

Math 5760/6890: Introduction to Mathematical Finance

The Cox-Ross-Rubinstein model

See Petters and Dong 2016, Section 5.2

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We have modeled a security's price $S_j = S(t_j)$ via,

$$S_{j+1} = G_{j+1}S_j, \quad G_j = \begin{cases} u, & \text{with probability } p \\ d, & \text{with probability } 1 - p \end{cases}$$

From this model, we've concluded:

- $L := \log(S_n/S_0)$ is a scaled/shifted Binomial(n, p) random variable.
- $S_n = S_0 e^L$ is the exponential of a scaled/shifted Binomial random variable
- The triple (p, u, d) determines the distribution entirely.

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The CRR model places the following additional constraints on our standard Binomial tree model:

- Geometric symmetry of tree prices: $u = 1/d$
- The continuous-time limit of the expected log-return matches the real-world drift:

$$\mu = \lim_{n \rightarrow \infty} \frac{1}{h_n} \mathbb{E}L_j$$

- The continuous-time limit of the variance of the log-return matches the real-world (squared) volatility:

$$\sigma^2 = \lim_{n \rightarrow \infty} \frac{1}{h_n} \text{Var}L_j$$

Hence, for finite n , (p, u, d) should depend on the time discretization parameter n . I.e.:

$$(p, u, d) = (p_n, u_n, d_n).$$

Goal: use CRR constraints to choose (p_n, u_n, d_n) .

The problem setup

D19-S03(a)

We seek to construct a fixed, finite- n Binomial tree model over the time period $[0, T]$. I.e., we seek to compute (p_n, u_n, d_n) for a fixed n and $h_n = T/n$.

We assume that the (continuous-time) drift and volatility parameters (μ, σ) are available to us. (E.g., we've computed approximations to them from historical data.)

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- $d_n = 1/u_n \implies$ need only determine (p_n, u_n) .
- Drift matching: Ideally, we have,

$$\frac{\mathbb{E}L_j}{h_n} = \mu_n \xrightarrow{n \uparrow \infty} \mu.$$

We can't really do this directly since we only want to construct (p_n, u_n) for finite n . Hence, we will instead impose:

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- We have a similar condition for matching the volatility:

$$\frac{\text{Var}L_j}{h_n} = \sigma_n^2 \approx \sigma^2$$

Our CRR conditions require statistics of the inter-period log-returns, e.g.,

$$\mathbb{E}L_j, \quad \text{Var}L_j.$$

$$L_j = \begin{cases} \log u_n, & \text{w/prob } p_n \\ -\log u_n, & \text{w/prob } 1-p_n \end{cases} \quad (d_n = 1/u_n)$$

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Of course, we know how to compute these: We have,

$$L_j = \log d_n + X_j \log \frac{u_n}{d_n} = -\log u_n + 2X_j \log u_n,$$

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$$L_j = \log d_n + X_j \log \frac{u_n}{d_n} = -\log u_n + 2X_j \log u_n, \quad \text{or } (2X_j - 1) \log u_n$$

where $X_j \sim \text{Bernoulli}(p_n)$.

$$\text{(Recall: } \mathbb{E}X_j = p_n, \quad \text{Var}X_j = p_n(1-p_n) \text{)}$$

Therefore:

$$\mathbb{E}L_j = (2p_n - 1) \log u_n,$$

$$\text{Var}L_j = 4p_n(1 - p_n)(\log u_n)^2$$

Therefore, our CRR constraints are the following:

$$d_n = \frac{1}{u_n}$$

$$\mu = \frac{2p_n - 1}{h_n} \log u_n \quad (\mu = \mathbb{E} L/h)$$

$$\sigma^2 = \frac{4p_n(1-p_n)}{h_n} (\log u_n)^2. \quad (\sigma^2 = \frac{1}{h} \text{Var } L)$$

where we have replaced some instances of “ \approx ” with “ $=$ ”.

We can solve this (nonlinear) system of equations for (p_n, u_n) , then d_n .

Instead: we'll come up w/ approximate solutions.

Idea: for large n , $p_n \rightarrow 1/2 \Rightarrow 4p_n(1-p_n) \rightarrow 1$

So we approximate $4p_n(1-p_n) \approx 1$

Then the conditions above reduce to $\mu = \frac{2p_n - 1}{h_n} \log u_n$ (\star)

$$\sigma^2 = \frac{(\log u_n)^2}{h_n}$$

$$\Rightarrow u_n = \exp\left(\frac{\mu}{h_n}\right) \exp(\sigma\sqrt{h_n})$$

$$d_n = \exp\left(-\frac{\mu}{h_n}\right) \exp(-\sigma\sqrt{h_n})$$

$$(\star): p_n = \left(\frac{h_n \mu}{\sigma \sqrt{h_n} \log u_n} + 1\right) \frac{1}{2}$$

$$= \left(\frac{h_n \mu}{\sigma \sqrt{h_n}} + 1\right) \frac{1}{2}$$

$$= \frac{1}{2} \left(1 + \sqrt{h_n} \frac{\mu}{\sigma}\right)$$

Therefore, our CRR constraints are the following:

$$\begin{aligned}d_n &= \frac{1}{u_n} \\ \mu &= \frac{2p - 1}{h_n} \log u_n \\ \sigma^2 &= \frac{4p_n(1 - p_n)}{h_n} (\log u_n)^2.\end{aligned}$$

where we have replaced some instances of “ \approx ” with “ $=$ ”.

After some computations and approximations, we arrive at the following *real-world CRR equations*:

$$p_n \approx \frac{1}{2} \left(1 + \frac{\mu}{\sigma} \sqrt{h_n} \right), \quad u_n \approx \exp(\sigma \sqrt{h_n}), \quad d_n \approx \exp(-\sigma \sqrt{h_n}).$$

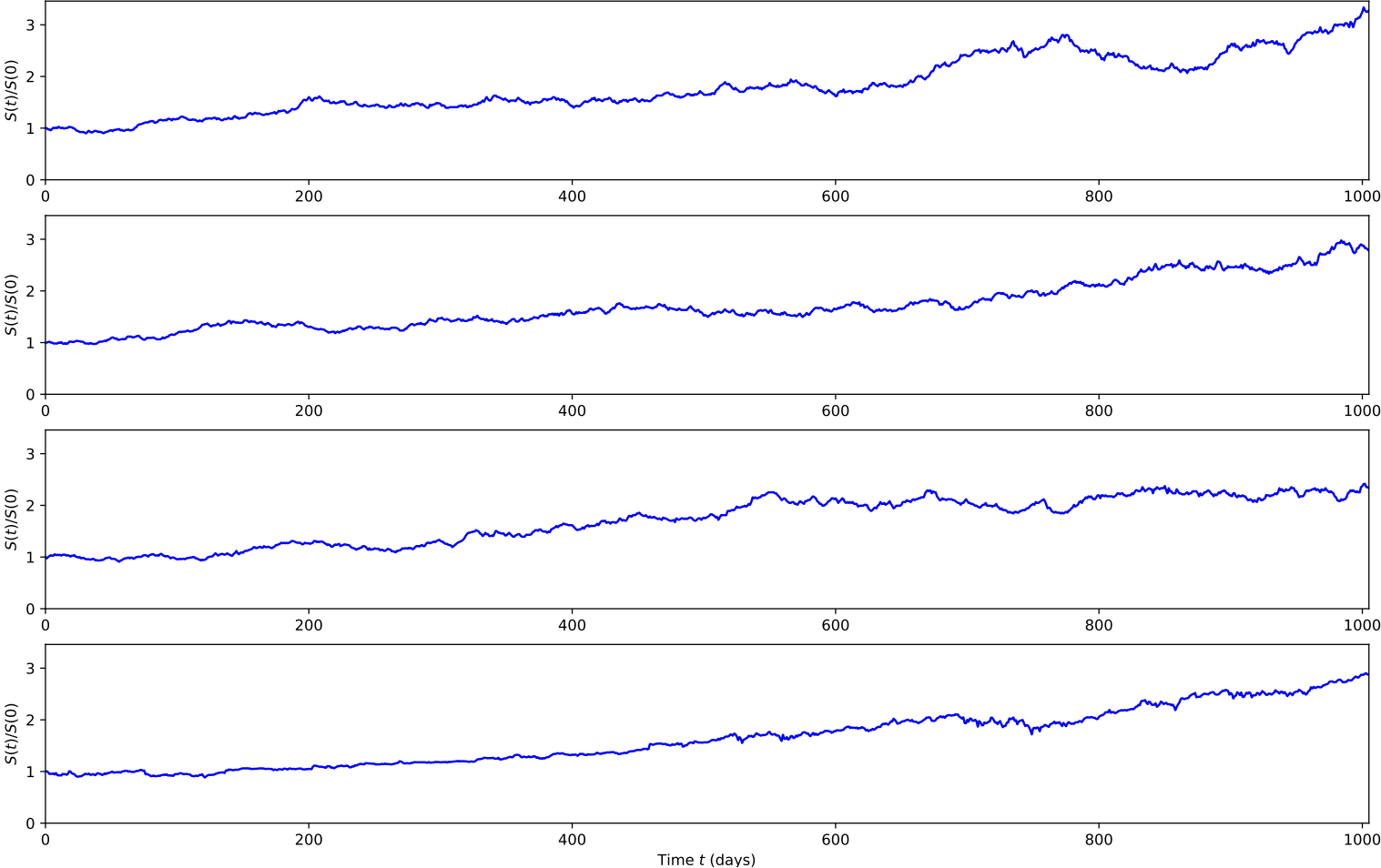
A “real-world” CRR tree/model is therefore constructed in the following way:

- Historical data is used to compute an asset’s continuous-time drift and volatility (μ, σ)
- The terminal time T and number of periods n is determined. $h_n = T/n$.
- The real-world CRR equations are used to set (p_n, u_n, d_n) :

$$p_n = \frac{1}{2} \left(1 + \frac{\mu}{\sigma} \sqrt{h_n} \right), \quad u_n = \exp(\sigma \sqrt{h_n}), \quad d_n = \exp(-\sigma \sqrt{h_n}).$$

Let's play a game

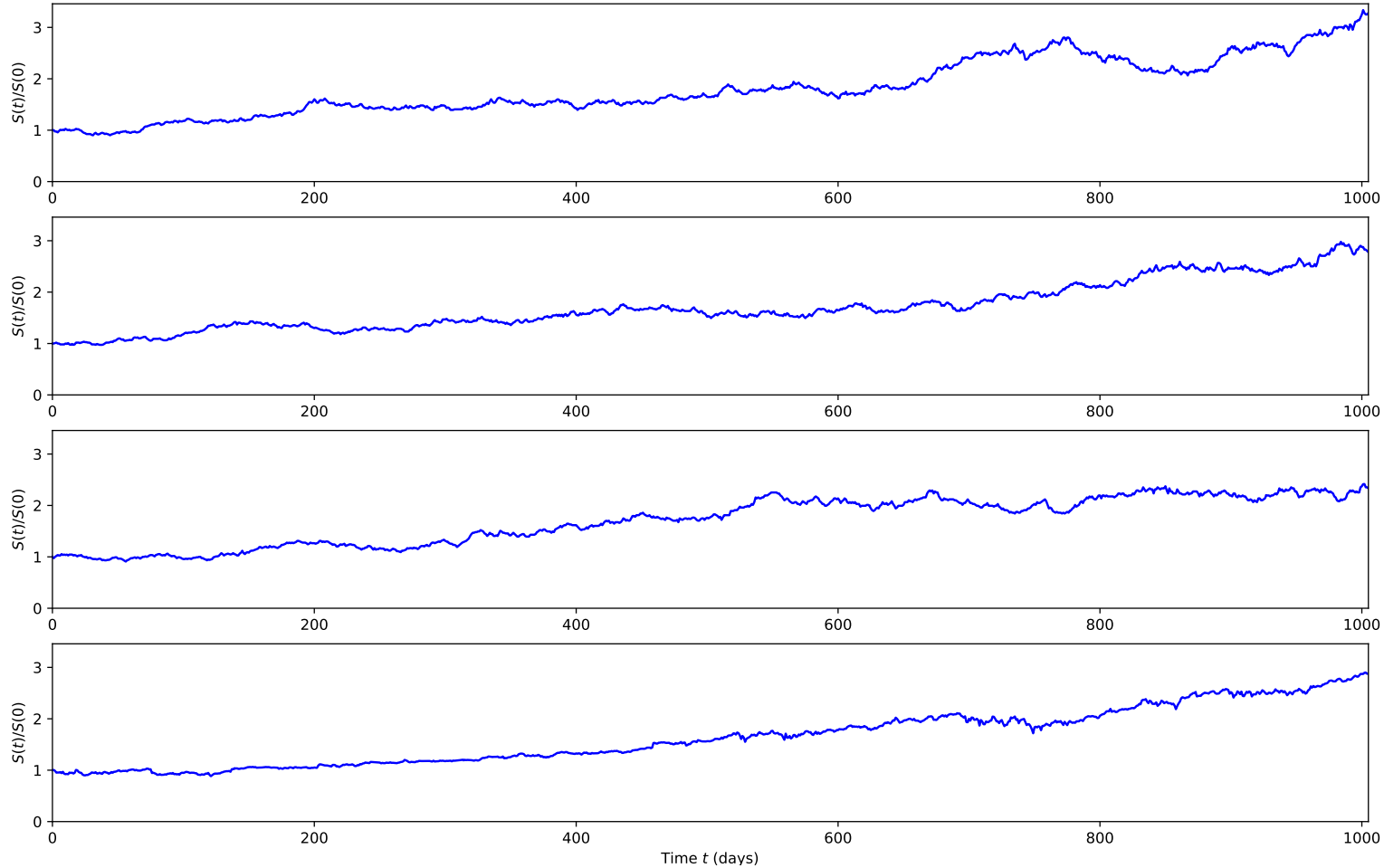
Which is the simulated price?



Let's play a game

D19-S07(b)

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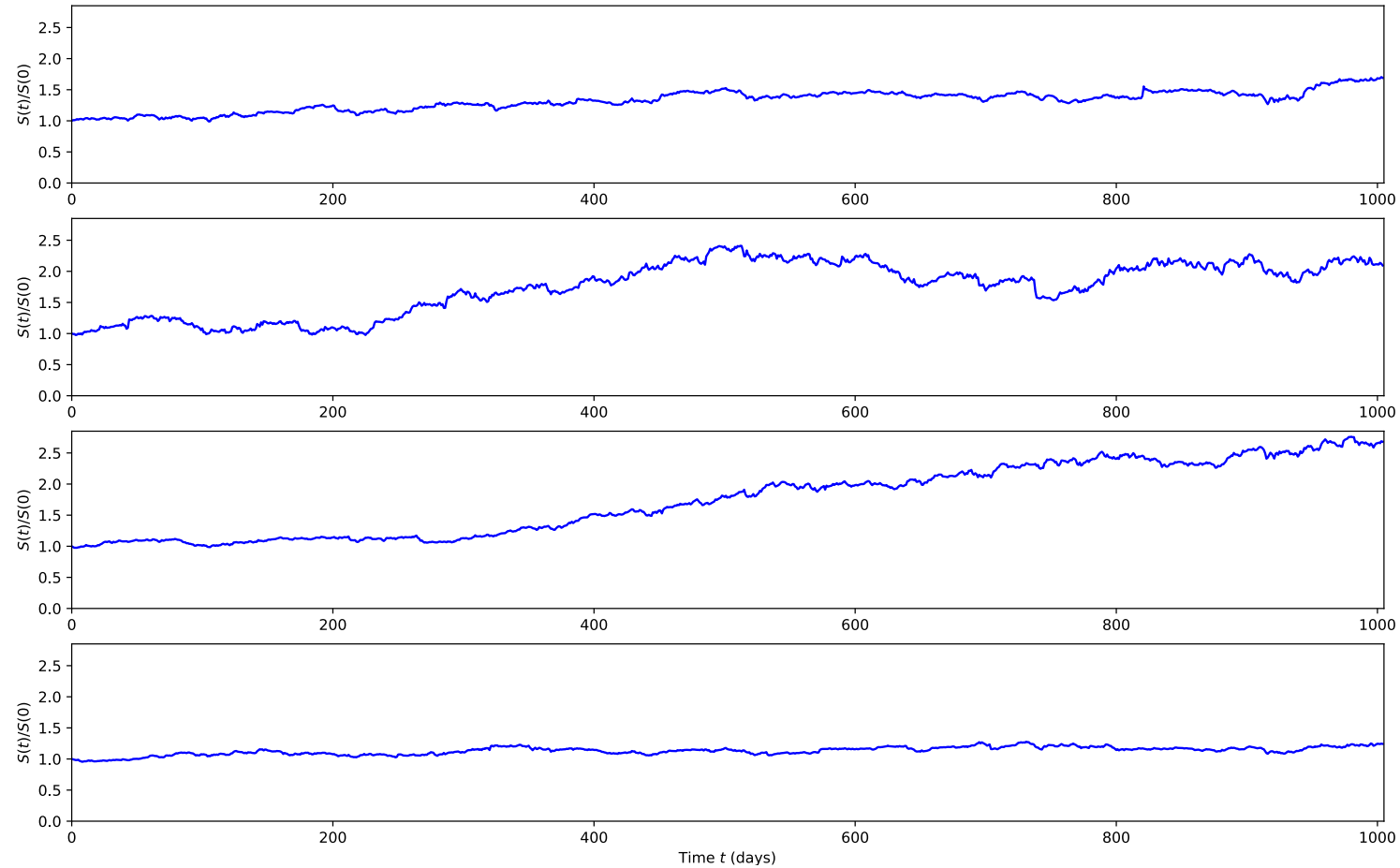


MSFT

Let's play a game, II

D19-S08(a)

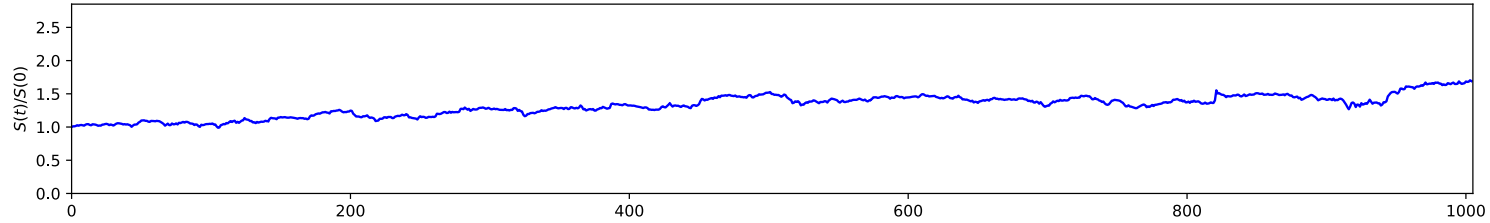
Which prices are simulated?



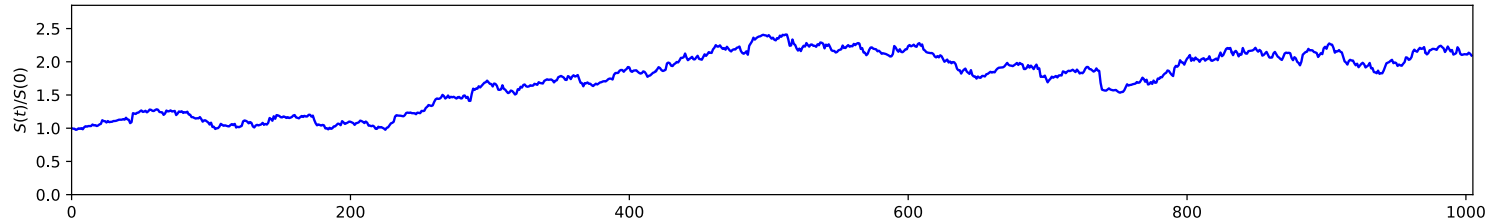
Let's play a game, II

D19-S08(b)

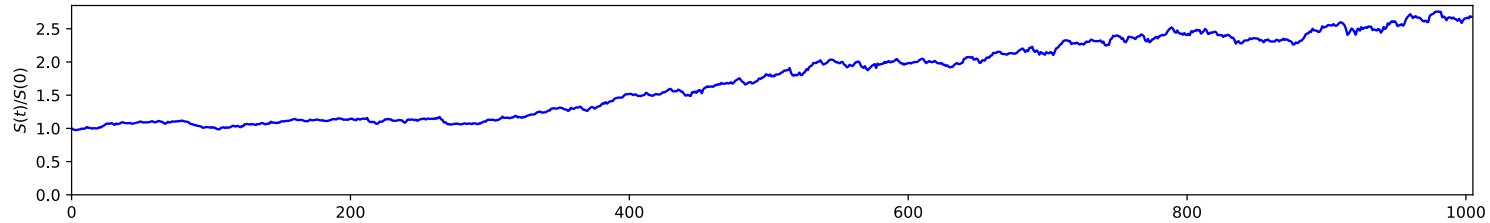
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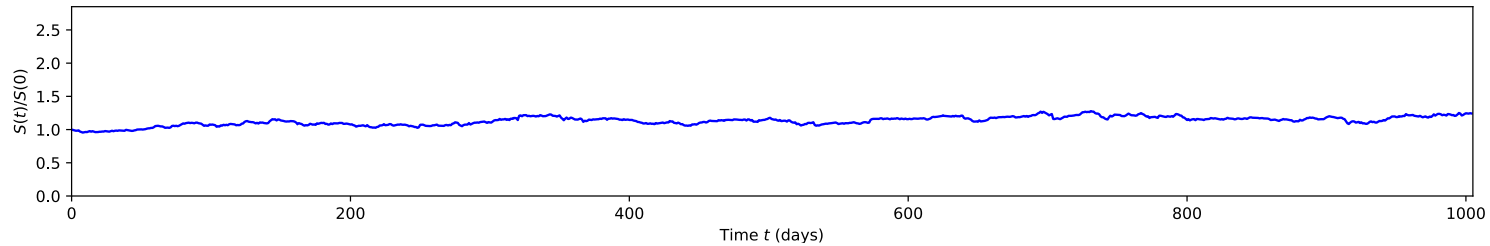
GE



Airbus



Lockheed
Martin



Coca cola

Some initial observations about the tuple (p_n, u_n, d_n) of the real-world CRR model:

- Because $u_n = \exp(\sigma\sqrt{h_n})$, and $h_n = T/n$, then

$$\lim_{n \uparrow \infty} u_n = 1,$$

and similarly for $d_n = 1/u_n$.

I.e., the uptick and downtick geometric rates become very close to unity for large n .

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- Because $p_n = \frac{1}{2} \left(1 + \frac{\mu}{\sigma} \sqrt{h_n} \right)$, then

$$\lim_{n \uparrow \infty} p_n = \frac{1}{2},$$

so that for large n the CRR tree tends toward fair coin flips.

What kind of statistics does S_n have under this model? We have,

$$S_n = S_0 e^L = S_0 \exp\left(\sum_{j=1}^n L_j\right).$$

We've seen that

$$\mathbb{E}S_n = S_0 (p_n u_n + (1 - p_n) d_n)^n,$$

and we have the real-world CRR equations:

$$p_n = \frac{1}{2} \left(1 + \frac{\mu}{\sigma} \sqrt{h_n}\right), \quad u_n = \exp(\sigma \sqrt{h_n}), \quad d_n = \exp(-\sigma \sqrt{h_n}).$$

$$d_n = 1/u_n$$

$$\mathbb{E}S_n = S_0 \left(p_n u_n + \underbrace{(1-p_n)}_{\frac{1}{2} - \frac{\mu}{2\sigma} \sqrt{h_n}} d_n \right)^n = S_0 \left[u_n \left(\frac{1}{2} + \frac{\mu}{2\sigma} \sqrt{h_n} \right) + \frac{1}{u_n} \left(\frac{1}{2} - \frac{\mu}{2\sigma} \sqrt{h_n} \right) \right]^n$$

$$= S_0 \left[\frac{1}{2}(u_n + \frac{1}{u_n}) + \frac{\mu}{2\sigma} \sqrt{h_n} (u_n - \frac{1}{u_n}) \right]^n$$

$$u_n = \exp(\sigma\sqrt{h_n})$$

$$\approx 1 + \sigma\sqrt{h_n} + \frac{(\sigma\sqrt{h_n})^2}{2!} + \dots$$

$$\frac{1}{u_n} = \exp(-\sigma\sqrt{h_n}) \approx 1 - \sigma\sqrt{h_n} + \frac{(\sigma\sqrt{h_n})^2}{2!} + \dots$$

$$\Rightarrow u_n + \frac{1}{u_n} \approx \cancel{1} + 0 + \sigma^2 h_n$$

$$u_n - \frac{1}{u_n} \approx 2\sigma\sqrt{h_n}$$

$$\Rightarrow \mathbb{E}S_n \xrightarrow{n \uparrow \infty} S_0 \left[\frac{1}{2}(2 + \sigma^2 h_n) + \frac{\mu}{2\sigma} \sqrt{h_n} (2\sigma\sqrt{h_n}) \right]^n$$

$$= S_0 \left[1 + \frac{\sigma^2}{2} h_n + \mu h_n \right]^n$$

$$= S_0 \left[1 + \left(\mu + \frac{\sigma^2}{2} \right) \frac{T}{n} \right]^n \quad (\text{recall: } \lim_{n \rightarrow \infty} \left(1 + \frac{k}{n} \right)^n = e^k)$$

$$\stackrel{n \uparrow \infty}{=} S_0 \exp\left(\left(\mu + \frac{\sigma^2}{2} \right) T \right)$$

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These allow us to conclude:

$$\lim_{n \uparrow \infty} \mathbb{E}S_n = S_0 \exp\left[\left(\mu + \frac{\sigma^2}{2}\right) T\right],$$

i.e., there is a well-defined limit independent of the discretization parameters n and h_n .

What kind of distribution does S_n have? It will be useful to write S_n in terms of *standardizations* of L_j .

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A standardization of L_j (or of any random variable) is

$$\widetilde{L}_j = \frac{L_j - \mathbb{E}L_j}{\sqrt{\text{Var}L_j}},$$

i.e., it is a centered version of L_j , inversely scaled by its standard deviation: standardizations of random variables are mean-0 and variance-1.

With the standardization of the L_j variables, we have,

$$S_n = S_0 \exp \left(\sum_{j=1}^n \left(\mathbb{E}L_j + \sqrt{\text{Var}L_j} \widetilde{L}_j \right) \right).$$



Petters, Arlie O. and Xiaoying Dong (2016). *An Introduction to Mathematical Finance with Applications: Understanding and Building Financial Intuition*. Springer. ISBN: 978-1-4939-3783-7.