# Courant Institute of Mathematical Sciences 

New York University
Mathematics in Finance

## Derivative Securities, Fall 2009

Class 3, final version

Jonathan Goodman
http://www.math.nyu.edu/faculty/goodman/teaching/DerivSec09/index.html

## Hedging and pricing with a forward

1. Forward price for forward contract settled at time $T^{\prime} \geq T$ :

$$
F_{t}=e^{r\left(T^{\prime}-t\right)} S_{t}=e^{r T^{\prime}} e^{-r t} S_{t}=C_{T^{\prime}} e^{-r t} S_{t}
$$

2. (Up to a constant) $F_{t}=$ exponentially discounted version of $S_{t}$
3. $F_{0}=E_{R N}\left[F_{t}\right]=E_{P}\left[F_{t}\right]$, if $0 \leq t \leq T^{\prime}$
4. If the possible values of $F_{T}$ are $F_{u}$ and $F_{d}$, then 3 implies

$$
p_{u}=\frac{F_{0}-F_{d}}{F_{u}-F_{d}}
$$

5. Replicating portfolio with a forward and case: same

## Random process

- $S_{t}=S(t)=$ price at time $t$
- $S$ is the whole path, $S_{t}$ is the value at time $t$
- $\mathcal{F}_{t}=$ all information available at time $t$, including $S_{t^{\prime}}$ for $t^{\prime} \leq t$ (see stochastic calculus)
- $u\left(s, t^{\prime} \mid \mathcal{F}_{t}\right)$ (with $t^{\prime} \geq t$ ) is the probability distribution of $S_{t^{\prime}}$ given all information available at time $t$
- Discrete time: $0=t_{0}<t_{1}<\cdots<t_{n}=T$
- Binomial tree model, homogeneous, $t_{k}=k \delta t$ :
- $S_{t_{k+1}}=u S_{t_{k}}$ with probability $p_{u}$
- $S_{t_{k+1}}=d S_{t_{k}}$ with probability $p_{d}$
- all steps independent


## Martingale

- $\mathcal{F}_{t}$ is the information available at time $t$
- Assume nothing is forgotten: $\mathcal{F}_{t} \subseteq \mathcal{F}_{t^{\prime}}$ if $t^{\prime}>t$
- $X_{t}$ is a stochastic process with respect to $\mathcal{F}_{t}$ if the value of $X_{t}$ is determined by $\mathcal{F}_{t}$.
- Example: $\mathcal{F}_{t}$ is the prices of all listed stocks up to time $t, X_{t}$ is an index.
- Example: $X_{t}$ is the average of a stochastic process up to time $t$.
- $M_{t}$ is a martingale if $E\left[M_{t^{\prime}} \mid \mathcal{F}_{t}\right]=M_{t}$, for $t^{\prime} \geq t$.
- Example, simple random walk: $a>0>b, a p_{u}+b p_{d}=0$
- $M_{t_{k+1}}=M_{t_{k}}+a$ with probability $p_{u}$
- $M_{t_{k+1}}=M_{t_{k}}+b$ with probability $p_{d}$
- All steps independent, $p_{u}+p_{d}=1$
- $\mathcal{F}_{t_{k}}=$ values of $M_{t_{j}}$, for all $j \leq k$, (including $M_{t_{k}}$, so $\mathcal{F}_{t_{k}}$ determines $M_{t_{k}}$ )


## Risk neutral model worlds

- In the risk neutral measure, $F_{t}=e^{-r t} S_{t}$ is a martingale.
- $F_{t}=E_{R N}\left[F_{t^{\prime}} \mid \mathcal{F}_{t}\right] \Longleftrightarrow E_{R N}\left[S_{t^{\prime}} \mid \mathcal{F}_{t}\right]=e^{r\left(t^{\prime}-t\right)} S_{t}$
- Lognormal model:

$$
S_{t^{\prime}}=S_{t} \exp \left\{\left(r-\sigma^{2} / 2\right)\left(t^{\prime}-t\right)+\sigma \sqrt{t^{\prime}-t} Z\right\}
$$

- Binomial tree model, $t_{k}=k \delta t$, all steps independent
- $S_{t_{k+1}}=u S_{t_{k}}$ with probability $p_{u}$
- $S_{t_{k+1}}=d S_{t_{k}}$ with probability $p_{d}$
$-u p_{u}+d p_{d}=e^{r \delta t}, p_{u}+p_{d}=1$
- $t^{\prime}-t=\Delta t$ small, calibrate the binomial model so that
$\Delta S=S_{t+\Delta t}-S_{t}$ have the same mean and variance as the lognormal model, conditional on $\mathcal{F}_{t}$.
- Price today of $V\left(S_{T}\right)$ at time $T$ is $e^{-r T} E_{R N}\left[V\left(S_{T}\right)\right]$
- Discounted expected value, in the Risk neutral model


## The log process and log tree

- If $S_{t}$ is a lognormal process, then $X_{t}=\log \left(S_{t}\right)$ is a "normal" process
- $X_{t^{\prime}}=X_{t}+\left(\mu-\frac{\sigma^{2}}{2}\right)\left(t^{\prime}-t\right)+\sigma \sqrt{t^{\prime}-t} Z$
- $\Delta t=t^{\prime}-t, \Delta X=X_{t^{\prime}}-X_{t}$
- $\Delta X \sim \mathcal{N}\left(\left(\mu-\frac{\sigma^{2}}{2}\right) \Delta t, \sigma^{2} \Delta t\right)$
- $\Delta X^{2}=O(\Delta t) \Longrightarrow \Delta X \sim O(\sqrt{\Delta t}) \gg \Delta t$

The Ito calculus: $E\left[e^{\Delta x}\right] \approx 1+E[\Delta X]+\frac{1}{2} E\left[\Delta X^{2}\right]$

- If $S_{t}$ is a binomial tree process, then $X_{t}=\log \left(S_{t}\right)$ is a simple random walk
- $p_{u}$ and $p_{d}$ do not change
- $a=\log (u), b=\log (d)$.


## Continuous time limit

- Find an approximate description of geometric random walk (the binomial tree process) or ordinary random walk when $\delta t$ is small
- Calculus vs. algebra
- Algebra: simple foundations, complicated formulas

$$
S(n)=\sum_{k=0}^{n} k^{2}=\frac{1}{3} n^{3}+\frac{1}{2} n^{2}+\frac{1}{6} n .
$$

- Calculus: mathematically challenging foundations, simple formulas

$$
\begin{aligned}
& \int_{a}^{b} f(x) d x=\lim _{\delta x \rightarrow 0} \sum_{x_{k}} f\left(x_{k}\right) \delta x, \quad x_{k}=a+k \delta x . \\
& I(n)=\int_{x=0}^{n} x^{2} d x=\frac{1}{3} n^{3} . \\
& S(n) \approx I(n) \text { for large } n .
\end{aligned}
$$

## Key 1: Central Limit Theorem

- $X_{k+1}=X_{k}+Y_{k}, \operatorname{Pr}\left(Y_{k}=a, b\right)=p_{u}, p_{d}, X_{0}=0$
- $X_{n}=\sum_{k=1}^{n} Y_{k}$, with the $Y_{k}$ i.i.d. (independent, identically distributed)
- $\mu_{Y}=\bar{Y}=E[Y], \sigma_{Y}^{2}=\operatorname{var}(Y)=E\left[(Y-\bar{Y})^{2}\right]$.
- Central Limit Theorem: $X_{n}$ is approximately Gaussian with mean $n \mu$ and variance $n \sigma^{2}$.
- Probability density of $X_{n}$ is $f_{n}(x)$

$$
f_{n}(x) \approx \frac{1}{\sqrt{2 \pi n \sigma_{Y}^{2}}} e^{-\left(x-n \mu_{Y}\right)^{2} /\left(2 n \sigma_{Y}^{2}\right)}
$$

- If $x=j a+(n-j) b$, then (in binomial simple random walk)

$$
\operatorname{Pr}\left(X_{n}=x\right)=\frac{n(n-1) \cdots(n-j+1)}{j(j-1) \cdots 1} p_{d}^{j} p_{u}^{(n-j)}
$$

## Key 2: Scaling

- $T=t_{n}=n \delta t$
- $\mu_{Y}=\delta t \mu$ ( $\mu=$ growth rate).
- $\mu_{y}=$ mean in a single time step, scales like $\delta t$
- $\sigma_{Y}^{2}=\delta t \sigma^{2}$ ( $\sigma=$ volatility)
- $\sigma_{y}=$ standard deviation in a single time step, scales like $\sqrt{\delta t}$
- Then $E\left[X_{T}\right]=\mu T$ and $\operatorname{var}\left(X_{T}\right)=\sigma^{2} T$
- If $f(x, T)$ is the density of $X_{T}$, then

$$
f(x, T)=\frac{1}{\sqrt{2 \pi \sigma^{2} T}} e^{-(x-\mu T)^{2} /\left(2 \sigma^{2} T\right)}
$$

- In simple random walk, have $\delta X=O(\sqrt{\delta t})$, could take
- $a=-\sigma \sqrt{\delta t}+\mu \delta t, b=\sigma \sqrt{\delta t}+\mu \delta t, p_{d}=p_{u}=\frac{1}{2}$
- $a=-\sigma \sqrt{\delta t}, b=\sigma \sqrt{\delta t}$,

$$
p_{d}=\frac{1}{2}-\frac{\mu}{2 \sigma} \sqrt{\delta t}, p_{u}=\frac{1}{2}+\frac{\mu}{2 \sigma} \sqrt{\delta t}
$$

## Brownian motion

- $X_{t}=\sum_{t_{k} \leq t} Y_{k} \sim$ normal mean $\mu t$, variance $\sigma^{2} t$.
- $X_{t^{\prime}}-X_{t}=$ increment between $t$ and $t^{\prime}$ $\sim$ normal mean $\left(t^{\prime}-t\right) \mu$, variance $\left(t^{\prime}-t\right) \sigma^{2}$.
- Increments from disjoint intervals are independent
- $\left|X_{t^{\prime}}-X_{t}\right|=O\left(\sqrt{t^{\prime}-t}\right)$ for small increments
- Rough paths, not differentiable


## Geometric random walk/binomial tree model

- $S_{t}=S_{0} e^{X_{t}}$
- $d=e^{b} \approx 1-b+\frac{1}{2} b^{2}$ (need the $b^{2}$, Ito)
- $u=e^{a} \approx 1-b+\frac{1}{2} b^{2}$ (need the $b^{2}$, Ito)
- In the limit $\delta t \rightarrow 0, S_{t}$ is Geometric Brownian motion
- $S_{t}=S_{0} e^{X_{t}}$, where $X_{t}$ is Brownian motion (gaussian).

