

Chp 11. Application to stochastic control.

Problem 6 (An optimal portfolio problem) Example 11.2.5

A person w two investment possibilities:  $\left\{ \begin{array}{l} \text{(i) safe asset: } dX_0 = bX_0 dt \quad b < a \\ \text{(ii) risky asset: } dX_1 = \alpha X_1 dt + \sigma X_1 dB_t \quad ; \quad \alpha > 0 \end{array} \right.$

At each time, a fraction  $u(t)$  is in the risky asset,  $1-u(t)$  in the safe asset. Total  $Z_t$

$$dZ_t = \alpha u Z_t dt + \sigma u Z_t dB_t + (1-u) b Z_t dt = Z_t [\alpha u + b(1-u)] dt + \sigma u Z_t dB_t.$$

• No borrowing,  $u \leq 1$ ; No short selling,  $u \geq 0$ .  $u \in [0, 1]$ .

• Given a utility function  $N: [0, \infty) \rightarrow [0, \infty)$ ;  $N(0) = 0$ . increasing and concave.

Problem, starting w  $Z_s = x$ , to maximize the expected utility of the wealth at  $t_0 > s$ :

find a control  $u^* = u^*(t, Z_t)$  and the value function:

$$\Phi(s, x) = \sup_u \{ J^u(s, x) : u = u(t, Z_t), 0 \leq u \leq 1 \} = J^{u^*}(s, x)$$

$$J^u(s, x) = E^{s, x} [N(Z_{t_0}^u)], \quad \tau_G = \text{the first exit time from } G = \{(t, Z) : t < t_0, Z > 0\}$$


Some solutions,

$$N(x) = x^\gamma, \quad 0 < \gamma < 1 : \quad u^*(t, x) = \frac{a-b}{\alpha^2(1-\gamma)}$$

$$N(x) = \log x, \quad u^*(t, x) = \frac{a-b}{\alpha^2}$$

By Dynkin's formula:  $L^u \phi(t, x) = \partial_t \phi + x(\alpha u + b(1-u)) \partial_x \phi + \frac{1}{2} \alpha^2 u^2 x^2 \partial_{xx} \phi. \quad \forall \phi \in C_b^{1,2}$

$$E[N(Z_{t_0}^u)] = N(x) + E^{s, x} \left[ \int_0^{\tau_G} \underbrace{[(\alpha-b)u + b] Z_t \partial_x N + \frac{1}{2} \alpha^2 u^2 Z_t^2 \partial_{xx} N}_{\text{generator}} dt \right]$$

• when  $\partial_x N > 0, \partial_{xx} N < 0$ ,   $\Rightarrow u^*(t, x) = - \frac{(a-b) \partial_x N}{x \alpha^2 \partial_{xx} N}$ .

•  $\Phi(s, x) = J^{u^*}(s, x) = E^{s, x} [N(Z_{t_0}^{u^*})] = ?$

1. Statement of the problem (general)

An Ito process  $X_t$ :  $dX_t = b(t, X_t, u_t) dt + \sigma(t, X_t, u_t) dB_t$ ;  $X_s = x \in \mathbb{R}^n$

$u_t = u(t, \omega) \in U \subseteq \mathbb{R}^k$ ,  $\mathcal{F}_t^B$  adapted

Given profit rate fun:  $f: \mathbb{R} \times \mathbb{R}^n \times U \rightarrow \mathbb{R}$ , both continuous,

bequest fun:  $g: \mathbb{R} \times \mathbb{R}^n \rightarrow \mathbb{R}$ ,

a fixed domain:  $G \subseteq \mathbb{R} \times \mathbb{R}^n$ ,  $\hat{T} =$  the 1st exit time  $= \inf\{t > s: (t, X_t^{s,x}) \notin G\}$

Goal: Find  $u^*$ , maximizing the performance function:

$$J^u(s, x) = \mathbb{E}^{s,x} \left[ \int_0^{\hat{T}} f(u_r(r, X_r)) dr + g(\hat{T}, X_{\hat{T}}) \mathbb{1}_{\{\hat{T} < \infty\}} \right]$$

$$\bar{J}(s, x) = \sup_{u \in \mathcal{A}} J^u(s, x) = J^{u^*}(s, x) \quad . \quad u^*: \text{optimal control.}$$

$\mathcal{A}$  = admissible controls =  $\{ u: u_t \in \mathcal{F}_t, \text{ with values in } U \}$ .

1. Deterministic / open loop control:  $u(t, \omega) = u(t)$ : NOT dependent on  $\omega$ .

2. Feedback / closed loop control:  $u(t, \omega) \in \mathcal{F}_t^X$

3. Partial information control:  $u(t, \cdot) \in \mathcal{F}_t^R$ ,  $\{R_t\}$  is a noisy observation of  $X_t$ .

4. Markov control:  $u(t, \omega) = u(t, X_t(\omega))$ .  $dR_t = a(X_t) dt + \gamma(X_t) dB_t$ . Filtering.

$\rightarrow X_t$  is an Ito diffusion, a Markov process.

Notation:  $Y_t = (s+t, X_{s+t})_{t \geq 0}$ ;  $Y_0 = (s, x)$ . Then

$$dY_t = b(Y_t, u_t) dt + \sigma(Y_t, u_t) dB_t \quad (*)$$

$\tau_G = \inf\{t > 0: Y_t \notin G\} = \hat{T} - s$ ;  $g(\hat{T}, X_{\hat{T}}) = g(Y_{\tau_G})$

$J^u(y) = J^u(s, x) = \mathbb{E}^y \left[ \int_0^{\tau_G} f^u(Y_t) dt + g(Y_{\tau_G}) \mathbb{1}_{\{\tau_G < \infty\}} \right]$ .

Remark: we only need to consider  $Y_t \in \mathbb{R}^n$  in Eq. (\*) with  $u_t = u(Y_t)$ , and  $G \subseteq \mathbb{R}^n$ .

$$\bar{J}(y) = \sup_{u \in \mathcal{A}} J^u(y) = J^{u^*}(y).$$

2. The Hamilton-Jacobi-Bellman Equ.

For any  $v \in U$  and  $\phi \in C_0^2$ , define  $[L^v \phi](y) = \int_S \phi(y) + \sum_i b_i(y, v) \partial_i \phi + \sum_{ij} a_{ij}(y, v) \partial_{ij} \phi$   
 $=$  generator of  $(x)$

Thm 11.2.1 (HJB1) Define  $\Phi(y) = \sup \{ J^u(y) : u = u(y) \text{ a Markov control } \}$

i) Sps that  $\Phi \in C^2(G) \cap C(\bar{G})$  satisfies:  $|E^y[\Phi(Y_\alpha) + \int_0^\alpha L^v \Phi(Y_t) dt]| < \infty, \forall \alpha \in \mathcal{T}_G, \forall y \in G, \forall v \in U$ .

ii) Moreover, sps that an optimal control  $u^*$  exists and  $\partial G$  is regular for  $Y_t^{u^*}$  (i.e.  $Q^y(\tau_D=0) = 1, \forall y \in G$ ).

Then,

$$\boxed{\begin{aligned} \sup_{v \in U} \{ f^v(y) + (L^v \Phi)(y) \} &= 0, \quad \forall y \in G. & f^v(y) &= f(y, v) \\ \Phi|_{\partial G} &= g & (z) \end{aligned}}$$

with the supremum obtained when  $v = u^*$ :  $f(y, u^*(y)) + [L^{u^*(y)} \Phi](y) = 0, \forall y \in G$ .

Rmk: ①. Stochastic control  $\Rightarrow$  optimization w/ PDE. (deterministic)

② Need the assumptions i)iii); (Example 11.2.6)

③ HJB1: it is necessary that  $u^*$  is the maximizer of (z).

HJB2: it is sufficient under some conditions.

$\Rightarrow$  We only need to find  $u^*$  &  $\Phi$  satisfying (z) above.

Thm 11.2.2 (HJB2) Let  $\phi \in C^2(G) \cap C(\bar{G})$  s.t.

(i)  $\forall v \in U, f^v(y) + [L^v \phi](y) \leq 0, \forall y \in G$ .

$\lim_{t \rightarrow \tau_G} \phi(Y_t) = g(Y_{\tau_G}) \mathbb{1}_{\{\tau_G < \infty\}}$ , a.s.  $(Q^y)$

(ii)  $\{ \phi(Y_\tau) : \tau \text{ stopping time; } \tau \leq \tau_G \}$  is uniformly  $Q^y$ -integrable  $\forall$  Markov controls  $u$  and all  $y \in G$ .

Then,  $\phi(y) \geq J^u(y), \forall u$  Markov control,  $\forall y \in G$ .

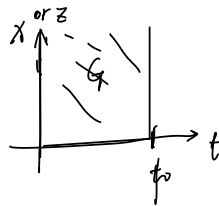
Moreover, if for each  $y \in G$ , we have  $u_0(y)$  s.t.  $f^{u_0(y)}(y) + L^{u_0(y)} \phi(y) = 0$

and  $\{ \phi(Y_\tau) : \tau \text{ stopping time; } \tau \leq \tau_G \}$  is uniformly  $Q^y$ -integrable,  $\forall y \in G$ .

Then,  $u_0 = u_0(y)$  is a Markov control s.t.  $\phi(y) = J^{u_0}(y)$ . i.e. an optimal control.

Rmk: an optimal Markov control is also an optimal  $F_t$ -adapted control (Thm 11.2.3)

## Application to the Portfolio selection problem



- $f=0$ ;  $g=N(z)$ ;  $G=\{(t,z) : t < t_0, z > 0\}$
- The operator  $L^v$ ;  $dz_t = z_t[a + b(1-u)]dt + u z_t dB_t$

$$L^v \bar{\Phi}(t,x) = \partial_t \bar{\Phi} + \lambda(a + b(1-v)) \partial_x \bar{\Phi} + \frac{1}{2} \lambda^2 v^2 x^2 \partial_{xx} \bar{\Phi}$$

- The HJB Eqn.  $\sup_{v \in U} L^v \bar{\Phi}(t,x) = 0, \quad \forall (t,x) \in G$ .
- $\bar{\Phi}|_{\partial G} = N : \begin{cases} \bar{\Phi}(t,x) = N(x), & \text{for } t=t_0, x > 0 \\ \bar{\Phi}(t,0) = N(0) & \text{for } t < t_0, x=0 \end{cases}$

$\Rightarrow \forall (t,x)$ , we find the  $v = v(t,x)$  that maximizes

$$J(v) = L^v \bar{\Phi} = \partial_t \bar{\Phi} + \lambda((a-b)v + b) \partial_x \bar{\Phi} + \frac{1}{2} \lambda^2 v^2 x^2 \partial_{xx} \bar{\Phi}, \quad \text{quadratic in } v \downarrow$$

- If  $\partial_x \bar{\Phi} > 0$ ,  $\partial_{xx} \bar{\Phi} < 0$ , the soln is:  $v = v(t,x) = - \frac{(a-b) \partial_x \bar{\Phi}}{\lambda^2 \partial_{xx} \bar{\Phi}}$

$$\Rightarrow \begin{cases} \partial_t \bar{\Phi} + \lambda b \partial_x \bar{\Phi} - \frac{(a-b)^2 (\partial_x \bar{\Phi})^2}{2 \lambda^2 \partial_{xx} \bar{\Phi}} = 0, & t < t_0, x > 0. \\ \bar{\Phi}(t,x) = N(x), & \text{for } t=t_0 \text{ or } x=0. \end{cases} \quad (3)$$

- (3) is a **fully nonlinear PDE**, hard to solve in general.

• Special cases:

1.  $N(x) = x^p, \quad 0 < p < 1$ . Separation of variables.  $\bar{\Phi}(t,x) = f(t) x^p$

$$f'(t) x^p + f(t) [\lambda b p x^{p-1} - \frac{(a-b)^2 p^2 x^{p-1}^2}{2 \lambda^2 p(p-1) x^{p-2}}] = 0$$

$$[f'(t) + \lambda f(t)] x^p = 0, \quad \lambda = b p + \frac{(a-b)^2}{2 \lambda^2 (1-p)}$$

$$\Rightarrow \bar{\Phi}(t,x) = e^{\lambda(t_0-t)} x^p$$

$$u^*(t,x) = \frac{a-b}{\lambda^2(1-p)} \quad (\text{if it is in } (0,1)).$$

$\Rightarrow$  Similarly,  $N(x) = \log x$

Remark: Such simple  $N(x)$  can be solved directly by Dynkin's formula (Aase 1984).