

Courant Institute of Mathematical Sciences

New York University

Mathematics in Finance

Derivative Securities, Fall 2009

Class 4

last corrected October 13 to fix page 12

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<http://www.math.nyu.edu/faculty/goodman/teaching/DerivSec09/index.html>

Ito calculus: keep small, neglect tiny

- Keep δt : $\sum_{t_k < T} a(t_k) \delta t \rightarrow \int_0^T a(t) dt \neq 0$, as $\delta t \rightarrow 0$
- Neglect higher powers:
$$\sum_{t_k < T} a(t_k) \delta t^{3/2} \approx \left[\int_0^T a(t) dt \right] \delta t^{1/2} \rightarrow 0 \text{ as } \delta t \rightarrow 0$$
- Application: suppose $F_{k+1} = (1 + b(t_k) \delta t) F_k$
- Taylor series: $1 + \epsilon = e^{\epsilon - \frac{1}{2} \epsilon^2}$ ($\epsilon = \text{small}$, $\epsilon^2 = \text{tiny}$)
- $F_n \approx F_0 \exp\left(\sum_{t_k < T} b(t_k) \delta t\right) \exp\left(\sum_{t_k < T} \frac{1}{2} b(t_k)^2 \delta t^2\right)$
- $F_n \rightarrow F_0 \exp\left(\int_0^T b(t) dt\right)$ as $\delta t \rightarrow 0$

Geometric random walk/Brownian motion

- $S_{k+1} = X_k S_k$, $E[X_k] = 1 + \mu\delta t$, $\text{var}(X_k^2) = \sigma^2\delta t$
- Write $X_k = 1 + Y_k$, with $E[Y_k] = \mu\delta t$
- $E[Y_k^2] = \sigma^2\delta t$ (small) + $\mu^2\delta t^2$ (tiny) $\approx \sigma^2\delta t$.
- $S_n \approx S_0 \exp\left(\sum_{t_k < T} Y_k - \frac{1}{2} \sum_{t_k < T} Y_k^2\right)$
- Central limit theorem: $\sum_{t_k < T} Y_k \approx \mu T + \sigma W_T$
- Law of large numbers: $\sum_{t_k < T} Y_k^2 \approx \sigma^2 T$
- Altogether: $S_n \approx S_0 \exp\left((\mu - \frac{1}{2}\sigma^2) T + \sigma W_T\right)$
- The limit $\delta t \rightarrow 0$ depends only on $E[Y_k]$ and $\text{var}(Y_k)$

Brownian motion

- $W(t)$ is a random function of t . W is a random path.
- Let $s_1 \leq t_1 \leq s_2 \leq t_2 \leq \dots \leq s_n \leq t_n$ be start and end times for disjoint intervals: $I_k = [s_k, t_k]$
- *Increments* of Brownian motion are $Y_k = W(t_k) - W(s_k)$
- It's standard ($\mu = 0$, $\sigma = 1$) Brownian motion if the following properties hold:
 1. W is a continuous function of t
 2. $W(0) = 0$
 3. The increments are independent Gaussian random variables with $\text{var}(Y_k) = t_k - s_k$.
- **Theorem:** Arithmetic (ordinary) random walk can be scaled and normalized so that it converges to Brownian motion as $\delta t \rightarrow 0$
- Therefore, a path whose increments are the sum of many smaller independent increments may be modeled as Brownian motion

Newton/Leibnitz/Reimann to Ito: Tiny becomes small

- $\delta W(t) = W(t + \delta t) - W(t)$ has
 - $E[\delta W^2] = \delta t$ and
 - $|\delta W| = O(\sqrt{\delta t})$
- Riemann sum, left ended
 $R_- = \sum_{t_k < T} f(t_k) \delta g(t_k) \longrightarrow \int_0^T f(t) dg(t)$
as $\delta t \rightarrow 0$
- Right ended: $R_+ = \sum_{t_k < T} f(t_{k+1}) \delta g(t_k)$
- If f and g are smooth, then $R_+ - R_-$ is tiny, because
 $R_+ - R_- = \sum_{t_k < T} \delta f(t_k) \delta g(t_k) = \sum_{t_k < T} O(\delta t^2) = O(\delta t T)$
- If $f = g =$ Brownian motion, then the difference is small:
 $R_+ - R_- = \sum_{t_k < T} \delta W(t_k)^2 \rightarrow T$ (law of large numbers)

Ito integral with respect to Brownian motion

- $\int_0^T F(t)dW(t) = \lim_{\delta t \rightarrow 0} F(t_k)\delta W(t_k)$
left ended approximations only
- F may be random, but it must be *nonanticipating*
 - $F(t)$ is known at time t
 - Increments of W beyond t completely unknown
 - $E[F(t_k)\delta W(t_k)] = E[F(t_k)]E[\delta W(t_k)] = 0$
- $\int_0^T W(t)dW(t) = \frac{1}{2}(W(T)^2 - T)$
 - The expected value is zero, as it must be
 - If $W(t)$ were a smooth function of t , would not have $\frac{1}{2}T$
 - The right ended approximation gives $\frac{1}{2}(W(T)^2 + T)$, as it should

The Ito differential

- If $F(t)$ is a random function, then dF is defined by
 - $\int_{t_1}^{t_2} dF(t) = F(t_2) - F(t_1)$
- Get a formula for dF by calculating δF and keeping small terms and neglecting tiny terms.
- ϵ is *tiny* if
 - $|\epsilon| = O(\delta t^p)$ with $p > 1$, or
 - $|\epsilon| = O(\delta t)$ and $E[\epsilon] = 0$
- *Ito's rule*: if $|\epsilon| = O(\delta t)$, then $\epsilon = E[\epsilon] + \text{tiny}$.
- Example: $\delta(W^2)(t)$
 - = $(W(t) + \delta W)^2 - W(t)^2 = 2W(t)\delta W(t) + (\delta W(t))^2$
 - $d(W(t)^2) = 2W(t)dW(t) + dt$
 - $W(T)^2 - W(0)^2 = \int_0^T d(W(t)^2) = 2 \int_0^T W(t)dW(t) + \int_0^T dt$

Ito's lemma

- Suppose $u(w, t)$ is a smooth function of w and t .
What is $du(W(t), t)$?

$$\begin{aligned}\delta u &= u(W + \delta W, t + \delta t) - u(W, t) \\ &= \partial_w u \delta W + \frac{1}{2} \partial_w^2 u \delta W^2 + \partial_t u \delta t + \text{tiny terms} \\ &= \partial_w u \delta W + \frac{1}{2} \partial_w^2 u \delta t + \partial_t u \delta t + \text{tiny terms}\end{aligned}$$

- Ito's lemma: $du(W, t) = u_w dW + \left(\frac{1}{2}u_{ww} + u_t\right) dt$
- Meaning #1: $u(W(T), T) - u(0, 0) = \int_0^T u_w(W(t), t)dW(t) + \int_0^T \left(\frac{1}{2}u_{ww} + u_t\right) dt$
- Meaning #2: $dF = a(t)dt + b(t)dW$ if
 - $E[\delta F] = a(t)\delta t + \text{tiny}$
 - $E[(\delta F)^2] = b^2(t)\delta t + \text{tiny}$
 - $E[(\delta F)^4] = \text{tiny}$ (very technical – don't worry about it)

Ito differential equation

- An equation of the form $dX = a(X)dt + b(X)dW$.
- Seek a solution in the sense of meaning 2 above:
 - $E[\delta X] = a(t)\delta t + \text{tiny}$
 - $E[(\delta X)^2] = b^2(t)\delta t + \text{tiny}$
 - $E[(\delta X)^4] = \text{tiny}$
- Stock price process: $dS(t) = \mu Sdt + \sigma SdW$
- Solution: $S(t) = S(0) \exp(\sigma W(t) + (\mu + \frac{1}{2}\sigma^2) t)$. Check it!

Black Scholes formula for a European put

- $S_T \sim S_0 \exp\left(\left(r - \frac{\sigma^2}{2}\right) T + \sigma\sqrt{T}Z\right)$ (same distribution)
- $I_A(s) =$ indicator function $= 1$ (if $s \in A$) or 0 (if $s \notin A$)
Here, $A = \{S \leq K\}$
- $P =$ Put price
 $= e^{-rT} E[(K - S_T)_+]$
 $= e^{-rT} E[(K - S_T) I_{S_T < K}(S_T)]$
 $= e^{-rT} K \Pr(S_T < K) + e^{-rT} E[S_T I_{S_T < K}(S_T)]$
- $S_T \leq K \iff Z \leq \frac{\ln(K/S_0) - (r - \sigma^2/2)T}{\sigma\sqrt{T}} = -d_2$
- $d_2 = \frac{\ln(S_0 e^{rT}/K) - \sigma^2 T/2}{\sigma\sqrt{T}}$, $\ln(S_0 e^{rT}/K) =$ moneyness
- $e^{-rT} K \Pr(S_T \leq K) = Ke^{-rT} N(-d_2)$

BS, European put, cont...

- Need $e^{-rT} E[S_T | S_T < K(S_T)]$, with $S_T = S_0 e^{rT} e^{-\sigma^2 T/2} e^{\sigma\sqrt{T}Z}$
- Get $S_0 e^{-\sigma^2 T/2} \int_{S_T \leq K} e^{\sigma\sqrt{T}z} e^{-z^2/2} \frac{dz}{\sqrt{2\pi}}$
- We just saw that $S_T < K \iff z \leq -d_2$.

- Complete the square in the exponent:

$$\frac{-1}{2} (z^2 - 2z\sigma\sqrt{T}) = \frac{-1}{2} \left((z - \sigma\sqrt{T})^2 - \sigma^2 T \right)$$

- So need (after cancellations):

$$S_0 \int_{z \leq -d_2} e^{-(z - \sigma\sqrt{T})^2/2} \frac{dz}{\sqrt{2\pi}} = S_0 N(-d_2 - \sigma\sqrt{T})$$

- $d_1 = d_2 + \sigma\sqrt{T}$,

BS, European put, final

- moneyness = $\ln(S_0 e^{rT} / K)$
 - dimensionless measure of the spot relative to the strike
 - moneyness $\rightarrow \infty$ (or $-\infty$) as $S_0 \rightarrow \infty$ (or 0) .
- $d_2 = \frac{\text{moneyness} - \frac{\sigma^2 T}{2}}{\sigma \sqrt{T}}$
 $= \frac{\text{moneyness}}{\sigma \sqrt{T}} - \frac{\sigma \sqrt{T}}{2}$
- $d_1 = d_2 + \sigma \sqrt{T} = \frac{\text{moneyness}}{\sigma \sqrt{T}} + \frac{\sigma \sqrt{T}}{2}$
- $P = e^{-rT} K N(-d_2) - S_0 N(-d_1)$
- Check: $S_0 \rightarrow 0$ recovers forward contract price.

Black Scholes European call

- Do it all over again ... NO!
- Use put/call parity
 - In payouts (diagram): $\text{Call}(K, S_T) - \text{Put}(K, S_T) = S_T - K$
 - Prices today: $C(K, S_0) - P(K, S_0) = S_0 - e^{-rT}K$
- $C = P - Ke^{-rT} + S_0$, and
- $N(d) = 1 - N(-d)$
- Get:

$$C(K, S_0) = S_0N(d_1) - e^{-rT}KN(d_2)$$

The Greeks

- Delta = $\Delta = \partial_S(\text{option value})$
 - Used for Delta hedging: replicate using $\Delta_t S_t + \text{cash}_t$
- Gamma = $\Gamma = \partial_S^2(\text{option value})$
 - Convexity: how nonlinear is your position?
 - How much rebalancing is needed?
- Vega = $\Lambda = \partial_\sigma(\text{option value})$
 - Vol is unknown and/or has large unpredictable moves
 - The hedge depends on the vol.
 - A more robust hedge works well over a range of σ .
- Theta = $\Theta = \partial_t(\text{option value})$
- Rho = $\rho = \partial_r(\text{option value})$