

## ~~4~~ 4 Binomial Trees and Random Walks

1-Step model :

$$S_0 \qquad S_1$$

$$\frac{S_1}{S_0} = \text{Return}$$

$$S_1 = \left( \frac{S_1}{S_0} \right) \cdot S_0$$

$$\frac{S_1}{S_0} > 1 \quad \text{positive return}$$

$$\frac{S_1}{S_0} < 1 \quad \text{negative return}$$

## 1-step model

$$\frac{S_1}{S_0} = \begin{cases} \frac{1+u}{1+d} & \text{prob } p \\ \frac{1+d}{1+u} & \text{prob } 1-p \end{cases}$$

where  $u > 0$      $d < 0$

are the up and down factors.

$$K = \frac{S_1}{S_0}^{\textcolor{red}{1}} = \begin{cases} u & \text{prob } p \\ d & \text{prob } 1-p \end{cases}$$

$$E[K] = pu + (1-p)d$$

$$\text{Var}(K) = pu^2 + (1-p)d^2 - (pu + (1-p)d)^2$$

Case of  $p = \frac{1}{2}$

$$K = \begin{cases} u & \text{prob } \frac{1}{2} \\ d & \text{prob } \frac{1}{2} \end{cases}$$

$$E[K] = \mu = \frac{u+d}{2}$$

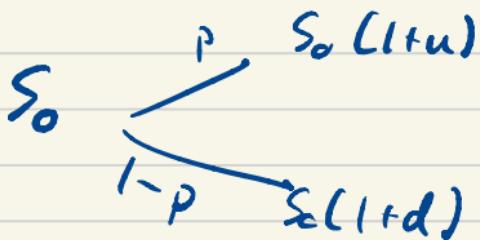
$$\text{Var}(K) = \frac{u^2 + d^2}{2} - \left( \frac{u+d}{2} \right)^2$$

$$\begin{aligned} 4 \text{Var}(K) &= 2(u^2 + d^2) - (u+d)^2 \\ &= u^2 - 2ud + d^2 \\ &= (u-d)^2 \\ \text{Var}(K) &= \left( \frac{u-d}{2} \right)^2. \end{aligned}$$

$$\sigma = \sqrt{\text{Var}(K)} = \frac{u-d}{2}$$

$$\mu = \frac{u+d}{2}$$

$$K = \begin{cases} \frac{u}{d} & \frac{1}{2} \\ \frac{1}{2} & \frac{u-d}{2} \end{cases} = \begin{cases} \underline{\mu + \sigma} \\ \underline{\mu - \sigma} \end{cases}$$



## 2-step binomial tree model

$$K = \begin{cases} u & p \\ d & 1-p \end{cases}$$

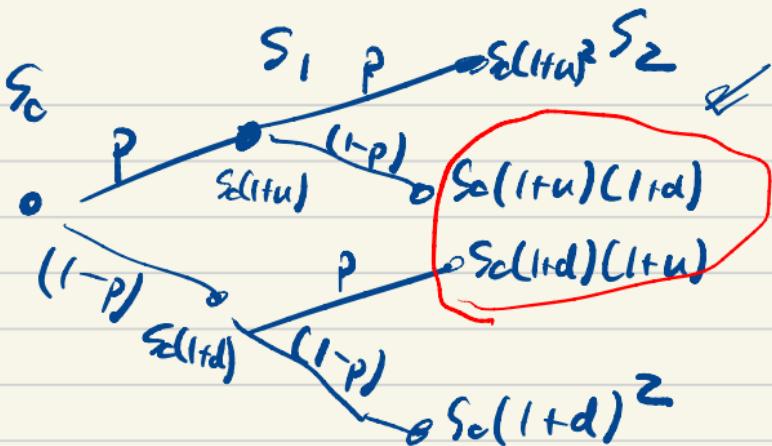
$$S_0, S_1, S_2$$

$$\frac{S_2}{S_0} = \frac{S_1}{S_0} \cdot \frac{S_2}{S_1}$$



Assume independent

$$= \begin{cases} (1+u)^2 & p^2 \\ (1+u)(1+d) & 2p(1-p) \\ (1+d)^2 & (1-p)^2 \end{cases}$$



$$E[S_2 | S_0] = p^2(1+u)^2 + 2p(1-p)(1+u)(1+d) + (1-p)^2(1+d)^2$$

$$= (p(1+u) + (1-p)(1+d))^2.$$

More generally:

$N$ -step binomial tree  
models.

$s_0, s_1, \dots, s_N$

$$\frac{s_N}{s_0} = \frac{s_1}{s_0} \cdot \frac{s_2}{s_1} \cdots \frac{\cancel{s_N}}{\cancel{s_0}} \frac{\cancel{s_{N-1}}}{\cancel{s_{N-1}}}$$

$$= \left\{ \cancel{\binom{N}{i}} (1+u)^i (1+d)^{Ni} \right. \begin{matrix} \text{prob} \\ \left( \binom{N}{i} p^i (1-p)^{Ni} \right) \end{matrix} \right\}$$

How to "discover" Brownian Motion  
in stock movements.

Want to understand the  
distribution of a stock path  
from time 0 to time  $t$ .

(continuous)

$\frac{1}{4}$

Assume <sup>1</sup> distribution of stock  
paths is a limit of  
discrete  $N$ -step binomial tree  
models and for each  $N$   
the  $N$ -step model has

up factor and down factor  
probabilities of  ~~$\frac{1}{2}$~~   $\frac{1}{2}$ .

Fix  $N \geq 0$

$$\tilde{c} = \frac{t}{N} \quad (\tilde{c} = \frac{1}{N} \text{ if } t=1)$$

$$\underline{K_N} = \begin{cases} u_N & \frac{t_2}{2} \\ d_N & \frac{1}{2} \end{cases}$$

Because product is naturally appear in expected values / variance of Binomial tree, we'll consider the distribution of  $\ln(\frac{S_t}{S_0})$ .

$$k_N = \begin{cases} \ln(1+u_N) & Y_2 \\ \ln(1+d_N) & Y_2 \end{cases}$$

$$\frac{s_t}{s_0} = \frac{s_{t/N}}{s_0} \cdot \frac{s_{t/N}}{s_{t/N}} \cdots \cdot \frac{s_{t/N}}{\frac{s_{t(N-1)}}{N}}$$

~~so~~

$$\ln\left(\frac{s_t}{s_0}\right) = \sum \ln\left(\frac{s_{it/N}}{\frac{s_{(i-1)t/N}}{s_{it/N}}}\right)$$

$$= \sum k_N(i)$$

$$\text{Set } \mu = E\left[\ln\left(\frac{s_t}{s_0}\right)\right]$$

$$\sigma = \text{std}\left(\ln\left(\frac{s_t}{s_0}\right)\right)$$

$$\mu = E\left[\sum k_N(i)\right]$$

$$= N E[k_N]$$

or  $E[k_N] = \frac{\mu}{N}$

$$\sigma^2 = \text{Var}\left(\ln\left(\frac{s_t}{s_0}\right)\right)$$

$$= E\left[\left(\sum k_N(i)\right)^2\right] - \underbrace{E\left[\sum k_N(i)\right]}_{\text{all } i \text{ i.i.d}}^2$$

$$= N \text{Var}(k_N)$$

or  $\text{Var}(k_N) = \frac{\sigma^2}{N}$

$t = \frac{1}{t}$   
time goes from  
 $0$  to  $t$

$$k_N = \begin{cases} \ln(1+u) & \frac{1}{2} \\ \ln(1+d) & \frac{1}{2} \end{cases}$$

$$= \begin{cases} \frac{\mu}{\sqrt{n}} + \frac{\sigma}{\sqrt{n}} & \frac{1}{2} \\ \frac{\mu}{\sqrt{n}} - \frac{\sigma}{\sqrt{n}} & \frac{1}{2} \end{cases}$$

We'll introduce 2 more distributions:

$$\underline{\zeta_N} = \begin{cases} \frac{1}{\sqrt{n}} & \frac{1}{2} \\ -\frac{1}{\sqrt{n}} & \frac{1}{2} \end{cases}$$

$$\underline{W_N} = \underline{\zeta_N}(1) + \dots + \underline{\zeta_N}(n)$$

$$\underline{W_{N,i}} = \underbrace{\zeta_N(1) + \dots + \zeta_N(i)}_{i.i.d.}.$$

$$\underline{k_N} = \underline{\frac{\mu}{\sqrt{n}}} + \sigma \underline{\zeta_N} \leftarrow$$

$$\begin{aligned}
 & \frac{\ln\left(\frac{s_t}{s_c}\right)}{N} \\
 &= \sum k_n(i) \\
 &= \sum \frac{\mu}{N} + \sigma \xi_n(i) \\
 &= \underline{\mu} + \underline{\sigma w_N}
 \end{aligned}$$

$$\frac{s_t}{s_c} \xrightarrow{w_N} e^{\mu + \sigma w_N}$$

Where  $w_N = \text{sum of } N\text{-random draws cf } \begin{cases} \frac{1}{\sqrt{N}} & \frac{1}{2} \\ -\frac{1}{\sqrt{N}} & \frac{1}{2} \end{cases}$

What is

$$\lim_{N \rightarrow \infty} e^{\mu + \sigma w_N} ?$$

Only care about

$$\lim_{N \rightarrow \infty} w_N ?$$

Limit distribution exists,

denoted by  $W_t$