

Mathematical Finance Solution 9

Solution 9-1

Let Q be the martingale measure; we can write $\tilde{S}_t = S_0 \exp(\sigma W_t^Q + (r - \frac{1}{2}\sigma^2)t)$ for a Q -Brownian motion W^Q . Using the risk neutral valuation formula, we have

$$\begin{aligned}\tilde{V}_t &= e^{-r(T-t)} E_Q[\tilde{H}|\mathcal{F}_t] = e^{-r(T-t)} E_Q[1_{\{\tilde{S}_T > \tilde{K}\}}|\mathcal{F}_t] = e^{-r(T-t)} Q[\tilde{S}_T > \tilde{K}|\mathcal{F}_t] \\ &= e^{-r(T-t)} Q\left[\tilde{S}_t \exp\left(\sigma(W_T^Q - W_t^Q) + (r - \frac{1}{2}\sigma^2)(T-t)\right) > \tilde{K} \mid \mathcal{F}_t\right] \\ &= e^{-r(T-t)} Q\left[-\sigma(W_T^Q - W_t^Q) < \ln \frac{x}{\tilde{K}} + (r - \frac{1}{2}\sigma^2)(T-t)\right] \Big|_{x=\tilde{S}_t} \\ &= e^{-r(T-t)} Q\left[\xi < \frac{\ln \frac{x}{\tilde{K}} + (r - \frac{1}{2}\sigma^2)(T-t)}{\sigma\sqrt{T-t}}\right] \Big|_{x=\tilde{S}_t} \\ &= e^{-r(T-t)} \Phi\left(\frac{\ln \frac{x}{\tilde{K}} + (r - \frac{1}{2}\sigma^2)(T-t)}{\sigma\sqrt{T-t}}\right) \Big|_{x=\tilde{S}_t} \\ &= \tilde{v}(t, \tilde{S}_t).\end{aligned}$$

where $\xi = -(W_T^Q - W_t^Q)/\sqrt{T-t}$ has a standard Gaussian law and Φ is the standard normal c.d.f. As in the lecture, the strategy is given by the spatial derivative,

$$\tilde{\vartheta}_t = \frac{\partial \tilde{v}}{\partial x}(t, \tilde{S}_t) = e^{-r(T-t)} \phi\left(\frac{\ln \frac{\tilde{S}_t}{\tilde{K}} + (r - \frac{1}{2}\sigma^2)(T-t)}{\sigma\sqrt{T-t}}\right) \frac{1}{\tilde{S}_t \sigma \sqrt{T-t}}.$$

Here $\phi = \Phi'$ is the standard normal density.

Solution 9-2

Let Q be the martingale measure. Let q be the ‘up’-probability under Q and Z_k the Q -(i.i.d.) returns of \tilde{S} with values in $\{1+d, 1+u\}$.

a) $\tilde{V}_k(\tilde{H}) = (1+r)^{k-T} E_Q[\tilde{h}(\tilde{S}_T)|\mathcal{F}_k] = (1+r)^{k-T} E_Q[\tilde{h}(\tilde{S}_k Z_{k+1} \cdots Z_T)|\mathcal{F}_k] =: \tilde{v}(k, x)|_{x=\tilde{S}_k}$ for $\tilde{v}(k, x) = (1+r)^{k-T} E_Q[\tilde{h}(x Z_{k+1} \cdots Z_T)]$ by the Q -i.i.d. property of the (Z_k) .

b) Clearly $\tilde{v}(T, \tilde{S}_T) = \tilde{h}(\tilde{S}_T)$. Furthermore,

$$\begin{aligned}\tilde{v}(k, x) &= (1+r)^{k-T} E_Q[\tilde{h}(x Z_{k+1} \cdots Z_T)] = (1+r)^{-1} E_Q[\tilde{v}(k+1, x Z_{k+1})] \\ &= (1+r)^{-1} q \tilde{v}(k+1, x(1+u)) + (1+r)^{-1} (1-q) \tilde{v}(k+1, x(1+d)).\end{aligned}$$

c) Expanding the recursion of **b)** we obtain

$$\tilde{V}_0(H) = \tilde{v}(0, \tilde{S}_0) = (1+r)^{-T} \sum_{k=0}^T \binom{T}{k} q^k (1-q)^{T-k} \tilde{h}(\tilde{S}_0 (1+u)^k (1+d)^{T-k}).$$

Alternativ argument: $\prod_{j=1}^T Z_j$ has value $(1+u)^k(1+d)^{T-k}$, $k = 0, 1, \dots, T$, if and only if there are k -times up-moves and $T - k$ -times down-moves, and that has binomial distribution $\binom{T}{k} q^k(1-q)^{T-k}$ under Q .

d) For each t we should have, using b),

$$\begin{aligned}\tilde{\vartheta}_{k+1}(\tilde{S}_{k+1} - \tilde{S}_k) &= \tilde{V}_{k+1}(\tilde{H}) - \tilde{V}_k(\tilde{H}) - \tilde{\eta}_{k+1}(\tilde{B}_{k+1} - \tilde{B}_k) \\ &= \tilde{v}(k+1, \tilde{S}_{k+1}) - \tilde{v}(k, \tilde{S}_k) - \tilde{\eta}_{k+1}(\tilde{B}_{k+1} - \tilde{B}_k)\end{aligned}$$

This equation on the event $\{Z_{k+1} = 1+u\}$ reads

$$\tilde{\vartheta}_{k+1}(\tilde{S}_k(1+u) - \tilde{S}_k) = \tilde{v}(k+1, (1+u)\tilde{S}_k) - \tilde{v}(k, \tilde{S}_k) - \tilde{\eta}_{k+1}(\tilde{B}_{k+1} - \tilde{B}_k),$$

and on $\{Z_{k+1} = 1+d\}$ it reads

$$\tilde{\vartheta}_{k+1}(\tilde{S}_k(1+d) - \tilde{S}_k) = \tilde{v}(k+1, (1+d)\tilde{S}_k) - \tilde{v}(k, \tilde{S}_k) - \tilde{\eta}_{k+1}(\tilde{B}_{k+1} - \tilde{B}_k).$$

Taking the difference we get $\tilde{\vartheta}_{k+1}(u-d)\tilde{S}_k = \tilde{v}(k+1, (1+u)\tilde{S}_k) - \tilde{v}(k+1, (1+d)\tilde{S}_k)$ and hence

$$\tilde{\vartheta}_{k+1} = \frac{\tilde{v}(k+1, (1+u)\tilde{S}_k) - \tilde{v}(k+1, (1+d)\tilde{S}_k)}{(u-d)\tilde{S}_k}, \quad (1)$$

which is indeed predictable. Going backwards the above steps we see that $\tilde{\vartheta}$ indeed replicates \tilde{H} . Equation (1) can be read as

$$\tilde{\vartheta}_{k+1} = \frac{\tilde{V}_{k+1}(\tilde{H})|_{up} - \tilde{V}_{k+1}(\tilde{H})|_{down}}{\tilde{S}_{k+1}|_{up} - \tilde{S}_{k+1}|_{down}} = \frac{\Delta(\text{price of derivative } \tilde{H})}{\Delta(\text{price of underlying})}$$

and is sometimes called discrete Delta hedging. In the Black–Scholes world, “Delta” is the derivative of the price of a financial product with respect to the price of the underlying.

e) From b) we see that if \tilde{h} is increasing, then $\tilde{v}(k, \cdot)$ is increasing for each k . The formula from d) then shows that $\tilde{\vartheta} \geq 0$.

Solution 9-3

a) Write $X_t = \sum_{k=1}^{N_t} Y_k$, where N is a Poisson process with rate λ and $(Y_k)_{k \in \mathbb{N}}$ a sequence of random variables independent of N such that the Y_i are i.i.d. with distribution ν . Note that W , N and $(Y_k)_{k \in \mathbb{N}}$ are independent. If R is a martingale, then in particular $E[R_T] = 0$, and hence $E[X_T] = -aT$. Since $E[X_T] = \lambda T E[Y_1]$, this gives $E[Y_1] = -\frac{a}{\lambda}$. Since $\mathcal{E}(R)$ is a nonnegative local martingale and hence a supermartingale, it suffices to show that $E[\mathcal{E}(R)_T] = 1$. Using the formula for $\mathcal{E}(R)$, the fact that X is a simple jump process, i.e. $X_t = \sum_{0 < s \leq t} \Delta X_s$ and hence $\exp(X_t) \prod_{0 < s \leq t} \exp(-\Delta X_s) = 1$, the fact that W , N and $(Y_k)_{k \in \mathbb{N}}$ are independent and that $\Delta Y_s = \Delta X_s$ gives

$$\begin{aligned}E[\mathcal{E}(R)_T] &= E \left[\exp(aT) \exp \left(\sigma W_T - \frac{1}{2} \sigma^2 T \right) \prod_{k=1}^{N_T} (1 + Y_k) \right] \\ &= \exp(aT) E \left[\left(1 - \frac{a}{\lambda} \right)^{N_T} \right] = \exp(aT) \exp \left(\left(-\frac{a}{\lambda} \right) \lambda T \right) \\ &= 1.\end{aligned} \quad (2)$$

Remark: One can show in general that if R is a Lévy process and a local martingale, then $\mathcal{E}(R)$ is a martingale.

- b) First, assume that the paths of R are not monotone. We try to find a measure under which Q is a Lévy process and a martingale.

Let $\tilde{\nu} \approx \nu$ be an equivalent probability measure on \mathbb{R} with finite mean $\tilde{\mu}$ (if ν already has finite mean, we can take $\tilde{\nu} = \nu$). Define as in Exercise **8-2** (with $\tilde{\lambda} := \lambda$) the measure $\tilde{P} \approx P$ on \mathcal{F}_T by

$$\frac{d\tilde{P}}{dP} := \exp \left(\sum_{k=1}^{N_T} \phi(Y_k) \right), \quad (3)$$

where $\phi = \log \frac{d\tilde{\nu}}{d\nu}$. Then by the hint, W and X are still independent under \tilde{P} and W is a Brownian motion under \tilde{P} . Hence, R is an integrable jump diffusion under \tilde{P} with mean function

$$E_{\tilde{P}}[R_t] = at + 0 + \tilde{\mu}\tilde{\lambda}t = t(a + \tilde{\mu}\tilde{\lambda}), \quad t \in [0, T]. \quad (4)$$

Now we distinguish two cases. First, assume that $\sigma > 0$. Define the measure $Q \approx \tilde{P}$ on \mathcal{F}_T by

$$\frac{dQ}{d\tilde{P}} := \mathcal{E} \left(-\frac{a + \tilde{\mu}\tilde{\lambda}}{\sigma} W \right)_T.$$

Then by Girsanov's theorem, it follows that $\tilde{W} = (\tilde{W}_t)_{t \in [0, T]}$ defined by $\tilde{W}_t = W_t + \frac{a + \tilde{\mu}\tilde{\lambda}}{\sigma} t$ is a Q -Brownian motion, and by the hint, \tilde{W} and X are still independent under Q and the distributions of X under \tilde{P} and Q coincide. Since $R_t = \sigma \tilde{W}_t - \tilde{\lambda}\tilde{\mu}t + X_t$, this implies that R is under Q again an integrable jump-diffusion with mean function 0, and hence a Q -martingale.

Next, assume that $\sigma = 0$. Since R has paths which are not monotone, we are in one of the following three cases:

- (a) $\tilde{\nu}((-1, 0)) > 0$ and $\tilde{\nu}((0, \infty)) > 0$, i.e., R has positive and negative jumps.
- (b) $\tilde{\nu}((-1, 0)) = 0$ and $a < 0$, i.e, R has only positive jumps but a strictly negative drift.
- (c) $\tilde{\nu}((0, \infty)) = 0$ and $a > 0$, i.e, R has only negative jumps but a strictly positive drift.

In each of the three cases, it suffices to find $\hat{\lambda} > 0$ and an equivalent probability measure $\hat{\nu} \approx \tilde{\nu}$ on \mathbb{R} with mean $\hat{\mu}$ such that $\hat{\lambda}\hat{\mu} = -a$ and to define as in Exercise **8-2** the measure $Q \approx \tilde{P}$ on \mathcal{F}_T by

$$\frac{dQ}{d\tilde{P}} := \exp \left(\sum_{k=1}^{N_T} \hat{\phi}(Y_k) + (\tilde{\lambda} - \hat{\lambda})T \right), \quad (5)$$

where $\hat{\phi} = \log \left(\frac{\hat{\lambda}}{\tilde{\lambda}} \frac{d\hat{\nu}}{d\tilde{\nu}} \right)$. Then it follows as in the first step that R is a jump-diffusion under Q with mean function

$$E_Q[R_t] = t(a + \hat{\mu}\hat{\lambda}) = 0, \quad t \in [0, T], \quad (6)$$

which implies that R is a Q -martingale.

To find $\hat{\lambda}$ and $\hat{\nu}$ as above, we proceed as follows: In the first case, choose $\hat{\lambda} > 0$ such that $\frac{-a}{\hat{\lambda}} \in (\inf \text{supp } \nu, \sup \text{supp } \nu)$, and let $\hat{\nu} \approx \tilde{\nu}$ be an equivalent probability measure on \mathbb{R} with mean $\frac{-a}{\hat{\lambda}}$. The existence of such a measure can be shown similarly as in Exercise **3-2 a)**. In the second and third case, set $\hat{\lambda} := \frac{-a}{\tilde{\mu}}$ and $\hat{\nu} := \tilde{\nu}$.

Conversely, assume that the paths of R are monotone. We only consider the case that they are nondecreasing, the argument for the nonincreasing case is similar. Then $\sigma = 0$, $a \geq 0$ and ν is concentrated on $(0, \infty)$. Hence by the formula in the hint, using the same arguments as in a), $S = s_0 \mathcal{E}(R)$ satisfies

$$S_t = s_0 \exp(at) \prod_{k=1}^{N_t} (1 + Y_k), \quad t \in [0, T], \quad (7)$$

and so also S has nondecreasing paths. Consider the strategy $\theta = (\theta_t)_{t \in [0, T]}$ where $\theta \equiv 1$. Then its gains process $G(\theta)$ satisfies

$$G_t(\theta) = S_t - S_0, \quad t \in [0, T]. \quad (8)$$

Since S has nondecreasing paths and $P[S_T > S_0] \geq P[N_T \geq 1] > 0$, it follows that θ is 0-admissible and that S fails NA.