

# Maximum principles for jump diffusion processes with infinite horizon

Sven Haadem\*, Frank Proske† and Bernt Øksendal‡

8 May 2012

Keywords: Optimal control; Lévy processes; Maximum principle; Hamiltonian; Infinite horizon; Adjoint process; Partial information

2010 Mathematics Subject Classification:  
Primary 93EXX; 93E20; 60J75  
Secondary 60H10; 60H20; 49J55

## Abstract

We prove maximum principles for the problem of optimal control for a jump diffusion with infinite horizon and partial information. The results are applied to partial information optimal consumption and portfolio problems in infinite horizon.

## 1 Introduction

In this paper we consider a control problem for a performance functional

$$J(u) = E \left[ \int_0^\infty f(t, X(t), u(t), \omega) dt \right],$$

where  $X(t)$  is a controlled jump diffusion and  $u(t)$  is the control process. We allow for the case where the controller only has access to partial-information. Thus, we have a infinite horizon problem with partial information. Infinite-horizon optimal control problems arise in many fields of economics, in particular in models of economic growth. Note that because of the general nature of the partial information filtration  $\mathcal{E}_t$ , we cannot use dynamic programming and Hamilton-Jacobi-Bellman (HJB) equations to solve the optimization problem. Thus our problem is different from partial observation control problems.

---

\*Center of Mathematics for Applications (CMA), University of Oslo, Box 1053 Blindern, N-0316 Oslo, Norway. Email: sven.haadem@cma.uio.no

†Center of Mathematics for Applications (CMA), University of Oslo, Box 1053 Blindern, N-0316 Oslo, Norway. Email: proske@math.uio.no

‡Center of Mathematics for Applications (CMA), University of Oslo, Box 1053 Blindern, N-0316 Oslo, Norway. The research leading to these results has received funding from the European Research Council under the European Community's Seventh Framework Programme (FP7/2007-2013) / ERC grant agreement no [228087]. Email: oksendal@math.uio.no

In the deterministic case the maximum principle by Pontryagin (1962) has been extended to infinite-horizon problems, but transversality conditions have not been given in general. The 'natural' transversality condition in the infinite case would be a zero limit condition, meaning in the economic sense that one more unit of good at the limit gives no additional value. But this property is not necessarily verified. In fact [4] provides a counterexample for a 'natural' extension of the finite-horizon transversality conditions. Thus some care is needed in the infinite horizon case.

There have been a variety of articles on infinite-horizon problems. E.g. in [6] it is stated a 'natural' extension to infinite horizon discounted control problems.

We refer to [13] for more information about stochastic control in jump diffusion markets, to [8] for a background on infinite-horizon backward stochastic differential equations and [11] for a general introduction to infinite-horizon control problems in a deterministic environment.

In this paper we prove several maximum principles for an infinite horizon optimal control problem with partial information. The paper is structured as follows: In Section 4 we prove a maximum principle version of sufficient type (a verification theorem). In section 5 we give some examples, before we prove a (weak) version of a necessary type of the maximum principle in section 6.

In a forthcoming paper [1], the case of infinite horizon for delay equations is treated.

## 2 Preliminaries

Let  $B(t) = B(t, \omega) = (B_1(t, \omega), \dots, B_n(t, \omega))$ ,  $t \geq 0$ ,  $\omega \in \Omega$  and  $\tilde{N}(dz, dt) = N(dz, dt) - \nu(dz)dt = (\tilde{N}_1(dz, dt), \dots, \tilde{N}_n(dz, dt))$  be a  $n$ -dimensional Brownian motion and  $n$  independent compensated Poisson random measures, respectively, on a filtered probability space  $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t \geq 0}, P)$ . Let  $X(t) = X^u(t)$  be a controlled jump diffusion, described by the stochastic differential equation

$$\begin{aligned} dX(t) &= b(t, X(t), u(t), \omega)dt + \sigma(t, X(t), u(t), \omega)dB(t) \\ &\quad + \int_{\mathbb{R}_0^n} \theta(t, X(t), u(t), z, \omega) \tilde{N}(dz, dt); 0 \leq t < \infty \\ X(0) &= x \in \mathbb{R}^n, \end{aligned} \tag{1}$$

where  $b : [0, \infty] \times \mathbb{R}^n \times U \times \Omega \rightarrow \mathbb{R}^n$  is adapted,  $\sigma : [0, \infty] \times \mathbb{R}^n \times U \times \Omega \rightarrow \mathbb{R}^{n \times n}$  is adapted and  $\theta : [0, \infty] \times \mathbb{R}^n \times U \times \Omega \rightarrow \mathbb{R}^{n \times n}$  is predictable (see [9]). See e.g. [2], [13] for notation and more information. Let

$$\mathcal{E}_t \subset \mathcal{F}_t,$$

be a given subfiltration, representing the information available to the controller at time  $t$ ;  $t \geq 0$ . The process  $u(t)$  is our control, assumed to be  $\{\mathcal{E}_t\}_{t \geq 0}$  predictable and with values in a set  $U \subset \mathbb{R}^n$ . Let  $\mathcal{A}_{\mathcal{E}}$  be our family of  $\mathcal{E}_t$ -predictable

controls. Let  $\mathcal{R}$  denote the set of functions  $r : [0, \infty] \times \mathbb{R}_0^n \rightarrow \mathbb{R}^{n \times n}$  such that

$$\int_{\mathbb{R}_0^n} |\theta_{i,j}(t, x, u, z) r_{i,j}(t, z)| \nu_j(dz) < \infty \text{ for all } i, j, t, x.$$

Let  $f : [0, \infty] \times \mathbb{R}^n \times U \times \Omega \rightarrow \mathbb{R}^n$  be adapted and assume that

$$E \left[ \int_0^\infty |f(t, X(t), u(t), \omega)| dt \right] < \infty \text{ for all } u \in \mathcal{A}_{\mathcal{E}}.$$

Then we define

$$J(u) = E \left[ \int_0^\infty f(t, X(t), u(t), \omega) dt \right]$$

to be our performance functional. We study the problem to find  $\hat{u} \in \mathcal{A}_{\mathcal{E}}$  such that

$$J(\hat{u}) = \sup_{u \in \mathcal{A}_{\mathcal{E}}} J(u). \quad (2)$$

Let us define the Hamiltonian  $H : [0, T] \times \mathbb{R}^n \times U \times \mathbb{R}^n \times \mathbb{R}^{n \times n} \times \mathcal{R} \rightarrow \mathbb{R}$ , by

$$\begin{aligned} H(t, x, u, p, q, r) &= f(t, x, u, \omega) + b^T(t, x, u, \omega)p + \text{tr}(\sigma^T(t, x, u, \omega)q) \\ &+ \sum_{i,j=1}^n \int_{\mathbb{R}_0^n} \theta_{i,j}(t, x, u, z, \omega) r_{i,j}(t, z) \nu_j(dz). \end{aligned} \quad (3)$$

For notational convenience we will in the rest of the paper suppress any  $\omega$  from the notation. The adjoint equation in the unknown  $\mathcal{F}_t$ -predictable processes  $(p(t), q(t), r(t, z))$  is the following

$$\begin{aligned} dp(t) &= -\nabla_x H(t, X(t), \hat{u}(t), p(t), q(t), r(t, \cdot)) dt + q(t) dB(t) \\ &+ \int_{\mathbb{R}_0^n} r(t, z) \tilde{N}(dz, dt). \end{aligned} \quad (4)$$

### 3 Existence and Uniqueness

In this section we prove a result about existence and uniqueness of the solution  $(Y(t), Z(t), K(t, \zeta))$  of infinite horizon BSDEs of the form;

$$\begin{aligned} dY(t) &= -g(t, Y(t), Z(t), K(t, \cdot)) dt + Z(t) dB(t) \\ &+ \int_{\mathbb{R}_0^n} K(t, \zeta) \tilde{N}(d\zeta, dt); 0 \leq t \leq \tau, \end{aligned} \quad (5)$$

$$\lim_{t \rightarrow \tau} Y(t) = \xi(\tau) \mathbf{1}_{[0, \infty)}(\tau), \quad (6)$$

where  $\tau \leq \infty$  is a given  $\mathcal{F}_t$ -stopping time, possibly infinite. Our result is an extension to jumps of Theorem 4.1 in [7], Theorem 4 in [8] and Theorem 3.1 in [15]. It is also an extension to infinite horizon of Theorem Lemma 2.1 in [5]. See also [14], [10], [3] and [12]. We assume the following:

1. The function  $g : \Omega \times \mathbb{R}_+ \times \mathbb{R}^k \times \mathbb{R}^{k \times d} \times \mathcal{R} \rightarrow \mathbb{R}^k$  is such that there exist real numbers  $\mu, \lambda, K_1$  and  $K_2$ , such that  $K_1, K_2 > 0$  and

$$\lambda > 2\mu + K_1^2 + K_2^2. \quad (7)$$

We assume that the function  $g$  satisfies the following requirements:

- (a)  $g(\cdot, y, z, k)$  is progressively measurable for all  $y, z, k$ , and

$$|g(t, y, z, k(\cdot)) - g(t, y, z', k'(\cdot))| \leq K_1 \|z - z'\| + K_2 \|k(\cdot) - k'(\cdot)\|_R, \quad (8)$$

where

$$\|k(\cdot)\|_R^2 = \int_{\mathbb{R}_0^n} k^2(\zeta) \nu(d\zeta),$$

and  $\|z\| = [\text{Tr}(zz^*)]^{1/2}$ .

- (b)

$$\langle y - y', g(t, y, z, k) - g(t, y', z, k) \rangle \leq \mu |y - y'|^2 \quad (9)$$

for all  $y, y', z, k$  a.s.

- (c)

$$E \int_0^\tau e^{\lambda t} |g(t, 0, 0, 0)|^2 dt < \infty. \quad (10)$$

- (d) Finally we require that

$$y \mapsto g(t, y, z, k), \quad (11)$$

is continuous for all  $t, z, k$  a.s.

2. We have a final condition  $\xi$ , which is  $\mathcal{F}_\tau$ -measurable such that  $E(e^{\lambda\tau} |\xi|^2) < \infty$  and

$$E \int_0^\tau e^{\lambda t} |g(t, \xi_t, \eta_t, \psi_t)|^2 dt < \infty, \quad (12)$$

where  $\xi_t = E(\xi | \mathcal{F}_t)$  and  $\eta, \psi$  are s.t.

$$\xi = E\xi + \int_0^t \eta(s) dB_s + \int_0^t \int_{\mathbb{R}_0^n} \psi(s, \zeta) \tilde{N}(d\zeta, ds). \quad (13)$$

A solution of the BSDE (5)-(6), is a trippel  $(Y_t, Z_t, K_t)$  of progressively measurable processes with values in  $\mathbb{R} \times \mathbb{R} \times \mathbb{R}$  s.t.  $Z_t, K_t = 0$  when  $t > \tau$ ,

1.  $E[\sup_{t \geq 0} e^{\lambda t} |Y_t|^2 + \int_0^\tau e^{\lambda s} |Z_s|^2 ds + \int_0^\tau \int_{\mathbb{R}_0^n} e^{\lambda s} K^2(s, \zeta) \nu(d\zeta) ds] < \infty$ ,
2.  $Y_t = Y_{T \wedge \tau} + \int_{t \wedge \tau}^{T \wedge \tau} g_s ds - \int_{t \wedge \tau}^{T \wedge \tau} Z_s dB_s - \int_{t \wedge \tau}^{T \wedge \tau} \int_{\mathbb{R}_0^n} K(s, \zeta) \tilde{N}(d\zeta, ds)$  for all deterministic  $T < \infty$  and
3.  $Y_t = \xi$  on the set  $\{t \geq \tau\}$ .

*Remark 3.1 (Infinite Horizon).* This incorporates the case where  $\tau(\omega) = \infty$  on some set  $A$  with  $P(A) > 0$ , possibly  $P(A) = 1$ .

**Theorem 3.1 (Existence and uniqueness).** *Under the above conditions there exists a unique solution  $(Y_t, Z_t, K_t)$  of the BSDE (5)-(6), which satisfies the condition;*

$$\begin{aligned} & E\left[\sup_{0 \leq t \leq \tau} e^{\lambda t} |Y_t|^2 + \int_0^\tau e^{\lambda s} (|Y_s|^2 + \|Z_s\|^2) ds + \int_0^\tau e^{\lambda s} \int_{\mathbb{R}_0^n} K^2(s, \zeta) \nu(d\zeta) ds\right] \\ & \leq cE[e^{\lambda \tau} |\xi|^2 + \int_0^\tau e^{\lambda s} |g(s, 0, 0, 0)|^2 ds], \end{aligned} \quad (14)$$

for some positive number  $c$ .

*Proof.* First, let us show uniqueness. Let  $(Y, Z, K)$  and  $(Y', Z', K')$  be two solutions satisfying (14) and let  $(\bar{Y}, \bar{Z}, \bar{K}) = (Y - Y', Z - Z', K - K')$ . From Itô's Lemma we have that

$$\begin{aligned} & e^{\lambda t \wedge \tau} |\bar{Y}_{t \wedge \tau}|^2 + \int_{t \wedge \tau}^{T \wedge \tau} \left[ e^{\lambda s} (\lambda |\bar{Y}_s|^2 + \|\bar{Z}_s\|^2) + e^{\lambda s} \int_{\mathbb{R}_0^n} \bar{K}^2(s, \zeta) \nu(d\zeta) \right] ds \\ & \leq e^{\lambda s} |\bar{Y}_T|^2 + 2 \int_{t \wedge \tau}^{T \wedge \tau} \left[ e^{\lambda s} (\mu |\bar{Y}_s|^2 + K_1 |\bar{Y}_s| \times \|\bar{Z}_s\|) \right. \\ & \quad \left. + K_2 |\bar{Y}_s| e^{\lambda s} \left( \int_{\mathbb{R}_0^n} \bar{K}^2(s, \zeta) \nu(d\zeta) \right)^{\frac{1}{2}} \right] ds \\ & \quad - 2 \int_{t \wedge \tau}^{T \wedge \tau} e^{\lambda s} \langle \bar{Y}_s, \bar{Z}_s dB_s \rangle \\ & \quad - \int_{t \wedge \tau}^{T \wedge \tau} e^{\lambda s} \int_{\mathbb{R}_0^n} [\bar{K}^2(s, \zeta) + 2\bar{K}(s, \zeta) \bar{Y}(s)] \tilde{N}(d\zeta, ds). \end{aligned}$$

Combining the above with the fact that  $2ab \leq a^2 + b^2$  we deduce since  $\lambda > 2\mu + K_1^2 + K_2^2$ , that for  $t < T$

$$E[e^{\lambda t \wedge \tau} |\bar{Y}_{t \wedge \tau}|^2] \leq E[e^{\lambda T \wedge \tau} |\bar{Y}_T|^2]$$

the same holds with  $\lambda$  replaced by  $\lambda'$ , with  $\lambda > \lambda' > 2\mu + K_1^2 + K_2^2$

$$E[e^{\lambda' t \wedge \tau} |\bar{Y}_{t \wedge \tau}|^2] \leq e^{(\lambda - \lambda')T} E[e^{\lambda T \wedge \tau} |\bar{Y}_T|^2 \mathbf{1}_{\{T < \tau\}}]$$

Condition (14) implies that the second factor on the right hand side remains bounded as  $T \rightarrow \infty$ , while the first factor tends to 0. This proves uniqueness.

*Proof of existence.* For each  $n \in \mathbb{N}$  we construct a solution  $(Y_t^n, Z_t^n, K_t^n)$  of the BSDE

$$Y_t^n = \xi + \int_{t \wedge \tau}^{n \wedge \tau} g(s, Y_s^n, Z_s^n, K_s^n) ds - \int_{t \wedge \tau}^\tau Z_s^n dB_s - \int_{t \wedge \tau}^\tau \int_{\mathbb{R}_0^n} K^n(s, \zeta) \tilde{N}(d\zeta, ds)$$

by letting  $\{(Y_t^n, Z_t^n, K_t^n); 0 \leq t \leq n\}$  be defined as a solution of the following BSDE:

$$Y_t^n = E[\xi | \mathcal{F}_t^n] + \int_t^n \mathbf{1}_{[0, \tau]}(s) g(s, Y_s^n, Z_s^n, K_s^n) ds - \int_t^n Z_s^n dB_s - \int_t^n \int_{\mathbb{R}_0^n} K^n(s, \zeta) \tilde{N}(d\zeta, ds)$$

for  $0 \leq t \leq n$  and  $\{(Y_t^n, Z_t^n, K_t^n); t \geq n\}$  defined by

$$Y_t^n = \xi_t,$$

$$Z_t^n = \eta_t,$$

and

$$K_t^n = \psi_t,$$

for  $t > n$ . Next, we find some a priori estimates for the sequence  $(Y^n, Z^n, K^n)$ . For any  $\epsilon > 0$ ,  $\rho < 1$  and  $\alpha$  we have for all  $t \geq 0$ ,  $y \in \mathbb{R}^k$ ,  $z \in \mathbb{R}^{k \times d}$ ,  $k \in \mathcal{R}$  with  $c = \frac{1}{\epsilon}$ ,

$$\begin{aligned} 2\langle y, g(t, y, z, k) \rangle &= 2\langle y, g(t, y, z, k) - g(t, 0, z, k) \rangle \\ &\quad + 2\langle y, g(t, 0, z, k) - g(t, 0, 0, 0) \rangle + 2\langle y, g(t, 0, 0, 0) \rangle \\ &\leq (2\mu + \frac{1}{\rho}K_1^2 + \frac{1}{\alpha}K_2^2 + \epsilon)|y|^2 + \rho \|z\|^2 + \alpha \int_{\mathbb{R}_0^n} k^2(\zeta) \nu(d\zeta) \\ &\quad + c|g(t, 0, 0, 0)|^2. \end{aligned}$$

From Itô's Lemma we have

$$\begin{aligned} e^{\lambda t \wedge \tau} |Y_{t \wedge \tau}^n|^2 &+ \int_{t \wedge \tau}^{\tau} \left[ e^{\lambda s} (\bar{\lambda} |Y_s^n|^2 + \bar{\rho} \|Z_s^n\|^2) + \bar{\alpha} \int_{\mathbb{R}_0^n} e^{\lambda s} (K^n)^2(s, \zeta) \nu(d\zeta) \right] ds \\ &\leq e^{\lambda s} |\eta|^2 + c \int_{t \wedge \tau}^{\tau} e^{\lambda s} |g(s, 0, 0, 0)|^2 ds \\ &\quad - 2 \int_{t \wedge \tau}^{\tau} e^{\lambda s} \langle Y_s^n, Z_s^n dB_s \rangle \\ &\quad - \int_{t \wedge \tau}^{\tau} e^{\lambda s} \int_{\mathbb{R}_0^n} [(K^n)^2(s, \zeta) + 2K^n(s, \zeta) Y^n(s)] \tilde{N}(d\zeta, ds), \end{aligned}$$

with  $\bar{\lambda} = \lambda - 2\mu - \frac{1}{\rho}K_1^2 - \frac{1}{\alpha}K_2^2 - \epsilon > 0$ ,  $\bar{\rho} = 1 - \rho > 0$  and  $\bar{\alpha} = 1 - \alpha$ . From this and the martingale inequality it follows that

$$\begin{aligned} E \left[ \sup_{t \geq s} e^{\lambda t \wedge \tau} |Y_{t \wedge \tau}^n|^2 + \int_{s \wedge \tau}^{\tau} \left[ e^{\lambda r} (|Y_r^n|^2 + \|Z_r^n\|^2) + e^{\lambda r} \int_{\mathbb{R}_0^n} (K^n)^2(r, \zeta) \nu(d\zeta) \right] dr \right] \\ \leq 4E \left[ e^{\lambda \tau} |\xi|^2 + \int_{s \wedge \tau}^{\tau} e^{\lambda r} |g(r, 0, 0, 0)|^2 dr \right]. \end{aligned}$$

Let  $m > n$  and define  $\Delta Y_t := Y_t^m - Y_t^n$ ,  $\Delta Z_t := Z_t^m - Z_t^n$  and  $\Delta K_t := K_t^m - K_t^n$ , so that for  $n \leq t \leq m$ ,

$$\Delta Y_t = \int_{t \wedge \tau}^{m \wedge \tau} g(s, Y_s^m, Z_s^m, K_s^m) ds - \int_{t \wedge \tau}^{m \wedge \tau} \Delta Z_s dB_s - \int_{t \wedge \tau}^{m \wedge \tau} \int_{\mathbb{R}_0^n} \Delta K(s, \zeta) \tilde{N}(d\zeta, ds).$$

It then follows that

$$\begin{aligned}
& e^{\lambda t \wedge \tau} |\Delta Y_{t \wedge \tau}|^2 + \int_{t \wedge \tau}^{m \wedge \tau} \left\{ e^{\lambda s} (\lambda |\Delta Y_s|^2 + \|\Delta Z_s\|^2) + e^{\lambda s} \int_{\mathbb{R}_0^n} (\Delta K)^2(s, \zeta) \nu(d\zeta) \right\} ds \\
&= \int_{t \wedge \tau}^{m \wedge \tau} e^{\lambda s} \langle \Delta Y_s, g(s, Y_s^m, Z_s^m, K_s^m) \rangle ds \\
&\quad - 2 \int_{t \wedge \tau}^{m \wedge \tau} e^{\lambda s} \langle \Delta Y_s, \Delta Z_s dB_s \rangle \\
&\quad - \int_{t \wedge \tau}^{m \wedge \tau} e^{\lambda s} \int_{\mathbb{R}_0^n} [(\Delta K)^2(s, \zeta) + 2\Delta K(s, \zeta) \Delta Y(s)] \tilde{N}(d\zeta, ds) \\
&\leq e^{\lambda s} |\eta|^2 c \int_{t \wedge \tau}^{m \wedge \tau} e^{\lambda s} |g(s, 0, 0, 0)|^2 ds - 2 \int_{t \wedge \tau}^{m \wedge \tau} e^{\lambda s} \langle \Delta Y_s, \Delta Z_s dB_s \rangle \\
&\quad - \int_{t \wedge \tau}^{m \wedge \tau} e^{\lambda s} \int_{\mathbb{R}_0^n} [(\Delta K)^2(s, \zeta) + 2\Delta K(s, \zeta) \Delta Y(s)] \bar{N}(d\zeta, ds).
\end{aligned}$$

From the same arguments as above

$$\begin{aligned}
& E \left[ \sup_{n \leq t \leq m} e^{\lambda t \wedge \tau} |\Delta Y_{t \wedge \tau}|^2 \right. \\
& \quad \left. + \int_{n \wedge \tau}^{m \wedge \tau} \left\{ e^{\lambda s} (\lambda |\Delta Y_s|^2 + \|\Delta Z_s\|^2) + e^{\lambda s} \int_{\mathbb{R}_0^n} (\Delta K)^2(s, \zeta) \nu(d\zeta) \right\} ds \right] \\
& \leq 4E \left[ \int_{n \wedge \tau}^{\tau} e^{\lambda s} |g(s, \xi, \eta, \psi)|^2 ds \right].
\end{aligned}$$

The last term in the above equation goes to zero as  $n \rightarrow \infty$ . Now, for  $t \leq n$

$$\begin{aligned}
\Delta Y_t &= \Delta Y_n + \int_{t \wedge \tau}^{n \wedge \tau} \left\{ g(s, Y_s^m, Z_s^m, K_s^m) - g(s, Y_s^n, Z_s^n, K_s^n) \right\} ds - \int_{t \wedge \tau}^{n \wedge \tau} \Delta Z_s dB_s \\
&\quad - \int_{t \wedge \tau}^{n \wedge \tau} \int_{\mathbb{R}_0^n} \Delta K(s, \zeta) \tilde{N}(d\zeta, ds).
\end{aligned}$$

Using the same argument as in the case of uniqueness, we have that

$$E[e^{\lambda t \wedge \tau} |\Delta Y_{t \wedge \tau}|^2] \leq E[e^{\lambda t \wedge \tau} |\Delta Y_n|^2] \leq cE \left[ \int_{n \wedge \tau}^{\tau} e^{\lambda s} |g(s, \xi_s, \eta_s, \psi_s)|^2 ds \right].$$

It now follows that the sequence  $(Y^n, Z^n, K^n)$  is Cauchy in the norm

$$\begin{aligned}
\|(Y, Z, K)\| &:= E \left[ \sup_{0 \leq t \leq \tau} e^{\lambda t} |Y_t|^2 + \int_0^{\tau} e^{\lambda s} (|Y_s|^2 + \|Z_s\|^2) ds \right. \\
&\quad \left. + \int_0^{\tau} e^{\lambda s} \int_{\mathbb{R}_0^n} K^2(s, \zeta) \nu(d\zeta) ds \right].
\end{aligned}$$

So, we have that there is a unique solution to the BSDE (5)-(6), which satisfies for all  $\lambda > 2\mu + K_1^2 + K_2^2$ , the condition

$$\begin{aligned}
& E \left[ \sup_{0 \leq t \leq \tau} e^{\lambda t} |Y_t|^2 + \int_0^{\tau} e^{\lambda s} (|Y_s|^2 + \|Z_s\|^2) ds + \int_0^{\tau} e^{\lambda s} \int_{\mathbb{R}_0^n} K^2(s, \zeta) \nu(d\zeta) ds \right] \\
& \leq cE \left[ e^{\lambda \tau} |\xi|^2 + \int_0^{\tau} e^{\lambda s} |g(s, 0, 0, 0)|^2 ds \right].
\end{aligned}$$

□

## 4 Optimal control with partial information and infinite horizon

Now, let us get back to the problem of maximizing the performance functional

$$J(u) = E \left[ \int_0^\infty f(t, X(t), u(t)) dt \right],$$

where  $X(t)$  is of the form (1). Our aim is to find a  $\hat{u} \in \mathcal{A}_\mathcal{E}$  such that

$$J(\hat{u}) = \sup_{u \in \mathcal{A}_\mathcal{E}} J(u),$$

where  $u(t)$  is our previsible control adapted to a subfiltration

$$\mathcal{E}_t \subset \mathcal{F}_t,$$

with values in a set  $U \subset \mathbb{R}^n$ . Let  $H$  be the Hamiltonian defined by (3) and  $p$  the solution to the adjoint equation (4). Then we have the following maximum principle;

**Theorem 4.1 (Sufficient Infinite Horizon Maximum Principle).** *Let  $\hat{u} \in \mathcal{A}_\mathcal{E}$  and let  $(\hat{p}(t), \hat{q}(t), \hat{r}(t, z))$  be an associated solution to the equation (4). Assume that for all  $u \in \mathcal{A}_\mathcal{E}$  the following terminal condition holds:*

$$0 \leq E \left[ \overline{\lim}_{t \rightarrow \infty} [\hat{p}(t)^T (X(t) - \hat{X}(t))] \right] < \infty. \quad (15)$$

Moreover, assume that  $H(t, x, u, \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot))$  is concave in  $x$  and  $u$  and

$$\begin{aligned} & E \left[ H(t, \hat{X}(t), \hat{u}(t), \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot)) | \mathcal{E}_t \right] \\ &= \max_{u \in U} E \left[ H(t, \hat{X}(t), u, \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot)) | \mathcal{E}_t \right]. \end{aligned} \quad (16)$$

In addition we assume that

$$E \left[ \int_0^\infty (\hat{X}(t) - X^u(t))^T [\hat{q}\hat{q}^T + \int_{\mathbb{R}_0^n} \hat{r}\hat{r}^T(t, z) \nu(dz)] (\hat{X}(t) - X^u(t)) dt \right] < \infty, \quad (17)$$

$$E \left[ \int_0^\infty \hat{p}(t)^T [\sigma\sigma^T(t, X(t), u(t)) + \int_{\mathbb{R}_0^n} \theta\theta^T(t, X(t), u(t)) \nu(dz)] p(t) dt \right] < \infty, \quad (18)$$

$$E \left[ |\nabla_u H(t, \hat{X}(t), \hat{u}(t), \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot))|^2 \right] < \infty, \quad (19)$$

and that

$$E \left[ \int_0^\infty |H(s, X(s), u(s), \hat{p}(s), \hat{q}(s), \hat{r}(s, \cdot))| \right] < \infty \quad (20)$$

for all  $u$ .

Then we have that  $\hat{u}(t)$  is optimal.



*Remark 4.1.* Note that, since  $p(t)$  has the economic interpretation as the marginal value of the resource (alternatively the shadow price if representing an outside resource), the requirement

$$0 \leq E \left[ \overline{\lim}_{t \rightarrow \infty} [\hat{p}(t)^T (X(t) - \hat{X}(t))] \right] < \infty,$$

has the economic interpretation that if the marginal value is positive at infinity we want to have as little resources left as possible.

*Remark 4.2.* The requirement in the finite horizon case that  $p(T) = 0$  does not translate into  $\lim_{T \rightarrow \infty} p(T) = 0$  as was shown in the deterministic case in [4].

*Proof.* Let  $I^\infty := E[\int_0^\infty (f(t, X(t), u(t)) - f(t, \hat{X}(t), \hat{u}(t)))dt] = J(u) - J(\hat{u})$ . Then  $I^\infty = I_1^\infty - I_2^\infty - I_3^\infty - I_4^\infty$ , where

$$\begin{aligned} I_1^\infty &:= E \left[ \int_0^\infty (H(s, X(s), u(s), \hat{p}(s), \hat{q}(s), \hat{r}(s, \cdot)) \right. \\ &\quad \left. - H(t, \hat{X}(s), \hat{u}(t), \hat{p}(s), \hat{q}(s), \hat{r}(s, \cdot)))ds \right], \\ I_2^\infty &:= E \left[ \int_0^\infty \hat{p}(s)^T (b(s, X(s), u(s)) - \hat{b}(s, \hat{X}(s), \hat{u}(s)))ds \right], \\ I_3^\infty &:= E \left[ \int_0^\infty \text{tr}[q(s)^T (\sigma(s, X(s), u(s)) - \hat{\sigma}(s, \hat{X}(s), \hat{u}(s)))]ds \right], \end{aligned}$$

and

$$\begin{aligned} I_4^\infty &:= E \left[ \int_0^\infty \sum_{i,j} \int_{\mathbb{R}_0^n} (\theta(s, X(s), u(s), z) \right. \\ &\quad \left. - \hat{\theta}(s, \hat{X}(s), \hat{u}(s), z))^T \hat{r}_{i,j}(s, z) \nu_j(dz) ds \right]. \end{aligned}$$

We have from concavity that

$$H(t, X(t), u(t), \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot)) - H(t, \hat{X}(t), \hat{u}(t), \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot)) \quad (21)$$

$$\begin{aligned} &\leq \nabla_x H(t, \hat{X}(t), \hat{u}(t), \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot))^T (X(t) - \hat{X}(t)) \\ &+ \nabla_u H(t, \hat{X}(t), \hat{u}(t), \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot))^T (u(t) - \hat{u}(t)). \end{aligned} \quad (22)$$

Then we have from (16),(19) and that  $u(t)$  is adapted to  $\mathcal{E}_t$ ,

$$\begin{aligned} 0 &\geq \nabla_u E \left[ H(t, \hat{X}(t), u, \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot)) | \mathcal{E}_t \right]_{u=\hat{u}(t)}^T (u(t) - \hat{u}(t)) \\ &= E \left[ \nabla_u H(t, \hat{X}(t), \hat{u}(t), \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot))^T (u(t) - \hat{u}(t)) | \mathcal{E}_t \right]. \end{aligned} \quad (23)$$

Combining (4), (17), (21), (22) and (23)

$$\begin{aligned} I_1^\infty &\leq E \left[ \int_0^\infty \nabla_x H(t, \hat{X}(s), \hat{u}(s), \hat{p}(s), \hat{q}(s), \hat{r}(s, \cdot))^T (X(s) - \hat{X}(s)) ds \right] \\ &= E \left[ \int_0^\infty (X(s) - \hat{X}(s))^T d\hat{p}(s) \right] =: -J_1. \end{aligned}$$

Now, using (15) and Itô's formula

$$\begin{aligned}
0 &\leq E \left[ \overline{\lim}_{t \rightarrow \infty} [\hat{p}(t)^T (X(t) - \hat{X}(t))] \right] \\
&= E \left[ \overline{\lim}_{t \rightarrow \infty} \left[ \int_0^t \hat{p}(s)^T (b(s, X(s), u(s)) - \hat{b}(s, \hat{X}(s), \hat{u}(s))) ds \right. \right. \\
&\quad + \int_0^t \hat{p}(s)^T (\sigma(s, X(s), u(s)) - \hat{\sigma}(s, \hat{X}(s), \hat{u}(s))) dB(s) \\
&\quad + \int_0^t \int_{\mathbb{R}_0^n} \hat{p}(s)^T (\theta(s, X(s), u(s), z) - \hat{\theta}(s, \hat{X}(s), \hat{u}(s), z)) \tilde{N}(dz, ds) \\
&\quad + \int_0^t (X(s) - \hat{X}(s))^T (-\nabla_x \hat{H}(s, \hat{X}(s), \hat{u}(s), \hat{p}(s), \hat{q}(s), \hat{r}(s, \cdot))) ds \\
&\quad + \int_0^t \hat{q}(s)^T (X(s) - \hat{X}(s)) dB(s) \\
&\quad + \int_0^t \int_{\mathbb{R}_0^n} \hat{r}(s, z) (X(s) - \hat{X}(s)) \tilde{N}(dz, ds) \\
&\quad + \int_0^t \text{tr} \left[ \hat{q}(s)^T (\sigma(s, X(s), u(s)) - \hat{\sigma}(s, \hat{X}(s), \hat{u}(s))) \right] ds \\
&\quad + \int_0^t \sum_{i,j} \int_{\mathbb{R}_0^n} (\theta(s, X(s), u(s), z) - \hat{\theta}(s, \hat{X}(s), \hat{u}(s), z))^T \hat{r}_{i,j}(s, z) \nu_j(dz) ds \\
&\quad \left. + \int_0^t \int_{\mathbb{R}_0^n} (\theta(s, X(s), u(s), z) - \hat{\theta}(s, \hat{X}(s), \hat{u}(s), z))^T \hat{r}(s, z) \tilde{N}(dz, ds) \right] \right]
\end{aligned}$$

From (17), (18), we have that

$$\begin{aligned}
0 &\leq E \left[ \overline{\lim}_{t \rightarrow \infty} \left[ \int_0^t \hat{p}(s)^T (b(s, X(s), u(s)) - \hat{b}(s, \hat{X}(s), \hat{u}(s))) ds \right. \right. \\
&\quad + \int_0^t (X(s) - \hat{X}(s))^T (-\nabla_x \hat{H}(s, \hat{X}(s), \hat{u}(s), \hat{p}(s), \hat{q}(s), \hat{r}(s, \cdot))) ds \\
&\quad + \int_0^t \text{tr} \left[ \hat{q}(s)^T (\sigma(s, X(s), u(s)) - \hat{\sigma}(s, \hat{X}(s), \hat{u}(s))) \right] ds \\
&\quad \left. \left. + \int_0^t \sum_{i,j} \int_{\mathbb{R}_0^n} (\theta(s, X(s), u(s), z) - \hat{\theta}(s, \hat{X}(s), \hat{u}(s), z))^T \hat{r}_{i,j}(s, z) \nu_j(dz) ds \right] \right] \\
&= E \left[ \int_0^\infty \hat{p}(s)^T (b(s, X(s), u(s)) - \hat{b}(s, X(s), u(s))) ds \right. \\
&\quad + \int_0^\infty (X(s) - \hat{X}(s))^T (-\nabla_x \hat{H}(s, X(s), u(s), p(s), q(s), r(s, \cdot))) ds \\
&\quad + \int_0^\infty \text{tr} \left[ \hat{q}(s)^T (\sigma(s, X(s), u(s)) - \hat{\sigma}(s, \hat{X}(s), \hat{u}(s))) \right] ds \\
&\quad \left. + \int_0^\infty \sum_{i,j} \int_{\mathbb{R}_0^n} (\theta(s, X(s), u(s), z) - \hat{\theta}(s, \hat{X}(s), \hat{u}(s), z))^T \hat{r}_{i,j}(s, z) \nu_j(dz) ds \right] \\
&= I_{1,2}^\infty + J_1^\infty + I_{1,3}^\infty + I_{1,4}^\infty.
\end{aligned}$$

Finally, combining the above we get

$$\begin{aligned}
J(u) - J(\hat{u}) &\leq I_1^\infty - I_2^\infty - I_3^\infty - I_4^\infty \\
&\leq -J_1^\infty - I_2^\infty - I_3^\infty - I_4^\infty \\
&\leq 0.
\end{aligned}$$

This holds for all  $u \in \mathcal{A}_\mathcal{E}$ , so the proof is complete.  $\square$

## 5 Examples

**Example 5.1 (Optimal Consumption Rate Part I).** *Let*

$$J(u) = E \left[ \int_0^\infty e^{-\rho t} \ln(u(t)X(t)) dt \right],$$

where

$$\begin{aligned}
dX(t) &= X(t)(\mu(t) - u(t))dt + X(t)\sigma(t)dB(t), \\
X(0) &= x_0,
\end{aligned}$$

and  $\rho \geq 0$ . We have that

$$X(t) = X_0 \exp \left[ \int_0^t [(\mu(s) - u(s)) - \frac{1}{2}\sigma^2(s)] ds + \int_0^t \sigma(s) dB(s) \right].$$

Then we deal with the problem of maximizing  $J(u)$  over all  $u(t) \geq 0$ . We have the Hamilton function takes the form

$$H(t, x, u, p, q) = e^{-\rho t} \ln(ux) + x(\mu - u)p + x\sigma q,$$

so that we get the partial derivatives

$$\nabla_x H(t, x, u, p, q) = \frac{e^{-\rho t}}{x} + (\mu - u)p + \sigma q,$$

and

$$\nabla_u H(t, x, u, p, q) = \frac{e^{-\rho t}}{u} - xp,$$

This gives us that

$$-dp(t) = \left[ \frac{e^{-\rho t}}{X(t)} + (\mu(t) - u(t))p(t) + \sigma(t)q(t) \right] dt - q(t)dB(t).$$

so that

$$\hat{u}(t) = \frac{e^{-\rho t}}{\hat{X}(t)\hat{p}(t)}.$$

Let us try the infinite horizon BSDE with terminal condition  $\lim_{t \rightarrow \infty} p(t) = 0$ ,

$$-dp(t) = \left[ \frac{e^{-\rho t}}{X(t)} + (\mu(t) - u(t))p(t) + \sigma(t)q(t) \right] dt - q(t)dB(t), \quad (24)$$

$$\lim_{t \rightarrow \infty} p(t) = 0. \quad (25)$$

**Lemma 5.1 (Solution of infinite horizon linear BSDE with jumps).** Let  $A(t), \beta(t)$  and  $\alpha(t, \zeta)$  be  $\mathcal{F}_t$ -predictable processes such that

$$E \left[ \int_0^\infty \{ |A(t)| + \beta^2(t) + \int_{\mathbf{R}} \alpha^2(s, \zeta) \nu(d\zeta) \} dt \right] < \infty,$$

and define  $\Gamma_{t,s}$  as the solution of the linear SDE

$$d\Gamma_{t,s} = \Gamma_{t-,s} \left( A(t)dt + \beta(t)dB(t) + \int_{\mathbb{R}_0^n} \alpha(t, \zeta) \bar{N}(d\zeta, dt) \right), \quad s \geq t \geq 0,$$

$$\Gamma_{t,t} = 1.$$

Let  $C(t)$  be a predictable process such that

$$E \left[ \int_0^\infty \Gamma_{0,s} |C(s)| ds \right] < \infty.$$

Then a solution  $(Y(t), Z(t), K(t, \zeta))$  of the linear BSDE

$$\begin{aligned} -dY(t) &= \left[ A(t)Y(t) + Z(t)\beta(t) + C(t) + \int_{\mathbb{R}_0^n} \alpha(t, \zeta) K(t, \zeta) d\nu(\zeta) \right] dt \\ &\quad - Z(t)dB(t) - \int_{\mathbb{R}_0^n} K(t, \zeta) \bar{N}(d\zeta, dt), \end{aligned}$$

$$\lim_{t \rightarrow \infty} Y(t) = 0,$$

is given by

$$Y(t) = E \left[ \int_t^\infty \Gamma_{t,s} C(s) ds | \mathcal{F}_t \right], t \geq 0.$$

If in additon

$$E \left[ \int_0^\infty e^{\lambda t} |Y(t)|^2 dt \right] < \infty,$$

where  $\lambda$  as in (7), then  $Y(t)$  is the unique solution.

*Proof.* By Itô's Lemma we have that

$$\begin{aligned} d(\Gamma_{0,t} Y_t) &= -\Gamma_{0,t} C_t dt + \Gamma_{0,t} (Z_t + Y_t \beta_t) dB_t \\ &\quad + \int_{\mathbb{R}_0^n} \left[ Y(t) \alpha(t, \zeta) \Gamma_{0,t} + K(t, \zeta) \Gamma_{0,t} + K(t, \zeta) \alpha(t, \zeta) \Gamma_{0,t} \right] \tilde{N}(d\zeta, dt). \end{aligned}$$

So

$$\begin{aligned} \Gamma_{0,t} Y_t + \int_t^\infty \Gamma_{0,s} C_s ds &= \int_t^\infty \Gamma_{0,s} (Z_s + Y_s \beta_s) dB(s) \\ &\quad + \int_t^\infty \int_{\mathbb{R}_0^n} \left[ Y(s) \alpha(s, \zeta) \Gamma_{0,s} + K(s, \zeta) \Gamma_{0,s} + K(s, \zeta) \alpha(s, \zeta) \Gamma_{0,s} \right] \tilde{N}(d\zeta, ds). \end{aligned}$$

By taking expectation we get the desired result. The uniqueness follows from Theorem 3.1.  $\square$

From the above lemma we see that the solution of the linear, infinite horizon BSDE (24) - (25) is

$$\hat{p}(t) = E \left[ \int_t^\infty \frac{\hat{\Gamma}_s e^{-\rho s}}{\hat{\Gamma}_t \hat{X}_s} ds | \mathcal{F}_t \right],$$

where

$$\hat{\Gamma}_t = e^{\int_0^t [(\mu(s) - u(s)) - \frac{1}{2} \sigma^2(s)] ds + \int_0^t \sigma(s) dB(s)} = \frac{\hat{X}(t)}{x_0}.$$

Hence

$$\hat{p}(t) = \frac{1}{\rho} e^{-\rho t} \frac{1}{\hat{X}(t)}.$$

and

$$\overline{\lim}_{t \rightarrow \infty} \hat{p}(t) (X(t) - \hat{X}(t)) \geq \overline{\lim}_{t \rightarrow \infty} \hat{p}(t) X(t) \geq 0.$$

So

$$\hat{u}(t) = \rho,$$

is an optimal control.

**Example 5.2 (Optimal Consumption Rate - part II).** Let

$$J(u) = E \left[ \int_0^\infty e^{-\rho t} \ln(u(t) X(t)) dt \right],$$

where

$$\begin{aligned} dX(t) &= X(t)\mu(t)(1-u(t))dt + X(t)\sigma(t)(1-u(t))dB(t), \\ X(0) &= x_0, \end{aligned}$$

and  $\rho \geq 0$ . We have that

$$\begin{aligned} X(t) &= X_0 \exp \left[ \int_0^t [\mu(s)(1-u(s)) - \frac{1}{2}\sigma^2(s)(1-u(s))^2]ds \right. \\ &\quad \left. + \int_0^t \sigma(s)(1-u(s))dB(s) \right]. \end{aligned}$$

Then we deal with the problem of maximizing  $J(u)$  over all  $u(t) \geq 0$ . We have the Hamilton function takes the form

$$H(t, x, u, p, q) = e^{-\rho t} \ln(ux) + x\mu(1-u)p + x\sigma(1-u)q,$$

so that we get the partial derivatives

$$\nabla_x H(t, x, u, p, q) = \frac{e^{-\rho t}}{x} + \mu(1-u)p + \sigma(1-u)q,$$

and

$$\nabla_u H(t, x, u, p, q) = \frac{e^{-\rho t}}{u} - x\mu p - x\sigma q.$$

This gives us that

$$-dp(t) = \left[ \frac{e^{-\rho t}}{X(t)} + \mu(t)(1-u(t))p(t) + \sigma(t)(1-u(t))q(t) \right] dt - q(t)dB(t).$$

So that

$$\hat{u}(t) = \frac{e^{-\rho t}}{\hat{X}(t)(\mu\hat{p}(t) + \sigma\hat{q}(t))}.$$

Let us try the infinite horizon BSDE with terminal condition

$\lim_{t \rightarrow \infty} p(t) = 0$ , so that

$$\begin{aligned} -dp(t) &= \left[ \frac{e^{-\rho t}}{X(t)} + \mu(t)(1-u(t))p(t) + \sigma(t)(1-u(t))q(t) \right] dt \\ &\quad - q(t)dB(t), \end{aligned} \tag{26}$$

$$\lim_{t \rightarrow \infty} p(t) = 0. \tag{27}$$

From the above lemma we see that the solution of the linear, infinite horizon BSDE (26) - (27) is

$$\hat{p}(t) = E \left[ \int_t^\infty \frac{\hat{\Gamma}_{0,s} e^{-\rho s}}{\hat{\Gamma}_{0,t} \hat{X}_s} ds \middle| \mathcal{F}_t \right],$$

where

$$\begin{aligned}\hat{\Gamma}_t &= \exp \left[ \int_0^t \left[ \mu(s)(1-u(s)) - \frac{1}{2}\sigma^2(s)(1-u(s))^2 \right] ds \right. \\ &\quad \left. + \int_0^t \sigma(s)(1-u(s))dB(s) \right] \\ &= \frac{\hat{X}(t)}{x_0}.\end{aligned}$$

Hence

$$\hat{p}(t) = \frac{1}{\rho} e^{-\rho t} \frac{1}{\hat{X}(t)}.$$

and

$$\overline{\lim}_{t \rightarrow \infty} \hat{p}(t)(X(t) - \hat{X}(t)) \geq \overline{\lim}_{t \rightarrow \infty} \hat{p}(t)X(t) \geq 0.$$

Since

$$\begin{aligned}d(e^{-\rho t} \frac{1}{X(t)}) &= e^{-\rho t} \frac{1}{X(t)} dt - e^{-\rho t} \frac{1}{X(t)} (\mu(t) - u(t)) dt \\ &\quad + e^{-\rho t} \frac{1}{X(t)} \sigma^2(t) dt + e^{-\rho t} \frac{1}{X(t)} \sigma(t) dB(t),\end{aligned}$$

we must have that

$$\hat{q}(t) = \frac{1}{\rho} e^{-\rho t} \frac{1}{\hat{X}(t)} \sigma(t).$$

So

$$\hat{u}(t) = \frac{\rho}{\mu + \sigma},$$

is an optimal control.

**Example 5.3 (Optimal consumption rate - part III).** As above, let

$$J(u) = E \left[ \int_0^\infty e^{-\rho t} \ln(u(t)X(t)) dt \right].$$

But add a jump part

$$\begin{aligned}dX(t) &= X(t)(\mu(t) - u(t))dt + X(t)\sigma(t)dB(t) + X(t) \int_{\mathbb{R}_0} \theta(t)z\tilde{N}(dz, dt) \\ X(0) &= x_0,\end{aligned}$$

and we also add the assumption that we only know a subset of the information given by the market available at time  $t$ , represented by  $\mathcal{E}_t \subset \mathcal{F}_t$ . Let  $\rho \geq 0$ , be a random variable adapted to  $\mathcal{F}_t$ . Then we deal with the problem of maximizing  $J(u)$  over all  $u(t) \geq 0$ . We have

$$\begin{aligned}H(t, x, u, p, q, r) &= e^{-\rho t} \ln(ux) + x(\mu - u)p + x\sigma q + x \int_{\mathbb{R}_0} \theta(t)zr(t, z)\nu(dz) \\ \nabla_x H(t, x, u, p, q, r) &= \frac{e^{-\rho t}}{x} + (\mu - u)p + \sigma q + \int_{\mathbb{R}_0} \theta(t)zr(t, z)\nu(dz),\end{aligned}$$

$$\nabla_u H(t, x, u, p, q, r) = \frac{e^{-\rho t}}{u} - xp$$

and

$$\begin{aligned} -dp(t) &= \left[ \frac{e^{-\rho t}}{X(t)} + (\mu(t) - u(t))p(t) + \sigma(t)q(t) + \int_{\mathbb{R}_0} \theta(t)zr(t, z)\nu(dz) \right] dt \\ &\quad - q(t)dB(t) - \int_{\mathbb{R}_0} \theta(t)z\tilde{N}(dz, dt), \\ \lim_{t \rightarrow \infty} p(t) &= 0. \end{aligned}$$

If we maximize

$$E[H(t, \hat{X}(t), u, \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot)) | \mathcal{E}_t],$$

we get that

$$\begin{aligned} \nabla_u E[H(t, \hat{X}(t), u, \hat{p}(t), \hat{q}(t)) | \mathcal{E}_t] &= E[\nabla_u H(t, \hat{X}(t), u, \hat{p}(t), \hat{q}(t)) | \mathcal{E}_t] \\ &= E\left[ \frac{e^{-\rho t}}{u} - \hat{X}(t)\hat{p}(t) | \mathcal{E}_t \right]. \end{aligned}$$

So that

$$\hat{u}(t) = E\left[ \frac{e^{-\rho t}}{\hat{X}(t)\hat{p}(t)} | \mathcal{E}_t \right].$$

The solution of the linear, infinite horizon BSDE (24) - (25) is (see [10])

$$\hat{p}(t) = E\left[ \int_t^\infty \frac{\hat{\Gamma}_s}{\hat{\Gamma}_t} \frac{e^{-\rho s}}{\hat{X}_s} ds | \mathcal{F}_t \right],$$

where

$$\begin{aligned} d\hat{\Gamma}_t &= X(t)(\mu(t) - u(t))dt + X(t)\sigma(t)dB(t) + X(t^-) \int_{\mathcal{R}_0} \theta(t)z\tilde{N}(dz, dt), \\ X(0) &= 1. \end{aligned}$$

So

$$\hat{\Gamma}_t = \frac{\hat{X}(t)}{x_0}.$$

Hence

$$\hat{p}(t) = \frac{1}{x_0 \hat{\Gamma}_t} \frac{1}{\rho} e^{-\rho t} = \frac{1}{\rho} e^{-\rho t} \frac{1}{\hat{X}(t)}.$$

Therefore we have that

$$\overline{\lim}_{t \rightarrow \infty} \hat{p}(t)(X(t) - \hat{X}(t)) = \overline{\lim}_{t \rightarrow \infty} \hat{p}(t)X(t) \geq 0.$$

So

$$\hat{u}(t) = E[\rho, | \mathcal{E}_t]$$

is an optimal control.

**Example 5.4 (Optimal Portfolio Selection With Consumption).** For this example let us look at a market with two investment possibilities:



1. A bond or bank account

$$dZ_0(t) = \rho Z_0(t)dt.$$

2. A stock

$$dZ_1(t) = \mu Z_1(t)dt + \sigma Z_1(t)dB(t).$$

Let  $(Y_0, Y_1)$  denote the amount the agent has invested in the bonds and stocks respectively at time  $t$ . Consider then  $u(t, \omega) = u(t)$ , the fraction of the wealth invested in the stocks, e.g.

$$u(t) = \frac{Z_1(t)}{Z_0(t) + Z_1(t)}.$$

Further let  $\lambda(t, \omega) = \lambda(t)$  be the consumption rate relative to the wealth so that the investor controls

$$c(t) = (u(t), \lambda(t)).$$

Then let

$$J^{\lambda, u}(s, z) = E^{s, z} \left[ \int_0^\infty e^{-\delta(s+t)} \frac{(\lambda(t)X(t))^\gamma}{\gamma} dt \right],$$

be a performance functional, where

$$dX(t) = X(t) [(\rho + u(t)(\mu - \rho) - \lambda(t))dt + \sigma u(t)dB(t)],$$

and  $\rho \geq 0$ . We have that

$$X(t) = x_0 \exp \left[ \int_0^t [\rho + u(s)(\mu - \rho) - \lambda(s) - \frac{1}{2}\sigma^2 u^2] ds + \int_0^t \sigma u(s)dB(s) \right].$$

Then we want to maximize  $J^{u, \lambda}(s, t)$  over all  $l = (u(t), \lambda(t))$ ,  $\lambda \geq 0$ . We have that

$$H(t, x, l, p, q) = e^{-\delta(s+t)} \frac{(\lambda(t)X(t))^\gamma}{\gamma} + x(\rho + u(s)(\mu - \rho) - \lambda)p + x\sigma uq,$$

so that

$$\nabla_x H(t, x, l, p, q) = e^{-\delta(s+t)} \lambda^\gamma x^{\gamma-1} + (\rho + u(\mu - \rho) - \lambda)p + \sigma uq.$$

Further, we also have

$$-dp(t) = [e^{-\delta(s+t)} \lambda^\gamma(t) X^{\gamma-1}(t) + (\rho + u(t)(\mu - \rho) - \lambda(t))p + \sigma u(t)q]dt - qdB(t).$$

and

$$\begin{aligned} \nabla_u H(t, x, l, p, q) &= (\mu - \rho)xp + x\sigma q, \\ \nabla_\lambda H(t, x, l, p, q) &= e^{-\delta(s+t)} (\lambda(t))^{\gamma-1} X^\gamma - xp. \end{aligned}$$

So that

$$q(t) = -\frac{(\mu - \rho)}{\sigma} p(t),$$

and

$$\hat{\lambda} = \frac{1}{x} p^{\frac{1}{\gamma-1}} e^{\frac{\delta(s+t)}{\gamma-1}}.$$

Then

$$\begin{aligned} dp(t) &= -e^{\frac{\delta(s+t)}{\gamma-1}} \frac{1}{X} p^{\frac{\gamma}{\gamma-1}}(t) dt - [\rho + u(t)(\mu - \rho) - \frac{1}{X}(t) p^{\frac{1}{\gamma-1}} e^{\frac{\delta(s+t)}{\gamma-1}}] p(t) dt \\ &\quad + \sigma u(t) \frac{(\mu - \rho)}{\sigma} p(t) dt - \frac{(\mu - \rho)}{\sigma} p(t) dB(t) \\ &= -\rho p(t) dt - \frac{(\mu - \rho)}{\sigma} p(t) dB(t). \end{aligned}$$

So to ensure that the requirement

$$E[\overline{\lim}_{t \rightarrow \infty} \hat{p}(t)(X(t) - \hat{X}(t))] \geq 0,$$

is satisfied we need that

$$E[\overline{\lim}_{t \rightarrow \infty} -\hat{p}(t)\hat{X}(t)] \geq 0.$$

Since

$$\hat{p}(t) = (\hat{\lambda}(t)\hat{X}(t))^{(\gamma-1)} e^{\delta(s+t)},$$

we see that

$$-\hat{p}(t)\hat{X}(t) = \hat{\lambda}^{(\gamma-1)}(t)\hat{X}^\gamma(t) e^{\delta(s+t)}.$$

So, by considering

$$\hat{\lambda} = \frac{1}{x} p^{\frac{1}{\gamma-1}} e^{\frac{\delta(s+t)}{\gamma-1}},$$

we try to let

$$p^{\frac{1}{\gamma-1}}(t) = X(t)Ke^{Bt},$$

for some constants  $K$  and  $B$ . It is now clear that

$$\begin{aligned} d(p^{\frac{1}{\gamma-1}}(t)) &= p^{\frac{1}{\gamma-1}}(t) \frac{1}{\gamma-1} (-\rho dt - \frac{(\mu - \rho)}{\sigma} dB(t)) \\ &\quad + p^{\frac{1}{\gamma-1}} \frac{1}{2} \frac{1}{\gamma-1} \frac{2 - \gamma}{\gamma-1} \frac{(\mu - \rho)^2}{\sigma^2} dt. \end{aligned}$$

On the other hand we have that

$$\begin{aligned} d(X(t)Ke^{Bt}) &= BX(t)Ke^{Bt} dt + X(t)Ke^{Bt} [\rho + u(t)(\mu - \rho) - Ke^{Bt} e^{\frac{\delta(s+t)}{\gamma-1}}] dt \\ &\quad + X(t)Ke^{Bt} \sigma u(t) dB(t). \end{aligned}$$

Consider

$$\hat{u}(t) = -\frac{(\mu - \rho)}{\sigma^2(\gamma - 1)},$$

and

$$K = e^{-Bt} e^{-\frac{\delta(s+t)}{\gamma-1}} [B + \frac{\gamma\rho}{\gamma-1} - \frac{1}{2}\gamma \frac{(\mu - \rho)^2}{\sigma^2(\gamma - 1)^2}].$$

For  $K$  to be independent of  $t$ , we must have  $B = -\frac{\delta}{\gamma-1}$ , which gives us

$$K = \left[ -\frac{\delta}{\gamma-1} + \frac{\gamma\rho}{\gamma-1} - \frac{1}{2}\gamma \frac{(\mu - \rho)^2}{\sigma^2(\gamma - 1)^2} \right].$$

With this  $K$  and

$$\hat{u}(t) = -\frac{(\mu - \rho)}{\sigma^2(\gamma - 1)}$$

we can conclude that we have

$$p^{\frac{1}{\gamma-1}}(t) = X(t)Ke^{Bt}.$$

It is now clear that

$$\hat{\lambda}(t) = K = \hat{\lambda}.$$

which gives us that

$$\begin{aligned}\hat{p}(t)\hat{X}(t) &= X^\gamma(t)K^\gamma(t)e^{\gamma Bt} \\ &= X^\gamma(t)\hat{\lambda}^\gamma,\end{aligned}$$

so that

$$\begin{aligned}-\hat{p}(t)\hat{X}(t) &= -e^{-\frac{\gamma\delta(s+t)}{\gamma-1}}\hat{\lambda}^\gamma x_0^\gamma e^{\gamma \int_0^t \rho - \frac{(\mu-\rho)^2}{\sigma^2(\gamma-1)} - \hat{\lambda} - \frac{(\mu-\rho)^2}{\sigma^2(\gamma-1)^2} ds - \gamma \int_0^t \frac{(\mu-\rho)}{\sigma(\gamma-1)} dB(s)} \\ &= -e_0^{-\frac{\gamma\delta(s+t)}{\gamma-1}}\hat{\lambda}^\gamma e^{\gamma \rho t - \gamma \frac{(\mu-\rho)^2}{\sigma^2(\gamma-1)^2} t - \gamma \hat{\lambda} t - \gamma \frac{(\mu-\rho)^2}{\sigma^2(\gamma-1)^2} t - \gamma \frac{(\mu-\rho)}{\sigma(\gamma-1)} B(t)} \\ &\geq -e^{-\frac{\gamma\delta(s+t)}{\gamma-1}}\hat{\lambda}^\gamma x_0^\gamma e^{-\gamma^2 \frac{(\mu-\rho)^2}{\sigma^2(\gamma-1)^2} - \gamma \frac{(\mu-\rho)}{\sigma(\gamma-1)} B(t)}.\end{aligned}$$

If  $\delta, \gamma, \rho$  deterministic, then

$$\begin{aligned}E[\overline{\lim}_{t \rightarrow \infty} \hat{p}(t)(X(t) - \hat{X}(t))] &\geq -\lim e^{-\delta(s+t)}\hat{\lambda}^\gamma x_0^\gamma e^{-\gamma^2 \frac{(\mu-\rho)^2}{\sigma^2(\gamma-1)^2}} E[e^{-\frac{(\mu-\rho)}{\sigma(\gamma-1)} B(t)}] \\ &= 0.\end{aligned}$$

So we have that  $E[\overline{\lim}_{t \rightarrow \infty} \hat{p}(t)(X(t) - \hat{X}(t))] = 0$ , which gives us that  $(\hat{\lambda}, \hat{u})$ , where

$$\hat{\lambda} = \left[ -\frac{\delta}{\gamma-1} + \frac{\gamma\rho}{\gamma-1} - \frac{1}{2}\gamma \frac{(\mu-\rho)^2}{\sigma^2(\gamma-1)^2} \right],$$

and

$$\hat{u} = -\frac{(\mu - \rho)}{\sigma^2(\gamma - 1)}$$

is an optimal control.

## 6 Necessary Maximum Principle

To answer the question: if  $\hat{u}$  is optimal does it satisfy

$$\begin{aligned}&E \left[ H(t, \hat{X}(t), \hat{u}(t), \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot)) | \mathcal{E}_t \right] \\ &= \max_{u \in U} E \left[ H(t, \hat{X}(t), u, \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot)) | \mathcal{E}_t \right],\end{aligned}\tag{28}$$

we assume the following two requirements:

**A1** For all  $t, h$  such that  $0 \leq t < t+h \leq T$ , all  $i = 1, \dots, k$  and for all bounded  $\mathcal{E}_t$ -measurable  $\alpha = \alpha(\omega)$ , the control  $\beta(s) := (0, \dots, \beta_i(s), 0, \dots, 0) \in U \subset \mathbb{R}^k$  with

$$\beta(s) := \alpha_i \mathbf{1}_{[t, t+h]}(s),$$

belongs to  $\mathcal{A}_{\mathcal{E}}$ .

**A2** For all  $u, \beta \in \mathcal{A}_{\mathcal{E}}$  with  $\beta$  bounded, there exists  $\delta > 0$  such that  $\hat{u} + \epsilon\beta \in \mathcal{A}_{\mathcal{E}}$  for all  $\epsilon \in (-\delta, \delta)$ .

Given  $u, \beta \in \mathcal{A}_{\mathcal{E}}$  with  $\beta$  bounded, define the process  $Y(t) = Y^{(u, \beta)}(t)$  by

$$Y(t) = \frac{d}{d\epsilon} X^{\hat{u} + \epsilon\beta}(t)|_{\epsilon=0} = (Y_1(t), \dots, Y_n(t))^T.$$

Notice that  $Y(0) = 0$  and

$$dY_i(t) = \lambda_i(t)dt + \sum_{j=1}^n \xi_{ij}(t)dB_j(t) + \sum_{j=1}^n \int_{\mathbb{R}_0^n} \zeta_{ij}(t, z) \tilde{N}_j(dz, dt),$$

where

$$\begin{aligned} \lambda_i(t) &= \nabla_x b_i(t, X(t), u(t))^T Y(t) + \nabla_u b_i(t, X(t), u(t))^T \beta(t), \\ \xi_{ij}(t) &= \nabla_x \sigma_{ij}(t, X(t), u(t))^T Y(t) + \nabla_u \sigma_{ij}(t, X(t), u(t))^T \beta(t), \\ \zeta_{ij}(t, z) &= \nabla_x \theta_{ij}(t, X(t), u(t))^T Y(t) + \nabla_u \theta_{ij}(t, X(t), u(t))^T \beta(t). \end{aligned}$$

We can then give an answer to the question.

**Theorem 6.1 (Partial Information Necessary Maximum Principle).**

Suppose  $\hat{u} \in \mathcal{A}_{\mathcal{E}}$  is a local maximum for  $J(u)$ , meaning that for all bounded  $\beta \in \mathcal{A}_{\mathcal{E}}$  there exists a  $\delta > 0$  such that  $\hat{u} + \epsilon\beta \in \mathcal{A}_{\mathcal{E}}$  for all  $\epsilon \in (-\delta, \delta)$  and

$$h(\epsilon) := J(\hat{u} + \epsilon\beta), \epsilon \in (-\delta, \delta)$$

is maximal at  $\epsilon = 0$ . Suppose there exists a solution  $(\hat{p}(t), \hat{q}(t), \hat{r}(t, z))$  to the adjoint equation

$$\begin{aligned} d\hat{p}(t) &= -\nabla_x H(t, \hat{X}(t), \hat{u}(t), \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot))dt + \hat{q}(t)dB(t) \\ &\quad + \int_{\mathbb{R}_0^n} \hat{r}(z, t) \tilde{N}(dz, dt), \end{aligned}$$

and

$$0 \leq E \left[ \overline{\lim}_{t \rightarrow \infty} [\hat{p}(t)^T (X(t) - \hat{X}(t))] \right] < \infty,$$

for all  $u \in \mathcal{A}_{\mathcal{E}}$  and  $p(t)Y(t, \epsilon)$  converges as  $t \rightarrow \infty$ , uniformly in  $\epsilon$ , where  $Y(t, \epsilon) := \frac{\partial}{\partial \epsilon} X^{\hat{u} + \epsilon\beta}$ . Moreover assume that if  $\hat{Y}(t) = Y^{(\hat{u}, \beta)}(t)$ , with corresponding coefficients  $\hat{\lambda}_i, \hat{\xi}_{ij}, \hat{\zeta}_{ij}$ , we have

$$E \left[ \hat{Y}(t)^T [\hat{q}\hat{q}^T(t) + \int_{\mathbb{R}_0^n} \hat{r}\hat{r}^T(t, z) \nu(dx)] \hat{Y}(t) dt \right] < \infty,$$

and

$$E \left[ \int_0^\infty \hat{p}^T(t) [\hat{\xi} \hat{\xi}^T(t, \hat{X}(t), \hat{u}(t)) + \int_{\mathbb{R}_0^n} \hat{\zeta} \hat{\zeta}^T(t, \hat{X}(t), \hat{u}(t), z) \nu(dz)] \hat{p}(t) dt \right] < \infty.$$

Then  $\hat{u}$  is a stationary point for  $E[H|\mathcal{E}]$  in the sense that for all  $t \geq 0$ ,

$$E[\nabla_u H(t, \hat{X}(t), \hat{u}(t), \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot)) | \mathcal{E}_t] = 0.$$

*Proof.* Since

$$0 \leq E \left[ \overline{\lim}_{t \rightarrow \infty} [\hat{p}(t)^T (X(t) - \hat{X}(t))] \right],$$

we have that

$$E \left[ \overline{\lim}_{t \rightarrow \infty} [\hat{p}(t)^T X^{\hat{u} + \epsilon \beta}(t)] \right] \geq E \left[ \overline{\lim}_{t \rightarrow \infty} [\hat{p}(t)^T X^{\hat{u}}(t)] \right],$$

for all  $\beta \in \mathcal{A}_{\mathcal{E}}$  for some  $\epsilon$ . Define

$$g(\epsilon) = \overline{\lim}_{t \rightarrow \infty} [\hat{p}(t)^T X^{\hat{u} + \epsilon \beta}(t)],$$

so that

$$Eg(\epsilon) \geq Eg(0),$$

for all  $\beta \in \mathcal{A}_{\mathcal{E}}$ . This means that

$$\frac{d}{d\epsilon} (Eg(\epsilon))_{\epsilon=0} = 0.$$

So

$$\begin{aligned} 0 &= \frac{\partial}{\partial \epsilon} (E \left[ \overline{\lim}_{t \rightarrow \infty} [\hat{p}(t)^T X^{\hat{u} + \epsilon \beta}(t)] \right])_{\epsilon=0} \\ &= E \left[ \frac{\partial}{\partial \epsilon} (\overline{\lim}_{t \rightarrow \infty} [\hat{p}(t)^T X^{\hat{u} + \epsilon \beta}(t)])_{\epsilon=0} \right] \\ &= E \left[ \overline{\lim}_{t \rightarrow \infty} [\hat{p}(t)^T \frac{\partial}{\partial \epsilon} (X^{\hat{u} + \epsilon \beta}(t)) |_{\epsilon=0}] \right]. \end{aligned}$$

the interchanging of the limit w.r.t. the derivative operator holds for uniform limits with uniform convergence of the derivative. Interchanging derivative and integration is justified if

$$\left| \frac{\partial}{\partial \epsilon} (\overline{\lim}_{t \rightarrow \infty} [\hat{p}(t)^T X^{\hat{u} + \epsilon \beta}(t, \omega)])_{\epsilon=0} \right| \leq F(\omega),$$

for some integrable function  $F$ . Now let

$$h(\epsilon) = J(\hat{u} + \epsilon \beta),$$

so that we have

$$\begin{aligned} 0 &= h'(0) \\ &= E \left[ \int_0^\infty \left\{ \nabla_x f(t, \hat{X}(t), \hat{u}(t))^T \frac{d}{d\epsilon} X^{\hat{u} + \epsilon \beta}(t) |_{\epsilon=0} + \nabla_u f(t, \hat{X}(t), \hat{u}(t))^T \beta(t) \right\} dt \right. \\ &\quad \left. + \overline{\lim}_{t \rightarrow \infty} [\hat{p}(t)^T \frac{d}{d\epsilon} (X^{\hat{u} + \epsilon \beta}(t)) |_{\epsilon=0}] \right]. \end{aligned}$$

Using Itô's Lemma we get

$$\begin{aligned}
& E \left[ \overline{\lim}_{t \rightarrow \infty} [\hat{p}(t)^T \frac{d}{d\epsilon} (X^{\hat{u}+\epsilon\beta}(t))|_{\epsilon=0}] \right] \\
&= E \left[ \int_0^\infty \left\{ \hat{p}(t) [\nabla_x b(t, \hat{X}(t), \hat{u}(t))]^T \frac{d}{d\epsilon} X^{\hat{u}+\epsilon\beta}(t)|_{\epsilon=0} + \nabla_u b(t, \hat{X}(t), \hat{u}(t))^T \beta(t) \right\}^T \right. \\
&+ \frac{d}{d\epsilon} X^{\hat{u}+\epsilon\beta}(t)|_{\epsilon=0} (-\nabla_x H(t, \hat{X}(t), \hat{u}(t), \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot))) \\
&+ q(t) (\nabla_x \sigma(t, \hat{X}(t), \hat{u}(t)))^T \frac{d}{d\epsilon} X^{\hat{u}+\epsilon\beta}(t)|_{\epsilon=0} + \nabla_u \sigma(t, \hat{X}(t), \hat{u}(t))^T \beta(t) \\
&\left. + \hat{r}(t, z) (\nabla_x \theta(t, \hat{X}(t), \hat{u}(t)))^T \frac{d}{d\epsilon} X^{\hat{u}+\epsilon\beta}(t)|_{\epsilon=0} + \nabla_u \theta(t, \hat{X}(t), \hat{u}(t))^T \beta(t) \nu(dz) \right\} dt \right].
\end{aligned}$$

Since

$$\begin{aligned}
\nabla_u H(t, x, u, p, q, r) &= \nabla_u f(t, x, u) + \nabla_u b(t, x, u) p(t) + \nabla_u \sigma(t, x, u) q(t) \\
&+ \int_{\mathbb{R}_0^n} \nabla_u \theta(t, x, u, z) r(t, z) \nu(dz),
\end{aligned}$$

and

$$\begin{aligned}
\nabla_x H(t, x, u, p, q, r) &= \nabla_x f(t, x, u) + \nabla_x b(t, x, u) p(t) + \nabla_x \sigma(t, x, u) q(t) \\
&+ \int_{\mathbb{R}_0^n} \nabla_x \theta(t, x, u, z) r(t, z) \nu(dz),
\end{aligned}$$

we have

$$\begin{aligned}
0 &= E \left[ \int_0^\infty \left\{ \nabla_u f(t, \hat{X}(t), \hat{u}(t)) + \nabla_u b(t, \hat{X}(t), \hat{u}(t)) \hat{p}^T + \nabla_u \sigma(t, \hat{X}(t), \hat{u}(t)) \hat{q}^T \right. \right. \\
&\left. \left. + \hat{r} \nabla_u \theta(t, \hat{X}(t), \hat{u}(t)) \beta(t) \right\} dt \right] \\
&= E \left[ \int_0^\infty \nabla_u H(t, \hat{X}(t), \hat{u}(t), \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot))^T \beta(t) dt \right].
\end{aligned}$$

Define

$$\beta(s) := \alpha \mathbf{1}_{[t, t+h]}(s).$$

Then

$$E \left[ \int_t^{t+h} \nabla_u H(t, \hat{X}(t), \hat{u}(t), \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot))^T \alpha(t) dt \right] = 0.$$

Differentiating with respect to  $h$  at  $h = 0$  gives

$$E \left[ \nabla_u H(t, \hat{X}(t), \hat{u}(t), \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot))^T \alpha \right] = 0.$$

Since this holds for all  $\mathcal{E}$  measurable  $\alpha$ , we have that

$$E \left[ \nabla_u H(t, \hat{X}(t), \hat{u}(t), \hat{p}(t), \hat{q}(t), \hat{r}(t, \cdot))^T \alpha | \mathcal{E} \right] = 0,$$

which proves the theorem.  $\square$

## References

- [1] N. Agram, S. Haadem, B. Øksendal, and F. Proske. A maximum principle for infinite horizon delay equations. *Preliminary version*, 2012.
- [2] F. Bagheri and B. Øksendal. A maximum principle for stochastic control with partial information. *Stochastic Analysis and Applications*, 25(3):705–717, 2007.
- [3] E. Pardoux G. Barles, R. Buckdahn. Backward stochastic differential equations and integral-partial differential equations. *Stochastics and Stochastics Reports*, 60:57–83, 2009.
- [4] H. Halkin. Necessary conditions for optimal control problems with infinite horizons. *Econometrica*, 42:267–272, 1974.
- [5] J.Li and S. Peng. Stochastic optimization theory of backward stochastic differential equations with jumps and viscosity solutions of Hamilton-Jacobi-Bellman equations. *Nonlinear Analysis*, 70:1779–1796, 2009.
- [6] B. Maslowski and P. Veverka. Infinite horizon maximum principle for the discounted control problem - incomplete version. *arXiv*, 2011.
- [7] E. Pardoux. Bsd's, weak convergence and homogenizations of semilinear pdes. In F.H. Clark and R.J. Stern, editors, *Nonlinear Analysis, Differential Equations and Control*, pages 503–549. Kluwer Academic, Dordrecht, 1999.
- [8] S. Peng and Y. Shi. infinite horizon forward-backward stochastic differential equations. *Stoch. Proc. and their Appl.*, 85:75–92, 2000.
- [9] L. C. G. Rogers and D. Williams. *Diffusions, Markov Processes, and Martingales*. Cambridge University Press, second edition, 2000.
- [10] M. Royer. Backward stochastic differential equations with jumps and related non-linear expectations. *Stochastic Processes and Their Applications*, 116:1358–1376, 2006.
- [11] A. Seierstad, A. Strøm, and K. Sydsæter. *Matematisk Analyse*. Gyldendal Akademisk, 4 edition, 2006.
- [12] R. Situ. On solutions of backward stochastic differential equations with jumps and with non-Lipschitzian coefficients in Hilbert spaces and stochastic control. *Statistics and Probability Letters*, 60:279–288, 2002.
- [13] A. Sulem and B. Øksendal. *Applied Stochastic Control of Jump Diffusions*. Springer, second edition, 2007.
- [14] X.Li and S. Tang. Necessary conditions for optimal control of stochastic systems with random jumps. *SIAM Journal of Control and Optimization*, 32:1447–1475, 1994.
- [15] J. Yin. On solutions of a class of infinite horizon fbsdes. *Statistics and Probability Letters*, 78:2412–2419, 2008.