

$$4.10. (i) \quad X_t = \Delta_t S_t + P_t M_t \quad (4.10.16)$$

$$dX_t = \Delta_t dS_t + r(X_t - \Delta_t S_t) dt \quad (4.10.19)$$

$$\text{Proof: } S_t d\Delta_t + dS_t d\Delta_t + M_t dP_t + dM_t dP_t = 0 \quad (4.10.15)$$

4.10.15, 4.10.9 is as Ito differential equations.

Using Ito's Lemma into 4.10.16 (Train rule)

$$dX_t = \Delta_t dS_t + S_t d\Delta_t + dS_t d\Delta_t + P_t dM_t + M_t dP_t + \\ dP_t dM_t \quad (1)$$

Substitute 4.10.16 into 4.10.19

$$dX_t = \Delta_t dS_t + r P_t M_t dt \quad (2)$$

Combine (1) and (2) $\Delta_t dS_t$ can be canceled.

$$S_t d\Delta_t + dS_t d\Delta_t + P_t dM_t + M_t dP_t + dP_t dM_t - r P_t M_t dt =$$

$$\text{Moreover } M_t = e^{rt} \quad dM_t = r M_t dt,$$

We have proved 4.10.15.

(ii) The correct version of the value that long and short Δ_t short of underlying asset is

$$N_t = c(t, S_t) - \Delta_t S_t$$

$$dN_t = dc - \Delta_t dS_t - S_t d\Delta_t - d\Delta_t dS_t \quad (3)$$

$$P_t = N_t / M_t$$

$$dP_t = d(e^{-rt} N_t) = -r \frac{N_t}{M_t} dt + e^{-rt} dN_t \quad (4)$$

$$\Rightarrow M_t dP_t = -r N_t dt + dN_t \quad (5)$$

Substitute (4), (5) into 4.10.15

We get =

$$S_t d\Delta t + dS_t d\Delta t = r N_t d\Delta t + dN_t + \frac{dM_t}{M_t} (-r N_t d\Delta t + dN_t) \quad (6)$$

Moreover we have dN_t formed in (3)

$$we have dM_t = r M_t dt \quad (7)$$

Then, $S_t d\Delta t + dS_t d\Delta t - r N_t d\Delta t + dC - \Delta_t dS_t - S_t d\Delta t - d\Delta_t dS_t +$
 $r d\Delta t (-r N_t d\Delta t + dC - \Delta_t dS_t - S_t d\Delta t - d\Delta_t dS_t) = 0$

$$-r N_t d\Delta t + dC - \Delta_t dS_t + o(dt) = 0$$

Ignore the higher order items, we get the equation

$$r N_t d\Delta t = dC - \Delta_t dS_t, \text{ the same as previous } \cancel{\text{again}}$$

Similarly to cancel the stochastic item, we have
expand dC as Ito Lemma =

$$r N_t d\Delta t = C_x dS_t + \frac{1}{2} C_{xx} dS_t dS_t + C_t d\Delta t - \Delta_t dS_t$$

$$(C_x dS_t + \frac{1}{2} C_{xx} \sigma^2 S_0^2 + C_t) d\Delta t + (C_x dS_t - \Delta_t) d\Delta t$$

a) $\Delta_t = C_x$

b) $r N_t = \frac{1}{2} C_{xx} \sigma^2 S_0^2 + C_t$

or $C_t + \frac{1}{2} C_{xx} \sigma^2 S_0^2 = r (C(t, S_t) - C_x S_t)$

$$C_t + \frac{1}{2} C_{xx} \sigma^2 S_0^2 + r C_x S_t = r C(t, S_t) \dots (4)$$

$$4.11. \quad dX_t = dC(t, S_t) - C_x(t, S_t) dS_t + r[X_t - C(t, S_t) + S_t C_x] dt \\ - \frac{1}{2} (\sigma_2^2 - \sigma_1^2) S^2 C_{xx} dt$$

$$dC(t, S_t) = (C_t + \frac{1}{2} C_{xx} \sigma_2^2 S_t^2) dt + C_x dS_t$$

$$\text{Then } dX_t = dt [C_t + \frac{1}{2} C_{xx} \sigma_2^2 S_t^2 + r[X_t - C(t, S_t) + S_t C_x] - \frac{1}{2} (\sigma_2^2 - \sigma_1^2) S_t^2 C_{xx}] \\ = dt \left\{ C_t + \frac{1}{2} C_{xx} \sigma_1^2 S_t^2 + r[X_t - C(t, S_t) + S_t C_x] \right\} \quad (1)$$

Moreover

From Black-Scholes formula $\rightarrow c(t, x)$ satisfies :

$$\left(\frac{\partial}{\partial t} + rx \frac{\partial}{\partial x} + \frac{1}{2} x^2 \sigma_1^2 \frac{\partial^2}{\partial x^2} - r \right) c(t, x) = 0$$

$$C_t + rx C_x + \frac{1}{2} x^2 \sigma_1^2 C_{xx} - rc = 0 \quad (2)$$

$$\text{Substitute to (1)} \Rightarrow dX_t = r X_t dt$$

$$\text{Then, } X_t = E \left(\int r dt \right) = \exp \left(\int_0^t r ds - 0 - \frac{1}{2} \cdot 0 + C \right) \\ = X_0 e^{rt}$$

$$\text{or } d(e^{-rt} X_t) = 0$$

4.12. (i) the value of a forward contract

$$f(t, x) = x - e^{-r(T-t)} K \quad 4.5.26$$

put-call parity

$$f(t, x) = c(t, x) - p(t, x) \quad 4.5.29$$

$$p(t, x) = c(t, x) - f(t, x) = c(t, x) - x + e^{-r t} K$$

Since $p_x(t, x) = \frac{\partial}{\partial x} p(t, x) = \frac{\partial}{\partial x} (c(t, x) - x + e^{-r t} K)$

$$= c_x(t, x) - 1 + 0$$

$$= N(d_+) - 1$$

$$= -N(-d_+)$$

$$d_+ = d_- + \sqrt{e^r - 1}$$

$$P_{xx}(t, x) = \frac{\partial^2}{\partial x^2} p(t, x) = \frac{\partial^2}{\partial x^2} (c(t, x) - x + e^{-r t} K)$$

$$= \frac{\partial^2}{\partial x^2} c(t, x) = c_{xx} = \frac{N'(d_+)}{\sqrt{e^r - 1}}$$

$$P_t(t, x) = \frac{\partial}{\partial t} p(t, x) = \frac{\partial}{\partial t} (c(t, x) - x + e^{-r t} K)$$

$$= c_t(t, x) + e^{-r t} K$$

$$= [1 - N(d_-)] e^{-r t} K - \frac{\sigma x}{\sqrt{e^r - 1}} N'(d_+)$$

$$= +N(-d_-) e^{-r t} K - \frac{\sigma x}{\sqrt{e^r - 1}} N'(d_+)$$

(ii) Let X_t be a portfolio with ~~short position in~~ put, underlying and money account

$$dX_t = dP(t, x) + \Delta dS_t + \cancel{f(X_t - P - \Delta S_t) dt}$$

$$= \cancel{\left(\frac{\partial}{\partial x} + \frac{\partial}{\partial t} + \frac{1}{2} \sigma^2 x^2 \frac{\partial^2}{\partial x^2} \right) P dt} + -\frac{\partial}{\partial x} P dx + \Delta dS_t$$

$$+ \cancel{f(X_t - P - \Delta S_t) dt}$$

$$= \frac{\partial}{\partial t} \cancel{(P_t + \frac{1}{2} \sigma^2 x^2 P_{xx}) dt} + (-P_x + \Delta) dx$$

In order to cancel risk here we should make stochastic item equals to zero such that:

$$(-P_x + \Delta) dx = 0 \quad \Delta = -P_x = -N(d_+) < 0$$

So, the agent should short underlying asset.

In order to be arbitrage free, there should satisfy:

$$dX_t = rX_t dt = r(-P + \Delta x) dt$$

$$- \left(P_t^{(t,x)} + \frac{1}{2} \sigma^2 x^2 P_{xx}^{(t,x)} \right) = r(-P^{(t,x)} + \Delta x)$$

$$= r(-P^{(t,x)} + P_x x)$$

$$\text{or } \left(rX \frac{\partial}{\partial x} + \frac{1}{2} \sigma^2 x^2 \frac{\partial^2}{\partial x^2} + \frac{\partial}{\partial t} - r \right) P^{(t,x)} = 0$$

Since $X_t = -P + \Delta S_t = -P + P_x S_t < 0$

So, the agent can long ($P - P_x S_t > 0$) position in money market

(vii)

↓ See (vi). It is the same SDE as call option

$$4.13 \quad \begin{cases} B_1(t) = W_1(t) \\ B_2(t) = \int_0^t p(s) dW_1(s) + \int_0^t \sqrt{1-p(s)} dW_2(s) \end{cases}$$

$$\text{Let } B(t) = \begin{pmatrix} B_1(t) \\ B_2(t) \end{pmatrix}, \quad W(t) = \begin{pmatrix} W_1(t) \\ W_2(t) \end{pmatrix}$$

$$dB(t) = \begin{pmatrix} 1 & 0 \\ p(t) & \sqrt{1-p(t)} \end{pmatrix} dW(t) = A dW(t) \quad (A \text{ is invertible})$$

$$A^{-1} = \begin{pmatrix} 1 & 0 \\ -\frac{p}{1-p} & \frac{1}{1-p} \end{pmatrix} \quad A^{-1} dB(t) = dW(t)$$

$$dW_1 = dB_1$$

$$dW_2 = -\frac{p}{1-p} dB_1 + \frac{1}{1-p} dB_2$$

$$d[W_1, W_2] = -\frac{p}{1-p} dB_1^2 + \frac{1}{1-p} dB_1 dB_2 = 0 \Rightarrow \text{Independence.}$$

4.14 (i) Define $Z_j = f''(W(t_j)) [(W(t_{j+1}) - W(t_j))^2 - (t_{j+1} - t_j)]$
 $W(t_j), t_j$ is $\mathcal{F}(t_j)$ -measurable, it is surely $\mathcal{F}(t_{j+1})$ -measurable
 $W(t_{j+1}), t_{j+1}$ is $\mathcal{F}(t_{j+1})$ -measurable
So, Z_j is $\mathcal{F}(t_{j+1})$ -measurable

$$E[Z_j | \mathcal{F}(t_j)] \stackrel{\substack{\text{taking out} \\ \text{what is known}}}{=} f''(W(t_j)) \left(E[(W(t_{j+1}) - W(t_j))^2 | \mathcal{F}(t_{j+1})] - (t_{j+1} - t_j) \right)$$

$$= f''(W(t_j)) \left[E[W^2 | t_{j+1} - t_j] - (t_{j+1} - t_j) \right] = 0$$

1: Markov property for Ito diffusion $E^x [f(X_{t+h}) | \mathcal{F}_t^{(m)}]_{(w)} = E^{X_{t(w)}} [f(X_h)]$

2: Using the truth that the transition probability of Brownian motion
 $p(x, t, x, y) = \frac{1}{\sqrt{2\pi t}} \exp(-\frac{|x-y|^2}{2t})$, variance equals to time spent t

$$\begin{aligned}
\mathbb{E}[Z_j^2 | \mathcal{F}(t_j)] &= \mathbb{E}\left[f''(W(t_j)) \left[(W(t_{j+1}) - W(t_j))^4 + (t_{j+1} - t_j)^2 \right]\right] \\
&= f''(W(t_j)) \left(\mathbb{E}[(W(t_{j+1}) - W(t_j))^4] + (t_{j+1} - t_j)^2 - 2(t_{j+1} - t_j)(W(t_{j+1}) - W(t_j)) \right) \\
&= f''(W(t_j)) \left(\mathbb{E}[W_{t_{j+1}-t_j}^4] + (t_{j+1} - t_j)^2 - 2(t_{j+1} - t_j)^3 \right) \\
&\quad \xrightarrow{\text{Independence increment property}} \mathbb{E}[W_{t_{j+1}-t_j}^2] \\
&= f''(W(t_j)) (3 + 1 - 2)(t_{j+1} - t_j)^2 = 2f''(W(t_j))(t_{j+1} - t_j)^2
\end{aligned}$$

where $\mathbb{E}[W^4] = 3\mathbb{E}[W^2]$ as W is a Gaussian process

$$\begin{aligned}
(ii) \quad \mathbb{E}\sum_{j=0}^{n-1} Z_j &= \mathbb{E}[Z_0 | \mathcal{F}(t_0)] + \dots + \mathbb{E}[Z_{n-1} | \mathcal{F}(t_{n-1})] \\
&= 0
\end{aligned}$$

$$\begin{aligned}
(iii) \quad \text{Var}\left[\sum_{j=0}^{n-1} Z_j\right] &= \mathbb{E}\left[\left(\sum_{j=0}^{n-1} Z_j\right)^2\right] - \mathbb{E}\left(\sum_{j=0}^{n-1} Z_j\right)^2 \\
&= \mathbb{E}\left[\left(\sum_{j=0}^{n-1} Z_j\right)^2\right] = \mathbb{E}\left[\sum_{i,j} Z_i Z_j\right] = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} \mathbb{E}[Z_i Z_j] \\
&= \mathbb{E}\left[\sum_{j=0}^{n-1} Z_j^2 + 2 \sum_{0 \leq i < j \leq n-1} Z_i Z_j\right] \\
&= \sum_{j=0}^{n-1} 2f''(W(t_j))(t_{j+1} - t_j)^2 + 2 \sum_{0 \leq i < j \leq n-1} \mathbb{E}[Z_i \mathbb{E}[Z_j | \mathcal{F}(t_j)]] \\
&= \sum_{j=0}^{n-1} 2f''(W(t_j))(t_{j+1} - t_j)^2
\end{aligned}$$

$$\text{So, } \lim_{\|\Pi\| \rightarrow 0} \text{Var}\left[\sum_{j=0}^{n-1} Z_j\right] = \lim_{\|\Pi\| \rightarrow 0} 2 \sum_{j=0}^{n-1} f''(W(t_j))(t_{j+1} - t_j)^2 = 0$$

$$4.15 \quad (i) \quad B_i = \sum_{j=1}^d \int_0^t \frac{V_{ij}(u)}{V_i(u)} dW_j(u)$$

a) Continuity: B_i is the sum of integral with respect to a

a) continuity continuous and Martingale function, so, B_i is and martingale continuous and a martingale

$$b) B_i(0) = 0$$

c) Since B_i is continue process, its quadratic variation

$$[B_i]_t = \int_0^t d[B_i]_s = \int_0^t \left(\sum_{j=1}^d \frac{V_{ij}^2(s)}{V_i^2(s)} \right) ds$$

$$= \int_0^t 1 \cdot ds = t$$

Using Lévy's characterization, it's a Brownian motion.

$$(ii) \quad dB_i(u) = \sum_{j=1}^d \frac{V_{ij}(u)}{V_i(u)} dW_j(u)$$

$$dB_i(t) dB_j(t) = \sum_{k=1}^d \frac{V_{ik}(t)}{V_i(t)} \sum_{l=1}^d \frac{V_{jl}(t)}{V_j(t)} dW_k(t) dW_l(t)$$

$$= \sum_{k=1}^d \frac{V_{ik}(t) V_{jk}(t)}{V_i(t) V_j(t)} dt + o(dt)$$

$$= \rho_{ij}(t) dt$$

$$\text{where } \rho_{ij}(t) = \frac{\sum_{k=1}^d V_{ik}(t) V_{jk}(t)}{V_i(t) V_j(t)}$$

5.1

$$(i) dX_t = \pi_t dW_t + (\alpha_t - R_t - \frac{1}{2} \sigma_t^2) dt$$

$$f: x \mapsto \sin e^x \quad \frac{\partial f}{\partial x} = f \quad \frac{\partial^2 f}{\partial x^2} = f$$

$$df(x) = \frac{\partial f}{\partial x}(x) dx + \frac{1}{2} \frac{\partial^2 f}{\partial x^2}(x) dx^2$$

$$\begin{aligned} df(X_t) &= f(X_t) \left(\pi_t dW_t + (\alpha_t - R_t - \frac{1}{2} \sigma_t^2) dt \right) + \frac{1}{2} f(X_t) \sigma_t^2 dt \\ &= f(X_t) [(\alpha_t - R_t) dt + \pi_t dW_t] \end{aligned}$$

Because $f(X_t) = D_t S_t \quad df(X_t) = D_t S_t \pi_t [\Theta dt + dW_t]$

$$(ii) dS_t = \alpha_t S_t dt + \pi_t S_t dW_t$$

$$dD_t = -R_t D_t dt \Rightarrow D_t = e^{-\int_0^t R_s ds}$$

$$\begin{aligned} d(D_t S_t) &= D_t dS_t + S_t dD_t + dD_t dS_t \\ &= D_t dS_t + (S_t \Theta - R_t D_t dt) \end{aligned}$$

$dD_t dS_t = d[D, S]_t$ since D_t is a FV process, S is a semimartingale, $d[D, S]_t = 0$

$$\text{So, } d(D_t S_t) = D_t dS_t + S_t dD_t$$

$$= D_t (\alpha_t S_t dt + \pi_t S_t dW_t) - R_t D_t S_t dt$$

$$= (\alpha_t - R_t) D_t S_t dt + D_t \pi_t S_t dW_t$$

$$= D_t [(\alpha_t - R_t) S_t dt + \pi_t S_t dW_t]$$

$$= \pi_t D_t S_t [\Theta dt + dW_t]$$

5.2 risk-neutral pricing formula

$$D_t V_t = \tilde{E}[D_T V_T | \mathcal{F}_t]$$

Preliminary

$$1) \tilde{E}[\cdot] = E[Z_t \cdot]$$

$$2) \text{For any } \mathcal{F}_t\text{-measurable variable } Y \quad \tilde{E}[Y] = E[Z_t Y]$$

3) Let Y be an \mathcal{F}_t -measurable random variable

$$\tilde{E}[Y | \mathcal{F}_s] = \frac{1}{Z_s} E[Y Z_t | \mathcal{F}_s] = E[Y \frac{d\tilde{P}}{dP}| \mathcal{F}_s]$$

In this case $D_T V_T$ is \mathcal{F}_T -measurable, using Preliminary 3)

$$\tilde{E}[D_T V_T | \mathcal{F}_t] = E[D_T V_T Z_T | \mathcal{F}_t] \frac{1}{Z_t}$$

$$\text{So, } D_t V_t Z_t = E[D_T V_T Z_T | \mathcal{F}_t]$$

$$5.3. (ii) C(t, x) = \tilde{E}[e^{-rT} (S_T - k)^+]$$

$$\frac{\partial C}{\partial x} = \tilde{E}[e^{-rx} \frac{\partial}{\partial x} (S_T - k)^+]$$

$$\begin{aligned} \text{In risk neutral measure} &= \tilde{E}[e^{-rx} 1_{(x>k)}] \quad dS_T = r S_T dt + \sigma S_T d\tilde{W}_T \\ &\Rightarrow S_T = S_0 \exp \left(\int_0^T r ds + \int_0^T \sigma d\tilde{W}_s - \frac{1}{2} \int_0^T \sigma^2 ds \right) \\ &= S_0 \exp \left(\int_0^T (r - \frac{1}{2}\sigma^2) ds + \int_0^T \sigma d\tilde{W}_s \right) \\ &= x \exp \left(\int_0^T (r - \frac{1}{2}\sigma^2) ds + \sigma \tilde{W}_T \right) \end{aligned}$$

$$\frac{\partial}{\partial x} C(t, x) = \tilde{E}[e^{-rx} (S_T - k)^+ 1_{S_T > k}]$$

$$\text{Then } \frac{\partial C(t, x)}{\partial x} = \tilde{E}[e^{-rx} \frac{\partial}{\partial x} (x \exp((r - \frac{1}{2}\sigma^2)T + \sigma \tilde{W}_T - k)) 1_{S_T > k}]$$

$$\frac{\partial}{\partial x} (S_T - K)^+ = \mathbb{1}_{S_T > K} \frac{\partial S_T}{\partial x} = \mathbb{1}_{S_T > K} \frac{\partial}{\partial x} \left[x \exp((r - \frac{1}{2}\sigma^2)T + \sigma \tilde{W}_T) \right]$$

$$= \mathbb{1}_{S_T > K} \exp\left[(r - \frac{1}{2}\sigma^2)T + \sigma \tilde{W}_T\right]$$

$$\frac{\partial c(0, x)}{\partial x} = \tilde{E} [e^{-rx} \mathbb{1}_{S_T > K} \exp\left[(r - \frac{1}{2}\sigma^2)T + \sigma \tilde{W}_T\right]]$$

$$= \tilde{E} [e^{rt} \mathbb{1}_{S_T > K} \exp\left[\phi - \frac{1}{2}\sigma^2 T + \sigma \tilde{W}_T\right]]$$

$$= e^{rt} e^{-\frac{\sigma^2}{2}T} \tilde{E} [\mathbb{1}_{S_T > K} \exp(\sigma \tilde{W}_T)]$$

here $S_T = x \exp((r - \frac{1}{2}\sigma^2)T + \sigma \tilde{W}_T) > K$

 $\Leftrightarrow (r - \frac{1}{2}\sigma^2)T + \sigma \tilde{W}_T > \ln \frac{K}{x}$

$$-\frac{\tilde{W}_T}{T} < \frac{\ln \frac{K}{x} + (r - \frac{1}{2}\sigma^2)T}{\sigma T}$$

Define random variable $Z = -\frac{\tilde{W}_T}{\sqrt{T}} \sim N(0, 1)$, $d_- = \frac{\ln \frac{K}{x} + (r - \frac{1}{2}\sigma^2)T}{\sigma \sqrt{T}}$

$$\frac{\partial c(0, x)}{\partial x} = e^{-\frac{r^2}{2}T} \int_0^{d_-} \exp(-\frac{r^2}{2T}z) \frac{e^{-\frac{z^2}{2}}}{\sqrt{2\pi}} dz$$

$$= e^{-\frac{r^2}{2}T} \int_0^{d_-} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2 + 2r\sqrt{T}z + r^2T}{2}} e^{\frac{r^2T}{2}} dz$$

$$= \int_0^{d_-} \frac{1}{\sqrt{2\pi}} e^{-\frac{(z + r\sqrt{T})^2}{2}} dz$$

$$d_+ = d_- + \sigma \sqrt{T}$$

$$= \int_0^{d_+} \frac{1}{\sqrt{2\pi}} e^{-\frac{(z + r\sqrt{T})^2}{2}} dz$$

$$= N(d_+)$$

$$(ii) \quad \hat{W}_t = \tilde{W}_t - \sigma t$$

$$[X_t, \tilde{W}_t] = \sigma t, \quad \text{let } X_t = \sigma \tilde{W}_t$$

Girsanov's Theorem: $\frac{d\hat{P}}{dP|_{\mathcal{F}_t}} = E(X_t) = \exp\left(X_t - X_0 - \frac{1}{2}[X]_t\right)$

$$= \exp\left(\sigma \tilde{W}_t - \frac{1}{2}\sigma^2 t\right)$$

In measure \hat{P} , \hat{W} is a Brownian motion

$$\text{Moreover, } \frac{\partial}{\partial x} c(t, x) = \hat{E}\left[1_{S_T > K} \exp(\sigma \tilde{W}_T)\right] e^{-\frac{\sigma^2}{2} T}$$

$$= \hat{E}\left[\frac{d\hat{P}}{dP|_{\mathcal{F}_T}} 1_{S_T > K} \exp(\sigma \tilde{W}_T)\right]$$

$$\hat{P}(S_T > K) = \hat{E}[1_{S_T > K}]$$

$$= \hat{E}\left[1_{S_T > K} \frac{d\hat{P}}{dP|_{\mathcal{F}_T}}\right] = \hat{E}\left[1_{S_T > K} \exp(\sigma \tilde{W}_T - \frac{1}{2}\sigma^2 T)\right]$$

$$= \frac{\partial c}{\partial x}(0, x)$$

$$(iii) \quad S_T = x \exp\left((r - \frac{1}{2}\sigma^2)T + \sigma \tilde{W}_T\right)$$

$$= x \exp\left((r + \frac{\sigma^2}{2})T + \sigma \hat{W}_T\right)$$

$$S_T > K \Rightarrow (\frac{\sigma^2}{2} + r)T + \sigma \hat{W}_T > \ln \frac{K}{x} \Rightarrow \frac{\hat{W}_T}{\sigma T} < \frac{\ln \frac{K}{x} + (\frac{\sigma^2}{2} + r)T}{\sigma T} = c$$

$$\hat{P}(S_T > K) = \hat{E}[1_{S_T > K}] = \int_0^{d+} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz = N(d+)$$

SPE

J.4

$$\frac{dS_t}{S_t} = r_t dt + \sigma_t d\tilde{W}_t$$

$$dD_t = -r_t D_t dt$$

$$c(0, x) = \tilde{E} [D_T (S_T - K)^+]$$

$$(i) \quad dS_t = S_t (r_t dt + \sigma_t d\tilde{W}_t) = S_t dX_t$$

$$\text{Let } dX_t = r_t dt + \sigma_t d\tilde{W}_t$$

Then, using Ito's exponential

$$\begin{aligned} S_t &= \exp \left(X_t - X_0 - \frac{1}{2} [X]_t \right) \\ &= S_0 \exp \left(\int_0^t r_u du + \int_0^t \sigma_u d\tilde{W}_u - \frac{1}{2} \int_0^t \sigma_u^2 du \right) \\ &= S_0 \exp \left(\int_0^t \left(r_u - \frac{\sigma_u^2}{2} \right) du + \int_0^t \sigma_u d\tilde{W}_u \right) \end{aligned}$$

$$\text{Let } X_t = \int_0^t \left(r_u - \frac{\sigma_u^2}{2} \right) du + \int_0^t \sigma_u d\tilde{W}_u$$

The first term is a constant

The second term is a Gaussian random variable
whose distribution satisfies: $N(0, \int_0^t \sigma_u^2 du)$

Then, X_t is a normal random variable

$$X_t \sim N \left(\int_0^t \left(r_u - \frac{\sigma_u^2}{2} \right) du, \int_0^t \sigma_u^2 du \right)$$

(ii) In the case, r_t , σ_t is not constant but deterministic

Risk-neutral pricing formula

$$c(0, x) = \tilde{E} [D_T (S_T - K)^+] \\ = \int D_T (S_T - K)^+ I_{S_T > K} d\tilde{\pi}_T P(X_T)$$

$$S_T > K \Rightarrow S_0 \exp \left(\int_0^T (r_u - \frac{\sigma_u^2}{2}) du + \int_0^T \sigma_u d\tilde{W}_u \right) > K$$

$$X_T = \int_0^T (r_u - \frac{\sigma_u^2}{2}) du + \int_0^T \sigma_u d\tilde{W}_u > \ln \frac{K}{S_0}$$

$$X_T \sim N \left(\int_0^T (r_u - \frac{\sigma_u^2}{2}) du, \sqrt{\int_0^T \sigma_u^2 du} \right)$$

$$c(0, x) = \int_{\ln \frac{K}{S_0}}^{+\infty} D_T \exp \left(S_0 e^{x+} - K \right) \frac{e^{-\frac{(x - \int_0^T (r_u - \frac{\sigma_u^2}{2}) du)^2}{2 \int_0^T \sigma_u^2 du}} dx$$

$$\text{Let } \bar{r} = \frac{1}{T} \int_0^T r_u dt$$

$$\bar{\sigma} = \sqrt{\frac{1}{T} \int_0^T \sigma_u^2 du}$$

$$Z = - \frac{X_T - \int_0^T (r_u - \frac{\sigma_u^2}{2}) du}{\sqrt{\int_0^T \sigma_u^2 du}} \sim N(0, 1) \quad Z = - \frac{X_T - T\bar{r} + \int_0^T \frac{\sigma_u^2}{2} du}{\sqrt{T \bar{\sigma}^2}}$$

$$c(0, x) = S_0 e^{x+} > K \Rightarrow -\bar{r}\bar{\sigma}Z + T\bar{r} - \int_0^T \frac{\sigma_u^2}{2} du > \ln \frac{K}{S_0}$$

$$\Rightarrow Z < \frac{\ln \frac{S_0}{K} + T\bar{r} - \int_0^T \frac{\sigma_u^2}{2} du}{\bar{r}\bar{\sigma}}$$

$$D(T) = e^{-\int_0^T r_u du} = e^{-\bar{r}T}$$

$$c(0, x) = \tilde{E}[D(T)(S_T - K)^+]$$

$$= \tilde{E}[D(T)(S_0 e^{x_T} - K)^+] \quad -\bar{r}\bar{\sigma}Z + \left(r - \frac{\bar{\sigma}^2}{2}\right)T$$

$$= \tilde{E}[D(T) \left\{ S_0 \exp\left(-\bar{r}\bar{\sigma}Z + T\bar{r} - \int_0^T \frac{\bar{\sigma}u}{2} du\right) - K \right\}^+]$$

$$= \cancel{D(T)} \int_{-\infty}^{\frac{1}{\bar{r}\bar{\sigma}} \left[\ln \frac{S_0}{K} + \left(r - \frac{\bar{\sigma}^2}{2}\right)T \right]} \left(S_0 \exp\left(-\bar{r}\bar{\sigma}Z + \left(r - \frac{\bar{\sigma}^2}{2}\right)T\right) - K \right) \frac{e^{-\frac{z^2}{2}}}{\sqrt{2\pi}} dz$$

Comparing with BSM formula with constant rate r and volatility σ .

$$c(0, x) = e^{-r} \int_{-\infty}^{\frac{1}{\bar{r}\bar{\sigma}} \left[\ln \frac{S_0}{K} + \left(r - \frac{\bar{\sigma}^2}{2}\right)T \right]} \left(S_0 \exp\left(-\bar{r}\bar{\sigma}Z + \left(r - \frac{\bar{\sigma}^2}{2}\right)T\right) - K \right) \frac{e^{-\frac{z^2}{2}}}{\sqrt{2\pi}} dz$$

Only replace r with $\bar{r} = \frac{1}{T} \int_0^T r_u du$

replace T with $\bar{T} = \sqrt{\frac{1}{T} \int_0^T \sigma_u^2 du}$