

Further calculations for the McKean stochastic game for a spectrally negative Lévy process: from a point to an interval *

Erik Baurdoux

London School of Economics and Political Science
e.j.baurdoux@lse.ac.uk

Workshop on Stochastic Models and Control
Bad Herrenalb, March 31

*Based on joint work with Kees van Schaik (Univ. of Manchester)



Outline

- Lévy processes

Outline

- Lévy processes
- Stochastic game

Outline

- Lévy processes
- Stochastic game
- McKean optimal stopping problem (American put)

Outline

- Lévy processes
- Stochastic game
- McKean optimal stopping problem (American put)
- Spectrally negative Lévy process: Laplace exponent and scale function

Outline

- Lévy processes
- Stochastic game
- McKean optimal stopping problem (American put)
- Spectrally negative Lévy process: Laplace exponent and scale function
- McKean stochastic game: point to interval

Lévy process

Lévy process $\{X_t\}_{t \geq 0}$ has stationary, independent increments w.r.t. some $(\Omega, \{\mathcal{F}_t\}_{t \geq 0}, \mathbb{P})$.

Lévy process

Lévy process $\{X_t\}_{t \geq 0}$ has stationary, independent increments w.r.t. some $(\Omega, \{\mathcal{F}_t\}_{t \geq 0}, \mathbb{P})$.

Denote by \mathbb{P}_x the translation of \mathbb{P} under which $X_0 = x$.

Lévy process

Lévy process $\{X_t\}_{t \geq 0}$ has stationary, independent increments w.r.t. some $(\Omega, \{\mathcal{F}_t\}_{t \geq 0}, \mathbb{P})$.

Denote by \mathbb{P}_x the translation of \mathbb{P} under which $X_0 = x$.

Examples are

- Brownian motion.

Lévy process

Lévy process $\{X_t\}_{t \geq 0}$ has stationary, independent increments w.r.t. some $(\Omega, \{\mathcal{F}_t\}_{t \geq 0}, \mathbb{P})$.

Denote by \mathbb{P}_x the translation of \mathbb{P} under which $X_0 = x$.

Examples are

- Brownian motion.
- Stable process.

Lévy process

Lévy process $\{X_t\}_{t \geq 0}$ has stationary, independent increments w.r.t. some $(\Omega, \{\mathcal{F}_t\}_{t \geq 0}, \mathbb{P})$.

Denote by \mathbb{P}_x the translation of \mathbb{P} under which $X_0 = x$.

Examples are

- Brownian motion.
- Stable process.
- Compound Poisson process.

Lévy process

Lévy process $\{X_t\}_{t \geq 0}$ has stationary, independent increments w.r.t. some $(\Omega, \{\mathcal{F}_t\}_{t \geq 0}, \mathbb{P})$.

Denote by \mathbb{P}_x the translation of \mathbb{P} under which $X_0 = x$.

Examples are

- Brownian motion.
- Stable process.
- Compound Poisson process.

Spectrally negative Lévy process (SNLP): no upwards jumps and paths not monotone.

Stochastic game

- Two player stochastic game: maximiser Max, minimiser Min, pay-off function f of observable X . We take f bounded.

Stochastic game

- Two player stochastic game: maximiser Max, minimiser Min, pay-off function f of observable X . We take f bounded.
- When Max stops first at time s , Max receives $e^{-qs}f(X_s)$ from Min.

Stochastic game

- Two player stochastic game: maximiser Max, minimiser Min, pay-off function f of observable X . We take f bounded.
- When Max stops first at time s , Max receives $e^{-qs}f(X_s)$ from Min.
- When Min stops first at time t , Max receives $e^{-qt}(f(X_t) + \delta)$ from Min.

Stochastic game

- Two player stochastic game: maximiser Max, minimiser Min, pay-off function f of observable X . We take f bounded.
- When Max stops first at time s , Max receives $e^{-qs}f(X_s)$ from Min.
- When Min stops first at time t , Max receives $e^{-qt}(f(X_t) + \delta)$ from Min. Here $\delta > 0$ penalty.

Stochastic game

- Two player stochastic game: maximiser Max, minimiser Min, pay-off function f of observable X . We take f bounded.
- When Max stops first at time s , Max receives $e^{-qs}f(X_s)$ from Min.
- When Min stops first at time t , Max receives $e^{-qt}(f(X_t) + \delta)$ from Min. Here $\delta > 0$ penalty.
- Discount rate $q > 0$.

Stochastic game

- Two player stochastic game: maximiser Max, minimiser Min, pay-off function f of observable X . We take f bounded.
- When Max stops first at time s , Max receives $e^{-qs}f(X_s)$ from Min.
- When Min stops first at time t , Max receives $e^{-qt}(f(X_t) + \delta)$ from Min. Here $\delta > 0$ penalty.
- Discount rate $q > 0$.

Saddle point problem:

$$\mathbb{E}_x[e^{-q(\sigma \wedge \tau)} (f(X_{\sigma \wedge \tau}) + \delta \mathbf{1}_{\{\sigma < \tau\}})]$$

to be minimised over σ and maximised over τ .

Stochastic game

- Two player stochastic game: maximiser Max, minimiser Min, pay-off function f of observable X . We take f bounded.
- When Max stops first at time s , Max receives $e^{-qs}f(X_s)$ from Min.
- When Min stops first at time t , Max receives $e^{-qt}(f(X_t) + \delta)$ from Min. Here $\delta > 0$ penalty.
- Discount rate $q > 0$.

Saddle point problem:

$$\mathbb{E}_x[e^{-q(\sigma \wedge \tau)} (f(X_{\sigma \wedge \tau}) + \delta \mathbf{1}_{\{\sigma < \tau\}})]$$

to be minimised over σ and maximised over τ .

So: American put option which can be terminated by seller for penalty δ .

More precise

Denote by \mathcal{T} the set stopping times.

More precise

Denote by \mathcal{T} the set stopping times. For $\tau, \sigma \in \mathcal{T}$, denote

$$Z_x(\tau, \sigma) = \mathbb{E}_x[e^{-q(\sigma \wedge \tau)} (f(X_{\sigma \wedge \tau}) + \delta \mathbf{1}_{\{\sigma < \tau\}})].$$

More precise

Denote by \mathcal{T} the set stopping times. For $\tau, \sigma \in \mathcal{T}$, denote

$$Z_x(\tau, \sigma) = \mathbb{E}_x[e^{-q(\sigma \wedge \tau)} (f(X_{\sigma \wedge \tau}) + \delta \mathbf{1}_{\{\sigma < \tau\}})].$$

Find $\sigma^*, \tau^* \in \mathcal{T}$ such that

$$Z_x(\tau, \sigma^*) \leq Z_x(\tau^*, \sigma^*) \leq Z_x(\tau^*, \sigma)$$

for all $x \in \mathbb{R}$ and $\sigma, \tau \in \mathcal{T}$.

More precise

Denote by \mathcal{T} the set stopping times. For $\tau, \sigma \in \mathcal{T}$, denote

$$Z_x(\tau, \sigma) = \mathbb{E}_x[e^{-q(\sigma \wedge \tau)} (f(X_{\sigma \wedge \tau}) + \delta \mathbf{1}_{\{\sigma < \tau\}})].$$

Find $\sigma^*, \tau^* \in \mathcal{T}$ such that

$$Z_x(\tau, \sigma^*) \leq Z_x(\tau^*, \sigma^*) \leq Z_x(\tau^*, \sigma)$$

for all $x \in \mathbb{R}$ and $\sigma, \tau \in \mathcal{T}$. Then

$$\inf_{\sigma} \sup_{\tau} Z_x(\tau, \sigma) = \sup_{\tau} \inf_{\sigma} Z_x(\tau, \sigma) = Z_x(\tau^*, \sigma^*).$$

McKean optimal stopping problem

We take $f(x) = (K - e^x)^+$ with $K > 0$.

McKean optimal stopping problem

We take $f(x) = (K - e^x)^+$ with $K > 0$.

McKean optimal stopping problem

$$U(x) = \sup_{\tau \in \mathcal{T}} \mathbb{E}_x[e^{-q\tau} (K - e^{X_\tau})^+].$$

McKean optimal stopping problem

We take $f(x) = (K - e^x)^+$ with $K > 0$.

McKean optimal stopping problem

$$U(x) = \sup_{\tau \in \mathcal{T}} \mathbb{E}_x[e^{-q\tau} (K - e^{X_\tau})^+].$$

Considered (for B.M.) by McKean (1965); American put option: right to sell stock at pre-determined price.

McKean optimal stopping problem

We take $f(x) = (K - e^x)^+$ with $K > 0$.

McKean optimal stopping problem

$$U(x) = \sup_{\tau \in \mathcal{T}} \mathbb{E}_x[e^{-q\tau} (K - e^{X_\tau})^+].$$

Considered (for B.M.) by McKean (1965); American put option: right to sell stock at pre-determined price.

Mordecki (2002) proved $\tau^* = \tau_{k^*}^- = \inf\{t \geq 0 : X_t \leq k^*\}$. Here

$$k^* = \log(K \mathbb{E}[e^{X_{e_q}}]),$$

where e_q is independent exponentially(q) distributed and

$$\underline{X}_t = \inf_{0 \leq s \leq t} X_s.$$

McKean optimal stopping problem

We take $f(x) = (K - e^x)^+$ with $K > 0$.

McKean optimal stopping problem

$$U(x) = \sup_{\tau \in \mathcal{T}} \mathbb{E}_x[e^{-q\tau} (K - e^{X_\tau})^+].$$

Considered (for B.M.) by McKean (1965); American put option: right to sell stock at pre-determined price.

Mordecki (2002) proved $\tau^* = \tau_{k^*}^- = \inf\{t \geq 0 : X_t \leq k^*\}$. Here

$$k^* = \log(K\mathbb{E}[e^{X_{e_q}}]),$$

where e_q is independent exponentially(q) distributed and

$\underline{X}_t = \inf_{0 \leq s \leq t} X_s$. Also

$$U(x) = \frac{\mathbb{E} \left[\left(K\mathbb{E}[e^{X_{e_q}}] - e^{x + \underline{X}_{e_q}} \right)^+ \right]}{\mathbb{E}[e^{X_{e_q}}]}.$$

McKean stochastic game

(Lower) Value of McKean stochastic game:

$$V(x) : = \sup_{\tau \in \mathcal{T}} \inf_{\sigma \in \mathcal{T}} \mathbb{E}_x \left[e^{-q(\tau \wedge \sigma)} \left((K - e^{X_{\tau \wedge \sigma}})^+ + \delta \mathbf{1}_{\{\sigma < \tau\}} \right) \right].$$

McKean stochastic game

(Lower) Value of McKean stochastic game:

$$V(x) : = \sup_{\tau \in \mathcal{T}} \inf_{\sigma \in \mathcal{T}} \mathbb{E}_x \left[e^{-q(\tau \wedge \sigma)} \left((K - e^{X_{\tau \wedge \sigma}})^+ + \delta \mathbf{1}_{\{\sigma < \tau\}} \right) \right].$$

Aim: Find “optimal” σ^* , τ^* such that

$$\begin{aligned} V(x) &= \inf_{\sigma \in \mathcal{T}} \sup_{\tau \in \mathcal{T}} \mathbb{E}_x \left[e^{-q(\tau \wedge \sigma)} \left((K - e^{X_{\tau \wedge \sigma}})^+ + \delta \mathbf{1}_{\{\sigma < \tau\}} \right) \right] \\ &= \mathbb{E}_x \left[e^{-q(\tau^* \wedge \sigma^*)} \left((K - e^{X_{\tau^* \wedge \sigma^*}})^+ + \delta \mathbf{1}_{\{\sigma^* < \tau^*\}} \right) \right]. \end{aligned}$$

McKean stochastic game

(Lower) Value of McKean stochastic game:

$$V(x) := \sup_{\tau \in \mathcal{T}} \inf_{\sigma \in \mathcal{T}} \mathbb{E}_x \left[e^{-q(\tau \wedge \sigma)} \left((K - e^{X_{\tau \wedge \sigma}})^+ + \delta \mathbf{1}_{\{\sigma < \tau\}} \right) \right].$$

Aim: Find “optimal” σ^* , τ^* such that

$$\begin{aligned} V(x) &= \inf_{\sigma \in \mathcal{T}} \sup_{\tau \in \mathcal{T}} \mathbb{E}_x \left[e^{-q(\tau \wedge \sigma)} \left((K - e^{X_{\tau \wedge \sigma}})^+ + \delta \mathbf{1}_{\{\sigma < \tau\}} \right) \right] \\ &= \mathbb{E}_x \left[e^{-q(\tau^* \wedge \sigma^*)} \left((K - e^{X_{\tau^* \wedge \sigma^*}})^+ + \delta \mathbf{1}_{\{\sigma^* < \tau^*\}} \right) \right]. \end{aligned}$$

Taking $\tau = 0$ and $\sigma = 0$ resp. leads to

$$(K - e^x)^+ \leq V(x) \leq (K - e^x)^+ + \delta.$$

McKean stochastic game

(Lower) Value of McKean stochastic game:

$$V(x) := \sup_{\tau \in \mathcal{T}} \inf_{\sigma \in \mathcal{T}} \mathbb{E}_x \left[e^{-q(\tau \wedge \sigma)} \left((K - e^{X_{\tau \wedge \sigma}})^+ + \delta \mathbf{1}_{\{\sigma < \tau\}} \right) \right].$$

Aim: Find “optimal” σ^* , τ^* such that

$$\begin{aligned} V(x) &= \inf_{\sigma \in \mathcal{T}} \sup_{\tau \in \mathcal{T}} \mathbb{E}_x \left[e^{-q(\tau \wedge \sigma)} \left((K - e^{X_{\tau \wedge \sigma}})^+ + \delta \mathbf{1}_{\{\sigma < \tau\}} \right) \right] \\ &= \mathbb{E}_x \left[e^{-q(\tau^* \wedge \sigma^*)} \left((K - e^{X_{\tau^* \wedge \sigma^*}})^+ + \delta \mathbf{1}_{\{\sigma^* < \tau^*\}} \right) \right]. \end{aligned}$$

Taking $\tau = 0$ and $\sigma = 0$ resp. leads to

$$(K - e^x)^+ \leq V(x) \leq (K - e^x)^+ + \delta.$$

Taking $\sigma = \infty$, we see that $V(x) \leq U(x)$.

Laplace exponent

From now on, X is a SNLP.

Laplace exponent ψ of X is defined for $\lambda \geq 0$

$$\mathbb{E}[e^{\lambda X_t}] = e^{\psi(\lambda)t} \quad \forall t \geq 0.$$

Laplace exponent

From now on, X is a SNLP.

Laplace exponent ψ of X is defined for $\lambda \geq 0$

$$\mathbb{E}[e^{\lambda X_t}] = e^{\psi(\lambda)t} \quad \forall t \geq 0.$$

ψ is C^∞ on $(0, \infty)$, convex, $\psi(0) = 0$ and $\psi(\infty) = \infty$.

Laplace exponent

From now on, X is a SNLP.

Laplace exponent ψ of X is defined for $\lambda \geq 0$

$$\mathbb{E}[e^{\lambda X_t}] = e^{\psi(\lambda)t} \quad \forall t \geq 0.$$

ψ is C^∞ on $(0, \infty)$, convex, $\psi(0) = 0$ and $\psi(\infty) = \infty$.

Denote

$$\Phi(q) := \sup\{x : \psi(x) = q\}.$$

Laplace exponent

From now on, X is a SNLP.

Laplace exponent ψ of X is defined for $\lambda \geq 0$

$$\mathbb{E}[e^{\lambda X_t}] = e^{\psi(\lambda)t} \quad \forall t \geq 0.$$

ψ is C^∞ on $(0, \infty)$, convex, $\psi(0) = 0$ and $\psi(\infty) = \infty$.

Denote

$$\Phi(q) := \sup\{x : \psi(x) = q\}.$$

Equivalent measure: for $c > 0$

$$\left. \frac{d\mathbb{P}^c}{d\mathbb{P}} \right|_{\mathcal{F}_t} = e^{cX_t - \psi(c)t}.$$

Under \mathbb{P}^c , X is still a SNLP.

Scale functions

Scale function for $q \geq 0$ $W^{(q)} : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0}$ “defined” as continuous function satisfying

$$\int_0^{\infty} e^{-\lambda x} W^{(q)}(x) dx = \frac{1}{\psi(\lambda) - q} \quad \forall \lambda > \Phi(q).$$

Scale functions

Scale function for $q \geq 0$ $W^{(q)} : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0}$ “defined” as continuous function satisfying

$$\int_0^{\infty} e^{-\lambda x} W^{(q)}(x) dx = \frac{1}{\psi(\lambda) - q} \quad \forall \lambda > \Phi(q).$$

Extend to \mathbb{R} by: $W^{(q)}(y) = 0$ when $y < 0$.

Scale functions

Scale function for $q \geq 0$ $W^{(q)} : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0}$ “defined” as continuous function satisfying

$$\int_0^{\infty} e^{-\lambda x} W^{(q)}(x) dx = \frac{1}{\psi(\lambda) - q} \quad \forall \lambda > \Phi(q).$$

Extend to \mathbb{R} by: $W^{(q)}(y) = 0$ when $y < 0$.

Define $Z^{(q)} : \mathbb{R} \rightarrow \mathbb{R}_{\geq 1}$ by

$$Z^{(q)}(x) = 1 + q \int_0^x W^{(q)}(y) dy.$$

Exit problems

Two-sided exit problems: let

$$\tau_b^+ = \inf\{t \geq 0 : X_t \geq b\}$$

and

$$\tau_a^- = \inf\{t \geq 0 : X_t \leq a\}.$$

Exit problems

Two-sided exit problems: let

$$\tau_b^+ = \inf\{t \geq 0 : X_t \geq b\}$$

and

$$\tau_a^- = \inf\{t \geq 0 : X_t \leq a\}.$$

For $a < x < b$

$$\mathbb{E}_x[e^{-q\tau_b^+} \mathbf{1}_{\{\tau_b^+ < \tau_a^-\}}] = \frac{W^{(q)}(x - a)}{W^{(q)}(b - a)}.$$

Exit problems

Two-sided exit problems: let

$$\tau_b^+ = \inf\{t \geq 0 : X_t \geq b\}$$

and

$$\tau_a^- = \inf\{t \geq 0 : X_t \leq a\}.$$

For $a < x < b$

$$\mathbb{E}_x[e^{-q\tau_b^+} \mathbf{1}_{\{\tau_b^+ < \tau_a^-\}}] = \frac{W^{(q)}(x-a)}{W^{(q)}(b-a)}.$$

Also

$$\mathbb{E}_x[e^{-q\tau_a^-} \mathbf{1}_{\{\tau_a^- < \tau_b^+\}}] = Z^{(q)}(x-a) - W^{(q)}(x-a) \frac{Z^{(q)}(b-a)}{W^{(q)}(b-a)}.$$

McKean Optimal Stopping Problem for SNLP

Recall

$$U(x) = \sup_{\tau \in \mathcal{T}} \mathbb{E}_x[e^{-q\tau}(K - e^{X_\tau})^+]$$

and $\tau^* = \inf\{t > 0 : X_t < k^*\}$,

where

$$k^* = \log(K\mathbb{E}[e^{X_{e_q}}]).$$

McKean Optimal Stopping Problem for SNLP

Recall

$$U(x) = \sup_{\tau \in \mathcal{T}} \mathbb{E}_x[e^{-q\tau}(K - e^{X_\tau})^+]$$

and $\tau^* = \inf\{t > 0 : X_t < k^*\}$,

where

$$k^* = \log(K\mathbb{E}[e^{X_{e_q}}]).$$

Using scale functions (and Wiener–Hopf) we find

$$U(x) = KZ^{(q)}(x - k^*) - e^x Z_1^{(q)}(x - k^*),$$

where

$$k^* = \log\left(K \frac{q}{\Phi(q)} \frac{\Phi(q) - 1}{q - \psi(1)}\right)$$

and where Z_1 plays the role of Z under \mathbb{P}^1 .

Critical delta

Value of McKean OSP

$$U(x) = KZ^{(q)}(x - k^*) - e^x Z_1^{(q)}(x - k^*).$$

Critical delta

Value of McKean OSP

$$U(x) = KZ^{(q)}(x - k^*) - e^x Z_1^{(q)}(x - k^*).$$

When $\delta \geq U(\log K)$ it can be shown that $\sigma^* = \infty$, which implies $V = U$.

Critical delta

Value of McKean OSP

$$U(x) = KZ^{(q)}(x - k^*) - e^x Z_1^{(q)}(x - k^*).$$

When $\delta \geq U(\log K)$ it can be shown that $\sigma^* = \infty$, which implies $V = U$.

When $\delta < U(\log K)$ we always have $U \neq V$, since $V(x) \leq (K - e^x)^+ + \delta$ implies

$$V(\log K) \leq \delta < U(\log K).$$

“Solution” to McKean stochastic game (B. and Kyprianou (2008))

Theorem

Suppose $q > 0$, $0 \leq \psi(1) \leq q$ and $\delta < U(\log K)$.

“Solution” to McKean stochastic game (B. and Kyprianou (2008))

Theorem

Suppose $q > 0$, $0 \leq \psi(1) \leq q$ and $\delta < U(\log K)$. Then

$$\tau^* = \tau_{x^*}^- \text{ and } \sigma^* = \inf\{t > 0 : X_t \in [\log K, y^*]\}$$

where x^* uniquely solves

$$Z^{(q)}(\log K - x) - Z_1^{(q-\psi(1))}(\log K - x) = \frac{\delta}{K},$$

and $y^* \geq \log K$.

“Solution” to McKean stochastic game (B. and Kyprianou (2008))

Theorem

Suppose $q > 0$, $0 \leq \psi(1) \leq q$ and $\delta < U(\log K)$. Then

$$\tau^* = \tau_{x^*}^- \text{ and } \sigma^* = \inf\{t > 0 : X_t \in [\log K, y^*]\}$$

where x^* uniquely solves

$$Z^{(q)}(\log K - x) - Z_1^{(q-\psi(1))}(\log K - x) = \frac{\delta}{K},$$

and $y^* \geq \log K$. The value function is given by

$$V(x) = KZ^{(q)}(x - x^*) - e^x Z_1^{(q-\psi(1))}(x - x^*)$$

for $x \leq \log K$.

“Solution” to McKean stochastic game (B. and Kyprianou (2008))

Theorem

Suppose $q > 0$, $0 \leq \psi(1) \leq q$ and $\delta < U(\log K)$. Then

$$\tau^* = \tau_{x^*}^- \text{ and } \sigma^* = \inf\{t > 0 : X_t \in [\log K, y^*]\}$$

where x^* uniquely solves

$$Z^{(q)}(\log K - x) - Z_1^{(q-\psi(1))}(\log K - x) = \frac{\delta}{K},$$

and $y^* \geq \log K$. The value function is given by

$$V(x) = KZ^{(q)}(x - x^*) - e^x Z_1^{(q-\psi(1))}(x - x^*)$$

for $x \leq \log K$.

When $\sigma = 0$ it holds that $y^* > \log K$.

Point or interval

No jumps, then $y^* = \log K$ (Kyprianou 2004).

Point or interval

No jumps, then $y^* = \log K$ (Kyprianou 2004).

When $\sigma = 0$ we have $y^* > \log K$ (smooth/continuous fit for unbounded/bounded variation).

Point or interval

No jumps, then $y^* = \log K$ (Kyprianou 2004).

When $\sigma = 0$ we have $y^* > \log K$ (smooth/continuous fit for unbounded/bounded variation).

When $\sigma > 0$ either $y^* = \log K$ (continuous fit) or $y^* > \log K$ (smooth fit).

Point or interval

No jumps, then $y^* = \log K$ (Kyprianou 2004).

When $\sigma = 0$ we have $y^* > \log K$ (smooth/continuous fit for unbounded/bounded variation).

When $\sigma > 0$ either $y^* = \log K$ (continuous fit) or $y^* > \log K$ (smooth fit).

Questions: $y^* = \log K$ or $y^* > \log K$ and characterisation of y^* when $y^* > \log K$?

Point or interval

No jumps, then $y^* = \log K$ (Kyprianou 2004).

When $\sigma = 0$ we have $y^* > \log K$ (smooth/continuous fit for unbounded/bounded variation).

When $\sigma > 0$ either $y^* = \log K$ (continuous fit) or $y^* > \log K$ (smooth fit).

Questions: $y^* = \log K$ or $y^* > \log K$ and characterisation of y^* when $y^* > \log K$?

Let $T_{\log K} = \inf\{t \geq 0 : X_t = \log K\}$ and define

$$f_\delta(x) = \sup_{\tau} \mathbb{E}_x[e^{-q\tau}(K - e^{X_\tau})\mathbf{1}_{\{\tau \leq T_{\log K}\}} + \delta e^{-qT_{\log K}}\mathbf{1}_{\{T_{\log K} < \tau\}}]$$

i.e. the optimal value for the maximiser provided the minimiser only exercises when X hits $\log K$.

Point or interval

No jumps, then $y^* = \log K$ (Kyprianou 2004).

When $\sigma = 0$ we have $y^* > \log K$ (smooth/continuous fit for unbounded/bounded variation).

When $\sigma > 0$ either $y^* = \log K$ (continuous fit) or $y^* > \log K$ (smooth fit).

Questions: $y^* = \log K$ or $y^* > \log K$ and characterisation of y^* when $y^* > \log K$?

Let $T_K = \inf t \geq 0 : X_t = \log K$ and define

$$f(x) = \sup \mathbf{E}_x [e^{-q} (K - e^x) \mathbf{1}_{\{t \leq T_K\}} + \delta e^{-qT_K} \mathbf{1}_{\{T_K < t\}}]$$

i.e. the optimal value for the maximiser provided the minimiser only exercises when X hits $\log K$.

Some properties of f_δ

Recall

$$f_\delta(x) = \sup_{\tau} \mathbb{E}_x [e^{-q\tau} (K - e^{X_\tau}) \mathbf{1}_{\{\tau \leq T_{\log K}\}} + \delta e^{-qT_{\log K}} \mathbf{1}_{\{T_{\log K} < \tau\}}]$$

and value function of game

$$V(x) = KZ^{(q)}(x - x^*) - e^x Z_1^{(q-\psi(1))}(x - x^*)$$

for $x \leq \log K$.

Some properties of f_δ

Recall

$$f_\delta(x) = \sup_{\tau} \mathbb{E}_x [e^{-q\tau} (K - e^{X_\tau}) \mathbf{1}_{\{\tau \leq T_{\log K}\}} + \delta e^{-qT_{\log K}} \mathbf{1}_{\{T_{\log K} < \tau\}}]$$

and value function of game

$$V(x) = KZ^{(q)}(x - x^*) - e^x Z_1^{(q-\psi(1))}(x - x^*)$$

for $x \leq \log K$.

Lemma

Suppose $\sigma > 0$ and $0 < \delta \leq U(\log K)$. The function f_δ is differentiable on $\mathbb{R} \setminus \{\log K\}$. Furthermore, $f_\delta = V$ on $(-\infty, \log K]$, $f_\delta \geq V$ on \mathbb{R} and $f'_\delta(\log K+)$ is a strictly decreasing continuous function of δ .

Some properties of f_δ

Recall

$$f_\delta(x) = \sup_{\tau} \mathbb{E}_x [e^{-q\tau} (K - e^{X_\tau}) \mathbf{1}_{\{\tau \leq T_{\log K}\}} + \delta e^{-qT_{\log K}} \mathbf{1}_{\{T_{\log K} < \tau\}}]$$

and value function of game

$$V(x) = KZ^{(q)}(x - x^*) - e^x Z_1^{(q-\psi(1))}(x - x^*)$$

for $x \leq \log K$.

Lemma

Suppose $\sigma > 0$ and $0 < \delta \leq U(\log K)$. The function f_δ is differentiable on $\mathbb{R} \setminus \{\log K\}$. Furthermore, $f_\delta = V$ on $(-\infty, \log K]$, $f_\delta \geq V$ on \mathbb{R} and $f'_\delta(\log K+)$ is a strictly decreasing continuous function of δ .

Proof makes use of scale function results for exit problems for SNLPs.

Point-interval

Theorem

Suppose $\sigma > 0$. When $\Pi \neq 0$, then there exists a unique $\delta_0 \in (0, U(\log K))$ such that an optimal stopping time for the minimiser is given by

- $T_{\log K}$ when $\delta \in [\delta_0, U(\log K)]$,
- $T_{[\log K, y^*(\delta)]}$ for some $y^*(\delta) > \log K$ when $\delta \in (0, \delta_0)$.

Point-interval

Theorem

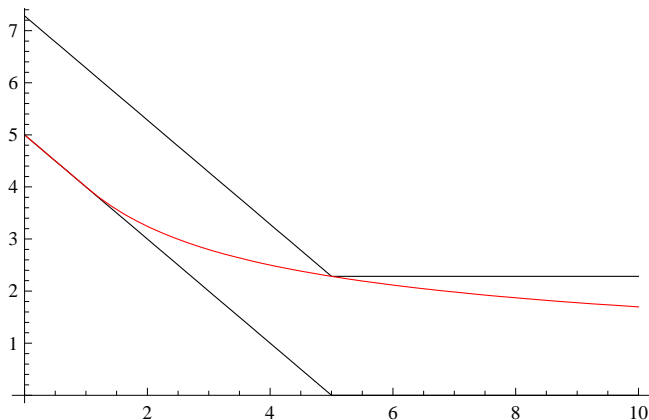
Suppose $\sigma > 0$. When $\Pi \neq 0$, then there exists a unique $\delta_0 \in (0, U(\log K))$ such that an optimal stopping time for the minimiser is given by

- $T_{\log K}$ when $\delta \in [\delta_0, U(\log K)]$,
- $T_{[\log K, y^*(\delta)]}$ for some $y^*(\delta) > \log K$ when $\delta \in (0, \delta_0)$.

Proof mostly based on the previous lemma.

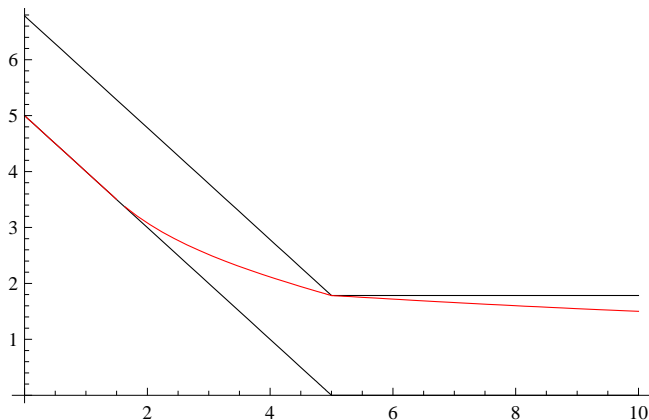
$$\sigma > 0$$

For $\delta = U(\log K)$ we have $f'_\delta(\log K+) < 0$.



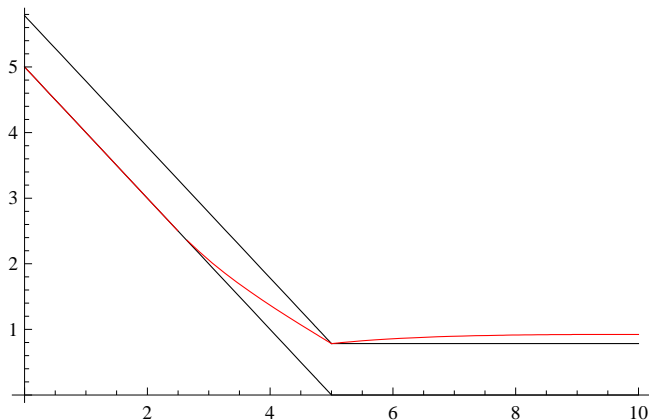
$$\sigma > 0$$

For $\delta \in (\delta_0, U(\log K))$ we have $f'_\delta(\log K+) < 0$.



$$\sigma > 0$$

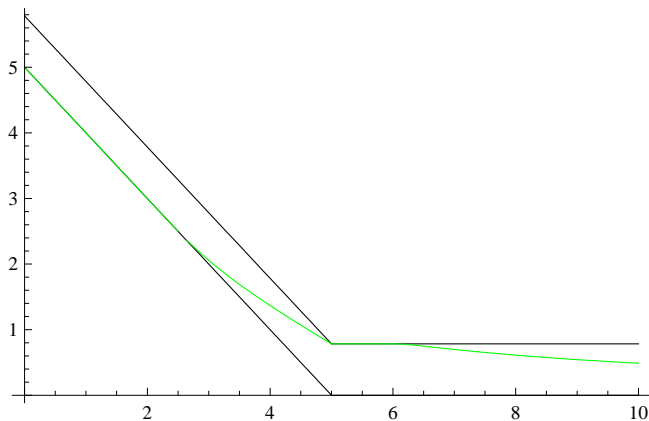
For $\delta < \delta_0$ we have $f'_\delta(\log K+) > 0$



Upper bound violated $\implies y^* > \log K$

$$\sigma > 0$$

$\delta < \delta_0$, actual value function:



Equations for δ_0 and y^*

Define

$$w_\delta(x) = \begin{cases} V(x) & \text{for } x < \log K \\ \delta & \text{for } x \geq \log K. \end{cases}$$

Equations for δ_0 and y^*

Define

$$w_\delta(x) = \begin{cases} V(x) & \text{for } x < \log K \\ \delta & \text{for } x \geq \log K. \end{cases}$$

Theorem

Suppose $\Pi \neq 0$.

(i) Suppose $\sigma > 0$. Then δ_0 is the unique solution on $(0, U(\log K))$ to

$$\int_{t < 0} \int_{u < t} (w_\delta(t + \log K) - \delta) e^{-\Phi(q)(t-u)} \Pi(du) dt = \frac{\delta q}{\Phi(q)}.$$

Equations for δ_0 and y^*

Define

$$w_\delta(x) = \begin{cases} V(x) & \text{for } x < \log K \\ \delta & \text{for } x \geq \log K. \end{cases}$$

Theorem

Suppose $\Pi \neq 0$.

(i) Suppose $\sigma > 0$. Then δ_0 is the unique solution on $(0, U(\log K))$ to

$$\int_{t < 0} \int_{u < t} (w_\delta(t + \log K) - \delta) e^{-\Phi(q)(t-u)} \Pi(du) dt = \frac{\delta q}{\Phi(q)}.$$

(ii) Suppose $y^* > \log K$. Then y^* is the unique solution on $(\log K, \infty)$ to

$$\int_{t < 0} \int_{u < t} (w_\delta(t + y) - \delta) e^{-\Phi(q)(t-u)} \Pi(du) dt = \frac{\delta q}{\Phi(q)}.$$

Equations for δ_0 and y^*

Define

$$w_\delta(x) = \begin{cases} V(x) & \text{for } x < \log K \\ \delta & \text{for } x \geq \log K. \end{cases}$$

Theorem

Suppose $\Pi \neq 0$.

(i) Suppose $\sigma > 0$. Then δ_0 is the unique solution on $(0, U(\log K))$ to

$$\int_{t < 0} \int_{u < t} (w_\delta(t + \log K) - \delta) e^{-\Phi(q)(t-u)} \Pi(du) dt = \frac{\delta q}{\Phi(q)}.$$

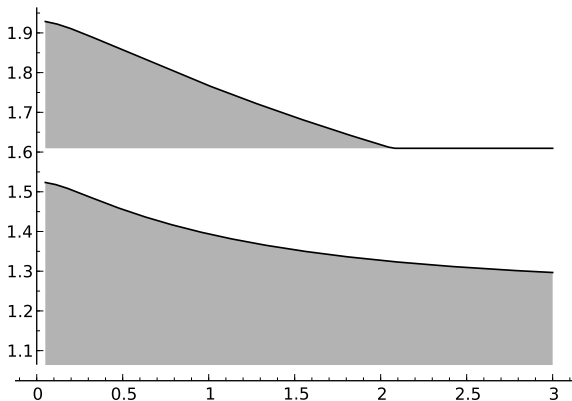
(ii) Suppose $y^* > \log K$. Then y^* is the unique solution on $(\log K, \infty)$ to

$$\int_{t < 0} \int_{u < t} (w_\delta(t + y) - \delta) e^{-\Phi(q)(t-u)} \Pi(du) dt = \frac{\delta q}{\Phi(q)}.$$

Proof makes use of compensation formula, potential measure of X , and smooth/continuous fit

Stopping regions as a function of σ

When $\sigma > 0$ and exponential jumps, stopping region for minimiser (top one) and maximiser (bottom one) as a function of σ .



Conclusion

- Solution of the McKean stochastic game for SNLP.

Conclusion

- Solution of the McKean stochastic game for SNLP.
- Stopping region for maximiser of the form $(-\infty, x^*]$.

Conclusion

- Solution of the McKean stochastic game for SNLP.
- Stopping region for maximiser of the form $(-\infty, x^*]$.
- Stopping region for the minimiser $\{\log K\}$ when $\sigma > 0$ and $\delta < \delta_0$.

Conclusion

- Solution of the McKean stochastic game for SNLP.
- Stopping region for maximiser of the form $(-\infty, x^*]$.
- Stopping region for the minimiser $\{\log K\}$ when $\sigma > 0$ and $\delta < \delta_0$.
- Otherwise, stopping region for the minimiser $[\log K, y^*]$, with $y^* > \log K$ solution to equation involving scale functions.

Some references

- B. and KYPRIANOU, A.E. (2008). The McKean stochastic game driven by a spectrally negative Lévy process. *Elec. J. Probab.* **8** 173–197.
- B. and VAN SCHAIK, K. (2011). Further calculations for the McKean stochastic game: from a point to an interval. *To appear in J. Appl. Probab.*
- EKSTRÖM, E. and PESKIR, G. (2008). *SIAM J. Control Optim.* **47** 684–702.
- KYPRIANOU, A.E. (2004). Some calculations for Israeli options. *Finance Stoch.* **8** 73–86.
- MORDECKI, E. (2002) Optimal stopping and perpetual options for Lévy processes. *Finance Stoch. Stoch.* **6** 473–493.