

SFCT 2024/12/19 Very concise solutions

1(a)  $dV = h(ds + dD) + kdF \stackrel{Q}{=} h((r-s)S^1 dt + \sigma S dW^Q + \delta S dt) + kdF = (Ito) =$   
 $= h(\dots)dt + k(F_t dt + F_s ds + \frac{1}{2} F_{ss} (ds)^2) = h(\dots)dt + k[F_t dt + F_s((r-s)S dt + \sigma S dW^Q) + \frac{1}{2} F_{ss} \sigma^2 S^2 dt]$   
 $= [hrS + kF_t + kF_s(r-s)S + \frac{1}{2} \sigma^2 S^2 k]dt + (h + kF_s)\sigma S dW^Q$

(b)  $h + kF_s = 0, h = -kF_s$

(c) Combine with  $dV = rV dt$ ; gives  $-kF_s rS + kF_t + kF_s(r-s)S + \frac{1}{2} \sigma^2 S^2 k = r(-kF_s S + kF)$   
 Divide by  $k$  (assume non zero) to get the PDE.  $F(T, s) = \Phi(s)$

2(a) First  $d(\frac{1}{s}) = -\frac{1}{s^2} ds + \frac{1}{2} \cdot \frac{2}{s^3} (ds)^2 = -\frac{1}{s^2} (\mu S dt + \sigma S dW) + \frac{1}{s^3} \sigma^2 S^2 dt$  (combine to get)  
 As  $B$  has no Brownian term  $d(\frac{B}{s}) = \frac{1}{s} dB + B d(\frac{1}{s})$

$d(\frac{B}{s}) = \frac{B}{s} \underbrace{(-\mu + \sigma^2 - \sigma\varphi + r)}_{=0!} dt + -\frac{B\sigma}{s} dW^1$ , using  $dW = \varphi dt + dW^1$ .

(b) let  $L^0$  denote the likelihood ratio process for  $P \rightarrow Q$ . Theory says  $\frac{L^1(t)}{L^0(t)} = \frac{1}{S(t)} \frac{S(t)}{B(t)}$

Then  $E^Q[\Phi | \mathcal{F}_t] = E^{Q^1}[\Phi \frac{L^0(T)}{L^1(T)} | \mathcal{F}_t] / \frac{L^0(t)}{L^1(t)} = \frac{B(t)}{S(t)} E^{Q^1}[\frac{\Phi}{S(T)} | \mathcal{F}_t]$   
 So  $\pi(t) = S(t) E^{Q^1}[\frac{\Phi}{S(T)} | \mathcal{F}_t]$

(c) From (b), or realizing that  $S$  is used as numeraire:  $\frac{\pi(t)}{S(t)}$  is a  $Q^1$ -martingale  $\Rightarrow$  Result.

(d) Use  $dW^1 = \varphi dt + dW^1$ , with  $\varphi$  as in (a) and  $ds = \dots$  to get the result.

(e)  $\pi_1(t) = e^{-(r+\sigma^2)(T-t)} E^{Q^1}[\pi(T) | \mathcal{F}_t]$ . Plug this into the expression in (c).

(f) Equation for  $ds(t)$  suggests  $B_1(t) = e^{(r+\sigma^2)t}$ . You may use  $d(\frac{S(t)}{B_1(t)}) = \frac{dS(t)}{B_1(t)} - \frac{S(t)}{B_1(t)^2} dB_1(t)$ .

4(a). Start with  $dX = r^S ds + r^B dB = r^S (\mu S dt + \sigma S dW) + r^B r B dt$  and use  $r^S S = W X, r^B B = (1-W)X$

(b) General theory with  $dX = b dt + \sigma dW$  gives  $V_t + \sup_w \{w V_x + \frac{1}{2} \sigma^2 V_{xx}\} = 0$ . Use now  $b \rightarrow r(w\mu + (1-r)w)$  and  $\sigma^2 \rightarrow \sigma^2 x^2 w^2$ .

(c) Educated guess is  $V(t, x) = f(t) \log x + g(t) \rightarrow V_x = \frac{f}{x}, V_{xx} = -\frac{f}{x^2}$ . Compute derivative w.r.t.  $w$  in  $\{\dots\}$ :  $x V_x (\mu - r) + \sigma^2 x^2 V_{xx} w = 0$ , use  $V_x, V_{xx}$ , to get  $w = \frac{\mu - r}{\sigma^2}$

(d) Solve HJB with  $w$  and  $V$  as above, i.e. solve  $f(t) \log x + g(t) + \{ \frac{\mu - r}{\sigma^2} \mu + (1 - \frac{\mu - r}{\sigma^2}) r - \frac{\sigma^2}{2} f(t) \frac{(\mu - r)^2}{\sigma^2} \} = 0$   
 Separate terms with  $x$  and without:  $f'(t) \log x = 0, g'(t) + \{\dots\} = 0$

We see  $f'(t) = 0$ . But  $V(T, x) = f(T) \log x + g(T) = \log x \Rightarrow f(T) = 1, g(T) = 0$ .

So  $f(t) = 1, \forall t$ . Then  $g'(t) + \{\dots\} = g'(t) + c = 0$ , with  $c = \frac{1}{2} \frac{(\mu - r)^2}{\sigma^2} + r \Rightarrow g(t) = c(T - t)$ .

The optimal  $E \log X(T)$  is  $V(0, x) = \log x + cT = \log x + [\frac{1}{2} \frac{(\mu - r)^2}{\sigma^2} + r]T$ .

(e) Use Ito:  $dY(t) = d[\log X(t)] = (w\mu + r(1-w))dt + \sigma^w dW + -\frac{1}{2} \sigma^2 w^2 dt$ , or  $Y(T) = Y(0) + \int_0^T \dots$   
 The Ito integral has expectation zero. So  $EY(T) = \log x + E \int_0^T [w(t)\mu + r(1-w(t)) - \frac{1}{2} \sigma^2 w(t)^2] dt$

(f) Optimize under  $E$  and the integral, differentiate w.r.t.  $w(t)$  the term in  $[\dots]$ . This gives  $\mu - r - \sigma^2 w(t) = 0 \Rightarrow w(t) = \frac{\mu - r}{\sigma^2}$ , as in (c)!

3(a) Suppose  $h$  is SF,  $dV = h ds$ . Then  $dV^z = d(RV) = R dV + V dR + dR dV = R h ds + h S dR + dR h ds$   
 $= h(R ds + S dR + dR ds) = h d(RS) = h dz \Rightarrow h$  is  $z$ -self financing.

Conversely, if  $h$  is  $z$ -SF,  $dV^z = h dz$ . Then  $dV = d(S^1 V^z) = S^1 dV^z + V^z dS^1 + dS^1 dV^z =$   
 $= S^1 h dz + R^z ds^1 + dS^1 h dz = h(S^1 dz + z dS^1 + dS^1 dz) = h d(S^1 z) = h dV$ .

(b) If  $X$  is replicable, there is SF  $h$  s.t.  $X = V(T)$ , so  $X R(T) = V(T) R(T) = V^z(T) \Rightarrow X R(T)$  is replicable in the  $z$ -market, as  $h$  is  $z$ -SF in view of (a). Converse is similar.