# Exam-prep (FinKont)

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## Exam sets (2017/18-2021/22)

## In progress

#### Problem 3

Consider a two-dimensional model. The market model consist of three assets: A bank account  $B_t$  and two stocks  $S_1$  and  $S_2$ . The P-dynamics of  $B_t$  is

$$dB_t = rB_t dt$$
,  $B_0 = 1$ ,

where  $r \in \mathbb{R}$  is a constant interest rate. The P-dynamics of  $S_1$  and  $S_2$  are given by

$$dS_1(t) = \alpha_1 S_1(t) \ dt + \sigma_1 S_1(t) \ d\overline{W}_1(t), \qquad S_1(0) = s_1 > 0,$$
  
$$dS_2(t) = \alpha_2 S_2(t) \ dt + \sigma_2 S_2(t) \ d\overline{W}_2(t), \qquad S_2(0) = s_2 > 0,$$

where  $\alpha_1, \alpha_2 \in \mathbb{R}$  are constants. Moreover,  $\sigma_1 > 0$  is a constant and  $\sigma_2(t) = \sigma_0 e^{-\gamma t}$  where  $\sigma_0 > 0$  and  $\gamma > 0$  are constants and  $\overline{W}_1(t)$  and  $\overline{W}_2(t)$  are two independent *P*-Brownian motions. The filtration is the one generated by the two Brownian motions, that is,  $\mathcal{F}_t = \sigma(\overline{W}_1(s), \overline{W}_2(s) \mid 0 \le s \le t)$ . Let T > 0 be a given and fixed (expiry) date.

- a. i. Is the model arbitrage free?
  - ii. Is the model complete?

Consider the derivative that at time T pays  $X = S_1(T)S_2(T)$  and let  $F(t, s_1, s_2)$  be the pricing function of the derivative.

- b. i. Determine the arbitrage free price of derivative X at time t=0.
  - ii. Determine the equation satisfied by the pricing function  $F(t, s_1, s_2)$ .

Consider a new derivative that at time T pays  $Y = \log(S_2(T))$ .

- c. Determine the arbitrage free price of derivative Y at time t < T.
- Solution (a).
- Solution (b).
- Solution (c).

### Exam 2017/18

#### Problem 1

Let  $W_t$  denote a Brownian motion and let

$$\mathcal{F}_t = \mathcal{F}_t^W = \sigma(\{W_s \mid 0 \le s \le t\}).$$

Let T > 0 be a given and fixed time.

Let f(t) be a bounded deterministic continuous function. Define the two processes

$$\begin{cases} X_t = \int_0^t f(u) \ dW_u, \\ M_t^{(\lambda)} = \exp\left\{\lambda X_t - \frac{\lambda^2}{2} \int_0^t f^2(u) \ du\right\}, \end{cases}$$

where  $\lambda \in \mathbb{R}$  is a constant.

a. Show that  $M^{(\lambda)}$  is a martingale with  $E[M_t^{(\lambda)}] = 1$ .

Let 0 < s < t and  $\lambda_1, \lambda_2 \in \mathbb{R}$  be given and fixed.

b. i. Show that

$$\begin{split} M_s^{(\lambda_1)} &= E\left[\frac{M_s^{(\lambda_1)} M_t^{(\lambda_2)}}{M_s^{(\lambda_2)}} \middle| \mathcal{F}_s\right] \\ &= E\left[\exp\left\{\lambda_1 X_s + \lambda_2 (X_t - X_s) - \frac{1}{2}\lambda_1^2 \int_0^s f^2(u) \ du - \frac{1}{2}\lambda_2^2 \int_s^t f^2(u) \ du\right\} \middle| \mathcal{F}_s\right] \end{split}$$

ii. Show that  $X_s$  and  $X_t - X_s$  are normally distributed and independent.

c. Compute the mean value of  $M_T^{(\lambda)} \log(M_T^{(\lambda)})$ .

### Solution (a).

First, we see that since  $X_t$  is on integral form we know that

$$\begin{cases} dX_t = f(t) \ dW_t \\ X_0 = 0. \end{cases}$$

Hence we may represent M as  $M_t^{(\lambda)} = g(t, X_t, Y_t)$  given by

$$g(t, x, y) = \exp\left\{\lambda x - \frac{\lambda^2}{2}y\right\},$$

where  $Y_t = \int_0^t f^2(u) \ du$  with dynamics

$$\begin{cases} dY_t = f^2(t) \ dt \\ Y_0 = 0. \end{cases}$$

Hence by the multidimensional Ito's formula we have the dynamics of M given by

$$\begin{split} dM_t^{(\lambda)} &= g_t \ dt + g_x \ dX_t + g_y \ dY_t + \frac{1}{2} g_{yy} \ (dY_t)^2 + \frac{1}{2} g_{xx} \ (dX_t)^2 + f_{xy} (dX_t) (dY_t) \\ &= 0 + \lambda g \ dX_t - \frac{\lambda^2}{2} g \ dY_t + 0 + \frac{1}{2} \lambda^2 g \ (dX_t)^2 + 0 \\ &= \lambda M_t^{(\lambda)} f(t) \ dW_t - \frac{1}{2} \lambda^2 M_t^{(\lambda)} f^2(t) \ dt + \frac{1}{2} \lambda M_t^{(\lambda)} f^2(t) \ dt \\ &= \lambda f(t) M_t^{(\lambda)} \ dW_t, \end{split}$$

And so we see that M is a martingale as it only has dynamics wrt. the Brownian motion W (assuming  $\lambda f_t M_t^{(\lambda)} \in \mathcal{L}^2$ ). Furthermore we have that

$$M_0^{(\lambda)} = g(0, X_0, Y_0) = \exp\left\{\lambda X_0 - \frac{1}{2}\lambda^2 Y_0\right\} = e^0 = 1$$

and so we have  $E[M_t^{(\lambda)}]=M_0^{(\lambda)}=1$  as desired.  $\Box$ 

#### Solution (b).

"(i)" We have from the previous exercise

$$\begin{split} &\frac{M_s^{(\lambda_1)} M_t^{(\lambda_2)}}{M_s^{(\lambda_2)}} \\ &= \exp\left\{\lambda_1 X_s - \frac{1}{2} \lambda_1^2 \int_0^s f^2(u) \ du\right\} \exp\left\{\lambda_2 X_t - \frac{1}{2} \lambda_2^2 \int_0^t f^2(u) \ du\right\} \exp\left\{\frac{1}{2} \lambda_2^2 \int_0^s f^2(u) \ du - \lambda_2 X_s\right\} \\ &= \exp\left\{\lambda_1 X_s - \frac{1}{2} \lambda_1^2 \int_0^s f^2(u) \ du + \lambda_2 X_t - \frac{1}{2} \lambda_2^2 \int_0^t f^2(u) \ du + \frac{1}{2} \lambda_2^2 \int_0^s f^2(u) \ du - \lambda_2 X_s\right\} \\ &= \exp\left\{\lambda_1 X_s + \lambda_2 (X_t - X_s) - \frac{1}{2} \lambda_1^2 \int_0^s f^2(u) \ du - \frac{1}{2} \lambda_2^2 \int_s^t f^2(u) \ du\right\} \end{split}$$

and so the conclusion follows.  $\square$ 

"(ii)" We have that from lemma 4.18 that

$$X_s = \int_0^s f(u) \ dW_u \sim \mathcal{N}\left(0, \int_0^s f^2(u) \ dW_u\right)$$

furthermore we have that

$$X_t - X_s = \int_s^t f(u) \ dW_u \sim \mathcal{N}\left(0, \int_s^t f^2(u) \ dW_u\right).$$

In regard to the independence claim we could check identity below

$$E[e^{t_1X}e^{t_2Y}] = E[e^{t_1X}]E[e^{t_2Y}]$$

where X, Y are independent random variables. The above identity holds if and only if X and Y are independent. From above we have that

$$M_s^{(\lambda_1)} = E[e^{\lambda_1 X_s} e^{\lambda_2 (X_t - X_s)} \mid \mathcal{F}_s] e^{-\frac{1}{2} \lambda_1^2 \int_0^s f^2(u) \ du - \frac{1}{2} \lambda_2^2 \int_s^t f^2(u) \ du}$$

and so taking expectation we have

$$1 = E[e^{\lambda_1 X_s} e^{\lambda_2 (X_t - X_s)}] e^{-\frac{1}{2}\lambda_1^2 \int_0^s f^2(u) \ du - \frac{1}{2}\lambda_2^2 \int_s^t f^2(u) \ du}$$

Which the gives

$$E[e^{\lambda_1 X_s} e^{\lambda_2 (X_t - X_s)}] = e^{\frac{1}{2} \lambda_1^2 \int_0^s f^2(u) \ du + \frac{1}{2} \lambda_2^2 \int_s^t f^2(u) \ du} = E[e^{\lambda_1 X_s}] E[e^{\lambda_2 (X_t - X_s)}]$$

and so the conclusion is that  $X_s$  and  $X_t - X_s$  are independent.  $\square$ 

#### Solution (c).

We recall the definition of  $M_t^{(\lambda)}$  and observe that

$$\log M_t^{(\lambda)} = \lambda X_t - \frac{1}{2}\lambda^2 \int_0^t f^2(u) \ du.$$

Furthermore we have the dynamics of  $M^{(\lambda)}$  given by the differential form

$$dM_t^{(\lambda)} = \lambda f(t) M_t^{(\lambda)} dW_t.$$

with  $M_0^{(\lambda)}=1.$  Since we know that  $M_t^{(\lambda)}$  is a martingale we have

$$E^{P}[M_{T}^{(\lambda)}] = E^{P}[M_{0}^{(\lambda)}] = 1,$$

and so we may define a new probability measure as

$$d\tilde{P} = M_T^{(\lambda)} dP$$

on  $\mathcal{F}_T$ . We then have a new Brownian motion  $\tilde{W}$  such that

$$dW_t = \lambda f(t) dt + d\tilde{W}_t.$$

We can then see

$$\begin{split} E^P[M_T^{(\lambda)}\log M_T^{(\lambda)}] &= \int M_T^{(\lambda)}\log M_T^{(\lambda)} \ dP = \int M_T^{(\lambda)}\log M_T^{(\lambda)} \frac{1}{M_T^{(\lambda)}} \ d\tilde{P} \\ &= \int \log M_T^{(\lambda)} \ d\tilde{P} = E^{\tilde{P}}[\log M_T^{(\lambda)}]. \end{split}$$

Then we can evaluate the mean value by seeing the X has representation wrt.  $\tilde{P}$  by

$$X_{t} = \int_{0}^{t} f(u) (\lambda f(u) du + d\tilde{W}_{u}) = \lambda \int_{0}^{t} f^{2}(u) du + \int_{0}^{t} f(u) d\tilde{W}_{u}.$$

Giving that

$$\begin{split} E^P[M_T^{(\lambda)}\log M_T^{(\lambda)}] &= E^{\tilde{P}}[\log M_T^{(\lambda)}] \\ &= E^{\tilde{P}}\left[\lambda X_T - \frac{1}{2}\lambda^2 \int_0^T f^2(u) \ du\right] \\ &= E^{\tilde{P}}\left[\lambda^2 \int_0^T f^2(u) \ du + \lambda \int_0^T f(u) \ d\tilde{W}_u - \frac{1}{2}\lambda^2 \int_0^T f^2(u) \ du\right] \\ &= \lambda E^{\tilde{P}}\left[\frac{1}{2}\lambda \int_0^T f^2(u) \ du + \int_0^T f(u) \ d\tilde{W}_u\right] \\ &= \frac{1}{2}\lambda^2 \int_0^T f^2(u) \ du + \lambda E^{\tilde{P}}\left[\int_0^T f(u) \ d\tilde{W}_u\right] \\ &= \frac{1}{2}\lambda^2 \int_0^T f^2(u) \ du \end{split}$$

Since

$$\tilde{X}_T = \int_0^T f(u) \ d\tilde{W}_u,$$

is a  $\tilde{P}$ -martingale.  $\square$ 

#### Problem 2

Consider a standard Black-Scholes model, that is, a model consisting of a bank account  $B_t$  with P-dynamics given by

$$dB_t = rB_t dt, B_0 = 1$$

and a stock  $S_t$  with P-dynamics given by

$$dS_t = \alpha S_t dt + \sigma S_t d\overline{W}_t, S_0 = s > 0$$

where  $r, \alpha \in \mathbb{R}$  and  $\sigma > 0$  are constants and  $\overline{W}_t$  is a P-Brownian motion. Let T > 0 be a given and fixed date.

Consider the derivative that at time T pays

$$X = \max \left\{ \min \left\{ S_T, K_2 \right\}, K_1 \right\},\,$$

where  $0 < K_1 < K_2$  are constants.

a. Determine the arbitrage free price of derivative X at time t < T.

Consider a new derivative that at time T pays

$$Y = (S_T^2 - K^2)^+ - (K^2 - S_T^2)^+.$$

- b. i. Determine the arbitrage free price of derivative Y at time t < T.
  - ii. Find a hedging portfolio for derivative Y.

Let  $h(t) = (h_0(t), h_1(t))$  be a portfolio where

$$h_0(t) = -e^{r(T-2t)+\sigma^2(T-t)}S^2(t)$$

is the number of units in the bank account at time t and

$$h_1(t) = 2e^{(r+\sigma^2)(T-t)}S(t)$$

is the number of shares in the stock at time t. Let  $V^h(t)$  denote the associated value process.

- c. Determine whether the portfolio h is self-financing or not.
- d. Compute  $V^h(T)$ .

### Solution (a).

We see that the derivative is the bull spread given by the payout function

$$X = \begin{cases} K_2 & \text{if } S_T > K_2, \\ S_T & \text{if } K_1 \le S_T \le K_2, \\ K_1 & \text{if } S_T < K_1. \end{cases}$$

We know from exercise 10.3 that this can be replicated by holding  $K_1$  bonds, one call option with strike  $K_1$  and a short on a call with strike  $K_2$ . The arbitrage free price of the derivative is then the value process of the mentioned portfolio i.e.

$$\Pi_t[X] = K_1 e^{-r(T-t)} + c(K_1; t, T) - c(K_2; t, T),$$

where c denotes the pricing function for a European call option (non-instructive parameters supressed).  $\square$  Solution (b).

(i): We start by seeing that the derivative pays out

$$Y = \begin{cases} S_T^2 - K^2 & \text{if } S_T^2 \ge K^2, \\ -(K^2 - S_T^2) & \text{if } S_T^2 < K^2. \end{cases}$$

hence the payout is  $Y = S_T^2 - K^2 = \Phi(S_T)$  where  $\Phi(s) = s^2 - K^2$ . That is Y is in fact a simple claim. We have from the risk neutral valueation formula 7.11 that

$$\begin{split} \Pi_t[Y] &= e^{-r(T-t)} E_{t,s}^Q [S_T^2 - K^2] \\ &= e^{-r(T-t)} E_{t,s}^Q [S_T^2] - e^{-r(T-t)} K^2. \end{split}$$

Recall that under the martingale measure Q we have that  $S_t$  is a GBM hence

$$S_t = s \cdot \exp\left\{ \left( r - \frac{1}{2}\sigma^2 \right) (T - t) + \sigma \left( W_T^Q - W_t^Q \right) \right\}$$

then

$$S_T^2 = s^2 \cdot \exp\left\{2\left(r - \frac{1}{2}\sigma^2\right)(T - t) + 2\sigma\left(W_T^Q - W_t^Q\right)\right\}.$$

Inserting this into the risk neutral valuation formula we get

$$\begin{split} \Pi_t[Y] &= e^{-r(T-t)} E_{t,s}^Q[S_T^2] - e^{-r(T-t)} K^2 \\ &= e^{-r(T-t)} s^2 e^{2\left(r - \frac{1}{2}\sigma^2\right)(T-t)} E^Q \left[ \exp\left\{2\sigma\left(W_T^Q - W_t^Q\right)\right\} \right] - e^{-r(T-t)} K^2 \\ &= e^{-r(T-t)} s^2 e^{2\left(r - \frac{1}{2}\sigma^2\right)(T-t)} e^{\frac{1}{2}4\sigma^2(T-t)} - e^{-r(T-t)} K^2 \\ &= e^{-r(T-t)} \left( s^2 e^{(2r - \sigma^2)(T-t) + \frac{1}{2}4\sigma^2(T-t)} - K^2 \right) \\ &= e^{-r(T-t)} \left( s^2 e^{(2r + \sigma^2)(T-t)} - K^2 \right). \end{split}$$

The arbitrage free price of the derivative is then given above.  $\square$ 

(ii): From theorem 8.5 we can determine a hedging portfolio with weightings

$$\begin{split} w^B_t &= \frac{\Pi_t - S_t \frac{\partial \Pi}{\partial s}}{\Pi_t} \\ &= 1 - \frac{S_t 2 S_t e^{-r(T-t)} e^{(2r+\sigma^2)(T-t)}}{e^{-r(T-t)} \left( S_t^2 e^{(2r+\sigma^2)(T-t)} - K^2 \right)} \\ &= 1 - \frac{2 S_t^2 e^{(2r+\sigma^2)(T-t)}}{S_t^2 e^{(2r+\sigma^2)(T-t)} - K^2} \\ &= 1 - \frac{2}{1 - K^2 S_t^{-2} e^{(2r+\sigma^2)(t-T)}} \\ w^S_t &= \frac{2}{1 - K^2 S_t^{-2} e^{(2r+\sigma^2)(t-T)}}. \end{split}$$

In absolute terms we will hold the portfolio

$$h_t^S = 2S_t e^{-r(T-t)} e^{(2r+\sigma^2)(T-t)}$$

$$h_t^B = \frac{e^{-r(T-t)} \left( s^2 e^{(2r+\sigma^2)(T-t)} - K^2 \right) - S_t h_t^S}{B_t}$$

$$= \frac{e^{-r(T-t)} \left( s^2 e^{(2r+\sigma^2)(T-t)} - K^2 \right) - S_t h_t^S}{e^{rt}}$$

$$= e^{-rT} s^2 e^{(2r+\sigma^2)(T-t)} - e^{-rT} K^2 - e^{-rt} S_t h_t^S.$$

The portfolio above will hedge Y with probability one.  $\square$ 

## Solution (c).

We assume no dividends and no consumption that is  $c_t = 0$  and  $dD_t^i = 0$  for i = 0, 1. Then the portfolio is self-financing if and only if the value process has dynamics.

$$h_0(t) dB_t + h_1(t) dS_t = 0$$

This is given in lemma 6.12.

#### THE BELOW IS IN WORKS AND NOT CORRECT!

Now we have that the value process is given by

$$V_t^h = h_0(t)B_t + h_1(t)S_t.$$

Using the representation  $V_t^h = f(h_0(t), B_t) + f(h_1(t), S_t)$  given by f(x, y) = xy we have

$$dV_t^h = df(h_0(t), B_t) + df(h_1(t), S_t).$$

Using Ito's formula on each term we have

$$df(h_0(t), B_t) = B_t dh_0(t) + h_0(t) dB_t + (dB_t)(dh_0(t)),$$
  
$$df(h_1(t), S_t) = S_t dh_1(t) + h_1(t) dS_t + (dS_t)(dh_1(t)),$$

since of cause  $f_{xx} = f_{yy} = 0$ . We can the determine the dynamics of the portfolio by

$$dh_0(t) = -(-2t - \sigma^2)S_t^2 e^{r(T-2t) + \sigma^2(T-t)} dt$$

$$-2S_t e^{r(T-2t) + \sigma^2(T-t)} dS_t$$

$$-\frac{1}{2} 2e^{r(T-2t) + \sigma^2(T-t)} (dS_t)^2$$

$$= (-2t - \sigma^2)h_0(t) dt + \frac{2}{S_t}h_0(t) (\mu S_t dt + \sigma S_t dW_t) + \frac{1}{S_t^2}h_0(t)\sigma^2 S_t^2 dt$$

$$= (\mu - 1)2h_0(t) dt + 2\sigma h_0(t) dW_t$$

and

$$dh_1(t) = (-r - \sigma^2) 2e^{(r+\sigma^2)(T-t)} S_t dt$$

$$+ 2e^{(r+\sigma^2)(T-t)} dS_t + 0$$

$$= (-r - \sigma^2) h_1(t) dt + \frac{1}{S_t} h_1(t) (\mu S_t dt + \sigma S_t dW_t)$$

$$= (-r - \sigma^2 + \mu) h_1(t) dt + h_1(t) \sigma dW_t$$

And so in total

$$\begin{split} dV_t^h(t) &= df(h_0(t), B_t) + df(h_1(t), S_t) \\ &= B_t \ dh_0(t) + h_0(t) \ dB_t + (dB_t)(dh_0(t)) \\ &+ S_t \ dh_1(t) + h_1(t) \ dS_t + (dS_t)(dh_1(t)) \\ &= B_t \ ((\mu - 1)2h_0(t) \ dt + 2\sigma h_0(t) \ dW_t) + h_0(t) \ rB_t \ dt + 0 \\ &+ S_t \ ((-r - \sigma^2 + \mu)h_1(t) \ dt + h_1(t)\sigma \ dW_t) + h_1(t) \ (\mu S_t \ dt + \sigma S_t \ dW_t) + \sigma^2 S_t h_1(t) \ dt \\ &= \left[ B_t(\mu - 1)2h_0(t) + h_0(t)rB_t + S_t(-r - \sigma^2 + \mu)h_1(t) + h_1\mu S_t + \sigma^2 S_t h_1(t) \right] \ dt \\ &+ \left[ B_t 2\sigma h_0(t) + S_t h_1\sigma + h_1\sigma S_t \right] \ dW_t \\ &= \left[ (2\mu - 2 + r)B_t h_0(t) + (-r + 2\mu)S_t h_1(t) \right] \ dt \\ &+ \left[ B_t h_0(t) + h_1 S_t \right] 2\sigma \ dW_t \\ &= V_t^h 2\mu \ dt + V_t^h \ dW_t \end{split}$$

#### Solution (d).

We compute  $V_T^h$  easily by inserting  $h_0$  and  $h_1$  below

$$\begin{split} V_T^h &= B_T h_0(T) + S_T h_1(T) \\ &= B_T \left( -e^{r(T-2T) + \sigma^2(T-T)} S_T^2 \right) + S_T \left( 2e^{(r+\sigma^2)(T-T)} S_T \right) \\ &= -S_T^2 + 2S_T^2 = S_T^2. \end{split}$$

and so h hedge the payout  $\Phi(S_T) = S_T^2$ .  $\square$ 

## Exam 2018/19

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## Exam 2019/20

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## Exam 2020/21

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## Exam 2021/22

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## $Exam\ 2022/23$

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