}(0)} \le 1 + C \int_a^\infty [\lambda_j + b_j(s)] e^{-\int_0^s [\lambda_j + b_j(u)] du} ds \times e^{\int_0^a [\lambda_j + b_j(s)] ds}$$

SM2

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Again, using hypotheses 2.4 and 2.2, we obtain: 53

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$$\int_{a}^{\infty} [\lambda_j + b_j(s)] e^{-\int_{0}^{s} [\lambda_j + b_j(u)] du} ds = \left[-e^{-\int_{0}^{s} [\lambda_j + b_j(u)] du} \right]_{a}^{\infty} = e^{-\int_{0}^{a} [\lambda_j + b_j(u)] du}$$

We deduce

$$orall a \geq A, \quad rac{\hat{\phi}^{(j)}(a)}{2p_S^{(j)}\hat{\phi}^{(j)}(0)} \leq 1+C\,.$$

As $\hat{\phi}^{(j)}$ is continuous, we conclude that

$$orall a\in\mathbb{R}_+\cup\{+\infty\},\quad rac{\hat{\phi}^{(j)}(a)}{2p^{(j)}_S\hat{\phi}^{(j)}(0)}<\infty\,.$$

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Proof of lemma 3.3. Deriving $\ll e^{-\lambda_c t} \rho(t, \cdot), \phi \gg$ with respect to t, we obtain 60

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$$\frac{d}{dt} \ll e^{-\lambda_c t} \rho(t, \cdot), \phi \gg = -e^{-\lambda_c t} \ll (\lambda_c \mathbb{1} + \mathcal{B} + \partial_a) \rho(t, \cdot), \phi \gg .$$

By integration by part and using that $\rho \in \mathbf{L}^1(\mathbb{R}_+)^J$ and $\phi \in \mathcal{C}^1_b(\mathbb{R}_+)^J$, we have 62

$$\ll \partial_a \rho(t, \cdot), \phi \gg = -\rho(t, 0)^T \phi(0) - \ll \rho(t, \cdot), \partial_a \phi \gg t$$

and we deduce

$$\frac{d}{dt} \ll e^{-\lambda_c t} \rho(t, \cdot), \phi \gg = e^{-\lambda_c t} \left[\rho(t, 0)^T \phi(0) + \ll \rho(t, \cdot), \partial_a \phi \gg - \ll (\lambda_c \mathbb{1} + \mathcal{B}) \rho(t, \cdot), \phi \gg \right].$$

As we have $(\lambda_c \mathbb{1} + \mathcal{B})^T = (\lambda_c \mathbb{1} + \mathcal{B})$, it comes $\ll \rho(t, \cdot), \partial_a \phi \gg - \ll (\lambda_c \mathbb{1} + \mathcal{B})\rho(t, \cdot), \phi \gg = \ll \rho(t, \cdot), \partial_a \phi - (\lambda_c \mathbb{1} + \mathcal{B})\phi \gg$. Then, using that $\mathcal{L}^D \phi = \lambda_c \phi$, we deduce $(\partial_a - \lambda_c \mathbb{1} - \mathcal{B})\phi = -K(\cdot)^T \phi(0)$. Thus, 69 70 71

72
$$\frac{d}{dt} \ll e^{-\lambda_c t} \rho(t, \cdot), \phi \gg = e^{-\lambda_c t} \left[\rho(t, 0)^T \phi(0) - \ll \rho(t, \cdot), K(\cdot)^T \phi(0) \gg \right].$$

Note that $\ll \rho(t,\cdot), K(\cdot)^T \phi(0) \gg = \ll K(\cdot)\rho(t,\cdot), \phi(0) \gg = \rho(t,0)^T \phi(0).$ Consequently,

$$\frac{d}{dt} \ll e^{-\lambda_c t} \rho(t, \cdot), \phi \gg = 0.$$

Hence, 73

$$\forall t, \quad \ll e^{-\lambda_c t} \rho(t, \cdot), \phi \gg \quad = \quad \ll \rho_0(\cdot), \phi \gg \quad = \eta$$

Thanks to the renormalization $\ll \hat{\rho}, \phi \gg = 1$, we obtain the conservation principle: 75

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$$\ll e^{-\lambda_c t} \rho(t, \cdot) - \eta \hat{\rho}, \phi \gg = \ll e^{-\lambda_c t} \rho(t, \cdot), \phi \gg -\eta \ll \hat{\rho}, \phi \gg = 0.$$

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Proof of lemma 3.4. From the linearity of the system, it can be easily shown that h is solution of

SM4

$$\begin{cases} \partial_t h(t,a) + \partial_a h(t,a) + [\lambda_c + B(a)]h(t,a) = 0, \quad t \ge 0, \quad a \ge 0, \\ h(t,a=0) = \int_0^\infty K(a)h(t,a)da. \end{cases}$$

Let f be a derivable function. Applying the chain rules, it comes, for $j \in [\![1, J]\!]$,

82
$$\partial_t f[h^{(j)}(t,a)] + \partial_a f[h^{(j)}(t,a)] = f'(h^{(j)}(t,a))[\partial_t h^{(j)}(t,a) + \partial_a h^{(j)}(t,a)] = -[\lambda_c + b_j(a)] \times h^{(j)}(t,a)f'(h^{(j)}(t,a)).$$

83 For $f(x) = |x|, f'(x) = \frac{|x|}{x}$, we deduce

84
$$\partial_t |h^{(j)}(t,a)| + \partial_a |h^{(j)}(t,a)| = -[\lambda_c + b_j(a)] |h^{(j)}(t,a)|.$$

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LEMMA SM1.1. [Modified Grönwall lemma] Let $N \in \mathbb{N}^*$. Suppose that $\forall i \in [1, N]$, there exist $\kappa_i \in \mathbb{R}^*_+$, $\gamma \in \mathbb{R}^*_+$ and P_i polynomials of degree $\alpha_i \in \mathbb{N}$ such that

$$F'(t) \le \sum_{i=1}^{N} P_i(t) e^{-\kappa_i t} - \gamma F(t)$$

90 Then,

$$F(t) \le K e^{-\gamma t} + \sum_{i=1}^{N} \widetilde{P}_i(t) e^{-\kappa_i t}$$

92 where K is a constant and for all $i \in [\![1, N]\!]$, \widetilde{P}_i is a polynomial of degree $\widetilde{\alpha}_i \leq \alpha_i + 1$. 93 Proof. Note that $\frac{d}{dt}(e^{\gamma t}F(t)) = (F'(t) + \gamma F(t)) \times e^{\gamma t}$. Hence,

94
$$\frac{d}{dt}(e^{\gamma t}F(t)) \le \sum_{i=1}^{N} P_i(t)e^{(-\kappa_i + \gamma)t}$$

95 Then, integrating on the interval [0, t], we obtain:

96
$$e^{\gamma t}F(t) - F(0) \le \sum_{i=1}^{N} \widetilde{P}_i(t)e^{(\gamma - \kappa_i)t} + K$$

97
98
$$F(t) \le (F(0) + K)e^{-\gamma t} + \sum_{i=1}^{N} \widetilde{P}_i(t)e^{-\kappa_i t}$$

99 where K is a constant and for all $i \in [\![1, N]\!]$, \tilde{P}_i a polynomial of degree $\tilde{\alpha}_i \leq \alpha_i + 1$ 100 (the degree increases when $\gamma = \kappa_i$).

101 **SM1.2. Stochastic model.** For any $f : (t, a) \mapsto (f_t^{(j)}(a))_{j \in [\![1,J]\!]} \in \mathcal{B}^1_b(\mathbb{R}_+ \times \mathbb{R}_+, \mathbb{R})^J$ (the space product of the set of bounded functions with bounded derivatives), 103 we note ∂_1 and ∂_2 respectively its derivative with respect to time (t) and age (a).

104 LEMMA SM1.2. Let
$$F \in C^{1}(\mathbb{R}, \mathbb{R})$$
, $f \in \mathcal{B}_{b}^{1}(\mathbb{R}_{+} \times \mathbb{R}_{+}, \mathbb{R})^{J}$.

$$F[\ll Z_{t}, f_{t} \gg] = F[\ll f_{0}, Z_{0} \gg] + \int_{0}^{t} \ll \partial_{1}f_{s} + \partial_{2}f_{s}, Z_{s} \gg F'[\ll f_{s}, Z_{s} \gg] ds$$

$$+ \int_{[0,t] \times \mathcal{E}} \left[\mathbbm{1}_{k \le N_{s^{-}}} \left(F[\ll f_{s}, 2\delta_{I_{s^{-}}^{(k)}, 0} - \delta_{I_{s^{-}}^{(k)}, A_{s^{-}}^{(k)}} + Z_{s^{-}} \gg] \right] -F[\ll f_{s}, Z_{s^{-}} \gg] \right] \mathbbm{1}_{0 \le \theta \le m_{1}(s, k, Z)}$$

$$+ \left(F[\ll f_{s}, \delta_{I_{s^{-}}^{(k)}+1, 0} + \delta_{I_{s}^{(k)}, 0} - \delta_{I_{s^{-}}^{(k)}, A_{s^{-}}^{(k)}} + Z_{s^{-}} \gg] \right] -F[\ll f_{s}, Z_{s^{-}} \gg] \mathbbm{1}_{m_{1}(s, k, Z) \le \theta \le m_{2}(s, k, Z)}$$

$$+ \left(F[\ll f_{s}, 2\delta_{I_{s^{-}}^{(k)}+1, 0} - \delta_{I_{s^{-}}^{(k)}, A_{s^{-}}^{(k)}} + Z_{s^{-}} \gg] \right) -F[\ll f_{s}, Z_{s^{-}} \gg] \mathbbm{1}_{m_{2}(s, k, Z) \le \theta \le m_{3}(s, k, Z)} \right] Q(ds, dk, d\theta).$$

Proof. We integrate f_t against the measure Z_t 106

$$\ll Z_{t}, f_{t} \gg = \sum_{k=1}^{N_{0}} f_{t}^{(I_{0}^{(k)})}(A_{0}^{(k)} + t)$$

$$+ \int_{[0,t] \times \mathcal{E}} \left[\mathbbm{1}_{k \le N_{s^{-}}} \left(2f_{t}^{(I_{s^{-}}^{(k)})}(t-s) - f_{t}^{(I_{s^{-}}^{(k)})}(A_{s^{-}}^{(k)} + t-s) \right) \mathbbm{1}_{0 \le \theta \le m_{1}(s,k,Z)}$$

$$+ \left(f_{t}^{(I_{s^{-}}^{(k)})}(t-s) + f_{t}^{(I_{s^{-}}^{(k)} + 1)}(t-s) - f_{t}^{(I_{s^{-}}^{(k)})}(A_{s^{-}}^{(k)} + t-s) \right) \mathbbm{1}_{m_{1}(s,k,Z) \le \theta \le m_{2}(s,k,Z)}$$

$$+ \left(2f_{t}^{(I_{s^{-}}^{(k)} + 1)}(t-s) - f_{t}^{(I_{s^{-}}^{(k)})}(A_{s^{-}}^{(k)} + t-s) \right) \mathbbm{1}_{m_{2}(s,k,Z) \le \theta \le m_{3}(s,k,Z)} \right] Q(ds,dk,d\theta).$$

108 Derivating $f_t^{(j)}[a+t-s]$, we obtain

$$\begin{split} \frac{d}{dt} \left[f_t^{(j)}[a+t-s] \right] &= \partial_1 f_t^{(j)}[a+t-s] + \partial_2 f_t^{(j)}[a+t-s] \\ \Rightarrow \quad \int_s^t \frac{d}{du} \left[f_u^{(j)}[a+u-s] \right] du = \int_s^t \left[\partial_1 f_u^{(j)}[a+u-s] + \partial_2 f_u^{(j)}[a+u-s] \right] du \\ \Rightarrow \quad f_t^{(j)}[a+t-s] &= f_s^{(j)}[a] + \int_s^t \left[\partial_1 f_u^{(j)}[a+u-s] + \partial_2 f_u^{(j)}[a+u-s] \right] du. \end{split}$$

Then, replacing j by the index $I_{s^-}^{(k)}$ and a by $A_{s^-}^{(k)}$ or 0, it comes 110

$$\ll Z_t, f_t \gg = \sum_{k=1}^{N_0} f_0^{(I_0^{(k)})}(A_0^{(k)}) + T_0 + T_1 + T_2 + T_3$$

$$+ \int_{[0,t]\times\mathcal{E}} \mathbb{1}_{k \le N_{s^-}} \left[\left(2f_s^{(I_{s^-}^{(k)})}(0) - f_s^{(I_{s^-}^{(k)})}(A_{s^-}^{(k)}) \right) \mathbb{1}_{0 \le \theta \le m_1(s,k,Z)} \right]$$

$$+ \left(f_s^{(I_{s^-}^{(k)})}(0) + f_s^{(I_{s^-}^{(k)}+1)}(0) - f_s^{(I_{s^-}^{(k)})}(A_{s^-}^{(k)}) \right) \mathbb{1}_{m_1(s,k,Z) \le \theta \le m_2(s,k,Z)}$$

$$+ \left(2f_s^{(I_{s^-}^{(k)}+1)}(0) - f_s^{(I_{s^-}^{(k)})}(A_{s^-}^{(k)}) \right) \mathbb{1}_{m_2(s,k,Z) \le \theta \le m_3(s,k,Z)} \right] Q(ds,dk,d\theta),$$

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112where

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$$\begin{split} T_{0} &= \sum_{k=1}^{N_{0}} \int_{0}^{t} \left[\partial_{1} f_{u}^{(I_{0}^{(k)})}(A_{0}^{(k)} + u) + \partial_{2} f_{u}^{(I_{0}^{(k)})}(A_{0}^{(k)} + u) \right] du, \\ T_{1} &= \int_{[0,t] \times \mathcal{E}} \mathbf{1}_{k \leq N_{s^{-}}} \int_{s}^{t} \left[2\partial_{1} f_{u}^{(I_{s}^{(k)})}(u - s) + 2\partial_{2} f_{u}^{(I_{s}^{(k)})}(u - s) - \partial_{1} f_{u}^{(I_{s}^{(k)})}(A_{s^{-}}^{(k)} + u - s) - \partial_{2} f_{u}^{(I_{s}^{(k)})}(A_{s^{-}}^{(k)} + u - s) \mathbf{1}_{0 \leq \theta \leq m_{1}(s,k,Z)} \right] duQ(ds, dk, d\theta), \\ T_{2} &= \int_{[0,t] \times \mathcal{E}} \mathbf{1}_{k \leq N_{s^{-}}} \int_{s}^{t} \left[\partial_{1} f_{u}^{(I_{s}^{(k)})}(u - s) + \partial_{1} f_{u}^{(I_{s}^{(k)} + 1)}(u - s) + \partial_{2} f_{u}^{(I_{s}^{(k)})}(u - s) + \partial_{2} f_{u}^{(I_{s}^{(k)})}(u - s) - \partial_{1} f_{u}^{(I_{s}^{(k)})}(A_{s^{-}}^{(k)} + u - s) - \partial_{2} f_{u}^{(I_{s}^{(k)} + 1)}(u - s) - \partial_{1} f_{u}^{(I_{s}^{(k)})}(A_{s^{-}}^{(k)} + u - s) - \partial_{2} f_{u}^{(I_{s}^{(k)} + 1)}(u - s) - \int_{s} \left[2\partial_{1} f_{u}^{(I_{s}^{(k)} + 1)}(u - s) + \partial_{2} f_{u}^{(I_{s}^{(k)} + 1)}(u - s) + 2\partial_{2} f_{u}^{(I_{s}^{(k)} + 1)}(u - s) - \partial_{1} f_{u}^{(I_{s}^{(k)} + 1)}(u - s) - \partial_{1} f_{u}^{(I_{s}^{(k)} + 1)}(u - s) + 2\partial_{2} f_{u}^{(I_{s}^{(k)} + 1)}(u - s) - \partial_{1} f_{u}^{(I_{s}^{(k)} + 1)}(u - s) + \partial_{1} f_{u}^{(I_{s}^{(k)} + 1)}(u - s) - \partial_{1} f_{u}^{(I_{s}^{(k)} + 1}(u - s) - \partial_{1} f_{u}^{(I_{s}^{(k)} + 1)}(u - s) - \partial_{1} f_{u}^{(I_{s}^{(k)} + 1)}(u - s) - \partial_{1} f_{u}^{(I_{s}^{(k)} + 1)}(u - s) - \partial_{1} f_{u}^{(I_{s}^{(k)} + 1}(u - s) - \partial_{1} f_{u}^{($$

$$-\partial_2 f_u^{(I_{s^-}^{(k)})} (A_{s^-}^{(k)} + u - s) \mathbb{1}_{m_2(s,k,Z) \le \theta \le m_3(s,k,Z)} \bigg] du Q(ds,dk,d\theta) \,.$$

114 As the partial differential of each $f^{(j)}$ are uniformly bounded, we can apply Fubini 115 theorem on T_0, T_1, T_2 and T_3 :

$$\begin{split} T_{0} &= \int_{0}^{t} \ll \partial_{1} f_{u} + \partial_{2} f_{u}, \sum_{k=1}^{N_{0}} \delta_{I_{0}^{(k)}, A_{0}^{(k)} + u} \gg du, \\ T_{1} &= \int_{0}^{t} \left[\ll \partial_{1} f_{u} + \partial_{2} f_{u}, \int_{0}^{u} \int_{\mathcal{E}} \mathbb{1}_{k \leq N_{s^{-}}} \left(2\delta_{I_{s^{-}}^{(k)}, u - s} - \delta_{I_{s^{-}}^{(k)}, A_{s^{-}}^{(k)} + u - s} \right) \mathbb{1}_{0 \leq \theta \leq m_{1}(s, k, Z)} Q(ds, dk, d\theta) \gg \right] du, \\ T_{2} &= \int_{0}^{t} \left[\ll \partial_{1} f_{u} + \partial_{2} f_{u}, \int_{0}^{u} \int_{\mathcal{E}} \mathbb{1}_{k \leq N_{s^{-}}} \left(\delta_{I_{s^{-}}^{(k)}, u - s} + \delta_{I_{s^{-}}^{(k)} + 1, u - s} - \delta_{I_{s^{-}}^{(k)}, A_{s^{-}}^{(k)} + u - s} \right) \mathbb{1}_{m_{1}(s, k, Z) \leq \theta \leq m_{2}(s, k, Z)} Q(ds, dk, d\theta) \gg \right] du, \\ T_{3} &= \int_{0}^{t} \left[\ll \partial_{1} f_{u} + \partial_{2} f_{u}, \int_{0}^{u} \int_{\mathcal{E}} \mathbb{1}_{k \leq N_{s^{-}}} \left(2\delta_{I_{s^{-}}^{(k)+1}, u - s} - \delta_{I_{s^{-}}^{(k)}, A_{s^{-}}^{(k)} + u - s} \right) \mathbb{1}_{m_{2}(s, k, Z) \leq \theta \leq m_{3}(s, k, Z)} Q(ds, dk, d\theta) \gg \right] du. \end{split}$$

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Finally, using the stochastic differential equation (2)117

$$T_0 + T_1 + T_2 + T_3 = \int_0^t \ll \partial_1 f_u + \partial_2 f_u, Z_u \gg du.$$

- *t*

Consequently, we obtain 119

$$\begin{split} \ll f_t, Z_t \gg &= \ll f_0, Z_0 \gg + \int_0^t \ll \partial_1 f_s + \partial_2 f_s, Z_s \gg ds \\ &+ \int_{[0,t] \times \mathcal{E}} \mathbbm{1}_{k \le N_{s^-}} \left[\ll f_s, 2\delta_{I_{s^-}^{(k)}, 0} - \delta_{I_{s^-}^{(k)}, A_{s^-}^{(k)}} \gg \mathbbm{1}_{0 \le \theta \le m_1(s, k, Z)} \right. \\ &+ \ll f_s, \delta_{I_{s^-}^{(k)}, 0} + \delta_{I_{s^-}^{(k)} + 1, 0} - \delta_{I_{s^-}^{(k)}, A_{s^-}^{(k)}} \gg \mathbbm{1}_{m_1(s, k, Z) \le \theta \le m_2(s, k, Z)} \\ &+ \ll f_s, 2\delta_{I_{s^-}^{(k)} + 1, 0} - \delta_{I_{s^-}^{(k)}, A_{s^-}^{(k)}} \gg \mathbbm{1}_{m_2(s, k, Z) \le \theta \le m_3(s, k, Z)} \right] Q(ds, dk, d\theta), \end{split}$$

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118

which gives us lemma SM1.2 for
$$F(x) = x$$
. We conclude by applying the Ito's formula (see [SM5], p.68-70).

123We introduce the sequence of stopping times ξ_N .

DEFINITION SM1.3. Let ξ_N a sequence of stopping times defined as 124

125
$$\xi_N = \sup \left(t : N_t < N, \quad \ll a, Z_t \gg < N \right).$$

Proof of theorem 3.6. We first start by showing (32). 126

$$N_t = N_0 + \int_{[0,t] \times \mathcal{E}} \mathbb{1}_{k \le N_s -} \mathbb{1}_{0 \le \theta \le b_{I_{s^{-}}^{(k)}}(A_{s^{-}}^{(k)})} Q(ds, dk, d\theta).$$

Thus, 128

127

129
$$\sup_{s \le t \land \xi_N} N_s \le N_0 + \int_0^{t \land \xi_N} \int_{\mathcal{E}} \mathbb{1}_{k \le N_{s^-}} \mathbb{1}_{0 \le \theta \le \overline{b}} Q(ds, dk, d\theta),$$

where $\bar{b} := \sup \bar{b}_j$. Taking the expectation and using Poisson measure properties, 130 $j \in [\![0, J]\!]$ we obtain 131

132
$$\mathbb{E}[\sup_{s \le t \land \xi_N} N_s] \le \mathbb{E}[N_0] + \bar{b}\mathbb{E}\left[\int_0^{t \land \xi_N} N_s ds\right] \le \mathbb{E}[N_0] + \bar{b}\mathbb{E}\left[\int_0^{t \land \xi_N} \sup_{u \le s \land \xi_N} N_u ds\right].$$

Hence, 133

134
$$\mathbb{E}[\sup_{s \le t \land \xi_N} N_s] \le \mathbb{E}[N_0] + \bar{b}\mathbb{E}\left[\int_0^t \sup_{u \le s \land \xi_N} N_u ds\right].$$

By Fubini theorem, we deduce that 135

136
$$\mathbb{E}[\sup_{s \le t \land \xi_N} N_s] \le \mathbb{E}[N_0] + \bar{b} \int_0^t \mathbb{E}\left[\sup_{u \le s \land \xi_N} N_u\right] ds.$$

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137 Applying Grönwall lemma, we deduce for all $t \leq T$ that

138
$$\mathbb{E}[\sup_{s \le t \land \xi_N} N_s] \le \mathbb{E}[N_0]e^{\bar{b}t}.$$

139 Hence,

SM8

140
$$\mathbb{E}[\sup_{t \le T \land \xi_N} N_t] \le \mathbb{E}[N_0] e^{\bar{b}T} \quad < \infty \,.$$

Using the same method, we also deduce that $\mathbb{E}\left[\sup_{t \leq T} \ll a, Z_t \gg\right] < \infty$. 141

Then, we use the same approach as [SM8] (Theorem 2.2.8) to compute the in-142finitesimal generator of Z_t , denoted by \mathcal{G} . By construction, $(Z_t)_{t \in \mathbb{R}_+}$ is a marko-143vian process of $\mathbb{D}([0,T], \mathcal{M}_P(\llbracket 1, J \rrbracket \times \mathbb{R}_+))$. Let $f \in \mathbf{C}_b^1(\mathcal{E}, \mathbb{R})$, by definition, $\mathcal{G}F :=$ 144 $\lim_{t\to 0} \frac{d}{dt} \mathbb{E} \left[F[\ll f, Z_t \gg] \right].$ Taking the expectation of the expression of $\ll f, Z_{t \wedge \xi_N} \gg$ 145 $t \to 0$ at lemma SM1.2, we obtain 146

$$\mathbb{E}\left[F[\ll f, Z_{t \wedge \xi_N} \gg]\right] = \mathbb{E}\left[F[\ll f, Z_0 \gg]\right] \\ + \mathbb{E}\left[\int_0^{t \wedge \xi_N} \ll \partial_a f, Z_s \gg F'[\ll f, Z_s \gg] ds\right] + \mathbb{E}\left[\chi^{f, F}(t \wedge \xi_N, Z)\right],$$

148where

$$\chi^{f,F}(t,Z) := \int_0^t \int_{\mathcal{E}} \left[\left(F[\ll f, 2\delta_{j,0} - \delta_{j,a} + Z_s \gg] - F[\langle f, Z_s \rangle] \right) p_{2,0}^{(j)} + \left(F[\langle f, \delta_{j+1,0} + \delta_{j,0} - \delta_{j,a} + Z_s \rangle] - F[\ll f, Z_s \gg] \right) p_{1,1}^{(j)} + \left(F[\langle f, 2\delta_{j+1,0} - \delta_{j,a} + Z_s \rangle] \right)$$

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+
$$(F[< f, 2\delta_{j+1,0} - \delta_{j,a} + Z_s >]$$

-F $[< f, Z_s >]) p_{0,2}^{(j)} b_j(a) Z_s(dj, da) ds.$

We have the following estimates, 150

151

$$\mathbb{E}\left[\chi^{f,F}(t \wedge \xi_N, Z)\right] \le 2\mathbb{E}\left[\sup_{t \le T} N_t\right] T \|F\|_{\infty} \bar{b},$$

$$\mathbb{E}[\int_0^{t \wedge \xi_N} \ll \partial_a f_s, Z_s \gg F'[\ll f, Z_s \gg] ds] \le \mathbb{E}\big[\sup_{t \le T} N_t\big]T \times \|\partial_a f\|_{\infty} \times \|F'\|_{\infty}$$

Those bounds are independent of N thanks to (32), so that we may let N goes to infinity. Moreover,

$$\frac{d}{dt} \int_0^t \ll \partial_a f, Z_s \gg F'[\ll f, Z_s \gg] ds = \ll \partial_a f, Z_t \gg F'[\ll f, Z_t \gg]$$

which is also dominated by $\mathbb{E}\left[\sup_{t \leq T} N_t\right] \times \|\partial_a f\|_{\infty} \times \|F'\|_{\infty}$. Also, 152

$$\frac{\partial}{\partial t}\chi(t, Z_t) = \int_{\mathcal{E}} \left[(F[\langle f, 2\delta_{j,0} - \delta_{j,a} + Z_t \rangle] - F[\langle f, Z_t \rangle]) p_{2,0}^{(j)} + (F[\ll f, \delta_{j+1,0} + \delta_{j,0} - \delta_{j,a} + Z_t \gg] - F[\ll f, Z_t \gg]) p_{1,1}^{(j)} + (F[\ll f, 2\delta_{j+1,0} - \delta_{j,a} + Z_t \gg] - F[\ll f, Z_t \gg]) p_{0,2}^{(j)} \right] b_j(a) Z_t(dj, da).$$

153

154
$$\left|\frac{\partial}{\partial t}\chi(t,Z_t)\right|$$
 is dominated \mathbb{P} -p.s by $2\mathbb{E}\left[\sup_{t\leq T} N_t\right] \|F\|_{\infty} \bar{b}$. We can thus apply the
155 differentiating theorem under the integral sign \mathbb{E} and conclude.

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Proof of lemma 3.7. Introducing the compensated Poisson measure \tilde{Q} , 156 $\tilde{Q}(ds, dk, d\theta) := Q(ds, dk, d\theta) - ds dk d\theta$, we define the process: 157

$$\begin{split} M_t^{F,f} &:= \int \int_{[0,t \wedge \xi_N] \times \mathcal{E}} \mathbbm{1}_{k < N_{s-}} \left[\left(F[\ll f, 2\delta_{I_{s-}^k, 0} - \delta_{I_{s-}^k, A_{s-}^k} + Z_{s-} \gg] \right) \\ &- F[\ll f, Z_{s-} \gg] \right) \mathbbm{1}_{0 \le \theta \le m_1(s,k,Z)} \\ &+ \left(F[\ll f, \delta_{I_{s-}^k+1, 0} + \delta_{I_{s-}^k, 0} - \delta_{I_{s-}^k, A_{s-}^k} + Z_{s-} \gg] \\ &- F[\ll f, Z_{s-} \gg] \right) \mathbbm{1}_{m_1(s,k,Z) \le \theta \le m_2(s,k,Z)} \\ &+ \left(F[\ll f, 2\delta_{I_{s-}^k+1, 0} - \delta_{I_{s-}^k, A_{s-}^k} + Z_{s-} \gg] \\ &- F[\ll f, Z_{s-} \gg] \right) \mathbbm{1}_{m_2(s,k,Z) \le \theta \le m_3(s,k,Z)} \right] \tilde{Q}(ds, dk, d\theta). \end{split}$$

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159 We can verify that
$$M_t^{F,f}$$
 is a martingale as an integral against a compensated
160 Poisson measure. Then, applying lemma SM1.2 and the definition of the generator
161 given in theorem 3.6, we show that

162 (SM5)
$$M_t^{F,f} = F[\ll f, Z_t \gg] - F[\ll f, Z_0 \gg] - \int_0^t \mathcal{G}F[\ll f, Z_s \gg] ds$$

We turn now to the computation of the quadratic variation and use the same approach 163 as in [SM1]. We apply (SM5) for $F(x) = x^2$. Note that we cannot use directly this 164result as $x \mapsto x^2$ is not bounded and we need to first use a localizing sequence (see 165[SM4] p. 382, theorem 13.14). We obtain that 166

$$\ll f, Z_t \gg^2 - \ll f, Z_0 \gg^2 - \int_0^t 2 \ll f, Z_s \gg \times \ll \partial_a f, Z_s \gg ds$$

167 (SM6)

$$-\int_0^t \sum_{j=1}^J \int_{\mathbb{R}_+} \left[\left(\ll f, 2\delta_{j,0} - \delta_{j,a} + Z_s \gg^2 - \ll f, Z_s \gg^2 \right) b_j(a) p_{2,0}^{(j)} - \left(\ll f, \delta_{j,0} + \delta_{j+1,0} - \delta_{j,a} + Z_s \gg^2 - \ll f, Z_s \gg^2 \right) b_j(a) p_{1,1}^{(j)} Z_s(dj, da)$$

$$- \left(\ll f, 2\delta_{j+1,0} - \delta_{j,a} + Z_s \gg^2 - \ll f, Z_s \gg^2 \right) b_j(a) p_{0,2}^{(j)} Z_s(dj, da) ds \right]$$

is a martingale. Then, applying (SM5) for F(x) = x (using a localizing sequence 168 again), we get that 169

$$\ll f, Z_t \gg = \ll f, Z_0 \gg + \int_0^t \ll \partial_a f, Z_s \gg ds + \int_0^t \left[\sum_{j=1}^J \int_{\mathbb{R}_+} \ll f, 2\delta_{j,0} - \delta_{j,a} \gg b_j(a) p_{2,0}^{(j)} Z_s(dj, da) \right] ds + \int_0^t \left[\sum_{j=1}^J \int_{\mathbb{R}_+} \ll f, \delta_{j,0} + \delta_{j+1,0} - \delta_{j,a} \gg b_j(a) p_{1,1}^{(j)} Z_s(dj, da) \right] ds + \int_0^t \left[\sum_{j=1}^J \int_{\mathbb{R}_+} \ll f, 2\delta_{j+1,0} - \delta_{j,a} \gg b_j(a) p_{0,2}^{(j)} Z_s(dj, da) \right] ds + M_t^J$$

170

Comment citer ce document : Yvinec, R., Clément, F., Robin, F. (2017). Analysis and calibration of a linear model for structured cell populations with isomersion prosting in the provide a population of ovarian follicles. arxiv preprint, arXiv:1712.05372, 1-21. 171 is a semi-martingale. Applying the Ito formula (see [SM5], p. 78-79), we obtain:

$$\ll f, Z_t \gg^2 - \ll f, Z_0 \gg^2 - \int_0^t 2 \ll f, Z_s \gg \times \ll \partial_a f, Z_s \gg ds + \sum_{j=1}^J \int_{\mathbb{R}_+} (2 \ll f, Z_s \gg \times \ll f, 2\delta_{j,0} - \delta_{j,a} \gg) b_j(a) p_{2,0}^{(j)} Z_s(dj, da) + \sum_{j=1}^J \int_{\mathbb{R}_+} (2 \ll f, Z_s \gg \times \ll f, \delta_{j,0} + \delta_{j+1,0} - \delta_{j,a} \gg) b_j(a) p_{1,1}^{(j)} Z_s(dj, da) + \sum_{j=1}^J \int_{\mathbb{R}_+} (2 \ll f, Z_s \gg \times \ll f, 2\delta_{j+1,0} - \delta_{j,a} \gg) b_j(a) p_{0,2}^{(j)} Z_s(dj, da)] ds - \langle M^f, M^f \rangle_t$$

173 is a martingale. We consider the jump corresponding to the case when the two 174 daughter cells remain on their mother layer. Note that

175
$$\ll f, 2\delta_{j,0} - \delta_{j,a} + Z_s \gg^2 - \ll f, Z_s \gg^2 = 2 \ll f, Z_s \gg \times \ll f, 2\delta_{j,0} - \delta_{j,a} \gg + \ll f, 2\delta_{j,0} - \delta_{j,a} \gg^2 .$$

We proceed similarly for the two other jumps. Applying the Doob-Meyer theorem ([SM5], p. 106), we deduce the quadratic variation $\langle M^f, M^f \rangle_t$ comparing (SM6) and (SM7).

179 SM1.3. Moment study.

180 Generating functions.

Proof of lemma 3.9. Let $a \ge 0$. Remind that the generating function is given by

$$F^{(i,a)}[\mathbf{s};t] = \sum_{\mathbf{k} \in \mathbb{N}^J} \mathbf{s}^{\mathbf{k}} \mathbb{P}\left[Y_t^a = \mathbf{k} | Z_0 = \delta_{i,0}\right]$$

181 Let $i \in [\![1, J]\!]$ and $\mathbf{j}, \mathbf{k} \in \mathbb{N}^J$. We note $P^a_{\mathbf{j}, \mathbf{k}}(t) := \mathbb{P}[Y^a_t = \mathbf{k}|Z_0 = \sum_{i=1}^J j_i \delta_{i,0}]$. We 182 write the backward equation for the probability $P^a_{e_i, \mathbf{k}}(t) := \mathbb{P}[Y^a_t = \mathbf{k}|Z_0 = \delta_{i,0}]$. 183 Starting from a single mother cell of age 0 and layer *i*, there are three possibilities at 184 time *t*: (i) the cell has not divided and $t \leq a$, (ii) the cell has not divided and t > a, 185 and (iii) the cell has divided. Thus,

186
187 (SM8)
$$P_{e_i,\mathbf{k}}^a(t) = (\delta_{e_i,\mathbf{k}} \mathbb{1}_{t \le a} + \delta_{\mathbf{0},\mathbf{k}} \mathbb{1}_{t > a}) \mathbb{P}[\tau^{(i)}(a_0 = 0) \ge t]$$

$$+ \int_{0}^{t} [p_{2,0}^{(i)} P_{2e_{i},\mathbf{k}}^{a}(t-y) + p_{1,1}^{(i)} P_{e_{i}+e_{i+1},\mathbf{k}}^{a}(t-y) + p_{0,2}^{(i)} P_{2e_{i+1},\mathbf{k}}^{a}(t-y)] d\mathcal{B}_{i}(y) dy$$

190 where $\mathbb{P}[\tau^{(i)}(a_0=0) \ge t] = e^{-\int_0^t b_i(s)ds} \mathbb{1}_{t\ge 0} = 1 - \mathcal{B}_i(t).$ Applying the branching property, we have for all $y \in [0, t]$, for all $i \in [1, J]$

$$P^{a}_{2e_{i},\mathbf{k}}(y) = \sum_{\mathbf{k}_{1},\mathbf{k}_{2}/\mathbf{k}_{1}+\mathbf{k}_{2}=\mathbf{k}} [P^{a}_{e_{i},\mathbf{k}_{1}}(y)P^{a}_{e_{i},\mathbf{k}_{2}}(y)]$$

and also, for all $i \in [\![1, J - 1]\!]$,

$$P_{e_i+e_{i+1},\mathbf{k}}^a(y) = \sum_{\mathbf{k}_1,\mathbf{k}_2/\mathbf{k}_1+\mathbf{k}_2=\mathbf{k}} P_{e_{i+1},\mathbf{k}_1}^a(y) P_{e_i,\mathbf{k}_2}^a(y)$$

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SM10

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Hence, we can rewrite the expression of

,

$$A_t := \int_0^t [p_{2,0}^{(i)} P_{2e_i,\mathbf{k}}^a(t-y) + p_{1,1}^{(i)} P_{e_i+e_{i+1},\mathbf{k}}^a(t-y) + p_{0,2}^{(i)} P_{2e_{i+1},\mathbf{k}}^a(t-y)] d\mathcal{B}_i(y) dy$$

191as192

193
$$A_{t} = p_{2,0}^{(i)} \int_{0}^{t} \sum_{\mathbf{k}_{1},\mathbf{k}_{2}/\mathbf{k}_{1}+\mathbf{k}_{2}=\mathbf{k}} P_{e_{i},\mathbf{k}_{1}}^{a}(t-y) P_{e_{i},\mathbf{k}_{2}}^{a}(t-y) d\mathcal{B}_{i}(y) dy$$
194
$$+ p_{1,1}^{(i)} \int_{0}^{t} \sum_{\mathbf{k}_{2},\mathbf{k}_{3}} P_{e_{i+1},\mathbf{k}_{3}}^{a}(t-y) P_{e_{i},\mathbf{k}_{3}}^{a}(t-y) d\mathcal{B}_{i}(y) dy$$

$$+ p_{1,1}^{(i)} \int_0^{\cdot} \sum_{\mathbf{k}_1, \mathbf{k}_2/\mathbf{k}_1 + \mathbf{k}_2 = \mathbf{k}} P_{e_{i+1}, \mathbf{k}_1}^a(t-y) P_{e_i, \mathbf{k}_2}^a(t-y) d\mathcal{B}_i(y) dy$$

195
$$+ p_{0,2}^{(i)} \int_0^t \sum_{\mathbf{k}_1, \mathbf{k}_2/\mathbf{k}_1 + \mathbf{k}_2 = \mathbf{k}} P_{e_{i+1}, \mathbf{k}_1}^a(t-y) P_{e_{i+1}, \mathbf{k}_2}^a(t-y) d\mathcal{B}_i(y) dy.$$

197 Note that

199
$$\sum_{\mathbf{k}\in\mathbb{N}^{J}}\mathbf{s}^{\mathbf{k}}P_{2e_{i},\mathbf{k}}^{a}(t-y) = \sum_{\mathbf{k}\in\mathbb{N}^{J}}\mathbf{s}^{\mathbf{k}}\sum_{\mathbf{k}_{1},\mathbf{k}_{2}/\mathbf{k}_{1}+\mathbf{k}_{2}=\mathbf{k}}P_{e_{i},\mathbf{k}_{1}}^{a}(t-y)P_{e_{i},\mathbf{k}_{2}}^{a}(t-y)$$
200
$$=\sum_{\mathbf{k}\in\mathbb{N}^{J}}\sum_{\mathbf{k}_{1}=0}^{\mathbf{k}}\mathbf{s}^{\mathbf{k}_{1}}P_{e_{i},\mathbf{k}_{1}}^{a}(t-y)\mathbf{s}^{\mathbf{k}-\mathbf{k}_{1}}P_{e_{i},\mathbf{k}-\mathbf{k}_{1}}^{a}(t-y).$$
201

We note $\sum_{k_1=0}^{k}$ the sum of all the $k_1 \in \mathbb{N}^J$ vectors such that $k_1 \leq k$ component by component. We have 202 203 204

205
$$\sum_{\mathbf{k}\in\mathbb{N}^{J}}\mathbf{s}^{\mathbf{k}}P_{2e_{i},\mathbf{k}}^{a}(t-y) = \sum_{\mathbf{k}\in\mathbb{N}^{J}}\sum_{\mathbf{k}_{1}=0}^{\mathbf{k}}\mathbf{s}^{\mathbf{k}_{1}}P_{e_{i},\mathbf{k}_{1}}^{a}(t-y)\mathbf{s}^{\mathbf{k}-\mathbf{k}_{1}}P_{e_{i},\mathbf{k}-\mathbf{k}_{1}}^{a}(t-y)$$
206
$$=\sum_{\mathbf{k}_{1}\in\mathbb{N}^{J}}\mathbf{s}^{\mathbf{k}_{1}}P_{e_{i},\mathbf{k}_{1}}^{a}(t-y)\sum_{\mathbf{k}\geq\mathbf{k}_{1}}\mathbf{s}^{\mathbf{k}-\mathbf{k}_{1}}P_{e_{i},\mathbf{k}-\mathbf{k}_{1}}^{a}(t-y)$$
207
$$=(\sum_{\mathbf{k}_{1}\in\mathbb{N}^{J}}\mathbf{s}^{\mathbf{k}_{1}}P_{e_{i},\mathbf{k}_{1}}^{a}(t-y))(\sum_{\mathbf{k}\geq\mathbb{N}^{J}}\mathbf{s}^{\mathbf{k}_{2}}P_{e_{i},\mathbf{k}_{2}}^{a}(t-y)).$$
208

210 (SM9)
$$\sum_{\mathbf{k}\in\mathbb{N}^J} \mathbf{s}^{\mathbf{k}} P^a_{2e_i,\mathbf{k}}(t-y) = (F^{(i,a)}[\mathbf{s};t-y])^2.$$

In the same way, we also obtain 211

212 (SM10)
$$\sum_{\mathbf{k}\in\mathbb{N}^J} \mathbf{s}^k P^a_{e_i+e_{i+1},k}(t-y) = F^{(i,a)}[\mathbf{s};t-y]F^{(i+1,a)}[\mathbf{s};t-y]$$

and 213

214 (SM11)
$$\sum_{\mathbf{k}\in\mathbb{N}^J} \mathbf{s}^{\mathbf{k}} P^a_{2e_{i+1},\mathbf{k}}(t-y) = (F^{(i+1,a)}[\mathbf{s};t-y])^2.$$

Finally, multiplying (SM8) by $\mathbf{s}^{\mathbf{k}}$, summing on $\mathbf{k} \in \mathbb{N}^{J}$ and applying (SM9)-(SM11), 215we obtain: 216

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217
$$\forall i \in [\![1, J]\!], F^{(i,a)}[\mathbf{s}; t] = (s_i \mathbb{1}_{t \le a} + \mathbb{1}_{t > a})(1 - \mathcal{B}_i(t)) + \int_0^t f^{(i)}(F[\mathbf{s}; t - y]) d\mathcal{B}_i(y) dy.$$

218

219 First moments.

Proof of lemma 3.10. By classical property, $M_{i,j}^a(t) = \frac{\partial}{\partial s_j} F^{(i,a)}[s;t]|_{s=1}$. From 220 (38) it comes that 221

222 (SM12)
$$\frac{\partial}{\partial s_j} F^{(i,a)}[s;t] = \delta_{i,j} (1 - \mathcal{B}_{i,i}(t)) \mathbb{1}_{a \ge t} + \int_0^t \frac{\partial}{\partial s_j} f^{(i)}[F^a(s,y)] d\mathcal{B}_i(t-y) dy$$

223 where

$$224
225 \qquad \frac{\partial}{\partial s_j} f^{(i)}[F^a(s,t)] = 2p_{2,0}^{(i)} F^{(i,a)}[s;t] \frac{\partial}{\partial s_j} F^{(i,a)}[s;t] + 2p_{0,2}^{(i)} F^{(i+1,a)}[s;t] \frac{\partial}{\partial s_j} F^{(i+1,a)}[s;t]
226
227 \qquad + p_{1,1}^{(i)} [F^{(i+1,a)}[s;t] \frac{\partial}{\partial s_j} F^{(i,a)}[s;t] + F^{(i,a)}[s;t] \frac{\partial}{\partial s_j} F^{(i+1,a)}[s;t]].$$

For $\mathbf{s} = 1$, knowing that $F^{(i,a)}(1,t) = 1$, we get 228

230
$$M_{i,j}^{a}(t) = \delta_{i,j}(1 - \mathcal{B}_{i}(t))\mathbb{1}_{t \le a} + \int_{0}^{t} \left[2p_{2,0}^{(i)}M_{i,j}^{a}(y) + p_{1,1}^{(i)}[M_{i,j}^{a}(y) + M_{i+1,j}^{a}(y)] + 2p_{0,2}^{(i)}M_{i+1,j}^{a}(y)\right] d\mathcal{B}_{i}(t - y))dy$$

which can be rewritten as 233

$$M_{i,j}^{a}(t) = \delta_{i,j}(1 - \mathcal{B}_{i}(t))\mathbb{1}_{t \le a} + \left[2p_{S}^{(i)}M_{i,j}^{a} + 2p_{L}^{(i)}M_{i+1,j}^{a}\right] * d\mathcal{B}_{i}(t).$$

235

234

229

Harris lemmas. We recall some results on the renewal theory presented in [SM3], 236237p.161-163.

Let G be a distribution function on $(0, \infty)$ with the additional assumption G(0+) = 0. 238We consider the renewal equation 239

240 (SM13)
$$K(t) = f(t) + m \int_0^t K(t-u) dG(u) = f(t) + mK * G(t)$$

where m is a positive constant representing the mean number of children, f is a 241continuous function representing a source term and G is the life time distribution. In 242addition, we suppose that G is not lattice. 243

LEMMA SM1.4 (Harris's lemma 2, p.161). Suppose that there exists a Malthus parameter α such that $m \int_0^\infty e^{-\alpha t} dG(t) = 1$, and that the following conditions also 244 245hold: 246

(a) $f(t)e^{-\alpha t}$ is a continuous function such that $f(t)e^{-\alpha t} \in \mathbf{L}^1(\mathbb{R}_+)$. 247(b) $\int_0^\infty t^2 dG(t) < \infty.$ 248

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Then, $K(t) \sim n_f e^{\alpha t}$, where 249

$$n_f = \frac{\int_0^\infty f(t)e^{-\alpha t}dt}{m\int_0^\infty te^{-\alpha t}dG(t)}$$

LEMMA SM1.5 (Harris's lemma 4, p.163). Suppose that m < 1 and $\lim_{t \to \infty} f(t) = c$. 251then $K(t) \to \frac{c}{1-m}$. 252

Additional computation details for the proof of theorem 2.14. We detail how to 253obtain formula (49). We first take the Laplace transform of (39) for $\alpha = \lambda_c$ for 254i = c + 1 and $j \in [[c + 1, J]]$. We distinguish the case i = j from the others. If 255256 j = c + 1, we obtain 257

258
$$\int_{0}^{\infty} M_{j,j}^{a}(t)e^{-\lambda_{c}t}dt =$$
259
$$\frac{1}{\hat{\rho}^{(j)}(0)}\int_{0}^{a}\hat{\rho}^{(j)}(t)dt + 2p_{S}^{(j)}\int_{0}^{\infty}\left[\int_{0}^{t}d\mathcal{B}_{j}(t-u)M_{j,j}^{a}(u)du\right]e^{-\lambda_{c}t}dt.$$

261 By the Laplace transform property for the convolution, we deduce that

$$\int_0^\infty \left[\int_0^t d\mathcal{B}_j(t-u)M^a_{j,j}(u)du\right]e^{-\lambda_c t}dt = d\mathcal{B}_j^*(\lambda_c)\int_0^\infty M^a_{j,j}(t)e^{-\lambda_c t}dt$$

263hence

$$\int_{0}^{\infty} M_{j,j}^{a}(t) e^{-\lambda_{c}t} dt = \frac{1}{\hat{\rho}^{(j)}(0)} \int_{0}^{a} \hat{\rho}^{(j)}(t) dt + 2p_{S}^{(j)} d\mathcal{B}_{j}^{*}(\lambda_{c}) \int_{0}^{\infty} M_{j,j}^{a}(t) e^{-\lambda_{c}t} dt$$
$$= \frac{1}{\hat{\rho}^{(j)}(0) \times (1 - 2p_{S}^{(j)} d\mathcal{B}_{j}^{*}(\lambda_{c}))} \int_{0}^{a} \hat{\rho}^{(j)}(t) dt.$$

When j > c+1, we have:

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$$\int_{0}^{\infty} M_{c+1,j}^{a}(t) e^{-\lambda_{c}t} dt = 2p_{S}^{(c+1)} d\mathcal{B}_{c+1}^{*}(\lambda_{c}) \int_{0}^{\infty} M_{c+1,j}^{a}(t) e^{-\lambda_{c}t} dt + 2p_{L}^{(c+1)} d\mathcal{B}_{j}^{*}(\lambda_{c}) \int_{0}^{\infty} M_{c+2,j}^{a}(t) e^{-\lambda_{c}t} dt.$$

273 Hence,

274
$$\int_0^\infty M^a_{c+1,j}(t)e^{-\lambda_c t}dt = \frac{2p_L^{(c+1)}}{1-2p_S^{(c+1)}}d\mathcal{B}^*_{c+1}(\lambda_c)}\int_0^\infty M^a_{c+2,j}(t)e^{-\lambda_c t}dt.$$

Here, we obtain a recurrence formula between $\int_{0}^{\infty} M_{c+1,j}^{a}(t) e^{-\lambda_{c}t} dt$ and 275 $\int_{0}^{\infty} M_{c+2,j}^{a}(t) e^{-\lambda_{c}t} dt, \text{ and we obtain (49).}$ 276 277

Second moments.

DEFINITION SM1.6. Let $a \ge 0$. We define the second moment

$$L^{a}(t) := (\mathbb{E}[(Y_{t}^{(a,j)})^{2} | Z_{0} = \delta_{i,0}])_{i,j \in [\![1,J]\!]}$$

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LEMMA SM1.7. $L^{a}(t)$ is solution of the renewal equation: $\forall (i, j) \in [\![1, J]\!]^{2}$, 278

279 (SM14)
$$L_{i,j}^{a}(t) = \frac{\delta_{i,j}(1 - \mathcal{B}_{i}(t))\mathbb{1}_{t \leq a} + [2p_{S}^{(i)}L_{i,j}^{a} + 2p_{L}^{(i)}L_{i+1,j}^{a}] * d\mathcal{B}_{i}(t) }{+[2p_{2,0}^{(i)}(M_{i,j}^{a})^{2} + 2p_{1,1}^{(i)}M_{i,j}^{a}M_{i+1,j}^{a} + 2p_{0,2}^{(i)}(M_{i+1,j}^{a})^{2}] * d\mathcal{B}_{i}(t). }$$

Proof of lemma (SM1.7). Note that $\frac{\partial^2}{\partial s_j}F^{(i,a)}[s;t]|_{s=1} = L^a_{i,j}(t) - M^a_{i,j}(t)$. We 280derive (SM12) with respect to s_j and obtain: 281

282
$$\frac{\partial^2}{\partial s_j^2} F^{(i,a)}[\mathbf{s};t] = \int_0^t \frac{\partial}{\partial s_j^2} f^{(i)}(F^a[\mathbf{s},u]) d\mathcal{B}_i(t-u) du$$

283 284 where

$$\frac{\partial^2}{\partial s_j^2} f^{(i)} \left(F^a[\mathbf{s}, t] \right) = 2p_{2,0}^{(i)} \left(F^{(i,a)}[\mathbf{s}; t] \frac{\partial^2}{\partial s_j} F^{(i,a)}[\mathbf{s}; t] + \left(\frac{\partial}{\partial s_j} F^{(i,a)}[\mathbf{s}; t] \right)^2 \right)$$

$$+ 2p_{0,2}^{(i)} \left(F^{(i+1,a)}[\mathbf{s}; t] \frac{\partial^2}{\partial s_j} F^{(i+1,a)}[\mathbf{s}; t] + \left(\frac{\partial}{\partial s_j} F^{(i+1,a)}[\mathbf{s}; t] \right)^2 \right)$$

$$(i) \left(F^{(i,a)}[\mathbf{s}; t] + \left(\frac{\partial}{\partial s_j} F^{(i,a)}[\mathbf{s}; t] \right)^2 \right)$$

$$+ p_{1,1}^{(i)} \left(F^{(i+1,a)}[\mathbf{s};t] \frac{\partial^2}{\partial s_j} F^{(i,a)}[\mathbf{s};t] + 2 \frac{\partial}{\partial s_j} F^{(i,a)}[\mathbf{s};t] \frac{\partial}{\partial s_j} F^{(i+1,a)}[\mathbf{s};t] + F^{(i,a)}[\mathbf{s};t] \frac{\partial^2}{\partial s_j} F^{(i+1,a)}[\mathbf{s};t] \right).$$

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291

When $\mathbf{s} = 1$, we get

292
$$L_{i,j}^{a}(t) - M_{i,j}^{a}(t) = 2p_{2,0}^{(i)} \left(L_{i,j}^{a} - M_{i,j}^{a} + (M_{i,j}^{a})^{2} \right) * d\mathcal{B}_{i}(t)$$
293
$$+ 2p_{0,2}^{(i)} \left(L_{i+1,j}^{a} - M_{i+1,j}^{a} + (M_{i+1,j}^{a})^{2} \right) * d\mathcal{B}_{i}(t)$$
294
$$+ p_{1,1}^{(i)} \left(L_{i,j}^{a} - M_{i,j}^{a} + 2M_{i,j}^{a} M_{i+1,j}^{a} + L_{i+1,j}^{a} - M_{i+1,j}^{a} \right) * d\mathcal{B}_{i}(t).$$

THEOREM SM1.8. Under the same hypotheses as in theorem 2.14, and supposing 297 that for all $i \in [[1, J]], \lambda_i > 0$, we have, for all $a \ge 0$: 298

299
$$\forall i \in \llbracket 1, J \rrbracket, \quad \forall k \in \llbracket 0, J - i \rrbracket \quad L^a_{i,i+k}(t) \sim \widetilde{L}_{i,i+k}(a) e^{2\lambda_{i,i+k}t}, \text{ as } t \to \infty$$

such that 300

$$\widetilde{L}_{i,i}(a) = \frac{2p_{2,0}^{(i)} d\mathcal{B}_i^*(2\lambda_i) (\widetilde{M}_{i,i}^a)^2}{1 - 2p_S^{(i)} d\mathcal{B}_i^*(2\lambda_i)},$$

and for $k \in [\![1, J - i]\!]$, 302

303 (SM15)
$$\widetilde{L}_{i,i+k}(a) = \begin{cases} \frac{2p_{2,0}^{(i)}(\widetilde{M}_{i,i+k}^{a})^2 d\mathcal{B}_{i}^{*}(2\lambda_{i,i+k})}{1-2p_{S}^{(i)} d\mathcal{B}_{i}^{*}(2\lambda_{i,i+k})} + l_{i,i+k}(a), & \text{if } \lambda_{i,i+k} \neq \lambda_{i} \\ \frac{2p_{2,0}^{(i)}(\widetilde{M}_{i,i+k}^{a})^2 d\mathcal{B}_{i}^{*}(2\lambda_{i,i+k})}{1-2p_{S}^{(i)} d\mathcal{B}_{i}^{*}(2\lambda_{i,i+k})}, & \text{if } \lambda_{i,i+k} = \lambda_{i} \end{cases}$$

where

$$l_{i,i+k}(a) = \frac{\left[\widetilde{L}_{i+1,i+k}(a) + 2p_{1,1}^{(i)}\widetilde{M}_{i,i+k}^{a}\widetilde{M}_{i+1,i+k}^{a} + 2p_{0,2}^{(i)}(\widetilde{M}_{i+1,i+k}^{a})^{2}\right]d\mathcal{B}_{i}^{*}(2\lambda_{i,i+k})}{1 - 2p_{S}^{(i)}d\mathcal{B}_{i}^{*}(2\lambda_{i,i+k})}$$

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SM14

 $\widehat{L}^a_{i,i+k}(t) = L^a_{i,i+k}(t)e^{-2\lambda_{i,i+k}t}, \quad \widehat{d\mathcal{B}_i}(t) = \frac{d\mathcal{B}_i(t)}{d\mathcal{B}^*_i(2\lambda_{i,i+k})}e^{-2\lambda_{i,i+k}t}.$

304 *Proof.* Let $a \ge 0$. We introduce the following notations

We use the same approach as that performed for the proof of theorem 2.14, and 306 proceed by recurrence: 307

308
$$\mathcal{H}^k: \quad \forall i \in \llbracket 1, J-k \rrbracket, \ L^a_{i,i+k}(t) \sim \widetilde{L}^a_{i,i+k} e^{2\lambda_{i,i+k}t}, \text{ as } t \to \infty.$$

When k = 0, according to (SM14) $L_{i,i}^{a}$ is solution of the renewal equation: 309

310 (SM16)
$$L_{i,i}^{a}(t) = (1 - \mathcal{B}_{i}(t)) \mathbb{1}_{t \leq a} + 2p_{2,0}^{(i)} (M_{i,i}^{a})^{2} * d\mathcal{B}_{i}(t) + 2p_{S}^{(i)} L_{i,i}^{a} * d\mathcal{B}_{i}(t) + 2p_{S}^{(i)} L_{i,i}^{a} * d\mathcal{B}_{i}(t) + 2p_{S}^{(i)} L_{i,i}^{a} + + 2p_{S}^{(i)}$$

We rescale (SM16) by $e^{-2\lambda_i t}$ and obtain: 311

312
$$\widehat{L}_{i,i}^{a}(t) = e^{-2\lambda_{i}t} \left[(1 - \mathcal{B}_{i}(t)) \mathbb{1}_{t \leq a} + 2p_{2,0}^{(i)}(M_{i,i}^{a})^{2} * d\mathcal{B}_{i}(t) \right] + 2p_{S}^{(i)} d\mathcal{B}_{i}^{*}(2\lambda_{i}) \widehat{L}_{i,i}^{a} * \widehat{d\mathcal{B}}_{i}(t).$$

Note that as $2\lambda_i > \lambda_i > 0$, we have $2p_S^{(i)}d\mathcal{B}_i^*(2\lambda_i) < 1$, so that we can use lemma SM1.5. We compute the limit of the source term : 313 314

315
$$\lim_{t \to \infty} e^{-2\lambda_i t} \left[(1 - \mathcal{B}_i(t)) \, \mathbb{1}_{t \le a} + 2p_{2,0}^{(i)}(M_{i,i}^a)^2 * d\mathcal{B}_i(t) \right].$$

From hypothesis 2.2, we have: 316

317
$$\int_0^\infty (1 - \mathcal{B}_i(t)) \, \mathbb{1}_{t \le a} e^{-\lambda_i t} dt \le \frac{1}{\overline{b}_i} \int_0^\infty d\mathcal{B}_i(t) e^{-\lambda_i t} dt < \infty.$$

Thus, $(1 - \mathcal{B}_i(t)) \mathbb{1}_{t \leq a} e^{-\lambda_i t} \in \mathbf{L}^1(\mathbb{R}_+)$ and, $\lim_{t \to \infty} e^{-\lambda_i t} [1 - \mathcal{B}_i(t)] = 0$. Using the hypothesis $\lambda_i > 0$, we obtain that $\lim_{t \to \infty} e^{-2\lambda_i t} [1 - \mathcal{B}_i(t)] = 0$. Then, 318 319

320
$$e^{-2\lambda_i t} (M_{i,i}^a)^2 * d\mathcal{B}_i(t) = \int_0^\infty \mathbb{1}_{[0,t]} (M_{i,i}^a(t-u)e^{-\lambda_i(t-u)})^2 d\mathcal{B}_i(u)e^{-2\lambda_i u} du.$$

Using theorem 2.14, we have $M_{i,i}^a(t) \sim e^{\lambda_i t} \widetilde{M}_{i,i}(a)$, as $t \to \infty$. Applying Lebesgue 321 dominated convergence theorem, we obtain 322

$$\lim_{t \to \infty} e^{-2\lambda_i t} (M_{i,i}^a)^2 * d\mathcal{B}_i(t) = (\widetilde{M}_{i,i}(a))^2 d\mathcal{B}_i^*(2\lambda_i).$$

Then, applying lemma SM1.5, we deduce: 324

325
$$L_{i,i}^a(t) \sim \widetilde{L}_{i,i}(a)e^{2\lambda_i t}, \text{ as } t \to \infty, \text{ where } \widetilde{L}_{i,i}(a) = \frac{2p_{2,0}^{(i)}d\mathcal{B}_i^*(2\lambda_i)(\widetilde{M}_{i,i}(a))^2}{1-2p_S^{(i)}d\mathcal{B}_i^*(2\lambda_i)}.$$

Hence, \mathcal{H}^0 is true. Then, we suppose that \mathcal{H}^{k-1} holds and we show \mathcal{H}^k . According to (SM14), we write the equation for $L^a_{i,i+k}$ and rescale it by $e^{-2\lambda_{i,i+k}t}$: 326 327

$$\hat{L}_{i,i+k}^{a}(t) = 2p_{S}^{(i)}d\mathcal{B}_{i}^{*}(2\lambda_{i,i+k})\hat{L}_{i,i+k}^{a}*\widehat{d\mathcal{B}}_{i}(t) + e^{-2\lambda_{i,i+k}t}2p_{L}^{(i)}L_{i+1,i+k}^{a}*d\mathcal{B}_{i}(t)$$

$$+ e^{-2\lambda_{i,i+k}t}\left[2p_{2,0}^{(i)}(M_{i,i+k}^{a})^{2} + 2p_{1,1}^{(i)}M_{i,i+k}^{a}M_{i+1,i+k}^{a} + 2p_{0,2}^{(i)}(M_{i+1,i+k}^{a})^{2}\right]*d\mathcal{B}_{i}(t).$$

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Here, $m = 2p_S^{(i)} d\mathcal{B}_i^*(2\lambda_{i,i+k}) < 1$, so that we can use lemma SM1.5. We first compute the limit of $e^{-2\lambda_{i,i+k}t}L^a_{i+1,i+k} * d\mathcal{B}_i(t)$ when t goes to infinity when either $\lambda_{i,i+k} = \lambda_i$ or $\lambda_{i,i+k} \neq \lambda_i$. We start with the case $\lambda_{i,i+k} \neq \lambda_i$ (so, $\lambda_{i,i+k} = \lambda_{i+1,i+k}$). For all $t \ge 0$, we have:

336

SM16

337 $e^{-2\lambda_{i,i+k}t}L^a_{i+1,i+k} * d\mathcal{B}_i(t) =$

$$d\mathcal{B}_{i}^{*}(2\lambda_{i,i+k}) \int_{0}^{\infty} \mathbb{1}_{[0,t]} e^{-2\lambda_{i,i+k}(t-u)} L_{i+1,i+k}^{a}(t-u) \widehat{d\mathcal{B}_{i}}(u) du.$$

According to \mathcal{H}^{k-1} , we know that $L^a_{i+1,i+k}(t) \sim \widetilde{L}_{i+1,i+k}(a)e^{2\lambda_{i,i+k}t}$. We deduce with a Lebesgue dominated convergence theorem that:

$$\lim_{t \to \infty} e^{-2\lambda_{i,i+k}t} L^a_{i+1,i+k} * d\mathcal{B}_i(t) = d\mathcal{B}^*_i(2\lambda_{i,i+k}) \widetilde{L}_{i+1,i+k}(a).$$

We apply the same method as above for the other terms of the source term. Theorem 2.14 gives us that $M^a_{i,i+k} \sim e^{\lambda_{i,i+k}t} \widetilde{M}_{i,i+k}(a)$ and $M^a_{i+1,i+k} \sim e^{\lambda_{i,i+k}t} \widetilde{M}_{i+1,i+k}(a)$. Using Lebesgue dominated convergence theorem, we obtain: 346

347
$$\lim_{t \to \infty} e^{-2\lambda_{i,i+k}t} \left[2p_{2,0}^{(i)}(M_{i,i+k}^a)^2 + 2p_{1,1}^{(i)}M_{i,i+k}^a M_{i+1,i+k}^a + 2p_{0,2}^{(i)}(M_{i+1,i+k}^a)^2 \right] * d\mathcal{B}_i(t)$$

$$= \left[2p_{2,0}^{(i)}(\widetilde{M}_{i,i+k}(a))^2 + 2p_{1,1}^{(i)}\widetilde{M}_{i,i+k}(a)\widetilde{M}_{i+1,i+k}(a) + 2p_{0,2}^{(i)}(\widetilde{M}_{i+1,i+k}(a))^2 \right] d\mathcal{B}_i^*(2\lambda_{i,i+k})$$

We then consider the case $\lambda_{i,i+k} = \lambda_i > \lambda_{i+1,i+k}$ and start by computing the limit of $e^{-2\lambda_{i,i+k}t}L^a_{i+1,i+k} * d\mathcal{B}_i(t)$.

$$e^{-2\lambda_{i,i+k}t}L^{a}_{i+1,i+k} * d\mathcal{B}_{i}(t) = d\mathcal{B}^{*}_{i}(2\lambda_{i,i+k})e^{-2(\lambda_{i,i+k}-\lambda_{i+1,i+k})t} \int_{0}^{\infty} \mathbb{1}_{[0,t]}e^{-2\lambda_{i+1,i+k}(t-u)}L^{a}_{i+1,i+k}(t-u)\widehat{d\mathcal{B}_{i}}(u)du.$$

Using \mathcal{H}^{k-1} and Lebesgue dominated convergence theorem, we first obtain that $_{358}$

359
$$\lim_{t \to \infty} \int_0^\infty \mathbb{1}_{[0,t]} e^{-2\lambda_{i+1,i+k}(t-u)} L^a_{i+1,i+k}(t-u) \widehat{d\mathcal{B}_i}(u) du$$

360
$$= d\mathcal{B}_i^*(2\lambda_{i+1,i+k}) \widetilde{L}_{i+1,i+k}(a) < \infty,$$

362 hence,

353

$$\lim_{t \to \infty} e^{-2\lambda_{i,i+k}t} L^a_{i+1,i+k} * d\mathcal{B}_i(t) = 0.$$

We conclude by applying lemma SM1.5 that
$$\mathcal{H}^k$$
 holds

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371 Variance.

DEFINITION SM1.9. We write $v_i^a(t)$, the variance of $Y_t^{(j,a)}$ starting from a mother 372 cell on the first layer such that: 373

374 (SM17)
$$v_j^a(t) = \mathbb{E}[(Y_t^{(j,a)})^2 | Z_0 = \delta_{1,0}] - \mathbb{E}[Y_t^{(j,a)} | Z_0 = \delta_{1,0}]^2.$$

We study the asymptotic behavior of the variance $v_i^a(t)$ when the first layer is the 375 leading one. 376

COROLLARY SM1.10. Let $a \ge 0$. Under the same hypotheses as in theorem SM1.8 377 and supposing that c = 1, we have 378

379
$$\forall k \in \llbracket 1, J \rrbracket \quad v_j^a(t) \sim \widetilde{v}_j(a) e^{2\lambda_c t}, \text{ as } t \to \infty$$

where 380

381
$$\widetilde{v}_j(a) = \widetilde{L}_{1,j}(a) - (m_j(a))^2 = \left[\frac{2p_{2,0}^{(1)}d\mathcal{B}_1^*(2\lambda_1)}{1 - 2p_S^{(1)}d\mathcal{B}_1^*(2\lambda_1)} - 1\right](m_j(a))^2.$$

Proof. Let $a \ge 0$. According to theorem SM1.8 and using that c = 1, we have: 382

3
$$\forall j \in \llbracket 1, J \rrbracket, \quad L^a_{1,j}(t) \sim \widetilde{L}_{1,j}(a) e^{2\lambda_1 t}, \quad \text{as } t \to \infty.$$

Using theorem 2.14 and SM1.8, we deduce for all $j \in [1, J]$: 384

385
$$\widetilde{v}_j(a) = \widetilde{L}_{1,j}(a) - (m_j(a))^2 = \left[\frac{2p_{2,0}^{(1)}d\mathcal{B}_1^*(2\lambda_1)}{1 - 2p_S^{(1)}d\mathcal{B}_1^*(2\lambda_1)} - 1\right](m_j(a))^2.$$

386

38

SM2. Numerical simulation procedures. 387

SM2.0.1. Stochastic simulation procedures. 388

Markov case. Considering a markovian case, we simulate the process Z_t solution 389of the SDE (2) with the Gillespie algorithm. We use the package StochSS [SM2]. We consider that for each layer $j \in [\![1,3]\!]$, $p_{1,1}^{(j)} = 0$. Hence, $p_{2,0}^{(j)} = p_S^{(j)}$ and $p_{0,2}^{(j)} = p_S^{(j)}$ 390391 $1-p_S^{(j)}$. Considering a system with 4 layers, our system is ruled by the 7-th reactions 392 below: 393

$$\begin{array}{lll} \mathcal{R}_{1}: & N_{1} \to N_{1} + N_{1} & \text{with rate } b_{1}p_{S}^{(1)}, \\ \mathcal{R}_{2}: & N_{1} \to N_{2} + N_{2} & \text{with rate } b_{1}(1 - p_{S}^{(1)}), \\ \mathcal{R}_{3}: & N_{2} \to N_{2} + N_{2} & \text{with rate } b_{2}p_{S}^{(2)}, \\ \mathcal{R}_{4}: & N_{2} \to N_{3} + N_{3} & \text{with rate } b_{2}(1 - p_{S}^{(2)}), \\ \mathcal{R}_{5}: & N_{3} \to N_{3} + N_{3} & \text{with rate } b_{3}p_{S}^{(3)}, \\ \mathcal{R}_{6}: & N_{3} \to N_{4} + N_{4} & \text{with rate } b_{3}(1 - p_{S}^{(3)}), \\ \mathcal{R}_{7}: & N_{4} \to N_{4} + N_{4} & \text{with rate } b_{4}. \end{array}$$

General case. We simulate our process using the algorithm SM1, on a predefine 395 396 time horizon T_{max} .

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Algorithm SM1 Simulation stochastic process

- 1: Define a sequence \mathcal{S} of cells of a given age and layer.
- 2: Simulate the time of division of each cell in \mathcal{S}
- 3: while $t < T_{\text{max}}$ do
- 4: Select the next cell m that will divide. l^m is its layer index and l^m is the age at division.
- 5: Randomly draw the layer of its daughters cell l^{d_1} and l^{d_2} according to the probabilities $p_{2,0}^{(l^m)}, p_{1,1}^{(l^m)}$ and $p_{2,0}^{(l^m)}$.
- 6: Randomly draw the next time of division of daughter cell d_1 according to its layer index l^{d_1} .
- 7: Randomly draw the next time of division of daughter cell d_2 according to its layer index l^{d_2} .
- 8: Add d_1 and d_2 into the sequence S
- 9: $t \leftarrow t + t^m$
- 10: end while

397 SM2.0.2. Deterministic simulation protocol. To solve numerically the pro-398 blem (3), we design a dedicated finite volume scheme adapted to the non-conservative 399 form with proper boundary conditions. We define the time step Δt and the age step 400 Δa . The time discretization is defined by

408

$$t_0 = 0, \quad t_{n+1} = t_n + \Delta t, \quad \text{for } n = 0, \dots, N_t$$

402 where $(N_t + 1)\Delta t$ is the time horizon of the simulation. Similarly, N_a is the number 403 of cells¹ in the domain. The cells C_i are indexed by a rational number i $(\frac{1}{2}, \frac{3}{2}, \text{ etc.})$ 404 with $i \in [[\frac{1}{2}, N_a - \frac{1}{2}]]$. The edges of each cell are located at $a_{i-\frac{1}{2}} = (i - \frac{1}{2})\Delta a$ and 405 $a_{i+\frac{1}{2}} = (i + \frac{1}{2})\Delta a$ (remark that $\Delta a = a_{i+\frac{1}{2}} - a_{i-\frac{1}{2}}$ and $a_0 = 0$). As age and time 406 evolve at the same speed, we chose N_a such that $t_{N_t} - a_{\max}^0 < N_a\Delta a$ where a_{\max}^0 is 407 the maximal age of the initial distribution.

409 Let $j \in [\![1, J]\!]$. We define $P_{n,i}^j$ as the mean value of the density $\rho^{(j)}$ in cell C_i at 410 time t_n :

411
$$P_{n,i}^{j} := \frac{1}{\Delta a} \int_{a_{i-\frac{1}{2}}}^{a_{i+\frac{1}{2}}} \rho^{(j)}(t_n, a) \, da$$

412 We integrate the equation $\partial_t \rho^{(j)} + \partial_a \rho^{(j)} = -b_j \rho^{(j)}$ with respect to age in cell C_i and 413 obtain:

414
$$\frac{d}{dt} \int_{a_{i-\frac{1}{2}}}^{a_{i+\frac{1}{2}}} \rho^{(j)}(t,a) \, da = -\rho^{(j)}(t,a_{i+\frac{1}{2}}) + \rho^{(j)}(t,a_{i-\frac{1}{2}}) - \int_{a_{i-\frac{1}{2}}}^{a_{i+\frac{1}{2}}} b_j(a)\rho^{(j)}(t,a) \, da.$$

Then, we suppose that all b_j s functions are regular enough so that we can approximate b_j , for all $j \in [\![1, J]\!]$ on each cell C_i by their mean value \bar{b}_j^i . We obtain:

417
$$\frac{d}{dt} \int_{a_{i-\frac{1}{2}}}^{a_{i+\frac{1}{2}}} \rho^{(j)}(t,a) \, da = -\rho^{(j)}(t,a_{i+\frac{1}{2}}) + \rho^{(j)}(t,a_{i-\frac{1}{2}}) - \bar{b}_{j}^{i} \int_{a_{i-\frac{1}{2}}}^{a_{i+\frac{1}{2}}} \rho^{(j)}(t,a) \, da.$$

 $^1{\rm The}$ cell is here the standard name used for each elementary volume in the framework of finite volume methods.

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We approximate the derivative in time with a finite difference scheme: 418

419
$$\frac{d}{dt} \int_{a_{i-\frac{1}{2}}}^{a_{i+\frac{1}{2}}} \rho^{(j)}(t_n, a) \, da = \frac{1}{\Delta t} \left[\int_{a_{i-\frac{1}{2}}}^{a_{i+\frac{1}{2}}} \rho^{(j)}(t_{n+1}, a) \, da - \int_{a_{i-\frac{1}{2}}}^{a_{i+\frac{1}{2}}} \rho^{(j)}(t_n, a) \, da \right] + \mathcal{O}(\Delta t)$$

and we deduce: 420

421
$$\frac{\Delta a}{\Delta t} \left[P_{n+1,i}^j - P_{n,i}^j \right] = -\rho^{(j)}(t, a_{i+\frac{1}{2}}) + \rho^{(j)}(t, a_{i-\frac{1}{2}}) - \bar{b}_j^i \Delta a P_{n,i}^j.$$

The edge terms $\rho^{(j)}(t, a_{i+\frac{1}{2}})$ and $\rho^{(j)}(t, a_{i-\frac{1}{2}})$ correspond to the fluxes that cross the 422 boundaries of cell \mathcal{C}_i . When $i = \frac{1}{2}$, the boundary condition of equation (3) gives us 423 the value of this term: 424

426
$$\rho^{(j)}(t_n, a_0) = 2p_S^{(j)} \int_0^\infty b_j(a) \rho^{(j)}(t_n, a) da + 2(1 - p_S^{(j-1)}) \int_0^\infty b_{j-1}(a) \rho^{(j-1)}(t_n, a) da$$

$$= 2p_S^{(j)} \sum_i \int_{\mathcal{C}_i} b_j(a)\rho^{(j)}(t_n, a)da + 2(1 - p_S^{(j-1)}) \sum_i \int_{\mathcal{C}_i} b_{j-1}(a)\rho^{(j-1)}(t_n, a)da$$

428
$$= 2p_S^{(j)}\Delta t \sum_i \bar{c}_i P_{n,i}^j + 2(1 - p_S^{(j-1)})\Delta t \sum_i \bar{c}_i^{j-1} P_{n,i}^{j-1}.$$

438

When
$$i \neq \frac{1}{2}$$
, we approximate each term $\rho^{(j)}(t_n, a_{i+\frac{1}{2}})$ by

432
$$\rho^{(j)}(t_n, a_{i+\frac{1}{2}}) = P^j_{n, i+\frac{1}{2}} + \mathcal{O}(\Delta a).$$

Hence, we obtain the following numerical scheme: 433

$$P_{n+1,i}^{j} = \left[1 - \bar{b}_{i}^{j}\Delta t - \frac{\Delta t}{\Delta x}\right]P_{n,i}^{j} + \frac{\Delta t}{\Delta x}P_{n,i-1}^{j}$$

435

434

436
$$P_{n+1,\frac{1}{2}}^{j} = \left[1 - \bar{c}_{\frac{1}{2}}^{j} \Delta t - \frac{\Delta t}{\Delta x}\right] P_{n,\frac{1}{2}}^{j} + 2s_{j} \Delta t \sum_{i} \bar{c}_{i} P_{n,i}^{j} + 2(1 - s_{j-1}) \Delta t \sum_{i} \bar{c}_{i}^{j-1} P_{n,i}^{j-1}.$$

SM2.1. Construction of figure 4. In this part, we give some details about the 437 construction of figure 4. We simulate the SDE (2) using the algorithm SM1 and the 438 439 PDE (3) using the algorithm described in the subsection below (see SM2.0.2) taking $\Delta a = 9.5 \times 10e - 3$ and $\Delta t = 10e - 4$. 440

We discretized the age according to a sequence of integers $k \in [1, 50]$. Let 441 $j \in [1, J]$ be a layer index. The color bar associated with age k for the j-th layer cor-442 responds to the total number of cells on the j-th layer of age $a \in [k, k+1]$ renormalized 443 by the total number of cells: 444

445
$$\frac{<< Z_t, \mathbb{1}_{j,k \le a < k+1} >>}{<< Z_t, \mathbb{1}>>}$$

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446 The dashed black line with the age k for the j-th layer corresponds to:

447
$$\frac{\int_{k}^{k+1} \rho^{(j)}(t,a) da}{\sum_{j=1}^{4} \int_{0}^{+\infty} \rho^{(j)}(t,a) da} \sim \frac{\sum_{i=\lfloor \frac{k}{\Delta x} \rfloor}^{\lfloor \frac{k+1}{\Delta x} \rfloor - 1} P_{n,i}^{j}}{\sum_{j=1}^{4} \sum_{i} P_{n,i}^{j}}.$$

448 The color solid lines which represent the stable distribution $\hat{\rho}$ and compute their 449 value at each age point k by

450
$$\frac{\int_{k}^{k+1} \hat{\rho}^{(j)}(a) da}{\sum_{i=1}^{4} \int_{0}^{+\infty} \hat{\rho}^{(j)}(a) da}.$$

SM20

SM2.2. Parameter estimation procedure. Using the software D2D [SM7], 451we estimate the parameters of our model, using an additive Gaussian noise statistical 452model (standard least squares likelihood). The standard deviation and the initial 453number N of cells on the first layer are also estimated. To investigate the practical 454 identifiability, we compute the profile likelihood estimate (PLE) [SM6]. We observe 455that all the parameters are practically identifiable except the probability of staying on 456the second layer $p_S^{(2)}$ (see Figure SM1a). In contrast, most of the parameters are not practically identifiable when we consider the total number of cells as the observable function ($\sigma(t;p) = \sum_{j=1}^{J} M^{(j)}(t;p)$, Figure SM1b). 457 458 459

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FIGURE SM1. Practical Identifiability. Figure SM1a Profile likelihood estimate (PLE) for each parameter in the set $\mathbf{P}_{exp} = \{N, b_1, \alpha, p_S^{(1)}, p_S^{(2)}, p_S^{(3)}\}$ when the observation function is $\sigma(t; p) = (M^{(j)}(t; p))_{j \in [\![1, J]\!]}$. The red dashed lines correspond to the 95%-statistical threshold while the blue dashed lines correspond to the optimum value of the likelihood. Figure SM1b Parameter estimation results for $\sigma(t; p) = \sum_{j=1}^{J} M^{(j)}(t; p)$. Left panel: Data fitting model with model (8). The black diamonds represent the experimental data (total number of cells), the solid line is the best fit solution of (8) and the dashed lines are drawn from the estimated variance. Left panel: Profile likelihood estimates of each parameter in the set P_{exp} .

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