

# HJM: A Unified Approach to Dynamic Models in Financial Mathematics

René Carmona\*

\*Bendheim Center for Finance  
Department of Operations Research & Financial Engineering  
Princeton University

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- 1 Implied Volatility of the Equity Market Models
- 2 Pricing using Local Volatility
- 3 Setting Dupire in Motion

- $\{S_t\}_{t \geq 0}$  price process
- 0 interest rate (discount factor  $\beta_t \equiv 1$ )
- No dividend

## Classical Approach

- Specify dynamics for  $S_t$ , e.g. GBM in Black Scholes case

$$dS_t = S_t \sigma_t dW_t$$

- Compute prices of derivatives by expectation, e.g.

$$C_0(T, K) = \mathbb{E}\{(S_T - K)^+\}$$

## Main Assumptions

- At each time  $t \geq 0$  we observe  $C_t(T, K)$  the market price at time  $t$  of European call options of strike  $K$  and maturity  $T > t$ .
- Market prices by expectation

$$C_t(T, K) = \mathbb{E}\{(S_T - K)^+ | \mathcal{F}_t\}$$

for some measure (**not necessarily unique**)  $\mathbb{P}$

## Empirical Fact

Many observed option price movements cannot be attributed to changes in  $S_t$

- Fundamental market data: **Surface**  $\{C_t(T, K)\}_{T, K}$  **instead** of  $S_t$

## No arbitrage implies

- $C_0(T, K)$  increasing in  $T$
- $C_0(T, K)$  non-increasing and convex in  $K$
- $\lim_{K \nearrow \infty} C_0(T, K) = 0$
- $\lim_{K \searrow 0} C_0(T, K) = S_0$

## Realistic Set-Up

- We actually observe

$$C_t(T_i, K_{ij}) \quad i = 1, \dots, m, \quad j = 1, \dots, n_i$$

- Switch to notation  $\tau = T - t$  for **time to maturity**
- Call surface  $\{\tilde{C}_t(\tau, K)\}$  of prices  $C_t(T, K)$  parameterized by  $\tau \geq 0$  and  $K \geq 0$ .

$$\tilde{C}_t(\tau, K) = \mathbb{E}\{(S_{t+\tau} - K)^+ | \mathcal{F}_t\} = \mathbb{E}^{\mathbb{P}^t}\{(S_{t+\tau} - K)^+\}.$$

$$\tilde{C}_t(\tau, K) = \int_0^\infty (x - K)^+ d\mu_{t, t+\tau}(dx)$$

## Crucial Fact

For each  $\tau > 0$ , the **knowledge of all the prices**  $\tilde{C}_t(\tau, K)$  completely **determines** the **marginal** distribution  $\mu_{t, t+\tau}$  on  $[0, \infty)$ .

# Black-Scholes Formula

Dynamics of the underlying asset

$$dS_t = S_t \sigma dW_t, \quad S_0 = s_0$$

Wiener process  $\{W_t\}_t$ ,  $\sigma > 0$ .

Price of a call option

$$\tilde{C}_t(\tau, K) = S_t \Phi(d_1) - K \Phi(d_2)$$

with

$$d_1 = \frac{-\log M_t + \tau \sigma^2 / 2}{\sigma \sqrt{\tau}}, \quad d_2 = \frac{-\log M_t - \tau \sigma^2 / 2}{\sigma \sqrt{\tau}}$$

- $M_t = K/S_t$  moneyness of the option
- $\Phi$  error function

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-y^2/2} dy, \quad x \in \mathbb{R}.$$

- Classical Black-Scholes framework
- On any given day  $t$  fix
  - **maturity**  $T$  (or **time to maturity**  $\tau$ )
  - **strike**  $K$
- price is an **increasing function** of the parameter  $\sigma$

$$\sigma \Leftrightarrow \tilde{C}_t^{(BS)}(\tau, K) \quad \text{one-to-one}$$

Given an option **price quoted** on the market, its **implied volatility** is the unique number  $\sigma = \Sigma_t(\tau, K)$  for which  $\tilde{C}_t(\tau, K) = C$ .

Used by **ALL** market participants as the *currency* for options

*the **wrong** number to put in the **wrong** formula to get the **right** price.*



$$\{\tilde{C}_t(\tau, K); \tau > 0, K > 0\} \Leftrightarrow \{\Sigma_t(\tau, K); \tau > 0, K > 0\}$$

- **Static** ( $t = 0$ ) "No arbitrage" conditions difficult to formulate
  - (B. Dupire, Derman-Kani, P.Carr, ....)
- **Dynamic** No arbitrage conditions difficult to check in a dynamic framework
  - (Derman-Kani for tree models)

$$dS_t = S_t \sigma_t dW_t, \quad S_0 = s_0$$

If  $t > 0$  is fixed, for any  $\tau_1$  and  $\tau_2$  such that  $0 < \tau_1 < \tau_2$ , then for any convex function  $\phi$  on  $[0, \infty)$  we have (Jensen)

$$\int_0^\infty \phi(x) \mu_{t, t+\tau_1}(dx) \leq \int_0^\infty \phi(x) \mu_{t, t+\tau_2}(dx)$$

Or

$$\mu_{t, t+\tau_1} \preceq \mu_{t, t+\tau_2}$$

- $\{\mu_{t, t+\tau}\}_{\tau > 0}$  non-decreasing in the **balayage order**
- Existence of a Markov martingale  $\{Y_\tau\}_{\tau \geq 0}$  with marginal distributions  $\{\mu_{t, t+\tau}\}_{\tau > 0}$ .
- **NB**  $\{Y_\tau\}_{\tau \geq 0}$  contains more information than the mere marginal distributions  $\{\mu_{t, t+\tau}\}_{\tau > 0}$

On Wiener space (in Brownian filtration)

**Martingale Property** implies

$$Y_\tau = Y_0 + \int_0^\tau Y_s a(s) dB_s$$

**Markov Property** implies

$$a(s, \omega) = a_t(s, Y_s(\omega))$$

At each time  $t$ , I choose surface  $\{a_t(\tau, K)\}_{\tau>0, K>0}$  as an alternative code-book for  $\{\tilde{C}(\tau, K)\}_{\tau>0, K>0}$ .

$\{a_t(\tau, K)\}_{\tau>0, K>0}$  was introduced in a static framework (i.e. for  $t = 0$ ) simultaneously by Dupire and Derman and Kani **local volatility surface**

Assume

$$dY_\tau = Y_\tau a_t(\tau, Y_\tau) d\tilde{B}_\tau, \quad \tau > 0$$

with initial condition

$$Y_0 = S_t$$

and  $\mu_{t,t+\tau}$  has density  $g_t(\tau, x)$ .

**Breeden-Litzenberger** argument (specific to the *hockey-stick* pay-off)

$$\tilde{C}_t(\tau, K) = \int_0^\infty (x - K)^+ g_t(\tau, x) dx$$

Differentiate both sides twice with respect to  $K$

$$\frac{\partial^2}{\partial K^2} \tilde{C}_t(\tau, K) = g_t(\tau, K). \quad (1)$$

$$(Y_\tau - K)^+ = (Y_0 - K)^+ + \int_0^\tau \mathbf{1}_{[K, \infty)}(Y_s) dY_s + \frac{1}{2} \int_0^\tau \delta_K(Y_s) d[Y, Y]_s$$

and taking  $\mathbb{E}_t$  - expectations on both sides using the fact that  $Y$  is a martingale satisfying  $d[Y, Y]_s = Y_s^2 a_t(s, Y_s)^2 ds$ , we get:

$$\begin{aligned} \tilde{C}_t(\tau, K) &= (S_t - K)^+ + \frac{1}{2} \int_0^\tau \mathbb{E}_t\{\delta_K(Y_s) Y_s^2 a_t(s, Y_s)^2\} ds \\ &= (S_t - K)^+ + \frac{1}{2} \int_0^\tau K^2 a_t(s, K)^2 g_t(s, K) ds. \end{aligned}$$

Take derivatives with respect to  $\tau$  on both sides

$$\frac{\partial \tilde{C}(\tau, K)}{\partial \tau} = \frac{1}{2} K^2 a_t(\tau, K)^2 g_t(\tau, K).$$

Equate both expressions of  $g_t(\tau, K)$

$$a_t(\tau, K)^2 = \frac{2\partial_\tau \tilde{C}(\tau, K)}{K^2 \partial_{KK}^2 \tilde{C}(\tau, K)}$$

Smooth **Call Prices**  $\leftrightarrow$  **Local Volatilities**

From local volatility surface  $\{a_t(\tau, K)\}_{\tau, K}$  to call option prices  $\{\tilde{C}_t(\tau, K)\}_{\tau, K}$  solve PDE (Dupire's PDE)

$$\partial_\tau \tilde{C}(\tau, K) = \frac{1}{2} K^2 a^2(\tau, K) \partial_{KK}^2 \tilde{C}(\tau, K), \quad \tau > 0, K > 0$$

$$\tilde{C}(0, K) = (S_t - K)^+$$

$$\{\tilde{C}_t(\tau, K); \tau > 0, K > 0\} \leftrightarrow \{a_t(\tau, K); \tau > 0, K > 0\}$$

Why is that better?

**NEED ONLY POSITIVITY** for no arbitrage

If

$$dS_t = S_t \sigma_t dW_t$$

for some Wiener process  $\{W_t\}_t$  and some adapted non-negative process  $\{\sigma_t\}_t$ , then

$$a_t(\tau, K)^2 = \mathbb{E}_t\{\sigma_{t+\tau}^2 | S_{t+\tau} = K\}.$$



- Compute  $a_0(\tau, K)$  from **market call prices (Initial condition)**
- Define a dynamic model by defining the **dynamics of the local volatility surface**

$$da_t(\tau, K) = \alpha_t(\tau, K)dt + \beta_t(\tau, K)dW_t$$

- **Question** Under what conditions do the Call Prices computed from the dynamics of  $a_t(\tau, K)$  come from a model of the form of the form

$$dS_t = S_t \sigma_t dB_t^1$$

with initial condition  $S_0 = s$  the underlying instrument?

- **Answer**

$$\sigma_t = a_t(0, S_t)$$

# No-Arbitrage Condition

- **Question** Under what conditions on the dynamics of  $a_t(\tau, K)$  are the call prices (local) martingales?
- **Answer**

$$\left(\alpha + \frac{\|\beta\|^2}{2}\right) \cdot \frac{\partial^2}{\partial K^2} C + \frac{\partial}{\partial t} \langle a, \frac{\partial^2}{\partial K^2} C \rangle_t = \frac{\partial}{\partial T} a \cdot \frac{\partial^2}{\partial K^2} C$$

Recall classical HJM drift condition

$$\alpha(t, T) = \beta(t, T) \cdot \int_t^T \beta(t, s) ds = \sum_{j=1}^d \beta^{(j)}(t, T) \int_t^T \beta^{(j)}(t, s) ds.$$

# Main Result Statement

The dynamic model of the local volatility surface given by the system of equations

$$d\tilde{a}_t(\tau, K) = \tilde{\alpha}_t(\tau, K)dt + \tilde{\beta}_t(\tau, K)dW_t, \quad t \geq 0, \quad (2)$$

is **consistent** with a spot price model of the form

$$dS_t = S_t \sigma_t dB_t$$

for some Wiener process  $\{B_t\}_t$ , and **does not allow for arbitrage** if and only if a.s. for all  $t > 0$ :

$$\bullet \tilde{a}_t(0, S_t) = \sigma_t \quad (3)$$

$$\bullet \partial_\tau \tilde{a}_t(\tau, K) \partial_{KK}^2 \tilde{C}_t(\tau, K) = \quad (4)$$

$$\left( \tilde{a}_t(\tau, K) \tilde{\alpha}_t(\tau, K) + \frac{\|\beta_t(\tau, K)\|^2}{2} \right) \partial_{KK}^2 \tilde{C}_t(\tau, K) + \frac{d}{dt} \langle \tilde{a}_t(\tau, K)^2, \partial_{KK}^2 \tilde{C}_t(\tau, K) \rangle_t$$

$\langle \cdot \cdot \rangle_t$  quadratic covariation of two semi-martingales.

# Practical Monte Carlo Implementation

- Start from a model for  $\beta_t(\tau, K)$  (say a stochastic differential equation);
- Get  $S_0$  and  $C_0(\tau, K)$  from the market and compute  $\partial_{KK}^2 C_0$ ,  $a_0$  and  $\beta_0$  from its model;
- Loop: for  $t = 0, \Delta t, 2\Delta t, \dots$ 
  - ① Get  $\alpha_t(\tau, K)$  from the drift condition (??);
  - ② Use Euler to get
    - $a_{t+\Delta t}(\tau, K)$  from the dynamics of the local volatility given by (??);
    - $S_{t+\Delta t}$  from  $S_t$  Dynamics;
    - $\beta_{t+\Delta t}$  from its own model;

# Markovian Spot Models ( $\beta \equiv 0$ )

$$\tilde{\alpha}_t(\tau, K) = \frac{d}{dt} \tilde{a}_t(\tau, K).$$

Drift condition reads

$$\partial_\tau \tilde{a}_t(\tau, K) = \tilde{\alpha}_t(\tau, K)$$

Hence

$$\partial_\tau \tilde{a}_t(\tau, K) = \frac{d}{dt} \tilde{a}_t(\tau, K)$$

which shows that for fixed  $K$ ,  $\tilde{a}_t(\tau, K)$  is the solution of a transport equation whose solution is given by:

$$\tilde{a}_t(\tau, K) = \tilde{a}_0(\tau + t, K)$$

and the consistency condition forces the special form

$$\sigma_t = a_0(t, S_t)$$

of the spot volatility. Hence we proved:

*The local volatility is a process of bounded variation for each  $\tau$  and  $K$  fixed if and only if it is the deterministic shift of a constant shape and the underlying spot is a Markov process.*

# A First Parametric Family

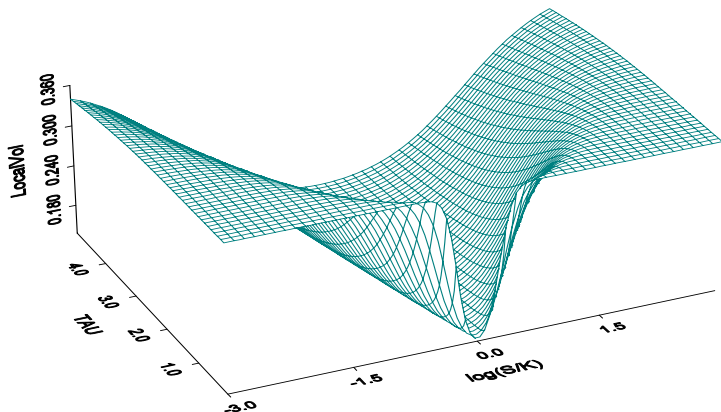
$$a^2(\tau, x, \Theta) = \frac{\sum_{i=0}^2 p_i \sigma_i e^{-x^2/(2\tau\sigma_i^2) - \tau\sigma_i^2/8}}{\sum_{i=0}^2 (p_i/\sigma_i) e^{-x^2/(2\tau\sigma_i^2) - \tau\sigma_i^2/8}}$$

for

$$\Theta = (\sigma_0, \sigma_1, \sigma_2, p_1, p_2)$$

- Mixture of Black-Scholes Call surfaces for 3 different volatilities
- **Singularity** when  $\tau \searrow 0$

# Numerical Evidence of Singularity





# A Second Parametric Family

- Still a mixture of Black-Scholes Call surfaces for 3 different volatilities
- Each volatility is time dependent  $t \mapsto \sigma_i(t)$
- $\sigma_0(0) = \sigma_1(0) = \sigma_2(0)$

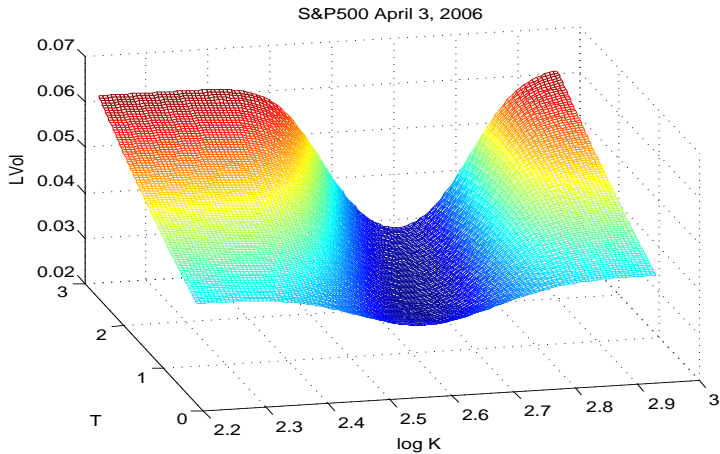
$$a^2(\Theta, \tau, x) = \frac{(1 - (p_1 + p_2)\tau) \sigma e^{-d^2(\sigma)/2} + p_1 \tau \sigma_1 e^{-d^2(\sigma_1)/2} + p_2 \tau \sigma_2 e^{-d^2(\sigma_2)/2}}{(1 - (p_1 + p_2)\tau) \frac{1}{\sigma} e^{-d^2(\sigma)/2} + p_1 \tau \frac{1}{\sigma_1} e^{-d^2(\sigma_1)/2} + p_2 \tau \frac{1}{\sigma_2} e^{-d^2(\sigma_2)/2}}$$

where

$$d(\sigma) = \frac{s - x + (r + \frac{1}{2}\sigma^2) \tau}{\sigma \sqrt{\tau}}$$

$$\Theta = (p_1, p_2, \sigma, \sigma_1, \sigma_2, s, r)$$

# Fit to Real Data



# Stochastic Volatility Models

$$dS_t = \sigma_t S_t dW_t$$

with

$$d\sigma_t^2 = b(\sigma_t^2)dt + a(\sigma_t^2)d\tilde{W}_t$$

where

$$d\langle W, \tilde{W} \rangle_t = \rho dt.$$

Usually

$$b(\sigma^2) = -\kappa(\sigma^2 - \overline{\sigma^2})$$

Special cases:

$$a(\sigma^2) = \gamma, \quad (\text{Hull-White})$$

$$a(\sigma^2) = \gamma\sqrt{\sigma^2} \quad (\text{Heston})$$

# Local Volatility of SV Models

$$a^2(\tau, K) = \frac{2\partial_\tau C}{K^2 \partial_{KK}^2 C} = \sigma_0^2 \sqrt{1 - \rho^2} \cdot \frac{\mathbb{E} \left\{ S \frac{\tilde{\sigma}_\tau^2}{\bar{\sigma}_\tau} e^{-\frac{d_1^2}{2}} \right\}}{\mathbb{E} \left\{ \frac{S}{\bar{\sigma}_\tau} e^{-\frac{d_1^2}{2}} \right\}}$$

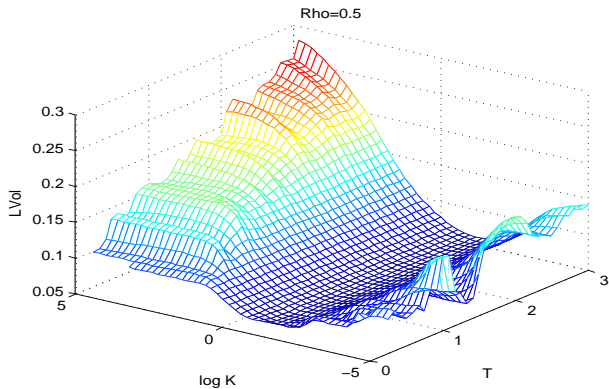
where  $\tilde{\sigma}_\tau = \frac{\sigma_\tau}{\sigma_0}$ , and  $\bar{\sigma}_\tau = \sqrt{\frac{1}{\tau} \int_0^\tau \tilde{\sigma}_s^2 ds}$

$$S = s_0 \exp \left( \frac{\rho \sigma_0}{\hat{\sigma}} (\tilde{\sigma}_\tau - 1) - \frac{1}{2} \sigma_0^2 \rho^2 \bar{\sigma}_\tau^2 \tau \right)$$

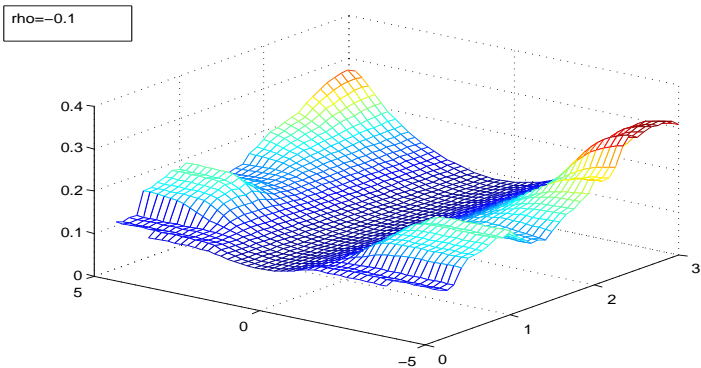
and

$$d_1 = \frac{\log(s_0) - \log(K) + \frac{\rho \sigma_0}{\hat{\sigma}} (\tilde{\sigma}_\tau - 1) + (\frac{1}{2} - \rho^2) \sigma_0^2 \bar{\sigma}_\tau^2 \tau}{\sqrt{1 - \rho^2} \sigma_0 \bar{\sigma}_\tau \sqrt{\tau}}$$

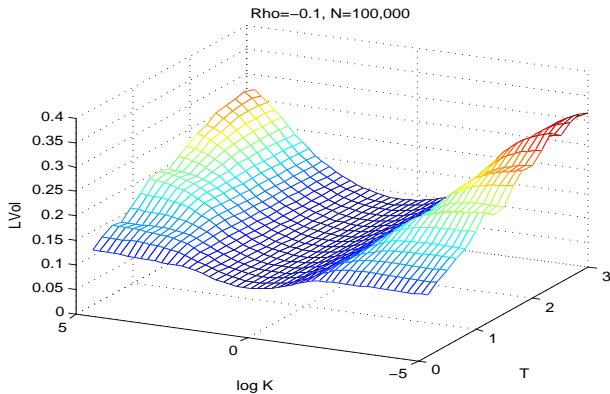
# First Example: $\rho = 0.5$



# Second Example: $\rho = -0.1$



# Third Example: $\rho = -0.75$



# Comparing SV Models

