

$$dS_t = \mu S_t dt + \sigma S_t dW_t \text{ under } P$$

$$v(T, S_T) = h(S_T)$$

For European call $h(S_T) = (S_T - K)^+$
 of $v(t, S_t)$ is the price of the derivative security at time t

$$v(t, S_t) = \tilde{E}(e^{-r(T-t)} h(S_T) | \mathcal{F}_t)$$

$$dS_t = rS_t dt + \sigma S_t d\tilde{W}_t$$

$$\text{Portfolio } (\pi) = v(t, S_t) + \Delta(t) S_t$$

$$d\pi = dv(t, S_t) + \Delta(t) dS_t$$

$$= \frac{\partial v}{\partial t}(t, S_t) dt + \frac{\partial v}{\partial S} dS_t + \frac{1}{2} \frac{\partial^2 v}{\partial S^2} (dS_t)^2 + \Delta(t) dS_t$$

$$= \left\{ \frac{\partial v}{\partial t} + \frac{\partial v}{\partial S} \mu S_t + \frac{1}{2} \frac{\partial^2 v}{\partial S^2} \sigma^2 S_t^2 + \Delta(t) \mu S_t \right\} dt$$

$$+ \left\{ \frac{\partial v}{\partial S} \sigma S_t + \Delta(t) \sigma S_t \right\} dW_t$$

$$\Delta(t) \sigma S_t + \frac{\partial v}{\partial S}(t, S_t) \sigma S_t = 0$$

$$\Rightarrow \Delta(t) = -\frac{\partial v}{\partial S}(t, S_t)$$

$$d\pi = r\pi dt$$

$$= r(v(t, S_t) - \frac{\partial v}{\partial S}(t, S_t) S_t) dt$$

$$d\pi = \left\{ \frac{\partial v}{\partial t} + \frac{\partial v}{\partial s} \mu s(t) + \frac{1}{2} \frac{\partial^2 v}{\partial s^2} \sigma^2 s^2(t) - \frac{\partial v}{\partial s} \sigma s(t) \right\} dt \quad (2)$$

$$= r \left(v(t, s(t)) - \frac{\partial v}{\partial s} (t, s(t)) s(t) \right) dt$$

$$\Rightarrow \frac{\partial v}{\partial t} + r s(t) \frac{\partial v}{\partial s} (t, s(t)) + \frac{1}{2} \sigma^2 s^2(t) \frac{\partial^2 v}{\partial s^2} = r v(t, s(t))$$

$$v(t, s(t)) = h(s(t))$$

~~done~~

$$\frac{\partial F}{\partial t} (t, x, y) + \frac{1}{2} \sigma^2 \frac{\partial^2 F}{\partial x^2} (t, x, y) + \frac{1}{2} \delta^2 \frac{\partial^2 F}{\partial y^2} (t, x, y) = 0$$

$$F(t, x, y) = xy, \quad F(t, x, y)$$

$$dx_t = \sigma dW_t^1$$

$$dx_t = \sigma dW_t^1$$

$$dx_t = a dt + b dW_t^1$$

$$W_t^1 \perp W_t^2$$

$$dy_t = \delta dW_t^2$$

$$dy_t = r dt + s dW_t^2$$

$$dF(t, x_t, y_t) = \frac{\partial F}{\partial t} dt + \frac{\partial F}{\partial x} dx_t + \frac{\partial F}{\partial y} dy_t + \frac{1}{2} \frac{\partial^2 F}{\partial x^2} (dx_t)^2 + \frac{1}{2} \frac{\partial^2 F}{\partial y^2} (dy_t)^2 + \frac{\partial^2 F}{\partial x \partial y} dx_t dy_t$$

$$= \left\{ \frac{\partial F}{\partial t} + a \frac{\partial F}{\partial x} (t, x_t, y_t) + \frac{\partial F}{\partial y} (t, x_t, y_t) + \frac{1}{2} \frac{\partial^2 F}{\partial x^2} b^2 \right.$$

$$\left. + \frac{1}{2} \frac{\partial^2 F}{\partial y^2} s^2 \right\} dt + \text{Martingale terms}$$

$$a = 0, \quad b = \sigma, \quad r = 0, \quad s = \delta$$

$$dF(t, x_t, y_t) = \left\{ \frac{\partial F}{\partial t} + \frac{1}{2} \sigma^2 \frac{\partial^2 F}{\partial x^2}(t, x_t, y_t) + \frac{1}{2} \delta^2 \frac{\partial^2 F}{\partial y^2}(t, x_t, y_t) \right\} dt \quad (3)$$

+ Martingale terms

$$dF(t, x_t, y_t) = \text{---} dW_t^1 + \text{---} dW_t^2$$

$$F(T, x_T, y_T) - F(t, x_t, y_t) = \int_t^T \text{---} dW_s^1 + \int_t^T \text{---} dW_s^2$$

$$F(t, x_t, y_t) = E(F(T, x_T, y_T) | \mathcal{F}_t)$$

$$F(t, x_t, y_t) = E(x(T) y(T) | \mathcal{F}_t) = x(t) y(t)$$

$$dx_t = \sigma dW_t^1 \quad x_t - x_0 = \int_0^t \sigma dW_s^1 \Rightarrow x_t \sim N(x_0, \sigma^2 t)$$

$$dy_t = \delta dW_t^2$$

~~$$d(x(t)y(t)) = x(t)dy(t) + y(t)dx(t) + dx(t)dy(t)$$~~

~~$$= y(t)dx(t)$$~~

$$x_T - x_t = \int_t^T \sigma dW_s^1 \Rightarrow x_T \sim N(x_t, \sigma^2 (T-t))$$

$$y(T) \sim N(y(t), \delta^2 (T-t))$$

x & y are independent

$$x_T = x_t + \sigma (W_T^1 - W_t^1)$$

$$y_T = y_t + \delta (W_T^2 - W_t^2)$$

$$\frac{\partial F}{\partial t} + \mu(t, x) \frac{\partial F}{\partial x} + \frac{1}{2} \sigma^2(t, x) \frac{\partial^2 F}{\partial x^2} + \text{~~0000~~} = -rF$$

$$F(t, x) = \phi(x)$$

$$dx(t) = a dt + b dW(t)$$

$$dF(t, x_t) = \frac{\partial F}{\partial t} dt + \frac{\partial F}{\partial x} dx_t + \frac{1}{2} \frac{\partial^2 F}{\partial x^2} (dx_t)^2$$

$$= \left(\frac{\partial F}{\partial t} + a \frac{\partial F}{\partial x} + \frac{1}{2} b^2 \frac{\partial^2 F}{\partial x^2} \right) dt + \text{Martingale term}$$

$$a = \mu(t, x_t) \quad b = \sigma(t, x(t))$$

$$dx(t) = \mu(t, x_t) dt + \sigma(t, x(t)) dW(t)$$

$$dF(t, x_t) = -rF(t, x_t) dt + \sigma(t, x(t)) \frac{\partial F(t, x(t))}{\partial x} dW_t$$

$$d e^{rt} F(t, x_t) = e^{rt} dF(t, x_t) + r e^{rt} dt F(t, x(t)) + \frac{dF(t, x(t)) d e^{rt}}{0}$$

$$d e^{rt} F(t, x_t) = e^{rt} \left(-rF(t, x_t) dt + \sigma(t, x(t)) \frac{\partial F(t, x(t))}{\partial x} dW_t \right) + r e^{rt} F(t, x(t)) dt$$

$$= e^{rt} \sigma(t, x(t)) \frac{\partial F}{\partial x} dW(t)$$

$$e^{rT} F(T, x_T) - e^{rt} F(t, x_t) = \int_t^T e^{rs} \sigma(s, x(s)) \frac{\partial F}{\partial x} dW(s)$$

Taking conditional Expectation on both sides, we get

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$$e^{rt} F(t, x_t) = E(e^{rT} F(T, x_T) | \mathcal{F}_t)$$

$$F(t, x_t) = E(e^{r(T-t)} \phi(x_T) | \mathcal{F}_t)$$

Black Scholes PDE

$$\frac{\partial V}{\partial t} + rS \frac{\partial V}{\partial S} + \frac{1}{2} \sigma^2 S^2 \frac{\partial^2 V}{\partial S^2} = rV$$

$$V(T, S) = (S - K)^+ \text{ or } h(S) \text{ more generally}$$

$$dS(t) = a dt + b d\tilde{W}_t$$

$$dV(t, S(t)) = \frac{\partial V}{\partial t} dt + \frac{\partial V}{\partial S} dS(t) + \frac{1}{2} \frac{\partial^2 V}{\partial S^2} (dS(t))^2$$

$$= \left\{ \frac{\partial V}{\partial t} + a \frac{\partial V}{\partial S} + \frac{1}{2} b^2 \frac{\partial^2 V}{\partial S^2} \right\} dt$$

$$+ \frac{\partial V}{\partial S} b d\tilde{W}_t$$

$$a = rS(t) \quad b = \sigma S(t)$$

$$dV(t, S(t)) = \left\{ \frac{\partial V}{\partial t} + rS(t) \frac{\partial V}{\partial S}(t, S(t)) + \frac{1}{2} \sigma^2 S(t)^2 \frac{\partial^2 V}{\partial S^2}(t, S(t)) \right\} dt$$

$$+ \frac{\partial V}{\partial S} \sigma S(t) d\tilde{W}_t$$

$$= rV(t, S(t)) dt + \frac{\partial V}{\partial S} \sigma S(t) d\tilde{W}_t$$

$$d e^{-rt} V(t, S(t)) = -r e^{-rt} V(t, S(t)) dt + e^{-rt} dV(t, S(t))$$

$$= e^{-rt} \sigma S(t) \frac{\partial V}{\partial S}(t, S(t)) d\tilde{W}_t$$

$$e^{-rT} V(T, S(T)) - e^{-rt} V(t, S(t)) = \int_t^T e^{-ru} \sigma S(u) \frac{\partial V(t, S(u))}{\partial S} d\tilde{W}_u \quad (6)$$

Taking conditional Expectation on both sides we get

$$e^{-rt} V(t, S(t)) = \tilde{E} \left(e^{-rT} V(T, S(T)) \mid \mathcal{F}_t \right)$$

$$V(t, S(t)) = \tilde{E} \left(e^{-r(T-t)} V(T, S(T)) \mid \mathcal{F}_t \right)$$

$$V(t, S(t)) = \tilde{E} \left(e^{-r(T-t)} h(S(T)) \mid \mathcal{F}_t \right)$$

$$dS(t) = rS(t) dt + \sigma S(t) d\tilde{W}(t)$$

$$d \ln S_t = \left(r - \frac{\sigma^2}{2} \right) dt + \sigma d\tilde{W}(t)$$

$$\Rightarrow \ln S_T = \ln S_t + \left(r - \frac{\sigma^2}{2} \right) (T-t) + \sigma (\tilde{W}(T) - \tilde{W}(t))$$

$$\Rightarrow \ln S_T \sim N(m, v^2)$$

$$\text{where } m = \ln S_t + \left(r - \frac{\sigma^2}{2} \right) (T-t)$$

$$v^2 = \sigma^2 (T-t)$$

$$P(S_T = x, x+dx) = \frac{1}{\sqrt{2\pi v^2} x} e^{-\frac{(\ln x - m)^2}{2v^2}}$$

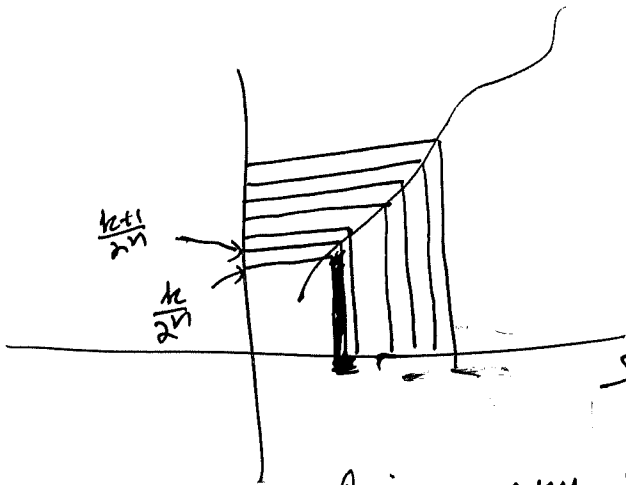
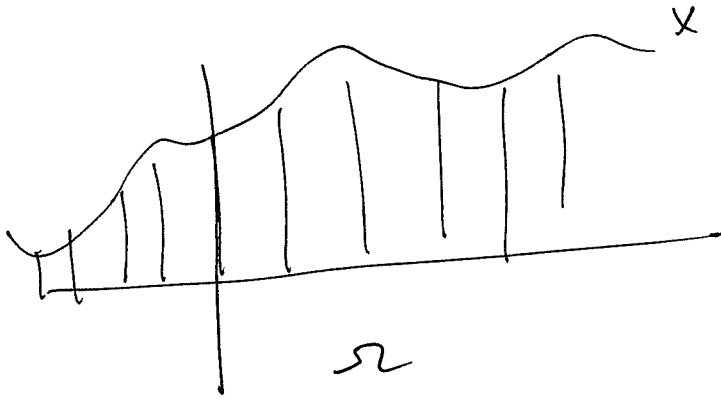
$$V(t, S(t)) = \int_0^{\infty} e^{-r(T-t)} h(x) \frac{1}{\sqrt{2\pi v^2} x} e^{-\frac{(\ln x - m)^2}{2v^2}} dx$$

Girsanov's theorem & change of Measure

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change of Measure:

$$E(X) = \int X dP \quad X: \Omega \rightarrow \mathbb{R}$$



Given any set (almost) in Ω , $P(\Omega) = 1$

$$P(E) = \int E dP$$

$$E = \left\{ \omega \in \Omega \mid f(\omega) \in \left[\frac{k}{2^n}, \frac{k+1}{2^n} \right) \right\}$$

$$\frac{k}{2^n} P(E)$$

Probability Measures:

if you have a +ve Random variable whose $E^P(X) = 1$

$$\int_{\Omega} X dP = 1 \quad Q(A) = \int_A X dP \quad A \subseteq \Omega$$

$$Q(\Omega) = \int_{\Omega} X dP = E^P(X) = 1$$

$$Q(A) = \int X dP \quad X \geq 0 \quad \text{with } E^P(X) = 1 \quad (8)$$

$$dQ = X dP$$

$$\frac{dQ}{dP} = X$$

$X \rightarrow$ Radon Nikodym derivative

$$Z_t = e^{\frac{M_t - \langle M \rangle_t}{2}} \quad M_0 = 0$$

$$Z_t = e^{\int_0^t \theta_s dW_s - \frac{1}{2} \int_0^t \theta_s^2 ds}$$

$$E(Z_t) = 1$$

$$\text{Fix: } T \quad E^P(Z_T) = 1$$

$$Q(A) = \int_A Z_T dP$$

$$Q(\Omega) = \int_{\Omega} Z_T dP = E^P(Z_T) = 1$$

$$dQ = Z_T dP$$

$$E^Q(Y) = \int_{\Omega} Y dQ$$

$$= \int Y Z_T dP$$

$$= E^P(Y Z_T)$$

$$E^Q(Y) = E^P(Y Z_T)$$

$$E^P(Y) = E^Q\left(\frac{Y}{Z_T}\right)$$

$$E^Q\left(\frac{Y}{Z_T}\right) = \int_{\Omega} \frac{Y}{Z_T} dQ \quad dQ$$

$$= \int_{\Omega} \frac{Y}{Z_T} Z_T dP$$

$$= E^P(Y)$$

⑨.

Girsanov's theorem:

$$d\tilde{W}_t = \theta(t) dt + dW_t \quad W_t \text{ is } P \text{ Brownian Motion}$$

\tilde{W}_t is not a Brownian Motion under P

$$Q(A) = \int_A Z_T dP$$

$$\text{where } Z_t = e^{\int_0^t -\theta(s) dW_s - \frac{1}{2} \int_0^t \theta^2(s) ds}$$

$$Z_T = e^{-\int_0^T \theta(s) dW_s - \frac{1}{2} \int_0^T \theta^2(s) ds}$$

Under Q

\tilde{W}_t is a Brownian Motion for $0 \leq t \leq T$

(Ω, \mathcal{F}, P) \mathcal{F}_T

(Ω, \mathcal{F}, Q) \mathcal{F}_T

$$E^Q(Y) = E^P(Y Z_T) \quad dQ = Z_T dP \quad (10)$$

$$E^P(Y) = E^Q\left(\frac{Y}{Z_T}\right)$$

||

$$\frac{dQ}{dP} = Z_T \Rightarrow \frac{dP}{dQ} = \frac{1}{Z_T}$$

$$\int Y \frac{dP}{dQ} dQ = \int \frac{Y}{Z_T} dQ$$

Bayes theorem:

Given any Random variable X which is F_T measurable.

$$E^Q(X | F_t) = \frac{1}{Z_t} E^P(X Z_T | F_t) \quad \left. \vphantom{E^Q(X | F_t)} \right\} \text{Bayes' Rules}$$

$$E^P(X | F_t) = Z_t E^Q\left(\frac{X}{Z_T} | F_t\right)$$

\tilde{M}_t is a Martingale under $Q \Leftrightarrow \tilde{M}_t Z_t$ is a P Martingale