

Loss rate for a general Lévy process with downward periodic barrier

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Joint work with P. Świątek

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Based on Soren's idea
as it is in many of my papers...

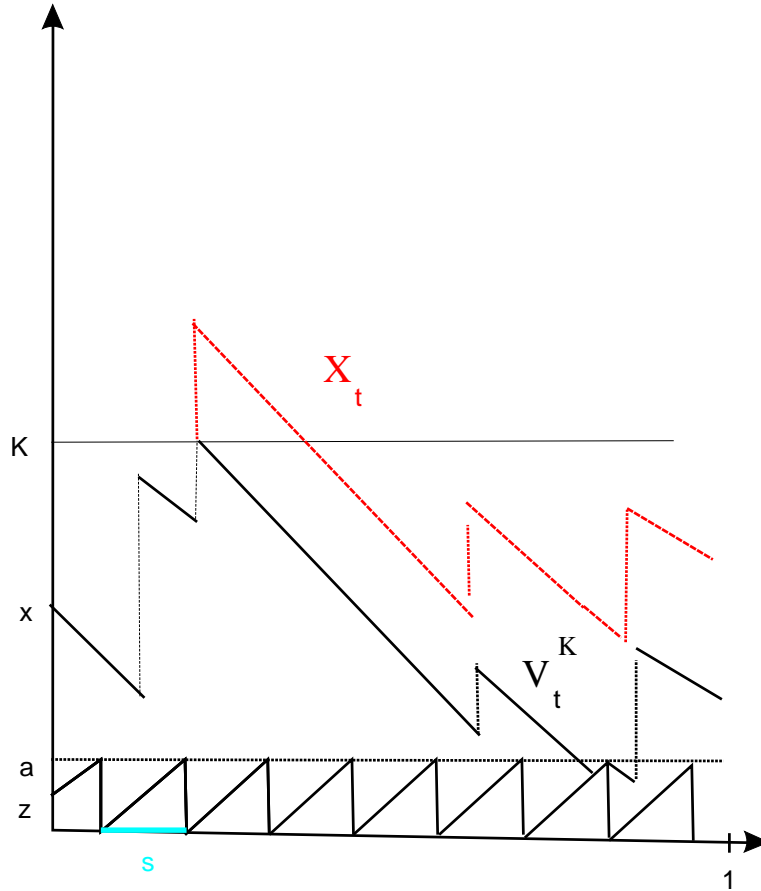
Extraordinariness



Snails and central station



Reflected Lévy process



Reflected Lévy process

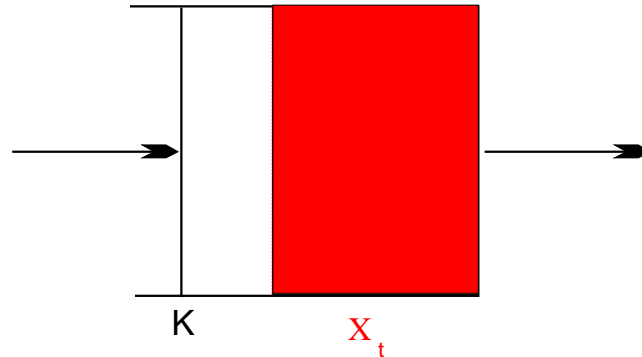
X_t - general Lévy process which is not subordinator

models netto input to buffer of **finite capacity** K fluid queue

Reflected Lévy process

X_t - general Lévy process which is not subordinator

models netto input to buffer of finite capacity K fluid queue



$$V_t = X_t - \sup_{0 \leq s \leq t} \left(\max \left(\min \{ X_s - K, \inf_{u \in [0, t]} X_u \}, \inf_{u \in [s, t]} X_u \right) \right)$$
$$\stackrel{D}{=} \sup_{s \in [0, t]} \max \{ X_t - X_s, \inf_{u \in [s, t]} (K + X_t - X_u) \}$$

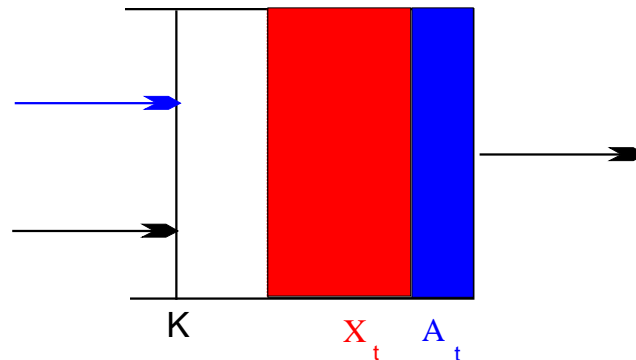
Reflected Lévy process

X_t - general Lévy process which is not subordinator

models netto input to buffer of finite capacity K fluid queue

A_t

models additional input which is not available on liquid basis



Reflected Lévy process

X_t - general Lévy process which is not subordinator

models netto input to buffer of finite capacity K fluid queue

Downward periodic barrier

$$A_t = \varphi(t + U)$$

models additional input which is not available on liquid basis for

$\varphi(t)$ nonnegative periodic function with period s

$$U \stackrel{D}{=} U[0, s]$$

Reflected Lévy process

X_t - general Lévy process which is not subordinator

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Downward periodic barrier

$$A_t = \varphi(t + U)$$

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$\varphi(t)$ nonnegative function

$$U \stackrel{D}{=} U[0, s]$$

Reflected process:

$$V_t^K = X_t + L_t^A - L_t^K$$

being solution of respective Skorohod problem

X_t - general Lévy process which is not subordinator

Downward periodic barrier $A_t = \varphi(t + U)$

Reflected process:

$$V_t^K = X_t + L_t^A - L_t^K$$

with the stationary measure

$$\pi_K$$

Loss rate:

$$l^K = \mathbb{E}L_1^K$$

where expectation is taken for the stationary V_t^K

Goals: identification of l^K in terms of Lévy triple and finding its asymptotics as $K \rightarrow \infty$

Asmussen & Pihlsgard (2010):

$$A(t) \equiv 0$$

Denote $l^{K,0}$ loss rate in this case. Then:

$$l^{K,0} \leq l^K \leq l^{K-a,0}$$

and

$$\frac{1}{K} \log l^K = -\gamma$$

for some γ .

We want to get more explicit asymptotics and exact expressions.

The ultimate goal is better understanding reflection for more general (lower and upper) barriers (both possibly tending to infinity).

Invariant measure of lower barrier

Assume that: $\varphi \in \mathcal{C}^1(\text{int } J_k)$ is invertible on some disjoint intervals J_k satisfying $\cup_{k=1}^n J_k = [0, s]$ with $\varphi'(x) \neq 0$ for $x \in \text{int } J_k$

Lemma 1. Process $A_t = \varphi(t + U)$ has invariant measure:

$$\xi(dy) = \sum_{k=1}^n \frac{1}{s} |h'_k(y)| \mathbf{1}_{\varphi(\text{int } J_k)}(y) dy$$

where h_k is a inverse of φ on $\text{int } J_k$.

Example 1

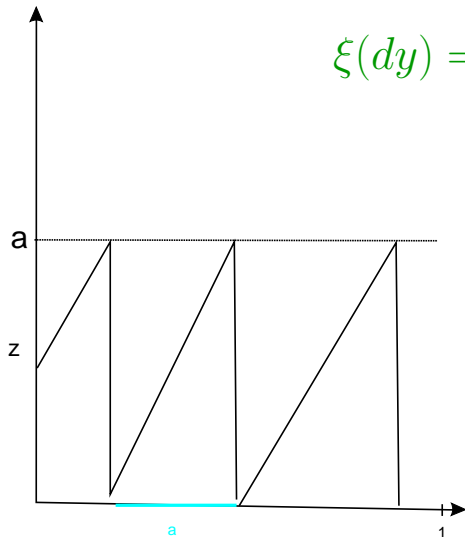
Saw-like lower boundary modeling constant intensity input (with rate 1 for simplicity)

$$\varphi(t) = t \bmod a$$

with $0 < a < K$.

In this case $n = 1$, $J_1 = [0, a]$, $s = a$ and

$$\xi(dy) = \frac{dy}{a} \mathbf{1}_{(y \in [0, a])}$$



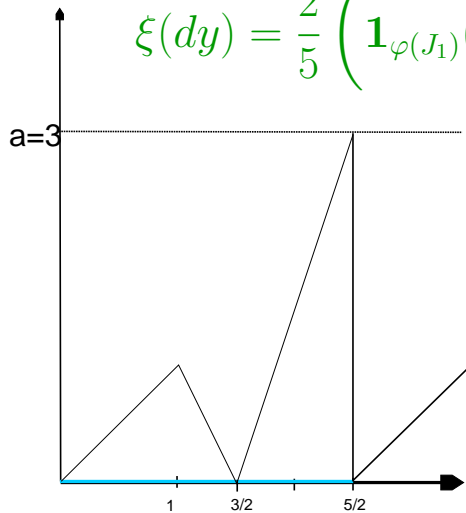
Example 2

Few lines with different slopes

$$\varphi(t) = \begin{cases} t & \text{for } t \in [0, 1) \\ 1 - 2(t - 1) & \text{for } t \in [1, \frac{3}{2}) \\ 3(t - \frac{3}{2}) & \text{for } t \in [\frac{3}{2}, \frac{5}{2}) \end{cases}$$

In this case $n = 3$, $J_1 = [0, 1]$, $J_2 = [1, \frac{3}{2}]$, $J_3 = [\frac{3}{2}, \frac{5}{2}]$, $s = \frac{5}{2}$ and

$$\xi(dy) = \frac{2}{5} \left(\mathbf{1}_{\varphi(J_1)}(y) + \frac{1}{2} \mathbf{1}_{\varphi(J_2)}(y) + \frac{1}{3} \mathbf{1}_{\varphi(J_3)}(y) \right) dy$$



Lemma 2. Stationary distribution V_∞^K

$$\pi_K(x, \infty) = \mathbb{P}(V_\infty^K \geq x) = \underbrace{\int_0^a \sum_{k=1}^n \mathbb{P}(X_\tau \geq \widehat{A}_\tau^{-z,k} + x) p_k(z) \xi(dz)}_{\bar{\pi}_K^z(x)}$$

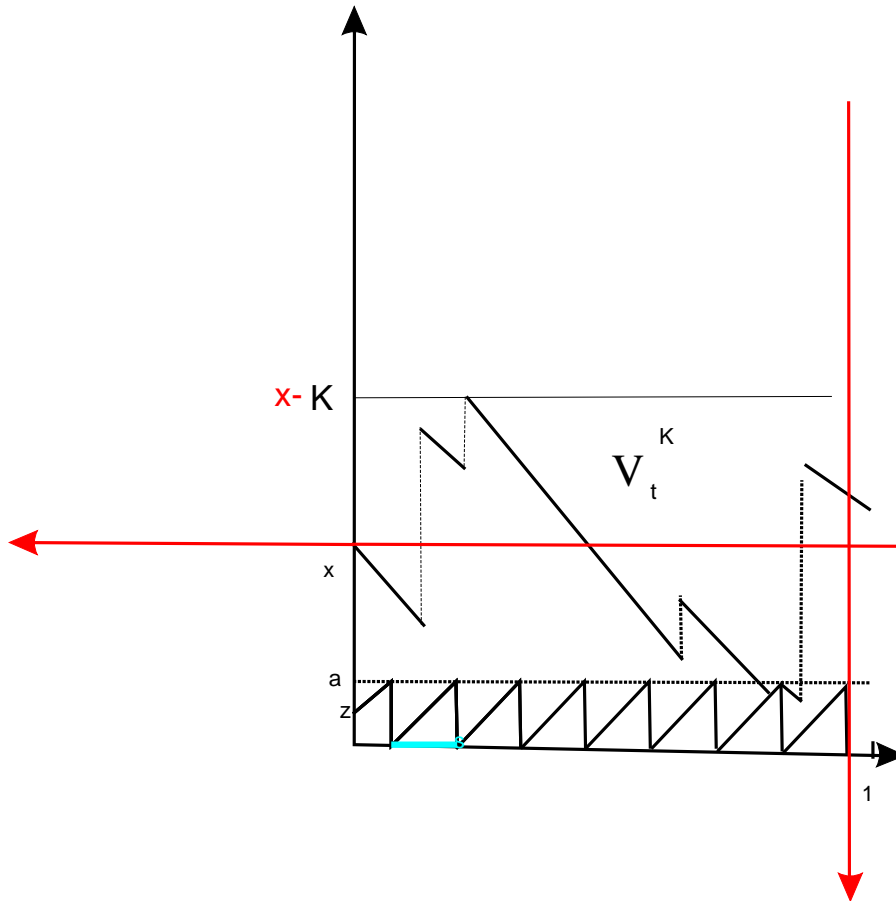
where

$$\tau = \inf\{t \geq 0 : X_t \notin [x - K, \widehat{A}_t^{-z,k} + x]\}$$

$$\widehat{A}_t^{-z,k} = -\varphi(h_k(z) - t) \quad \text{for } z \in \varphi(J_k)$$

$$p_k(z) = \mathbb{P}(U \in J_k | \varphi(U) = z) = \frac{|h'_k(z)| \mathbf{1}_{\varphi(J_k)}(z)}{\sum_{j=1}^n |h'_j(z)| \mathbf{1}_{\varphi(J_j)}(z)}$$

Duality



Lemma 2. Stationary distribution V_∞^K

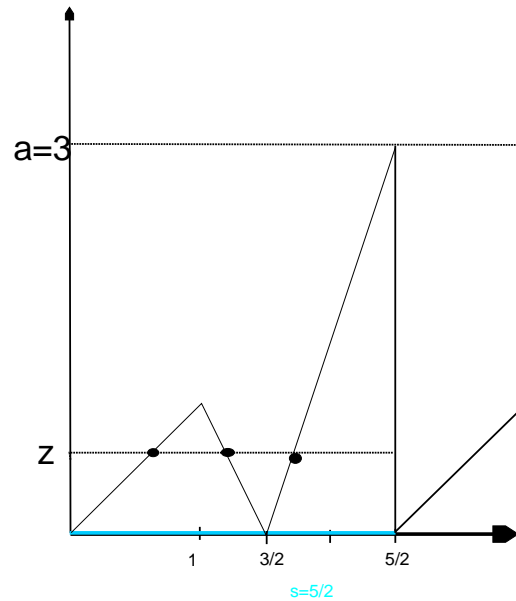
$$\pi_K(x, \infty) = \mathbb{P}(V_\infty^K \geq x) = \underbrace{\int_0^a \sum_{k=1}^n \mathbb{P}(X_\tau \geq \widehat{A}_\tau^{-z,k} + x) p_k(z) \xi(dz)}_{\bar{\pi}_K^z(x)}$$

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$$p_1(z) = \frac{1}{1 + \frac{1}{2} + \frac{1}{3}} = \frac{6}{11}, \quad z \in [0, 1]$$

$$p_2(z) = \frac{\frac{1}{2}}{1 + \frac{1}{2} + \frac{1}{3}} = \frac{3}{11}, \quad z \in \left[1, \frac{3}{2}\right]$$

$$p_3(z) = \frac{\frac{1}{3}}{1 + \frac{1}{2} + \frac{1}{3}} = \frac{2}{11}, \quad z \in \left[\frac{3}{2}, \frac{5}{2}\right]$$

Theorem 1. If $\int_1^\infty y\nu(dy) = \infty$, then $l^K = \infty$, and otherwise

$$l^K = \mathbb{E}X_1 \left[\frac{1}{K - \mathbb{E}A_0} \int_0^K x\pi_K(dx) - \frac{\mathbb{E}A_0}{(K - \mathbb{E}A_0)} \right] + \frac{\sigma^2}{2(K - \mathbb{E}A_0)} \\ + \frac{1}{2(K - \mathbb{E}A_0)} \int_0^a \int_z^K \int_{-\infty}^\infty \varphi_K(x, y, z)\nu(dy)\pi_K^z(dx)\xi(dz)$$

where

$$\varphi_K(x, y, z) = \begin{cases} -(x - z)^2 - 2y(x - z) & \text{if } y \leq -x + z \\ y^2 & \text{if } -x + z < y < K - x \\ 2y(K - x) - (K - x)^2 & \text{if } y \geq K - x \end{cases}$$

and ν is a Lévy measure of X

Idea of the proof will be given on next slides.

Step 1.

$$M_t = \kappa(\alpha) \int_0^t e^{\alpha V_s^K} ds + e^{\alpha V_0^K} - e^{\alpha V_t^K} + \alpha \int_0^t e^{\alpha A_s} dL_s^{A,c} \\ + \sum_{0 \leq s \leq t} e^{\alpha A_s} (1 - e^{-\alpha \Delta L_s^A}) - \alpha e^{\alpha K} L_t^{K,c} + e^{\alpha K} \sum_{0 \leq s \leq t} (1 - e^{\alpha \Delta L_s^K})$$

is a zero-mean martingale, where

$$\kappa(\alpha) = \log \mathbb{E} \exp\{\alpha X(1)\}$$

is a Laplace exponent of X .

Step 2.

Take $t = 1$, start V_0^K according to the stationary distribution and use expansion

$$e^{\alpha x} = 1 + \alpha x + \frac{(\alpha x)^2}{2} + \frac{(\alpha x)^3}{6} e^{\theta \alpha x}, \quad \theta \in [-1, 1]$$

Step 2.

This produces:

$$\begin{aligned}
 \alpha(1 - e^{\alpha K} + \alpha \mathbb{E}(A_0))l^K &= -\kappa(\alpha)\mathbb{E}e^{\alpha V_0^K} + \alpha \mathbb{E}X_1 - \alpha e^{\alpha K} \bar{l}_j^K + \alpha \bar{l}_j^A \\
 &+ \frac{\alpha^2}{2} \mathbb{E} \sum_{0 \leq s \leq 1} (\underline{\Delta}L_s^K)^2 + \frac{\alpha^2}{2} \mathbb{E} \sum_{0 \leq s \leq 1} (\underline{\Delta}L_s^A)^2 \\
 &- e^{\alpha K} \mathbb{E} \sum_{0 \leq s \leq 1} (1 - e^{\alpha \bar{\Delta}L_s^K}) \\
 &- \mathbb{E} \sum_{0 \leq s \leq 1} e^{\alpha A_s} (1 - e^{-\alpha \bar{\Delta}L_s^A}) \\
 &+ \alpha^2 \mathbb{E}(A_0)\mathbb{E}X_1 + \alpha^2 \mathbb{E} \sum_{0 \leq s \leq 1} A_s \bar{\Delta}L_s^A + o(\alpha^2)
 \end{aligned}$$

as $\alpha \downarrow 0$

We split ΔL_t^K into two parts, $\underline{\Delta}L_t^K$ and $\bar{\Delta}L_t^K$, corresponding to $\Delta X_s \in [0, L]$ and $\Delta X_s \in (L, \infty)$, respectively

We split ΔL_t^A into two parts, $\underline{\Delta}L_t^A$ and $\bar{\Delta}L_t^A$, corresponding to $\Delta X_s \in [-L, 0]$ and $\Delta X_s \in (-\infty, -L)$, respectively

Step 3.

$$\begin{aligned}\alpha(1 - e^{\alpha K} + \alpha\mathbb{E}(A_0))l^K &= -\kappa(\alpha)\mathbb{E}e^{\alpha V_0^K} + \alpha\mathbb{E}X_1 - \alpha e^{\alpha K}\bar{l}_j^K + \alpha\bar{l}_j^A \\ &+ \frac{\alpha^2}{2}\mathbb{E}\sum_{0\leq s\leq 1}(\underline{\Delta}L_s^K)^2 + \frac{\alpha^2}{2}\mathbb{E}\sum_{0\leq s\leq 1}(\underline{\Delta}L_s^A)^2 \\ &- e^{\alpha K}\mathbb{E}\sum_{0\leq s\leq 1}(1 - e^{\alpha\bar{\Delta}L_s^K}) \\ &- \mathbb{E}\sum_{0\leq s\leq 1}e^{\alpha A_s}(1 - e^{-\alpha\bar{\Delta}L_s^A}) \\ &+ \alpha^2\mathbb{E}(A_0)\mathbb{E}X_1 + \alpha^2\mathbb{E}\sum_{0\leq s\leq 1}A_s\bar{\Delta}L_s^A + o(\alpha^2).\end{aligned}$$

Step 4.

After sending L to ∞ we get:

$$\begin{aligned}\alpha(1 - e^{\alpha K} + \alpha \mathbb{E}A_0)l^K &= -\mathbb{E}X_1 \alpha^2 \int_0^K x \pi_K(dx) - \frac{\sigma^2 \alpha^2}{2} \\ &\quad - \frac{\alpha^2}{2} \int_0^a \int_z^K \int_{-x+z}^{K-x} y^2 \nu(dy) \pi_K^z(dx) \xi(dz) \\ &\quad + \frac{\alpha^2}{2} \int_0^a \int_z^K \int_{K-x}^{\infty} ((x-K)^2 + 2y(x-K)) \nu(dy) \\ &\quad + \frac{\alpha^2}{2} \int_0^a \int_z^K \int_{-\infty}^{-x+z} ((x-z)^2 + 2y(x-z)) \nu(dy) \\ &\quad + \alpha^2 \mathbb{E}A_0 \mathbb{E}X_1 + o(\alpha^2)\end{aligned}$$

The proof follows by dividing both sides of above equation by $\alpha(1 - e^{\alpha K} + \alpha \mathbb{E}A_0)$ and sending α to 0

Assume that jump measure ν is non-lattice and there exists $\gamma > 0$ such that

$$\kappa(\gamma) = 0$$

with $\kappa'(\gamma) < \infty$ (hence $EX_1 < 0$)

Define:

$$\left. \frac{d\mathbb{P}^\gamma}{d\mathbb{P}} \right|_{\mathcal{F}_t} = e^{\gamma X_t}$$

$$\tau_z^A(x) = \inf\{t \geq 0 : X_t \geq \widehat{A}_t^{-z} + x\}, \quad \tau_{-z}^- = \inf\{t \geq 0 : X_t < -z\}$$

$$\tau^A(x) = \inf\{t \geq 0 : X_t \geq \widehat{A}_t^\xi + x\} \quad \text{where } \widehat{A}_t^\xi = \int_0^\infty A_t^{-y} \xi(dy)$$

$$B^A(x) = X_{\tau^A(x)} - x$$

- overshoot of the **dual** of the downward periodic barrier

We will write $f(K) \sim g(K)$ when $\lim_{K \rightarrow \infty} f(K)/g(K) = 1$

Theorem 2.

$$l^K \sim D e^{-\gamma K}$$

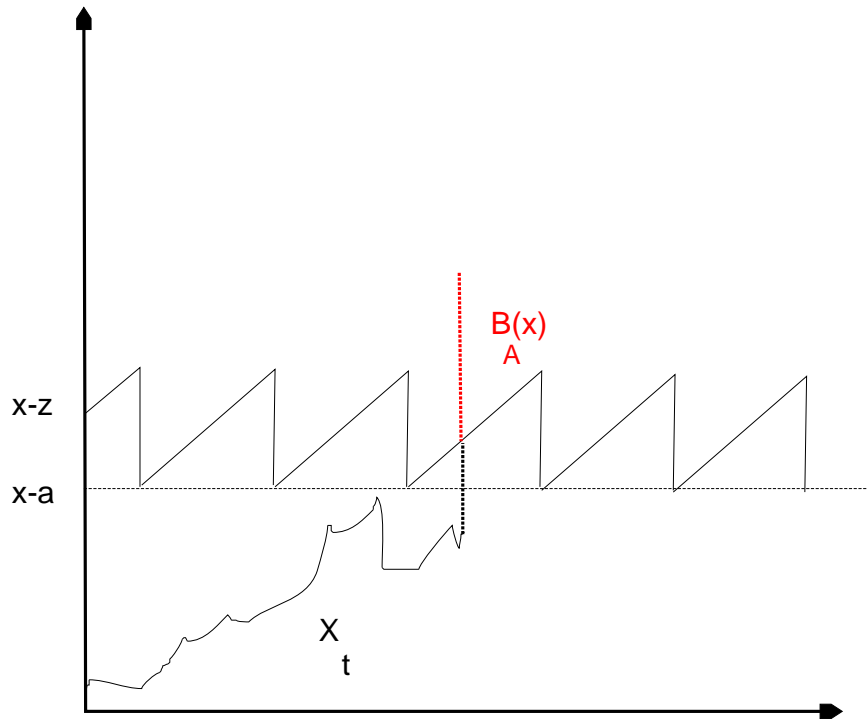
where

$$\begin{aligned} D = & -\mathbb{E}X_1 C_\gamma + \mathbb{E}^\gamma e^{-\gamma B^A(\infty)} \int_0^\infty e^{\gamma x} \mathbb{P}^\gamma(\tau_{-x}^- = \infty) \int_x^\infty (1 - e^{\gamma(y-x)}) \nu(dy) \\ & + \int_{-\infty}^0 (y + \gamma^{-1} (1 - e^{\gamma y})) \nu(dy) \\ & + \int_0^\infty \int_0^{a \wedge x} \mathbb{P}(\tau_z^A(x) < \infty) \int_{-\infty}^{-x+z} (1 - e^{\gamma(x+y-z)}) \nu(dy) \xi(dz) dx \end{aligned}$$

with

$$C_\gamma = \mathbb{E}e^{\gamma A_s}, \quad B^A(x) \xrightarrow{D} B^A(\infty)$$

Asymptotic overshoot



The proof is based on the exponential change of measure and regenerative arguments.

$$X_t = \sum_{i=1}^{N_t} \sigma_i - t$$

with $\{\sigma_i\}_{i \geq 1}$ being i.i.d. $\text{Exp}(\mu)$

and

N_t being a Poisson process with intensity $\lambda < \mu$

$$\varphi(t) = t \bmod a.$$

Then we have:

$$D = \frac{1}{a} \left(e^{a(\mu-\lambda)} - 1 \right) \frac{\mu - \lambda}{\mu} \frac{\lambda}{\mu}$$

Assume:

$$EX_1 < \infty$$

Define:

$$\nu_I(x) = \int_x^\infty \nu(y, \infty) dy$$

Theorem 3. (Andersen (2011)) If ν_I is subexponential and one of the following conditions holds:

- (i) $EX_1^2 < \infty$ and $\int_K^\infty \nu_I(y) dy / \nu_I(x) = O(K)$,
- (ii) $\nu(K, \infty) \sim L(K)K^{-\alpha}$ for locally bounded slowly varying function L and $0 < \alpha < 2$,

then

$$l^K \sim \nu_I(K)$$

The proof is based on Theorem 1 and finding appropriate bounds.

Assume:

$$EX_1 = 0$$

Theorem 4. (Andersen & Asmussen (2010)) (i) If $EX_1^2 < \infty$ then

$$l_K \sim \frac{1}{2K} \int_{-\infty}^{\infty} y^2 \nu(dy) + \frac{\sigma^2}{2K}$$

where σ is a Gaussian coefficient.

Theorem 4. (Andersen & Asmussen (2010)) (ii) If for $1 < \alpha < 2$ and slowly varying functions L_1 and L_2 :

$$\nu(x, \infty) = L_1(x)x^{-\alpha}, \quad \nu(-\infty, x) = L_2(x)|x|^{-\alpha}$$

such that

$$\lim_{x \rightarrow \infty} \frac{L_1(x)}{L_1(x) + L_2(x)} = d := \frac{\beta + 1}{2}, \quad \lim_{x \rightarrow \infty} L_0(x)^\alpha (L_1(x) + L_2(x)) = 1$$

for some slowly varying function L_0 , then

$$l^K \sim \frac{\zeta}{K^{\alpha-1} L_0(K)^\alpha}$$

for

$$\zeta = \frac{cB(2 - \alpha\rho, \alpha\rho) + dB(2 - \alpha(1 - \rho), \alpha(1 - \rho))}{B(\alpha\rho, \alpha(1 - \rho))(2 - \alpha)(\alpha - 1)}$$

and $c = 1 - d$, $\rho = P(X_t > 0) = \frac{1}{2} + (\pi\alpha)^{-1} \arctan(\beta \tan(\pi\alpha/2))$

The proof is done by approximation.

THANK YOU
for Your Attention !