

# Preliminary

i) Random:  $\bar{s} = (s_t^0, s_t)_{t \in [0, T]}$ . coding. 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)  $\bar{s} = (s_t^*, s_t)_{t \in [0, T]}$ . predictable SP.

describes investment strategy.

And  $\bar{V} \bar{s} := \bar{s} \bar{X}$ . discounted wealth

Exp:  $\bar{s}$  is predictable means it

can be approx. by simple

strategies:  $\sum_i \eta_i I_{[T_{i-1}, T_i]}(s)$

where  $\eta_i \in \mathcal{F}_{T_{i-1}}$

iv)  $V_t^{s,g} = V + \int_s^t g_s dX_s \stackrel{\Delta}{=} V + h_t(s).$

$h_t(s)$  is gains by time  $t$  with  
strategy  $s$ .

Rmk:  $h_t(\zeta)$  is extended from  $\zeta =$

$$\sum \eta_i: I_{(t_{i-1}, t_i]} \cdot \eta_i \in \mathbb{P}_{2:i-1} \text{ with the}$$

Lemma below for pointwise  $t$ .

cZ integral wif in  $L^2$ -limit is

not pointwise. will depend on  $(P)$

Lemma.  $(\zeta_t^n)$  simple  $\rightarrow \zeta$  in  $L^\infty(P) \Rightarrow h_t(\zeta)$

$\xrightarrow{\text{pr}}$   $h_t(\zeta)$ ,  $\forall t \in [0, T]$  iff the adapt  
cadlag process  $X$  is semipart.

Rmk: If we require  $(\zeta_t^n)$  be arb-

trary bdd seq. i.e.  $|\zeta_t^n| \leq 1$ .  $\zeta_t^n$

$\xrightarrow{L^\infty} \zeta_t$ . Then.  $X$  must be FV.

So we ref  $\int \zeta dX$  from simple  
func.

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

$$\bar{I} - \sum g \in L^- \mid g \geq 0. \exists \text{ simple. } G_T(g) = \{0\}.$$

Can also imply that  $X$  is a semipart.

without addressing the stability abore.  
from Girsanov Thm.

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

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

Rank:  $\{\mu_t = \tilde{\mu}_t, \forall t\}$  may not be measurable! (uncountable state).

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

Find  $(T_n) \nearrow \infty$ . Now  $\cup \{T_n > t\} = 1$ .

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

Uniqueness if from consider  $\{Q \wedge [0, T]\}$ .

So next, we want to model the asset price as Semimart:  $X = \mu + A$ .

i)  $A$  is FV. process. i.e. average price charged over next  $hT$ -period.

ii)  $\mu$  is local mart. specify price fluctuations.

Permit:  $L(X) = \left\{ \int_0^{\cdot} f_s^2 d\langle M \rangle_s + \int_0^{\cdot} |f_s| |A_s| < \infty \right\}$ .

## ② Quadratic Variation:

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

We have on a "iterated interval":  $\int_0^t \mu_s dM_s$

$= \frac{1}{2} \mu_t^2 - \frac{1}{2} [\mu]_t$ . i.e. we consider:

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

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

$Z_t$  equals:  $\sum_i M_{t_{i-1}^n} (\mu_{t_i^n} - \mu_{t_{i-1}^n}) \xrightarrow{\Delta} X_t^n$ .

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

$Z_t$  has  $L^2$ -limit. Since  $X_t^n = I_t^n(\zeta^n)$ . st.

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

$J_1: X_t^n \xrightarrow{L^2} X_t$  is mart. And limit above exist

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

Rank:  $\langle m \rangle, [\mu]$  coincides if  $m$  is conti.

But they have some difference:

$\langle m \rangle_t$  is from Doob-Meyer's theorem

i.e.  $\mu_t^2 - \langle m \rangle_t \in \mu^{loc}$  for  $\mu \in \mu^{loc}$ .

It can also be on some merely càdlàg local mart, which's called predictable RV.

While  $[X]_t$  is characterized by:

$X_t^2 - [X]_t = 2 \int_0^t X_s - \bar{X}_s ds$ . And it's not predictable generally. (But both càdlàg)

And for càdlàg) mart  $X_t = \bar{X}_t + \hat{X}_t$ .

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

i) The convergence of  $\sum (\mu_{t_i} - \hat{\mu}_{t_i})^2 - [u]_t$  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 Itô's

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

So we need a compensator on exp.:

$$[dL]_t = \exp(L_{0,t} - \frac{1}{2} [dL]_t). \Rightarrow X = x_0 e^{L_t}$$

Def:  $L_t$  is called stochastic logarithm. which

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

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

the discounted Black-Scholes model:

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

(\*) Mart. measure:

i) Ticker 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

happened by the time  $= T_n = (1-2^{-n})T$

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

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

rk: It's possible since if we set

$S_{n+1} = X \cdot \epsilon \eta^k$ . Note that

$$\mathbb{P} \subset \frac{1 - V_{T_n}}{\sup_{[T_n, T_{n+1}]} |X_t - X_{T_n}|} = \mathbb{P}(g_{T_n}) + 1. (x \rightarrow \infty)$$

(It's not removable if no fluctuation on  $X_t$ . i.e.  $\forall X_t = x_{T_n}$ )

Lemma: The SF strategy  $S$  above yields

$V_T = 1.$  a.s. And it can be completed

by finite many operations a.s.

$$Pf: \mathbb{P} \subset V_T < 1 \Rightarrow \mathbb{P} \subset \bigcap_n \{ \text{unlucky at } t = T_n \})$$

$$= \lim_N \mathbb{E} \subset \mathbb{P} \subset \text{unlucky at } t = T_n | g_{T_{n-1}}' \\ \cdot \prod_{i=1}^{N-1} I \{ \text{unlucky at } t = T_{n-i} \})$$

$$\leq \lim_N \frac{1}{2} \mathbb{E} \subset \frac{1}{2} \Rightarrow \dots \leq \lim_n 2^{-n} = 0.$$

And  $\sum_n \mathbb{P} \subset \text{unlucky at } t = T_n \leq$

$$\sum_n 2^{-n} < \infty \Rightarrow \mathbb{P}(\dots, i.o) = 0.$$

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

But it's not admissible strategy  
 (i.e.  $\exists c > -\infty$  s.t.  $\int_0^t \mathbb{E}[X_s] ds \leq c$ )

- i) Admissible isn't needed in discrete time because it only performs finite operations in finite time
- ii) It's origin of martingale.

Thm. Local mart. p.m.  $\mathbb{P}^*$  ~ if exists.  $\Leftrightarrow$   
 i.e.  $X_t$  is local mart. under  $\mathbb{P}^*$ .

$$\overline{L} = \{g \in L^{\mathbb{P}} \mid g \leq \int_0^t f_s ds, \exists f \in L^{\mathbb{P}} \text{ adm}\} \\ = \{0\}. \text{ i.e. NFLVR.}$$

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

Set  $Z_t = \lambda \mathbb{P}^*/\lambda \mathbb{P} \Big|_{\mathcal{F}_t}$  if it exists < then  
 $Z_t$  will be u.i. mart.)

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

$$\begin{aligned} \text{By } Z_t \text{'s: } \mathbb{E}(XZ) &= X \mathbb{E}Z + Z \mathbb{E}X + d\langle X, Z \rangle \\ &= X \mathbb{E}Z + Z \mathbb{E}1 + (Z \mathbb{E}A + d\langle X, Z \rangle) \end{aligned}$$

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

Note  $\exists t \geq 0$ . Assume  $\exists_t = \mathbb{E}^{\mathcal{L}}(L)$ .

$$\text{So: } \lambda_A = -\lambda X \cdot \lambda z / z = -\lambda X \cdot \lambda L = -\lambda < X, L >$$

which is necessary for  $X^t \in \mathcal{M}^{<\infty}$ .

Proof: i) (Sufficient)

We see if such  $z_t$  exists. Then:

$$X = \mu - < X, L > = \mu - < \mu, L > \in \mathbb{P}^* - \mathcal{M}^{<\infty}.$$

where we can see  $\mathbb{P}^*(A) = E_{\mathbb{P}}(\mathbb{I}_A z_\infty)$

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

$$\text{Since } \mu + A = \mu - < \mu, L > + (A + < \mu, L >)$$

$$\Rightarrow L(x) \text{ under } \mathbb{P} = L(x) \text{ under } \mathbb{P}^*$$

iii) From ii): After constructing  $\mathbb{Z}$ , we had to check it's true mart. to get  $\mathbb{P}^* \sim \mathbb{P}$ .

Apply on Black-Scholes model:

$$\lambda X_t / X_t = \sigma + \lambda w_t + (\mu_t - r_t) \lambda t.$$

Set  $\mathbb{Z}_t = \mathbb{E}^{\mathcal{L}}(L)_t$ . Then:

$$\lambda < X, L >_t + X_t (\mu_t - r_t) \lambda t = 0.$$

$$\Rightarrow \lambda [X, L]_t = \sigma_t \lambda [W, L]_t = -X_t (\mu_t - r_t) (\lambda w_t)^2.$$

$$\int_0^t \mathbb{E} e^{Ls} ds = - \int_0^t \frac{\mu_s - r_s}{\sigma_s} dW_s$$

$$= - \int_0^t \theta_s dW_s$$

We require Novikov condition :-

$$\mathbb{E} e^{-\alpha \int_0^T \theta_s dW_s} < \infty \text{ holds.}$$

$\Rightarrow \zeta_t = e^{-\int_0^t \theta_s dW_s}$  is the density which yields  $\mathbb{E} \mu_m$

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

$$\mathbb{E} e^{Ls} \in \mathcal{M}_c^{\infty} \text{ with } \mathbb{E} e^{Ls} \geq 0. \quad \text{So:}$$

$\mathbb{E} e^{Ls}$  is supermart. And  $\mathbb{E} e^{Ls}$  is mart.

$$\text{on } [0, T] \Leftrightarrow \mathbb{E} e^{Ls}|_T = 1.$$

$$\underline{\text{Pf: }} \mathbb{E} e^{\mathbb{E} e^{Ls}} = 1 \geq \mathbb{E} e^{\mathbb{E} e^{Ls}|_T} \geq \mathbb{E} e^{\mathbb{E} e^{Ls}|_s} = 1$$

$$\int_0^s \mathbb{E} e^{\mathbb{E} e^{Ls}|_t} d\mathbb{E} e^{Ls} = \mathbb{E} e^{\mathbb{E} e^{Ls}|_s}.$$

Cor. (Exponential inequality for  $\mathcal{M}_c^{\infty}$ )

$$\mathbb{P} \left( \sup_{s \in [0, T]} (M_s - q \mathbb{E} M_s) \geq k \right) \leq e^{-2qk}$$

$$\underline{\text{Pf: }} \text{LHS} = \mathbb{P} \left( \max_{s \in [0, T]} \mathbb{E} e^{2(M_s - q \mathbb{E} M_s)} \geq e^{2qk} \right)$$

Doob's

$$\leq e^{-2qk} \mathbb{E} e^{\mathbb{E} e^{2qM}} = e^{-2qk}$$

supermart.  
?

rk: Although for supermart / submart.

we always think on  $\bar{m}_t^+ / m_t^+$ .

It's just for retaining its mart prop. by  $x^- / x^+$ . The Doob's inequ.

also work for supermart.  $M \geq 0$ :

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

Also for submart.  $M$ :

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

ur. (Borsigain's inequality.)

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

$$P(M_n^* \geq x, \langle M \rangle_n \leq y) \leq e^{-x^2/2y}.$$

Pf: LHS  $\leq P(\sup(M_t - \lambda \langle M \rangle_t) + \lambda \langle M \rangle_\infty \geq x, \square)$

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

$$= P(\sup \sum \lambda m) \geq e^{\lambda(x - \frac{\lambda y}{2})},$$

Doob  $- \lambda(x - \lambda y/2) \leq \bar{E}(\sum \lambda m)_0$ )

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