

Goal \rightarrow ① Multi Dimensional Ito formula. (Today).

② Risk Neutral Measures. (RN Pricing formula).

③ Convergence: Re-denom Black Sides formula.

Joint Stochastic Variations:

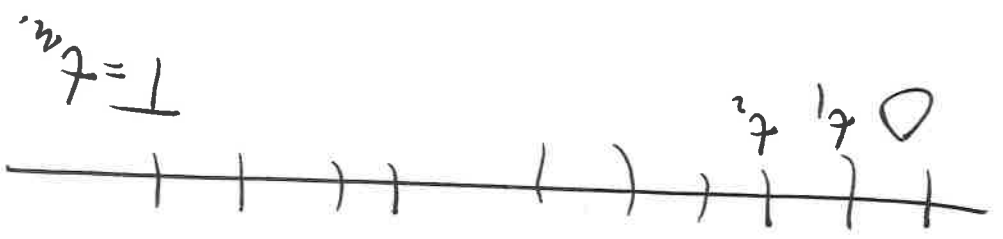
$$P = \{0 = t_0 < t_1 < \dots < t_n = T\}$$

QV: $X \rightarrow$ some process.

$$[X, X](T) = \lim_{\|P\| \rightarrow 0} \sum (\Delta^i X)^2$$

$$\|P\| = \max_i t_{i+1} - t_i \quad \& \quad \Delta^i X = X(t_{i+1}) - X(t_i)$$

Worked reverse for mg's, $(\Delta^i X)^2 \approx O(t_{i+1} - t_i)$



$[X, Y]$ is an adapted process.

$(P \rightarrow$ partition of $[0, T]$).

$$\lim_{\|P\| \rightarrow 0} [X, Y](T) =$$

The Joint Quadratic Variation

Joint QV: X & Y the

limit the processes X & Y :

$$\Rightarrow (\Delta_i X) \approx O((t_{i+1} - t_i)^{1/2}).$$

$$(\Delta_i X)(\Delta_i Y) \approx O(t_{i+1} - t_i)$$

processes.

of X & Y is

$$\sum_{i=0}^{n-1} [X(t_{i+1}) - X(t_i)] [Y(t_{i+1}) - Y(t_i)]$$

Finance Notation.

$$d[X, Y] = dX dY$$

$$d[X, X] = dX dX$$

Recall: $4ab = (a+b)^2 - (a-b)^2$

$$\Rightarrow 4 \sum (\Delta_i x)(\Delta_i y) = \sum (\Delta_i(x+y))^2 - \sum (\Delta_i(x-y))^2$$

$$= \sum (\Delta_i(x+y))^2 - \sum (\Delta_i(x-y))^2$$

$$\Rightarrow 4 [x, y] \quad \begin{array}{l} \text{Int of } \Delta V \\ \text{of } x \text{ \& } y \end{array}$$

$$= [x+y, x+y] \quad \begin{array}{l} \text{Int of } \Delta V \\ \text{of } x+y \end{array}$$

$$- [x-y, x-y] \quad \begin{array}{l} \text{Int of } \Delta V \\ \text{of } x-y \end{array}$$

Prop: (Product Rule). X, Y - 2 processes.

$$d(XY) = X dy + Y dX + d[X, Y].$$

$$\begin{aligned} \text{Pg: } d(X+Y)^2 &\stackrel{It\ddot{o}}{=} 2(X+Y)d(X+Y) + \frac{1}{2} d[X+Y, X+Y] \\ d(X-Y)^2 &\stackrel{It\ddot{o}}{=} 2(X-Y)d(X-Y) + d[X-Y, X-Y]. \end{aligned}$$

Subst: 6.

$$d(4XY) = 4X dY + 4Y dX + 4 d[X, Y].$$

$$\Rightarrow d(XY) = X dY + Y dX + d[X, Y]$$

//

Rules to compute Joint PV.

- ① Say $B \rightarrow$ cfs & find first variation. (adapted).
- $X \rightarrow$ cfs, adapted.

Then $[X, B] = 0 = [B, X]$.

Check: $4 [X, B] = [X+B, X+B] - [X-B, X-B]$.
 $[X, X] = 0$ //

Thm: Mult Dim Ito formula (Ito Doobin formula).

X_1, X_2, \dots, X_n \rightarrow n - stochastic processes.

let $X = (X_1, X_2, \dots, X_n)$. (random vector).

$f = f(t, x_1, x_2, \dots, x_n)$ is a fn. (let $x = (x_1, \dots, x_n)$).

① $\partial_t f$ exists and is cts.

② $\partial_i \partial_j f$ all exist & are cts ($i, j \in \{1, \dots, n\}$).

$$\frac{\partial^2 f}{\partial x_i \partial x_j}$$

$$\frac{\partial f}{\partial x_i} = f_i$$

Then $d(f(t, X_1, X_2, \dots, X_n)) = d(f(t, X))$

$$= \frac{\partial f}{\partial t}(t, X) dt + \sum_{i=1}^n \frac{\partial f}{\partial X_i}(t, X) dX_i(t)$$

$$+ \frac{1}{2} \sum_{j=1}^n \frac{\partial^2 f}{\partial X_j^2}(t, X_j) [dX_j(t)]^2$$

Joint QV.

$$[\frac{\partial^2 f}{\partial X_i \partial X_j}] = \frac{\partial^2 f}{\partial X_i \partial X_j}$$

Intuition: Taylor expand
 Δ follows the 1D argument

~~Facto.~~ Recall: M is a cts mgy $\Rightarrow M^2 - [M, M]$ is also a cts mgy.

Joint Qv: ① Let M & N be two cts mgy's.

$$EM(t)^2 < \infty \text{ \& \ } EN(t)^2 < \infty.$$

Then $MN - [M, N]$ is again a cts mgy.

② If B is any cts adapted process of finite 1st variation

such that $MN - B$ is a mgy & $B(0) = 0$,
then $B = [M, N]$.

Prop: X, Y, Z 3 processes. $a \in \mathbb{R}$.

Q: Is QV of $(X+Y) = QV$ of $X + QV$ of Y ?

Yes.
No.

$$\leftarrow [X, Y + aZ] = [X, Y] + a[X, Z] \text{ (dot prod)}$$

Prop: X_1, X_2 two Ito processes. $\sigma_1, \sigma_2 \rightarrow 2$ adapted proc.

Let $I_1(t) = \int_t^0 \sigma_1(s) dX_1(s)$ & $I_2(t) = \int_t^0 \sigma_2(s) dX_2(s)$.

Then $[I_1, I_2](t) = \int_t^0 \nabla_1(s) \nabla_2(s) d[X_1, X_2](s)$.

I.e. if $dI_1 = \nabla_1 dx_1$ & $dI_2 = \nabla_2 dx_2$.

Then $d[I_1, I_2] = \nabla_1 \nabla_2 d[X_1, X_2]$... (*)

Note: Special case. $X_1 = X_2$ & $\nabla_1 = \nabla_2$. $\Rightarrow I_1 = I_2$.

Kruskal $d[I_1, I_1] = \nabla_1^2 d[X_1, X_1]$ from before
 $= \nabla_1 \nabla_1 d[X_1, X_1]$ from (*)

Intuition behind $(*)$:

$$[I_1, I_2](T) = \lim_{\|P\| \rightarrow 0} \sum_{i=0}^{n-1} (\Delta_i I_1) (\Delta_i I_2)$$

$$= \lim_{\|P\| \rightarrow 0} \sum_{i=0}^{n-1} \left(\int_{t_{i+1}}^{t_i} \sigma_1 dX_1 \right) \left(\int_{t_{i+1}}^{t_i} \sigma_2 dX_2 \right)$$

$$= \lim_{\|P\| \rightarrow 0} \sum_{i=0}^{n-1} \left(\sigma_1(t_i) (X(t_{i+1}) - X(t_i)) - X(t_{i+1}) \sigma_2(t_i) + X(t_i) \sigma_2(t_{i+1}) - X(t_{i+1}) \sigma_1(t_{i+1})) \right)$$

$$= \lim_{\|P\| \rightarrow 0} \sum_{i=0}^{n-1} \sigma_1(t_i) \sigma_2(t_i) (\Delta_i X_1) (\Delta_i X_2)$$

$$= \int_T^0 \sigma_1(t) \sigma_2(t) d[X_1, X_2](t)$$

$\Delta_i [X_1, X_2]$

Prop. Say M & N are 2 dfs. $E M(t)^2 < \infty$ & $E N(t)^2 < \infty$.

If M & N are independent then $[M, N] = 0$.

Warning: If M & N are 2 mgs (not necessarily dfs) $E M(t)^2 < \infty$

$$E N(t)^2 < \infty$$

& M & N are ind.

$$\not\Rightarrow [M, N] = 0$$

Try #1 at Prop: M & N are ind. & are mgs.

Shows MN is a mgs. $\Rightarrow [M, N] = 0$.

Knows $E M(t)N(t) = E M(t) E N(t)$ (ind).

To check MN is a $m \times n$ matrix

$$E(M(t)N(t) | R_s) \stackrel{\text{indep}}{=} E(M(t) | R_s) E(N(t) | R_s)$$

$$= M(s)N(s)$$

$\Rightarrow MN$ is a $m \times n$ matrix $\Rightarrow [M, N] = 0$.

$$M \& N \text{ indep} \not\Rightarrow E(M(t)N(t) | R_s) = E(M(t) | R_s) \cdot E(N(t) | R_s)$$

Correct Proof: Assume M, N , cts, $\overline{\text{cts}}$ mgs's. $\Delta M, N$ indep.

NTS. $[M, N] = 0$.

Will show $E([M, N](T))^2 = 0 \Rightarrow$

\Rightarrow Done.

$P = \{0 = t_0 < t_1 < \dots < t_n = T\}$.

$E\left(\sum_{i=0}^{n-1} (\Delta_i M)(\Delta_i N)\right)^2 = E\sum_{i=0}^{n-1} (\Delta_i M)^2 (\Delta_i N)^2$

$+ 2 E \sum_{i=1}^{n-1} \sum_{j=0}^{i-1} (\Delta_i M)(\Delta_i N)(\Delta_j M)(\Delta_j N)$

Claim: Note $E(\Delta_i M)(\Delta_i N)(\Delta_j M)(\Delta_j N) \stackrel{\text{indep}}{=} [E(\Delta_i M)(\Delta_j M)][E(\Delta_i N)(\Delta_j N)]$

(*)

1st form in (*)

$$F \sum_{i=0}^{M-1} (\Delta \cdot M)^2 (\Delta \cdot N)^2 \stackrel{\text{indep}}{=} \sum_{i=0}^{M-1} E(\Delta \cdot M)^2 E(\Delta \cdot N)^2$$

$$\leq \left(\max_i E(\Delta \cdot M)^2 \right) \sum_{i=0}^{M-1} E(\Delta \cdot N)^2$$

$\uparrow \|P\| \rightarrow 0$
 $\uparrow \|P\| \rightarrow 0$
 $O(\because M \text{ is cts.})$
 $E(N, N](T)$

$O(\because N \text{ is a mgf})$

$$= (E_{\Delta \cdot M \Delta \cdot M}^{\mathcal{P}}) E \left[(N(t_{i+1}^{\mathcal{P}}) - N(t_i^{\mathcal{P}})) E(N(t_{i+1}^{\mathcal{P}}) - N(t_i^{\mathcal{P}})) \middle| \mathcal{G}_{t_i^{\mathcal{P}}} \right]$$

$$= (E_{\Delta \cdot M \Delta \cdot M}^{\mathcal{P}}) E \left((N(t_{i+1}^{\mathcal{P}}) - N(t_i^{\mathcal{P}})) (N(t_{i+1}^{\mathcal{P}}) - N(t_i^{\mathcal{P}})) \middle| \mathcal{G}_{t_i^{\mathcal{P}}} \right)$$

Math Dim B.M.

Def: We say $M = (w_1, w_2, \dots, w_d)$ is a d -dim ^{std.} B.M.

B.M. if ① Each w_i is a std 1dim B.M.

& ② If $i \neq j$, w_i & w_j are indep.

\therefore from \otimes : $\lim_{\|P\| \rightarrow 0} F(\sum_{i=1}^d (v_i \cdot N)) = 0$

$F([M, N](T))^2$

$\Rightarrow [M, N](T) = 0$ //

Note :
$$\begin{cases} dt & d[W_i, W_j](t) = \\ dt & \end{cases}$$
 if $i \neq j$
 $i = j$

Theorem (key) : let $M = (M_1, M_2, \dots, M_d)$ be

a set of d -dimensional vgs.

then If $M(t) = 0$ &

$$\begin{cases} dt & \\ dt & \end{cases} d[M_i, M_j](t) = \begin{cases} i = j \\ i \neq j \end{cases}$$

Then M is a std B.M.

[Reverts question 7.5]