

## Week 3-4

(continuous)  
GBM

(discrete)  
Binomial

$$S(t) \leftarrow S_n(t) \quad \text{as } n \rightarrow \infty$$

### 4. CLT & GBM

#### 4.1 Central Limit Theorem

Let  $Y_1, Y_2, \dots, Y_n$  be a sequence of iid random variables,

$$E(Y_n) = a, \quad \text{Var}(Y_n) = \sigma^2, \quad |Y_n| < C.$$

Then the sequence

$$Z_n = \frac{\sum_{j=1}^n Y_j - na}{\sqrt{n} \sigma}$$

to the standard normal random variable.

converges in distribution, as  $n \rightarrow \infty$

Namely,

1. For all  $x$ ,  $\lim_{n \rightarrow \infty} P(Z_n < x) = \Phi(x)$ ,  $\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{y^2}{2}} dy$ . CDF of  $N(0,1)$

2. Let  $g: \mathbb{R} \rightarrow \mathbb{R}$  be a continuous function satisfying, for some  $C_1 > 0, C_2 > 0$ , the estimate  $|g(x)| < C_1 e^{C_2|x|}$ .

CLT 2:

Then

$$\lim_{n \rightarrow \infty} E(g(z_n)) = E(g(z)) \quad \text{where } z \sim N(0, 1)$$

In other words, we have

$$\lim_{n \rightarrow \infty} E(g(z_n)) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} g(x) e^{-\frac{x^2}{2}} dx$$

$\uparrow$  discrete                       $\uparrow$  continuous

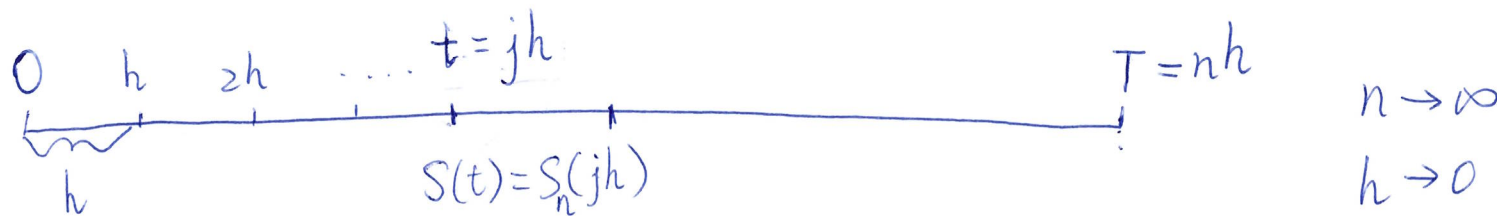
1  $\Leftrightarrow$  2

4.2 Why does the GBM describe the behaviour of the prices?

Target: prove  $\lim_{n \rightarrow \infty} S_n(t) = S(t)$

$\uparrow$  Bin                       $\uparrow$  GBM

Step 1:



Divide  $[0, T]$  into  $n$  equal intervals of length  $h = \frac{T}{n}$

①  $t=0$   $S_n(0) = S(0)$ , where  $S(0)$  is the same as in the GBM

②  $t=jh$ ,  $1 \leq j \leq n$ , set  $S_n(jh) = S(0) e^{\mu hj + \sigma \sqrt{h} (Y_1 + Y_2 + \dots + Y_j)}$  (1)

Multiperiod Binomial model.

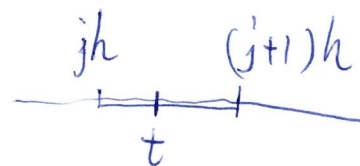
$$= S(0) e^{\mu hj + \sigma \sqrt{h} \sum_{k=1}^j Y_k}$$

$$Y_1, \dots, Y_j = \begin{cases} -1 & d \\ 1 & u \end{cases}$$

$Y_1, Y_2, \dots, Y_n, \dots$  is a sequence of iid r.v.s 1 or -1

$$P(Y_j = 1) = \frac{1}{2}, \quad P(Y_j = -1) = \frac{1}{2}$$

$p$   $1-p$



Step. 2: For  $t \in [0, T]$  set  $S_n(t) = S_n(jh)$  where  $j$  is s.t.  $jh \leq t \leq (j+1)h$ .

Remarks.

① For each fixed  $n$ ,  $S_n(jh)$  evolves according to a Binomial model.

$$S_n(jh) = S_n((j-1)h) e^{\mu h + \sigma \sqrt{h} Y_j}$$

Binomial Model

$$S_n(jh) = \begin{cases} S_n((j-1)h) u \\ S_n((j-1)h) d \end{cases}$$

$$u = e^{\mu h + \sigma \sqrt{h}} \leftarrow Y_j = 1$$

$$d = e^{\mu h - \sigma \sqrt{h}} \leftarrow Y_j = -1$$

② Realisation of the path  $S_n(jh)$ ,  $j = 0, 1, 2, \dots, n$

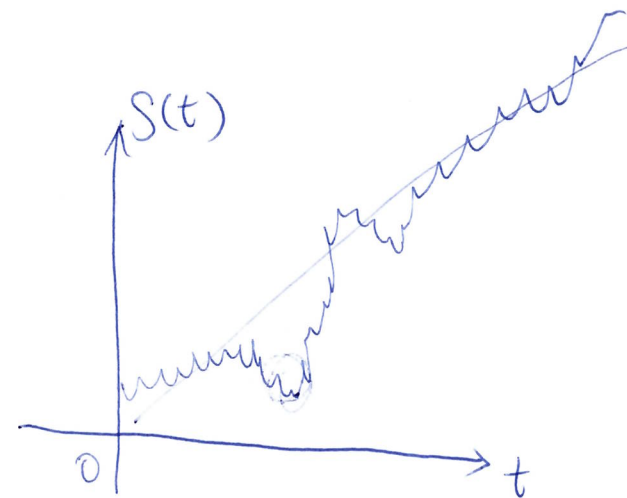
$$P(\text{each path}) = 2^{-n} = \left(\frac{1}{2}\right)^n$$

③ two key factors:  $e^{\mu h}$ ,  $e^{\pm \sigma \sqrt{h}}$

•  $e^{\mu h}$ : not random  
pushes price up,  $\mu > 0$

•  $e^{\pm \sigma \sqrt{h}}$ : random

pushes price  $\begin{cases} \text{up} & \frac{1}{2} \\ \text{down} & \frac{1}{2} \end{cases}$



$h$  is small,  $\sqrt{h}$  much larger than  $h$   $\frac{\sqrt{h}}{h} \rightarrow \infty$  as  $h \rightarrow 0$

at each particular step:  $e^{\pm \sigma \sqrt{h}}$  more important

in a long run: sum of  $\pm \sigma \sqrt{h} \rightarrow 0$  cancel out each other

$e^{\mu h}$  more important

Theorem 4.2  $S_n(t) \rightarrow S(t)$

When  $n \rightarrow \infty$ , the process  $S_n(t) \rightarrow S(t)$  in the following sense:

if  $g(z_1, \dots, z_k)$  is a "good enough" function of  $k$  variables (say, continuous, growing no faster than exponentially in each variable)

and

$$0 < t_1 < t_2 < \dots < t_k \leq T$$

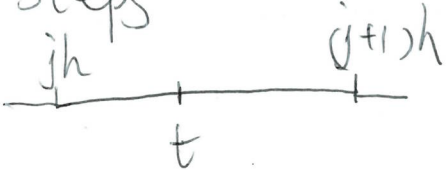
then:  $\lim_{n \rightarrow \infty} E[g(S_n(t_1), S_n(t_2), \dots, S_n(t_k))] = E[g(S(t_1), \dots, S(t_k))]$  (4)

Proof:  $k=1$   $g(S_n(t_1))$  for simplicity  $Z_n = S_n(t)$

Target:  $E(g(S_n(t))) \xrightarrow{n \rightarrow \infty} E(g(S(t))) \stackrel{\text{CLT 2}}{=} \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} g(S(t)) e^{-\frac{1}{2}(S(t)-\mu)^2/\sigma^2} dS(t)$

$$\frac{\text{CLT2}}{\text{---}} \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} g \left( \underbrace{S(0) e^{\mu t + \sigma \sqrt{t} x}}_{g(x) = S_n(t)} \right) e^{-\frac{x^2}{2}} dx$$

According to the 2 Steps  
 $jh \leq t < (j+1)h$



$$t = jh \quad \because h \rightarrow 0$$

$$\Rightarrow h = \frac{t}{j}$$

$$S_n(t) \stackrel{\text{Step 1}}{=} S_n(jh) \stackrel{\text{Eq (1)}}{=} S(0) e^{\mu jh + \sigma \sqrt{jh} (Y_1 + Y_2 + \dots + Y_j)} = S(0) e^{\mu t + \sigma \sqrt{\frac{t}{j}} \sum_{k=1}^j Y_k}$$

$$E(Y_j) = 1 \times \frac{1}{2} - 1 \times \frac{1}{2} = 0, \quad \text{Var}(Y_j) = E(Y_j^2) - [E(Y_j)]^2 = 1$$

$$\underbrace{\sqrt{\frac{t}{j}} \sum_{k=1}^j Y_k}_{\text{---}} = \sqrt{t} \times \underbrace{\frac{1}{\sqrt{j}} \sum_{k=1}^j Y_k}_{\text{---}} \stackrel{\text{CLT}}{\rightarrow} \sqrt{t} Z \text{ as } j \rightarrow \infty$$

$$\mu = 0, \sigma = 1, n = j$$

Compare to  $Z_n$

$$Z \sim N(0, 1)$$

For a "good" function  $g$  we have

$$E \left[ g \left( \frac{1}{\sqrt{j}} \sum_{k=1}^j Y_k \right) \right] \rightarrow E(g(z)), \text{ where } z \sim N(0, 1)$$

In particular, as  $n \rightarrow \infty$

$$E \left( g(S_n(t)) \right) = E \left[ g \left( S(0) \cdot e^{\mu t + \sigma \sqrt{t} \frac{1}{\sqrt{j}} \sum_{k=1}^j Y_k \right) \right]$$

$\downarrow$   
 $z_n$

$$\rightarrow E \left( g \left( S(0) e^{\mu t + \sigma \sqrt{t} z} \right) \right)$$

$$\stackrel{\text{CLT 2}}{=} \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} g \left( S(0) e^{\mu t + \sigma \sqrt{t} x} \right) e^{-\frac{x^2}{2}} dx \quad \square$$

Theorem 4.2  $S_n(t) \leftrightarrow S(t)$

Theorem 5.1  $S(t) \leftrightarrow S_n(t) \rightarrow \tilde{S}(t)$

↑  
Bridge

↑  
RNP

⊕ pricing

Suppose  $S(t) = S e^{\mu t + \sigma W_t}$

$r$ : interest rate compound continuously

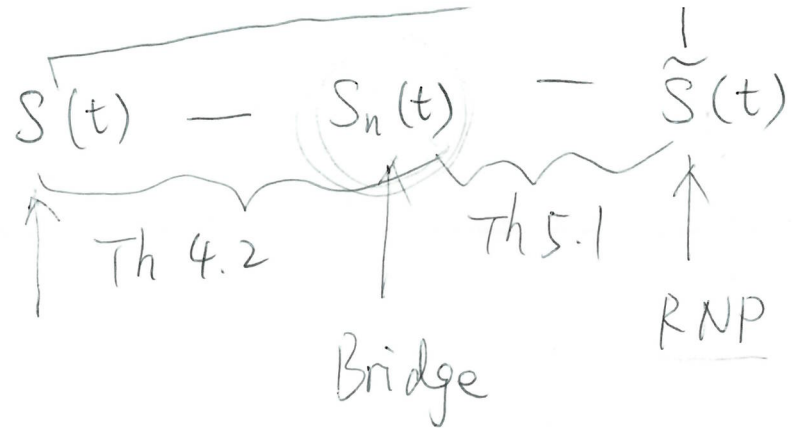
Then the RNP defined on the ~~space~~ <sup>space</sup> of function  $S_n(t)$

converges to a RNP on the space of trajectories of

the GBM given by  $\tilde{S}(t) = S e^{\tilde{\mu} t + \sigma W_t}$ ,  $\tilde{\mu} = r - \frac{1}{2} \sigma^2$

↓  
RN GBM





$$\tilde{p} = u, d, r$$

$$\tilde{q} = 1 - \tilde{p}$$

Theorem 5.2

$$C = e^{-rT} \tilde{E}$$

↑ price
↑ RNP

Suppose that

- ①  $R(T)$ : payoff function of a derivative on a share
- ②  $T$ : The payoff time
- ③  $r$ : interest rate compounded continuously

Then: the price  $C = e^{-rT} \tilde{E}[R(T)]$

$\tilde{E}$  is the expectation over the RNP.

If we buy the derivative for  $C$

Then Return at time  $T$  is  $R(T) - Ce^{rT}$

According to the Arbitrage Theorem:

$$\tilde{E}(R(T) - Ce^{rT}) = 0 \quad (\text{Th 2.1})$$

$$C = e^{-rT} \tilde{E}(R(T)) \quad \square$$

Theorem 5.3  $C = e^{-rT} E(\tilde{\cdot})$

Suppose that

① GBM  $S(t) = S e^{\mu t + \sigma W_t}$

② Payoff function of the derivative  
where  $0 \leq t_1 < t_2 < \dots < t_k \leq T$

③  $T$ : payoff time

④  $r$ : interest rate compounded continuously.

$0$	$T$
$C$	$-Ce^{rT}$
to buy the derivative	$R(T)$
$-C$	$R(T)$
$0$	$-Ce^{rT} + R(T)$

Then the price  $C$  of the derivative is

$$C = e^{-rT} E \left[ R(\tilde{S}(t_1), \tilde{S}(t_2), \dots, \tilde{S}(t_k)) \right],$$

$$\tilde{S}(t) = S e^{\tilde{\mu}t + \sigma W_t}, \quad \tilde{\mu} = r - \frac{1}{2}\sigma^2$$

Proof:  $R(T) = R(S(t_1), S(t_2), \dots, S(t_k))$

By Th 5.2  $C = e^{-rT} \tilde{E} \left[ R(S(t_1), S(t_2), \dots, S(t_k)) \right]$

By Th 5.1  $S(t) = \underline{S_n(t)} = \tilde{S}(t)$  Replace  $\begin{matrix} S(t_1), \dots, S(t_k) \\ S(t_1), \dots, \tilde{S}(t_k) \end{matrix}$  with  $\tilde{S}(t_1), \tilde{S}(t_2), \dots, \tilde{S}(t_k)$

$$C = e^{-rT} E \left[ R(\tilde{S}(t_1), \tilde{S}(t_2), \dots, \tilde{S}(t_k)) \right]$$

where  $\tilde{S}(t) = S e^{\tilde{\mu}t + \sigma W_t}, \quad \tilde{\mu} = r - \frac{1}{2}\sigma^2$   $\square$

## 5.2 Examples (applications)

### 5.2.1 The European Call Option

Call  $(k, T)$

Payoff function of Call  $(k, T)$  is  $R(S(T)) = (S(T) - k)^+ \leftarrow$  special case

Compare to Th 5.3:  $R(S(t_1), S(t_2), \dots, S(t_k))$   $k=1$   
 $t_1 = T$

$$C = e^{-rT} E[\tilde{V}] \rightarrow C = e^{-rT} E[(\tilde{S}(T) - k)^+]$$

$$\tilde{S}(T) = S e^{\tilde{\mu}T + \sigma W_T}, \quad \tilde{\mu} = r - \frac{1}{2}\sigma^2$$

Calculate B-S formula

$$\tilde{S}(T) = \begin{cases} \tilde{S}(T) & \text{if } \tilde{S}(T) > k \\ 0 & \text{if } \tilde{S}(T) \leq k \end{cases}$$

$$C = C(S, T, k, \sigma, r) = S \Phi(w) - k e^{-rT} \Phi(w - \sigma\sqrt{T})$$

$$w = \frac{\ln \frac{S}{k} + rT}{\sigma\sqrt{T}} + \frac{1}{2}\sigma\sqrt{T}, \quad \Phi(x) = \int_{-\infty}^x \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}} du$$

Remark: another form of B-S formula

$$C = e^{-rT} \int_{x_0}^{\infty} \left( S e^{\tilde{\mu}T + \sigma\sqrt{T}x} - K \right)^+ \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx$$