

# Spatial Epidemic Models

Ténan YEO

Aix-Marseille Université

Supervisor: Etienne PARDOUX

Aussois, May 19th-23rd 2019

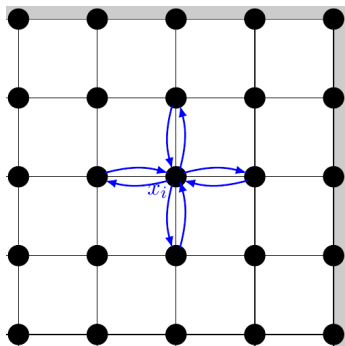


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- We consider an infectious disease which spreads in a human population ;
- $D \subset \mathbb{R}^d$  ( $d=1, 2$  or  $3$ ) ;
- Grid  $D_\varepsilon := [0, 1]^d \cap \varepsilon\mathbb{Z}^d$  ;

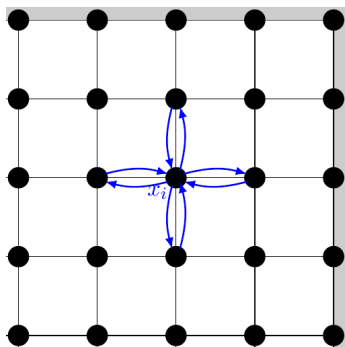
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- Total population size :  $N\varepsilon^{-d}$ .



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- $S_\varepsilon(t, x_i)$  : susceptible,  $I_\varepsilon(t, x_i)$  : infectious,  $R_\varepsilon(t, x_i)$  : removed

$$(1) \quad \left\{ \begin{array}{l} \frac{d S_\varepsilon}{dt}(t, x_i) = \mu_S \Delta_\varepsilon S_\varepsilon(t, x_i) - \frac{\beta(x_i) S_\varepsilon(t, x_i) I_\varepsilon(t, x_i)}{S_\varepsilon(t, x_i) + I_\varepsilon(t, x_i) + R_\varepsilon(t, x_i)} \\ \frac{d I_\varepsilon}{dt}(t, x_i) = \mu_I \Delta_\varepsilon I_\varepsilon(t, x_i) + \frac{\beta(x_i) S_\varepsilon(t, x_i) I_\varepsilon(t, x_i)}{S_\varepsilon(t, x_i) + I_\varepsilon(t, x_i) + R_\varepsilon(t, x_i)} - \alpha(x_i) I_\varepsilon(t, x_i) \\ \frac{d R_\varepsilon}{dt}(t, x_i) = \mu_R \Delta_\varepsilon R_\varepsilon(t, x_i) + \alpha(x_i) I_\varepsilon(t, x_i), \quad (t, x_i) \in (0, T) \times D_\varepsilon \\ \left. \begin{array}{l} S_\varepsilon(t, x_i) = S_\varepsilon(t, y_i) \\ I_\varepsilon(t, x_i) = I_\varepsilon(t, y_i) \\ R_\varepsilon(t, x_i) = R_\varepsilon(t, y_i) \end{array} \right\} \text{for } x_i \in \partial D_\varepsilon, x_i \sim y_i \text{ and } y_i \in \partial \vec{n}_{.out} D_\varepsilon \\ S_\varepsilon(0), I_\varepsilon(0), R_\varepsilon(0) \geq 0, 0 < S_\varepsilon(0) + I_\varepsilon(0) + R_\varepsilon(0) \leq M \end{array} \right.$$

# The limiting system

$$(2) \quad \left\{ \begin{array}{l} \frac{\partial \mathbf{s}}{\partial t}(t, x) = \mu_S \Delta \mathbf{s}(t, x) - \frac{\beta(x) \mathbf{s}(t, x) \mathbf{i}(t, x)}{\mathbf{s}(t, x) + \mathbf{i}(t, x) + \mathbf{r}(t, x)} \\ \frac{\partial \mathbf{i}}{\partial t}(t, x) = \mu_I \Delta \mathbf{i}(t, x) + \frac{\beta(x) \mathbf{s}(t, x) \mathbf{i}(t, x)}{\mathbf{s}(t, x) + \mathbf{i}(t, x) + \mathbf{r}(t, x)} - \alpha(x) \mathbf{i}(t, x) \\ \frac{\partial \mathbf{r}}{\partial t}(t, x) = \mu_S \Delta \mathbf{r}(t, x) + \alpha(x) \mathbf{i}(t, x), \quad (t, x) \in (0, T) \times D \\ \frac{\partial \mathbf{s}}{\partial n_{\text{out}}}(t, x) = \frac{\partial \mathbf{i}}{\partial n_{\text{out}}}(t, x) = \frac{\partial \mathbf{r}}{\partial n_{\text{out}}}(t, x) = 0, \quad \text{for } x \in \partial D \\ \mathbf{s}(0), \mathbf{i}(0), \mathbf{r}(0) \geq 0, \quad 0 < \mathbf{s}(0) + \mathbf{i}(0) + \mathbf{r}(0) \leq M \end{array} \right.$$



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$$X = (\mathbf{s}, \mathbf{i}, \mathbf{r})^T$$

# Theorem

$$\begin{aligned} \mathcal{S}_\varepsilon(t, x) &= \sum_{i=1}^{\varepsilon^{-d}} S_\varepsilon(t, x_i) \mathbf{1}_{V_i}(x), & \mathcal{I}_\varepsilon(t, x) &= \sum_{i=1}^{\varepsilon^{-d}} I_\varepsilon(t, x_i) \mathbf{1}_{V_i}(x), \\ \mathcal{R}_\varepsilon(t, x) &= \sum_{i=1}^{\varepsilon^{-d}} R_\varepsilon(t, x_i) \mathbf{1}_{V_i}(x), & \mathcal{X}_\varepsilon &= (\mathcal{S}_\varepsilon, \mathcal{I}_\varepsilon, \mathcal{R}_\varepsilon)^T. \end{aligned}$$

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## Theorem 1.1

Let us consider an initial condition  $X(0) \in (L^\infty(D))^3$ . For all  $T > 0$ ,

$$\sup_{t \in [0, T]} \left\| X_\varepsilon(t) - X(t) \right\|_\infty \longrightarrow 0, \text{ as } \varepsilon \rightarrow 0.$$

$$(3) \left\{ \begin{aligned} S_{N,\varepsilon}(t, x_i) &= S_{N,\varepsilon}(0, x_i) - \frac{1}{N} \mathbf{P}_{x_i}^{inf} \left( \int_0^t N \frac{\beta(x_i) S_{N,\varepsilon}(r, x_i) I_{N,\varepsilon}(r, x_i)}{S_{N,\varepsilon}(r, x_i) + I_{N,\varepsilon}(r, x_i) + R_{N,\varepsilon}(r, x_i)} dr \right) \\ &\quad - \sum_{y_i \sim x_i} \frac{1}{N} \mathbf{P}_{S, x_i, y_i}^{mig} \left( \int_0^t N \frac{\mu_S}{\varepsilon^2} S_{N,\varepsilon}(r, x_i) dr \right) + \sum_{y_i \sim x_i} \frac{1}{N} \mathbf{P}_{S, y_i, x_i}^{mig} \left( \int_0^t N \frac{\mu_S}{\varepsilon^2} S_{N,\varepsilon}(r, y_i) dr \right) \\ I_{N,\varepsilon}(t, x_i) &= I_{N,\varepsilon}(0, x_i) + \frac{1}{N} \mathbf{P}_{x_i}^{inf} \left( \int_0^t N \frac{\beta(x_i) S_{N,\varepsilon}(r, x_i) I_{N,\varepsilon}(r, x_i)}{S_{N,\varepsilon}(r, x_i) + I_{N,\varepsilon}(r, x_i) + R_{N,\varepsilon}(r, x_i)} dr \right) \\ &\quad - \frac{1}{N} \mathbf{P}_{x_i}^{rec} \left( \int_0^t N \alpha(x_i) I_{N,\varepsilon}(r, x_i) dr \right) - \sum_{y_i \sim x_i} \frac{1}{N} \mathbf{P}_{I, x_i, y_i}^{mig} \left( \int_0^t N \frac{\mu_I}{\varepsilon^2} I_{N,\varepsilon}(r, x_i) dr \right) \\ &\quad + \sum_{y_i \sim x_i} \frac{1}{N} \mathbf{P}_{I, y_i, x_i}^{mig} \left( \int_0^t N \frac{\mu_I}{\varepsilon^2} I_{N,\varepsilon}(r, y_i) dr \right), \\ (t, x_i) &\in [0, T] \times D_\varepsilon. \end{aligned} \right.$$

## Theorem 2.1

Let  $Z_{N,\varepsilon}$  denote the solution of the SDE and  $Z_\varepsilon$  the solution of the ODE

$$\frac{dZ_\varepsilon(t)}{dt} = b_\varepsilon(t, Z_\varepsilon(t)).$$

Let us fix an arbitrary  $T > 0$  and assume that  $\|Z_{N,\varepsilon}(0) - Z_\varepsilon(0)\| \rightarrow 0$ , as  $N \rightarrow +\infty$ .

Then  $\sup_{0 \leq t \leq T} \|Z_{N,\varepsilon}(t) - Z_\varepsilon(t)\| \rightarrow 0$  a.s. , as  $N \rightarrow +\infty$  .

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- $\{ k/N, 0 \leq k \leq N \}$

LLN in sup-norm :  $N \rightarrow \infty$  &  $\varepsilon \rightarrow 0$

$$\mathcal{S}_{N,\varepsilon}(t, x) = \sum_{i=1}^{\varepsilon^{-d}} \mathcal{S}_{N,\varepsilon}(t, x_i) \mathbf{1}_{V_i}(x),$$

$$\mathcal{I}_{N,\varepsilon}(t, x) = \sum_{i=1}^{\varepsilon^{-d}} \mathcal{I}_{N,\varepsilon}(t, x_i) \mathbf{1}_{V_i}(x),$$

$$\mathcal{R}_{N,\varepsilon}(t, x) = \sum_{i=1}^{\varepsilon^{-d}} \mathcal{R}_{N,\varepsilon}(t, x_i) \mathbf{1}_{V_i}(x),$$

$$X_{N,\varepsilon} = (\mathcal{S}_{N,\varepsilon}, \mathcal{I}_{N,\varepsilon}, \mathcal{R}_{N,\varepsilon})^T.$$

- Recall that  $X_\varepsilon = (\mathcal{S}_\varepsilon, \mathcal{I}_\varepsilon, \mathcal{R}_\varepsilon)^T$  and  $X = (\mathbf{s}, \mathbf{i}, \mathbf{r})^T$ .



## Theorem 3.1 (Law of Large Numbers in Sup-norm)

Let us assume that  $N \rightarrow \infty$  and  $\varepsilon \rightarrow 0$ , in such way that

- (i)  $\frac{N}{\log(1/\varepsilon)} \rightarrow \infty$ ;
- (ii)  $\|X_{N,\varepsilon}(0) - X(0)\|_\infty \rightarrow 0$  in probability.

Then for all  $T > 0$ ,  $\sup_{t \in [0, T]} \|X_{N,\varepsilon}(t) - X(t)\|_\infty \rightarrow 0$  in probability .

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(i) : D. Blount (1992).

$$\Psi_{N,\varepsilon}(t) = \begin{pmatrix} U_{N,\varepsilon}(t) \\ V_{N,\varepsilon}(t) \\ W_{N,\varepsilon}(t) \end{pmatrix},$$

where

$$(*) \quad U_{N,\varepsilon}(t) = \begin{pmatrix} \sqrt{N}(S_{N,\varepsilon}(t, x_1) - S_\varepsilon(t, x_1)) \\ \vdots \\ \sqrt{N}(S_{N,\varepsilon}(t, x_\ell) - S_\varepsilon(t, x_\ell)) \end{pmatrix}$$

## Theorem 4.1

Assume that

- (i)  $\|Z_{N,\varepsilon}(0) - Z_\varepsilon(0)\| \rightarrow 0$ , as  $N \rightarrow +\infty$  and
- (ii)  $\sqrt{N}(Z_{N,\varepsilon}(0) - Z_\varepsilon(0)) \rightarrow 0$ , as  $N \rightarrow \infty$ .

Then, as  $N \rightarrow +\infty$  ,  $\{ \Psi_{N,\varepsilon}(t), t \geq 0 \} \implies \{ \Psi_\varepsilon(t), t \geq 0 \}$ ,  
for the topology of locally uniform convergence, where the limit process

$$\Psi_\varepsilon(t) = \begin{pmatrix} U_\varepsilon(t) \\ V_\varepsilon(t) \\ W_\varepsilon(t) \end{pmatrix} \text{ satisfies, } t \geq 0$$

$$(4) \quad \Psi_\varepsilon(t) = \int_0^t \nabla_z b_\varepsilon(r, Z_\varepsilon(r)) \cdot \Psi_\varepsilon(r) dr + \sum_{j=1}^{k_\varepsilon} \int_0^t \sqrt{\beta_j(r, Z_\varepsilon(r))} dB_j(r).$$

$$\mathbb{U}_\varepsilon(t, x) = \frac{1}{\varepsilon^{d/2}} \sum_{i=1}^{\varepsilon^{-d}} U_\varepsilon(t, x_i) \mathbf{1}_{V_i}(x),$$

$$\mathbb{V}_\varepsilon(t, x) = \frac{1}{\varepsilon^{d/2}} \sum_{i=1}^{\varepsilon^{-d}} V_\varepsilon(t, x_i) \mathbf{1}_{V_i}(x),$$

$$\mathbb{W}_\varepsilon(t, x) = \frac{1}{\varepsilon^{d/2}} \sum_{i=1}^{\varepsilon^{-d}} W_\varepsilon(t, x_i) \mathbf{1}_{V_i}(x),$$

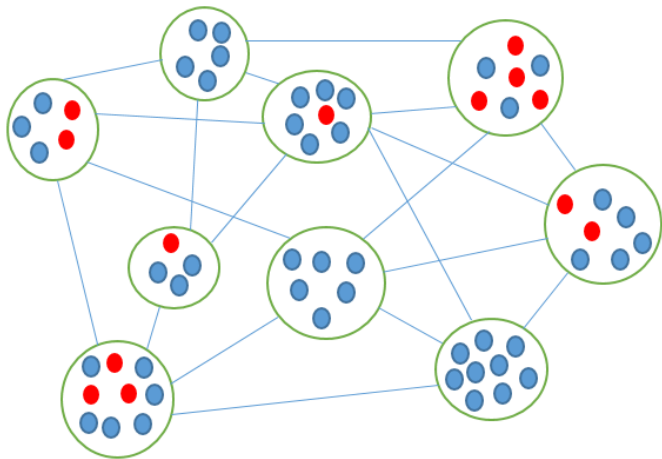
$$\text{and } \tilde{\Psi}_\varepsilon(t) = \begin{pmatrix} \mathbb{U}_\varepsilon(t) \\ \mathbb{V}_\varepsilon(t) \\ \mathbb{W}_\varepsilon(t) \end{pmatrix}.$$

# Limit as $\varepsilon \rightarrow 0$ ?

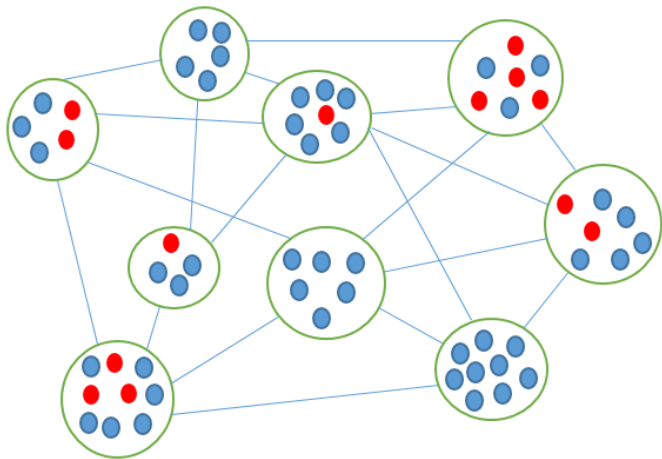
$\alpha > \frac{d}{2} + 1$ ,  $\{ \tilde{\Psi}_\varepsilon(t), t \geq 0 \} \implies \{ \tilde{\Psi}(t), t \geq 0 \}$  in  $C([0, T]; (H_{-\alpha})^3)$ ,  
where the limit  $\tilde{\Psi}$  is solution of the stochastic differential equation

$$(5) \quad \frac{\partial \tilde{\Psi}}{\partial t}(t, x) = \nabla_x b(t, X(t, x)) \cdot \tilde{\Psi}(t) + d\mathcal{M}(t, x)$$

# SIS Epidemic Patch Model



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- Total population size :  $N$



# The deterministic model

$$(6) \quad \left\{ \begin{array}{l} \frac{dS}{dt}(t, x_j) = -\lambda_j \frac{S(t, x_j)I(t, x_j)}{S(t, x_j) + I(t, x_j)} + \gamma_j I(t, x_j) \\ \quad + \nu_S \sum_{k=1}^{\ell} (a_{kj}S(t, x_k) - a_{jk}S(t, x_j)) \\ \frac{dI}{dt}(t, x_j) = \lambda_j \frac{S(t, x_j)I(t, x_j)}{S(t, x_j) + I(t, x_j)} - \gamma_j I(t, x_j) \\ \quad + \nu_I \sum_{k=1}^{\ell} (a_{kj}I(t, x_k) - a_{jk}I(t, x_j)) \\ j = 1, \dots, \ell. \end{array} \right.$$

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- Allen et al. (2007)

# The stochastic model

(7)

$$\left\{ \begin{aligned}
 S_N(t, x_j) &= S_N(0, x_j) - \frac{1}{N} \mathbf{P}_{x_j}^{inf} \left( \int_0^t N \lambda_j \frac{S_N(t, x_j) I_N(t, x_j)}{S_N(t, x_j) + I_N(t, x_j)} dr \right) \\
 &+ \frac{1}{N} \mathbf{P}_{x_j}^{rec} \left( \int_0^t N \gamma_j I_N(r, x_j) dr \right) - \sum_{k=1}^{\ell} \frac{1}{N} \mathbf{P}_{S, x_j, x_k}^{mig} \left( \int_0^t N \nu_S a_{jk} S_N(r, x_j) dr \right) \\
 &+ \sum_{k=1}^{\ell} \frac{1}{N} \mathbf{P}_{S, x_k, x_j}^{mig} \left( \int_0^t N \nu_S a_{kj} S_N(r, x_k) dr \right) \\
 I_N(t, x_j) &= I_N(0, x_j) + \frac{1}{N} \mathbf{P}_{x_j}^{inf} \left( \int_0^t N \lambda_j \frac{S_N(t, x_j) I_N(t, x_j)}{S_N(t, x_j) + I_N(t, x_j)} dr \right) \\
 &- \frac{1}{N} \mathbf{P}_{x_j}^{rec} \left( \int_0^t N \gamma_j I_N(r, x_j) dr \right) - \sum_{k=1}^{\ell} \frac{1}{N} \mathbf{P}_{I, x_j, x_k}^{mig} \left( \int_0^t N \nu_I a_{jk} I_N(r, x_j) dr \right) \\
 &+ \sum_{k=1}^{\ell} \frac{1}{N} \mathbf{P}_{I, x_k, x_j}^{mig} \left( \int_0^t N \nu_I a_{kj} I_N(r, x_k) dr \right), \quad j = 1, \dots, \ell.
 \end{aligned} \right.$$

## Theorem 5.1

Let  $Z_N$  denote the solution of the SDE (7) and  $Z$  the solution of the ODE

$$\frac{dZ(t)}{dt} = b(t, Z(t)).$$

Let us fix an arbitrary  $T > 0$  and assume that  $\|Z_N(0) - Z(0)\| \rightarrow 0$ , as  $N \rightarrow +\infty$ .

Then  $\sup_{0 \leq t \leq T} \|Z_N(t) - Z(t)\| \rightarrow 0$  a.s., as  $N \rightarrow +\infty$ .

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- $a_{kj} = a$ ,  $\nu_S = \nu_I$ ,  $\lambda_j = \lambda$ ,  $\gamma_j = \gamma$ , for all  $k, j$

$$(**) \quad \text{Var} \left( \sum_{i=1}^{\ell} I_N(t, x_i) \right) \approx \frac{1}{N} \frac{\gamma}{\lambda} (1 - e^{-2t(\lambda - \gamma)}).$$

# Set-up

- For  $\phi \in \mathcal{AC}_{T,2\ell}$ ,  $\mathcal{A}_{2\ell}(\phi)$  denotes the set of functions  $c \in L^1(0, T; \mathbb{R}_+^k)$  such that

$$(8) \quad c_t^j = 0 \text{ on the set } \left\{ t, \beta_j(\phi) = 0 \right\} \text{ and } \frac{d\phi}{dt} = \sum_{j=1}^k c_t^j(t) h_j.$$

We define the rate function

$$(9) \quad I_T(\phi) := \begin{cases} \inf_{c \in \mathcal{A}_k(\phi)} I_T(\phi | c), & \text{if } \phi \in \mathcal{AC}_{T,2\ell} \\ \infty, & \text{otherwise,} \end{cases}$$

where

$$(10) \quad I_T(\phi | c) = \int_0^T \sum_{j=1}^k g(c_t^j, \beta_j(\phi_t)) dt,$$

$$(11) \quad g(x, y) = x \log(x/y) - x + y.$$

## Theorem 5.2 (Lower bound)

Let set  $Z_N(0) = z_N$  and  $Z(0) = z$

For every open set  $O \subset \mathbb{D}([0, T]; \mathbb{R}^{2\ell})$ , if  $z_N \rightarrow z$  as  $N \rightarrow \infty$ , then

$$(12) \quad \liminf_{N \rightarrow \infty} \frac{1}{N} \log \mathbb{P}(Z_N^{z_N} \in O) \geq - \inf_{\phi \in O, \phi_0 = z} I_T(\phi).$$



# Large Deviations Principle

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## Theorem 5.3 (Upper bound)

For every closed set  $F \subset \mathbb{D}([0, T]; \mathbb{R}^{2\ell})$ , if  $z_N \rightarrow z$  as  $N \rightarrow \infty$ , then

$$(13) \quad \limsup_{N \rightarrow \infty} \frac{1}{N} \log \mathbb{P}(Z_N^{z_N} \in F) \leq - \inf_{\phi \in F, \phi_0 = z} I_T(\phi).$$

$$(14) \quad A = \left\{ (u_i)_{1 \leq i \leq 2\ell} : u_i \geq 0, \sum_{i=1}^{2\ell} u_i \leq 1 \right\},$$

$$(15) \quad \bar{V} = \inf_{z \in (0)_\ell \times [0,1]^\ell} V(z^*, z),$$

where

$$(16) \quad V(z, z', T) = \inf_{\phi \in D_{T,A}, \phi_0 = z, \phi_T = z'} I_T(\phi),$$

$$(17) \quad V(z, z') = \inf_{T > 0} V(z, z', T).$$

## Theorem 5.4

Let  $T_{Ext}^N := \inf\{t \geq 0, I_N = 0\}$  be the extinction time in the SIS model.  
Given  $\eta > 0$ , for all  $z \in A$ ,

$$(18) \quad \lim_{N \rightarrow \infty} \mathbb{P}\left(\exp\{N(\bar{V} - \eta)\} < T_{Ext}^{N,z} < \exp\{N(\bar{V} + \eta)\}\right) = 1,$$

and for  $N$  large enough,

$$(19) \quad \exp\{N(\bar{V} - \eta)\} \leq \mathbb{E}\left(T_{Ext}^{N,z}\right) \leq \exp\{N(\bar{V} + \eta)\}.$$

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$$(18) \quad \lim_{N \rightarrow \infty} \mathbb{P}\left(\exp\{N(\bar{V} - \eta)\} < T_{Ext}^{N,z} < \exp\{N(\bar{V} + \eta)\}\right) = 1,$$

and for  $N$  large enough,

$$(19) \quad \exp\{N(\bar{V} - \eta)\} \leq \mathbb{E}\left(T_{Ext}^{N,z}\right) \leq \exp\{N(\bar{V} + \eta)\}.$$

- Homogeneous case :  $\bar{V} = \log(\lambda/\gamma) + \frac{\gamma}{\lambda} - 1$ .

- $\lambda = 1.5, \gamma = 1 : \bar{V} = 0.07213177477$

"Bocop"

$\lambda_1$	$\lambda_2$	$\gamma_1$	$\gamma_2$	$\nu_I$	$\nu_S$	$\bar{V}$
1.5	1.5	1	1	0.1	0.1	0.0721371028211974
1.5	1.5	1	1	0.5	0.5	0.0721371450282178
2	1	1	1	0.1	0.1	0.0886235309304135
2	1	1	1	0.1	0.5	0.0706046844173944
2	1	1	1	0.5	0.5	0.0830048116870205
2	1	1	1	0.5	0.1	0.0986088149145697
2.5	0.5	1	1	0.1	0.1	0.12876843629610
2.5	0.5	1	1	0.5	0.5	0.10666120710127

# Thank you for your attention !