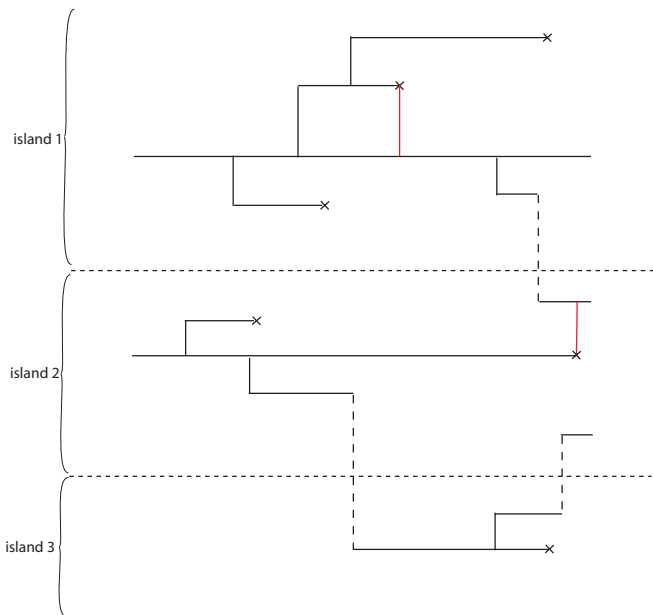


When mobility is not enough to make up for competition

Martin Hutzenthaler

Goethe-University Frankfurt

Marseille Luminy, May 29 2009



Interacting Feller diffusions with logistic drift

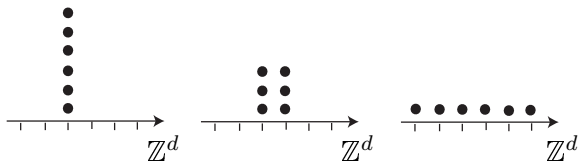
$$dX_t(i) = \left(\sum_{j \in \mathbb{Z}^2} X_t(j) m(j, i) - X_t(i) \right) dt + (cX_t(i) - \gamma X_t^2(i)) dt + \sqrt{\beta X_t(i)} dB_t(i) \quad i \in \mathbb{Z}^2$$

Interacting Feller diffusions with logistic drift

$$dX_t(i) = \left(\sum_{j \in \mathbb{Z}^2} X_t(j) m(j, i) - X_t(i) \right) dt \\ + (cX_t(i) - \gamma X_t^2(i)) dt + \sqrt{\beta X_t(i)} dB_t(i) \quad i \in \mathbb{Z}^2$$

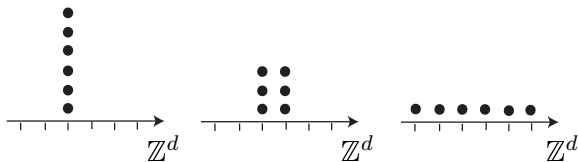
More generally: Interacting locally regulated diffusions

$$dX_t(i) = \left(\sum_{j \in \mathbb{Z}^d} X_t(j) m(j, i) - X_t(i) \right) dt \\ + \mu(X_t(i)) dt + \sqrt{\sigma^2(X_t(i))} dB_t(i) \quad i \in \mathbb{Z}^d$$



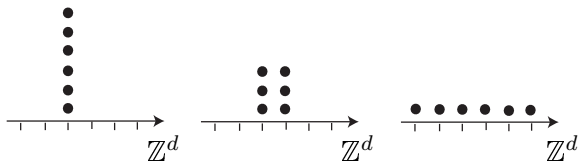
Idea for a comparison result:

- ▶ If mass is evenly distributed, then competition is low.



Idea for a comparison result:

- ▶ If mass is evenly distributed, then competition is low.
- ▶ Uniform migration distributes mass evenly.



Idea for a comparison result:

- ▶ If mass is evenly distributed, then competition is low.
- ▶ Uniform migration distributes mass evenly.

Uniform migration on \mathbb{Z}^d ???

Idea: Uniform migration on $\Lambda_N \subset \mathbb{Z}^d$, $\#\Lambda_N < \infty$.

Then $\Lambda_N \uparrow \mathbb{Z}^d$.

$$dX_t^N(i) = \left(\frac{1}{N} \sum_{j=1}^N X_t^N(j) - X_t^N(i) \right) dt + \mu(X_t^N(i)) dt + \sqrt{\sigma^2(X_t^N(i))} dB_t(i) \quad i \leq N.$$

Idea: $(|X_t| := \sum_{i \in \mathbb{Z}^d} X_t(i))$

$$\left(|X_t| \right)_{t \geq 0} \stackrel{?}{\leq} \lim_{N \rightarrow \infty} \left(|X_t^N| \right)_{t \geq 0}$$

$$dX_t^N(i) = \left(\frac{1}{N} \sum_{j=1}^N X_t^N(j) - X_t^N(i) \right) dt + \mu(X_t^N(i)) dt + \sqrt{\sigma^2(X_t^N(i))} dB_t(i) \quad i \leq N.$$

Idea: $(|X_t| := \sum_{i \in \mathbb{Z}^d} X_t(i))$

$$\left(|X_t| \right)_{t \geq 0} \stackrel{?}{\leq} \lim_{N \rightarrow \infty} \left(|X_t^N| \right)_{t \geq 0}$$

What is the limit of $|X_t^N|$ if $X_0^N(i) = x \mathbb{1}_{i=1}$?

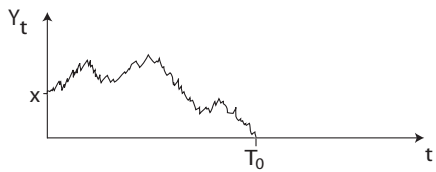
$$dX_t^N(i) = \left(\frac{1}{N} \sum_{j=1}^N X_t^N(j) - X_t^N(i) \right) dt + \mu(X_t^N(i)) dt + \sqrt{\sigma^2(X_t^N(i))} dB_t(i) \quad i \leq N.$$

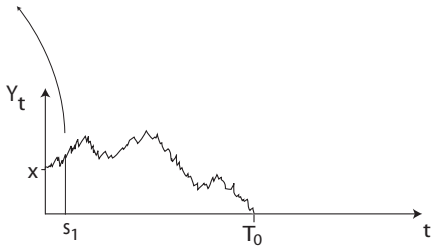
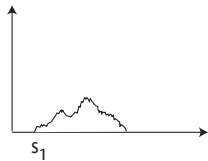
Idea: $(|X_t| := \sum_{i \in \mathbb{Z}^d} X_t(i))$

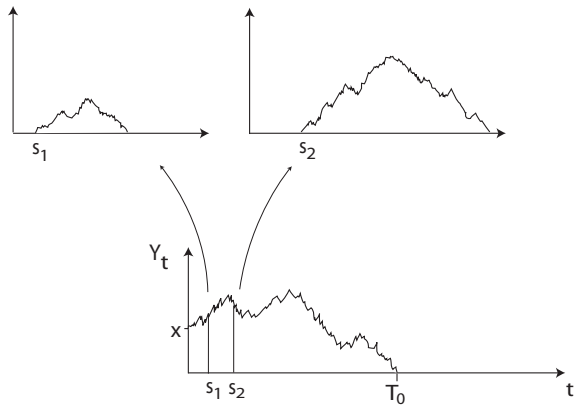
$$\left(|X_t| \right)_{t \geq 0} \stackrel{?}{\leq} \lim_{N \rightarrow \infty} \left(|X_t^N| \right)_{t \geq 0}$$

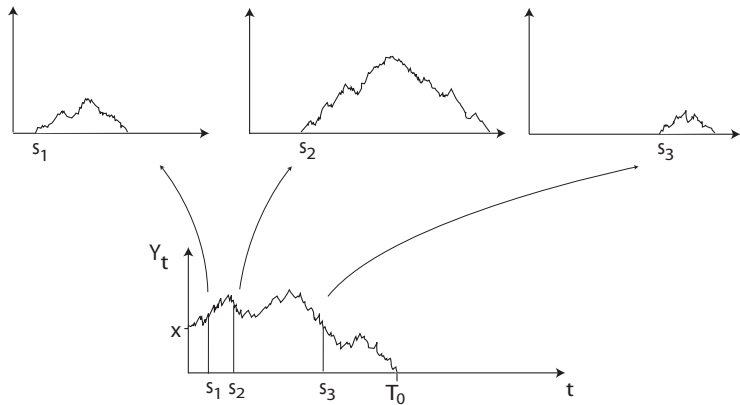
What is the limit of $|X_t^N|$ if $X_0^N(i) = x \mathbb{1}_{i=1}$?

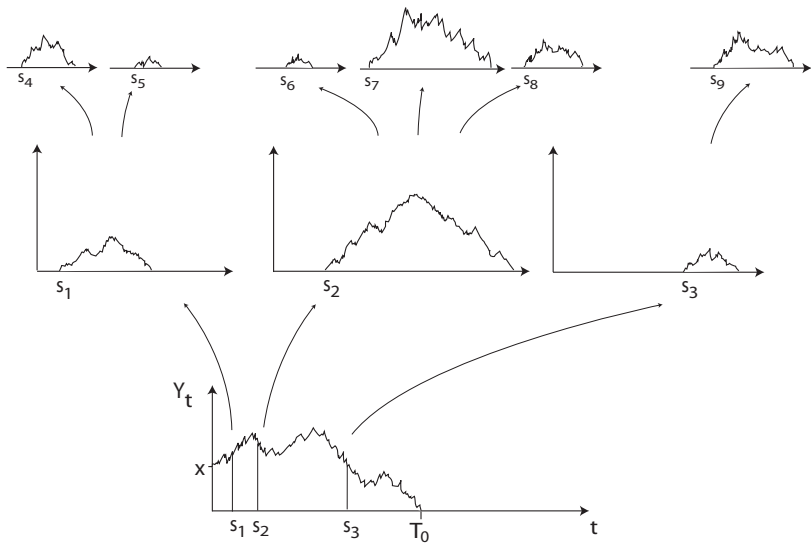
Heuristic: The first emigrant moves to some island. The probability that a later emigrant moves to the same island is $\frac{1}{N}$. In the limit $N \rightarrow \infty$ no two emigrants move to the same island.











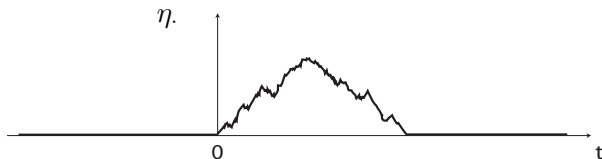
The virgin island model

- ▶ The population $(Y_t)_{t \geq 0}$ on island 1 evolves as

$$dY_t = -Y_t dt + \mu(Y_t) dt + \sqrt{\sigma^2(Y_t)} dB_t \quad Y_0 = x \geq 0,$$

- ▶ Every emigrant migrates to an unpopulated island
- ▶ The evolution on a newly populated island is modeled by excursions from zero of $(Y_t)_{t \geq 0}$. The excursion measure Q is defined by

$$\lim_{\varepsilon \rightarrow 0} \frac{1}{\varepsilon} \mathbf{E}^\varepsilon F((Y_t)_{t \geq 0}) =: \int F((\eta_t)_{t \geq 0}) Q(d\eta)$$



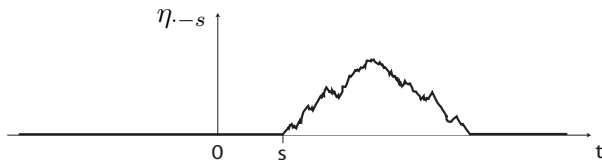
The virgin island model

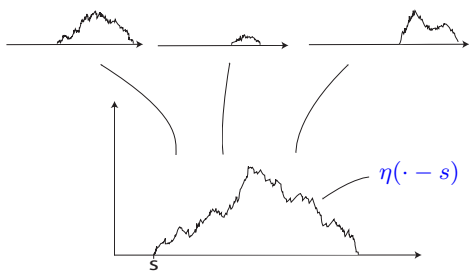
- ▶ The population $(Y_t)_{t \geq 0}$ on island 1 evolves as

$$dY_t = -Y_t dt + \mu(Y_t) dt + \sqrt{\sigma^2(Y_t)} dB_t \quad Y_0 = x \geq 0,$$

- ▶ Every emigrant migrates to an unpopulated island
- ▶ The evolution on a newly populated island is modeled by excursions from zero of $(Y_t)_{t \geq 0}$. The excursion measure Q is defined by

$$\lim_{\varepsilon \rightarrow 0} \frac{1}{\varepsilon} \mathbf{E}^\varepsilon F((Y_t)_{t \geq 0}) =: \int F((\eta_t)_{t \geq 0}) Q(d\eta)$$





If the mother island is populated at time s and has population $\eta(t - s)_{t \geq 0}$, then offspring islands are a **Poisson point process** Π with intensity measure

$$\mathbf{E}[\Pi(dt \otimes d\psi)] = \eta(t - s) dt \otimes Q(d\psi)$$

Theorem: (Comparison)

Let μ be sublinear ($\mu(x + y) \leq \mu(x) + \mu(y)$) and σ^2 be linear.

If $X_0(i) = x \mathbb{1}_{i=0}$, then

$$|X_t| \leq_{\text{st}} |V_t| \quad |V_0| = x, \quad \forall t \geq 0$$

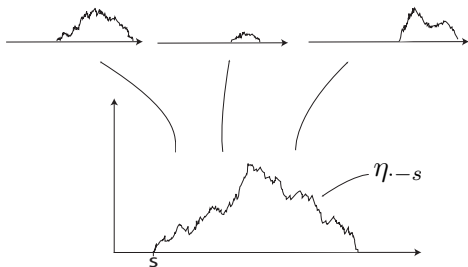
Theorem: (Comparison)

Let μ be sublinear ($\mu(x + y) \leq \mu(x) + \mu(y)$) and σ^2 be linear.

If $X_0(i) = x \mathbb{1}_{i=0}$, then

$$|X_t| \leq_{\text{st}} |V_t| \quad |V_0| = x, \quad \forall t \geq 0$$

Corollary: If $|V_t| \xrightarrow{w} 0$ as $t \rightarrow \infty$, then $|X_t| \xrightarrow{w} 0$.



Theorem: (Global Extinction of VIM)

The virgin island process dies out globally for every initial mass $x > 0$ if and only if

$$\int \left(\int_0^\infty \eta_t dt \right) Q(d\eta) \leq 1$$

Theorem: (Global Extinction of VIM)

The virgin island process dies out globally for every initial mass $x > 0$ if and only if

$$\int \left(\int_0^\infty \eta_t dt \right) Q(d\eta) \leq 1$$

Explicit formula for this:

$$\begin{aligned} \int \left(\int_{-\infty}^\infty \eta_t dt \right) Q(d\eta) &= \int y \int_{-\infty}^\infty Q(\eta_t \in dy) dt \\ &= \int y m(dy) \\ &= \int_0^\infty \frac{y}{\sigma^2(y)/2} \exp \left(\int_0^y \frac{-x + \mu(x)}{\sigma^2(x)/2} dx \right) dy \end{aligned}$$

$$dX_t(i) = \left(\sum_{j \in \mathbb{Z}^d} X_t(j) m(j, i) - X_t(i) \right) dt + \mu(X_t(i)) dt + \sqrt{\sigma^2(X_t(i))} dB_t(i) \quad i \in \mathbb{Z}^d$$

Corollary: (Global Extinction of X)

If μ is sublinear, σ^2 is linear and if

$$\int_0^\infty \frac{y}{\sigma^2(y)/2} \exp\left(\int_0^y \frac{-x + \mu(x)}{\sigma^2(x)/2} dx\right) dy \leq 1,$$

then every system of interacting locally regulated diffusions dies out globally ($|X_t| \xrightarrow{w} 0$) **for every migration kernel m .**

There exist comparison results if σ^2 is either superlinear or sublinear. Then the stochastic order is more complicated.

Example: Stepping stone model with selection and mutation

$$dX_t(i) = \left(\sum_{j \in \mathbb{Z}^d} X_t(j)m(j, i) - X_t(i) \right) dt + \left(sX_t(i)(1 - X_t(i)) - uX_t(i) \right) dt + \sqrt{2X_t(i)(1 - X_t(i))} dB_t(i)$$

for $i \in \mathbb{Z}^d$.

There exist comparison results if σ^2 is either superlinear or sublinear. Then the stochastic order is more complicated.

Example: Stepping stone model with selection and mutation

$$dX_t(i) = \left(\sum_{j \in \mathbb{Z}^d} X_t(j)m(j, i) - X_t(i) \right) dt + \left(sX_t(i)(1 - X_t(i)) - uX_t(i) \right) dt + \sqrt{2X_t(i)(1 - X_t(i))} dB_t(i)$$

for $i \in \mathbb{Z}^d$. If

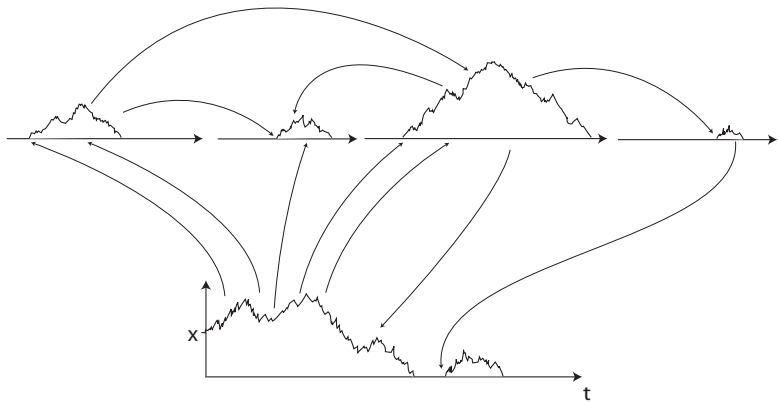
$$\int_0^1 (1 - y)^u e^{sy} dy < 1$$

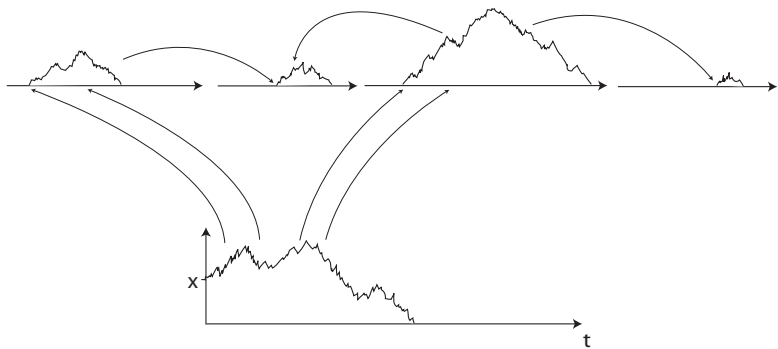
then $|X_t| \rightarrow 0$ as $t \rightarrow \infty$ in L^1 .

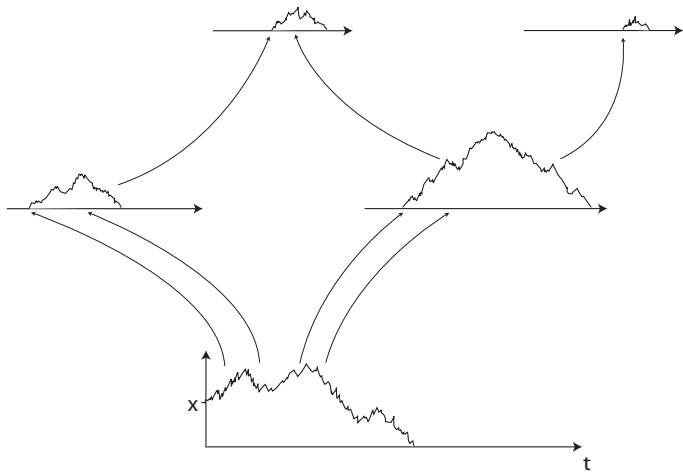
Theorem: (Convergence to the VIM)

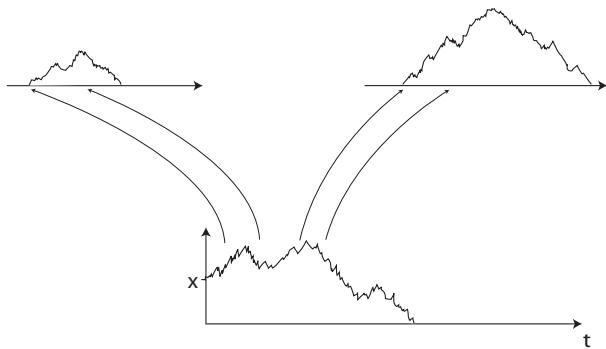
If $X_0(i) = x \mathbb{1}_{i=0}$, then

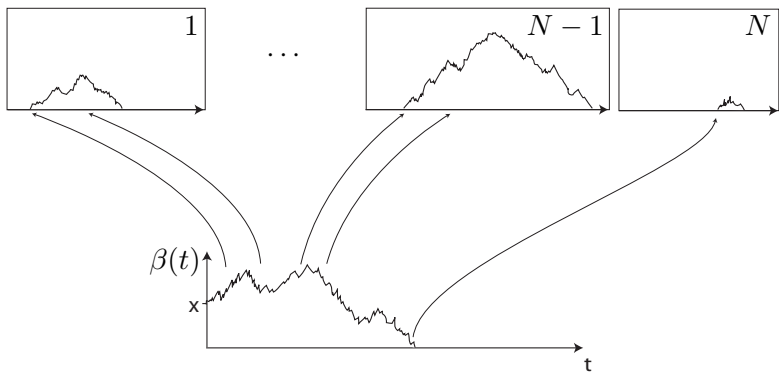
$$\sum_{i=1}^N X_t^N(i) \xrightarrow[N \rightarrow \infty]{w} |V_t| \quad \forall t \geq 0, |V_0| = x$$











Consider the one-dimensional diffusion

$$dY_t^N = \left(\frac{\beta(t)}{N} - Y_t^N + \mu(Y_t^N) \right) dt + \sqrt{\sigma^2(Y_t^N)} dB_t$$

where $Y_0^N = 0$.

Lemma:

$$\lim_{N \rightarrow \infty} N \mathbf{E}^0 f(Y_t^N) = \int \int_0^t f(\eta_{t-s}) \beta(s) ds Q(d\eta)$$

if f vanishes in a neighbourhood of zero.

Fancy duality: If $\mu(z) = \gamma x(K - x)$ and $\sigma^2(x) = 2\gamma x$, then

$$\mathbf{E}^x \exp(-yM_t) = \mathbf{E}^y \exp(-x|V_t|) \quad \forall x, y \in [0, \infty)$$

where

$$dM_t = (\mathbf{E}M_t - M_t) dt + \mu(M_t) dt + \sqrt{\sigma^2(M_t)} dB_t \quad M_0 = x$$

Fancy duality: If $\mu(z) = \gamma x(K - x)$ and $\sigma^2(x) = 2\gamma x$, then

$$\mathbf{E}^x \exp(-yM_t) = \mathbf{E}^y \exp(-x|V_t|) \quad \forall x, y \in [0, \infty)$$

where

$$dM_t = (\mathbf{E}M_t - M_t) dt + \mu(M_t) dt + \sqrt{\sigma^2(M_t)} dB_t \quad M_0 = x$$

Thank you

$$\begin{aligned}
dX_t^{(N,k)}(i) = & \alpha \left(\frac{1}{N} \sum_{j=1}^N X_t^{(N,k-1)}(j) - X_t^{(N,k)}(i) \right) dt \\
& + \frac{X_t^{(N,k)}(i)}{\sum_{m \geq 0} X_t^{(N,m)}(i)} \mu \left(\sum_{m \geq 0} X_t^{(N,m)}(i) \right) dt \\
& + \sqrt{\frac{X_t^{(N,k)}(i)}{\sum_{m \geq 0} X_t^{(N,m)}(i)} \sigma^2 \left(\sum_{m \geq 0} X_t^{(N,m)}(i) \right)} dB_t^k(i),
\end{aligned}$$

where $i = 1, \dots, N, k \geq 0$ and where $X_0^{(N,k)}(i) = X_0^N(i) \mathbb{1}_{k=0}$.

$$\begin{aligned}
dZ_t^{(N,k)}(i) = & \alpha \left(\frac{1}{N} \sum_{j=1}^N Z_t^{(N,k-1)}(j) - Z_t^{(N,k)}(i) + \mu(Z_t^{(N,k)}(i)) \right) dt \\
& + \sqrt{\sigma^2(Z_t^{(N,k)}(i))} dB_t^k(i) \quad i = 1, \dots, N.
\end{aligned}$$

Define the scale function of $(Y_t)_{t \geq 0}$ by

$$S(y) := \int_0^y s(z) dz \quad s(z) := \exp\left(-\int_0^z \frac{-x + \mu(x)}{\sigma^2(x)} dx\right).$$

$(S(Y_t))_{t \geq 0}$ is a local martingale and

$$\mathbf{P}^y(T_b < T_0) = \frac{S(y)}{S(b)} \quad 0 < y < b$$

where $T_b := \inf\{t > 0: Y_t = b\}$.

Define the scale function of $(Y_t)_{t \geq 0}$ by

$$S(y) := \int_0^y s(z) dz \quad s(z) := \exp\left(-\int_0^z \frac{-x + \mu(x)}{\sigma^2(x)} dx\right).$$

$(S(Y_t))_{t \geq 0}$ is a local martingale and

$$\mathbf{P}^y(T_b < T_0) = \frac{S(y)}{S(b)} \quad 0 < y < b$$

where $T_b := \inf\{t > 0: Y_t = b\}$.

The excursion measure Q satisfies

$$\lim_{y \rightarrow 0} \frac{1}{S(y)} \mathbf{E}^y F(Y) = \int F(\eta) Q(d\eta)$$

for all bounded continuous $F: \mathbf{C}([0, \infty), [0, \infty)) \rightarrow \mathbb{R}$ for which there exists an $\varepsilon > 0$ such that $F(\eta) = 0$ whenever $\sup_{t \geq 0} \eta_t < \varepsilon$.