

# MTH 9831 Homework 9 - Group5

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(1)

*Proof.* Recall that

$$\hat{W}(t) = \alpha t + \tilde{W}(t)$$

where  $\alpha = \frac{1}{\sigma}(r - \frac{1}{2}\sigma^2)$  is a constant and  $\tilde{W}(t)$  is a standard Brownian motion, since Brownian motion  $\tilde{W}(t)$  has independent increment, it follows that  $\hat{W}(t)$  also has independent increment, i.e.

$$\{\hat{W}(u) - \hat{W}(t)\}_{u \geq t} \text{ is independent with } \mathcal{F}(t) \quad (1)$$

We have

$$S(T) = S(0)e^{\sigma \hat{W}(T)} = S(0)e^{\sigma \tilde{W}(T)} \cdot e^{\sigma(\hat{W}(T) - \tilde{W}(T))} = S(t) \cdot e^{\sigma(\hat{W}(T) - \hat{W}(t))}$$

Also, since

$$Y(T) = \max_{0 \leq u \leq T} S(u) = S(0)e^{\sigma \hat{M}(T)}$$

where  $\hat{M}(T) = \max_{0 \leq u \leq T} \hat{W}(u)$ , note that

$$\begin{aligned} \hat{M}(T) &= \max\{\max_{0 \leq u \leq t} \hat{W}(u), \max_{t \leq u \leq T} \hat{W}(u)\} \\ &= \max\{\max_{0 \leq u \leq t} \hat{W}(u), \hat{W}(t) + \max_{t \leq u \leq T} [\hat{W}(u) - \hat{W}(t)]\} \end{aligned}$$

it follows that

$$\begin{aligned} Y(T) &= S(0)e^{\sigma \max\{\max_{0 \leq u \leq t} \hat{W}(u), \hat{W}(t) + \max_{t \leq u \leq T} [\hat{W}(u) - \hat{W}(t)]\}} \\ &= \max\{Y(t), S(t)e^{\sigma \max_{t \leq u \leq T} [\hat{W}(u) - \hat{W}(t)]}\} \end{aligned}$$

the last equality holds since function  $f(x) = e^x$  is a monotone increasing function.

In summary, we have for any measurable function  $f(x, y)$ ,

$$f(S(T), Y(T)) = f(S(t) \cdot e^{\sigma(\hat{W}(T) - \hat{W}(t))}, \max\{Y(t), S(t)e^{\sigma \max_{t \leq u \leq T} [\hat{W}(u) - \hat{W}(t)]}\}) \quad (2)$$

where  $\hat{M}(t, T) = \max_{t \leq u \leq T} [\hat{W}(u) - \hat{W}(t)]$ .

According to equation (2), we can see that  $f(S(T), Y(T))$  is a function of  $S(t)$ ,  $Y(t)$ ,  $\hat{W}(T) - \hat{W}(t)$  and  $\hat{M}(t, T) \triangleq \max_{t \leq u \leq T} [\hat{W}(u) - \hat{W}(t)]$ . Thus, define  $\tilde{f}$  as

$$\tilde{f}(S(t), Y(t), \hat{W}(T) - \hat{W}(t), \hat{M}(t, T)) \triangleq f(S(T), Y(T))$$

According to (1), we know that  $\hat{W}(T) - \hat{W}(t)$  and  $\hat{M}(t, T)$  are independent with  $\mathcal{F}(t)$ , let

$$g(s, y) = \mathbb{E}\tilde{f}(s, y, \hat{W}(T) - \hat{W}(t), \hat{M}(t, T))$$

then according to Independence Lemma 2.3.4,

$$\mathbb{E}[f(S(T), Y(T))|\mathcal{F}(t)] = \mathbb{E}[\tilde{f}(S(t), Y(t), \hat{W}(T) - \hat{W}(t), \hat{M}(t, T))|\mathcal{F}(t)] = g(S(t), Y(t))$$

thus we have proven that the pair of processes  $(S(t), Y(t))$  is a Markov process.  $\square$

**(2)**

(ii)

*Proof.*

$$\begin{aligned} \sum_{j=1}^m (Y(t_j) - Y(t_{j-1}))^2 &\leq \max_{1 \leq j \leq m} (Y(t_j) - Y(t_{j-1})) \cdot \sum_{j=1}^m (Y(t_j) - Y(t_{j-1})) \\ &= \max_{1 \leq j \leq m} (Y(t_j) - Y(t_{j-1})) \cdot (Y(T) - Y(0)) \end{aligned}$$

Since  $Y(t)$  is monotone increasing in  $t$ ,

$$Y(t_j) - Y(t_{j-1}) \geq 0, \forall 1 \leq j \leq m$$

thus for all  $1 \leq j \leq m$ ,

$$Y(t_j) - Y(t_{j-1}) \leq \sum_{j=1}^m (Y(t_j) - Y(t_{j-1})) = Y(T) - Y(0) \quad (3)$$

Plugging (3) into the above inequality, it follows that

$$\sum_{j=1}^m (Y(t_j) - Y(t_{j-1}))^2 \leq (Y(T) - Y(0))^2$$

$\square$

Next, we prove that the left hand side converges to 0 in  $L^2$ , i.e. that

$$\lim_{\|\Pi\| \rightarrow 0} \mathbb{E}[(\sum_{j=1}^m (Y(t_j) - Y(t_{j-1})))^2] = 0$$

Since

$$\sum_{j=1}^m (Y(t_j) - Y(t_{j-1}))^2 \leq (Y(T) - Y(0))^2$$

it follows that

$$\left( \sum_{j=1}^m (Y(t_j) - Y(t_{j-1}))^2 \right)^2 \leq (Y(T) - Y(0))^4$$

and according to the property of GBM,

$$\mathbb{E}(Y(T) - Y(0))^4 < \infty$$

By Domiant Covergence Theorem ( Hereinafter referred to as DCT), we have

$$\lim_{\|\Pi\| \rightarrow 0} \mathbb{E} \left[ \left( \sum_{j=1}^m (Y(t_j) - Y(t_{j-1}))^2 \right)^2 \right] = \mathbb{E} \left[ \left( \lim_{\|\Pi\| \rightarrow 0} \sum_{j=1}^m (Y(t_j) - Y(t_{j-1}))^2 \right)^2 \right]$$

Using part (i), we know that

$$\lim_{\|\Pi\| \rightarrow 0} \sum_{j=1}^m (Y(t_j) - Y(t_{j-1}))^2 = 0 \text{ a.s.}$$

so

$$\lim_{\|\Pi\| \rightarrow 0} \mathbb{E} \left[ \left( \sum_{j=1}^m (Y(t_j) - Y(t_{j-1}))^2 \right)^2 \right] = \mathbb{E}[0^2] = 0$$

(iii) We first prove that for each  $T > 0$  the cross-variation  $[S, Y]_T$  exists in a.s. and is equal to 0.

*Proof.*

$$\begin{aligned} 0 \leq \left| \sum_{j=1}^m (S(t_j) - S(t_{j-1}))(Y(t_j) - Y(t_{j-1})) \right| &\leq \sum_{j=1}^m |(S(t_j) - S(t_{j-1}))|(Y(t_j) - Y(t_{j-1})) \\ &\leq \max_{1 \leq j \leq m} |S(t_j) - S(t_{j-1})| \cdot (Y(T) - Y(0)) \end{aligned}$$

Let  $\|\Pi\| \rightarrow 0$  and take the limit on both sides of the inequality, then since  $S(t)$  is continuous a.s.,  $\max_{1 \leq j \leq m} |S(t_j) - S(t_{j-1})|$  has limit zero as  $\|\Pi\| = \max_{q \leq j \leq m} (t_j - t_{j-1})$  goes to zero.

Thus, we conclude that

$$\lim_{\|\Pi\| \rightarrow 0} \sum_{j=1}^m (S(t_j) - S(t_{j-1}))(Y(t_j) - Y(t_{j-1})) = 0 \text{ a.s.}$$

i.e.  $[S, Y]_T = 0$  a.s. □

Next, we turn to prove that  $[S, Y]_T$  exists in  $L^2$  sense and is equal to 0.

*Proof.*

$$\left| \sum_{j=1}^m (S(t_j) - S(t_{j-1}))(Y(t_j) - Y(t_{j-1})) \right| \leq \sum_{j=1}^m |S(t_j) - S(t_{j-1})|(Y(t_j) - Y(t_{j-1}))$$

Since

$$|S(t_j) - S(t_{j-1})| \leq |S(t_j)| + |S(t_{j-1})| = S(t_j) + S(t_{j-1}) \leq 2Y(T)$$

We have

$$\left| \sum_{j=1}^m (S(t_j) - S(t_{j-1}))(Y(t_j) - Y(t_{j-1})) \right| \leq 2Y(T) \sum_{j=1}^m (Y(t_j) - Y(t_{j-1})) = 2Y(T)(Y(T) - Y(0))$$

so

$$\left[ \sum_{j=1}^m (S(t_j) - S(t_{j-1}))(Y(t_j) - Y(t_{j-1})) \right]^2 \leq 4Y(T)^2 \cdot (Y(T) - Y(0))^2 \quad (4)$$

Since  $\mathbb{E}[Y(T)^2 \cdot (Y(T) - Y(0))^2] \leq \infty$ , use (4), DCT and  $[S, Y]_T = 0$  a.s., we have

$$\lim_{\|\Pi\| \rightarrow 0} \mathbb{E} \left[ \sum_{j=1}^m (S(t_j) - S(t_{j-1}))(Y(t_j) - Y(t_{j-1})) \right]^2 = \mathbb{E} \left[ \lim_{\|\Pi\| \rightarrow 0} \sum_{j=1}^m (S(t_j) - S(t_{j-1}))(Y(t_j) - Y(t_{j-1})) \right]^2 = 0$$

i.e.  $[S, Y]_T = 0$  in  $L^2$  sense.  $\square$

### (3)

(i)

$$\begin{aligned} \tilde{\mathbb{E}} \left[ \int_0^T S(u) du | \mathcal{F}(t) \right] &= \tilde{\mathbb{E}} \left[ \int_0^t S(u) du + \int_t^T S(u) du | \mathcal{F}(t) \right] \\ &= \int_0^t S(u) du + \tilde{\mathbb{E}} \left[ \int_t^T S(u) du | \mathcal{F}(t) \right] \end{aligned}$$

Since  $\tilde{\mathbb{E}} \left[ \int_0^T S(u) du \right] < \infty$ , then according to Fubini's theorem for conditional expectations, we have

$$\tilde{\mathbb{E}} \left[ \int_0^T S(u) du | \mathcal{F}(t) \right] = \int_0^t S(u) du + \int_t^T \tilde{\mathbb{E}}[S(u) | \mathcal{F}(t)] du$$

Since under  $\tilde{P}$ ,  $e^{-ru}S(u)$  is a martingale, we have

$$\int_t^T \tilde{\mathbb{E}}[S(u) | \mathcal{F}(t)] du = \int_t^T e^{ru} \tilde{\mathbb{E}}[e^{-ru}S(u) | \mathcal{F}(t)] du = \int_t^T e^{ru} S(t) du = \frac{S(t)}{r} (e^{r(T-t)} - 1)$$

Suppose we have  $S(t) = x \geq 0$  and  $\int_t^T S(u) du = y \geq 0$ , we conclude that

$$v(t, x, y) = \frac{e^{-r(T-t)}}{T} \left( \frac{x}{r} (e^{r(T-t)} - 1) + y \right)$$

(ii)

$$\begin{aligned}
v_t &= \frac{r}{T} e^{-r(T-t)} \left( \frac{x}{r} (e^{r(T-t)} - 1) + y \right) - \frac{x}{T} = rv - \frac{x}{T} \\
v_x &= \frac{1}{rT} e^{-r(T-t)} (e^{r(T-t)} - 1) \\
v_y &= \frac{1}{T} e^{-r(T-t)} \\
v_{xx} &= 0
\end{aligned}$$

Recall Black-Scholes-Merton equation,

$$v_t + rxv_x + xv_y + \frac{1}{2}\sigma^2 v_{xx} = rv$$

plugging the expression for  $v_t$ ,  $v_x$ ,  $v_y$  and  $v_{xx}$  derived above, we have

$$v_t + rxv_x + xv_y + \frac{1}{2}\sigma^2 v_{xx} = rv - \frac{x}{T} + \frac{x}{T} e^{-r(T-t)} (e^{r(T-t)} - 1) + \frac{x}{T} e^{-r(T-t)} = rv$$

Also,

$$\begin{aligned}
v(t, 0, y) &= \frac{1}{T} e^{-r(T-t)} y = e^{-r(T-t)} \left( \frac{y}{T} - 0 \right)^+ \\
v(T, x, y) &= \frac{y}{T} = \left( \frac{y}{T} - 0 \right)^+
\end{aligned}$$

Thus, we have verifies that the function  $v(t, x, y)$  satisfies required equations.

(iii) According to (ii),

$$\Delta(t) = v_x = \frac{1}{rT} (1 - e^{-r(T-t)})$$

which is not random.

(iv)

*Proof.* Denote the value of this portfolio at time  $t$  as  $X(t)$ , then after  $dt$ , the value of this portfolio changes and those changes consist of two parts:

1. The change in the cash position  $= r(X(t) - \Delta(t)S(t))dt - S(t)d\Delta(t)$
2. The change in the value of the underlying asset  $= (\Delta(t) + d\Delta(t))(S(t) + dS(t)) - \Delta(t)S(t)$

Ignore the higher order term  $d\Delta(t)dS(t)$ , and sum the above two parts up, we have

$$dX(t) = r(X(t) - \Delta(t)S(t))dt + \Delta(t)dS(t)$$

rearrange it, we have

$$\begin{aligned}
dX(t) - rX(t)dt &= \Delta(t)(dS(t) - rS(t)dt) \\
\iff d[e^{-rt}X(t)] &= \Delta(t)d[e^{-rt}S(t)]
\end{aligned}$$

Integrate on both sides,

$$e^{-rT}X(T) - X(0) = \Delta(t)e^{-rt}S(t)|_0^T - \int_0^T e^{-rt}S(t)d\Delta(t) \quad (5)$$

since

$$d\Delta(t) = -\frac{1}{T}e^{-r(T-t)}$$

equation (5) changes to

$$e^{-rT}X(T) - X(0) = -\Delta(0)S(0) + \frac{1}{T}e^{-rT} \int_0^T S(t)dt$$

since

$$X(0) = v(0, S(0), 0) = \frac{1}{rT}(1 - e^{-rT})S(0) = \Delta(0)S(0)$$

we conclude that

$$X(T) = \frac{1}{T} \int_0^T S(t)dt$$

□