

ROBUST MEAN-VARIANCE HEDGING IN THE SINGLE PERIOD MODEL

Tevzadze R.

**Abstract.** We give an explicit solution of robust mean-variance hedging problem in the continuous time model for some type of contingent claims.

**Keywords and phrases:** The min-max problem, mean-variance hedging, robust optimization.

**AMS subject classification:** 60H30, 90C47.

We consider a financial market with one riskless asset of price  $S^0 = 1$  and one risky asset of price process  $S$ . We shall fix throughout a canonical, filtered measurable space  $(\Omega, \mathcal{F}, F = (F_t)_{t \in T})$ , and assume that  $\Omega$  coincides with the space  $C[0, T]$  of all continuous functions,  $F_t = \sigma(w(s), 0 \leq s \leq t)$  and  $\mathcal{F} = F_T$ . We shall call admissible system a collection  $M$  consisting of the underlying filtered space  $(\Omega, \mathcal{F}, F)$ , of a probability measure  $P$  on it, and of a pair of processes  $(S, W)$ , with  $W$   $F$ -Brownian motion. These processes have the dynamics

$$dS_t = b_t(S)dt + \sigma_t(S)dW_t, \quad (1)$$

for some progressively measurable functionals  $b$  and  $\sigma$  with value in convex compact subset  $K \subset R \times R_+$ .

As proved by Krylov [2] the distribution laws of such type processes constitute weak compact convex subset  $\mathcal{P}_K$  in the set of probability measures on  $(\Omega, \mathcal{F})$ .

An agent, starting from a capital  $x$ , invests an amount  $\pi_t$  at any time  $t$  in the risky asset. His wealth process, controlled by  $X_t$ , is given by

$$X_t = x + \int_0^t \pi_u dS_u = x + \int_0^t \pi_u (b_u du + \sigma_u dW_u), \quad 0 \leq t \leq T. \quad (2)$$

We denote by  $\Pi$  the set of progressively measurable processes  $\pi$  on  $(\Omega, \mathcal{F}, F)$ , such that

$$E^P \int_0^T |\pi_t|^2 dt < \infty \text{ for all } P \in \mathcal{P}_K \quad (3)$$

and by  $U_K$  the set of progressively measurable processes  $(b, \sigma)$  on  $(\Omega, \mathcal{F}, F)$  valued in  $K$ . The robust mean-variance hedging problem (also called robust quadratic minimization problem) of a contingent claim  $H(S)$  is formulated as

$$\min_{\pi \in \Pi} \max_{(b, \sigma) \in U_K} E |H(S) - x - \int_0^T \pi_t dS_t|^2, \quad (4)$$

which by results of Krylov [2] and by a saddle point existence theorem of Neumann [1] can be reformulated as

$$\begin{aligned} & \min_{\pi \in \Pi} \max_{P \in \mathcal{P}_K} E^P |H(S) - x - \int_0^T \pi_t dS_t|^2 \\ &= \max_{P \in \mathcal{P}_K} \min_{\pi \in \Pi} E^P |H(S) - x - \int_0^T \pi_t dS_t|^2 \\ &= \max_{(b, \sigma) \in U_K} \min_{\pi \in \Pi} E |H(S) - x - \int_0^T \pi_t dS_t|^2. \end{aligned}$$

The mean-variance hedging problem with given coefficients

$$v_{\theta, \sigma}(x) = \min_{\pi \in \Pi} E |H(S) - x - \int_0^T \pi_t \sigma_t (\theta_t dt + dW_t)|^2, \quad (5)$$

has solution of the form (see [3])

$$\begin{aligned} v_{\theta, \sigma}(x) &= \frac{(x - EH(S) \mathcal{E}_T(-\int \theta dW))^2}{E \mathcal{E}_T^2(-\int \theta dW)} \\ \pi_t^* &= h_t - \theta_t / \sigma_t (E(H(S) | \mathcal{F}_t) - X_t^*), \end{aligned}$$

where  $\theta = \frac{b}{\sigma}$ ,  $\mathcal{E}_t(-\int \theta dW)$  is Doleans-Dade exponential and  $h$  is the integrand of the stochastic integral representation of  $E(H(S) | \mathcal{F}_t)$ . Suppose that

$$K = \{(b, \sigma) : \theta = b/\sigma \in [\underline{\theta}, \bar{\theta}], \sigma \in [\underline{\sigma}, \bar{\sigma}]\},$$

where  $\underline{\theta} \leq \bar{\theta}$ ,  $0 < \underline{\sigma} \leq \bar{\sigma}$  are given numbers. Hence

$$\begin{aligned} & \max_{(b, \sigma) \in U_K} \min_{\pi \in \Pi} E |H(S) - x - \int_0^T \pi_t dS_t|^2 \\ &= \max_{(b, \sigma) \in U_K} \frac{(x - EH(S) \mathcal{E}_T(-\int \theta dW))^2}{E \mathcal{E}_T^2(-\int \theta dW)} \\ &= \frac{\max_{\sigma} (x - EH(S) \mathcal{E}_T(-\int \theta dW))^2}{\min_{\theta} E \mathcal{E}_T^2(-\int \theta dW)} \\ &= \frac{\max_{\sigma} (x - EH(S) \mathcal{E}_T(-\int \theta dW))^2}{e^{\theta^2 T}}. \end{aligned}$$

Denote by  $\tilde{E}$  the expectation with respect to  $\tilde{P} = \mathcal{E}_t(-\int \theta dW)P$ . Then  $S$  is the solution of  $dS_t = \sigma_t(S) d\tilde{W}_t$  with respect to  $\tilde{P}$ . Since

$$\begin{aligned} & \max_{\underline{\sigma} \leq \sigma_t \leq \bar{\sigma}} (x - \tilde{E}H(S))^2 \\ &= \begin{cases} (x - \max_{\underline{\sigma} \leq \sigma_t \leq \bar{\sigma}} \tilde{E}H(S))^2 & \text{if } x < \frac{1}{2}(\max_{\underline{\sigma} \leq \sigma_t \leq \bar{\sigma}} \tilde{E}H(S) + \min_{\underline{\sigma} \leq \sigma_t \leq \bar{\sigma}} \tilde{E}H(S)), \\ (x - \min_{\underline{\sigma} \leq \sigma_t \leq \bar{\sigma}} \tilde{E}H(S))^2 & \text{if } x > \frac{1}{2}(\max_{\underline{\sigma} \leq \sigma_t \leq \bar{\sigma}} \tilde{E}H(S) + \min_{\underline{\sigma} \leq \sigma_t \leq \bar{\sigma}} \tilde{E}H(S)), \end{cases} \end{aligned}$$

the minimax problem reduces to the solution of problems

$$\max_{\underline{\sigma} \leq \sigma_t \leq \bar{\sigma}} \tilde{E}H(S) \text{ and } \min_{\underline{\sigma} \leq \sigma_t \leq \bar{\sigma}} \tilde{E}H(S).$$

If  $H$  is a terminal functional i.e.  $H(S) = g(S_T)$  for continuous function  $g(s)$  satisfying linear growth condition,  $\bar{v}(t, s) = \max_{\underline{\sigma} \leq \sigma_t \leq \bar{\sigma}} \tilde{E}_{t,s}g(S_T)$  satisfies the Barenblatt equation

$$\bar{v}_t(t, s) + \frac{1}{2}\bar{\sigma} \bar{v}_{ss}(t, s)^+ - \frac{1}{2}\bar{\sigma} \bar{v}_{ss}(t, s)^- = 0, \bar{v}(T, s) = g(s)$$

and

$$\sigma^*(t, s) = \begin{cases} \bar{\sigma} & \text{if } \bar{v}_{ss}(t, s) > 0, \\ \underline{\sigma} & \text{if } \bar{v}_{ss}(t, s) < 0. \end{cases}$$

Similarly for the value function  $\underline{v}(t, s) = \min_{\underline{\sigma} \leq \sigma_t \leq \bar{\sigma}} \tilde{E}_{t,s}g(S_T)$  we have the equation

$$\underline{v}_t(t, s) + \frac{1}{2}\underline{\sigma} \underline{v}_{ss}(t, s)^+ - \frac{1}{2}\underline{\sigma} \underline{v}_{ss}(t, s)^- = 0, \underline{v}(T, s) = g(s)$$

and

$$\sigma^*(t, s) = \begin{cases} \underline{\sigma} & \text{if } \underline{v}_{ss}(t, s) > 0, \\ \bar{\sigma} & \text{if } \underline{v}_{ss}(t, s) < 0. \end{cases}$$

Hence we have proved

**Theorem 1.** *The saddle point  $(\pi^*, \theta^*, \sigma^*)$  of the minimax problem is defined by the equation*

$$\begin{aligned} \theta_t^* &= \underline{\theta}, \\ \sigma_t^* &= \begin{cases} \bar{\sigma} & \text{if } \bar{v}_{ss}(t, S_t^*) > 0, x < \frac{1}{2}(\underline{v}(0, S_0) + \bar{v}(0, S_0)), \\ \underline{\sigma} & \text{if } \bar{v}_{ss}(t, S_t^*) < 0, x < \frac{1}{2}(\underline{v}(0, S_0) + \bar{v}(0, S_0)), \\ \underline{\sigma} & \text{if } \underline{v}_{ss}(t, S_t^*) > 0, x > \frac{1}{2}(\underline{v}(0, S_0) + \bar{v}(0, S_0)), \\ \bar{\sigma} & \text{if } \underline{v}_{ss}(t, S_t^*) < 0, x > \frac{1}{2}(\underline{v}(0, S_0) + \bar{v}(0, S_0)), \end{cases} \\ \pi_t^* &= h_t - \theta_t^*/\sigma_t^*(\tilde{E}(H(S^*)|\mathcal{F}_t) - X_t^*). \end{aligned}$$

**Corollary 1.** If  $g$  is a convex function then the optimal pair is

$$(\theta_t^*, \sigma_t^*) = \begin{cases} (\underline{\theta}, \bar{\sigma}) & \text{if } x < \frac{1}{2}(Eg(\bar{\sigma}W_T) + g(\underline{\sigma}W_T)), \\ (\underline{\theta}, \underline{\sigma}) & \text{if } x > \frac{1}{2}(Eg(\bar{\sigma}W_T) + g(\underline{\sigma}W_T)). \end{cases}$$

**R E F E R E N C E S**

1. Aubin J.P., Ekeland I. Applied Nonlinear Analysis. *Wiley*, 1984.
2. Krylov N.V. A supermartingale characterization of sets of stochastic integrals and applications. *Probability Theory Related Fields*, **123** (2002), 521-552.
3. Pham H. Continuous-time Stochastic Control and Optimization with Financial Applications. *Springer*, 2009.

Received 16.05.2012; revised 10.09.2012; accepted 29.10.2012.

Author's addresses:

R. Tevzadze  
Georgian-American University  
Business School, 3, Alleyway II  
17 a, Chavchavadze Ave., Tbilisi 0128  
Georgia

Institute of Cybernetics  
5, Euli St., Tbilisi 0186  
Georgia  
E-mail: rtevzadze@gmail.com