

# Preliminary

- ① Remark: i)  $\bar{S} = (S_t^0, S_t)_{t \in [0, T]}$ . ctdlag. SP  
describes price evolution of the numéraire  $S^0 > 0$  and risky asset  $S$ .
- ii)  $\bar{X} = (X^0, X) := S/S^0 = (1, S_t/S_t^0)$   
the discounted price.
- iii)  $\bar{S} = (S_t^0, S_t)_{t \in [0, T]}$ . predictable SP.  
describes investment strategy.

And  $V^{\bar{S}} := \bar{S} \bar{X}$ . Discounted wealth

prop:  $\bar{S}$  is predictable means it  
can be approxi. by simple  
strategies:  $\sum_i \eta_i \mathbb{I}_{[T_{i-1}, T_i]}$   
where  $\eta_i \in \mathcal{F}_{T_{i-1}}$

iv)  $V_t^{v, \bar{S}} = v + \int_0^t \bar{S}_s \cdot X_s \stackrel{\Delta}{=} v + G_t(\bar{S})$ .

$G_t(\bar{S})$  is gains by time  $t$  with  
strategy  $\bar{S}$ .

RMK:  $G_t(\xi)$  is extended from  $\xi = \sum \eta_i \mathbb{I}_{(t_{i-1}, t_i]}$ ,  $\eta_i \in \mathcal{F}_{t_{i-1}}$ . With the lemma below for pointwise  $t$ .  
 $\subset \mathcal{Z}^n$  integral def in  $L^2$ -limit is not pointwise, will depend on IP)

Lemma.  $(\xi_t^n)$  simple  $\rightarrow \xi$  in  $L^0(\mathbb{P}) \Rightarrow G_t(\xi) \xrightarrow{pr} G_t(\xi)$ ,  $\forall t \in [0, T]$  iff the adapted process  $X$  is semimart.

RMK: If we require  $(\xi_t^n)$  be arbitrary bounded seq. i.e.  $|\xi_t^n| \leq 1$ ,  $\xi_t^n \xrightarrow{L^0} \xi_t$ . Then  $X$  must be FV.  
 So we def  $\int \xi dX$  from simple func.

RMK: No arbitrage (NFLVR). i.e.

$\bar{L} = \{f \in L^- \mid f \geq 0, \exists f \text{ simple, } G_T(\xi) \geq f\} = \{0\}$ .

Can also imply that  $X$  is a semimart. without addressing the stability above.  
 from Girsanov Thm.



Next, we assume  $(\mathcal{F}_t)$  is complete.

Lemma. If local mart.  $M_t$  can have a unique modification  $\tilde{M}_t$  with cdlag path. i.e.  $\mathbb{P}(M_t = \tilde{M}_t) = 1, \forall t$ .

Remark:  $\{M_t = \tilde{M}_t, \forall t\}$  may not be measurable! (uncountable state).

Pf: Actually any mart. has a cdlag modification if  $(\mathcal{F}_t)$  is complete.

Find  $(T_n) \uparrow \infty$ . Note  $\mathbb{P}(\bigcup T_n > t) = 1$ .

$\tilde{M}_t := M_{t \wedge T_n}$ , if  $n$  satisfies  $T_n > t$ .

Uniqueness if from consider  $(Q \cap [0, T])$ .

So next, we want to model the asset price as semimart:  $X = M + A$ .

i)  $A$  is FV. process. i.e. average price change over next  $dt$ -period.

ii)  $M$  is local mart. specify price fluctuations.

Remark:  $L(X) = \int_0^T \dot{\sigma}_s^2 ds + \int_0^T |dX_s|$  (as.  $< \infty$ ).

## ① Quadratic Variation:

Recall in construction of QV of c.l.m.

We have on a "iterated integral":  $\int_0^t M_s \cdot dM_s$

$= \frac{1}{2} M_t^2 - \frac{1}{2} [M]_t$ . i.e. We consider:

$\lim_{n \rightarrow \infty} \frac{1}{2} (M_t^2 - \sum_i (M_{t_i^n} - M_{t_{i-1}^n})^2)$ . Note that

$M_t^2 = (\sum_i (M_{t_i^n} - M_{t_{i-1}^n}))^2$ . We have:

$I_t^n$  equals:  $\sum_i M_{t_{i-1}^n} (M_{t_i^n} - M_{t_{i-1}^n}) \stackrel{\Delta}{=} X_t^n$ .

Then: We check  $X_t^n$  is  $L^2$ -Cauchy.  $\Rightarrow$

$I_t$  has  $L^2$ -limit. Since  $X_t^n = I_t^n(\tilde{f})$ . st.

$\tilde{f}_s = \sum M_{t_{j-1}^n} I_{(t_{j-1}^n, t_j^n]}(s)$ .  $\Rightarrow X_t^n$  is mart.

$J_n: X_t^n \xrightarrow{L^2} X_t$  is mart. And limit above exist

For c.l.m. case: Set  $[M]_t := [M]_{t \wedge T_n}$  on  $[t \leq T_n]$

Remark:  $\langle M \rangle$ ,  $[M]$  coincide if  $M$  is conti.

But they have some difference:

$\langle M \rangle_t$  is from Doob-Meyer's lemma

i.e.  $M_t^2 - \langle M \rangle_t \in \mathcal{M}^{loc}$  for  $M \in \mathcal{M}^{loc}$ .



$I_t$  can also def on some merely cdlg local mart, which's called predictable QV.

While  $[X]_t$  is characterized by:

$X_t^2 - [X]_t = 2 \int_0^t X_s \cdot dX_s$ . And it's not predictable generally. (But both cdlg)

And for (cdlg) mart  $X_t = X_t^{\text{casi}} + X_t^{\text{discr}}$ .

$$\begin{aligned} [X]_t &= [X^c]_t + [X^d]_t \\ &= \langle X^c \rangle_t + \sum_{s \leq t} | \Delta X_s |^2. \end{aligned}$$

ii) The convergence of  $\sum (\mu_{t_i}^n - \mu_{t_{i-1}}^n)^2 - [m]_t$  can also hold in ucp. sense.

### ③ Stochastic exponential:

Recall for SDE:  $dX_t = X_t dL_t$ ,  $X_0 = x_0$ .

if we consider  $Y_t = x_0 e^{L_t} \Rightarrow$  Apply It's

$$dY_t = Y_t (dL_t + \frac{1}{2} d[L]_t).$$

So we need a compensator on exp.:

$$E[L]_t = \exp(L_{0,t} - \frac{1}{2} [L]_t) \Rightarrow X = x_0 \mathcal{E}(L)$$

Remark:  $L_t$  is called Stochastic logarithm. which

can be uniquely chosen by  $L_t = \int_0^t \frac{1}{X_s} dX_s$ .

$\Rightarrow$  For  $L_t = \sigma W_t + (\mu - r)t$ . We have

the discounted Black-Scholes model:

$$dX_t = X_t ((\mu - r)dt + \sigma dW_t)$$

(4) Mart. measure:

i) Lower is a mart.:

Consider the strategy performed inductively

on  $[0, T]$ :

$n=1$ : Set  $f_1 = 1$ . (hold one stock). until gain  
1\$. but at most wait until  $t = \frac{T}{2}$ .

From  $n$ : Once already gain 1\$, then leave  
to  $n+1$  the game. Otherwise if it hasn't  
happen by the time  $= T_n = (1 - 2^{-n})T$

Choose  $(n+1)^{th}$  strategy  $f_{n+1} \in \mathcal{F}_{T_n}$ . s.t.

$$\mathbb{P} \left( \sup_{t \in [T_n, T_{n+1}]} (V_{T_n} + f_{n+1}(X_t - X_{T_n})) \geq 1 \mid \mathcal{F}_{T_n} \right) \geq \frac{1}{2}.$$



Rmk: Zt's possible since if we set  
 $S_{n+1} = X \cdot \epsilon_k$ . Note that

$$|P| \leq \frac{1 - V_{T_n}}{\sup_{t \in [T_n, T_{n+1}]} X_t - X_{T_n}} = X(\mathcal{F}_{T_n}) \uparrow 1. (x \rightarrow \infty)$$

$\subset$  Zt's not reasonable if no fluctuation on  $X_t$ . i.e.  $\forall X_t = X_{T_n}$

Lemma. The SF strategy  $\phi$  above yields  
 $V_T = 1$  a.s. And it can be completed  
 by finite many operations a.s.

Pf:  $|P| \leq V_T < 1 \Rightarrow |P| \subset \bigcap_n \{ \text{unlucky at } t = T_n \}$   
 $= \lim_N \mathbb{E} \left[ |P| \subset \text{unlucky at } t = T_n \mid \mathcal{F}_{T_{n-1}} \right]$   
 $\cdot \frac{n-1}{n} \mathbb{I} \subset \text{unlucky at } t = T_n \Big)$   
 $\leq \lim_N \frac{1}{2} \mathbb{E} \left[ \frac{n-1}{n} \mathbb{I} \subset \dots \right] \leq \lim_N 2^{-n} = 0.$

And  $\sum_n |P| \subset \text{unlucky at } t = T_n \leq$   
 $\sum_n 2^{-n} < \infty \Rightarrow P(\dots, i.o.) = 0.$

Rmk: i) Zt's called doubling strategy which  
 can produce riskless profit.

But it's not admissible strategy  
(i.e.  $\exists c > -\infty$  s.t.  $\int_0^t \phi_s dX_s \geq c$ )

ii) Admissible isn't needed in discrete time because it only performs finite operations in finite time

iii) Z's origin of martingale.

Thm. Local mart. p.m.  $\mathbb{P}^* \sim \mathbb{P}$  exists.  
(i.e.  $X_t$  is local mart. under  $\mathbb{P}^*$ ).  $(\Rightarrow)$

$$\bar{L} = \{ g \in \bar{L}_+^* \mid g \leq \int_0^T \phi_s dX_s, \exists \phi \in L(X) \text{ adm} \} \\ = \{0\} \text{ i.e. NFLVR.}$$

To find the risk-neutral p.m.  $\mathbb{P}^*$ :

Def  $Z_t := \mathbb{P}^* / \mathbb{P} |_{\mathcal{F}_t}$  if it exists (then  $Z_t$  will be u.i. mart.)

J.:  $X$  is  $\mathbb{P}^*$ -local mart  $(\Rightarrow) XZ$  is  $\mathbb{P}$ -D.

$$\text{By It\^o's : } \mathbb{E}(XZ) = XZ + Z \mathbb{E}X + d\langle X, Z \rangle \\ = XZ + Z \mathbb{E}X + (Z \mathbb{E}A + d\langle X, Z \rangle)$$

$$\Rightarrow \text{We need : } Z \mathbb{E}A = -\mathbb{E}\langle X, Z \rangle.$$



Note  $z_t \geq 0$ . Assume  $z_t = \varepsilon \in L$ .

$$J_0: \lambda A = -\lambda X \cdot \lambda z / z = -\lambda X \cdot \lambda L = -\lambda \langle X, L \rangle$$

Which is necessary for  $xz \in M^{\leq}$ .

Prop: i) (Sufficient)

We see if such  $z_t$  exists, then:

$$X = m - \langle X, L \rangle = m - \langle m, L \rangle \in \mathbb{P}^* - M^{\leq}.$$

Where we can see  $\mathbb{P}^*(A) = E_{\mathbb{P}}(I_A z_m)$

ii) Note  $\{ \mathbb{P}\text{-Semimart} \} = \{ \mathbb{P}^* \text{-Semimart} \}$ .

$$\text{Since } m + A = m - \langle m, L \rangle + (A + \langle m, L \rangle)$$

$$\Rightarrow L \langle X \rangle \text{ under } \mathbb{P} = L \langle X \rangle \text{ under } \mathbb{P}^*$$

iii) From i): After constructing  $z$ , we had to

check it's true mart. to get  $\mathbb{P}^* \sim \mathbb{P}$ .

Apply on Black-Scholes model:

$$\lambda X_t / X_t = \sigma_t \lambda W_t + (\mu_t - r_t) \lambda t.$$

Set  $z_t = \langle \lambda L \rangle_t$ . Then:

$$\lambda \langle X, L \rangle_t + X_t (\mu_t - r_t) \lambda t = 0.$$

$$\Rightarrow \lambda \langle X, L \rangle_t = \sigma_t \lambda \langle W, L \rangle_t = -X_t (\mu_t - r_t) (\lambda W_t)^2.$$

$$J_0: \text{ Let } L_t = - \int_0^t \frac{\mu_s - r_s}{\sigma_s} dW_s$$

$$\stackrel{\Delta}{=} - \int_0^t \theta_s dW_s$$

We require Novikov condition:

$$\mathbb{E} \left( \exp \left( \frac{1}{2} \int_0^T |\theta_s|^2 ds \right) \right) < \infty \text{ holds.}$$

$\Rightarrow Z_t = \mathbb{E} \left( - \int_0^t \theta_s dW_s \right)$  is the density which yields EMM

Remark: generally, for  $L \in \mathcal{M}_{loc}^c$ ,  $L_0 = 0$ . Then:

$$\Sigma(L) \in \mathcal{M}_c^{loc} \text{ with } \Sigma(L) \geq 0. \text{ So:}$$

$\Sigma(L)$  is supermart. And  $\Sigma(L)$  is mart.

$$\text{on } [0, T] \Leftrightarrow \Sigma(L)_T = 1.$$

$$\text{Pf: } \mathbb{E}(\Sigma(L)_0) = 1 \geq \mathbb{E}(\Sigma(L)_t) \geq \mathbb{E}(\Sigma(L)_T) = 1$$

$$\text{So: } \mathbb{E}(\mathbb{E}(\Sigma(L)_t | \mathcal{F}_s)) = \mathbb{E}(\Sigma(L)_s).$$

Cor. Exponential inequality for  $\mathcal{M}_c^{loc}$

$$\mathbb{P} \left( \sup_{t \in [0, T]} (\mu_s - q \langle M \rangle_s) \geq k \right) \leq e^{-2qk}$$

$$\text{Pf: LHS} = \mathbb{P} \left( \max_{t \in [0, T]} \Sigma(2qM)_t \geq e^{2qk} \right)$$

Doob's

$\leq$

supermart.

$\geq 0$

$-2qk$

$$\mathbb{E}(\Sigma(2qM)_0) = e^{-2qk}$$



rmk: Although for supermart / submart.  
we always think on  $\mu_t^- / \mu_t^+$ .

It's just for retaining its mart  
prop. by  $X^- / X^+$ . The Doob's ineqs.  
also work for supermart.  $M \geq 0$ :

$$\lambda \mathbb{P}(\max_{s \in [0, t]} M_s \geq \lambda) \leq \mathbb{E}(M_0).$$

Also for submart.  $M$ :

$$\lambda \mathbb{P}(\max_{s \in [0, t]} M_s \geq \lambda) \leq \mathbb{E}(M_t^+)$$

cr. (Bernstein's ineq.)

$M \in \mathcal{M}_{\mathcal{F}}^{loc}$ .  $M_0 = 0$ . Then we have:

$$\mathbb{P}(M_t^* \geq x, \langle M \rangle_t \leq \eta) \leq e^{-x^2/2\eta}.$$

pf: LHS  $\leq \mathbb{P}(\sup(M_t - \lambda \langle M \rangle_t) \geq x - \lambda \langle M \rangle_t \geq x, \square)$

$$\leq \mathbb{P}(\sup(M_t - \frac{\lambda}{2} \langle M \rangle_t) \geq x - \frac{\lambda \eta}{2})$$

$$= \mathbb{P}(\sup \Sigma(\lambda M) \geq e^{\lambda(x - \frac{\lambda \eta}{2})})$$

$$\stackrel{\text{Doob}}{\leq} e^{-\lambda(x - \lambda \eta/2)} \mathbb{E}(\Sigma(\lambda M)_t)$$

choose  $\lambda = \frac{x}{\eta}$  to optimize