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## REMARK ON OPTIMAL INVESTMENT IN A MARKET WITH MEMORY

We consider a financial market model driven by a Gaussian semi-martingale with stationary increments. This driving noise process consists of  $n$  independent components and each component has memory described by two parameters. We extend results of the authors on optimal investment in this market.

### 1. INTRODUCTION

In this paper, we extend results of Inoue and Nakano [12] on optimal investment in a financial market model with memory. This market model  $\mathcal{M}$  consists of  $n$  risky and one riskless assets. The price of the riskless asset is denoted by  $S_0(t)$  and that of the  $i$ th risky asset by  $S_i(t)$ . We put  $S(t) = (S_1(t), \dots, S_n(t))'$ , where  $A'$  denotes the transpose of a matrix  $A$ . The dynamics of the  $\mathbf{R}^n$ -valued process  $S(t)$  are described by the stochastic differential equation

$$dS_i(t) = S_i(t) \left[ \mu_i(t)dt + \sum_{j=1}^n \sigma_{ij}(t)dY_j(t) \right], \quad t \geq 0, \quad S_i(0) = s_i, \quad (1) \\ i = 1, \dots, n,$$

while those of  $S_0(t)$  by the ordinary differential equation

$$dS_0(t) = r(t)S_0(t)dt, \quad t \geq 0, \quad S_0(0) = 1,$$

where the coefficients  $r(t) \geq 0$ ,  $\mu_i(t)$ , and  $\sigma_{ij}(t)$  are continuous deterministic functions on  $[0, \infty)$  and the initial prices  $s_i$  are positive constants. We assume that the  $n \times n$  volatility matrix  $\sigma(t) = (\sigma_{ij}(t))_{1 \leq i, j \leq n}$  is nonsingular for  $t \geq 0$ .

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Invited lecture.

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We define the  $j$ th component  $Y_j(t)$  of the  $\mathbf{R}^n$ -valued driving noise process  $Y(t) = (Y_1(t), \dots, Y_n(t))'$  of (1) by the autoregressive type equation

$$\frac{dY_j(t)}{dt} = - \int_{-\infty}^t p_j e^{-q_j(t-s)} \frac{dY_j(s)}{ds} ds + \frac{dW_j(t)}{dt}, \quad t \in \mathbf{R}, \quad Y_j(0) = 0,$$

where  $W(t) = (W_1(t), \dots, W_n(t))'$ ,  $t \in \mathbf{R}$ , is an  $\mathbf{R}^n$ -valued standard Brownian motion defined on a complete probability space  $(\Omega, \mathcal{F}, P)$ , the derivatives  $dY_j(t)/dt$  and  $dW_j(t)/dt$  are in the random distribution sense, and  $p_j$ 's and  $q_j$ 's are constants such that

$$0 < q_j < \infty, \quad -q_j < p_j < \infty, \quad j = 1, \dots, n \quad (2)$$

(see Anh–Inoue [1]). Equivalently, we may define  $Y_j(t)$  by the moving-average type representation

$$Y_j(t) = W_j(t) - \int_0^t \left[ \int_{-\infty}^s p_j e^{-(q_j+p_j)(s-u)} dW_j(u) \right] ds, \quad t \in \mathbf{R}$$

(see [1], Examples 2.12 and 2.14). The components  $Y_j(t)$ ,  $j = 1, \dots, n$ , are Gaussian processes with stationary increments that are independent of each other. Each  $Y_j(t)$  has short memory that is described by the two parameters  $p_j$  and  $q_j$ . Notice that, in the special case  $p_j = 0$ ,  $Y_j(t)$  reduces to the Brownian motion  $W_j(t)$ .

The underlying information structure of the market model  $\mathcal{M}$  is the filtration  $(\mathcal{F}_t)_{t \geq 0}$  defined by

$$\mathcal{F}_t := \sigma(\sigma(Y(s) : 0 \leq s \leq t) \cup \mathcal{N}), \quad t \geq 0,$$

where  $\mathcal{N}$  is the  $P$ -null subsets of  $\mathcal{F}$ . With respect to this filtration,  $Y(t)$  is a semimartingale. In fact, we have the following two kinds of semimartingale representations of  $Y(t)$  (see Anh et al. [2], Example 5.3, and Inoue et al. [13], Theorem 2.1):

$$Y_j(t) = B_j(t) - \int_0^t \left[ \int_0^s k_j(s, u) dY_j(u) \right] ds, \quad t \geq 0, \quad j = 1, \dots, n, \quad (3)$$

$$Y_j(t) = B_j(t) - \int_0^t \left[ \int_0^s l_j(s, u) dB_j(u) \right] ds, \quad t \geq 0, \quad j = 1, \dots, n, \quad (4)$$

where, for  $j = 1, \dots, n$ ,  $(B_j(t))_{t \geq 0}$  is the innovation process, i.e., an  $\mathbf{R}$ -valued standard Brownian motion such that

$$\sigma(Y_j(s) : 0 \leq s \leq t) = \sigma(B_j(s) : 0 \leq s \leq t), \quad t \geq 0,$$

and  $B_j$ 's are independent of each other. The point of (3) and (4) is that the deterministic kernels  $k_j(t, s)$  and  $l_j(t, s)$  are given explicitly by

$$k_j(t, s) = p_j(2q_j + p_j) \frac{(2q_j + p_j)e^{q_j s} - p_j e^{-q_j s}}{(2q_j + p_j)^2 e^{q_j t} - p_j^2 e^{-q_j t}}, \quad 0 \leq s \leq t, \quad (5)$$

$$l_j(t, s) = e^{-(p_j+q_j)(t-s)} l_j(s), \quad 0 \leq s \leq t, \quad (6)$$

with

$$l_j(s) := p_j \left[ 1 - \frac{2p_j q_j}{(2q_j + p_j)^2 e^{2q_j s} - p_j^2} \right], \quad s \geq 0. \quad (7)$$

There already exist many references in which the standard driving noise, that is, Brownian motion, is replaced by a different one, such as fractional Brownian motion, so that the market model can capture *memory effect*. See, e.g., Barndorff-Nielsen and Shephard [3], Hu et al. [11], Mishura [15] and Heyde and Leonenko [10]. Among such models, the above model  $\mathcal{M}$  driven by  $Y(t)$  which is a Gaussian semimartingale with *stationary increments* is possibly the simplest one. One advantage of  $\mathcal{M}$  is that, assuming  $\sigma_{ij}(t) = \sigma_{ij}$ , real constants, we can easily estimate the characteristic parameters  $p_j$ ,  $q_j$  and  $\sigma_{ij}$  from stock price data. See [12], Appendix C, for this parameter estimation from real market data.

In the market  $\mathcal{M}$ , an agent with initial endowment  $x \in (0, \infty)$  invests, at each time  $t$ ,  $\pi_i(t)X^{x,\pi}(t)$  dollars in the  $i$ th risky asset for  $i = 1, \dots, n$  and  $[1 - \sum_{i=1}^n \pi_i(t)]X^{x,\pi}(t)$  dollars in the riskless asset, where  $X^{x,\pi}(t)$  denotes the agent's wealth at time  $t$ . The wealth process  $X^{x,\pi}(t)$  is governed by the stochastic differential equation

$$\frac{dX^{x,\pi}(t)}{X^{x,\pi}(t)} = \left[ 1 - \sum_{i=1}^n \pi_i(t) \right] \frac{dS_0(t)}{S_0(t)} + \sum_{i=1}^n \pi_i(t) \frac{dS_i(t)}{S_i(t)}, \quad X^{x,\pi}(0) = x.$$

Here, the self-financing strategy  $\pi(t) = (\pi_1(t), \dots, \pi_n(t))'$  is chosen from the admissible class

$$\mathcal{A}_T := \left\{ \pi = (\pi(t))_{0 \leq t \leq T} : \begin{array}{l} \pi \text{ is an } \mathbf{R}^n\text{-valued, progressively measurable} \\ \text{process satisfying } \int_0^T \|\pi(t)\|^2 dt < \infty \text{ a.s.} \end{array} \right\}$$

for the finite time horizon of length  $T \in (0, \infty)$ , where  $\|\cdot\|$  denotes the Euclidean norm of  $\mathbf{R}^n$ . If the time horizon is infinite,  $\pi(t)$  is chosen from

$$\mathcal{A} := \{(\pi(t))_{t \geq 0} : (\pi(t))_{0 \leq t \leq T} \in \mathcal{A}_T \text{ for every } T \in (0, \infty)\}.$$

Let  $\alpha \in (-\infty, 1) \setminus \{0\}$  and  $c \in \mathbf{R}$ . In [12], the following three optimal investment problems for the model  $\mathcal{M}$  are considered:

$$V(T, \alpha) := \sup_{\pi \in \mathcal{A}_T} \frac{1}{\alpha} E[(X^{x,\pi}(T))^\alpha], \quad (8)$$

$$J(\alpha) := \sup_{\pi \in \mathcal{A}} \limsup_{T \rightarrow \infty} \frac{1}{\alpha T} \log E[(X^{x,\pi}(T))^\alpha], \quad (9)$$

$$I(c) := \sup_{\pi \in \mathcal{A}} \limsup_{T \rightarrow \infty} \frac{1}{T} \log P[X^{x,\pi}(T) \geq e^{cT}]. \quad (10)$$

Problem (8) is the classical optimal investment problem that dates back to Merton (cf. Karatzas and Shreve [14]). Hu et al. [11] studied this problem for

a Black–Scholes type model driven by fractional Brownian motion. Problem (9) is a kind of long term optimal investment problem which is studied by Bielecki and Pliska [4], and also by other authors under various settings, including Fleming and Sheu [5,6], Nagai and Peng [16], Pham [17,18], Hata and Iida [7], and Hata and Sekine [8,9]. Problem (10) is another type of long term optimal investment problem, the aim of which is to maximize the large deviation probability that the wealth grows at a higher rate than the given benchmark  $c$ . Pham [17,18] studied this problem and established a duality relation between Problems (9) and (10). Subsequently, this problem is studied by Hata and Iida [7] and Hata and Sekine [8,9] under different settings.

In [12], Problems (8)–(10) are studied for the market model  $\mathcal{M}$  which has memory. There, the following condition, rather than (2), is assumed in solving (8)–(10):

$$0 < q_j < \infty, \quad 0 \leq p_j < \infty, \quad j = 1, \dots, n. \quad (11)$$

Thus, in [12],  $p_j \geq 0$  rather than  $p_j > -q_j$  for  $j = 1, \dots, n$ . In this paper, we focus on Problems (8) and (9), and extends the results of [12] so that  $p_j$ 's may take negative values. The key to this extension is to show the existence of solution for a relevant Riccati type equation.

In Sections 2 and 3, we review the results of [12] on Problems (8) and (9), respectively, and, in Section 4, we extend these results.

## 2. OPTIMAL INVESTMENT OVER A FINITE HORIZON

In this section, we review the result of [12] on the finite horizon optimization problem (8) for the market model  $\mathcal{M}$ . We assume  $\alpha \in (-\infty, 1) \setminus \{0\}$  and (11).

Let  $Y(t) = (Y_1(t), \dots, Y_n(t))'$  and  $B(t) = (B_1(t), \dots, B_n(t))'$  be the driving noise and innovation processes, respectively, described in the previous section. We define an  $\mathbf{R}^n$ -valued deterministic function  $\lambda(t) = (\lambda_1(t), \dots, \lambda_n(t))'$  by

$$\lambda(t) := \sigma^{-1}(t) [\mu(t) - r(t)\mathbf{1}], \quad t \geq 0, \quad (12)$$

where  $\mathbf{1} := (1, \dots, 1)' \in \mathbf{R}^n$ . For  $k_j(t, s)$ 's in (5), we put

$$k(t, s) := \text{diag}(k_1(t, s), \dots, k_n(t, s)), \quad 0 \leq s \leq t.$$

Let  $\xi(t) = (\xi_1(t), \dots, \xi_n(t))'$  be the  $\mathbf{R}^n$ -valued process  $\int_0^t k(t, s) dY(s)$ , i.e.,

$$\xi_j(t) := \int_0^t k_j(t, s) dY_j(s), \quad t \geq 0, \quad j = 1, \dots, n. \quad (13)$$

Let  $\beta$  be the conjugate exponent of  $\alpha$ , i.e.,

$$(1/\alpha) + (1/\beta) = 1.$$

Notice that  $0 < \beta < 1$  (resp.  $-\infty < \beta < 0$ ) if  $-\infty < \alpha < 0$  (resp.  $0 < \alpha < 1$ ).

We put  $l(t) := \text{diag}(l_1(t), \dots, l_n(t))$ ,  $p := \text{diag}(p_1, \dots, p_n)$ , and  $q := \text{diag}(q_1, \dots, q_n)$  with  $l_j(t)$ 's as in (7). We also put

$$\rho(t) = (\rho_1(t), \dots, \rho_n(t))', \quad b(t) = \text{diag}(b_1(t), \dots, b_n(t))$$

with

$$\rho_j(t) := -\beta l_j(t) \lambda_j(t), \quad t \geq 0, \quad j = 1, \dots, n, \quad (14)$$

$$b_j(t) := -(p_j + q_j) + \beta l_j(t), \quad t \geq 0, \quad j = 1, \dots, n. \quad (15)$$

We consider the following one-dimensional backward Riccati equations: for  $j = 1, \dots, n$

$$\begin{aligned} \dot{R}_j(t) - l_j^2(t) R_j^2(t) + 2b_j(t) R_j(t) + \beta(1 - \beta) &= 0, \quad 0 \leq t \leq T, \\ R_j(T) &= 0. \end{aligned} \quad (16)$$

We have the following result on the existence of solution to (16).

**Lemma 1** ([12], Lemma 2.1). *Let  $j \in \{1, \dots, n\}$ .*

1. *If  $p_j = 0$ , then (16) has a unique solution  $R_j(t) \equiv R_j(t; T)$ .*
2. *If  $p_j > 0$  and  $-\infty < \alpha < 0$ , then (16) has a unique nonnegative solution  $R_j(t) \equiv R_j(t; T)$ .*
3. *If  $p_j > 0$  and  $0 < \alpha < 1$ , then (16) has a unique solution  $R_j(t) \equiv R_j(t; T)$  such that  $R_j(t) \geq b_j(t)/l_j^2(t)$  for  $t \in [0, T]$ .*

In what follows, we write  $R_j(t) \equiv R_j(t; T)$  for the unique solution to (16) in the sense of Lemma 1, and we put  $R(t) := \text{diag}(R_1(t), \dots, R_n(t))$ .

For  $j = 1, \dots, n$ , let  $v_j(t) \equiv v_j(t; T)$  be the solution to the following one-dimensional linear equation:

$$\begin{aligned} \dot{v}_j(t) + [b_j(t) - l_j^2(t) R_j(t; T)] v_j(t) + \beta(1 - \beta) \lambda_j(t) - R_j(t; T) \rho_j(t) &= 0, \\ 0 \leq t \leq T, \quad v_j(T) &= 0. \end{aligned} \quad (17)$$

We put  $v(t) \equiv v(t; T) := (v_1(t; T), \dots, v_n(t; T))'$ .

For  $j = 1, \dots, n$  and  $(t, T) \in \Delta$ , write

$$g_j(t; T) := v_j^2(t; T) l_j^2(t) + 2\rho_j(t) v_j(t; T) - l_j^2(t) R_j(t; T) - \beta(1 - \beta) \lambda_j^2(t),$$

where

$$\Delta := \{(t, T) : 0 < T < \infty, 0 \leq t \leq T\}.$$

Recall that we have assumed  $\alpha \in (-\infty, 1) \setminus \{0\}$  and (11). Here is the solution to Problem (8) under the condition (11).

**Theorem 2** ([12], Theorem 2.3). *For  $T \in (0, \infty)$ , the strategy  $(\hat{\pi}_T(t))_{0 \leq t \leq T} \in \mathcal{A}_T$  defined by*

$$\hat{\pi}_T(t) := (\sigma')^{-1}(t) [(1 - \beta)\lambda(t) - \{1 - \beta + l(t)R(t; T)\}\xi(t) + l(t)v(t; T)] \quad (18)$$

*is the unique optimal strategy for Problem (8). The value function  $V(T) \equiv V(T, \alpha)$  in (8) is given by*

$$V(T) = \frac{1}{\alpha} [xS_0(T)]^\alpha \exp \left[ \frac{(1 - \alpha)}{2} \sum_{j=1}^n \int_0^T g_j(t; T) dt \right].$$

### 3. OPTIMAL INVESTMENT OVER AN INFINITE HORIZON

In this section, we review the result of [12] on the infinite horizon optimization problem (9) for the financial market model  $\mathcal{M}$ . Throughout this section, we assume (11) and the following two conditions:

$$\lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T r(t) dt = \bar{r} \quad \text{with } \bar{r} \in \mathbf{R}, \quad (19)$$

$$\lim_{T \rightarrow \infty} \lambda(t) = \bar{\lambda} \quad \text{with } \bar{\lambda} = (\bar{\lambda}_1, \dots, \bar{\lambda}_n)' \in \mathbf{R}^n. \quad (20)$$

Here recall  $\lambda(t) = (\lambda_1(t), \dots, \lambda_n(t))'$  from (12).

Let  $\alpha \in (-\infty, 1) \setminus \{0\}$  and  $\beta$  be its conjugate exponent. Let  $j \in \{1, \dots, n\}$ . For  $b_j(t)$  in (15), we have  $\lim_{t \rightarrow \infty} b_j(t) = \bar{b}_j$ , where

$$\bar{b}_j := -(1 - \beta)p_j - q_j.$$

Notice that  $\bar{b}_j < 0$ . We consider the equation

$$p_j^2 x^2 - 2\bar{b}_j x - \beta(1 - \beta) = 0. \quad (21)$$

When  $p_j = 0$ , we write  $\bar{R}_j$  for the unique solution  $\beta(1 - \beta)/(2q_j)$  of this linear equation. If  $p_j > 0$ , then

$$\bar{b}_j^2 + \beta(1 - \beta)p_j^2 = (1 - \beta)[(p_j + q_j)^2 - q_j^2] + q_j^2 \geq q_j^2 > 0,$$

so that we may write  $\bar{R}_j$  for the larger solution to the quadratic equation (21). Let  $j \in \{1, \dots, n\}$ . For  $\rho_j(t)$  in (14), we have  $\lim_{t \rightarrow \infty} \rho_j(t) = \bar{\rho}_j$ , where

$$\bar{\rho}_j := -\beta p_j \bar{\lambda}_j.$$

Define  $\bar{v}_j$  by

$$(\bar{b}_j - p_j^2 \bar{R}_j) \bar{v}_j + \beta(1 - \beta) \bar{\lambda}_j - \bar{R}_j \bar{\rho}_j = 0.$$

For  $j = 1, \dots, n$  and  $-\infty < \alpha < 1$ ,  $\alpha \neq 0$ , we put

$$F_j(\alpha) := \frac{(p_j + q_j)^2 \bar{\lambda}_j^2 \alpha}{[(1 - \alpha)(p_j + q_j)^2 + \alpha p_j(p_j + 2q_j)]},$$

and

$$G_j(\alpha) := (p_j + q_j) - q_j \alpha - (1 - \alpha)^{1/2} [(1 - \alpha)(p_j + q_j)^2 + \alpha p_j(p_j + 2q_j)]^{1/2}.$$

Recall  $\xi(t)$  from (13). Taking into account (18), we consider  $\hat{\pi} = (\hat{\pi}(t))_{t \geq 0} \in \mathcal{A}$  defined by

$$\hat{\pi}(t) := (\sigma')^{-1}(t) [(1 - \beta)\lambda(t) - (1 - \beta + p\bar{R})\xi(t) + p\bar{v}], \quad t \geq 0,$$

where  $\bar{R} := \text{diag}(\bar{R}_1, \dots, \bar{R}_n)$ ,  $\bar{v} := (\bar{v}_1, \dots, \bar{v}_n)'$ , and  $p := \text{diag}(p_1, \dots, p_n)$ .

We define

$$\alpha_* := \max(\alpha_{1*}, \dots, \alpha_{n*}) \quad (22)$$

with

$$\alpha_{j*} := \begin{cases} -\infty & \text{if } -\infty < p_j \leq 2q_j, \\ -3 - \frac{8q_j}{p_j - 2q_j} & \text{if } 2q_j < p_j < \infty. \end{cases} \quad (23)$$

Notice that  $\alpha_* \in [-\infty, -3)$ .

Recall that we have assumed (11), (19) and (20). Here is the solution to Problem (9) under the condition (11).

**Theorem 3** ([12], Theorem 3.4). *Let  $\alpha_* < \alpha < 1$ ,  $\alpha \neq 0$ . Then  $\hat{\pi}$  is an optimal strategy for Problem (9) with limit rather than limsup in (9). The optimal growth rate  $J(\alpha)$  in (9) is given by*

$$J(\alpha) = \bar{r} + \frac{1}{2\alpha} \sum_{j=1}^n F_j(\alpha) + \frac{1}{2\alpha} \sum_{j=1}^n G_j(\alpha).$$

#### 4. EXTENSIONS

In this section, we extend Theorems 2 and 3 so that  $p_j$ 's may take negative values. The key is to extend Lemma 1 properly. We assume  $\alpha \in (-\infty, 1) \setminus \{0\}$  and (2).

We put, for  $j = 1, \dots, n$ ,

$$\begin{aligned} a_{1j}(t) &= l_j(t)^2, \\ a_{2j}(t) &= \beta l_j(t) - (p_j + q_j), \\ a_3 &= \beta(1 - \beta). \end{aligned}$$

Then the Riccati equation (16) becomes

$$\begin{aligned} \dot{R}_j(t) - a_{1j}(t)R_j^2(t) + 2a_{2j}(t)R_j(t) + a_3 &= 0, \quad 0 \leq t \leq T, \\ R_j(T) &= 0. \end{aligned}$$

Note that  $l_j(t)$  is increasing and satisfies

$$l_j(0) = \frac{p_j(p_j + 2q_j)}{2(p_j + q_j)} \leq l_j(t) \leq p_j, \quad t \geq 0.$$

**Proposition 4.** *Let  $j \in \{1, \dots, n\}$ . We assume  $-q_j < p_j < 0$  and*

$$0 < \alpha \leq \left( \frac{p_j + q_j}{p_j + q_j - l_j(0)} \right)^2. \quad (24)$$

1. *It holds that  $a_{2j}(t) \leq 0$  for  $t \geq 0$ .*
2. *It holds that  $a_{2j}(t)^2 + a_{1j}(t)a_3 \geq 0$  for  $t \geq 0$ .*

*Proof.* We have

$$a_{2j}(t) = \beta l_j(t) - (p_j + q_j) \leq \beta l_j(0) - (p_j + q_j),$$

whence  $a_{2j}(t) \leq 0$  if  $\beta \geq (p_j + q_j)/l_j(0)$  or

$$\alpha \leq \frac{(p_j + q_j)/l_j(0)}{[(p_j + q_j)/l_j(0)] - 1} = \frac{p_j + q_j}{p_j + q_j - l_j(0)}.$$

However,  $0 < (p_j + q_j)/[p_j + q_j - l_j(0)] < 1$ , whence

$$\frac{p_j + q_j}{p_j + q_j - l_j(0)} > \left( \frac{p_j + q_j}{p_j + q_j - l_j(0)} \right)^2.$$

Thus the first assertion follows.

We have

$$\begin{aligned} a_{2j}(t)^2 + a_{1j}(t)a_3 &= \beta l_j(t)^2 - 2(p_j + q_j)l_j(t)\beta + (p_j + q_j)^2 \\ &\geq \beta l_j(0)^2 - 2(p_j + q_j)l_j(0)\beta + (p_j + q_j)^2 \\ &= \beta[\{(p_j + q_j) - l_j(0)\}^2 - (p_j + q_j)^2] + (p_j + q_j)^2, \end{aligned}$$

whence  $a_{2j}(t)^2 + a_{1j}(t)a_3 \geq 0$  if

$$\beta \geq \frac{(p_j + q_j)^2}{(p_j + q_j)^2 - [(p_j + q_j) - l_j(0)]^2}.$$

However, this is equivalent to  $\alpha \leq [(p_j + q_j)/\{(p_j + q_j) - l_j(0)\}]^2$ . Thus the second assertion follows.

**Lemma 5.** *Let  $j \in \{1, \dots, n\}$ .*



1. We assume  $-q_j < p_j < 0$  and  $-\infty < \alpha < 0$ . Then (16) has a unique nonnegative solution  $R_j(t) \equiv R_j(t; T)$ .
2. We assume  $-q_j < p_j < 0$  and (24). Then (16) has a unique solution  $R_j(t) \equiv R_j(t; T)$  such that  $R_j(t) \geq R_j^*(t)$  for  $t \in [0, T]$ , where

$$R_j^*(t) := \frac{a_{2j}(t) + \sqrt{a_{2j}(t)^2 + a_{1j}(t)a_3}}{a_{1j}(t)}.$$

*Proof.* The first assertion follows in the same way as in the proof of [12], Lemma 2.1 (ii). Thus we prove the second assertion.

Notice that  $R_j^*(t)$  is the larger solution to the quadratic equation  $a_{1j}(t)x^2 - 2a_{2j}(t)x - a_3 = 0$ . Thus

$$a_{1j}(t)R_j^*(t)^2 - 2a_{2j}(t)R_j^*(t) - a_3 = 0. \quad (25)$$

Since  $a_{1j}(t) > 0$ ,  $a_{2j}(t) \leq 0$  and  $a_3 < 0$ , we see that  $R_j^*(t) \leq 0$ . The equation for  $V(t) := R_j(t) - R_j^*(t)$  becomes

$$\dot{V}(t) - a_{1j}(t)V(t)^2 + 2[a_{2j}(t) - a_{1j}(t)R_j^*(t)]V(t) + \dot{R}_j^*(t) = 0. \quad (26)$$

By differentiating (25), we get

$$\dot{a}_{1j}(t)R_j^*(t)^2 + 2a_{1j}(t)R_j^*(t)\dot{R}_j^*(t) - 2\dot{a}_{2j}R_j^*(t) - 2a_{2j}(t)\dot{R}_j^*(t) = 0,$$

whence

$$\dot{R}_j^*(t) = \frac{2\dot{a}_{2j}(t)R_j^*(t) - \dot{a}_{1j}(t)R_j^*(t)^2}{2\sqrt{a_{2j}(t)^2 + a_{1j}(t)a_3}}.$$

Now

$$2\dot{a}_{2j}(t)R_j^*(t) - \dot{a}_{1j}R_j^*(t)^2 = -2\dot{l}_j(t)R_j^*(t)\{l_j(t)R_j^*(t) - \beta\}.$$

Since

$$a_{2j}(t)^2 + a_{1j}(t)a_3 = \beta l_j(t)^2 - 2(p_j + q_j)l_j(t)\beta + (p_j + q_j)^2 < (p_j + q_j)^2,$$

we see that

$$l_j(t)R_j^*(t) - \beta = \frac{1}{l_j(t)} \left[ -(p_j + q_j) + \sqrt{a_{2j}(t)^2 + a_{1j}(t)a_3} \right] > 0.$$

Thus  $\dot{R}_j^*(t) \geq 0$ . This and  $a_{1j}(t) > 0$  imply that (26) has a unique nonnegative solution. The second assertion follows from this.

We define

$$\alpha^* := \min(\alpha_1^*, \dots, \alpha_n^*)$$

with

$$\alpha_j^* := \begin{cases} \left( \frac{p_j + q_j}{p_j + q_j - l_j(0)} \right)^2 & \text{if } -q_j < p_j < 0, \\ 1 & \text{if } 0 \leq p_j < \infty. \end{cases}$$

Notice that  $\alpha^* \in (0, 1]$ . Recall  $\alpha_*$  from (22).

Taking the solution  $R_j(t) \equiv R_j(t; T)$  of (16) in the sense of Lemma 1 or 5 and running through the same arguments as those in [12], Sections 2 and 3, we obtain the following extensions to Theorems 2 and 3.

**Theorem 6.** *We assume (2) and  $-\infty < \alpha < \alpha^*$ ,  $\alpha \neq 0$ . Then the same conclusions as those of Theorem 2 hold.*

**Theorem 7.** *We assume (2), (19), (20) and  $\alpha_* < \alpha < \alpha^*$ ,  $\alpha \neq 0$ . Then the same conclusions as those of Theorem 3 hold.*

#### BIBLIOGRAPHY

1. Anh, V. and Inoue, A., *Financial markets with memory I: Dynamic models*, Stoch. Anal. Appl., **23**, (2005), 275–300.
2. Anh, V., Inoue, A. and Kasahara, Y., *Financial markets with memory II: Innovation processes and expected utility maximization*, Stoch. Anal. Appl., **23**, (2005), 301–328.
3. Barndorff-Nielsen, O. E. and Shephard, N., *Non-Gaussian Ornstein–Uhlenbeck-based models and some of their uses in financial economics*, J. Roy. Statist. Soc. Ser. B, **63**, (2001), 167–241.
4. Bielecki, T. R. and Pliska, S. R., *Risk sensitive dynamic asset management*, Appl. Math. Optim., **39**, (1999), 337–360.
5. Fleming W. H. and Sheu, S. J., *Risk-sensitive control and an optimal investment model*, Math. Finance, **10**, (2000), 197–213.
6. Fleming, W. H. and Sheu, S. J., *Risk-sensitive control and an optimal investment model (II)*, Ann. Appl. Probab., **12**, (2000), 730–767.
7. Hata, H. and Iida, Y., *A risk-sensitive stochastic control approach to an optimal investment problem with partial information*, Finance Stoch., **10**, (2006), 395–426.
8. Hata, H. and Sekine, J., *Solving long term optimal investment problems with Cox-Ingersoll-Ross interest rates*, Adv. Math. Econ., **8**, (2006), 231–255.
9. Hata, H. and Sekine, J., *Solving a large deviations control problem with a nonlinear factor model*, preprint.
10. Heyde, C. C. and Leonenko, N. N., *Student processes*, Adv. in Appl. Probab., **37**, (2005), 342–365.
11. Hu, Y. Øksendal, B. and Sulem, A., *Optimal consumption and portfolio in a Black-Scholes market driven by fractional Brownian motion*, Infin. Dimens. Anal. Quantum Probab. Relat. Top., **6**, (2003), 519–536.

12. Inoue, A. and Nakano, Y., *Optimal long term investment model with memory*, Appl. Math. Optim., to appear.  
Available at <http://arxiv.org/abs/math.PR/0506621>.
13. Inoue, A. Nakano, Y. and Anh, V., *Linear filtering of systems with memory and application to finance*, J. Appl. Math. Stoch. Anal., **2006**, (2006), 1–26.
14. Karatzas, I. and Shreve, S. E., *Methods of mathematical finance*, Springer-Verlag, New York, (1998).
15. Mishura, Yu., *Fractional stochastic integration and Black–Scholes equation for fractional Brownian motion model with stochastic volatility*, Stoch. Stoch. Rep., **76**, (2004), 363–381.
16. Nagai, H. and Peng, S., *Risk-sensitive dynamic portfolio optimization with partial information on infinite time horizon*, Ann. Appl. Probab., **12**, (2002), 173–195.
17. Pham, H., *A large deviations approach to optimal long term investment*, Finance Stoch., **7**, (2003), 169–195.
18. Pham, H., *A risk-sensitive control dual approach to a large deviations control problem*, Systems Control Lett., **49**, (2003), 295–309.

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