

## Chapter 3 Continuous-Time Stochastic Processes

General Description of a continuous-time stochastic process

A collection of random variables

$$\{X_t; t \geq 0\}$$

For each  $t$ ,  $X_t$  is a RV.

$t$  represents time

There is a filtration or information structure

$\{\mathcal{F}_t, t \geq 0\}$ ,

$\mathcal{F}_t$  represents information from  $\{X_t, t \geq 0\}$

up to time  $t$ , Thus  $\mathcal{F}_s \subset \mathcal{F}_t, s \leq t$

may be interpreted as all the paths up to time  $t$ .

What is a path?

A scenario up to time  $t$ .

Example: Let  $S_t$  be the stock price at  $t$   
for  $0 \leq t \leq \infty$

A path up to time  $T$  is all the stock prices between time 0 and time  $T$ .

A special continuous-time stochastic process

The standard (Arithmetic) Brownian motion (BM)

p 48

(Wiener process)

$\{W_t; t \geq 0\}$

(i)  $W_t$  is continuous (has continuous paths)

No jumps in value

$$W_0 = 0$$

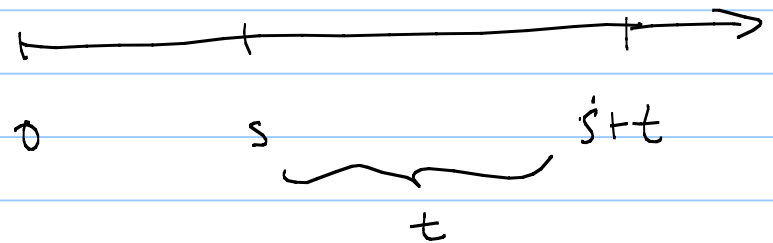
(ii) For a fixed  $t$ ,  $W_t \sim N(0, t)$

$$E(W_t) = 0, \quad \text{Var}(W_t) = t$$

(iii) Independent Increments

$$W_{s+t} = W_s + (W_{s+t} - W_s)$$

$\uparrow$  current                       $\uparrow$  increment



$W_{s+t} - W_s$  is independent of  $W_s$

Thus  $W_{s+t} - W_s \sim N(0, t)$

$\{W_t; t \geq 0\}$  with (i), (ii) and (iii)

is called the standard BM

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Ex 3.1 If  $Z \sim N(0, 1)$  and  $X_t = \sqrt{t} Z$

Is  $X_t$  a standard BM?

check (i), (ii) & (iii)

(i)  $X_t$  is continuous.  $X_0 = 0$   $Z = 0$ .

(ii)  $X_t \sim N(\mu, \sigma^2) = N(0, t)$

$E(X_t) = \sqrt{t} E(Z) = 0$ ,  $\text{Var}(X_t) = (\sqrt{t})^2 \text{Var}(Z) = t$

$$\begin{aligned} \text{(iii)} \quad X_{s+t} - X_s &= \sqrt{t+s} Z - \sqrt{s} Z \\ &= (\sqrt{t+s} - \sqrt{s}) Z \end{aligned}$$

$$\text{and } X_s = \sqrt{s} Z$$

$$\text{Cov}(X_s, X_{s+t} - X_s) = \text{Cov}(\sqrt{s} Z, (\sqrt{t+s} - \sqrt{s}) Z)$$

$$= \sqrt{s} (\sqrt{t+s} - \sqrt{s}) \text{Cov}(Z, Z)$$

$$= \sqrt{s} (\sqrt{t+s} - \sqrt{s}) \text{Var}(Z) = \sqrt{s} (\sqrt{t+s} - \sqrt{s}) \neq 0$$

Ex 3.2  $W_t$  and  $\tilde{W}_t$  are two independent standard  
BM's.  $-1 < \rho < 1$

Define

$$X_t = \rho W_t + \sqrt{1-\rho^2} \tilde{W}_t$$

Is  $X_t$  a std BM?

(i) Continuous  $X_0 = \rho W_0 + \sqrt{1-\rho^2} \tilde{W}_0 = 0 + 0 = 0$

(ii)  $X_t \sim N(\mu, \sigma^2) = N(0, t)$

$$E(X_t) = \rho E(W_t) + \sqrt{1-\rho^2} E(\tilde{W}_t) = \rho \times 0 + \sqrt{1-\rho^2} \times 0 = 0$$

$$\begin{aligned}
\text{Var}(X_t) &= \text{Var}(pW_t + \sqrt{1-p^2}\tilde{W}_t) \\
&= \text{Var}(pW_t) + \text{Var}(\sqrt{1-p^2}\tilde{W}_t) \\
&= p^2 \text{Var}(W_t) + (1-p^2) \text{Var}(\tilde{W}_t) \\
&= p^2 t + (1-p^2)t = t
\end{aligned}$$

$$\begin{aligned}
\text{(iii)} \quad X_{s+t} - X_s &= (pW_{s+t} + \sqrt{1-p^2}\tilde{W}_{s+t}) \\
&\quad - (pW_s + \sqrt{1-p^2}\tilde{W}_s) \\
&= p(W_{s+t} - W_s) + \sqrt{1-p^2}(\tilde{W}_{s+t} - \tilde{W}_s)
\end{aligned}$$



Independent of  $X_s = p W_s + \sqrt{1-p^2} \tilde{W}_s$  ? YES!

$X_t$  is a std BM. But  $X_t$  is correlated with  $W_t$   
and  $\text{cov}(X_t, W_t) = pt$

Other properties (P49)

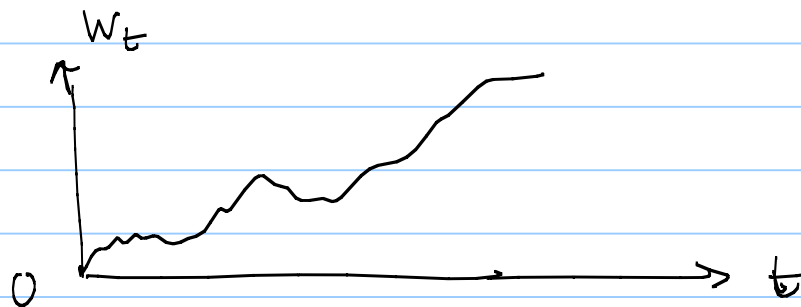
- Each path is not differentiable everywhere

$f(t)$

is differentiable

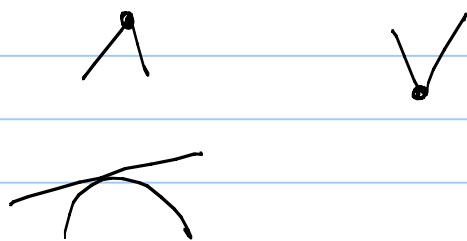
if  $f'(t)$

exists



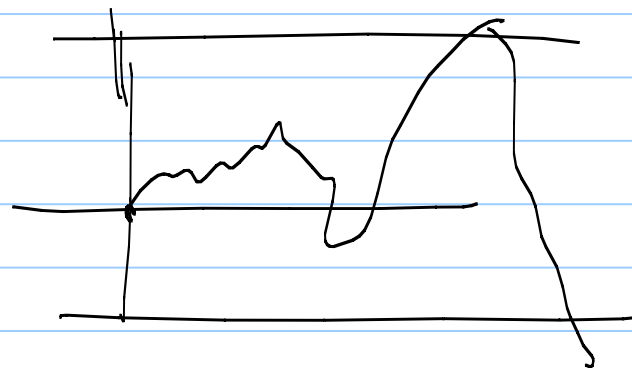
$$\lim_{\Delta t \rightarrow 0} \frac{f(t + \Delta t) - f(t)}{\Delta t} = f'(t)$$

The path takes sharp turn at any point

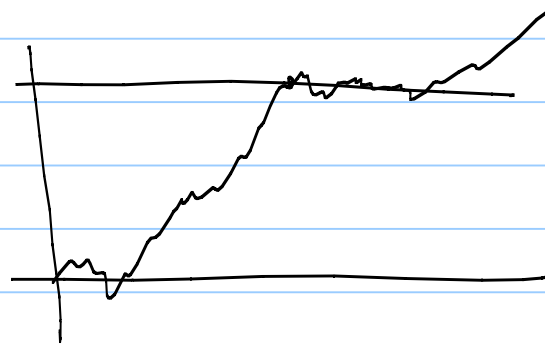


- A path will go everywhere.

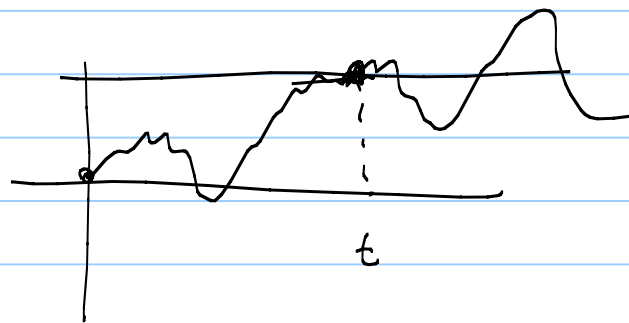
Covering  $(-\infty, \infty)$



- A path will oscillate intensively



- A path start at any future point all over again



General BM with drift  $\mu$  and volatility  $\sigma$

$X_t \sim$  General BM if

$$X_t = x_0 + \mu t + \sigma W_t$$

$x_0 =$  starting point



(i)  $X_t$  is continuous and  $X_0 = x_0$

(ii)  $X_t \sim N(x_0 + \mu t, \sigma^2 t)$  because

$$E(X_t) = x_0 + \mu t + \sigma E(W_t) = x_0 + \mu t$$

$$\text{Var}(X_t) = \text{Var}(\sigma W_t) = \sigma^2 \text{Var}(W_t) = \sigma^2 t.$$

(iii)  $X_{s+t} - X_s$  is independent of  $X_s$   
(independent increments)

$$\text{Since } X_{s+t} - X_s = \mu t + \sigma (W_{s+t} - W_s),$$

independent of  $X_0 + \mu s + \sigma W_s$

$$X_{s+t} - X_s \sim N(\mu t, \sigma^2 t)$$

P30 BM as stock model?

If it can be used, then

$$S_t = S_0 + \mu t + \sigma W_t$$

As a result,  $S_t < 0$  for any  $t$

because bullet point #2.

Ex 3.3  $P(S_T < 0) > 0$

Proof  $P(S_T < 0) = P(S_0 + \mu T + \sigma W_T < 0)$

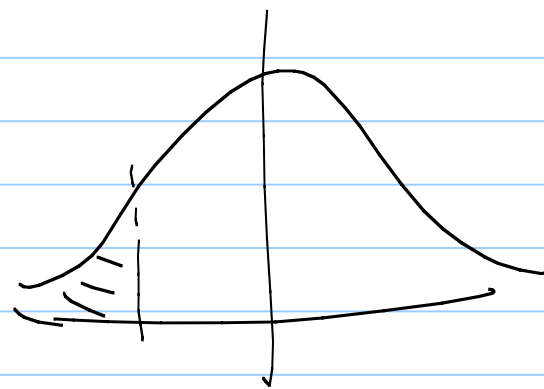
$$= P \left( W_T < \frac{-S_0 - \mu T}{\sigma} \right)$$

$$= P \left( \frac{W_T}{\sqrt{T}} < \frac{-S_0 - \mu T}{\sigma \sqrt{T}} \right)$$

$$= N \left( \frac{-S_0 - \mu T}{\sigma \sqrt{T}} \right) > 0$$

$$N(x) = \frac{1}{\sqrt{2\pi}} \int_0^x e^{-\frac{1}{2}y^2} dy$$

d.f. of  $N(0, 1)$



Use the geometric BM (GBM) as stock model

$$S_t = S_0 e^{\mu t + \sigma W_t}$$

$$\text{Let } x_0 = \ln S_0. \quad S_t = e^{x_0 + \mu t + \sigma W_t}$$

$$\left[ S_t = S_0 e^{\mu t + \sigma \sqrt{t} Z} \right] \text{ Wrong!!}$$

For fixed  $t$ ,  $S_t$  is lognormal

$$\text{and } E(S_t) = S_0 e^{(\mu + \frac{1}{2}\sigma^2)t}$$



## Section 3.2

- Deterministic Calculus p 52-54

### Differentiation

$f(t)$  is differentiable if

$\lim_{\Delta t \rightarrow 0} \frac{f(t+\Delta t) - f(t)}{\Delta t}$  exists and denoted  
by  $f'(t) = \frac{df}{dt}$

$f(t)$  is called a smooth function

### Integration

$$\int_a^b g(t) dt = \lim_{n \rightarrow \infty} \sum_{i=1}^n g\left(a + \frac{i}{n}(b-a)\right) \frac{b-a}{n}$$

Newton's Fundamental Theorem

$$f(b) - f(a) = \int_a^b f'(t) dt$$

Ordinary Differential Equations (ODE)

Example

$$a f''(t) + b f'(t) + c f(t) + d = 0, \quad f(0) = x_0$$

$$f'' = \frac{d^2 f}{dt^2}$$

$f(t)$  satisfying the above is called  
a solution of the ODE.

Partial Differential Equations (PDE)

$f(t, x)$ , more than one variable

It has two partial derivatives

$$\frac{\partial f}{\partial t} \quad \text{and} \quad \frac{\partial f}{\partial x}, \quad \frac{\partial^2 f}{\partial t^2}, \quad \frac{\partial^2 f}{\partial x^2}, \quad \frac{\partial^2 f}{\partial t \partial x}$$

$$\frac{\partial f}{\partial t} + a \frac{\partial^2 f}{\partial x^2} + b \frac{\partial f}{\partial x} + c f = 0 \quad (\text{PDE})$$

How to handle  $W_t$  ?

Can we have  $\frac{dW_t}{dt}$  ?

Stochastic calculus starts with integration

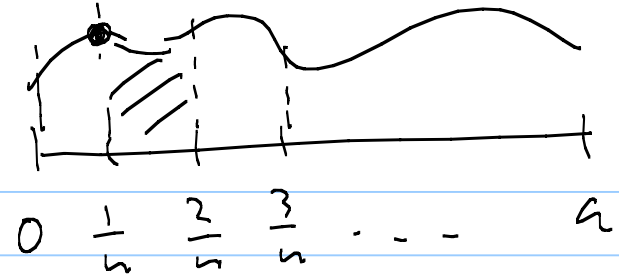
- Define stochastic integral with respect to  $W_t$   
(Ito integral)

For any given continuous-time stochastic process

$Y_t, t \geq 0$

Define  $\int_0^a Y_t dW_t = \lim_{n \rightarrow \infty} \sum_{i=1}^{\frac{a}{n}-1} Y_{\frac{i-1}{n}} \left[ W_{\frac{i}{n}} - W_{\frac{i-1}{n}} \right]$

limit always exists



Properties

$\int_0^a Y_t dW_t$  is a RV.

The mean

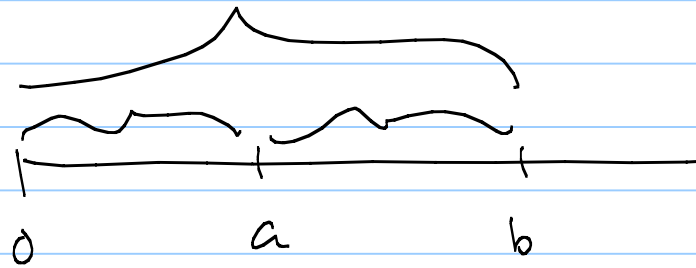
$$E \left\{ \int_0^a Y_t dW_t \right\} = 0$$

The variance

$$\begin{aligned}\text{Var} \left\{ \int_0^a Y_t dW_t \right\} &= E \left\{ \left[ \int_0^a Y_t dW_t \right]^2 \right\} \\ &= \int_0^a E(Y_t^2) dt\end{aligned}$$


$$\int_0^b Y_t dW_t = \int_0^a Y_t dW_t + \int_a^b Y_t dW_t$$

$$0 < a < b$$



## Stochastic Differential Equations (SDE)

$$X_t = X_0 + \int_0^t \mu_s ds + \int_0^t \sigma_s dW_s \quad \leftarrow \text{Real meaning}$$

$\mu_t, \sigma_t, t \geq 0$  are two stochastic processes 

$\mu_t$  = drift process,  $\sigma_t$  = volatility process

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Usually, it is written as

$$dX_t = \mu_t dt + \sigma_t dW_t \quad \leftarrow \text{convention}$$

There is an advantage of using the differential form:  
many rules apply

$X_t$  is called an Ito process.

$$\text{If } \mu_t = \mu(t, X_t), \quad \sigma_t = \sigma(t, X_t)$$

i.e

$$dX_t = \mu(t, X_t) dt + \sigma(t, X_t) dW_t$$

A differential equation (SDE)



$$2. \quad dX_t = \mu X_t dt + \sigma X_t dW_t$$

$$\mu_t = \mu X_t, \quad \sigma_t = \sigma X_t$$

What is  $X_t$ ?? (Later)

$X_t$  is a solution of the SDE with  
initial value  $x_0$



Examples.

$$\textcircled{1} \quad dX_t = \mu dt + \sigma dW_t, \quad X_0 = x_0$$

$$\Rightarrow X_t = x_0 + \int_0^t \mu ds + \int_0^t \sigma dW_s$$

$$= x_0 + \mu t + \sigma \int_0^t dW_s$$

$$= x_0 + \mu t + \sigma [W_t - W_0] = x_0 + \mu t + \sigma W_t$$

Brownian motion with initial value  $x_0$ ,  
drift  $\mu$  and volatility  $\sigma$ !

### 3.3. Ito's Lemma

Let  $X_t$  be a solution of the SDE

$$dX_t = \underbrace{\mu(t, X_t)}_{\mu_t} dt + \underbrace{\sigma(t, X_t)}_{\sigma_t} dW_t,$$

and  $g(t, x)$  is a deterministic function of  $t$  and  $x$ .

$Y_t = g(t, X_t)$  is a continuous process

Question: what SDE is  $Y_t$  satisfied?

$$dY_t = \left[ \frac{\partial}{\partial t} g(t, X_t) + \mu(t, X_t) \frac{\partial}{\partial x} g(t, X_t) + \frac{1}{2} [\sigma(t, X_t)]^2 \frac{\partial^2}{\partial x^2} g(t, X_t) \right] dt + \sigma(t, X_t) \frac{\partial}{\partial x} g(t, X_t) dW_t$$

$\frac{\partial}{\partial t} g(t, x)$  = partial derivative w.r.t.  $t$

$\frac{\partial}{\partial x} g(t, x)$  = partial derivative w.r.t.  $x$ .

p59  $g(t, x) = g(x)$

Example  $dX_t = \mu X_t dt + \sigma X_t dW_t$        $\mu_t = \mu X_t$

Let  $g(x) = \ln x \Rightarrow Y_t = \ln X_t$        $\sigma_t = \sigma X_t$

Apply Ito's Lemma

$$g'(x) = \frac{1}{x}, \quad g''(x) = -\frac{1}{x^2}$$

$$dY_t = \left[ \underbrace{\mu X_t \cdot \frac{1}{X_t}}_{\mu_t g'(X_t)} + \frac{1}{2} \underbrace{(\sigma X_t)^2 \left(-\frac{1}{X_t^2}\right)}_{\frac{1}{2} \sigma_t^2 g''(X_t)} \right] dt$$

$$+ (\sigma X_t) \cdot \frac{1}{X_t} dW_t \quad \leftarrow \quad \sigma_t g'(X_t)$$

$$dY_t = \left[ \mu - \frac{1}{2}\sigma^2 \right] dt + \sigma dW_t$$

$$Y_t = Y_0 + \left( \mu - \frac{1}{2}\sigma^2 \right) t + \sigma W_t$$

Since  $Y_t = \ln X_t$  ,  $Y_0 = \ln X_0$

$$\ln X_t = \ln X_0 + \left( \mu - \frac{1}{2}\sigma^2 \right) t + \sigma W_t$$

$$\Rightarrow X_t = X_0 e^{\left( \mu - \frac{1}{2}\sigma^2 \right) t + \sigma W_t} \quad \text{GBM!}$$

Can express a GBM stock price in two ways =

$$S_t = S_0 e^{(\mu - \frac{1}{2}\sigma^2)t + \sigma W_t}$$

OR

$$\frac{dS_t}{S_t} = \mu dt + \sigma dW_t$$

$\uparrow$  Instantaneous return  
 $\uparrow$  Instantaneous expected return  
 $\uparrow$  Instantaneous volatility

$$\begin{aligned}
 E(S_t) &= S_0 e^{[(\mu - \frac{1}{2}\sigma^2) + \frac{1}{2}\sigma^2]t} \\
 &= S_0 e^{\mu t}
 \end{aligned}$$

$\mu =$  expected return

$\mu - \frac{1}{2}\sigma^2$  is NOT!

### Exercise 3.5

$$dX_t = \mu_t X_t dt + \sigma_t X_t dW_t$$

Where  $\mu_t, \sigma_t$  are deterministic functions.

Try  $Y_t = \ln X_t$

$$dY_t = \left( \mu_t - \frac{1}{2} \sigma_t^2 \right) dt + \sigma_t dW_t$$

$$Y_t = Y_0 + \int_0^t \left( \mu_s - \frac{1}{2} \sigma_s^2 \right) ds + \int_0^t \sigma_s dW_s$$

$$\ln X_t = \ln X_0 + \int_0^t \left( \mu_s - \frac{1}{2} \sigma_s^2 \right) ds + \int_0^t \sigma_s dW_s$$



$$X_t = X_0 e^{\int_0^t [\mu_s - \frac{1}{2} \sigma_s^2] ds + \int_0^t \sigma_s dw_s}$$

$X_t$  is lognormal but not a GBM

This is a stock model to address the  
volatility smile.



\* Derivation of Ito's Lemma

Use the Taylor expansion!

$$\begin{aligned}
 dg(t, x) &= \\
 g(t+dt, x+dx) - g(t, x) &= \\
 &\cdot \left[ \frac{\partial}{\partial t} g(t, x) \right] dt + \left[ \frac{\partial}{\partial x} g(t, x) \right] dx \\
 &+ \underbrace{\frac{1}{2} \left[ \frac{\partial^2}{\partial t^2} g(t, x) \right] dt^2}_{0} + \underbrace{\left[ \frac{\partial^2}{\partial t \partial x} g(t, x) \right] dt dx}_{0} + \frac{1}{2} \left[ \frac{\partial^2}{\partial x^2} g(t, x) \right] (dx)^2
 \end{aligned}$$

+ higher order terms

Do the first-order approximation:

$$dY_t = dg(t, X_t)$$

$$= \left[ \frac{\partial}{\partial t} g(t, X_t) \right] dt + \left[ \frac{\partial}{\partial x} g(t, X_t) \right] dX_t$$

$$+ \frac{1}{2} \left[ \frac{\partial^2}{\partial x^2} g(t, X_t) \right] (dX_t)^2$$

$$dY_t = \left[ \frac{\partial}{\partial t} g(t, X_t) \right] dt + \left[ \frac{\partial}{\partial x} g(t, X_t) \right] (\mu_t dt + \sigma_t dW_t)$$

$$+ \frac{1}{2} \left[ \frac{\partial^2}{\partial x^2} g(t, X_t) \right] \sigma_t^2 dt$$

$$(\mu_t dt + \sigma_t dW_t)^2 = \mu_t^2 (dt)^2 + 2\mu_t \sigma_t dt dW_t + \sigma_t^2 (dW_t)^2$$

$$= \sigma_t^2 (dW_t)^2 = \sigma_t^2 dt$$

$$E(dW_t)^2 = E[W_{t+dt} - W_t]^2 = \text{Var}(W_{t+dt} - W_t) = dt$$

- Martingale.

A continuous process  $X_t$  is a martingale if for  $s < t$ ,

$$E(X_t | \mathcal{F}_s) = X_s$$

Think about a gambling scheme and

$X_t$  is the money at time  $t$

Martingale = fair game

Let  $X_t$  satisfy

$$dX_t = \mu_t dt + \sigma_t dW_t$$

$X_t$  is a martingale if  $\mu_t \equiv 0$  for all  $t \geq 0$

Example  $X_t = x_0 + \mu t + \sigma W_t$

$$dX_t = \mu dt + \sigma dW_t$$

$X_t$  is martingale if  $X_t = x_0 + \sigma W_t$ ; i.e.  $\mu = 0$

$$X_t = X_0 e^{(\mu - \frac{1}{2}\sigma^2)t + \sigma W_t}$$

GBM

$$dX_t = \mu X_t dt + \sigma X_t dW_t$$

$X_t$  = martingale if  $\mu X_t = 0 \iff \mu = 0$ .

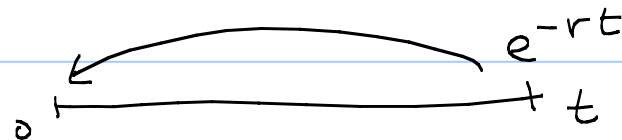
That is

$$X_t = X_0 e^{-\frac{1}{2}\sigma^2 t + \sigma W_t}$$

The present value (discounted value) of stock price

$$Z_t = e^{-rt} S_t$$

where  $S_t$  has GBM



$Z_t$  is the price evaluated at time 0

$$\begin{aligned} Z_t &= e^{-rt} S_0 e^{(\mu - \frac{1}{2}\sigma^2)t + \sigma W_t} \\ &= S_0 e^{(\mu - r - \frac{1}{2}\sigma^2)t + \sigma W_t} \end{aligned}$$

Risk-neutral valuation  $\Rightarrow Z_t$  is a martingale

$$\Rightarrow \mu - r = 0 \quad \text{i.e.}$$

$$S_t = S_0 e^{(r - \frac{1}{2}\sigma^2)t + \sigma W_t}$$

The product rule p62

Start with two Ito processes

$$dX_t = \mu_t dt + \sigma_t dW_t$$

$$dY_t = \nu_t dt + \rho_t dZ_t$$

$W_t$  and  $Z_t$  are two standard Brownian motions

The process  $X_t Y_t$  has

$$d(X_t Y_t) = X_t dY_t + Y_t dX_t + (dX_t)(dY_t)$$

Proof



$$d(X_t Y_t) = X_{t+dt} Y_{t+dt} - X_t Y_t$$

$$= X_{t+dt} Y_{t+dt} - X_{t+dt} Y_t - X_t Y_{t+dt} + X_t Y_t \\ + X_{t+dt} Y_t + X_t Y_{t+dt} - 2X_t Y_t$$

$$= (X_{t+dt} - X_t)(Y_{t+dt} - Y_t)$$

$$+ (X_{t+dt} - X_t) Y_t + X_t (Y_{t+dt} - Y_t)$$

$$= (dX_t)(dY_t) + (dX_t) Y_t + X_t (dY_t)$$

What is  $(dX_t)(dY_t)$

$$(dX_t)(dY_t) = [\mu_t dt + \sigma_t dW_t] [v_t dt + \rho_t (\rho dW_t + \sqrt{1-\rho^2} \tilde{W}_t)]$$

$$= \cancel{\mu_t v_t (dt)^2} + \cancel{\sigma_t v_t dt dW_t} + \cancel{\mu_t \rho_t \rho dt dW_t}$$

$$+ \cancel{\mu_t \rho_t \sqrt{1-\rho^2} dt d\tilde{W}_t}$$

$$+ \cancel{\sigma_t v_t dt dW_t} + \sigma_t \rho_t \rho \underbrace{(dW_t)(dW_t)}_{dt} + \cancel{\sigma_t \rho_t \sqrt{1-\rho^2} dW_t d\tilde{W}_t}$$

$$E(dW_t d\tilde{W}_t) = E(dW_t) E(d\tilde{W}_t) = 0 \times 0 = 0$$

$$(dX_t)(dY_t) = \sigma_t \rho_t \rho dt$$

$$d(X_t Y_t) = X_t dY_t + Y_t dX_t + \sigma_t \rho_t \rho dt$$

$\sigma_t, \rho_t$  are two volatilities.

$$\rho = \text{corr}(W_t, Z_t)$$

If  $Z_t = W_t, \rho = 1$

$$d(X_t Y_t) = X_t dY_t + Y_t dX_t + \sigma_t \rho_t dt$$

If  $Z_t = \tilde{W}_t, \rho = 0$

$$d(X_t Y_t) = X_t dY_t + Y_t dX_t$$

} P 62

# 2

} # 4

### Exercise 3.6

$S_t$  stock price with  $dS_t = \mu_t S_t dt + \sigma_t S_t dW_t$

$B_t = e^{-rt}$ , cash bond with  $B_0 = 1$

$Z_t = B_t^{-1} S_t = e^{-rt} S_t$  is the PV of  $S_t$

$$dB_t^{-1} = d e^{-rt} = -r e^{-rt} dt = -r B_t^{-1} dt + P_t dW_t$$

$$dZ_t = B_t^{-1} dS_t + S_t dB_t^{-1} + \sigma_t P_t dt \quad P_t = 0$$

$$= B_t^{-1} dS_t + S_t dB_t^{-1}$$

$$= e^{-rt} [\mu_t S_t dt + \sigma_t S_t dW_t] + S_t (-r B_t^{-1} dt)$$

$$= e^{-rt} \mu_t S_t dt + e^{-rt} \sigma_t S_t dW_t - r e^{-rt} S_t dt$$

$$= e^{-rt} (\mu_t - r) S_t dt + e^{-rt} \sigma_t S_t dW_t$$

$$\Rightarrow dZ_t = (\mu_t - r) Z_t dt + \sigma_t Z_t dW_t !!$$

$\Rightarrow Z_t$  is a martingale iff  $\mu_t = r$

$\Rightarrow$  Under the risk-neutral measure

$$dS_t = r S_t dt + \sigma_t S_t dW_t$$

Let  $r_t$  be stochastic, i.e. the interest rate is stochastic

$B_t = e^{\int_0^t r_s ds}$ .  $B_t$  is the value of the money market account

at  $t$  with  $B_0 = 1$

$$Z_t = B_t^{-1} S_t = e^{-\int_0^t r_s ds} S_t$$

show:  $dZ_t = [\mu_t - r_t] Z_t dt + \sigma_t S_t dW_t$

$\Rightarrow$  Under the R-N measure  $ds_t = r_t S_t dt + \sigma_t S_t dW_t$

Rules

$$dt dW_t = 0 \quad (dt)^2 = 0$$

$$dt d\tilde{W}_t = 0 \quad dW_t d\tilde{W}_t = 0$$

$$(dW_t)^2 = dt$$

## Probability

### 3.4 Change of $\Lambda$ Measure (from $P$ to $Q$ )

Consider a fixed time period  $[0, T]$

If there is a positive random variable  $\xi_T$  at  $T$

such that  $\xi_T > 0$  and  $E_P(\xi_T) = 1$   $P = \text{Physical probability}$

We can define a new probability  $Q$   
in the following:

For any random event  $A$ ,

define  $I(A) = \begin{cases} 1, & \text{if } A \text{ happens} \\ 0, & \text{if } A \text{ doesn't happen} \end{cases}$

and Probability of  $A$  under new probability  $Q$

is defined as

$$Q(A) = E_P \{ I(A) \zeta_T \}$$

Change Probability from  $P$  to  $Q$

And  $\zeta_T = \frac{dQ}{dP}$  called the Radon-Nikodym derivative!

For any Ito process  $X_t$ ,  $0 \leq t \leq T$

$$E_Q(X_t) = E_P(X_t \zeta_T)$$



Let  $\zeta_t = E_P(\zeta_T | \mathcal{F}_t)$ , then  $\zeta_t > 0$ ,  $E_P(\zeta_t) = 1$

and  $E_Q(X_t) = E_P(X_t \zeta_t)$ .

$\zeta_t$  = Radon-Nikodym process  
and it is a martingale.

Example

$$\zeta_T = e^{-\frac{1}{2}\gamma^2 T + \gamma W_T} > 0$$

P 71

$$E(\zeta_T | \mathcal{F}_t) = \zeta_t = e^{-\frac{1}{2}\gamma^2 t + \gamma W_t} \quad \text{and} \quad E(\zeta_t) = 1$$

$e^{-\frac{1}{2}\gamma^2 t + \gamma W_t}$  is a R-N process

### Cameron-Martin - Girsanov Theorem

Let  $W_t$  be a standard Brownian motion and

$\gamma_t$  is a process

Define  $\tilde{W}_t = \int_0^t \gamma_s ds + W_t$

$\tilde{W}_t$  is not a standard Brownian motion under  $\mathbb{P}$

There is a Radon-Nikodym derivative

$$\frac{d\mathbb{Q}}{d\mathbb{P}} = e^{-\int_0^T \gamma_t dW_t - \frac{1}{2} \int_0^T \gamma_t^2 dt} = \mathcal{Z}_T > 0, \quad E(\mathcal{Z}_T) = 1$$

Let  $Z_t = e^{-\int_0^t r_s ds - \frac{1}{2} \int_0^t r_s^2 ds} \Rightarrow$  show  $Z_t = E(Z_T | \mathcal{F}_t)$

such that  $\mathbb{Q}$  probability measure obtained from

$\frac{d\mathbb{Q}}{d\mathbb{P}}$  gives that

$\tilde{W}_t$  is a standard Brownian motion

Note that  $d\tilde{W}_t = r_t dt + dW_t$

Why do we need the Girsanov theorem?

Look at

$dS_t = \mu_t S_t dt + \sigma_t S_t dW_t$  under  $\mathbb{P}$  probability measure

If we want to price an option with underlying  $S_t$

$$dZ_t = d[e^{-rt} S_t]$$

$$= S_t d e^{-rt} + e^{-rt} d S_t$$

$$= -r e^{-rt} S_t dt + e^{-rt} [\mu_t S_t dt + \sigma_t S_t dW_t]$$

we can NOT use the SDE directly.

This is because  $Z_t = e^{-rt} S_t$  satisfies

$$dZ_t = [\mu_t - r] Z_t dt + \sigma_t Z_t dW_t$$

$Z_t$  is NOT a martingale since  $\mu_t - r \neq 0$ .

In order to use it for pricing purposes,

$$\text{Let } d\tilde{W}_t = \gamma_t dt + dW_t \text{ or}$$

$$dW_t = -\gamma_t dt + d\tilde{W}_t, \quad \gamma_t \text{ is to be determined!}$$

$$dZ_t = [\mu_t - r] Z_t dt + \sigma_t Z_t [-\gamma_t dt + d\tilde{W}_t]$$

$$= [\mu_t - r - \sigma_t \gamma_t] Z_t dt + \sigma_t Z_t d\tilde{W}_t$$

$Z_t$  is a martingale under  $\mathbb{Q}$ -probabilities if and only if  $\mu_t - r - \sigma_t \gamma_t \equiv 0 \iff \gamma_t = \frac{\mu_t - r}{\sigma_t}$

$\gamma_t =$  Sharpe Ratio.

and  $dZ_t = \sigma_t Z_t d\tilde{W}_t$ .

$$\begin{aligned} dS_t &= \mu_t S_t dt + \sigma_t S_t dW_t = \mu_t S_t dt + \sigma_t S_t \left[ -\frac{\mu_t - r}{\sigma_t} dt + d\tilde{W}_t \right] \\ &= \mu_t S_t dt - (\mu_t - r) S_t dt + \sigma_t S_t d\tilde{W}_t = r S_t dt + \sigma_t S_t d\tilde{W}_t, \end{aligned}$$

Under the  $\mathbb{Q}$  probability measure, by the Girsanov,

$\tilde{W}_t$  is a standard Brownian motion.

In practice, change the physical rate of return  $\mu_t$  to the interest rate  $r$  (or  $r_t$ ) and everything else remains the same! The interest rate can be stochastic! P 73-75

Examples (P 75)

1.  $X_t = \sigma W_t + \mu t$  under  $P$ -probabilities

$$Y_t = \frac{M}{\sigma} \quad d\tilde{W}_t = \frac{M}{\sigma} dt + dW_t$$

$$\text{or } \tilde{W}_t = \frac{M}{\sigma} t + W_t$$

Under  $\mathbb{Q}$ -probabilities,

$$X_t = \sigma \left[ -\frac{\mu}{\sigma} t + \tilde{W}_t \right] + \mu t = \sigma \tilde{W}_t$$

$X_t$  is a martingale ( $dX_t = \sigma d\tilde{W}_t$ )

How about  $E_P(X_t^2)$  and  $E_Q(X_t^2)$

$$\begin{aligned} E_P(X_t^2) &= E_P \left\{ \sigma^2 W_t^2 + 2\mu\sigma t W_t + \mu^2 t^2 \right\} \\ &= \sigma^2 E(W_t^2) + 2\mu\sigma t E(W_t) + \mu^2 t^2 \\ &= \sigma^2 t + \mu^2 t^2 \end{aligned}$$

$$E_Q(X_t^2) = E_Q(\sigma \tilde{W}_t)^2 = \sigma^2 E_Q(\tilde{W}_t^2) = \sigma^2 t$$



$$E_P(X_t^2) \geq E_Q(X_t^2)$$

$$2. \quad dX_t = X_t [\sigma dW_t + \mu dt] \quad \text{GBM}$$

Can we find  $Q$ -probabilities such that

$$dX_t = X_t [\sigma d\tilde{W}_t + \nu dt] \quad \text{for } \nu \neq \mu.$$

Yes we can!

$$dW_t = -\gamma_t dt + d\tilde{W}_t$$

$$dX_t = X_t [-\sigma \gamma_t dt + \sigma d\tilde{W}_t + \mu dt]$$

$$\Rightarrow -\sigma \gamma_t + \mu = \nu \Rightarrow \gamma_t = \frac{\mu - \nu}{\sigma}$$

### 3.6 Hedging/Replicating strategies

\* Self-financing in continuous time

Rebalancing a portfolio without putting in  
and taking out the money!

Begin with a trading strategy / portfolio

$(\phi_t, \psi_t)$  for a portfolio consisting a

stock and the cash bond,

-  $\phi_t$  is the number of shares of  $S_t$  at time  $t$

-  $\psi_t$  is the number of units of  $B_t$  at time  $t$

- The value of the portfolio

$$V_t = \phi_t S_t + \psi_t B_t \quad B_t = B_0 e^{rt}$$

A self-financing trading strategy is such that

$$dV_t = \phi_t ds_t + \psi_t dB_t \quad (P81)$$

Think about a very short time period  $(t, t+dt]$

LHS = increment of the portfolio value.

RHS = the gains from the 2 securities.

Examples (p 81)  $r=0$ ,  $B_0=1 \Rightarrow B_t=1$ .  $S_t = W_t$

(1)  $\phi_t = \psi_t = 1$ , the portfolio  $V_t = W_t + 1 \equiv \phi_t S_t + \psi_t B_t$

$$dV_t = d(W_t + 1) = dW_t \stackrel{?}{=} \phi_t dS_t + \psi_t dB_t$$

$$\text{RHS} = dS_t + 0 = dW_t \quad \text{Yes!}$$

(2)  $\phi_t = 2W_t$ ,  $\psi_t = -t - W_t^2$

$$V_t = 2W_t \cdot W_t + (-t - W_t^2) = W_t^2 - t$$

$$dV_t = \phi_t dS_t + \psi_t dB_t \quad ??$$

$$dV_t = d[W_t^2] - dt$$

$$= W_t dW_t + W_t dW_t + (dW_t)^2 - dt$$

$$= 2W_t dW_t + dt - dt = 2W_t dW_t$$

$$\phi_t dS_t + \psi_t dB_t = 2W_t dW_t + 0 = dV_t \quad \text{Yes!}$$

$V_t = W_t^2 - t$  is a martingale, (Exercise 3.12)

since no dt term.

Replicating strategy.

For any contingent claim / payoff of an option  $X_T$

if there is a self-financing trading strategy

$(\phi_t, \psi_t)$  such that  $\phi_T S_T + \psi_T B_T = X_T$ ,

i.e. the terminal value of the portfolio is

the same as the payoff of the option,

the portfolio is called a replicating portfolio

and the time- $t$  price of the option is  $V_t$

If the replication is not perfect (no risk)

then it is important to perform sensitivity analysis,

i.e. calculating greeks.

$\phi_t = \text{delta} = \Delta_t$ , the sensitivity of the option  
price to the stock price.  $\phi_t = \frac{dV_t}{dS_t}$

Other greeks will be introduced later.

### 3.7 Black-Scholes Model.

p83 One stock and the cash bond

The stock follows a GBM

$$dS_t = \mu S_t dt + \sigma S_t dW_t$$

The bond has a constant interest rate  $r$

$$dB_t = r B_t dt$$

There is no dividend payments.

Begin with page 87 with  $r \geq 0$

Two approaches to price an option

(i) Risk-neutral Pricing/Valuation

- Find  $Q$ -probabilities such that the discounted stock price is a martingale
- The price of a contingent claim / payoff of an option is the expected discounted payoff under  $Q$ -probabilities.



The  $Q$ -probabilities

$$dS_t = r S_t dt + \sigma S_t d\tilde{W}_t$$
$$\text{or } S_t = S_0 e^{(r - \frac{1}{2}\sigma^2)t + \sigma \tilde{W}_t}$$

The discounted stock price

$$Z_t = e^{-rt} S_t \text{ has}$$

$$dZ_t = \sigma Z_t d\tilde{W}_t$$

Let  $\Phi(S_T)$  be the payoff of an option.

The time- $t$  price  $V_t$  is

$$V_t = E_Q \left\{ e^{-r(T-t)} \Phi(S_T) \mid \mathcal{F}_t \right\}$$

Let  $U_t = e^{-rt} V_t$  be the present value of the option price

$$\text{Then } U_t = E_Q \left\{ e^{-rT} \Phi(S_T) \mid \mathcal{F}_t \right\}$$

$U_t$  is a martingale.

The discounted price of any tradable security is a martingale.

How to calculate an option price?

$$V_t = e^{-r(T-t)} E_Q \{ \Phi(S_T) \mid \mathcal{F}_t \} \quad \mathcal{F}_t = \{ S_t \}$$
$$= e^{-r(T-t)} E_Q \{ \Phi(S_T) \mid S_t \}$$

$$V_t = V(S_t, t)$$

$$(r - \frac{1}{2}\sigma^2)(T-t) + \sigma [\tilde{W}_T - \tilde{W}_t]$$

$$S_T = S_t e$$

$$V(S_t, t) = e^{-r(T-t)} E_Q \left\{ \Phi \left( S_t e^{(r - \frac{1}{2}\sigma^2)(T-t) + \sigma \sqrt{T-t} Z} \right) \right\}$$

because  $\tilde{W}_T - \tilde{W}_t \sim \sqrt{T-t} Z, \quad Z \sim N(0, 1)$

$$V(S_t, t) = e^{-r(T-t)} \int_{-\infty}^{\infty} \Phi\left(S_t e^{(r - \frac{1}{2}\sigma^2)(T-t) + \sigma\sqrt{T-t}z}\right) \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}z^2} dz$$

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If  $Z \sim N(0, 1)$ , and  $F$ ,  $\sigma$  and  $K$  are some constants, <sup>positive</sup>

then

$$\begin{aligned} V &= E \left\{ \max \left[ F e^{\sigma Z - \frac{1}{2}\sigma^2} - K, 0 \right] \right\} \\ &= F N \left( \frac{\ln \frac{F}{K} + \frac{1}{2}\sigma^2}{\sigma} \right) - K N \left( \frac{\ln \frac{F}{K} - \frac{1}{2}\sigma^2}{\sigma} \right). \end{aligned}$$

Derivation

$$\begin{aligned} & \mathbb{E} \left\{ \max \left[ \Pi e^{a_1 Z - \frac{1}{2} a_1^2} - K, 0 \right] \right\} \\ &= \int_{-\infty}^{\infty} \max \left[ \Pi e^{a_1 z - \frac{1}{2} a_1^2} - K, 0 \right] \times \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz \end{aligned}$$

Consider  $\Pi e^{a_1 z - \frac{1}{2} a_1^2} \geq K$

$$\Rightarrow e^{a_1 z - \frac{1}{2} a_1^2} \geq \frac{K}{\Pi}$$

$$\Rightarrow a_1 z - \frac{1}{2} a_1^2 \geq \ln \frac{K}{\Pi}$$

$$\Rightarrow a_1 z \gg \frac{1}{2} \frac{\pi}{k} + \frac{1}{2} a_1^2 z^2$$

$$\Rightarrow z \gg \frac{\frac{1}{2} \frac{\pi}{k} + \frac{1}{2} a_1^2 z^2}{a_1}$$

$$V = \int_{\frac{\frac{1}{2} \frac{\pi}{k} + \frac{1}{2} a_1^2 z^2}{a_1}}^{\infty} \left[ \pi e^{-a_1 z - \frac{1}{2} a_1^2 z^2} - k \right] \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} z^2} dz$$

$$\boxed{z \rightarrow -z}$$

$$= \int_{-\infty}^{\frac{\frac{1}{2} \frac{\pi}{k} - \frac{1}{2} a_1^2 z^2}{a_1}} \left[ \pi e^{-a_1 z - \frac{1}{2} a_1^2 z^2} - k \right] \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} z^2} dz$$

$$= \pi \int_{-\infty}^{\infty} \frac{\ln \frac{K}{\pi} - \frac{1}{2} a_1^2}{a_1} e^{-a_1 z - \frac{1}{2} a_1^2 - \frac{z^2}{2}} dz$$

$$= K \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz$$

The second term is  $KN \left( \frac{\ln \frac{K}{\pi} - \frac{1}{2} a_1^2}{a_1} \right)$

The first term

$$F \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2\sigma^2} \left( z - \frac{\mu}{\sigma} \right)^2} dz$$
$$= F \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} \left[ z^2 + 2\bar{\sigma} z + \sigma^2 \right]} dz$$



$$= F \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{(z+\sigma)^2}{2a^2}} dz$$

$$z + \sigma \rightarrow z$$

$$= F \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2a^2}} dz = FN \left( \frac{\ln \frac{F}{K} + \frac{1}{2} a^2}{a^2} \right)$$

Q.E.D

The Black-Scholes Call Option Pricing Formula

$$\bar{\Phi}(S_T) = \max [S_T - K, 0]$$

$$S_T = S_t e^{(r - \frac{1}{2}\sigma^2)(T-t) + \sigma [\tilde{W}_T - \tilde{W}_t]}$$

$$\approx S_t e^{(r - \frac{1}{2}\sigma^2)(T-t) + \sigma\sqrt{T-t} Z}, \quad Z \sim N(0, 1)$$

$$V(S_t, t) = e^{-r(T-t)} E_Q \left\{ \max [S_T - K, 0] \right\}$$

$$= e^{-r(T-t)} E_Q \left\{ \max \left[ S_t e^{(r - \frac{1}{2}\sigma^2)(T-t) + \sigma\sqrt{T-t} Z}, 0 \right] \right\}$$

$$\text{Let } \bar{\sigma} = \sigma\sqrt{T-t} \quad F = S_t e^{r(T-t)}$$

$$V(S_t, t) = e^{-r(T-t)} \left[ F N\left(\frac{\ln \frac{S_t}{K} + \frac{1}{2} \sigma^2 (T-t)}{\sigma \sqrt{T-t}}\right) - K N\left(\frac{\ln \frac{S_t}{K} - \frac{1}{2} \sigma^2 (T-t)}{\sigma \sqrt{T-t}}\right) \right]$$

$$= e^{-r(T-t)} \left[ S_t e^{r(T-t)} N\left(\frac{\ln \frac{S_t e^{r(T-t)}}{K} + \frac{1}{2} \sigma^2 (T-t)}{\sigma \sqrt{T-t}}\right) - K N\left(\frac{\ln \frac{S_t e^{r(T-t)}}{K} - \frac{1}{2} \sigma^2 (T-t)}{\sigma \sqrt{T-t}}\right) \right]$$

$$- K N\left(\frac{\ln \frac{S_t e^{r(T-t)}}{K} - \frac{1}{2} \sigma^2 (T-t)}{\sigma \sqrt{T-t}}\right)$$

$$= S_t N\left(\frac{\ln \frac{S_t}{K} + (r + \frac{1}{2} \sigma^2)(T-t)}{\sigma \sqrt{T-t}}\right) - K e^{-r(T-t)} N\left(\frac{\ln \frac{S_t}{K} + (r - \frac{1}{2} \sigma^2)(T-t)}{\sigma \sqrt{T-t}}\right)$$

$d_1$

$$d_2 = d_1 - \sigma \sqrt{T-t}$$

## (ii) Replicating Portfolio Approach

For the payoff of an option  $\bar{\Phi}(S_T)$ ,

if we can form a replicating portfolio  
(with a self-financing trading strategy  
( $\phi_t, \psi_t$ )), then the value of the portfolio  
at time  $t$  is the option price at time  $t$ .

Let  $V(S_t, t)$  be the value of the replicating  
portfolio with the self-financing trading  
strategy  $(\phi_t, \psi_t)$

On one hand, we have

$$V(S_t, t) = \phi_t S_t + \psi_t B_t$$

$$dV(S_t, t) = \phi_t dS_t + \psi_t dB_t$$

$$= \phi_t [\mu S_t dt + \sigma S_t dW_t] + \psi_t r B_t dt$$

$$= \mu \phi_t S_t dt + \sigma \phi_t S_t dW_t + r [V(S_t, t) - \phi_t S_t] dt$$

$$= [(\mu - r) \phi_t S_t + r V(S_t, t)] dt + \sigma \phi_t S_t dW_t$$

On the other hand, from Ito's Lemma

$$dV(S_t, t) = \left[ V_t + \frac{1}{2} V_{ss} \sigma^2 S_t^2 \right] dt + V_s dS_t$$

$$V_t = \frac{\partial V}{\partial t}, \quad V_s = \frac{\partial V}{\partial S}, \quad V_{ss} = \frac{\partial^2 V}{\partial S^2}$$

$$= \left[ V_t + \frac{1}{2} V_{ss} \sigma^2 S_t^2 \right] dt + V_s \left[ \mu S_t dt + \sigma S_t dW_t \right]$$

$$= \left[ V_t + \mu V_s S_t + \frac{1}{2} V_{ss} \sigma^2 S_t^2 \right] dt + \sigma V_s S_t dW_t$$

Two SDEs must be the same!

$$\sigma \phi_t S_t = \sigma V_s S_t \quad (\text{equal volatility})$$

$$\Rightarrow \phi_t = V_s$$

$$(\mu - r) \phi_t S_t + rV = V_t + \mu V_s S_t + \frac{1}{2} V_{ss} \sigma^2 S_t^2 \quad (\text{equal drift})$$

$$\Rightarrow (\mu - r) V_s S_t + rV = V_t + \mu V_s S_t + \frac{1}{2} \sigma^2 V_{ss} S_t^2$$

$$\Rightarrow -r S_t V_s + r V = V_t + \frac{1}{2} \sigma^2 S_t^2 V_{ss}$$

$$\text{or } V_t + r S_t V_s + \frac{1}{2} \sigma^2 S_t^2 V_{ss} = r V$$

The Black-Scholes PDE !!

Since  $S_t$  is arbitrary,

$$V_t + r S V_s(s, t) + \frac{1}{2} \sigma^2 S^2 V_{ss}(s, t) = r V(s, t)$$

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If we can solve this PDE, we obtain

the replicating portfolio with  $\phi_t = V_s$

and  $V(s, T) = \underline{\Phi}(S)$

check: the B-S call option pricing formula

is a solution of the PDE with

$$\underline{\Phi}(S) = \max\{S - K, 0\}$$

How to hedge an option

General idea = using a replicating portfolio

However, the hedging can not be perfect

in practice; the value of the portfolio is different from the option price / payoff

Need to minimize the hedging errors by

matching greeks!



Greeks: The sensitivity of the option price to its parameters.

B-S

$$\Delta_t = \frac{\partial V}{\partial S} = \phi_t$$

$N(d_1)$

$$\Gamma_t = \frac{\partial^2 V}{\partial S^2} = V_{SS}$$

$\frac{n(d_1)}{S_t \sigma \sqrt{T-t}}$

$n(x) = N'(x)$

$$\theta_t = \frac{\partial^2 V}{\partial t} = V_t$$

$-\frac{S_t n(d_1) \sigma}{2\sqrt{T-t}} - r K e^{-r(T-t)} N(d_2)$

$$\rho_t = \frac{\partial V}{\partial r} = \text{duration}$$

$K(T-t)e^{-r(T-t)} N(d_2)$

$$\text{Vega} = \frac{\partial V}{\partial \sigma}$$

$S_t n(d_1) \sqrt{T-t}$

Exercise 3.17 p 98

A stock has current price \$10 and follows a GBM.

$$\mu = 15\%, \quad \sigma = 20\%, \quad r = 5\%.$$

What is the value of a derivative that pays off \$1 if the stock price is more than \$10 in a year's time?

Under  $\mathbb{Q}$ -probabilities

$$S_t = 10 e^{(0.05 - \frac{1}{2} \times 0.2^2)t + 0.2 \tilde{W}_t}$$

$$S_t = 10 e^{0.03t + 0.2 \tilde{W}_t}$$

$$V(S_0, 0) = e^{-rT} \mathbb{E}_Q(\underline{\Phi}(S_T))$$

$$\underline{\Phi}(S_1) = \begin{cases} 1, & S_1 > 10 \\ 0, & S_1 \leq 10 \end{cases}$$

$$S_1 = 10 e^{0.03 + 0.2Z} \quad Z \sim N(0, 1)$$

$$S_1 > 10 \Rightarrow e^{0.03 + 0.2Z} > 1$$

$$\Rightarrow 0.03 + 0.2Z > 0 \Rightarrow Z > -\frac{0.03}{0.2} = -\frac{0.3}{2}$$

$$= -0.15$$

$$V(10, 0) = e^{-0.05} \int_{-0.15}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz = e^{-0.05} N(0.15)$$

How do you hedge this option?

Need to calculate  $\Delta_0$

Change the current price from \$10 to \$10.1

Recalculate the option price

$$V(10.1, 0)$$

$$\Delta_0 \equiv \frac{V(10.1, 0) - V(10, 0)}{10.1 - 10}$$

