

CHAPTER 2. Introduction to Stochastic Volatility Model

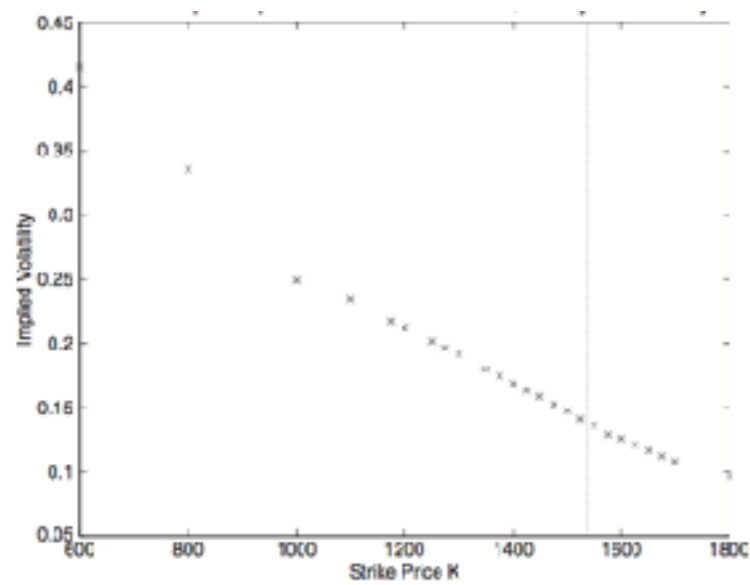
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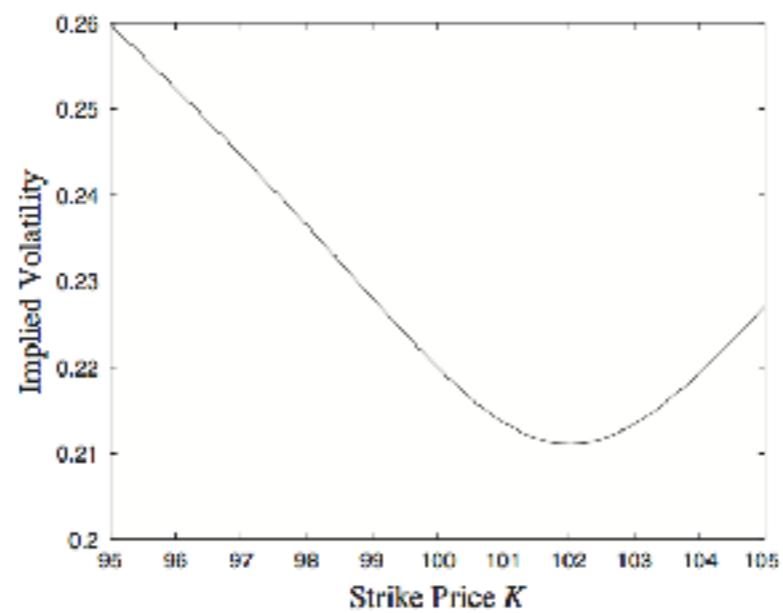
- 動機
- 隱含波動度的性質
- 原始模型、改進方法
 - Local Volatility Model (deterministic)
 - Stochastic Volatility Model (stochastic)
- 結論

動機

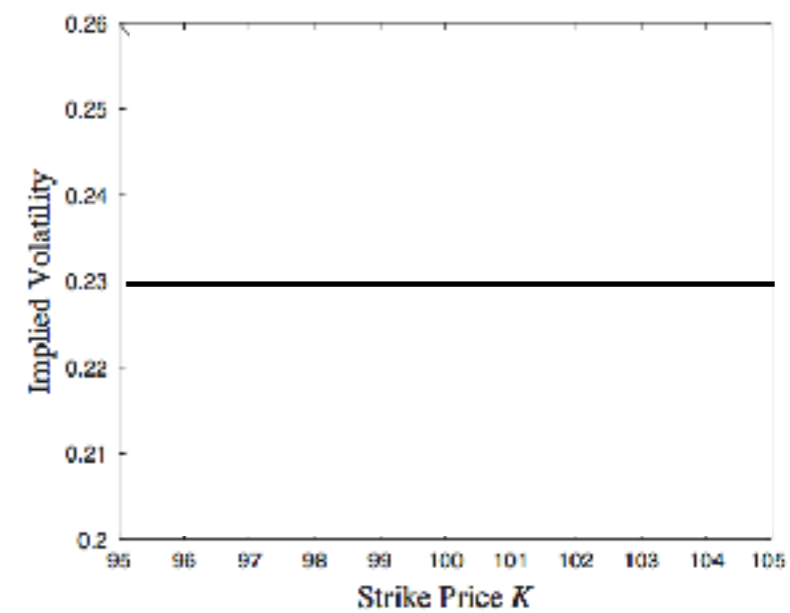
- 隱含波動度的圖形與B-S公式預期的不同
 - 隱含波動度：運用市場的報價反推B-S中的 σ
 - 為何會有此現象：對崩盤有所恐懼，所以價外的put會付出較高的貼水
- 實證分析也說明股價報酬的波動度有隨機現象



市場看跌



漲跌都要付貼水



B-S的預期下

隱含波動度的性質

1. 可以將觀察到的報價寫成B-S的函數

$$C_{BS}(t, x; K, T; I) = C^{\text{obs}}. \quad (2.1)$$

2. 觀察到的報價一定會有下界

$$C^{\text{obs}} > C_{BS}(t, x; K, T; 0)$$

because of the monotonicity of the Black–Scholes formula in the volatility parameter:

$$\frac{\partial C_{BS}}{\partial \sigma} = \frac{xe^{-d_1^2/2}\sqrt{T-t}}{\sqrt{2\pi}} > 0. \quad (2.2)$$

3. 買權跟賣權的隱含波動度會一樣 (put-call parity)
4. 隱含波動度對履約價的斜率有上下界

$$\frac{\partial C^{\text{obs}}}{\partial K} = \frac{\partial C_{BS}}{\partial K} + \frac{\partial C_{BS}}{\partial \sigma} \frac{\partial I}{\partial K} \leq 0,$$

履約價越高，賣權越貴、買權越便宜

$$\frac{\partial I}{\partial K} \leq -\frac{\partial C_{BS}/\partial K}{\partial C_{BS}/\partial \sigma}.$$

$$\frac{\partial I}{\partial K} \geq -\frac{\partial P_{BS}/\partial K}{\partial P_{BS}/\partial \sigma}.$$

$$-\frac{\sqrt{2\pi}}{x\sqrt{T-t}}(1 - N(d_2))e^{-r(T-t) + \frac{1}{2}d_1^2} \leq \frac{\partial I}{\partial K} \leq \frac{\sqrt{2\pi}}{x\sqrt{T-t}}N(d_2)e^{-r(T-t) + \frac{1}{2}d_1^2},$$

原始模型、修正方法

- B-S模型假設的價格過程：
 - 股價報酬率服從布朗運動： $dX_t = \mu X_t dt + \sigma X_t dW_t,$
 - 股價服從對數常態分佈： $X_t = X_0 \exp\left(\left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma W_t\right).$
- 修正方法：將 σ 條件放寬
 - Local Volatility Model (deterministic)
 - Stochastic Volatility Model (Stochastic)

Local Volatility Model

- 價格過程中sigma為標的物價格與時間的函數的模型

$$dX_t = \mu X_t dt + \sigma(t, X_t) X_t dW_t,$$

- Time Dependent $\sigma(t, x) = \sigma(t),$

- Level Dependent $\sigma(t, x) = \kappa x^{-\gamma},$

- Non-Parametric (Dupire's Formula) 不預設函數形式

Time Dependent

- 價格過程：

$$dX_t = \mu X_t dt + \sigma(t, X_t) X_t dW_t, \quad \sigma(t, x) = \sigma(t),$$

- 解開隨機偏微分方程得到：

$$X_T = X_t \exp \left(r(T-t) - \frac{1}{2} \int_t^T \sigma^2(s) ds + \int_t^T \sigma(s) dW_s^* \right),$$

- 如何解此隨機偏微分方程？*

- X_t 的分佈：

$$\log(X_T/X_t) \text{ is } \mathcal{N}\left((r - \frac{1}{2}\overline{\sigma^2})(T-t), \overline{\sigma^2}(T-t)\right).$$

$$\text{where } \overline{\sigma^2} = \frac{1}{T-t} \int_t^T \sigma^2(s) ds.$$

- 修正的B-S公式就是直接把 σ 換掉
- 假如觀察到隱含波動度有期間結構（但不是履約價函數），可以透過隱含波動度反找 σ 的積分

$$(T-t)I(t,T)^2 = \int_t^T \sigma^2(s) ds.$$

$$\int_{T_1}^{T_2} \sigma^2(s) ds = (T_2-t)I(t,T_2)^2 - (T_1-t)I(t,T_1)^2.$$

Level Dependent

- 價格過程：

$$dX_t = \mu X_t dt + \sigma(t, X_t) X_t dW_t, \quad \sigma(t, x) = \kappa x^{-\gamma},$$

- 缺點：股價跟波動度會高度相關
- 要fit 陡峭的隱含波動度可以採用 $3 < \gamma < 4$
- 書裡只介紹一種，其他沒有詳述

Dupire's Formula

1. 固定時間 t , 股價 x , 選擇權價格可以寫成

$$\begin{aligned} C(T, K) &= \mathbb{E}^* \{ e^{-r(T-t)} (X_T - K)^+ \mid X_t = x \} \\ &= e^{-r(T-t)} \int_0^\infty (\xi - K)^+ p(t, x; T, \xi) d\xi, \end{aligned}$$

2. 對 K 偏微分

$$\frac{\partial C}{\partial K}(T, K) = -e^{-r(T-t)} \int_0^\infty \mathbf{1}_{\{\xi > K\}} p(t, x; T, \xi) d\xi, \quad (2.5)$$

$$\begin{aligned} \frac{\partial^2 C}{\partial K^2}(T, K) &= e^{-r(T-t)} \int_0^\infty \delta(\xi - K) p(t, x; T, \xi) d\xi \\ &= e^{-r(T-t)} p(t, x; T, K), \end{aligned} \quad (2.6)$$

3. 對T偏微分

$$\begin{aligned}
& \frac{\partial C}{\partial T}(T, K) \\
&= e^{-r(T-t)} \int_0^\infty p(t, x; T, \xi) \mathcal{L}_T(\xi - K)^+ d\xi \\
&\quad - re^{-r(T-t)} \int_0^\infty (\xi - K)^+ p(t, x; T, \xi) d\xi, \\
&= e^{-r(T-t)} \int_0^\infty p(t, x; T, \xi) \left(\frac{1}{2} \sigma^2(T, \xi) \xi^2 \delta(\xi - K) + r\xi \mathbf{1}_{\{\xi > K\}} \right) d\xi \\
&\quad - re^{-r(T-t)} \int_0^\infty (\xi - K) \mathbf{1}_{\{\xi > K\}} p(t, x; T, \xi) d\xi,
\end{aligned}$$

Kolmogorov Forward Equation (Shreve p.291) :

$$\mathcal{L}_T^* = \frac{1}{2} \frac{\partial^2}{\partial \xi^2} (\sigma^2(T, \xi) \xi^2 \cdot) - \frac{\partial}{\partial \xi} (r\xi \cdot).$$

$$\begin{aligned}
&= \frac{1}{2} \sigma^2(T, K) K^2 e^{-r(T-t)} p(t, x; T, K) \\
&\quad + rK e^{-r(T-t)} \int_0^\infty \mathbf{1}_{\{\xi > K\}} p(t, x; T, \xi) d\xi \\
&= \frac{1}{2} \sigma^2(T, K) K^2 \frac{\partial^2 C}{\partial K^2}(T, K) - rK \frac{\partial C}{\partial K}(T, K),
\end{aligned}$$

化簡算式：

$$\frac{\partial C}{\partial T} = \frac{1}{2} \sigma^2(T, K) K^2 \frac{\partial^2 C}{\partial K^2} - rK \frac{\partial C}{\partial K}, \quad T > t, \quad (2.7)$$

整理：

$$\sigma^2(T, K) = \frac{\frac{\partial C}{\partial T}(T, K) + rK \frac{\partial C}{\partial K}(T, K)}{\frac{1}{2} K^2 \frac{\partial^2 C}{\partial K^2}(T, K)}.$$

Stochastic Volatility Model

- 模型假設
- 股價密度函數比較
- 如何定價？
- Market Price of risk 選取、 (K, T, t) 問題

模型假設

- σ 為另一隨機過程, 無風險利率 r 為常數

$$\begin{aligned}dX_t &= \mu(Y_t)X_t dt + \sigma_t X_t dW_t^{(0)}, \\ \sigma_t &= f(Y_t), \\ dY_t &= \alpha(Y_t) dt + \beta(Y_t) dW_t^{(1)},\end{aligned}\tag{2.9}$$

- Y_t 稱為 Driving Factor (Driving Process)
 f 要是一個遞增、恆正的函數
- σ 寫成函數形式可以比較容易整合更多因子

- 常見的Driving Process

LN lognormal

$$dY_t = \alpha Y_t dt + \beta Y_t dW_t^{(1)},$$

OU Ornstein–Uhlenbeck

$$dY_t = \alpha(m - Y_t)dt + \beta dW_t^{(1)},$$

CIR Feller, square-root, or Cox–Ingersoll–Ross

$$dY_t = \alpha(m - Y_t)dt + \beta \sqrt{Y_t} dW_t^{(1)}.$$

- OU , CIR Process 有mean reverting的特性 (觀察drift term)

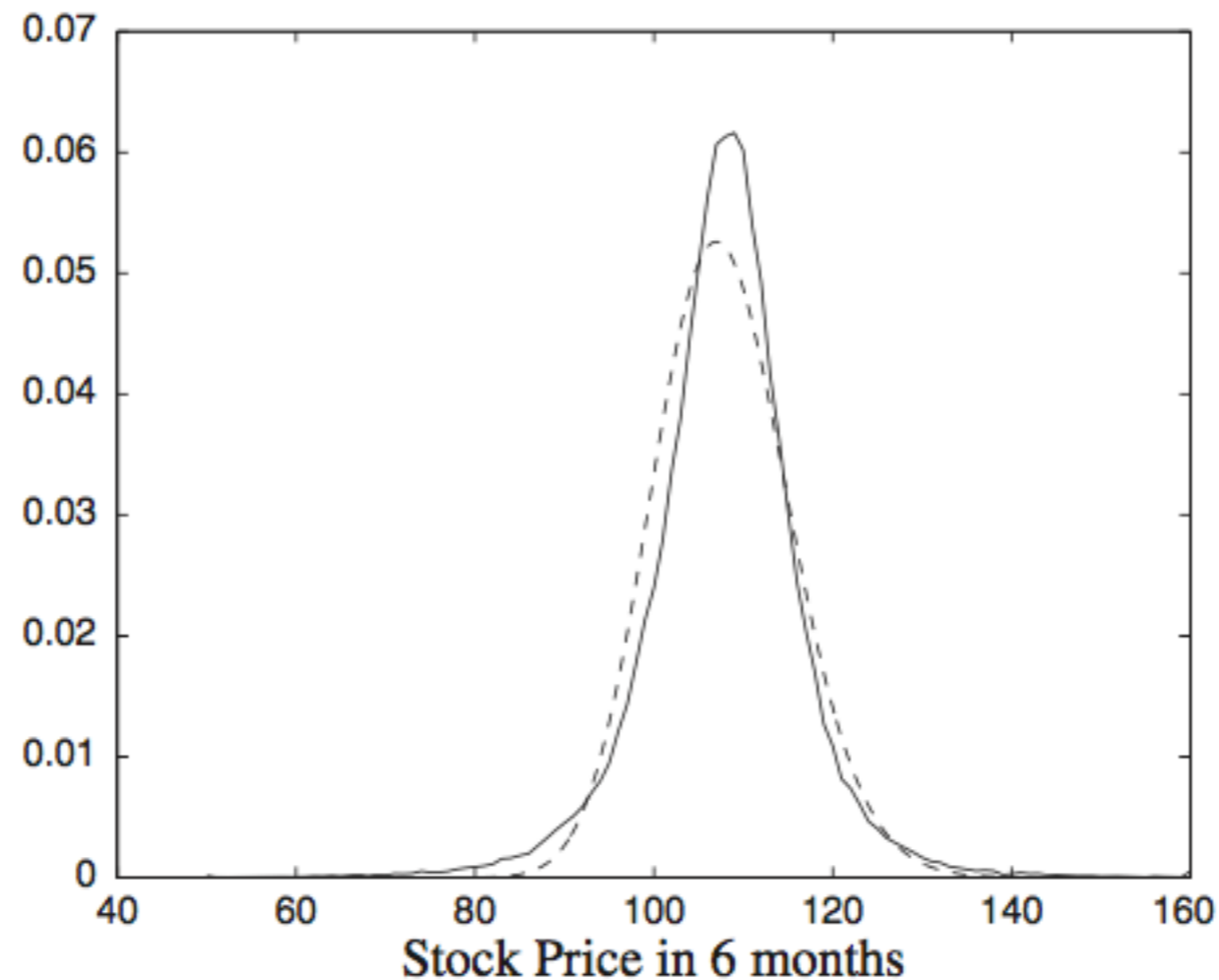
- 文獻中常用到的Stochastic Volatility Model

Authors	Correlation	$f(y)$	Y Process
Hull–White	$\rho = 0$	$f(y) = \sqrt{y}$	Lognormal
Scott	$\rho = 0$	$f(y) = e^y$	OU
Stein–Stein	$\rho = 0$	$f(y) = y $	OU
Ball–Roma	$\rho = 0$	$f(y) = \sqrt{y}$	CIR
Heston	$\rho \neq 0$	$f(y) = \sqrt{y}$	CIR

- 通常是因為容易分析，沒有太深的財務意涵

股價密度函數比較

- 實線是expOU模型下的股價密度函數（左端較厚）
- 虛線是B-S模型下股價密度函數



如何定價？

- 回顧模型假設：

$$\begin{aligned}dX_t &= \mu(Y_t)X_t dt + \sigma_t X_t dW_t^{(0)}, \\ \sigma_t &= f(Y_t), \\ dY_t &= \alpha(Y_t) dt + \beta(Y_t) dW_t^{(1)},\end{aligned}\tag{2.9}$$

- 將另一個布朗運動做分解：

$$W_t^{(1)} = \rho W_t^{(0)} + \sqrt{1 - \rho^2} W_t^\perp.\tag{2.10}$$

- 造一個無風險的self financing投組（無風險投組賺無風險利率）

$$d\Pi_t = r\Pi_t dt,$$

- 有兩個不確定性來源，因此無法只用股票避掉所有風險，因此需考慮另一個到期日較大的選擇權加入（市場不完備）

$$\Pi_t = N_t P^{(1)}(t, X_t, Y_t) - A_t X_t - \Sigma_t P^{(2)}(t, X_t, Y_t) \quad (2.11)$$

- 因為投組符合 Self-Financing

$$d\Pi_t = N_t dP^{(1)}(t, X_t, Y_t) - A_t dX_t - \Sigma_t dP^{(2)}(t, X_t, Y_t),$$

- 接著對 P_1, P_2 使用Ito's lemma

- 展開後

$$\begin{aligned}
 d\Pi_t = & \left(N_t \left[\frac{\partial}{\partial t} + \mathcal{L}_{(X,Y)} \right] P^{(1)} - A_t \mu(Y_t) X_t - \Sigma_t \left[\frac{\partial}{\partial t} + \mathcal{L}_{(X,Y)} \right] P^{(2)} \right) dt \\
 & + \left(X_t f(Y_t) \left[N_t \frac{\partial P^{(1)}}{\partial x} - \Sigma_t \frac{\partial P^{(2)}}{\partial x} - A_t \right] \right. \\
 & \left. + \rho \beta(Y_t) \left[N_t \frac{\partial P^{(1)}}{\partial y} - \Sigma_t \frac{\partial P^{(2)}}{\partial y} \right] \right) dW_t^{(0)} \\
 & + \sqrt{1 - \rho^2} \beta(Y_t) \left[N_t \frac{\partial P^{(1)}}{\partial y} - \Sigma_t \frac{\partial P^{(2)}}{\partial y} \right] dW_t^\perp.
 \end{aligned}$$

- 選取係數

$$\Sigma_t = N_t \left(\frac{\partial P^{(2)}}{\partial y} \right)^{-1} \left(\frac{\partial P^{(1)}}{\partial y} \right), \quad (2.13)$$

$$A_t = N_t \frac{\partial P^{(1)}}{\partial x} - \Sigma_t \frac{\partial P^{(2)}}{\partial x}. \quad (2.14)$$

- 不確定來源全部被消除，投組為無風險投組故可帶入

$$d\Pi_t = r\Pi_t dt,$$

- 帶入整理得到

$$\left(\frac{\partial P^{(1)}}{\partial y}\right)^{-1} \widehat{\mathcal{L}}P^{(1)} = \left(\frac{\partial P^{(2)}}{\partial y}\right)^{-1} \widehat{\mathcal{L}}P^{(2)}, \quad (2.15)$$

$$\text{where } \widehat{\mathcal{L}} = \frac{\partial}{\partial t} + \mathcal{L}_{(X,Y)} - (\mu(y) - r)x$$

- 觀察左右邊到期日不同，因此應該不是到期日的函數

令

$$\left(\frac{\partial P^{(1)}}{\partial y}\right)^{-1} \widehat{\mathcal{L}}P^{(1)} = \left(\frac{\partial P^{(2)}}{\partial y}\right)^{-1} \widehat{\mathcal{L}}P^{(2)} = -\alpha(y) + \beta(y)\Lambda(t, x, y),$$

$$\Lambda(t, x, y) = \rho \frac{(\mu(y) - r)}{f(y)} + \gamma(t, x, y) \sqrt{1 - \rho^2}, \quad (2.16)$$

- γ 可以是任意函數（但是會關係到選取的風險中立測度）
 γ 又稱作 market price of risk
- 整理完後得到微分方程（由 2.15 推到 2.17）

$$\left(\frac{\partial P^{(1)}}{\partial y} \right)^{-1} \widehat{\mathcal{L}} P^{(1)} = \left(\frac{\partial P^{(2)}}{\partial y} \right)^{-1} \widehat{\mathcal{L}} P^{(2)}, \quad (2.15)$$

$$\begin{aligned} \frac{\partial P}{\partial t} + \frac{1}{2} f^2(y) x^2 \frac{\partial^2 P}{\partial x^2} + \rho \beta(y) x f(y) \frac{\partial^2 P}{\partial x \partial y} + \frac{1}{2} \beta^2(y) \frac{\partial^2 P}{\partial y^2} \\ + r \left(x \frac{\partial P}{\partial x} - P \right) + (\alpha(y) - \beta(y) \Lambda(t, x, y)) \frac{\partial P}{\partial y} = 0, \end{aligned} \quad (2.17)$$

風險中立測度評價

- 測度轉換 (Shreve) :

$$\tilde{\mathbb{P}}(A) = \int_A Z(\omega) dP(\omega) \text{ for all } A \in \mathcal{F}. \quad (5.2.1)$$

- 由Girsanov定理可將模型轉換，使得在新的測度之下投組 H 的折現過程是Martingale

$$V_t = \mathbb{E}^{*(\gamma)} \{ e^{-r(T-t)} H \mid \mathcal{F}_t \}. \quad (2.21)$$

- Girsanov Theorem (Shreve P.212) :

Theorem 5.2.3 (Girsanov, one dimension). Let $W(t)$, $0 \leq t \leq T$, be a Brownian motion on a probability space $(\Omega, \mathcal{F}, \mathbb{P})$, and let $\mathcal{F}(t)$, $0 \leq t \leq T$, be a filtration for this Brownian motion. Let $\Theta(t)$, $0 \leq t \leq T$, be an adapted process. Define

$$Z(t) = \exp \left\{ - \int_0^t \Theta(u) dW(u) - \frac{1}{2} \int_0^t \Theta^2(u) du \right\}, \quad (5.2.11)$$

$$\tilde{W}(t) = W(t) + \int_0^t \Theta(u) du, \quad (5.2.12)$$

and assume that¹

$$\mathbb{E} \int_0^T \Theta^2(u) Z^2(u) du < \infty. \quad (5.2.13)$$

Set $Z = Z(T)$. Then $\mathbb{E}Z = 1$ and under the probability measure $\tilde{\mathbb{P}}$ given by (5.2.1), the process $\tilde{W}(t)$, $0 \leq t \leq T$, is a Brownian motion.

如何轉換？

- 將原本的價格過程分解，找尋適當的theta

$$W_t^{(0)*} = W_t^{(0)} + \int_0^t \frac{(\mu(Y_s) - r)}{f(Y_s)} ds.$$

$$W_t^{\perp*} = W_t^{\perp} + \int_0^t \gamma_s ds$$

- 有theta 之後可以造出新的測度

$$\frac{d\mathbb{P}^{*(\gamma)}}{d\mathbb{P}} = \exp \left(-\frac{1}{2} \int_0^T ((\theta_s^{(0)})^2 + (\theta_s^{\perp})^2) ds - \int_0^T \theta_s^{(0)} dW_s^{(0)} - \int_0^T \theta_s^{\perp} dW_s^{\perp} \right),$$

$$\theta_t^{(0)} = \frac{\mu(Y_t) - r}{f(Y_t)}, \quad \theta_t^{\perp} = \gamma_t.$$

- 在新的機率測度 $\mathbb{P}^*(\gamma)$ 下, $M_t = e^{-rt}V_t$ 是Martingale
由Martingale Representation Theorem (Shreve)
可以知道

$$M_t = M_0 + \int_0^t \eta_s^{(0)} dW_s^{(0)*} + \int_0^t \eta_s^\perp dW_s^{\perp*}, \quad (2.22)$$

- 經過化簡, 可以將投組化成:

$$dV_t = a_t dX_t + b_t r e^{rt} dt + c_t d\sigma_t,$$

- 說明了這是Incomplete Market Model

Market Price of risk 選取

- γ (Market price of risk) 可以任意選取，要如何選取？
- 本書採取的方法 (p.72 ,L.5) 是直接跟市場做連結，透過選擇權的價格直接推算出 γ
- 估計模型參數時可以用MLE或是其他計量方法
也可以使用Calibration (直接拿選擇權資料找最小MSE)

(K, T, t) 問題

- 如何透過選擇權價格、隱含波動度評價其他合約？
- 方法一：針對標的物做模型
 - K, T 的問題都容易克服
 - t 的問題最困難也最重要（模型的穩定度對路徑相關商品很重要）
- 方法二：針對隱含波動度做模型
 - 難以確認是否是無套利模型
 - 回推出來的標的物過程非馬可夫過程
 - 雖然價格fit的很好，但整個模型沒有推論能力（完全放棄 t ）