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# Credit Risk

Marek Capiński and Tomasz Zastawniak

## Solutions to Exercises

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### Chapter 1

- 1.1. If  $V(0)(1+U)(1+D) < F < V(0)(1+U)^2$ , then

$$F = V(0)(1+U)^2 - \frac{1}{q^2}E(0)(1+R)^2.$$

If  $V(0)(1+D)^2 < F < V(0)(1+U)(1+D)$ , then

$$F = \frac{q^2V(0)(1+U)^2 + 2q(1-q)V(0)(1+U)(1+D) - E(0)(1+R)^2}{q^2 + 2q(1-q)}.$$

The expected return on equity is 100.45%, and the standard deviation is 88.29%. For debt the corresponding values are 48.03% and 7.64%.

- 1.2. In the Black-Scholes model the value of a call option increases as the volatility  $\sigma$  of the underlying asset increases, all other parameters being constant. This is because the partial derivative of the option price with respect to  $\sigma$ , i.e. the vega of the option is positive,

$$\text{vega} = V(0) \sqrt{\frac{T}{2\pi}} e^{-d_+^2/2} > 0;$$

see [BSM]. Moreover, the value of a call option decreases if the strike price increases, all remaining parameters being constant.

As a result, since initial equity  $E(0)$  is the value of a call option with strike  $F$ , to keep  $E(0)$  fixed  $F$  must increase when  $\sigma$  increases. It follows that

$$k_D = \frac{1}{T} \ln \frac{F}{D(0)}$$

is an increasing function of  $\sigma$ .

For instance, for the data in Example 1.8 the value of  $k_D$  increases from 5.15% to 5.45% as  $\sigma$  increases from 30% to 35%.

- 1.3. For a company with  $w_E = 40\%$  equity financing we obtain  $F =$

63.5453 and compute the expected returns on equity and debt  $\mu_E = 18.22\%$ ,  $\mu_D = 5.38\%$ .

For one with  $w_E = 60\%$  equity financing, the corresponding values are  $F = 42.0571$  and  $\mu_E = 14.11\%$ ,  $\mu_D = 5.13\%$ .

- 1.4. For a company with 40% financing by equity we get  $\sigma_E = 83.54\%$  and  $\sigma_D = 3.18\%$ . For one with 60% equity,  $\sigma_E = 56.51\%$  and  $\sigma_D = 0.35\%$ .

- 1.5. From portfolio theory we have the formula

$$\sigma_V^2 = w_E^2 \sigma_E^2 + w_D^2 \sigma_D^2 + 2w_E w_D \sigma_E \sigma_D \rho_{ED}$$

for the variance of the return on the value of the company assets. It follows that the correlation between the returns on equity and debt can be written as

$$\rho_{ED} = \frac{\sigma_V^2 - w_E^2 \sigma_E^2 - w_D^2 \sigma_D^2}{2w_E w_D \sigma_E \sigma_D}.$$

Formulae for  $\sigma_E$  and  $\sigma_D$  are derived in Chapter 1. To use the formula

$$\begin{aligned} \sigma_V^2 &= \mathbb{E}_P \left( \left( \frac{V(T) - V(0)}{D(0)} \right)^2 \right) - \mu_V^2 \\ &= \frac{\mathbb{E}_P(V(T)^2)}{V(0)^2} - \frac{2\mathbb{E}_P(V(T))}{V(0)} + 1 - \mu_V^2 \end{aligned}$$

for  $\sigma_V$  we find

$$\begin{aligned} \mathbb{E}_P(V(T)) &= V(0)e^{(\mu - \frac{1}{2}\sigma^2)T} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} e^{\sigma\sqrt{T}x} dx \\ &= V(0)e^{(\mu - \frac{1}{2}\sigma^2)T} e^{\frac{1}{2}\sigma^2 T} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x - \sigma\sqrt{T})^2} dx \\ &= V(0)e^{\mu T} \end{aligned}$$

and

$$\begin{aligned} \mathbb{E}_P(V(T)^2) &= V(0)^2 e^{(2\mu - \sigma^2)T} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} e^{2\sigma\sqrt{T}x} dx \\ &= V(0)^2 e^{(2\mu - \sigma^2)T} e^{2\sigma^2 T} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x - 2\sigma\sqrt{T})^2} dx \\ &= V(0)^2 e^{(2\mu + \sigma^2)T}. \end{aligned}$$

This makes it possible to compute the correlation for various levels

of the debt ratio  $w_D$  using the data from Example 1.9:

$w_D$	0.8	0.7	0.6	0.5	0.4	0.3
$\rho_{ED}$	0.4162	0.3364	0.2359	0.1316	0.0496	0.0091

1.6. We start with the case when  $l = 1$ . In this case

$$d_+(T) = \frac{1}{2} \sqrt{T} \sigma, \quad d_-(T) = -\frac{1}{2} \sqrt{T} \sigma$$

and

$$\lim_{T \rightarrow 0} d_+(T) = \lim_{T \rightarrow 0} \frac{1}{2} \sqrt{T} \sigma = 0, \quad \lim_{T \rightarrow 0} d_-(T) = -\lim_{T \rightarrow 0} \frac{1}{2} \sqrt{T} \sigma = 0.$$

As a result,

$$\lim_{T \rightarrow 0} (N(-d_+(T)) + N(d_-(T))) = N(0) + N(0) = \frac{1}{2} + \frac{1}{2} = 1$$

and

$$\lim_{T \rightarrow 0} \ln (N(-d_+(T)) + N(d_-(T))) = 0.$$

It means that we can apply l'Hôpital's rule to compute the limit

$$\begin{aligned} \lim_{T \rightarrow 0} s(T) &= -\lim_{T \rightarrow 0} \frac{\frac{d}{dT} (\ln (N(-d_+(T)) + N(d_-(T))))}{\frac{d}{dT} (T)} \\ &= -\lim_{T \rightarrow 0} \frac{\frac{d}{dT} (N(-d_+(T)) + N(d_-(T)))}{N(-d_+(T)) + N(d_-(T))} \\ &= -\lim_{T \rightarrow 0} \frac{d}{dT} (N(-d_+(T))) - \lim_{T \rightarrow 0} \frac{d}{dT} (N(d_-(T))) \\ &= \lim_{T \rightarrow 0} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}d_+(T)^2} \frac{1}{4\sqrt{T}} \sigma + \lim_{T \rightarrow 0} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}d_-(T)^2} \frac{1}{4\sqrt{T}} \sigma = \infty. \end{aligned}$$

Finally, we take  $l > 1$ . In this case

$$\begin{aligned} \lim_{T \rightarrow 0} d_+(T) &= \lim_{T \rightarrow 0} \frac{-\ln l + \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} = -\infty, \\ \lim_{T \rightarrow 0} d_-(T) &= \lim_{T \rightarrow 0} \frac{-\ln l - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} = -\infty. \end{aligned}$$

As a result,

$$\lim_{T \rightarrow 0} \ln \left( \frac{1}{l} N(-d_+(T)) + N(d_-(T)) \right) = \ln \frac{1}{l} = -\ln l$$

and

$$\lim_{T \rightarrow 0} s(T) = \lim_{T \rightarrow 0} \frac{-\ln\left(\frac{1}{l}N(-d_+(T)) + N(d_-(T))\right)}{T} = \infty$$

since the limit in the numerator is  $\ln l$ , a finite positive number, and the limit in the denominator is  $\infty$ .

1.7. Default occurs when  $L + \Pi(T) < F$ . The probability of this event is

$$P(L + \Pi(T) < F) = P(X < a_2) = N(a_2).$$

1.8. Since,

$$D(T) = F\mathbf{1}_{\{L+\Pi(T) \geq F\}} + (L + \Pi(T))\mathbf{1}_{\{0 \leq L+\Pi(T) < F\}}.$$

we have

$$\mathbb{E}_P(D(T)^2) = \mathbb{E}_P\left(F^2\mathbf{1}_{\{L+\Pi(T) \geq F\}} + (L + \Pi(T))^2\mathbf{1}_{\{0 \leq L+\Pi(T) < F\}}\right).$$

Here  $\Pi(T) = \frac{1}{q}(G(T) - G(0))$  and  $G(T) = G(0)e^{(\mu - \frac{1}{2}\sigma^2)T + \sigma\sqrt{T}X}$ , where  $X$  is a random variable with the standard normal distribution under the real-life probability  $P$ . When  $-qL + G(0) > 0$ , we get

$$\begin{aligned} \mathbb{E}_P(D(T)^2) &= \mathbb{E}_P\left(F^2\mathbf{1}_{\{X \geq a_2\}} + \left(L - \frac{1}{q}G(0) + \frac{1}{q}G(T)\right)^2\mathbf{1}_{\{a_1 \leq X < a_2\}}\right) \\ &= F^2P(X \geq a_2) + \left(L - \frac{1}{q}G(0)\right)^2P(a_1 \leq X < a_2) \\ &\quad + \frac{2}{q}\left(L - \frac{1}{q}G(0)\right)G(0)\mathbb{E}_P\left(e^{(\mu - \frac{1}{2}\sigma^2)T + \sigma\sqrt{T}X}\mathbf{1}_{\{a_1 \leq X < a_2\}}\right) \\ &\quad + \frac{1}{q^2}G(0)^2\mathbb{E}_P\left(e^{(2\mu - \sigma^2)T + 2\sigma\sqrt{T}X}\mathbf{1}_{\{a_1 \leq X < a_2\}}\right) \\ &= F^2N(-a_2) + \left(L - \frac{1}{q}G(0)\right)^2(N(a_2) - N(a_1)) \\ &\quad + \frac{2}{q}\left(L - \frac{1}{q}G(0)\right)G(0)e^{\mu T}\left(N(a_2 - \sigma\sqrt{T}) - N(a_1 - \sigma\sqrt{T})\right) \\ &\quad + \frac{1}{q^2}G(0)^2e^{(2\mu + \sigma^2)T}\left(N(a_2 - 2\sigma\sqrt{T}) - N(a_1 - 2\sigma\sqrt{T})\right), \end{aligned}$$

where  $a_1, a_2$  are given by (1.5) and (1.6). When  $-qL + G(0) \leq 0$ , the

inequality  $0 \leq L + \Pi(T)$  is always satisfied, and we get

$$\begin{aligned}
 \mathbb{E}_P(D(T)^2) &= \mathbb{E}_P\left(F^2 \mathbf{1}_{\{X \geq a_2\}} + \left(L - \frac{1}{q}G(0) + \frac{1}{q}G(T)\right)^2 \mathbf{1}_{\{X < a_2\}}\right) \\
 &= F^2 P(X \geq a_2) + \left(L - \frac{1}{q}G(0)\right)^2 P(X < a_2) \\
 &\quad + \frac{2}{q}\left(L - \frac{1}{q}G(0)\right)G(0)\mathbb{E}_P\left(e^{(\mu - \frac{1}{2}\sigma^2)T + \sigma\sqrt{T}X} \mathbf{1}_{\{X < a_2\}}\right) \\
 &\quad + \frac{1}{q^2}G(0)^2\mathbb{E}_P\left(e^{(2\mu - \sigma^2)T + 2\sigma\sqrt{T}X} \mathbf{1}_{\{X < a_2\}}\right) \\
 &= F^2 N(-a_2) + \left(L - \frac{1}{q}G(0)\right)^2 N(a_2) \\
 &\quad + \frac{2}{q}\left(L - \frac{1}{q}G(0)\right)G(0)e^{\mu T}N(a_2 - \sigma\sqrt{T}) \\
 &\quad + \frac{1}{q^2}G(0)^2 e^{(2\mu + \sigma^2)T}N(a_2 - 2\sigma\sqrt{T}).
 \end{aligned}$$

Combining these formulae with (1.4) and (1.7) gives

$$\text{Var}_P(D(T)) = \mathbb{E}_P(D(T)^2) - \mathbb{E}_P(D(T))^2.$$

1.9. For any positive integer  $n$ ,

$$\begin{aligned}
 \{t \in [0, T] : V(t) \leq Fe^{-\gamma(T-t)} + \frac{1}{n}\} &\supseteq \{t \in [0, T] : V(t) \leq Fe^{-\gamma(T-t)} + \frac{1}{n+1}\} \\
 &\supseteq \{t \in [0, T] : V(t) \leq Fe^{-\gamma(T-t)}\},
 \end{aligned}$$

hence

$$\tau_n \leq \tau_{n+1} \leq \tau.$$

It follows that the non-decreasing sequence  $\tau_n$  has a limit  $\lim_{n \rightarrow \infty} \tau_n = \sigma$  and  $\sigma \leq \tau$ . Since  $V$  has continuous paths,

$$V(\sigma) = \lim_{n \rightarrow \infty} V(\tau_n) = \lim_{n \rightarrow \infty} \left(Fe^{-\gamma(T-\tau_n)} + \frac{1}{n}\right) = Fe^{-\gamma(T-\sigma)},$$

which means that  $\tau \leq \sigma$ . As a result,  $\tau = \sigma$ . It remains to verify that  $\tau_n < \tau$  for each  $n$  when  $\tau < \infty$ . Because  $V$  has continuous paths, for any positive integer  $n$  there is an  $\varepsilon > 0$  (which may depend on  $\omega \in \Omega$ ) such that

$$V(\tau - \varepsilon) \leq V(\tau) + \frac{1}{n} = Fe^{-\gamma(T-\tau)} + \frac{1}{n},$$

which means that

$$\tau_n \leq \tau - \varepsilon < \tau.$$

This shows that  $\tau$  is a predictable stopping time.

1.10. The time  $T$  debt payoff is

$$F_M \mathbf{1}_{\{V(T) \geq F_M\}} + V(T) \mathbf{1}_{\{V(T) < F_M\}}$$

in the Merton model, and

$$F_B e^{(r-\gamma)(T-\tau)} \mathbf{1}_{\{\tau \leq T\}} + F_B \mathbf{1}_{\{\tau > T\}}$$

in the barrier model. Hence

$$D(0) = e^{-rT} \mathbb{E}_Q(F_M \mathbf{1}_{\{V(T) \geq F_M\}} + V(T) \mathbf{1}_{\{V(T) < F_M\}})$$

and

$$D(0) = e^{-rT} \mathbb{E}_Q(F_B e^{(r-\gamma)(T-\tau)} \mathbf{1}_{\{\tau \leq T\}} + F_B \mathbf{1}_{\{\tau > T\}}).$$

It follows that

$$\begin{aligned} F_M &\geq \mathbb{E}_Q(F_M \mathbf{1}_{\{V(T) \geq F_M\}} + V(T) \mathbf{1}_{\{V(T) < F_M\}}) \\ &= \mathbb{E}_Q(F_B e^{(r-\gamma)(T-\tau)} \mathbf{1}_{\{\tau \leq T\}} + F_B \mathbf{1}_{\{\tau > T\}}) \\ &\geq F_B \mathbb{E}_Q(\mathbf{1}_{\{\tau \leq T\}} + \mathbf{1}_{\{\tau > T\}}) \\ &= F_B. \end{aligned}$$

1.11. When  $\gamma = r + \frac{1}{2}\sigma^2$ , we have

$$\begin{aligned} \alpha &= \frac{1}{\sigma^2} \left( r - \gamma - \frac{1}{2}\sigma^2 \right) = -1, \\ \beta &= -\sigma(\alpha + 1) = 0, \end{aligned}$$

and

$$\begin{aligned} d_3 &= \frac{\ln L + \sigma\beta T}{\sigma\sqrt{T}} = \frac{\ln L}{\sigma\sqrt{T}} = -\frac{a}{\sqrt{T}}, \\ d_4 &= \frac{\ln L - \sigma\beta T}{\sigma\sqrt{T}} = \frac{\ln L}{\sigma\sqrt{T}} = -\frac{a}{\sqrt{T}}, \end{aligned}$$

where

$$a = -\frac{\ln L}{\sigma}.$$

The distribution function of  $\tau$  is

$$Q(\tau \leq t) = N\left(\frac{-a + \sigma t}{\sqrt{t}}\right) + e^{2\sigma a} N\left(\frac{-a - \sigma t}{\sqrt{t}}\right),$$

and the left-hand side of (1.9) becomes

$$\begin{aligned}
 & \mathbb{E}_Q(e^{(\gamma-r)\tau} \mathbf{1}_{\{\tau \leq T\}}) \\
 &= \mathbb{E}_Q(e^{\frac{1}{2}\sigma^2\tau} \mathbf{1}_{\{\tau \leq T\}}) \\
 &= \int_0^T e^{\frac{1}{2}\sigma^2 t} dQ(\tau \leq t) \\
 &= \int_0^T e^{\frac{1}{2}\sigma^2 t} dN\left(\frac{-a + \sigma t}{\sqrt{t}}\right) + e^{2\sigma a} \int_0^T e^{\frac{1}{2}\sigma^2 t} dN\left(\frac{-a - \sigma t}{\sqrt{t}}\right).
 \end{aligned}$$

On the other hand, the right-hand side of (1.9) can be written as

$$L^{-1}N(d_3) + L^{2\alpha+1}N(d_4) = 2e^{\sigma a}N\left(-\frac{a}{\sqrt{T}}\right).$$

We compute and compare the derivatives of these two expressions with respect to  $T$ . We have

$$\begin{aligned}
 & \frac{d}{dT} \mathbb{E}_Q(e^{(\gamma-r)\tau} \mathbf{1}_{\{\tau \leq T\}}) \\
 &= e^{\frac{1}{2}\sigma^2 T} N'\left(\frac{-a + \sigma T}{\sqrt{T}}\right) \frac{a + \sigma T}{2\sqrt{T^3}} + e^{2\sigma a} e^{\frac{1}{2}\sigma^2 T} N'\left(\frac{-a - \sigma T}{\sqrt{T}}\right) \frac{a - \sigma T}{2\sqrt{T^3}} \\
 &= \frac{1}{\sqrt{2\pi}} e^{\frac{1}{2}\sigma^2 T} e^{-\frac{(-a+\sigma T)^2}{2T}} \frac{a + \sigma T}{2\sqrt{T^3}} + \frac{1}{\sqrt{2\pi}} e^{2\sigma a} e^{\frac{1}{2}\sigma^2 T} e^{-\frac{(-a-\sigma T)^2}{2T}} \frac{a - \sigma T}{2\sqrt{T^3}} \\
 &= \frac{1}{\sqrt{2\pi}} e^{a\sigma} e^{-\frac{a^2}{2T}} \frac{a}{\sqrt{T^3}}.
 \end{aligned}$$

On the other hand,

$$\frac{d}{dT} \left( 2e^{\sigma a} N\left(-\frac{a}{\sqrt{T}}\right) \right) = 2e^{\sigma a} N'\left(-\frac{a}{\sqrt{T}}\right) \frac{a}{2\sqrt{T^3}} = \frac{1}{\sqrt{2\pi}} e^{\sigma a} e^{-\frac{a^2}{2T}} \frac{a}{\sqrt{T^3}}.$$

We can see that these derivatives are the same, hence the left- and right-hand sides of (1.9) can differ only by a constant. To see that this constant is 0 we take the left-limit as  $T \searrow 0$  on both sides of (1.9). The left-hand side of (1.9) clearly tends to 0. The right-hand side also tends to 0 because  $-\frac{a}{\sqrt{T}}$  tends to  $-\infty$  (since  $L < 1$  so  $a = -\frac{1}{\sigma} \ln L > 0$ ), and so  $N\left(-\frac{a}{\sqrt{T}}\right)$  tends to 0.

1.12. According to Theorem 1.29,

$$D(0) = F e^{-rT} \left( N(-d_1) - L^{2\alpha} N(d_2) \right) + V(0) \left( N(d_3) + L^{2\alpha+2} N(d_4) \right),$$

where

$$L = \frac{Fe^{-\gamma T}}{V(0)},$$

$$\alpha = \frac{r - \gamma - \frac{1}{2}\sigma^2}{\sigma^2},$$

and

$$d_1 = \frac{\ln L - (r - \gamma - \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}} = \frac{\ln \frac{F}{V(0)} - (r - \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}},$$

$$d_2 = \frac{\ln L + (r - \gamma - \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}} = \frac{\ln \frac{F}{V(0)} + (r - 2\gamma - \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}},$$

$$d_3 = \frac{\ln L - (r - \gamma + \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}} = \frac{\ln \frac{F}{V(0)} - (r + \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}},$$

$$d_4 = \frac{\ln L + (r - \gamma + \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}} = \frac{\ln \frac{F}{V(0)} + (r - 2\gamma + \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}}.$$

To show that  $D(0)$  is a decreasing function of  $\gamma$  when the remaining parameters  $F, V(0), r, \sigma, T$  are fixed, we shall show that the partial derivative of  $D(0)$  with respect to  $\gamma$  is negative. Since  $d_1$  and  $d_2$  do not depend on  $\gamma$ ,

$$\begin{aligned} \frac{\partial}{\partial \gamma} D(0) &= \frac{\partial}{\partial \gamma} \left( -Fe^{-rT} L^{2\alpha} N(d_2) + V(0) L^{2\alpha+2} N(d_4) \right) \\ &= -Fe^{-rT} \frac{\partial}{\partial \gamma} (L^{2\alpha}) N(d_2) + V(0) \frac{\partial}{\partial \gamma} (L^{2\alpha+2}) N(d_4) \\ &\quad - Fe^{-rT} L^{2\alpha} \frac{\partial}{\partial \gamma} N(d_2) + V(0) L^{2\alpha+2} \frac{\partial}{\partial \gamma} N(d_4). \end{aligned}$$



Observe that the expression in the last line is 0,

$$\begin{aligned}
& -Fe^{-rT}L^{2\alpha}\frac{\partial}{\partial\gamma}N(d_2) + V(0)L^{2\alpha+2}\frac{\partial}{\partial\gamma}N(d_4) \\
&= -Fe^{-rT}L^{2\alpha}N'(d_2)\frac{\partial d_2}{\partial\gamma} + V(0)L^{2\alpha+2}N'(d_4)\frac{\partial d_4}{\partial\gamma} \\
&= -Fe^{-rT}L^{2\alpha}\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}d_2^2}\left(-\frac{2\sqrt{T}}{\sigma}\right) + V(0)L^{2\alpha+2}\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}d_4^2}\left(-\frac{2\sqrt{T}}{\sigma}\right) \\
&= \frac{2\sqrt{T}}{\sigma\sqrt{2\pi}}FL^{2\alpha}\left(e^{-rT}e^{-\frac{(\ln L+(r-\gamma-\frac{1}{2}\sigma^2)T)^2}{2\sigma^2T}} - e^{-\gamma T}Le^{-\frac{(\ln L+(r-\gamma+\frac{1}{2}\sigma^2)T)^2}{2\sigma^2T}}\right) \\
&= \frac{2\sqrt{T}}{\sigma\sqrt{2\pi}}FL^{2\alpha}e^{-\frac{(\ln L+rT-\gamma T)^2+(\frac{1}{2}\sigma^2T)^2}{2\sigma^2T}}\left(e^{-rT}e^{\frac{\ln L+rT-\gamma T}{2}} - e^{-\gamma T}Le^{\frac{\ln L+rT-\gamma T}{2}}\right) \\
&= \frac{2\sqrt{T}}{\sigma\sqrt{2\pi}}FL^{2\alpha}e^{-\frac{(\ln L+rT-\gamma T)^2+(\frac{1}{2}\sigma^2T)^2}{2\sigma^2T}}\left(e^{\frac{\ln L-rT-\gamma T}{2}} - e^{\frac{\ln L-rT-\gamma T}{2}}\right) \\
&= 0.
\end{aligned}$$

Hence

$$\begin{aligned}
\frac{\partial}{\partial\gamma}D(0) &= -Fe^{-rT}\frac{\partial}{\partial\gamma}(L^{2\alpha})N(d_2) + V(0)\frac{\partial}{\partial\gamma}(L^{2\alpha+2})N(d_4) \\
&= -Fe^{-rT}\left(\frac{\partial(2\alpha)}{\partial\gamma}L^{2\alpha}\ln L + 2\alpha\frac{\partial L}{\partial\gamma}L^{2\alpha-1}\right)N(d_2) \\
&\quad + V(0)\left(\frac{\partial(2\alpha+2)}{\partial\gamma}L^{2\alpha+2}\ln L + (2\alpha+2)\frac{\partial L}{\partial\gamma}L^{2\alpha+1}\right)N(d_4) \\
&= \frac{2}{\sigma^2}Fe^{-rT}L^{2\alpha}\left(\ln L + \left(r - \gamma - \frac{1}{2}\sigma^2\right)T\right)N(d_2) \\
&\quad - \frac{2}{\sigma^2}V(0)L^{2\alpha+2}\left(\ln L + \left(r - \gamma + \frac{1}{2}\sigma^2\right)T\right)N(d_4) \\
&= \frac{2}{\sigma^2}(\ln L + (r - \gamma)T)L^{2\alpha}e^{-rT}F(N(d_2) - e^{\ln L+(r-\gamma)T}N(d_4)) \\
&\quad - Fe^{-rT}L^{2\alpha}TN(d_2) - V(0)L^{2\alpha+2}TN(d_4) \\
&< \frac{2}{\sigma^2}(\ln L + (r - \gamma)T)L^{2\alpha}e^{-rT}F(N(d_2) - e^{\ln L+(r-\gamma)T}N(d_4)).
\end{aligned}$$

It remains to show that

$$N(d_2) - e^{\ln L+(r-\gamma)T}N(d_4) < 0.$$

With  $x = \frac{\ln L + (r-\gamma)T}{\sigma\sqrt{T}}$  and  $a = \frac{1}{2}\sigma\sqrt{T}$  this can be written as

$$N(x-a) - e^{2ax}N(x+a) < 0.$$

In fact, the last inequality holds for every  $x \in \mathbb{R}$  and  $a > 0$ . This is so because the limit of the left-hand side as  $x \rightarrow -\infty$  is 0, and the derivative with respect to  $x$  is negative,

$$\begin{aligned} & \frac{d}{dx} (N(x-a) - e^{2ax}N(x+a)) \\ &= N'(x-a) - e^{2ax}N'(x+a) - 2ae^{2ax}N(x+a) \\ &= \frac{1}{\sqrt{2\pi}}e^{-\frac{(x-a)^2}{2}} - e^{2ax}\frac{1}{\sqrt{2\pi}}e^{-\frac{(x+a)^2}{2}} - 2ae^{2ax}N(x+a) \\ &= \frac{1}{\sqrt{2\pi}}\left(e^{-\frac{x^2+a^2-2ax}{2}} - e^{2ax}e^{-\frac{x^2+a^2+2ax}{2}}\right) - 2ae^{2ax}N(x+a) \\ &= -2ae^{2ax}N(x+a) < 0. \end{aligned}$$

1.13. To show that  $D(0)$  is an increasing function of  $F$  when the remaining parameters  $\gamma, V(0), r, \sigma, T$  are fixed, we shall show that the partial derivative of  $D(0)$  with respect to  $F$  is negative. Differentiating the expression for  $D(0)$  in Theorem 1.29, we get

$$\begin{aligned} \frac{\partial}{\partial F}D(0) &= \frac{\partial}{\partial F}\left(Fe^{-rT}\left(N(-d_1) - L^{2\alpha}N(d_2)\right) + V(0)\left(N(d_3) + L^{2\alpha+2}N(d_4)\right)\right) \\ &= e^{-rT}\left(N(-d_1) - L^{2\alpha}N(d_2)\right) \\ &\quad + Fe^{-rT}\left(\frac{\partial}{\partial F}N(-d_1) - \frac{\partial L^{2\alpha}}{\partial F}N(d_2) - L^{2\alpha}\frac{\partial}{\partial F}N(d_2)\right) \\ &\quad + V(0)\left(\frac{\partial}{\partial F}N(d_3) + \frac{\partial L^{2\alpha+2}}{\partial F}N(d_4) + L^{2\alpha+2}\frac{\partial}{\partial F}N(d_4)\right) \\ &= e^{-rT}\left(N(-d_1) - L^{2\alpha}N(d_2)\right) - Fe^{-rT}\frac{\partial L^{2\alpha}}{\partial F}N(d_2) + V(0)\frac{\partial L^{2\alpha+2}}{\partial F}N(d_4) \\ &= e^{-rT}N(-d_1) - (2\alpha+1)e^{-rT}L^{2\alpha}N(d_2) + (2\alpha+2)\frac{V(0)}{F}L^{2\alpha+2}N(d_4) \\ &= e^{-rT}N(-d_1) + \frac{V(0)}{F}L^{2\alpha+2}N(d_4) \\ &\quad + (2\alpha+1)\left(-e^{-rT}L^{2\alpha}N(d_2) + \frac{V(0)}{F}L^{2\alpha+2}N(d_4)\right) \\ &> (2\alpha+1)\left(-e^{-rT}L^{2\alpha}N(d_2) + \frac{V(0)}{F}L^{2\alpha+2}N(d_4)\right). \end{aligned}$$

This is because

$$\begin{aligned}
& F e^{-rT} \frac{\partial}{\partial F} N(-d_1) + V(0) \frac{\partial}{\partial F} N(d_3) \\
&= -\frac{1}{\sigma \sqrt{2\pi T}} \left( e^{-rT} e^{-\frac{1}{2}d_1^2} - \frac{V(0)}{F} e^{-\frac{1}{2}d_3^2} \right) \\
&= -\frac{1}{\sigma \sqrt{2\pi T}} \left( e^{-rT} e^{-\frac{(\ln \frac{F}{V(0)} - rT + \frac{1}{2}\sigma^2 T)^2}{2\sigma^2 T}} - \frac{V(0)}{F} e^{-\frac{(\ln \frac{F}{V(0)} - rT - \frac{1}{2}\sigma^2 T)^2}{2\sigma^2 T}} \right) \\
&= -\frac{1}{\sigma \sqrt{2\pi T}} e^{-\frac{(\ln \frac{F}{V(0)} - rT)^2 + (\frac{1}{2}\sigma^2 T)^2}{2\sigma^2 T}} \left( e^{-rT} e^{\frac{-\ln \frac{F}{V(0)} + rT}{2}} - e^{-\ln \frac{F}{V(0)}} e^{\frac{\ln \frac{F}{V(0)} - rT}{2}} \right) \\
&= 0
\end{aligned}$$

and

$$\begin{aligned}
& -F e^{-rT} L^{2\alpha} \frac{\partial}{\partial F} N(d_2) + V(0) L^{2\alpha+2} \frac{\partial}{\partial F} N(d_4) \\
&= \frac{1}{\sigma \sqrt{2\pi T}} L^{2\alpha} \left( -e^{-rT} e^{-\frac{1}{2}d_2^2} + \frac{V(0)}{F} L^2 e^{-\frac{1}{2}d_4^2} \right) \\
&= \frac{1}{\sigma \sqrt{2\pi T}} L^{2\alpha} \left( -e^{-rT} e^{-\frac{(\ln \frac{F}{V(0)} - 2\gamma T + rT - \frac{1}{2}\sigma^2 T)^2}{2\sigma^2 T}} + \frac{V(0)}{F} L^2 e^{-\frac{(\ln \frac{F}{V(0)} - 2\gamma T + rT + \frac{1}{2}\sigma^2 T)^2}{2\sigma^2 T}} \right) \\
&= \frac{1}{\sigma \sqrt{2\pi T}} L^{2\alpha} e^{-\frac{(\ln \frac{F}{V(0)} - 2\gamma T + rT)^2 + (\frac{1}{2}\sigma^2 T)^2}{2\sigma^2 T}} \left( -e^{-rT} e^{\frac{\ln \frac{F}{V(0)} - 2\gamma T + rT}{2}} + e^{\ln \frac{F}{V(0)} - 2\gamma T} e^{\frac{-\ln \frac{F}{V(0)} + 2\gamma T - rT}{2}} \right) \\
&= 0.
\end{aligned}$$

Next, putting  $x = \frac{\ln \frac{F}{V(0)} - 2\gamma T + rT}{\sigma \sqrt{T}}$  and  $a = \frac{1}{2}\sigma \sqrt{T}$ , we can write

$$\begin{aligned}
\frac{\partial}{\partial F} D(0) &> (2\alpha + 1) \left( -e^{-rT} L^{2\alpha} N(d_2) + \frac{V(0)}{F} L^{2\alpha+2} N(d_4) \right) \\
&= (2\alpha + 1) L^{2\alpha} e^{-rT} \left( -N(x - a) + e^{2ax} N(x + a) \right) \\
&> 0.
\end{aligned}$$

where the inequality

$$-N(x - a) + e^{2ax} N(x + a) > 0$$

was proved in Solution 1.12. Hence, we have demonstrated that  $\frac{\partial D(0)}{\partial F} > 0$ , which shows that  $D(0)$  increases as  $F$  increases (with the other parameters fixed).

1.14. According to Theorems 1.29 and 1.30,

$$\begin{aligned} D(0) &= F e^{-rT} \left( N(-d_1) - L^{2\alpha} N(d_2) \right) + V(0) \left( N(d_3) + L^{2\alpha+2} N(d_4) \right), \\ E(0) &= V(0) \left( N(-d_3) - L^{2\alpha+2} N(d_4) \right) - e^{-rT} F \left( N(-d_1) - L^{2\alpha} N(d_2) \right), \end{aligned}$$

where

$$\begin{aligned} d_1 &= \frac{\ln \frac{F}{V(0)} - \left( r - \frac{1}{2} \sigma^2 \right) T}{\sigma \sqrt{T}}, \\ d_2 &= \frac{\ln \frac{F}{V(0)} + \left( r - 2\gamma - \frac{1}{2} \sigma^2 \right) T}{\sigma \sqrt{T}}, \\ d_3 &= \frac{\ln \frac{F}{V(0)} - \left( r + \frac{1}{2} \sigma^2 \right) T}{\sigma \sqrt{T}}, \\ d_4 &= \frac{\ln \frac{F}{V(0)} + \left( r - 2\gamma + \frac{1}{2} \sigma^2 \right) T}{\sigma \sqrt{T}} \end{aligned}$$

Hence, in the limit as  $\gamma \rightarrow \infty$  we have  $d_2 \rightarrow -\infty$  and  $d_4 \rightarrow -\infty$ , and so  $N(d_2) \rightarrow 0$  and  $N(d_4) \rightarrow 0$ . It follows that

$$\begin{aligned} D(0) &\rightarrow F e^{-rT} N(-d_1) + V(0) N(d_3), \\ E(0) &\rightarrow V(0) N(-d_3) - e^{-rT} F N(-d_1) \end{aligned}$$

as  $\gamma \rightarrow \infty$ , which is consistent with the formulae for the Merton model in Section 1.2.

1.15. Consider the function of two variables

$$\Phi(F, \gamma) = F e^{-rT} \left( N(-d_1) - L^{2\alpha} N(d_2) \right) + V(0) \left( N(d_3) + L^{2\alpha+2} N(d_4) \right),$$

where  $L, \alpha, d_1, d_2, d_3, d_4$  (which also depend on  $F, \gamma$ ) are given in Solution 1.12, with the parameters  $V(0), r, \sigma, T$  fixed. According to Theorem 1.29,

$$\Phi(F, \gamma) = D(0).$$

In Exercises 1.12 and 1.13 we saw that

$$\frac{\partial \Phi}{\partial \gamma} < 0 \quad \text{and} \quad \frac{\partial \Phi}{\partial F} > 0.$$

Now consider  $F$  as a function of  $\gamma$  such that

$$\Phi(F(\gamma), \gamma) = D(0)$$

for a fixed value of  $D(0)$ . It follows that

$$\frac{dF}{d\gamma} \frac{\partial \Phi}{\partial F} + \frac{\partial \Phi}{\partial \gamma} = 0,$$

hence

$$\frac{dF}{d\gamma} = -\frac{\frac{\partial \Phi}{\partial \gamma}}{\frac{\partial \Phi}{\partial F}} > 0.$$

This means that  $F$ , and therefore  $s = \frac{1}{T} \ln \frac{F}{D(0)} - r$ , is an increasing function of  $\gamma$  when the parameters  $D(0), V(0), r, \sigma, T$  are fixed.

## Chapter 2

2.1. If  $\bar{\tau}$  is defined as  $\bar{\tau}(\omega) = \sup \{t \geq 0 : F(t) < \omega\}$ , then

$$\{\bar{\tau} \leq t\} = \{\omega \in [0, 1] : \tau(\omega) \leq t\} = [0, F(t)].$$

It follows that

$$P(\bar{\tau} \leq t) = m([0, F(t)]) = F(t),$$

hence  $\tau$  and  $\bar{\tau}$  have the same probability distribution.

2.2. For any  $a \in [0, 1)$  take  $b = F(a) = 1 - e^{-\lambda a}$ . Then

$$[0, a] = \{\bar{\tau} \leq b\} \in \sigma(\bar{\tau}).$$

Because the intervals  $[0, a]$  for  $a \in [0, 1)$  generate the  $\sigma$ -field of Borel sets in  $[0, 1]$ , it follows that  $\sigma(\bar{\tau})$  contains all such Borel sets.

Next, for any  $b \geq 0$  take  $a = \bar{\tau}(b) = -\frac{1}{\lambda} \ln(1 - b)$ . Then

$$\{\bar{\tau} \leq b\} = [0, a]$$

is a Borel set on  $[0, 1]$ . Because sets of the form  $\{\bar{\tau} \leq b\}$  for  $b \geq 0$  generate the  $\sigma$ -field  $\sigma(\bar{\tau})$ , it follows that  $\sigma(\bar{\tau})$  is contained in the family of Borel sets in  $[0, 1]$ .

We conclude that  $\sigma(\bar{\tau})$  is equal to the family of Borel sets in  $[0, 1]$ .

2.3. The expected default time within the 20-year period is

$$\mathbb{E}(\tau \mathbf{1}_{\{\tau \leq 20\}}) = \int_0^{20} t \lambda e^{-\lambda t} dt = -20e^{-20\lambda} - \frac{1}{\lambda} e^{-20\lambda} + \frac{1}{\lambda}.$$

If 10 companies have been observed over 20 years, among which 2 companies defaulted in year 5 and 3 companies defaulted in year 12,

then an estimate of the expected default time  $\tau \mathbf{1}_{\{\tau \leq 2\}}$  within the 20 year period is

$$\frac{2}{10} \times 5 + \frac{3}{10} \times 12 = 4.6.$$

This gives

$$-20e^{-20\lambda} - \frac{1}{\lambda}e^{-20\lambda} + \frac{1}{\lambda} = 4.6.$$

Solving this equation numerically, we get  $\lambda = 0.19626$ .

For this value of  $\lambda$  we can compute the probability that a given company will survive beyond 5 years as

$$P(5 < \tau) = e^{-5\lambda} = e^{-5 \times 0.19626} = 0.37482.$$

The expected time of default is

$$\mathbb{E}(\tau) = \frac{1}{\lambda} = \frac{1}{0.19626} = 5.0953.$$

2.4. Since

$$\{\tau \leq t\} = \{I(t) = 1\} \in \mathcal{I}_t$$

for each  $t \geq 0$ , it follows that  $\tau$  is a stopping time with respect to the filtration  $(\mathcal{I}_t)_{t \geq 0}$ .

Now suppose that  $\tau$  is a stopping time with respect to some filtration  $(\mathcal{F}_t)_{t \geq 0}$ . It means that  $\{\tau \leq s\} \in \mathcal{F}_s \subset \mathcal{F}_t$  and therefore also  $\{s < \tau\} \in \mathcal{F}_t$  for each  $s \in [0, t]$ . This in turn means that  $I(s)$  is  $\mathcal{F}_t$ -measurable for each  $s \in [0, t]$ . Because  $\mathcal{I}_t$  is the smallest  $\sigma$ -field such that  $I(s)$  is  $\mathcal{I}_t$ -measurable for each  $s \in [0, t]$ , it follows that  $\mathcal{I}_t \subset \mathcal{F}_t$  for each  $t \geq 0$ .

This proves that  $(\mathcal{I}_t)_{t \geq 0}$  is the smallest filtration with respect to which  $\tau$  is a stopping time.

2.5. The random variable  $I(t)$  can take two values only, namely 1 or 0. We have

$$\begin{aligned} \{I(t) = 1\} &= \{\tau \leq t\}, \\ \{I(t) = 0\} &= \{t < \tau\}. \end{aligned}$$

It follows that the  $\sigma$ -field  $\sigma(I(t))$  consist of four events  $\emptyset, \Omega, \{\tau \leq t\}, \{t < \tau\}$  when  $t > 0$ . For  $t = 0$  we have  $\{\tau \leq 0\} = \emptyset$  and  $\{0 < \tau\} = \Omega$ , so  $\sigma(I(0))$  consists of just two events  $\emptyset, \Omega$ .

2.6. Take a sequence of sets  $B_1, B_2, \dots \in \mathcal{D}_1$ . By the definition of the family  $\mathcal{D}_1$ , each of these sets is of the form  $B_n = A_n \cap \{\tau \leq t\}$  for

some  $A_n \in \sigma(\tau)$ , where  $n = 1, 2, \dots$ . Then  $A_1 \cup A_2 \cup \dots \in \sigma(\tau)$ , hence

$$B_1 \cup B_2 \cup \dots = (A_1 \cup A_2 \cup \dots) \cap \{\tau \leq t\} \in \mathcal{D}_1.$$

Similarly, for a sequence of sets  $B_1, B_2, \dots \in \mathcal{D}_2$ , which by the definition of  $\mathcal{D}_2$  are of the form  $B_n = A_n \cup \{t < \tau\}$ , where  $A_n \in \sigma(\tau)$  for each  $n = 1, 2, \dots$ , we have  $A_1 \cup A_2 \cup \dots \in \sigma(\tau)$ , and so

$$B_1 \cup B_2 \cup \dots = (A_1 \cup A_2 \cup \dots) \cup \{t < \tau\} \in \mathcal{D}_2.$$

- 2.7. Suppose that  $C_1, C_2, \dots \in \mathcal{D}$ . By the definition of  $\mathcal{D}$ , we have  $C_n \cap \{\tau \leq t\} \in \mathcal{I}_t$  for each  $n = 1, 2, \dots$ . Then

$$(C_1 \cap C_2 \cap \dots) \cap \{\tau \leq t\} = (C_1 \cap \{\tau \leq t\}) \cap (C_2 \cap \{\tau \leq t\}) \cap \dots \in \mathcal{I}_t,$$

which means that  $C_1 \cap C_2 \cap \dots \in \mathcal{D}$ .

- 2.8. Take any  $s \in \mathbb{R}$ . Then  $\{\tau \wedge t \leq s\} = \Omega \in \mathcal{I}_t$  if  $t \leq s$ , and  $\{\tau \wedge t \leq s\} = \{\tau \leq s\}$  if  $t > s$ . In either case  $\{\tau \wedge t \leq s\} \in \mathcal{I}_t$ . Because the sets  $\{\tau \wedge t \leq s\}$  for  $s \in \mathbb{R}$  generate the  $\sigma$ -field  $\sigma(\tau \wedge t)$ , it follows that  $\sigma(\tau \wedge t) \subset \mathcal{I}_t$ . Moreover, since  $\{t < \tau\} \in \mathcal{I}_t$ , it follows that

$$\sigma(\{t < \tau\}, \sigma(\tau \wedge t)) \subset \mathcal{I}_t.$$

Now suppose that  $\mathcal{G}$  is a  $\sigma$ -field such that  $\{t < \tau\} \in \mathcal{G}$  and  $\sigma(\tau \wedge t) \subset \mathcal{G}$ . We will show that  $\{\tau \leq s\} \in \mathcal{G}$  for every  $s \in [0, t]$ . Because  $\mathcal{I}_t$  is the smallest  $\sigma$ -field containing  $\{\tau \leq s\}$  for every  $s \in [0, t]$ , this implies that  $\mathcal{I}_t \subset \mathcal{G}$ . Hence  $\mathcal{I}_t$  is the smallest  $\sigma$ -field such that  $\{t < \tau\} \in \mathcal{I}_t$  and  $\sigma(\tau \wedge t) \subset \mathcal{I}_t$ . As a result,

$$\sigma(\{t < \tau\}, \sigma(\tau \wedge t)) = \mathcal{I}_t.$$

It remains to show that  $\{\tau \leq s\} \in \mathcal{G}$  for every  $s \in [0, t]$ . If  $s \in [0, t)$ , then  $\{\tau \leq s\} = \{\tau \wedge t \leq s\} \in \mathcal{G}$  since  $\sigma(\tau \wedge t) \subset \mathcal{G}$ . For  $s = t$  we have  $\{\tau \leq t\} \in \mathcal{G}$  since  $\{t < \tau\} \in \mathcal{G}$ , which completes the argument.

- 2.9. By Corollary 2.20,  $\mathcal{I}_t \subset \sigma(\tau)$  for each  $t \geq 0$ , so  $\mathcal{I}_\infty \subset \sigma(\tau)$ .

We are going to show that  $\{\tau \leq t\} \in \mathcal{I}_\infty$  for every  $t \in \mathbb{R}$ . Indeed,  $\{\tau \leq t\} = \emptyset \in \mathcal{I}_\infty$  for any  $t < 0$ , and  $\{\tau \leq t\} \in \mathcal{I}_t \subset \mathcal{I}_\infty$  for any  $t \geq 0$ . Because  $\sigma(\tau)$  is the smallest  $\sigma$ -field containing the sets  $\{\tau \leq t\}$  for all  $t \in \mathbb{R}$ , it follows that  $\sigma(\tau) \subset \mathcal{I}_\infty$ .

We have proved that  $\sigma(\tau) = \mathcal{I}_\infty$ .

- 2.10. Let  $0 < t < u$ . Then, clearly,  $\{t < \tau \leq u\} \in \sigma(\tau)$ . However, since  $\{t < \tau\}$  is an atom in  $\mathcal{I}_t$  containing  $\{t < \tau \leq u\}$  and (under the assumptions adopted in Chapter 2)  $\{t < \tau \leq u\}$  is non-empty and differs from  $\{t < \tau\}$ , it follows that  $\{t < \tau \leq u\} \notin \mathcal{I}_t$ .

- 2.11. Since  $\sigma$  is a stopping time with respect to the filtration  $(\mathcal{I}_t)_{t \geq 0}$  and  $0 \leq \sigma \leq T$ , it follows that  $\sigma = \sigma \wedge T$  is  $\mathcal{I}_T$ -measurable, hence by Proposition 2.22 it can be written as

$$\sigma = \eta(\tau)\mathbf{1}_{\{\tau \leq T\}} + c\mathbf{1}_{\{T < \tau\}}$$

for some Borel function  $\eta : \mathbb{R} \rightarrow \mathbb{R}$  and some constant  $c \in \mathbb{R}$ . Since  $0 \leq \sigma \leq T$ , we have  $c \in [0, T]$ .

Now suppose that  $\tau \wedge c \leq \sigma$  does not hold, that is, the set  $\{\sigma < \tau \wedge c\}$  is non-empty. Then there is a  $t \in \mathbb{R}$  such that  $\{\sigma \leq t\} \cap \{t < \tau\} \supset \{\sigma \leq t < \tau \wedge c\}$  is non-empty. Because  $\{\sigma \leq t\} \in \mathcal{I}_t$  and  $\{t < \tau\}$  is an atom in  $\mathcal{I}_t$ , it follows that  $\{t < \tau\} \subset \{\sigma \leq t\}$ . Since  $t < c \leq T$ , we therefore have  $\{T < \tau\} \subset \{t < \tau\} \subset \{\sigma \leq t\} \subset \{\sigma < c\}$ . But  $\sigma = c$  on the non-empty set  $\{T < \tau\}$ , a contradiction, which proves that  $\tau \wedge c \leq \sigma$ .

Finally, suppose that  $c < \sigma$  on  $\{c < \tau\}$ , that is,  $\{c < \sigma\} \cap \{c < \tau\}$  is non-empty. Because  $\{c < \sigma\} \in \mathcal{I}_c$  and  $\{c < \tau\}$  is an atom in  $\mathcal{I}_c$ , it follows that  $\{c < \tau\} \subset \{c < \sigma\}$ . But this is impossible because  $c \leq T$ , so  $\{T < \tau\} \subset \{c < \tau\} \subset \{c < \sigma\}$  and  $\sigma = c$  on the non-empty set  $\{T < \tau\}$ . It proves that  $\sigma \leq c$  on  $\{c < \tau\}$ . Because  $\tau \wedge c \leq \sigma$ , it follows that  $\sigma = c$  on  $\{c < \tau\}$ .

- 2.12. By definition, the  $\sigma$ -field  $\mathcal{I}_\sigma$  consists of all events  $A \subset \Omega$  such that  $A \cap \{\sigma \leq t\} \in \mathcal{I}_t$  for each  $t \geq 0$ . From Exercise 2.11 we know that there is a deterministic constant  $c \in [0, T]$  such that  $\tau \wedge c \leq \sigma$  and  $\sigma = c$  on  $\{c < \tau\}$ . It follows that  $\{\sigma < \tau\} = \{c < \tau\}$ . It also follows that  $\{c < \tau\} \cap \{\sigma \leq t\} = \emptyset \in \mathcal{I}_t$  if  $t < c$ , and  $\{c < \tau\} \cap \{\sigma \leq t\} = \{c < \tau\} \in \mathcal{I}_c \subset \mathcal{I}_t$  if  $c \leq t$ . This means that  $\{c < \tau\} \in \mathcal{I}_\sigma$ . Now suppose that  $A \in \mathcal{I}_\sigma$  and  $A \subset \{c < \tau\}$ . Since  $\{c < \tau\} \subset \{\sigma \leq c\}$ , we have  $A = A \cap \{\sigma \leq c\} \in \mathcal{I}_c$ . Because  $\{c < \tau\}$  is an atom in  $\mathcal{I}_c$ , we therefore have  $A = \emptyset$  or  $A = \{c < \tau\}$ , proving that  $\{c < \tau\}$  is an atom in  $\mathcal{I}_\sigma$ .

- 2.13. Let  $\varphi = (\varphi_B, \varphi_D)$  be a strategy such that there is a sequence  $0 = \sigma_0 < \sigma_1 < \dots < \sigma_n = T$  of  $(\mathcal{I}_t)_{t \geq 0}$ -stopping times with the following properties:

- (i) the processes  $\varphi_B(t), \varphi_D(t)$  are constant on  $(\sigma_{k-1}, \sigma_k]$  for each  $k = 1, \dots, n$ ;
- (ii) the random variables  $\varphi_B(\sigma_k), \varphi_D(\sigma_k)$  are  $\mathcal{I}_{\sigma_{k-1}}$ -measurable for each  $k = 1, \dots, n$ , and  $\varphi_B(0), \varphi_D(0)$  are  $\mathcal{I}_0$ -measurable.

Moreover, suppose that the strategy satisfies the self-financing con-



dition

$$V_\varphi(\sigma_k) = \varphi_B(\sigma_{k+1})B(\sigma_k, T) + \varphi_D(\sigma_{k+1})D(\sigma_k, T)$$

for each  $k = 0, \dots, n-1$ , where

$$V_\varphi(t) = \varphi_B(t)B(t, T) + \varphi_D(t)D(t, T)$$

is the value of the strategy at any time  $t \in [0, T]$ .

We are going to show that if  $V_\varphi(0) = 0$  and  $V_\varphi(T) \neq 0$  with positive probability, then  $V_\varphi(T) > 0$  with positive probability and  $V_\varphi(T) < 0$  with positive probability, proving that arbitrage is impossible to achieve using this kind of strategy.

Take the smallest  $k$  such that  $V_\varphi(\sigma_k) \neq 0$  on a set of positive probability. Clearly, such  $k$  exists because  $V_\varphi(T) \neq 0$  with positive probability. We have  $k > 1$  because  $V_\varphi(0) = 0$ . The self-financing condition at time  $\sigma_{k-1}$  gives

$$0 = V_\varphi(\sigma_{k-1}) = \varphi_B(\sigma_k)B(\sigma_{k-1}, T) + \varphi_D(\sigma_k)D(\sigma_{k-1}, T).$$

On  $\{\tau \leq \sigma_{k-1}\}$  we therefore have  $\varphi_B(\sigma_k) = 0$  because  $D(\sigma_{k-1}, T) = 0$ . Since  $\varphi_B(\sigma_k)$  is  $\mathcal{I}_{\sigma_{k-1}}$ -measurable, it must be constant on  $\{\sigma_{k-1} < \tau\}$ , which is an atom in  $\mathcal{I}_{\sigma_{k-1}}$  according to Exercise 2.12. This constant must be non-zero or else  $\varphi_B(\sigma_k) = 0$ , hence  $\varphi_D(\sigma_k) = 0$  and so  $V_\varphi(\sigma_k) = 0$  everywhere, contradicting the choice of  $k$ . There are two possibilities:

*Case 1:*  $\varphi_B(\sigma_k) > 0$  on  $\{\sigma_{k-1} < \tau\}$ .

On  $\{\sigma_{k-1} < \tau \leq \sigma_k\}$  we have  $D(\sigma_k, T) = 0$ , and it follows that  $V_\varphi(\sigma_k) = \varphi_B(\sigma_k)B(\sigma_k, T) > 0$ . For all later times the defaultable bonds remain worthless, so the value of the strategy must remain positive on  $\{\sigma_{k-1} < \tau \leq \sigma_k\}$ . In particular,  $V_\varphi(T) > 0$  on the event  $\{\sigma_{k-1} < \tau \leq \sigma_k\}$ , which we can show to have positive probability. Indeed, according to Exercise 2.11, there are deterministic constants  $c_{k-1}, c_k \in [0, T]$  such that  $\sigma_i \geq \tau$  on  $\{\tau \leq c_i\}$  and  $\sigma_i = c_i$  on  $\{c_i < \tau\}$  for  $i = k-1, k$ . From Exercise 2.12 it follows that  $\{\sigma_{k-1} < \tau\} = \{c_{k-1} < \tau\}$  and  $\{\sigma_k < \tau\} = \{c_k < \tau\}$ . By taking complements, we can write the last equality as  $\{\tau \leq \sigma_k\} = \{\tau \leq c_k\}$ . As a result, we have  $\{\sigma_{k-1} < \tau \leq \sigma_k\} = \{c_{k-1} < \tau \leq c_k\}$ . Because  $\sigma_{k-1} < \sigma_k$ , we have  $c_{k-1} < c_k$ , and so the event  $\{\sigma_{k-1} < \tau \leq \sigma_k\} = \{c_{k-1} < \tau \leq c_k\}$  has positive probability in view of the assumptions about  $\tau$  adopted in Chapter 2.

On  $\{\sigma_k < \tau\}$  the long position  $\varphi_B(\sigma_k) > 0$  in non-defaultable bonds is balanced by the short position  $\varphi_D(\sigma_k) = -\frac{B(\sigma_{k-1}, T)}{D(\sigma_{k-1}, T)}\varphi_B(\sigma_k) < 0$

in defaultable bonds so that  $V_\varphi(\sigma_{k-1}) = 0$  at time  $\sigma_{k-1}$ . Prior to a default the defaultable bond grows faster than the non-defaultable one, so at time  $\sigma_k$  the long position will become dominated by the short one, hence  $V_\varphi(\sigma_k) < 0$  on  $\{\sigma_k < \tau\}$ . If  $k = n$ , then  $\sigma_k = T$ , so  $V_\varphi(T) < 0$  on the set  $\{T < \tau\}$  of positive probability. If  $k < n$ , then by the self-financing condition  $\varphi_B(\sigma_{k+1})B(\sigma_k, T) = V_\varphi(\sigma_k) < 0$  on the event  $\{\sigma_k < \tau \leq \sigma_{k+1}\}$ , so  $\varphi_B(\sigma_{k+1}) < 0$  and  $V_\varphi(\sigma_{k+1}) = \varphi_B(\sigma_{k+1})B(\sigma_{k+1}, T) < 0$  on  $\{\sigma_k < \tau \leq \sigma_{k+1}\}$ . For all times later than  $\sigma_{k+1}$  the defaultable bonds remain worthless, hence the value of the strategy must remain negative on the event  $\{\sigma_k < \tau \leq \sigma_{k+1}\}$ . In particular,  $V_\varphi(T) < 0$  on  $\{\sigma_k < \tau \leq \sigma_{k+1}\}$ , which we have shown to have positive probability. This completes the argument in Case 1.

Case 2:  $\varphi_B(\sigma_k) < 0$  on  $\{\sigma_{k-1} < \tau\}$ .

Taking the self-financing simple strategy  $-\varphi(t) = (-\varphi_B(t), -\varphi_D(t))$  for  $t \in [0, T]$  reduces this to Case 1.

2.14. For any  $t \in (-\infty, 0)$

$$\begin{aligned} F_Q(t) &= Q(\bar{\tau} \leq t) = Q(\tau \leq t) = 0, \\ G_Q(t) &= 1 - F_Q(t) = 1, \\ \Gamma_Q(t) &= -\ln G_Q(t) = 0. \end{aligned}$$

For any  $t \in [0, T]$

$$\begin{aligned} F_Q(t) &= Q(\bar{\tau} \leq t) = Q(\tau \leq t) = 1 - e^{-g(0)+g(t)} = 1 - e^{-\lambda t}, \\ G_Q(t) &= 1 - F_Q(t) = e^{-\lambda t}, \\ \Gamma_Q(t) &= -\ln G_Q(t) = \lambda t. \end{aligned}$$

For any  $t \in (T, \infty)$

$$\begin{aligned} F_Q(t) &= Q(\bar{\tau} \leq t) = 1 - Q(t < \bar{\tau}) = 1 - Q(T < \tau) = 1 - e^{-\lambda T}, \\ G_Q(t) &= 1 - F_Q(t) = e^{-\lambda T}, \\ \Gamma_Q(t) &= -\ln G_Q(t) = \lambda T. \end{aligned}$$

### Chapter 3

3.1. For  $r = 0.05$ ,  $T_0 = 0$ ,  $T_1 = \frac{1}{2}$ ,  $T_2 = \frac{3}{4}$ ,  $T_3 = 1$  and  $D(0, T_0) = 1$ ,  $D(0, T_1) = 0.9268$ ,  $D(0, T_2) = 0.8487$ ,  $D(0, T_3) = 0.7635$  we obtain

the following piecewise linear expression for  $D(0, T)$ :

$$D(0, T) = \begin{cases} \frac{T_1-T}{T_1-T_0} D(0, T_0) + \frac{T-T_0}{T_1-T_0} D(0, T_1) & \text{for } T_0 \leq T \leq T_1, \\ \frac{T_2-T}{T_2-T_1} D(0, T_1) + \frac{T-T_1}{T_2-T_1} D(0, T_2) & \text{for } T_1 < T \leq T_2, \\ \frac{T_3-T}{T_3-T_2} D(0, T_2) + \frac{T-T_2}{T_3-T_2} D(0, T_3) & \text{for } T_2 < T \leq T_3. \end{cases}$$

$$= \begin{cases} 1 - 0.1464T & \text{for } 0 \leq T \leq \frac{1}{2}, \\ 1.083 - 0.3124T & \text{for } \frac{1}{2} < T \leq \frac{3}{4}, \\ 1.1043 - 0.3408T & \text{for } \frac{3}{4} < T \leq 1. \end{cases}$$

Since

$$D(0, T) = e^{-rT} e^{-\Gamma(T)},$$

we have

$$\Gamma(T) = -rT - \ln D(0, T)$$

and

$$\gamma(T) = \frac{d\Gamma(T)}{dT} = -r - \frac{1}{D(0, T)} \frac{dD(0, T)}{dT}$$

$$= \begin{cases} -0.05 + \frac{0.1462}{1-0.1464T} & \text{for } 0 \leq T \leq \frac{1}{2}, \\ -0.05 + \frac{0.3124}{1.083-0.3124T} & \text{for } \frac{1}{2} < T \leq \frac{3}{4}, \\ -0.05 + \frac{0.3408}{1.1043-0.3408T} & \text{for } \frac{3}{4} < T \leq 1. \end{cases}$$

3.2. If  $\tau$  is exponentially distributed under  $Q$  with parameter  $\lambda$ , then

$$F(T) = 1 - e^{-\lambda T}.$$

On the other hand,

$$F(T) = 1 - e^{rT} D(0, T).$$

Hence

$$\lambda = -\frac{1}{T} \ln D(0, T) - r = -\frac{1}{\frac{1}{2}} \ln 0.9133 - 0.05 = 0.1314.$$

We can now compute

$$D(0, \frac{1}{4}) = e^{-\frac{1}{4}r} Q(\frac{1}{4} < \tau) = e^{-\frac{1}{4}(r+\lambda)} = e^{-\frac{1}{4}(0.05+0.1314)} = 0.9557.$$

3.3. With  $T_1 = \frac{1}{2}$ ,  $T_2 = 1$  and  $D(0, T_1) = 0.8679$ ,  $D(0, T_2) = 0.7055$ , the system of equations

$$aT_1^2 + bT_1 = -\ln D(0, T_1) - rT_1,$$

$$aT_2^2 + bT_2 = -\ln D(0, T_2) - rT_2,$$

becomes

$$\begin{aligned}\frac{1}{4}a + \frac{1}{2}b &= 0.11668, \\ a + b &= 0.29885,\end{aligned}$$

which gives

$$a = 0.13098, \quad b = 0.16787.$$

We can now compute  $D(0, T_3)$  for  $T_3 = \frac{3}{4}$ :

$$\begin{aligned}D(0, T_3) &= e^{-rT_3} e^{-\Gamma(T_3)} = e^{-rT_3} e^{-aT_3^2 - bT_3} \\ &= e^{-0.05 \times \frac{3}{4}} e^{-0.13098 \times (\frac{3}{4})^2 - 0.16787 \times \frac{3}{4}} = 0.7889.\end{aligned}$$

- 3.4. Let  $T_1 = \frac{1}{2}$  and  $T_2 = 1$ . Suppose the hazard rate is constant on  $(0, T_1]$ ,  $(T_1, T_2]$  with values  $\gamma_1, \gamma_2$ , respectively. Then

$$\begin{aligned}\gamma_1 &= \frac{1}{T_1} \ln \frac{1}{D(0, T_1)} - r = \frac{1}{\frac{1}{2}} \ln \frac{1}{0.85} - 0.05 = 0.2750, \\ \gamma_2 &= \frac{1}{T_2 - T_1} \ln \frac{D(0, T_1)}{D(0, T_2)} - r = \frac{1}{1 - \frac{1}{2}} \ln \frac{0.85}{0.80} - 0.05 = 0.0712.\end{aligned}$$

Since  $T = \frac{3}{4}$  belongs to the interval  $(T_1, T_2]$ ,

$$\begin{aligned}\Gamma(T) &= \int_0^T \gamma(t) dt = \gamma_1 T_1 + \gamma_2 (T - T_1) \\ &= 0.2750 \times \frac{1}{2} + 0.0712 \left( \frac{3}{4} - \frac{1}{2} \right) = 0.1553,\end{aligned}$$

and so

$$D(0, T) = e^{-rT} e^{-\Gamma(T)} = e^{-0.05 \times \frac{3}{4}} e^{-0.1553} = 0.8247.$$

- 3.5. Let  $T_1 = \frac{1}{2}$ ,  $T_2 = \frac{3}{4}$  and  $T_3 = 1$ . Suppose the hazard rate is constant on  $(0, T_1]$ ,  $(T_1, T_2]$ ,  $(T_2, T_3]$  with values  $\gamma_1, \gamma_2, \gamma_3$ , respectively. Then

$$\begin{aligned}\gamma_1 &= \frac{1}{T_1} \ln \frac{1}{D(0, T_1)} - r = \frac{1}{\frac{1}{2}} \ln \frac{1}{0.9037} - 0.05 = 0.1525, \\ \gamma_2 &= \frac{1}{T_2 - T_1} \ln \frac{D(0, T_1)}{D(0, T_2)} - r = \frac{1}{\frac{3}{4} - \frac{1}{2}} \ln \frac{0.9037}{0.8609} - 0.05 = 0.1441, \\ \gamma_3 &= \frac{1}{T_3 - T_2} \ln \frac{D(0, T_2)}{D(0, T_3)} - r = \frac{1}{1 - \frac{3}{4}} \ln \frac{0.8609}{0.7724} - 0.05 = 0.3839.\end{aligned}$$

- 3.6. We found in Exercise 3.4 that

$$\gamma(t) = \begin{cases} 0.2750 & \text{on } [0, \frac{1}{2}], \\ 0.0712 & \text{on } (\frac{1}{2}, 1]. \end{cases}$$

It follows that

$$\hat{D}(t, 1) = e^{-\int_t^1 (r+\gamma(s))ds} = \begin{cases} e^{0.3250t-0.2231} & \text{for } t \in [0, \frac{1}{2}], \\ e^{0.1212t-0.1212} & \text{for } t \in (\frac{1}{2}, 1]. \end{cases}$$

- 3.7. Let  $0 \leq s < t$ . Since the Poisson process has independent increments,  $N(t) - N(s)$  is independent of the  $\sigma$ -field  $\mathcal{N}_s$ . It follows that

$$\mathbb{E}(N(t) - N(s) | \mathcal{N}_s) = \mathbb{E}(N(t) - N(s)) = \lambda(t - s).$$

The last equality holds because  $N(t) - N(s)$  has the Poisson distribution with parameter  $\lambda(t - s)$ . As a result,

$$\mathbb{E}(N(t) - \lambda t | \mathcal{N}_s) = N(s) - \lambda s,$$

that is,  $N(t) - \lambda t$  is a martingale with respect to the filtration  $(\mathcal{N}_t)_{t \geq 0}$ .

- 3.8. Take any  $t \geq 0$  and let  $\tau$  be the time of the first jump of the Poisson process  $N(t)$ . Observe that  $t < \tau$  means that the first jump hasn't yet occurred at time  $t$ , which is equivalent to  $N(t) = 0$  given that the Poisson process starts with  $N(0) = 0$ . As a result,

$$Q(t < \tau) = Q(N(t) = 0) = e^{-\lambda t}.$$

Hence  $\tau$  is exponentially distributed with parameter  $\lambda$ .

- 3.9. Let  $0 \leq s < t$ . Since  $I(t) = \mathbf{1}_{\{\tau \leq t\}}$  and  $\tau$  has the exponential distribution, by Proposition 2.27 applied to the risk-neutral probability  $Q$ , we have

$$\begin{aligned} \mathbb{E}(I(t) | \mathcal{I}_s) &= \mathbb{E}(\mathbf{1}_{\{\tau \leq t\}} | \mathcal{I}_s) \\ &= \mathbf{1}_{\{\tau \leq s\}} \mathbb{E}(\mathbf{1}_{\{\tau \leq t\}} | \sigma(\tau)) + \mathbf{1}_{\{s < \tau\}} \frac{\mathbb{E}(\mathbf{1}_{\{s < \tau\}} \mathbf{1}_{\{\tau \leq t\}})}{Q(s < \tau)} \\ &= \mathbf{1}_{\{\tau \leq s\}} \mathbf{1}_{\{\tau \leq t\}} + \mathbf{1}_{\{s < \tau\}} \frac{Q(s < \tau \leq t)}{Q(s < \tau)} \\ &= I(s) + \mathbf{1}_{\{s < \tau\}} (1 - e^{-\lambda(t-s)}). \end{aligned}$$

On the other hand, using Proposition 2.27 once again, we have

$$\begin{aligned} \mathbb{E}(\lambda(t \wedge \tau) | \mathcal{I}_s) &= \lambda \mathbf{1}_{\{\tau \leq s\}} \mathbb{E}(t \wedge \tau | \sigma(\tau)) + \lambda \mathbf{1}_{\{s < \tau\}} \frac{\mathbb{E}(\mathbf{1}_{\{s < \tau\}} (t \wedge \tau))}{Q(s < \tau)} \\ &= \lambda \mathbf{1}_{\{\tau \leq s\}} (t \wedge \tau) + \lambda \mathbf{1}_{\{s < \tau\}} \frac{se^{-\lambda s} + \frac{1}{\lambda} (e^{-\lambda s} - e^{-\lambda t})}{e^{-\lambda s}} \\ &= \lambda \mathbf{1}_{\{\tau \leq s\}} \tau + \lambda \mathbf{1}_{\{s < \tau\}} s + \mathbf{1}_{\{s < \tau\}} (1 - e^{-\lambda(t-s)}) \\ &= \lambda(s \wedge \tau) + \mathbf{1}_{\{s < \tau\}} (1 - e^{-\lambda(t-s)}) \end{aligned}$$

since

$$\begin{aligned}\mathbb{E}(\mathbf{1}_{\{s < \tau\}}(t \wedge \tau)) &= \int_s^\infty (t \wedge u) \lambda e^{-\lambda u} du \\ &= \lambda \int_s^t u e^{-\lambda u} du + \lambda t \int_t^\infty e^{-\lambda u} du \\ &= s e^{-\lambda s} + \frac{1}{\lambda} (e^{-\lambda s} - e^{-\lambda t})\end{aligned}$$

and  $Q(s < \tau) = e^{-\lambda s}$ . It follows that

$$\mathbb{E}(I(t) - \lambda(t \wedge \tau) | \mathcal{I}_s) = I(s) - \lambda(s \wedge \tau).$$

Because  $\lambda(t \wedge \tau)$  is an  $(\mathcal{I}_t)_{t \geq 0}$ -adapted process with continuous trajectories, it follows that it is a compensator of  $I(t)$ .

3.10. We have

$$\begin{aligned}\mathbb{E}(\Gamma(t \wedge \tau)) &= \int_0^\infty \Gamma(t \wedge u) f(u) du \\ &= \int_0^t \Gamma(u) f(u) du + \Gamma(t) \int_t^\infty f(u) du \\ &= \int_0^t \Gamma(u) f(u) du + \Gamma(t) G(t) \\ &= F(t)\end{aligned}$$

since integration by parts gives

$$\begin{aligned}\Gamma(t)G(t) &= \Gamma(t)G(t) - \Gamma(0)G(0) \\ &= \int_0^t \gamma(u)G(u) du - \int_0^t \Gamma(u)f(u) du \\ &= \int_0^t f(u) du - \int_0^t \Gamma(u)f(u) du \\ &= F(t) - \int_0^t \Gamma(u)f(u) du.\end{aligned}$$

3.11. By Proposition 2.13

$$\gamma(t) = \frac{f(t)}{1 - F(t)}$$

and from Corollary 3.16 we have

$$\Gamma(t \wedge \tau) = \int_0^{t \wedge \tau} \gamma(u) du = \int_0^t (1 - I(u)) \gamma(u) du,$$

hence it follows immediately that

$$\Gamma(t \wedge \tau) = \int_0^{t \wedge \tau} \frac{1}{1 - F(u)} f(u) du = \int_0^t \frac{1 - I(u)}{1 - F(u)} f(u) du.$$

3.12. Since

$$L(t) = (1 - I(t)) e^{\Gamma(t)} = \mathbf{1}_{\{t < \tau\}} e^{\Gamma(t)}$$

is a martingale with respect to the filtration  $(\mathcal{I}_t)_{t \geq 0}$ , it follows that

$$\begin{aligned} \mathbb{E}(\mathbf{1}_{\{T < \tau\}} | \mathcal{I}_t) &= e^{-\Gamma(T)} \mathbb{E}(L(T) | \mathcal{I}_t) \\ &= e^{-\Gamma(T)} L(t) \\ &= \mathbf{1}_{\{t < \tau\}} e^{\Gamma(t) - \Gamma(T)} \\ &= \mathbf{1}_{\{t < \tau\}} e^{-\int_t^T \gamma(s) ds}. \end{aligned}$$

3.13. Let  $X(t) = \mathbf{1}_{[0, c]}(t)$  for some  $c \geq 0$ . By (3.4), we have

$$\begin{aligned} \int_0^t X(u) dM(u) &= \mathbf{1}_{\{\tau \leq t\}} \mathbf{1}_{[0, c]}(\tau) - \int_0^{t \wedge \tau} \mathbf{1}_{[0, c]}(u) \gamma(u) du \\ &= \mathbf{1}_{\{\tau \leq t \wedge c\}} - \int_0^{t \wedge c \wedge \tau} \gamma(u) du. \end{aligned}$$

Now take any  $0 \leq s < t$  and consider two cases:

Case 1:  $s < c$ . Then

$$\begin{aligned} \mathbb{E} \left( \int_0^t X(u) dM(u) \middle| \mathcal{I}_s \right) &= \mathbb{E} \left( \mathbf{1}_{\{\tau \leq t \wedge c\}} - \int_0^{t \wedge c \wedge \tau} \gamma(u) du \middle| \mathcal{I}_s \right) \\ &= \mathbf{1}_{\{\tau \leq s\}} \mathbb{E} \left( \mathbf{1}_{\{\tau \leq t \wedge c\}} - \int_0^{t \wedge c \wedge \tau} \gamma(u) du \middle| \mathcal{I}_s \right) + \mathbf{1}_{\{s < \tau\}} e^{\Gamma(s)} \mathbb{E} \left( \mathbf{1}_{\{\tau \leq t \wedge c\}} - \int_0^{t \wedge c \wedge \tau} \gamma(u) du \right) \\ &= \mathbf{1}_{\{\tau \leq s\}} \left( \mathbf{1}_{\{\tau \leq t \wedge c\}} - \int_0^{t \wedge c \wedge \tau} \gamma(u) du \right) + \mathbf{1}_{\{s < \tau\}} e^{\Gamma(s)} \mathbb{E} \left( \mathbf{1}_{\{s < \tau \leq t \wedge c\}} - \int_0^{t \wedge c} \mathbf{1}_{\{s \vee u < \tau\}} \gamma(u) du \right) \\ &= \mathbf{1}_{\{\tau \leq s \wedge c\}} - \mathbf{1}_{\{\tau \leq s\}} \int_0^{c \wedge \tau} \gamma(u) du + \mathbf{1}_{\{s < \tau\}} e^{\Gamma(s)} \left( F(t \wedge c) - F(s) - \int_0^{t \wedge c} G(s \vee u) \gamma(u) du \right) \\ &= \mathbf{1}_{\{\tau \leq s \wedge c\}} - \mathbf{1}_{\{\tau \leq s\}} \int_0^{c \wedge \tau} \gamma(u) du \\ &\quad + \mathbf{1}_{\{s < \tau\}} e^{\Gamma(s)} \left( F(t \wedge c) - F(s) - \int_0^s G(s) \gamma(u) du - \int_s^{t \wedge c} G(u) \gamma(u) du \right) \\ &= \mathbf{1}_{\{\tau \leq s \wedge c\}} - \mathbf{1}_{\{\tau \leq s\}} \int_0^{c \wedge \tau} \gamma(u) du - \mathbf{1}_{\{s < \tau\}} \int_0^s \gamma(u) du \\ &= \mathbf{1}_{\{\tau \leq s \wedge c\}} - \int_0^{s \wedge c \wedge \tau} \gamma(u) du = \int_0^s X(u) dM(u). \end{aligned}$$

Case 2:  $c \leq s$ . Then

$$\begin{aligned}
\mathbb{E} \left( \int_0^t X(u) dM(u) \middle| \mathcal{I}_s \right) &= \mathbb{E} \left( \mathbf{1}_{\{\tau \leq t \wedge c\}} - \int_0^{t \wedge c \wedge \tau} \gamma(u) du \middle| \mathcal{I}_s \right) \\
&= \mathbb{E} \left( \mathbf{1}_{\{\tau \leq c\}} - \int_0^{c \wedge \tau} \gamma(u) du \middle| \mathcal{I}_s \right) \\
&= \mathbf{1}_{\{\tau \leq s\}} \mathbb{E} \left( \mathbf{1}_{\{\tau \leq c\}} - \int_0^{c \wedge \tau} \gamma(u) du \middle| \sigma(\tau) \right) + \mathbf{1}_{\{s < \tau\}} e^{\Gamma(s)} \mathbb{E} \left( \mathbf{1}_{\{s < \tau\}} \left( \mathbf{1}_{\{\tau \leq c\}} - \int_0^{c \wedge \tau} \gamma(u) du \right) \right) \\
&= \mathbf{1}_{\{\tau \leq c\}} - \mathbf{1}_{\{\tau \leq s\}} \int_0^{c \wedge \tau} \gamma(u) du + \mathbf{1}_{\{s < \tau\}} e^{\Gamma(s)} \mathbb{E} \left( \mathbf{1}_{\{s < \tau\}} \mathbf{1}_{\{\tau \leq c\}} - \mathbf{1}_{\{s < \tau\}} \int_0^c \mathbf{1}_{\{u < \tau\}} \gamma(u) du \right) \\
&= \mathbf{1}_{\{\tau < c\}} - \mathbf{1}_{\{\tau \leq s\}} \int_0^{c \wedge \tau} \gamma(u) du - \mathbf{1}_{\{s < \tau\}} e^{\Gamma(s)} \int_0^c \mathbb{E}(\mathbf{1}_{\{s < \tau\}}) \gamma(u) du \\
&= \mathbf{1}_{\{\tau < c\}} - \mathbf{1}_{\{\tau \leq s\}} \int_0^{c \wedge \tau} \gamma(u) du - \mathbf{1}_{\{s < \tau\}} e^{\Gamma(s)} \int_0^c G(s) \gamma(u) du \\
&= \mathbf{1}_{\{\tau < c\}} - \mathbf{1}_{\{\tau \leq s\}} \int_0^{c \wedge \tau} \gamma(u) du - \mathbf{1}_{\{s < \tau\}} \int_0^{c \wedge \tau} \gamma(u) du \\
&= \mathbf{1}_{\{\tau < c\}} - \int_0^{c \wedge \tau} \gamma(u) du = \mathbf{1}_{\{\tau < s \wedge c\}} - \int_0^{s \wedge c \wedge \tau} \gamma(u) du = \int_0^s X(u) dM(u).
\end{aligned}$$

3.14. Let

$$X(t) = Z \mathbf{1}_{(a,b]}(t)$$

for some  $0 \leq a < b$  and some  $\mathcal{I}_a$ -measurable random variable  $Z$ . By Proposition 2.22,

$$Z = \eta(\tau) \mathbf{1}_{\{\tau \leq a\}} + c \mathbf{1}_{\{a < \tau\}}$$

for some Borel function  $\eta : \mathbb{R} \rightarrow \mathbb{R}$  and a deterministic number  $c \in \mathbb{R}$ . Then

$$\begin{aligned}
X(t) &= (\eta(\tau) \mathbf{1}_{\{\tau \leq a\}} + c \mathbf{1}_{\{a < \tau\}}) \mathbf{1}_{(a,b]}(t) \\
&= \eta(\tau) \mathbf{1}_{(a,b]}(t) \mathbf{1}_{\{\tau \leq a\}} + c \mathbf{1}_{(a,b]}(t) \mathbf{1}_{\{a < \tau\}}
\end{aligned}$$



and

$$\begin{aligned}
\int_0^t X(u) dM(u) &= \mathbf{1}_{\{\tau \leq t\}} X(\tau) - \int_0^{t \wedge \tau} X(u) \gamma(u) du \\
&= \mathbf{1}_{\{\tau \leq t\}} Z \mathbf{1}_{(a,b]}(\tau) - \int_0^{t \wedge \tau} Z \mathbf{1}_{(a,b]}(u) \gamma(u) du \\
&= \mathbf{1}_{\{\tau \leq t\}} (\eta(\tau) \mathbf{1}_{\{\tau \leq a\}} + c \mathbf{1}_{\{a < \tau\}}) \mathbf{1}_{(a,b]}(\tau) \\
&\quad - \int_0^{t \wedge \tau} (\eta(\tau) \mathbf{1}_{\{\tau \leq a\}} + c \mathbf{1}_{\{a < \tau\}}) \mathbf{1}_{(a,b]}(u) \gamma(u) du \\
&= c \mathbf{1}_{\{a < \tau \leq t \wedge b\}} - c \int_0^{t \wedge \tau} \mathbf{1}_{(a,b]}(u) \gamma(u) du \\
&= \mathbf{1}_{\{\tau \leq t\}} c \mathbf{1}_{(a,b]}(\tau) - \int_0^{t \wedge \tau} c \mathbf{1}_{(a,b]}(u) \gamma(u) du \\
&= \int_0^t Y(u) dM(u),
\end{aligned}$$

where

$$Y(t) = c \mathbf{1}_{(a,b]}(t)$$

is a deterministic function. It follows by Lemma 3.19 that

$$\int_0^t X(u) dM(u) = \int_0^t Y(u) dM(u)$$

is a martingale with respect to the filtration  $(\mathcal{I}_t)_{t \geq 0}$ .

## Chapter 4

4.1. We have

$$H(t) = e^{-rt} D(t, T) = \mathbb{E} \left( e^{-rT} D(T, T) | \mathcal{I}_t \right) = \mathbb{E} \left( e^{-rT} \mathbf{1}_{\{T < \tau\}} | \mathcal{I}_t \right),$$

so taking

$$h(t) = e^{-rT} \mathbf{1}_{\{T < t\}}$$

gives

$$H(t) = e^{-rt} D(t, T) = \mathbb{E} (h(\tau) | \mathcal{I}_t).$$

Substituting the expression for  $h$  into the formula for  $J$  gives

$$\begin{aligned}
J(t) &= \mathbb{E} (h(\tau) | t < \tau) = \mathbb{E} \left( e^{-rT} \mathbf{1}_{\{T < t\}} | t < \tau \right) \\
&= e^{-rT} \frac{Q(T < \tau)}{Q(t < \tau)} = e^{-rT} e^{-\Gamma(T)} e^{\Gamma(t)}.
\end{aligned}$$

Now can we substitute the expressions for  $h$  and  $J$  into right-hand side of (4.1) and apply formula (3.4) to get for any  $t \leq T$

$$\begin{aligned}
& \mathbb{E}(h(\tau)) + \int_0^t (h(s) - J(s)) dM(s) \\
&= \mathbb{E}\left(e^{-rT} \mathbf{1}_{\{T < \tau\}}\right) + \int_0^t \left(e^{-rT} \mathbf{1}_{\{T < s\}} - e^{-rT} e^{-\Gamma(T)} e^{\Gamma(s)}\right) dM(s) \\
&= e^{-rT} e^{-\Gamma(T)} + \mathbf{1}_{\{\tau \leq t\}} \left(e^{-rT} \mathbf{1}_{\{T < \tau\}} - e^{-rT} e^{-\Gamma(T)} e^{\Gamma(\tau)}\right) \\
&\quad - \int_0^{t \wedge \tau} \left(e^{-rT} \mathbf{1}_{\{T < s\}} - e^{-rT} e^{-\Gamma(T)} e^{\Gamma(s)}\right) \gamma(s) ds \\
&= e^{-rT} e^{-\Gamma(T)} - \mathbf{1}_{\{\tau \leq t\}} e^{-rT} e^{-\Gamma(T)} e^{\Gamma(\tau)} + e^{-rT} e^{-\Gamma(T)} \int_0^{t \wedge \tau} d(e^{\Gamma(s)}) \\
&= e^{-rT} e^{-\Gamma(T)} - \mathbf{1}_{\{\tau \leq t\}} e^{-rT} e^{-\Gamma(T)} e^{\Gamma(\tau)} + e^{-rT} e^{-\Gamma(T)} (e^{\Gamma(t \wedge \tau)} - e^{\Gamma(0)}) \\
&= -\mathbf{1}_{\{\tau \leq t\}} e^{-rT} e^{-\Gamma(T)} e^{\Gamma(\tau)} + \mathbf{1}_{\{\tau \leq t\}} e^{-rT} e^{-\Gamma(T)} e^{\Gamma(\tau)} + \mathbf{1}_{\{t < \tau\}} e^{-rT} e^{-\Gamma(T)} e^{\Gamma(t)} \\
&= \mathbf{1}_{\{t < \tau\}} e^{-rT} e^{-\Gamma(T)} e^{\Gamma(t)} \\
&= e^{-rt} D(t, T).
\end{aligned}$$

- 4.2. By linearity, it is enough to show that if  $\phi$  is a left-continuous deterministic function such that

$$\int_0^t \phi(s) dM(s) = 0$$

for each  $t \geq 0$ , then  $\phi = 0$  on  $(0, \infty)$ .

By formula (3.4),

$$\int_0^t \phi(s) dM(s) = \mathbf{1}_{\{\tau \leq t\}} \phi(\tau) - \int_0^{t \wedge \tau} \phi(s) \gamma(s) ds = 0.$$

On  $\{t < \tau\}$  we have

$$\int_0^t \phi(s) dM(s) = - \int_0^t \phi(s) \gamma(s) ds = 0.$$

As a result,

$$\int_0^t \phi(s) \gamma(s) ds = 0$$

for every  $t \geq 0$  since  $\{t < \tau\}$  has non-zero probability and  $\int_0^t \phi(s) \gamma(s) ds$  is deterministic. Because  $\gamma(t) = e^{\Gamma(t)} f(t) > 0$  for almost every  $t \in [0, \infty)$ , it follows that  $\phi(t) = 0$  for almost every  $t \in [0, \infty)$ . By left-continuity, we can conclude that  $\phi = 0$  on  $(0, \infty)$ .

## 4.3. Using the self-financing condition

$$V_\varphi(t) = V_\varphi(0) + \int_0^t \varphi_B(u)dB(u, T) + \int_0^t \varphi_D(u)dD(u, T),$$

by Theorem A.9 (the integration-by-parts formula for Lebesgue–Stieltjes integrals) and Theorems A.10 and A.11, we obtain

$$\begin{aligned} & \tilde{V}_\varphi(t) - V_\varphi(0) \\ &= e^{-rt}V_\varphi(t) - V_\varphi(0) \\ &= \int_0^t e^{-ru}dV_\varphi(u) + \int_0^t V_\varphi(u_-)d(e^{-ru}) \\ &= \int_0^t e^{-ru}\varphi_B(u)dB(u, T) + \int_0^t e^{-ru}\varphi_D(u)dD(u, T) + \int_0^t V_\varphi(u_-)d(e^{-ru}) \\ &= r \int_0^t e^{-ru}\varphi_B(u)B(u, T)du + r \int_0^t e^{-ru}\varphi_D(u)D(u, T)du \\ &\quad - \int_0^t e^{-ru}\varphi_D(u)D(u_-, T)dM(u) - r \int_0^t e^{-ru}V_\varphi(u_-)du \\ &= r \int_0^t e^{-ru}V_\varphi(u)du - \int_0^t e^{-ru}\varphi_D(u)D(u_-, T)dM(u) - r \int_0^t e^{-ru}V_\varphi(u_-)du \\ &= - \int_0^t \varphi_D(u)\tilde{D}(u_-, T)dM(u) \\ &= \int_0^t \varphi_D(u)d\tilde{D}(u, T). \end{aligned}$$

Here we use the fact that

$$V_\varphi(t) = \varphi_B(t)B(t, T) + \varphi_D(t)D(t, T) = V_\varphi(t_-)$$

for almost all  $t \in [0, T]$  and apply Proposition 3.23 in the last equality.

4.4. Using the identities  $f(t) = \gamma(t)e^{-\Gamma(t)}$  and  $G(T) = e^{-\Gamma(T)}$ , we compute

$$\begin{aligned} \mathbb{E}(\tilde{V}_\varphi(T)) &= e^{-rT}e^{-\Gamma(T)}\mathbb{E}(e^{\Gamma(T \wedge \tau)} - 1) \\ &= e^{-rT}e^{-\Gamma(T)}\left(\int_0^T e^{\Gamma(u)}f(u)du + e^{\Gamma(T)}\int_T^\infty f(u)du - 1\right) \\ &= e^{-rT}e^{-\Gamma(T)}\left(\int_0^T \gamma(u)du + e^{\Gamma(T)}G(T) - 1\right) \\ &= e^{-rT}e^{-\Gamma(T)}\Gamma(T), \end{aligned}$$

which is greater than 0.

- 4.5. Suppose that  $\varphi(t) = (\varphi_B(t), \varphi_D(t))$  is an admissible self-financing strategy such that  $V_\varphi(0) = 0$ . Admissibility means that  $\tilde{V}_\varphi(t)$  is a martingale under the risk-neutral probability  $Q$ . It follows that

$$\mathbb{E}(V_\varphi(T)) = e^{rT} \mathbb{E}(\tilde{V}_\varphi(T)) = e^{rT} \tilde{V}_\varphi(0) = e^{rT} V_\varphi(0) = 0.$$

It is therefore impossible for  $V_\varphi(T)$  to be non-negative almost surely and positive with positive probability. There is no admissible arbitrage strategy.

- 4.6. Using Proposition 2.27, for any  $t \in [0, T]$  we compute

$$\begin{aligned} & e^{-r(T-t)} \mathbb{E}(D_\delta(T, T) | \mathcal{I}_t) \\ &= e^{-r(T-t)} \mathbb{E}(\delta + (1 - \delta) \mathbf{1}_{\{T < \tau\}} | \mathcal{I}_t) \\ &= \delta e^{-r(T-t)} + (1 - \delta) e^{-r(T-t)} \mathbb{E}(\mathbf{1}_{\{T < \tau\}} | \mathcal{I}_t) \\ &= \delta e^{-r(T-t)} + (1 - \delta) e^{-r(T-t)} \left( \mathbf{1}_{\{\tau \leq t\}} \mathbb{E}(\mathbf{1}_{\{T < \tau\}} | \mathcal{G}(\tau)) + \mathbf{1}_{\{t < \tau\}} \frac{\mathbb{E}(\mathbf{1}_{\{T < \tau\}} \mathbf{1}_{\{t < \tau\}})}{Q(t < \tau)} \right) \\ &= \delta e^{-r(T-t)} + (1 - \delta) e^{-r(T-t)} \mathbf{1}_{\{t < \tau\}} \frac{Q(T < \tau)}{Q(t < \tau)} \\ &= \delta e^{-r(T-t)} + (1 - \delta) e^{-r(T-t)} \mathbf{1}_{\{t < \tau\}} e^{-(\Gamma(T) - \Gamma(t))}. \end{aligned}$$

This agrees with the formula for  $D_\delta(t, T)$  in Example 4.10.

- 4.7. In Example 4.10 we saw that

$$D_\delta(t, T) = \delta B(t, T) + (1 - \delta) D(t, T).$$

Hence

$$D(t, T) = \frac{1}{1 - \delta} D_\delta(t, T) - \frac{\delta}{1 - \delta} B(t, T).$$

This means that the zero-recovery bond  $D(t, T)$  can be replicated by a portfolio consisting of  $\frac{1}{1 - \delta}$  positive recovery bonds  $D_\delta(t, T)$  and  $-\frac{\delta}{1 - \delta}$  non-defaultable bonds  $B(t, T)$ .

- 4.8. Using (4.4) and Proposition 3.23 with

$$\varphi_D(t) = e^{\Gamma(T) - \Gamma(t)} (J(t) - h(t))$$

and

$$\tilde{D}(t, T) = \mathbf{1}_{\{t < \tau\}} e^{-rT} e^{-(\Gamma(T) - \Gamma(t))},$$

we obtain

$$\begin{aligned}
\varphi_B(t) &= \frac{1}{e^{-rt}B(t, T)} \left( V_\varphi(0) + \int_0^t \varphi_D(u) d\tilde{D}(u, T) - \varphi_D(t) \tilde{D}(t, T) \right) \\
&= \frac{1}{e^{-rt}} \left( V_\varphi(0) - \int_0^t \varphi_D(u) \tilde{D}(u, T) dM(u) - \varphi_D(t) \tilde{D}(t, T) \right) \\
&= \mathbb{E}(h(\tau)) - \int_0^t (J(u) - h(u)) \mathbf{1}_{\{u \leq \tau\}} dM(u) - (J(t) - h(t)) \mathbf{1}_{\{t < \tau\}} \\
&= \mathbb{E}(h(\tau)) - (J(\tau) - h(\tau)) \mathbf{1}_{\{\tau \leq t\}} \\
&\quad + \int_0^{t \wedge \tau} (J(u) - h(u)) \gamma(u) du - (J(t) - h(t)) \mathbf{1}_{\{t < \tau\}} \\
&= \mathbb{E}(h(\tau)) - (J(t \wedge \tau) - h(t \wedge \tau)) + \int_0^{t \wedge \tau} (J(u) - h(u)) \gamma(u) du.
\end{aligned}$$

In the proof of Theorem 4.1 (i.e. the martingale representation theorem) it is shown that

$$\begin{aligned}
\int_0^{t \wedge \tau} J(u) \gamma(u) du &= e^{\Gamma(t \wedge \tau)} \int_{t \wedge \tau}^\infty h(u) f(u) du - \int_0^\infty h(u) f(u) du \\
&\quad + \int_0^{t \wedge \tau} e^{\Gamma(u)} h(u) f(u) du \\
&= J(t \wedge \tau) - \mathbb{E}(h(\tau)) + \int_0^{t \wedge \tau} h(u) \gamma(u) du.
\end{aligned}$$

It follows that

$$\begin{aligned}
\varphi_B(t) &= \mathbb{E}(h(\tau)) - (J(t \wedge \tau) - h(t \wedge \tau)) + \int_0^{t \wedge \tau} (J(u) - h(u)) \gamma(u) du \\
&= h(t \wedge \tau).
\end{aligned}$$

- 4.9. The payoff of a defaultable bond with constant recovery can be expressed as

$$D_\delta(T, T) = h(\tau),$$

where

$$h(t) = \begin{cases} \delta & \text{if } t \leq T, \\ 1 & \text{if } T < t. \end{cases}$$

According to Theorem 4.11, the replicating strategy is given by

$$\begin{aligned}
\varphi_B(t) &= h(t \wedge \tau), \\
\varphi_D(t) &= e^{\Gamma(T) - \Gamma(t)} (J(t) - h(t))
\end{aligned}$$

for any  $t \in [0, T]$ . It follows that

$$\varphi_B(t) = h(t \wedge \tau) = \delta$$

since  $t \wedge \tau \leq T$  when  $t \leq T$ . Moreover,

$$\begin{aligned} J(t) &= \mathbb{E}(h(\tau) | t < \tau) = \frac{\mathbb{E}(\mathbf{1}_{\{t < \tau\}} h(\tau))}{Q(t < \tau)} \\ &= \frac{\delta Q(t < \tau \leq T) + Q(T < \tau)}{Q(t < \tau)} = \frac{\delta(e^{-\Gamma(t)} - e^{-\Gamma(T)}) + e^{-\Gamma(T)}}{e^{-\Gamma(t)}}, \end{aligned}$$

so for any  $t \leq T$

$$\begin{aligned} \varphi_D(t) &= e^{\Gamma(T) - \Gamma(t)} (J(t) - h(t)) \\ &= e^{\Gamma(T) - \Gamma(t)} \left( \frac{\delta(e^{-\Gamma(t)} - e^{-\Gamma(T)}) + e^{-\Gamma(T)}}{e^{-\Gamma(t)}} - \delta \right) \\ &= 1 - \delta. \end{aligned}$$

4.10. From Proposition 4.12 we have

$$\begin{aligned} D_\eta(t, T) &= \eta(\tau) \mathbf{1}_{\{\tau \leq t\}} \\ &\quad + \mathbf{1}_{\{t < \tau\}} \left( e^{-r(T-t)} e^{-(\Gamma(T) - \Gamma(t))} + e^{-r(T-t)} e^{\Gamma(t)} \int_t^T \eta(s) e^{r(T-s)} f(s) ds \right). \end{aligned}$$

For  $t = 0$  this gives

$$\begin{aligned} D_\eta(0, T) &= e^{-rT} e^{-\Gamma(T)} + e^{-rT} \int_0^T \eta(s) e^{r(T-s)} f(s) ds \\ &= e^{-rT} G(T) + \int_0^T \eta(s) e^{-rs} f(s) ds. \end{aligned}$$

4.11. Let

$$h(\tau) = \mathbf{1}_{\{T < \tau\}} + \eta(\tau) e^{r(T-\tau)} \mathbf{1}_{\{\tau \leq T\}}.$$

By Proposition 2.27, for any  $t \in [0, T]$  we have

$$\begin{aligned}
 D_\eta(t, T) &= e^{-r(T-t)} \mathbb{E}(h(\tau) | \mathcal{I}_t) \\
 &= e^{-r(T-t)} \mathbf{1}_{\{\tau \leq t\}} \mathbb{E}(h(\tau) | \sigma(\tau)) + e^{-r(T-t)} \mathbf{1}_{\{t < \tau\}} \frac{\mathbb{E}(h(\tau) \mathbf{1}_{\{t < \tau\}})}{Q(t < \tau)} \\
 &= e^{-r(T-t)} \mathbf{1}_{\{\tau \leq t\}} h(\tau) + e^{-r(T-t)} \mathbf{1}_{\{t < \tau\}} \frac{\mathbb{E}(h(\tau) \mathbf{1}_{\{t < \tau\}})}{Q(t < \tau)} \\
 &= \mathbf{1}_{\{\tau \leq t\}} e^{r(t-\tau)} \eta(\tau) + e^{-r(T-t)} \mathbf{1}_{\{t < \tau\}} \frac{\mathbb{E}(\mathbf{1}_{\{T < \tau\}})}{Q(t < \tau)} \\
 &\quad + e^{-r(T-t)} \mathbf{1}_{\{t < \tau\}} \frac{\mathbb{E}(\eta(\tau) e^{r(T-\tau)} \mathbf{1}_{\{t < \tau \leq T\}})}{Q(t < \tau)} \\
 &= \mathbf{1}_{\{\tau \leq t\}} e^{r(t-\tau)} \eta(\tau) + e^{-r(T-t)} \mathbf{1}_{\{t < \tau\}} e^{-(\Gamma(T) - \Gamma(t))} \\
 &\quad + e^{-r(T-t)} \mathbf{1}_{\{t < \tau\}} e^{\Gamma(t)} \int_t^T \eta(s) e^{r(T-s)} f(s) ds.
 \end{aligned}$$

4.12. Let

$$H(t) = \mathbb{E}(h(\tau) | \mathcal{I}_t).$$

By the martingale representation theorem (Theorem 4.1),

$$\begin{aligned}
 H(t) &= H(0) + \int_0^t (h(s) - J(s)) dM(s) \\
 &= H(0) + (h(\tau) - J(\tau)) \mathbf{1}_{\{\tau \leq t\}} - \int_0^{t \wedge \tau} (h(s) - J(s)) \gamma(s) ds.
 \end{aligned}$$

It follows that

$$\begin{aligned}
 &D_\eta(t, T) - D_\eta(0, T) \\
 &= e^{-r(T-t)} H(t) - e^{-rT} H(0) \\
 &= \int_0^t e^{-r(T-s)} dH(s) + \int_0^t H(s_-) d(e^{-r(T-s)}) \\
 &= \int_0^t e^{-r(T-s)} h(s) dM(s) - \int_0^t e^{-r(T-s)} J(s) dM(s) \\
 &\quad + r \int_0^t H(s_-) e^{-r(T-s)} ds.
 \end{aligned}$$

On  $\{t < \tau\}$  we have

$$\int_0^t \eta(s) dM(s) = - \int_0^t \eta(s) \gamma(s) (1 - I(s)) ds$$

and

$$H(t) = H(0) - \int_0^{t \wedge \tau} (h(s) - J(s)) \gamma(s) ds = H(t_-),$$

so

$$\begin{aligned} & D_\eta(t, T) - D_\eta(0, T) \\ &= - \int_0^t \eta(s) \gamma(s) (1 - I(s)) ds - \int_0^t e^{-r(T-s)} J(s) dM(s) \\ &\quad + r \int_0^t H(s) e^{-r(T-s)} ds \\ &= - \int_0^t \eta(s) \gamma(s) (1 - I(s)) ds - \int_0^t \hat{D}_\eta(s, T) dM(s) \\ &\quad + r \int_0^t D_\eta(s, T) ds \end{aligned}$$

since

$$\begin{aligned} \hat{D}_\eta(t, T) &= e^{-r(T-t)} \left( e^{-(\Gamma(T)-\Gamma(t))} - e^{\Gamma(t)} \int_t^T \eta(s) e^{r(t-s)} f(s) ds \right) \\ &= e^{-r(T-t)} J(t). \end{aligned}$$

and

$$D_\eta(t, T) = e^{-r(T-t)} \mathbb{E}(h(\tau) | \mathcal{I}_t) = e^{-r(T-t)} H(t).$$

This shows that

$$dD_\eta(t, T) = -\eta(t) \gamma(t) (1 - I(t)) dt - \hat{D}_\eta(s, T) dM(t) + r D_\eta(t, T) dt$$

on  $\{t < \tau\}$ .

- 4.13. The payoff of a defaultable zero-coupon bond maturing at time  $S$ , where  $0 < S < T$ , is equivalent to a payoff at time  $T$  of the form  $h(\tau)$ , where

$$h(t) = \mathbf{1}_{\{S < t\}} e^{r(T-S)}.$$

By Theorem 4.11, for any  $t \in [0, S]$ ,

$$\varphi_B(t) = h(t \wedge \tau) = \mathbf{1}_{\{S < t \wedge \tau\}} e^{r(T-S)} = 0$$

since  $t \wedge \tau \leq t \leq S$ . It means that the bond  $D(t, S)$  can be replicated by the  $D(t, T)$  bond alone. Since

$$\begin{aligned} D(t, S) &= \mathbf{1}_{\{t < \tau\}} e^{-r(S-t)} e^{-(\Gamma(S)-\Gamma(t))} \\ &= e^{r(T-S)} e^{(\Gamma(T)-\Gamma(S))} \mathbf{1}_{\{t < \tau\}} e^{-r(T-t)} e^{-(\Gamma(T)-\Gamma(t))} \\ &= e^{r(T-S)} e^{(\Gamma(T)-\Gamma(S))} D(t, T), \end{aligned}$$



we have

$$\varphi_D(t) = e^{r(T-S)} e^{(\Gamma(T)-\Gamma(S))}.$$

- 4.14. By Exercise 4.13, for each  $k = 1, \dots, N$  the zero-coupon bond  $D(t, T_k)$  with maturity  $T_k$  can be replicated by  $e^{r(T-T_k)} e^{(\Gamma(T)-\Gamma(T_k))}$  zero-coupon bonds  $D(t, T)$  with maturity  $T$ . Hence, to replicate the coupon bond we need to buy

$$\sum_{k=1}^N C_k e^{r(T-T_k)} e^{(\Gamma(T)-\Gamma(T_k))} + F e^{r(T-T_N)} e^{(\Gamma(T)-\Gamma(T_N))}$$

of the zero-coupon bonds maturing at time  $T$ . Then, at time  $T_k$  for each  $k = 1, \dots, T_N$  we need to sell  $C_k e^{r(T-T_k)} e^{(\Gamma(T)-\Gamma(T_k))}$  of the zero-coupon bonds maturing at  $T$ , which produces the defaultable coupon payment

$$C_k e^{r(T-T_k)} e^{(\Gamma(T)-\Gamma(T_k))} D(T_k, T) = C_k \mathbf{1}_{\{T_k < \tau\}}.$$

At time  $T_N$  we also need to sell the remaining holdings amounting to  $F e^{r(T-T_N)} e^{(\Gamma(T)-\Gamma(T_N))}$  of the zero-coupon bonds maturing at  $T$ , which pays

$$F e^{r(T-T_N)} e^{(\Gamma(T)-\Gamma(T_N))} D(T_N, T) = F \mathbf{1}_{\{T_N < \tau\}},$$

i.e. the face value of the defaultable coupon bond.

- 4.15. Consider a CDS on a defaultable bond  $D_\delta(t, T)$  with constant recovery  $\delta \in (0, 1)$  paid at maturity  $T$ . The recovery leg payment of the CDS is  $(1 - \delta) \mathbf{1}_{\{\tau \leq T\}}$  at time  $T$ . The premium leg payments are  $\alpha \mathbf{1}_{\{t_k < T\}}$  at times  $t_k$  for  $k = 1, \dots, N$ . Equating the time 0 values of the two legs, we get

$$\mathbb{E} \left( e^{-rT} (1 - \delta) \mathbf{1}_{\{\tau \leq T\}} \right) = \sum_{k=1}^N \mathbb{E} \left( \alpha e^{-rt_k} \mathbf{1}_{\{t_k < T\}} \right).$$

Hence

$$\begin{aligned} \alpha &= \frac{\mathbb{E} \left( e^{-rT} (1 - \delta) \mathbf{1}_{\{\tau \leq T\}} \right)}{\sum_{k=1}^N \mathbb{E} \left( e^{-rt_k} \mathbf{1}_{\{t_k < T\}} \right)} \\ &= \frac{\mathbb{E} \left( e^{-rT} (1 - \delta) (1 - \mathbf{1}_{\{T < \tau\}}) \right)}{\sum_{k=1}^N \mathbb{E} \left( e^{-rt_k} \mathbf{1}_{\{t_k < T\}} \right)} = (1 - \delta) \frac{B(0, T) - D(0, T)}{\sum_{k=1}^N D(0, t_k)}. \end{aligned}$$

- 4.16. The CDS spread is given by

$$\alpha = \frac{B(0, T) - D(0, T)}{\sum_{k=1}^N D(0, t_k)} = \frac{e^{-rT} - e^{-rT} e^{-\Gamma(T)}}{\sum_{k=1}^N e^{-rt_k} e^{-\Gamma(t_k)}}.$$

When  $\tau$  is exponentially distributed under  $Q$ , we have

$$e^{-\Gamma(t)} = G(t) = Q(t < \tau) = e^{-\lambda t}.$$

This gives

$$\alpha = \frac{e^{-rT} - e^{-rT} e^{-\lambda T}}{\sum_{k=1}^N e^{-rt_k} e^{-\lambda t_k}}.$$

For  $r = 0.05$ ,  $\lambda = 0.02$ ,  $T = 1$  and  $N = 12$  we get

$$\alpha = \frac{e^{-0.05 \times 1} - e^{-0.05 \times 1} e^{-0.02 \times 1}}{\sum_{k=1}^{12} e^{-0.05 \times \frac{k}{12}} e^{-0.02 \times \frac{k}{12}}} = 0.00163.$$

4.17. If the hazard rate  $\gamma$  is constant, then we have  $\Gamma(t) = \gamma t$ , so

$$\alpha = \frac{B(0, T) - D(0, T)}{\sum_{k=1}^N D(0, t_k)} = \frac{e^{-rT} - e^{-rT} e^{-\Gamma(T)}}{\sum_{k=1}^N e^{-rt_k} e^{-\Gamma(t_k)}} = \frac{e^{-rT} - e^{-rT} e^{-\gamma T}}{\sum_{k=1}^N e^{-rt_k} e^{-\gamma t_k}}.$$

This nonlinear equation can be solved numerically for  $\gamma$ . When  $r = 0.06$ ,  $T = 2$ ,  $N = 24$  and  $\alpha = 0.1$ , we get  $\gamma = 0.127$ . This yields the defaultable bond price

$$D(0, T) = e^{-rT} e^{-\Gamma(T)} = e^{-rT} e^{-\gamma T} = 0.6880.$$

4.18. For each  $n = 1, \dots, N$  we have  $t_n = \frac{nT}{N}$  and

$$\alpha_n = \frac{e^{-rt_n} (1 - G(t_n))}{\sum_{k=1}^n e^{-rt_k} G(t_k)},$$

hence

$$G(t_n) = \frac{1 - \alpha_n \sum_{k=1}^{n-1} e^{r(t_n - t_k)} G(t_k)}{\alpha_n + 1} = \frac{1 - \alpha_n \sum_{k=1}^{n-1} e^{r \frac{(n-k)T}{N}} G(t_k)}{\alpha_n + 1}.$$

Moreover, the piecewise linear hazard function can be written as

$$\Gamma(t_n) = \sum_{k=1}^n \gamma_k (t_k - t_{k-1}) = \sum_{k=1}^n \gamma_k \frac{T}{N},$$

where  $\gamma_1, \dots, \gamma_N$  are positive constants, so

$$G(t_n) = e^{-\Gamma(t_n)} = e^{-\sum_{k=1}^n \gamma_k \frac{T}{N}}.$$

For  $T = 1$ ,  $N = 4$ ,  $r = 0.05$  and

$$\alpha_1 = 0.012, \quad \alpha_2 = 0.009, \quad \alpha_3 = 0.011, \quad \alpha_4 = 0.010,$$

we get

$$\begin{aligned}
 G(t_1) &= \frac{1}{\alpha_1 + 1} = 0.98814, \\
 G(t_2) &= \frac{1 - \alpha_2 e^{r \frac{T}{N}} G(t_1)}{\alpha_2 + 1} = 0.98216, \\
 G(t_3) &= \frac{1 - \alpha_3 \left( e^{r \frac{2T}{4}} G(t_1) + e^{r \frac{T}{4}} G(t_2) \right)}{\alpha_3 + 1} = 0.96728, \\
 G(t_4) &= \frac{1 - \alpha_4 \left( e^{r \frac{3T}{4}} G(t_1) + e^{r \frac{2T}{4}} G(t_2) + e^{r \frac{T}{4}} G(t_3) \right)}{\alpha_4 + 1} = 0.96027.
 \end{aligned}$$

It follows that

$$\begin{aligned}
 \gamma_1 &= -\frac{N}{T} \ln G(t_1) = 0.047724, \\
 \gamma_2 &= -\frac{N}{T} \ln \frac{G(t_2)}{G(t_1)} = 0.024281, \\
 \gamma_3 &= -\frac{N}{T} \ln \frac{G(t_3)}{G(t_2)} = 0.061065, \\
 \gamma_4 &= -\frac{N}{T} \ln \frac{G(t_4)}{G(t_3)} = 0.029094.
 \end{aligned}$$

## Chapter 5

- 5.1. Since  $\tau$  is an  $(\mathcal{I}_t)_{t \geq 0}$ -stopping time and  $\mathcal{I}_t \subset \mathcal{G}_t$  for each  $t \geq 0$ , it follows that  $\tau$  is a  $(\mathcal{G}_t)_{t \geq 0}$ -stopping time.

Now let  $(\mathcal{H}_t)_{t \geq 0}$  be a filtration such that  $\tau$  is an  $(\mathcal{H}_t)_{t \geq 0}$ -stopping time and  $\mathcal{F}_t \subset \mathcal{H}_t$  for each  $t \geq 0$ . Fix any  $t \geq 0$ . Then, for any  $s \leq t$ , we have  $\{\tau \leq s\} \in \mathcal{H}_s \subset \mathcal{H}_t$  and so  $I(s) = \mathbf{1}_{\{\tau \leq s\}}$  is  $\mathcal{H}_t$ -measurable. As a result,  $\mathcal{I}_t \subset \mathcal{H}_t$ . It follows that  $\mathcal{G}_t \subset \mathcal{H}_t$  since  $\mathcal{G}_t = \sigma(\mathcal{F}_t \cup \mathcal{I}_t)$  and  $\mathcal{F}_t \cup \mathcal{I}_t \subset \mathcal{H}_t$ .

This proves that  $(\mathcal{G}_t)_{t \geq 0}$  is the smallest filtration such that  $\tau$  is an  $(\mathcal{G}_t)_{t \geq 0}$ -stopping time and  $\mathcal{F}_t \subset \mathcal{G}_t$  for each  $t \geq 0$ .

- 5.2. Let  $0 \leq s < t$ . Then  $\mathbf{1}_{\{\tau \leq s\}} \leq \mathbf{1}_{\{\tau \leq t\}}$ , which gives the result:

$$\begin{aligned}
 \mathbb{E}(F(t)|\mathcal{F}_s) &= \mathbb{E}(\mathbb{E}(\mathbf{1}_{\{\tau \leq t\}}|\mathcal{F}_t)|\mathcal{F}_s) \\
 &= \mathbb{E}(\mathbf{1}_{\{\tau \leq t\}}|\mathcal{F}_s) \\
 &\geq \mathbb{E}(\mathbf{1}_{\{\tau \leq s\}}|\mathcal{F}_s) \\
 &= F(s).
 \end{aligned}$$

- 5.3. For any  $0 \leq s \leq t$  we have  $\{\tau \leq s\} \subset \{\tau \leq t\}$ , and so  $\mathbf{1}_{\{\tau \leq s\}} \leq \mathbf{1}_{\{\tau \leq t\}}$ . By Lemma 5.15,

$$F(s) = \mathbb{E}(\mathbf{1}_{\{\tau \leq s\}} | \mathcal{F}_t) \leq \mathbb{E}(\mathbf{1}_{\{\tau \leq t\}} | \mathcal{F}_t) = F(t),$$

hence  $F(t)$  is non-decreasing.

- 5.4. The process  $\Gamma$  has increasing paths, so for every  $t \geq s \geq 0$  we have  $\Gamma(t) \geq \Gamma(s)$ , which implies that

$$\mathbb{E}(\Gamma(t) | \mathcal{F}_s) \geq \mathbb{E}(\Gamma(s) | \mathcal{F}_s) = \Gamma(s)$$

since  $\Gamma(s)$  is  $\mathcal{F}_s$ -measurable. It follows that  $\Gamma$  is a supermartingale with respect to the filtration  $(\mathcal{F}_t)_{t \geq 0}$ .

- 5.5. Let

$$X(t) = vt + \sigma W_Q(t),$$

where

$$v = r - \frac{1}{2}\sigma^2.$$

Then

$$\Gamma(t) = \max_{u \in [0, t]} \left( -\ln \frac{S(u)}{S(0)} \right) = -\min_{u \in [0, t]} X(u).$$

It follows from Lemma A.16 that the cumulative distribution function of  $\Gamma(t)$  is

$$\begin{aligned} F_{\Gamma(t)}(x) &= Q(\Gamma(t) \leq x) \\ &= Q(\min_{u \in [0, t]} X(u) \geq -x) \\ &= N\left(\frac{x + vt}{\sigma \sqrt{t}}\right) - e^{-\frac{2vx}{\sigma^2}} N\left(\frac{-x + vt}{\sigma \sqrt{t}}\right) \end{aligned}$$

for any  $x \geq 0$ , and  $F_{\Gamma(t)}(x) = 0$  for  $x < 0$ . Hence the density of  $\Gamma(t)$  is

$$f_{\Gamma(t)}(x) = \frac{1}{\sigma \sqrt{2\pi t}} e^{-\frac{(x+vt)^2}{2\sigma^2 t}} + e^{-\frac{2vx}{\sigma^2}} \frac{1}{\sigma \sqrt{2\pi t}} e^{-\frac{(-x+vt)^2}{2\sigma^2 t}} + \frac{2v}{\sigma^2} e^{-\frac{2vx}{\sigma^2}} N\left(\frac{-x + vt}{\sigma \sqrt{t}}\right)$$

for any  $x \geq 0$ , and  $f_{\Gamma(t)}(x) = 0$  for  $x < 0$ . It follows that for each  $t \geq 0$

$$\begin{aligned}
 Q(\tau \leq t) &= \mathbb{E}(\mathbf{1}_{\{\tau \leq t\}}) = \mathbb{E}(\mathbb{E}(\mathbf{1}_{\{\tau \leq t\}} | \mathcal{F}_t)) = \mathbb{E}(F(t)) = \mathbb{E}(e^{-\Gamma(t)}) \\
 &= \int_{-\infty}^{\infty} e^{-x} f_{\Gamma(t)}(x) dx \\
 &= \frac{1}{\sigma \sqrt{2\pi t}} \int_0^{\infty} e^{-x} e^{-\frac{(x+vt)^2}{2\sigma^2 t}} dx + \frac{1}{\sigma \sqrt{2\pi t}} \int_0^{\infty} e^{-x} e^{-\frac{2vx}{\sigma^2}} e^{-\frac{(-x+vt)^2}{2\sigma^2 t}} dx \\
 &\quad + \frac{2v}{\sigma^2} \int_0^{\infty} e^{-x} e^{-\frac{2vx}{\sigma^2}} N\left(\frac{-x+vt}{\sigma \sqrt{t}}\right) dx \\
 &= e^{vt + \frac{1}{2}\sigma^2 t} N\left(-\frac{vt + \sigma^2 t}{\sigma \sqrt{t}}\right) + e^{vt + \frac{1}{2}\sigma^2 t} N\left(-\frac{vt + \sigma^2 t}{\sigma \sqrt{t}}\right) \\
 &\quad + \frac{2v}{\sigma^2} \frac{\sigma^2}{2v + \sigma^2} N\left(\frac{vt}{\sigma \sqrt{t}}\right) - \frac{2v}{2v + \sigma^2} e^{vt + \frac{1}{2}\sigma^2 t} N\left(-\frac{vt + \sigma^2 t}{\sigma \sqrt{t}}\right) \\
 &= 2e^{vt + \frac{1}{2}\sigma^2 t} \frac{v + \sigma^2}{2v + \sigma^2} N\left(-\frac{vt + \sigma^2 t}{\sigma \sqrt{t}}\right) + \frac{2v}{2v + \sigma^2} N\left(\frac{vt}{\sigma \sqrt{t}}\right) \\
 &= e^{rt} \frac{2r + \sigma^2}{2r} N\left(-\frac{rt + \frac{1}{2}\sigma^2 t}{\sigma \sqrt{t}}\right) + \frac{2r + \sigma^2}{2r} N\left(\frac{rt - \frac{1}{2}\sigma^2 t}{\sigma \sqrt{t}}\right),
 \end{aligned}$$

which gives the probability distribution of  $\tau$  under  $Q$ .

- 5.6. Suppose that  $Y$  is a random variable with the unit exponential distribution. Then for any  $x \in [0, 1]$

$$Q(e^{-Y} \leq x) = Q(Y \geq -\ln x) = 1 - F_Y(-\ln x) = e^{\ln x} = x,$$

so  $e^{-Y}$  is uniformly distributed in  $[0, 1]$ .

Conversely, suppose that  $e^{-Y}$  is uniformly distributed in  $[0, 1]$ . Then for any  $x \in [0, \infty)$

$$Q(Y \leq x) = Q(e^{-Y} \geq e^{-x}) = 1 - e^{-x},$$

hence  $Y$  has the unit exponential distribution.

- 5.7. Let

$$\tau_1 = \inf\{t \geq 0 : e^{-\Gamma(t)} \leq X\},$$

where  $X$  is a random variable uniformly distributed in  $[0, 1]$  and independent of  $\mathcal{F}_{\infty}$ , and let

$$\tau_2 = \inf\{t \geq 0 : \Gamma(t) \geq Y\}$$

where  $Y$  is a random variable with the unit exponential distribution and independent of  $\mathcal{F}_{\infty}$ . By Exercise 5.6,  $e^{-Y}$  is uniformly distributed

in  $[0, 1]$ . It follows that

$$\tau_2 = \inf\{t \geq 0 : \Gamma(t) \geq Y\} = \inf\{t \geq 0 : e^{-\Gamma(t)} \leq e^{-Y}\}$$

has the same distribution as  $\tau_1$ .

- 5.8. Since  $\emptyset \cap \{\tau \leq t\} = \emptyset$  and  $\Omega \cap \{\tau \leq t\} = \{\tau \leq t\}$  belong to  $\mathcal{G}_t$ , both  $\emptyset$  and  $\Omega$  belong to  $\mathcal{A}$ . Suppose that  $A, B \in \mathcal{A}$ . Since  $A \cap \{\tau \leq t\}$  and  $B \cap \{\tau \leq t\}$  belong to  $\mathcal{G}_t$ ,

$$(A \setminus B) \cap \{\tau \leq t\} = (A \cap \{\tau \leq t\}) \setminus (B \cap \{\tau \leq t\})$$

also belongs to  $\mathcal{G}_t$ , so  $A \setminus B \in \mathcal{A}$ . Next, if  $A_n \in \mathcal{A}$  and so  $A_n \cap \{\tau \leq t\} \in \mathcal{G}_t$  for  $n = 1, 2, \dots$ , then

$$\left( \bigcup_{n=1}^{\infty} A_n \right) \cap \{\tau \leq t\} = \bigcup_{n=1}^{\infty} (A_n \cap \{\tau \leq t\})$$

belongs to  $\mathcal{G}_t$ , so  $\bigcup_{n=1}^{\infty} A_n \in \mathcal{A}$ . This shows that  $\mathcal{A}$  is a  $\sigma$ -field.

To see that  $\sigma(\tau) \subset \mathcal{A}$  we only need to verify that  $\{\tau \leq s\} \in \mathcal{A}$  for each  $s \geq 0$  since events of the form  $\{\tau \leq s\}$  for  $s \geq 0$  generate the  $\sigma$ -field  $\sigma(\tau)$ . Indeed, for any  $s \geq 0$  the event  $\{\tau \leq s\} \cap \{\tau \leq t\} = \{\tau \leq s \wedge t\}$  belongs to  $\mathcal{I}_{s \wedge t} \subset \mathcal{I}_t \subset \mathcal{G}_t$ , so  $\{\tau \leq s\} \in \mathcal{A}$ .

Finally, we take any  $A \in \mathcal{F}_t$ . Since  $\{\tau \leq t\} \in \mathcal{I}_t$ , we find that  $A \cap \{\tau \leq t\} \in \mathcal{G}_t$ , hence  $A \in \mathcal{A}$ . We have shown that  $\mathcal{F}_t \subset \mathcal{A}$ .

- 5.9. Take any  $t > 0$ . By left-continuity, for any  $\varepsilon > 0$  there is a  $\delta > 0$  such that  $|h(u) - h(t)| < \varepsilon$  when  $u \in (t - \delta, t]$ . Then for any  $n > \max(\frac{s}{\delta}, \frac{t}{s})$  we have  $|h_n(t) - h(t)| < \varepsilon$ . This proves that  $h(t) = \lim_{n \rightarrow \infty} h_n(t)$ .
- 5.10. Since  $\tau > 0$ , we have  $\mathbf{1}_{\{\tau \leq 0\}} = 0$  and  $\mathbf{1}_{\{0 < \tau\}} = 1$ , so we just need to show that

$$\mathbb{E}(h(\tau)) = \mathbb{E} \left( \int_0^{\infty} h(u) f(u) du \right).$$

Since  $h$  has left-continuous paths, we have, almost surely,

$$h(t) = \lim_{n \rightarrow \infty} h_n(t) \quad \text{for each } t > 0,$$

where

$$h_n(t) = \sum_{i=1}^{n^2} h(s_n^{i-1}) \mathbf{1}_{(s_n^{i-1}, s_n^i]}(t)$$

with  $s_n^i = \frac{i}{n}$  for each  $n, i = 1, 2, \dots$  (see Exercise 5.9 with  $s = 1$ ). It follows that, almost surely,

$$h(\tau) = \lim_{n \rightarrow \infty} h_n(\tau).$$

First we verify the desired equality for  $h_n(t)$ . Indeed,

$$\begin{aligned}
 \mathbb{E}(h_n(\tau)) &= \sum_{i=1}^{n^2} \mathbb{E}(h(s_n^{i-1}) \mathbf{1}_{(s_n^{i-1}, s_n^i]}(\tau)) \\
 &= \sum_{i=1}^{n^2} \mathbb{E}(\mathbb{E}(h(s_n^{i-1}) \mathbf{1}_{(s_n^{i-1}, s_n^i]}(\tau) | \mathcal{F}_{s_n^i})) \\
 &= \sum_{i=1}^{n^2} \mathbb{E}(h(s_n^{i-1}) \mathbb{E}(\mathbf{1}_{(s_n^{i-1}, s_n^i]}(\tau) | \mathcal{F}_{s_n^i})) \\
 &= \sum_{i=1}^{n^2} \mathbb{E}(h(s_n^{i-1}) (\mathbb{E}(\mathbf{1}_{\{\tau \leq s_n^i\}} | \mathcal{F}_{s_n^i}) - \mathbb{E}(\mathbf{1}_{\{\tau \leq s_n^{i-1}\}} | \mathcal{F}_{s_n^i}))) \\
 &= \sum_{i=1}^{n^2} \mathbb{E}(h(s_n^{i-1}) (F(s_n^i) - F(s_n^{i-1}))) \\
 &= \mathbb{E} \left( \int_0^\infty h_n(u) f(u) du \right),
 \end{aligned}$$

where we use Lemma 5.15 in the fifth equality. Hence, by dominated convergence, for a bounded  $h$  we find that

$$\begin{aligned}
 \mathbb{E}(h(\tau)) &= \lim_{n \rightarrow \infty} \mathbb{E}(h_n(\tau)) \\
 &= \lim_{n \rightarrow \infty} \mathbb{E} \left( \int_0^\infty h_n(u) f(u) du \right) \\
 &= \mathbb{E} \left( \int_0^\infty h(u) f(u) du \right).
 \end{aligned}$$

Then, for a non-negative  $h$  we obtain the formula by approximating  $h$  by a monotone sequence of bounded processes. Finally, for a general  $h$  we use the positive and negative parts  $h^+$  and  $h^-$  together with the assumption that  $h(\tau)$  is integrable, just like in the proof of Theorem 5.34 in the case when  $s > 0$ .

5.11. Note that

$$L(t) = (1 - \mathbf{1}_{\{\tau \leq t\}})e^{\Gamma(t)} = \mathbf{1}_{\{t < \tau\}}e^{\Gamma(t)}.$$

By Theorem 5.35 with  $Y = e^{\Gamma(t)}$ ,

$$\begin{aligned}\mathbb{E}(L(t)|\mathcal{G}_s) &= \mathbb{E}(e^{\Gamma(t)}\mathbf{1}_{\{t < \tau\}}|\mathcal{G}_s) \\ &= \mathbf{1}_{\{s < \tau\}}\mathbb{E}(e^{\Gamma(t)}e^{-(\Gamma(t)-\Gamma(s))}|\mathcal{F}_s) \\ &= \mathbf{1}_{\{s < \tau\}}e^{\Gamma(s)} \\ &= L(s).\end{aligned}$$

5.12. This is again a simple consequence of Theorem 5.35. For  $Y = X(t)e^{\Gamma(t)}$ , it gives

$$\begin{aligned}\mathbb{E}(X(t)L(t)|\mathcal{G}_s) &= \mathbb{E}(X(t)e^{\Gamma(t)}\mathbf{1}_{\{t < \tau\}}|\mathcal{G}_s) \\ &= \mathbf{1}_{\{s < \tau\}}e^{\Gamma(s)}\mathbb{E}(X(t)|\mathcal{F}_s) \\ &= L(s)X(s).\end{aligned}$$

## Chapter 6

6.1. It is shown in Section 6.1 that

$$\begin{aligned}\hat{D}(t, T) &= D(0, T) + \int_0^t (r + \gamma(u))\hat{D}(u, T)du \\ &\quad + \int_0^t e^{-r(T-u)}e^{\Gamma(u)}X_{G(T)}(u)dW_Q(u).\end{aligned}$$

By Itô's product rule (see [SCF]), it follows that

$$\begin{aligned}e^{-rt}\hat{D}(t, T) &= D(0, T) + \int_0^t \gamma(u)e^{-ru}\hat{D}(u, T)du \\ &\quad + \int_0^t e^{-rT}e^{\Gamma(u)}X_{G(T)}(u)dW_Q(u).\end{aligned}$$

Hence

$$\begin{aligned}e^{-r(t \wedge \tau)}\hat{D}(t \wedge \tau, T) &= D(0, T) + \int_0^{t \wedge \tau} \gamma(u)e^{-ru}\hat{D}(u, T)du \\ &\quad + \int_0^{t \wedge \tau} e^{-rT}e^{\Gamma(u)}X_{G(T)}(u)dW_Q(u) \\ &= D(0, T) + \int_0^t \gamma(u)\tilde{D}(u, T)du \\ &\quad + \int_0^{t \wedge \tau} e^{-rT}e^{\Gamma(u)}X_{G(T)}(u)dW_Q(u).\end{aligned}$$



On the left-hand side we have

$$\begin{aligned} e^{-r(t \wedge \tau)} \hat{D}(t \wedge \tau, T) &= \mathbf{1}_{\{\tau \leq t\}} e^{-r\tau} \hat{D}(\tau, T) + \mathbf{1}_{\{t < \tau\}} e^{-rt} \hat{D}(t, T) \\ &= \mathbf{1}_{\{\tau \leq t\}} e^{-r\tau} \hat{D}(\tau, T) + \tilde{D}(t, T). \end{aligned}$$

By formula (5.11),

$$\begin{aligned} \int_0^t \tilde{D}(u-, T) dM(u) &= \mathbf{1}_{\{\tau \leq t\}} \tilde{D}(\tau-, T) - \int_0^{t \wedge \tau} \tilde{D}(u-, T) \gamma(u) du \\ &= \mathbf{1}_{\{\tau \leq t\}} e^{-r\tau} \hat{D}(\tau, T) - \int_0^t \tilde{D}(u, T) \gamma(u) du. \end{aligned}$$

Combining the last three formulae gives

$$\begin{aligned} \tilde{D}(t, T) &= D(0, T) - \int_0^t \tilde{D}(u-, T) dM(u) \\ &\quad + \int_0^{t \wedge \tau} e^{-rT} e^{\Gamma(u)} X_{G(T)}(u) dW_Q(u). \end{aligned}$$

6.2. As shown in the proof of Proposition 6.9,

$$V_\varphi(\tau-) = V_\varphi(\tau) + \varphi_D(\tau) D(\tau-, T).$$

Taking the left limit as  $t \nearrow \tau$  in the expression for  $V_\varphi(t)$  in the pre-default region  $\{t < \tau\}$  in Definition 6.7, we get

$$\begin{aligned} V_\varphi(\tau-) &= V_\varphi(0) + \int_0^\tau \varphi_B(u) r B(u, T) du \\ &\quad + \int_0^\tau \varphi_S(u) r S(u) du + \int_0^\tau \varphi_S(u) \sigma S(u) dW_Q(u) \\ &\quad + \int_0^\tau \varphi_D(u) r D(u, T) du + \int_0^\tau \varphi_D(u) \gamma(u) D(u, T) du \\ &\quad + \int_0^\tau \varphi_D(u) e^{-r(T-u)} e^{\Gamma(u)} X_{G(T)}(u) dW_Q(u) \\ &= V_\varphi(0) + \int_0^\tau r V_\varphi(u) du + \int_0^\tau \varphi_S(u) \sigma S(u) dW_Q(u) \\ &\quad + \int_0^\tau \varphi_D(u) \gamma(u) D(u, T) du \\ &\quad + \int_0^\tau \varphi_D(u) e^{-r(T-u)} e^{\Gamma(u)} X_{G(T)}(u) dW_Q(u). \end{aligned}$$

It follows that

$$\begin{aligned}
V_\varphi(\tau) &= V_\varphi(\tau_-) - \varphi_D(\tau)D(\tau_-, T) \\
&= V_\varphi(0) + \int_0^\tau rV_\varphi(u)du + \int_0^\tau \varphi_S(u)\sigma S(u)dW_Q(u) \\
&\quad + \int_0^\tau \varphi_D(u)\gamma(u)D(u, T)du - \varphi_D(\tau)D(\tau_-, T) \\
&\quad + \int_0^\tau \varphi_D(u)e^{-r(T-u)}e^{\Gamma(u)}X_{G(T)}(u)dW_Q(u).
\end{aligned}$$

By inserting this into the expression for  $V_\varphi(t)$  in the post-default region  $\{\tau \leq t\}$  in Definition 6.7, we get

$$\begin{aligned}
V_\varphi(t) &= V_\varphi(\tau) + \int_\tau^t rV_\varphi(u)du + \int_\tau^t \varphi_S(u)\sigma S(u)dW_Q(u) \\
&= V_\varphi(0) + \int_0^t rV_\varphi(u)du + \int_0^t \varphi_S(u)\sigma S(u)dW_Q(u) \\
&\quad + \int_0^\tau \varphi_D(u)\gamma(u)D(u, T)du - \varphi_D(\tau)D(\tau_-, T) \\
&\quad + \int_0^\tau \varphi_D(u)e^{-r(T-u)}e^{\Gamma(u)}X_{G(T)}(u)dW_Q(u).
\end{aligned}$$

Combining this with the expression for  $V_\varphi(t)$  in the pre-default region  $\{t < \tau\}$  in Definition 6.7, we finally get

$$\begin{aligned}
V_\varphi(t) &= V_\varphi(0) + \int_0^t rV_\varphi(u)du + \int_0^t \varphi_S(u)\sigma S(u)dW_Q(u) \\
&\quad - \int_0^t \varphi_D(u)D(u-, T)dM(u) \\
&\quad + \int_0^{t \wedge \tau} \varphi_D(u)e^{-r(T-u)}e^{\Gamma(u)}X_{G(T)}(u)dW_Q(u).
\end{aligned}$$

for all  $t \in [0, T]$ .

- 6.3. Suppose that  $\varphi$  is a self-financing strategy such that  $V_\varphi$  is non-negative, hence  $\tilde{V}_\varphi$  is non-negative. In the expression (6.4) for the discounted value  $\tilde{V}_\varphi(t) = e^{-rt}V_\varphi(t)$  of the strategy in Proposition 6.9 the integrals with respect to  $W_Q$  are local martingales. By Remark 5.41, the integral with respect to  $M$  in (6.4) is also a local martingale. It follows that  $\tilde{V}_\varphi(t)$  is a local martingale. As a non-negative local martingale,  $\tilde{V}_\varphi$  must be a supermartingale, hence

$$0 \leq \mathbb{E}(V_\varphi(T)) \leq V_\varphi(0).$$

If  $\varphi$  were an arbitrage strategy, we would have  $V_\varphi(0) = 0$  and  $\mathbb{E}(V_\varphi(T)) > 0$ , so

$$0 < \mathbb{E}(V_\varphi(T)) \leq V_\varphi(0) = 0,$$

a contradiction.

6.4. We need to show that

$$(r + \gamma(t))e^{\Gamma(t)}V_\beta(t) = re^{\Gamma(t)}V_\beta(t) + \varphi_D(t)\gamma(t)D(t, T),$$

that is

$$e^{\Gamma(t)}V_\beta(t) = \varphi_D(t)D(t, T),$$

in the pre-default region  $\{t < \tau\}$ . The last equality holds because

$$D(t, T) = e^{-r(T-t)}e^{\Gamma(t)}\mathbb{E}(e^{-\Gamma(T)}|\mathcal{F}_t) = e^{\Gamma(t)}V_\alpha(t)$$

in  $\{t < \tau\}$ , and

$$\varphi_D(u) = \frac{V_\beta(u)}{V_\alpha(u)}.$$

6.5. By Proposition A.15, the joint density of the logarithmic return

$$R(T) = \ln \frac{S(T)}{S(0)} = rt - \frac{1}{2}\sigma^2 T + \sigma W_Q(t)$$

and its minimum  $\min_{u \in [0, T]} R(u)$  is

$$f(x, y) = \frac{1}{\sigma \sqrt{2\pi T}} \frac{2(x - 2y)}{T\sigma^2} e^{\frac{2y(r - \frac{1}{2}\sigma^2)}{\sigma^2}} e^{-\frac{(2y - x + rT - \frac{1}{2}\sigma^2 T)^2}{2\sigma^2 T}}.$$

when  $y \leq 0$  and  $y \leq x$ , and  $f(x, y) = 0$  otherwise. According to Example 6.17, the vulnerable call price can be computed as

$$\begin{aligned} H(0) &= e^{-rT} \mathbb{E}((S(T) - K)^+ e^{-\Gamma(T)}) \\ &= e^{-rT} \mathbb{E}((S(0)e^{R(T)} - K)^+ e^{\min_{u \in [0, T]} R(u)}) \\ &= e^{-rT} \int_{\ln \frac{K}{S(0)}}^{\infty} \left( \int_{-\infty}^{0 \wedge x} (S(0)e^x - K) e^y f(x, y) dy \right) dx \\ &= e^{-rT} \int_{\ln \frac{K}{S(0)}}^{\infty} (S(0)e^x - K) \left( \int_{-\infty}^{0 \wedge x} e^y f(x, y) dy \right) dx. \end{aligned}$$

We shall compute  $H(0)$  in the case when  $K \geq S(0)$ . In this case the upper limit in the inner integral is simply 0, and this

integral can be computed as follows:

$$\begin{aligned}
& \int_{-\infty}^0 e^y f(x, y) dy \\
&= \frac{1}{\sigma \sqrt{2\pi T}} \int_{-\infty}^0 e^y \frac{2(x-2y)}{\sigma^2 T} e^{-\frac{2y(r-\frac{1}{2}\sigma^2)}{\sigma^2}} e^{-\frac{(2y-x+rT-\frac{1}{2}\sigma^2 T)^2}{2\sigma^2 T}} dy \\
&= \frac{1}{\sigma \sqrt{2\pi T}} e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} e^{\frac{rx}{\sigma^2}} \int_{-\infty}^0 \frac{2(x-2y)}{\sigma^2 T} e^{-\frac{(2y-x-\frac{1}{2}\sigma^2 T)^2}{2\sigma^2 T}} dy \\
&= \frac{1}{\sigma \sqrt{2\pi T}} e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} e^{\frac{rx}{\sigma^2}} \int_{-\infty}^0 \left( \frac{d}{dy} \left( e^{-\frac{(2y-x-\frac{1}{2}\sigma^2 T)^2}{2\sigma^2 T}} \right) - e^{-\frac{(2y-x-\frac{1}{2}\sigma^2 T)^2}{2\sigma^2 T}} \right) dy \\
&= \frac{1}{\sigma \sqrt{2\pi T}} e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} e^{\frac{rx}{\sigma^2}} e^{-\frac{(x-\frac{1}{2}\sigma^2 T)^2}{2\sigma^2 T}} - e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} e^{\frac{rx}{\sigma^2}} N\left(\frac{-x-\frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}}\right) \\
&= \frac{1}{\sigma \sqrt{2\pi T}} e^{-\frac{(x-(r-\frac{1}{2}\sigma^2)T)^2}{2\sigma^2 T}} - e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} e^{\frac{rx}{\sigma^2}} N\left(\frac{-x-\frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}}\right).
\end{aligned}$$

Hence, we get

$$\begin{aligned}
& \int_{\ln \frac{K}{S(0)}}^{\infty} \left( \int_{-\infty}^0 e^y f(x, y) dy \right) dx \\
&= \int_{\ln \frac{K}{S(0)}}^{\infty} \frac{1}{\sigma \sqrt{2\pi T}} e^{-\frac{(x-(r-\frac{1}{2}\sigma^2)T)^2}{2\sigma^2 T}} dx - e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \int_{\ln \frac{K}{S(0)}}^{\infty} e^{\frac{rx}{\sigma^2}} N\left(\frac{-x-\frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}}\right) dx \\
&= N\left(\frac{\ln \frac{S(0)}{K} + (r-\frac{1}{2}\sigma^2)T}{\sigma \sqrt{T}}\right) - e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r} \int_{\ln \frac{K}{S(0)}}^{\infty} \frac{d}{dx} \left( e^{\frac{rx}{\sigma^2}} \right) N\left(\frac{-x-\frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}}\right) dx \\
&= N\left(\frac{\ln \frac{S(0)}{K} + (r-\frac{1}{2}\sigma^2)T}{\sigma \sqrt{T}}\right) + e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r} e^{\frac{r \ln \frac{K}{S(0)}}{\sigma^2}} N\left(\frac{-\ln \frac{K}{S(0)} - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}}\right) \\
&\quad + e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r} \int_{\ln \frac{K}{S(0)}}^{\infty} e^{\frac{rx}{\sigma^2}} \frac{d}{dx} N\left(\frac{-x-\frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}}\right) dx \\
&= N\left(\frac{\ln \frac{S(0)}{K} + (r-\frac{1}{2}\sigma^2)T}{\sigma \sqrt{T}}\right) + e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r} \left( \frac{K}{S(0)} \right)^{\frac{r}{\sigma^2}} N\left(\frac{\ln \frac{S(0)}{K} - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}}\right) \\
&\quad - e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r} \int_{\ln \frac{K}{S(0)}}^{\infty} e^{\frac{rx}{\sigma^2}} \frac{1}{\sigma \sqrt{2\pi T}} e^{-\frac{(x-\frac{1}{2}\sigma^2 T)^2}{2\sigma^2 T}} dx
\end{aligned}$$

and so

$$\begin{aligned}
& \int_{\ln \frac{K}{S(0)}}^{\infty} \left( \int_{-\infty}^0 e^y f(x, y) dy \right) dx \\
&= N \left( \frac{\ln \frac{S(0)}{K} + \left(r - \frac{1}{2}\sigma^2\right)T}{\sigma \sqrt{T}} \right) + e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r} \left( \frac{K}{S(0)} \right)^{\frac{r}{\sigma^2}} N \left( \frac{\ln \frac{S(0)}{K} - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} \right) \\
&\quad - \frac{\sigma^2}{r} \int_{\ln \frac{K}{S(0)}}^{\infty} \frac{1}{\sigma \sqrt{2\pi T}} e^{-\frac{(x-rT+\frac{1}{2}\sigma^2 T)^2}{2\sigma^2 T}} dx \\
&= N \left( \frac{\ln \frac{S(0)}{K} + \left(r - \frac{1}{2}\sigma^2\right)T}{\sigma \sqrt{T}} \right) + e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r} \left( \frac{K}{S(0)} \right)^{\frac{r}{\sigma^2}} N \left( \frac{\ln \frac{S(0)}{K} - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} \right) \\
&\quad - \frac{\sigma^2}{r} N \left( \frac{\ln \frac{S(0)}{K} + \left(r - \frac{1}{2}\sigma^2\right)T}{\sigma \sqrt{T}} \right) \\
&= \frac{r - \sigma^2}{r} N \left( \frac{\ln \frac{S(0)}{K} + \left(r - \frac{1}{2}\sigma^2\right)T}{\sigma \sqrt{T}} \right) + e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r} \left( \frac{K}{S(0)} \right)^{\frac{r}{\sigma^2}} N \left( \frac{\ln \frac{S(0)}{K} - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} \right).
\end{aligned}$$

We also get

$$\begin{aligned}
& \int_{\ln \frac{K}{S(0)}}^{\infty} e^x \left( \int_{-\infty}^0 e^y f(x, y) dy \right) dx \\
&= \int_{\ln \frac{K}{S(0)}}^{\infty} e^x \frac{1}{\sigma \sqrt{2\pi T}} e^{-\frac{(x-(r-\frac{1}{2}\sigma^2)T)^2}{2\sigma^2 T}} dx - e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \int_{\ln \frac{K}{S(0)}}^{\infty} e^x e^{\frac{rx}{\sigma^2}} N \left( \frac{-x - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} \right) dx \\
&= e^{rT} \int_{\ln \frac{K}{S(0)}}^{\infty} \frac{1}{\sigma \sqrt{2\pi T}} e^{-\frac{(x-(r+\frac{1}{2}\sigma^2)T)^2}{2\sigma^2 T}} dx - e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r + \sigma^2} \int_{\ln \frac{K}{S(0)}}^{\infty} \frac{d}{dx} \left( e^{\frac{(r+\sigma^2)x}{\sigma^2}} \right) N \left( \frac{-x - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} \right) dx \\
&= e^{rT} N \left( \frac{\ln \frac{S(0)}{K} + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma \sqrt{T}} \right) + e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r + \sigma^2} e^{\frac{(r+\sigma^2) \ln \frac{K}{S(0)}}{\sigma^2}} N \left( \frac{-\ln \frac{K}{S(0)} - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} \right) \\
&\quad + e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r + \sigma^2} \int_{\ln \frac{K}{S(0)}}^{\infty} e^{\frac{(r+\sigma^2)x}{\sigma^2}} \frac{d}{dx} N \left( \frac{-x - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} \right) dx \\
&= e^{rT} N \left( \frac{\ln \frac{S(0)}{K} + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma \sqrt{T}} \right) + e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r + \sigma^2} \left( \frac{K}{S(0)} \right)^{\frac{r+\sigma^2}{\sigma^2}} N \left( \frac{\ln \frac{S(0)}{K} - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} \right) \\
&\quad - e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r + \sigma^2} \int_{\ln \frac{K}{S(0)}}^{\infty} e^{\frac{(r+\sigma^2)x}{\sigma^2}} \frac{1}{\sigma \sqrt{2\pi T}} e^{-\frac{(x-\frac{1}{2}\sigma^2 T)^2}{2\sigma^2 T}} dx
\end{aligned}$$

and so

$$\begin{aligned}
& \int_{\ln \frac{K}{S(0)}}^{\infty} e^x \left( \int_{-\infty}^0 e^y f(x, y) dy \right) dx \\
&= e^{rT} N \left( \frac{\ln \frac{S(0)}{K} + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma \sqrt{T}} \right) + e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r + \sigma^2} \left( \frac{K}{S(0)} \right)^{\frac{r+\sigma^2}{\sigma^2}} N \left( \frac{\ln \frac{S(0)}{K} - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} \right) \\
&\quad - e^{rT} \frac{\sigma^2}{r + \sigma^2} \int_{\ln \frac{K}{S(0)}}^{\infty} \frac{1}{\sigma \sqrt{2\pi T}} e^{-\frac{(x-rT-\frac{1}{2}\sigma^2 T)^2}{2\sigma^2 T}} dx \\
&= e^{rT} N \left( \frac{\ln \frac{S(0)}{K} + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma \sqrt{T}} \right) + e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r + \sigma^2} \left( \frac{K}{S(0)} \right)^{\frac{r+\sigma^2}{\sigma^2}} N \left( \frac{\ln \frac{S(0)}{K} - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} \right) \\
&\quad - e^{rT} \frac{\sigma^2}{r + \sigma^2} N \left( \frac{\ln \frac{S(0)}{K} + rT + \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} \right) \\
&= e^{rT} \frac{r}{r + \sigma^2} N \left( \frac{\ln \frac{S(0)}{K} + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma \sqrt{T}} \right) + e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r + \sigma^2} \left( \frac{K}{S(0)} \right)^{\frac{r+\sigma^2}{\sigma^2}} N \left( \frac{\ln \frac{S(0)}{K} - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} \right).
\end{aligned}$$

It follows that in the case when  $K \geq S(0)$

$$\begin{aligned}
H(0) &= e^{-rT} \int_{\ln \frac{K}{S(0)}}^{\infty} (S(0)e^x - K) \left( \int_{-\infty}^0 e^y f(x, y) dy \right) dx \\
&= e^{-rT} S(0) \left[ e^{rT} \frac{r}{r + \sigma^2} N \left( \frac{\ln \frac{S(0)}{K} + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma \sqrt{T}} \right) + e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r + \sigma^2} \left( \frac{K}{S(0)} \right)^{\frac{r+\sigma^2}{\sigma^2}} N \left( \frac{\ln \frac{S(0)}{K} - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} \right) \right] \\
&\quad - e^{-rT} K \left[ \frac{r - \sigma^2}{r} N \left( \frac{\ln \frac{S(0)}{K} + \left(r - \frac{1}{2}\sigma^2\right)T}{\sigma \sqrt{T}} \right) + e^{-\frac{r(r-\sigma^2)T}{2\sigma^2}} \frac{\sigma^2}{r} \left( \frac{K}{S(0)} \right)^{\frac{r}{\sigma^2}} N \left( \frac{\ln \frac{S(0)}{K} - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} \right) \right] \\
&= S(0) \frac{r}{r + \sigma^2} N \left( \frac{\ln \frac{S(0)}{K} + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma \sqrt{T}} \right) - e^{-rT} K \frac{r - \sigma^2}{r} N \left( \frac{\ln \frac{S(0)}{K} + \left(r - \frac{1}{2}\sigma^2\right)T}{\sigma \sqrt{T}} \right) \\
&\quad - K \frac{\sigma^4}{r(r + \sigma^2)} e^{-\frac{r(r+\sigma^2)T}{2\sigma^2}} \left( \frac{K}{S(0)} \right)^{\frac{r}{\sigma^2}} N \left( \frac{\ln \frac{S(0)}{K} - \frac{1}{2}\sigma^2 T}{\sigma \sqrt{T}} \right).
\end{aligned}$$

6.6. Since the discounted defaultable bond price process is a  $(\mathcal{G}_t)_{t \geq 0}$ -martingale,

$$H(t) = e^{-rt} D(t, T) = \mathbb{E}(e^{-rT} D(T, T) | \mathcal{G}_t) = \mathbb{E}(e^{-rT} \mathbf{1}_{\{T < \tau\}} | \mathcal{G}_t)$$

for each  $t \in [0, T]$ . Hence, putting

$$h(t) = e^{-rT} \mathbf{1}_{\{T < \tau\}},$$

we have

$$H(t) = e^{-rt}D(t, T) = \mathbb{E}(h(\tau)|\mathcal{G}_t).$$

Next,

$$\begin{aligned} J(t) &= e^{\Gamma(t)}\mathbb{E}(\mathbf{1}_{\{t < \tau\}}h(\tau)|\mathcal{F}_t) \\ &= e^{\Gamma(t)}\mathbb{E}(\mathbf{1}_{\{t < \tau\}}e^{-rT}\mathbf{1}_{\{T < \tau\}}|\mathcal{F}_t) \\ &= e^{-rT}e^{\Gamma(t)}\mathbb{E}(\mathbf{1}_{\{T < \tau\}}|\mathcal{F}_t) \\ &= e^{-rT}e^{\Gamma(t)}\mathbb{E}(\mathbb{E}(\mathbf{1}_{\{T < \tau\}}|\mathcal{F}_T)|\mathcal{F}_t) \\ &= e^{-rT}e^{\Gamma(t)}\mathbb{E}(e^{-\Gamma(T)}|\mathcal{F}_t) \\ &= e^{-rT}e^{\Gamma(t)}\mathbb{E}(G(T)|\mathcal{F}_t). \end{aligned}$$

This can be expressed in terms of the value  $V_\alpha(t) = \alpha_B(t)B(t, T) + \alpha_S(t)S(t)$  of the admissible self-financing strategy  $(\alpha_B, \alpha_S)$  replicating a derivative security with payoff  $G(T)$  and exercise time  $T$  in the Black–Scholes model consisting of the assets  $B, S$ . Namely,

$$e^{-rt}\mathbb{E}(G(T)|\mathcal{F}_t) = V_\alpha(t),$$

so

$$J(t) = e^{-r(T-t)}e^{\Gamma(t)}V_\alpha(t).$$

6.7. We take

$$h(t) = X\mathbf{1}_{\{T < t\}},$$

so that

$$H(t) = \mathbb{E}(X\mathbf{1}_{\{T < \tau\}}|\mathcal{G}_t) = \mathbb{E}(h(\tau)|\mathcal{G}_t).$$

Moreover,

$$\begin{aligned} J(t) &= e^{\Gamma(t)}\mathbb{E}(\mathbf{1}_{\{t < \tau\}}h(\tau)|\mathcal{F}_t) \\ &= e^{\Gamma(t)}\mathbb{E}(\mathbf{1}_{\{t < \tau\}}X\mathbf{1}_{\{T < \tau\}}|\mathcal{F}_t) \\ &= e^{\Gamma(t)}\mathbb{E}(X\mathbf{1}_{\{T < \tau\}}|\mathcal{F}_t) \\ &= e^{\Gamma(t)}\mathbb{E}(X\mathbb{E}(\mathbf{1}_{\{T < \tau\}}|\mathcal{F}_T)|\mathcal{F}_t) \\ &= e^{\Gamma(t)}\mathbb{E}(Xe^{-\Gamma(T)}|\mathcal{F}_t) \\ &= e^{\Gamma(t)}\mathbb{E}(XG(T)|\mathcal{F}_t). \end{aligned}$$

This can be expressed in terms of the value  $V_\beta(t) = \beta_B(t)B(t, T) + \beta_S(t)S(t)$  of the admissible self-financing strategy  $(\beta_B, \beta_S)$  replicating a derivative security with payoff  $XG(T)$  and exercise time  $T$  in

the Black–Scholes model consisting of the assets  $B, S$ . Namely,

$$e^{-r(T-t)}\mathbb{E}(XG(T)|\mathcal{F}_t) = V_\beta(t),$$

so

$$J(t) = e^{r(T-t)}e^{\Gamma(t)}V_\beta(t).$$

- 6.8. Let  $(\alpha_B, \alpha_S)$  and  $(\beta_B, \beta_S)$  be the admissible self-financing strategies that replicate the derivative securities with exercise time  $T$  and payoff  $G(T)$  and, respectively,  $XG(T)$  in the Black–Scholes model consisting of the assets  $B, S$ . From Exercise 6.7, for any  $t \in [0, T]$  we have

$$\begin{aligned} h(t) &= X\mathbf{1}_{\{T < t\}} = 0, \\ J(t) &= e^{r(T-t)}e^{\Gamma(t)}V_\beta(t). \end{aligned}$$

By Theorem 6.20, it follows that

$$\begin{aligned} \varphi_D(t) &= \frac{e^{-r(T-t)}(J(t) - h(t))}{e^{\Gamma(t)}V_\alpha(t)} \\ &= \frac{V_\beta(t)}{V_\alpha(t)}. \end{aligned}$$

Further,

$$\begin{aligned} \varphi_S(t) &= \mathbf{1}_{\{t \leq \tau\}} \left( e^{\Gamma(t)}\beta_S(t) - \frac{e^{-r(T-t)}(J(t) - h(t))}{V_\alpha(t)}\alpha_S(t) \right) \\ &= \mathbf{1}_{\{t \leq \tau\}} e^{\Gamma(t)} \left( \beta_S(t) - \frac{V_\beta(t)}{V_\alpha(t)}\alpha_S(t) \right) \\ &= \mathbf{1}_{\{t \leq \tau\}} e^{\Gamma(t)} (\beta_S(t) - \varphi_D(t)\alpha_S(t)). \end{aligned}$$

Finally,

$$\begin{aligned} \varphi_B(t) &= h(t \wedge \tau) - e^{r(T-t)}\varphi_S(t)S(t) \\ &= -e^{r(T-t)}\varphi_S(t)S(t). \end{aligned}$$

These are the same formulae as (6.7), (6.8) and (6.11) in Section 6.3.

- 6.11. Since

$$D_\eta(0, T) = D(0, T) + V_\varphi(0),$$

where  $(\varphi_B, \varphi_S, \varphi_D)$  is the strategy in Theorem 6.21, we just need to compute  $V_\varphi(0)$ . By Corollary 6.22,

$$V_\varphi(0) = V_\beta(0),$$



where  $(\beta_B, \beta_S)$  is the strategy replicating the payoff  $\mathbb{E}(h(\tau)|\mathcal{F}_T)$  with

$$h(t) = \mathbf{1}_{\{t \leq T\}} e^{r(T-t)} \eta(t).$$

It follows that

$$\begin{aligned} V_\varphi(0) &= V_\beta(0) = e^{-rT} \mathbb{E}(h(\tau)) \\ &= e^{-rT} \mathbb{E} \left( \int_0^\infty h(u) f(u) du \right) = \mathbb{E} \left( \int_0^T e^{-ru} \eta(u) f(u) du \right). \end{aligned}$$

- 6.9. The payoff of a zero-recovery defaultable bond with maturity  $S$ , where  $0 < S < T$ , is  $\mathbf{1}_{\{S < \tau\}}$ , which will grow to become  $e^{r(T-S)} \mathbf{1}_{\{S < \tau\}}$  at time  $T$  if invested in the non-defaultable bond at time  $S$ . Hence we put

$$h(t) = e^{r(T-S)} \mathbf{1}_{\{S < t\}}.$$

The corresponding processes  $m(t)$  and  $J(t)$  are

$$\begin{aligned} m(t) &= \mathbb{E}(h(\tau)|\mathcal{F}_t) \\ &= e^{r(T-S)} \mathbb{E}(\mathbf{1}_{\{S < \tau\}}|\mathcal{F}_t) \\ &= e^{r(T-S)} e^{-\Gamma(S)} \mathbf{1}_{\{S < t\}} + e^{r(T-S)} \mathbb{E}(e^{-\Gamma(S)}|\mathcal{F}_t) \mathbf{1}_{\{t \leq S\}} \end{aligned}$$

and

$$\begin{aligned} J(t) &= e^{\Gamma(t)} \mathbb{E}(\mathbf{1}_{\{t < \tau\}} h(\tau)|\mathcal{F}_t) \\ &= e^{r(T-S)} e^{\Gamma(t)} \mathbb{E}(\mathbf{1}_{\{t < \tau\}} \mathbf{1}_{\{S < \tau\}}|\mathcal{F}_t) \\ &= e^{r(T-S)} e^{\Gamma(t)} \mathbb{E}(\mathbf{1}_{\{t < \tau\}}|\mathcal{F}_t) \mathbf{1}_{\{S < t\}} + e^{r(T-S)} e^{\Gamma(t)} \mathbb{E}(\mathbf{1}_{\{S < \tau\}}|\mathcal{F}_t) \mathbf{1}_{\{t \leq S\}} \\ &= e^{r(T-S)} \mathbf{1}_{\{S < t\}} + e^{r(T-S)} e^{\Gamma(t)} \mathbb{E}(e^{-\Gamma(S)}|\mathcal{F}_t) \mathbf{1}_{\{t \leq S\}}. \end{aligned}$$

By Theorem 6.20, for any  $t \in [0, S]$ , this gives

$$\varphi_D(t) = \frac{e^{-r(T-t)} (J(t) - h(t))}{e^{\Gamma(t)} V_\alpha(t)} = \frac{e^{-r(S-t)} \mathbb{E}(e^{-\Gamma(S)}|\mathcal{F}_t)}{V_\alpha(t)}.$$

Taking  $(\beta_B, \beta_S)$  to be the admissible self-financing strategy that replicates the derivative security with payoff  $m(T) = e^{r(T-S)} e^{-\Gamma(S)}$  and exercise time  $T$  in the Black–Scholes model consisting of the assets  $B$  and  $S$ , we then obtain, for any  $t \in [0, S]$ ,

$$\begin{aligned} \varphi_S(t) &= \mathbf{1}_{\{t \leq \tau\}} e^{\Gamma(t)} (\beta_S(t) - \varphi_D(t) \alpha_S(t)), \\ \varphi_B(t) &= h(t \wedge \tau) - e^{r(T-t)} \varphi_S(t) S(t) = -e^{r(T-t)} \varphi_S(t) S(t), \end{aligned}$$

which implies that

$$\varphi_B(t) B(t, T) + \varphi_S(t) S(t) = 0.$$

It follows that

$$\begin{aligned}
 D(t, S) &= V_\varphi(t) \\
 &= \varphi_B(t)B(t, T) + \varphi_S(t)S(t) + \varphi_D(t)D(t, T) \\
 &= \frac{e^{-r(S-t)}\mathbb{E}(e^{-\Gamma(S)}|\mathcal{F}_t)}{V_\alpha(t)}D(t, T) \\
 &= \frac{e^{-r(S-t)}\mathbb{E}(e^{-\Gamma(S)}|\mathcal{F}_t)}{V_\alpha(t)}\mathbf{1}_{\{t < \tau\}}e^{\Gamma(t)}V_\alpha(t) \\
 &= e^{-r(S-t)}\mathbf{1}_{\{t < \tau\}}e^{\Gamma(t)}\mathbb{E}(e^{-\Gamma(S)}|\mathcal{F}_t)
 \end{aligned}$$

for any  $t \in [0, S]$ . It is the same formula as (6.1) for  $D(t, T)$ , with  $T$  replaced by  $S$ .

- 6.10. The payoff of a zero-recovery defaultable bond with maturity  $S$ , where  $0 < S < T$ , is  $\mathbf{1}_{\{S < \tau\}}$ . Hence, by using Theorem 5.35, we get

$$\begin{aligned}
 D(t, S) &= e^{-r(S-t)}\mathbb{E}(\mathbf{1}_{\{S < \tau\}}|\mathcal{G}_t) \\
 &= e^{-r(S-t)}\mathbf{1}_{\{t < \tau\}}e^{\Gamma(t)}\mathbb{E}(e^{-\Gamma(S)}|\mathcal{F}_t)
 \end{aligned}$$

for any  $t \in [0, S]$ , that is, the same result as in Exercise 6.9.

- 6.11. The payoff of the defaultable bond is

$$\begin{aligned}
 D_\eta(T, T) &= \mathbf{1}_{\{T < \tau\}} + \mathbf{1}_{\{\tau \leq T\}}e^{r(T-\tau)}\eta(\tau) \\
 &= D(T, T) + h(\tau),
 \end{aligned}$$

where

$$h(t) = \mathbf{1}_{\{t \leq T\}}e^{r(T-t)}\eta(t).$$

It follows that

$$\begin{aligned}
 D_\eta(0, T) &= D(0, T) + e^{-rT}\mathbb{E}(h(\tau)) \\
 &= D(0, T) + e^{-rT}\mathbb{E}\left(\int_0^\infty h(u)f(u)du\right) \\
 &= D(0, T) + e^{-rT}\mathbb{E}\left(\int_0^\infty \mathbf{1}_{\{u \leq T\}}e^{r(T-u)}\eta(u)f(u)du\right) \\
 &= D(0, T) + \mathbb{E}\left(\int_0^T e^{-ru}\eta(u)f(u)du\right).
 \end{aligned}$$

6.12. In Example 6.25 it is shown that

$$\begin{aligned}
 D(0, T) &= F e^{-(\lambda+r)T} (1 - F_\theta(T)) + R e^{-rT} (1 - e^{-\lambda T} + e^{-\lambda T} F_\theta(T)) \\
 &\quad - R e^{-rT} \int_0^T e^{-\lambda t} dF_\theta(t) + F e^{-\gamma T} \int_0^T e^{-(\lambda+r-\gamma)t} dF_\theta(t) \\
 &= R e^{-rT} + (F - R) e^{-(\lambda+r)T} (1 - F_\theta(T)) \\
 &\quad - R e^{-rT} \int_0^T e^{-\lambda t} dF_\theta(t) + F e^{-\gamma T} \int_0^T e^{-(\lambda+r-\gamma)t} dF_\theta(t),
 \end{aligned}$$

where

$$F_\theta(t) = N(d_1(t)) + L^{2\alpha} N(d_2(t))$$

with

$$\begin{aligned}
 L &= \frac{F e^{-\gamma T}}{V(0)} < 1, \\
 \alpha &= \frac{r - \gamma - \frac{1}{2}\sigma^2}{\sigma^2}, \\
 d_1(t) &= \frac{\ln L - \left(r - \gamma - \frac{1}{2}\sigma^2\right)t}{\sigma \sqrt{t}} = \frac{\sigma^{-1} \ln L - \sigma \alpha t}{\sqrt{t}}, \\
 d_2(t) &= \frac{\ln L + \left(r - \gamma - \frac{1}{2}\sigma^2\right)t}{\sigma \sqrt{t}} = \frac{\sigma^{-1} \ln L + \sigma \alpha t}{\sqrt{t}}.
 \end{aligned}$$

We use formula (A.1) in Exercise A.12 to compute the integrals with respect to  $F_\theta(t)$ . Namely,

$$\begin{aligned}
 \int_0^T e^{-\lambda t} dF_\theta(t) &= \int_0^T e^{-\lambda t} dN(d_1(t)) + L^{2\alpha} \int_0^T e^{-\lambda t} dN(d_2(t)) \\
 &= \int_0^T e^{ct} dN\left(\frac{-a - bt}{\sqrt{t}}\right) + e^{-2ab} \int_0^T e^{ct} dN\left(\frac{-a + bt}{\sqrt{t}}\right),
 \end{aligned}$$

where

$$a = -\sigma^{-1} \ln L, \quad b = \sigma \alpha, \quad c = -\lambda.$$

We have  $a > 0$  and  $d = \sqrt{b^2 - 2c}$ , where

$$b^2 - 2c = \sigma^2 \alpha^2 + 2\lambda > 0,$$

and formula (A.1) gives

$$\begin{aligned}
& \int_0^T e^{-\lambda t} dF_\theta(t) \\
&= \frac{d+b}{2d} e^{-a(b-d)} N\left(\frac{-a-dT}{\sqrt{T}}\right) + \frac{d-b}{2d} e^{-a(b+d)} N\left(\frac{-a+dT}{\sqrt{T}}\right) \\
&\quad + e^{-2ab} \left( \frac{d-b}{2d} e^{-a(-b-d)} N\left(\frac{-a-dT}{\sqrt{T}}\right) + \frac{d+b}{2d} e^{-a(-b+d)} N\left(\frac{-a+dT}{\sqrt{T}}\right) \right) \\
&= e^{-a(b-d)} N\left(\frac{-a-dT}{\sqrt{T}}\right) + e^{-a(b+d)} N\left(\frac{-a+dT}{\sqrt{T}}\right) \\
&= L^{\alpha - \sqrt{\alpha^2 + 2\lambda/\sigma^2}} N\left(\frac{\ln L - T \sqrt{\alpha^2 + 2\lambda/\sigma^2}}{\sigma \sqrt{T}}\right) \\
&\quad + L^{\alpha + \sqrt{\alpha^2 + 2\lambda/\sigma^2}} N\left(\frac{\ln L + T \sqrt{\alpha^2 + 2\lambda/\sigma^2}}{\sigma \sqrt{T}}\right).
\end{aligned}$$

We also have

$$\begin{aligned}
& \int_0^T e^{-(\lambda+r-\gamma)t} dF_\theta(t) \\
&= \int_0^T e^{-(\lambda+r-\gamma)t} dN(d_1(t)) + L^\alpha \int_0^T e^{-(\lambda+r-\gamma)t} dN(d_2(t)) \\
&= \int_0^T e^{ct} dN\left(\frac{-a-bt}{\sqrt{t}}\right) + e^{-2ab} \int_0^T e^{ct} dN\left(\frac{-a+bt}{\sqrt{t}}\right),
\end{aligned}$$

where

$$a = -\sigma^{-1} \ln L, \quad b = \sigma\alpha, \quad c = -(\lambda + r - \gamma).$$

We have  $\alpha > 0$  and  $d = \sqrt{b^2 - 2c}$ , where

$$\begin{aligned}
b^2 - 2c &= \sigma^2 \alpha^2 + 2(\lambda + r - \gamma) \\
&= \sigma^{-2} \left( r - \gamma - \frac{1}{2} \sigma^2 \right)^2 + 2(\lambda + r - \gamma) \\
&= \sigma^{-2} \left( r - \gamma + \frac{1}{2} \sigma^2 \right)^2 + 2\lambda \\
&= \sigma^{-2} (\alpha + 1)^2 + 2\lambda > 0.
\end{aligned}$$

Formula (A.1) gives

$$\begin{aligned}
& \int_0^T e^{-(\lambda+r-\gamma)t} dF_\theta(t) \\
&= e^{-a(b-d)} N\left(\frac{-a-dT}{\sqrt{T}}\right) + e^{-a(b+d)} N\left(\frac{-a+dT}{\sqrt{T}}\right) \\
&= L^{\alpha-\sqrt{(\alpha+1)^2+2\lambda/\sigma^2}} N\left(\frac{\ln L - T\sqrt{(\alpha+1)^2+2\lambda/\sigma^2}}{\sigma\sqrt{T}}\right) \\
&\quad + L^{\alpha+\sqrt{(\alpha+1)^2+2\lambda/\sigma^2}} N\left(\frac{\ln L + T\sqrt{(\alpha+1)^2+2\lambda/\sigma^2}}{\sigma\sqrt{T}}\right).
\end{aligned}$$

It follows that

$$\begin{aligned}
& D(0, T) \\
&= Re^{-rT} + (F - R)e^{-(\lambda+r)T} \left(1 - N\left(\frac{\ln L - \sigma^2 \alpha T}{\sigma\sqrt{T}}\right) - L^{2\alpha} N\left(\frac{\ln L + \sigma^2 \alpha T}{\sigma\sqrt{T}}\right)\right) \\
&\quad - Re^{-rT} L^\alpha \left(L^{-\sqrt{\alpha^2+2\lambda/\sigma^2}} N\left(\frac{\ln L - T\sqrt{\alpha^2+2\lambda/\sigma^2}}{\sigma\sqrt{T}}\right) \right. \\
&\quad \quad \left. + L^{\sqrt{\alpha^2+2\lambda/\sigma^2}} N\left(\frac{\ln L + T\sqrt{\alpha^2+2\lambda/\sigma^2}}{\sigma\sqrt{T}}\right)\right) \\
&\quad + Fe^{-\gamma T} L^\alpha \left(L^{-\sqrt{(\alpha+1)^2+2\lambda/\sigma^2}} N\left(\frac{\ln L - T\sqrt{(\alpha+1)^2+2\lambda/\sigma^2}}{\sigma\sqrt{T}}\right) \right. \\
&\quad \quad \left. + L^{\sqrt{(\alpha+1)^2+2\lambda/\sigma^2}} N\left(\frac{\ln L + T\sqrt{(\alpha+1)^2+2\lambda/\sigma^2}}{\sigma\sqrt{T}}\right)\right).
\end{aligned}$$

## Appendix A

A.1. Let  $a > 0$ , and take a sequence  $x_n > 0$  such that  $x_n \nearrow a$  and so  $F(x_n) \nearrow F(a_-)$  as  $n \rightarrow \infty$ . Since

$$\{a\} = \bigcap_{n=1}^{\infty} (x_n, a]$$

and  $(x_{n+1}, a] \subset (x_n, a]$  for each  $n$ , it follows that

$$\mu_F(\{a\}) = \lim_{n \rightarrow \infty} \mu_F((x_n, a]) = \lim_{n \rightarrow \infty} (F(a) - F(x_n)) = F(a) - F(a_-).$$

A.2. Using Exercise A.1, we obtain

$$\begin{aligned}
 \mu_F([a, b]) &= \mu_F(\{a\} \cup (a, b]) \\
 &= \mu_F(\{a\}) + \mu_F((a, b]) \\
 &= (F(a) - F(a_-)) + (F(b) - F(a)) \\
 &= F(b) - F(a_-)
 \end{aligned}$$

since  $\{a\} \cap (a, b] = \emptyset$ . Next,

$$\begin{aligned}
 \mu_F([a, b)) &= \mu_F([a, b] \setminus \{b\}) \\
 &= \mu_F([a, b]) - \mu_F(\{b\}) \\
 &= (F(b) - F(a_-)) - (F(b) - F(b_-)) \\
 &= F(b_-) - F(a_-)
 \end{aligned}$$

since  $\{b\} \subset [a, b]$ . Finally, if  $b > a$ , then  $\{a\} \subset [a, b)$  and so

$$\begin{aligned}
 \mu_F((a, b)) &= \mu_F([a, b) \setminus \{a\}) \\
 &= \mu_F([a, b)) - \mu_F(\{a\}) \\
 &= (F(b_-) - F(a_-)) - (F(a) - F(a_-)) \\
 &= F(b_-) - F(a).
 \end{aligned}$$

A.3. To show that for each  $a \in \mathbb{R}$ ,  $b > 0$  and  $y > 0$

$$\int_0^y x dN\left(\frac{\ln x + a}{b}\right) = e^{\frac{1}{2}b^2 - a} N\left(\frac{\ln y + a - b^2}{b}\right)$$

we start by computing the derivative of the right-hand side with respect to  $y$ :

$$\begin{aligned}
 \frac{d}{dy} e^{\frac{1}{2}b^2 - a} N\left(\frac{\ln y + a - b^2}{b}\right) &= e^{\frac{1}{2}b^2 - a} N'\left(\frac{\ln y + a - b^2}{b}\right) \frac{1}{yb} \\
 &= \frac{1}{\sqrt{2\pi}} e^{\frac{1}{2}b^2 - a} e^{-\frac{1}{2}\left(\frac{\ln y + a - b^2}{b}\right)^2} \frac{1}{yb} \\
 &= \frac{1}{\sqrt{2\pi}} e^{-\frac{(\ln y + a)^2}{2b^2}} \frac{1}{b} \\
 &= N'\left(\frac{\ln y + a}{b}\right) \frac{1}{b},
 \end{aligned}$$

which is clearly equal to the derivative of the left-hand side with respect to  $y$ . Hence, the expressions on either side of the equality differ just by a constant. To see that this constant is 0, hence the

equality holds, observe that the right-limit as  $y \searrow 0$  of either side of the equality is the same (namely 0).

In the same manner, we can show that

$$\int_0^y x dN\left(\frac{-\ln x + a}{b}\right) = -e^{\frac{1}{2}b^2 + a} N\left(\frac{\ln y - a - b^2}{b}\right).$$

Alternatively, this formula can be verified by using the equality already proved above:

$$\begin{aligned} \int_0^y x dN\left(\frac{-\ln x + a}{b}\right) &= \int_0^y x d\left(1 - N\left(\frac{\ln x - a}{b}\right)\right) \\ &= - \int_0^y x dN\left(\frac{\ln x - a}{b}\right) \\ &= -e^{\frac{1}{2}b^2 + a} N\left(\frac{\ln y - a - b^2}{b}\right). \end{aligned}$$