

# Computational Finance

## FIN-472

### Polynomial expansion methods: The Jacobi model

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# Outline

- 1 Motivation and model specification
- 2 Log-price density
- 3 Density approximation and pricing algorithm
- 4 Numerical example

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# Stochastic volatility models

The volatility of stock price log-returns is stochastic

	Black-Scholes	Heston (affine)
volatility	constant	stochastic $\in \mathbb{R}_+$
calls and puts	closed-form	Fourier transform
exotic options	closed-form	...

Black-Scholes model  $\subset$  Jacobi model  $\rightarrow$  Heston model

- **stochastic volatility** on a parametrized **compact support**
- vanilla and exotic **option prices** have a **series representation**
- **fast and accurate** price approximations

# Jacobi Stochastic Volatility model

Fix  $0 \leq v_{min} < v_{max}$ . Define the quadratic function

$$Q(v) = \frac{(v - v_{min})(v_{max} - v)}{(\sqrt{v_{max}} - \sqrt{v_{min}})^2} \leq v$$

## Jacobi Model

Stock price dynamics  $S_t = e^{X_t}$  given by

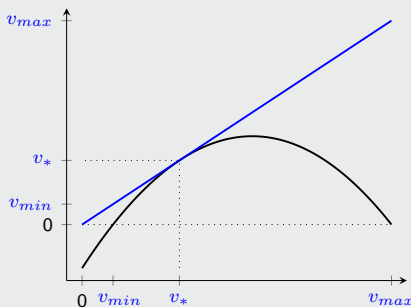
$$\begin{aligned} dV_t &= \kappa(\theta - V_t) dt + \sigma \sqrt{Q(V_t)} dW_{1t} \\ dX_t &= (r - V_t/2) dt + \rho \sqrt{Q(V_t)} dW_{1t} + \sqrt{V_t - \rho^2 Q(V_t)} dW_{2t} \end{aligned} \quad (1)$$

for  $\kappa, \sigma > 0$ ,  $\theta \in (v_{min}, v_{max}]$ , interest rate  $r$ ,  $\rho \in [-1, 1]$ , and 2-dimensional BM  $W = (W_1, W_2)$

# Some properties

## The function $Q(v)$

$v \geq Q(v)$ ,  $v = Q(v)$  if and only if  $v = \sqrt{v_{\min} v_{\max}}$ , and  $Q(v) \geq 0$  for all  $v \in [v_{\min}, v_{\max}]$



## Instantaneous variance

$d\langle X, X \rangle_t = V_t \in [v_{\min}, v_{\max}]$  is a **Jacobi process**

# Some properties (cont.)

## Polynomial model

$(V_t, X_t)$  is a polynomial diffusion – **efficient calculation of moments**

## Black-Scholes model nested

Take  $V_0 = \theta = v_{max} = \sigma_{BS}^2$

## Heston model as a limit case

If  $v_{min} = 0$  and  $v_{max} \rightarrow \infty$  then  $(V_t, X_t)$  converges to the Heston model

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# Log-price density

We define

$$C_T = \int_0^T (V_t - \rho^2 Q(V_t)) dt$$

## Theorem 1

Let  $\epsilon < 1/(2v_{max}T)$ . Then the distribution of  $X_T$  admits a density  $g_T(x)$  on  $\mathbb{R}$  that satisfies

$$\int_{\mathbb{R}} e^{\epsilon x^2} g_T(x) dx < \infty \quad (2)$$

If

$$\mathbb{E} [C_T^{-1/2}] < \infty \quad (3)$$

then  $g_T(x)$  and  $e^{\epsilon x^2} g_T(x)$  are uniformly bounded and continuous on  $\mathbb{R}$ .  
A sufficient condition for (3) to hold is

$$v_{min} > 0 \text{ and } \rho^2 < 1$$

**Remark:** The Heston model does not satisfy (2) for any  $\epsilon > 0$

# A crucial corollary

## Corollary 2

Assume (3) holds. Then  $\ell(x) = \frac{g_T(x)}{w(x)} \in L_w^2$ , where

$$L_w^2 := \left\{ h : \int_{\mathbb{R}} |h(x)|^2 w(x) dx \right\}$$

and  $w(x)$  is any Gaussian density with variance  $\sigma_w^2$  satisfying

$$\sigma_w^2 > \frac{v_{max} T}{2} \quad (4)$$

- **(Filipovic, Mayerhofer, Schneider 2013)** For the Heston model we have that  $\ell(x) = \frac{g_T(x)}{w(x)} \in L_w^2$ , where  $w(x)$  is a **(bilateral) Gamma density**
- **Corollary 2 is a consequence of Theorem 1 because any uniformly bounded and integrable function is square integrable**

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# Weighted $L^2$ -space

- **The weighted Hilbert space**

$$L_w^2 = \left\{ f(x) \mid \|f\|_w^2 = \int_{\mathbb{R}} f(x)^2 w(x) dx < \infty \right\}$$

where  $w(x)$  is a Gaussian density with mean  $\mu_w$  and variance  $\sigma_w^2$ .  
This is a Hilbert space with scalar product

$$\langle f, g \rangle_w = \int_{\mathbb{R}} f(x)g(x) w(x) dx$$

- **Orthonormal basis – Generalized Hermite polynomials**

$$H_n(x) = \frac{1}{\sqrt{n!}} \mathcal{H}_n \left( \frac{x - \mu_w}{\sigma_w} \right)$$

where  $\mathcal{H}_n(x)$  are the **standard (probabilists' / not physicists') Hermite polynomials**

- More precisely

$$\mathcal{H}_n(x) = (-1)^n e^{\frac{x^2}{2}} \frac{d^n}{dx^n} e^{-\frac{x^2}{2}}$$

# Price approximation

## Pricing problem

Assume that  $X_T$  has a density  $g_T(x)$

$$\pi_f = \mathbb{E}[f(X_T)] = \int_{\mathbb{R}} f(x) g_T(x) dx$$

## Price series expansion

Suppose  $\ell(x) = g_T(x)/w(x) \in L_w^2$  and  $f(x) \in L_w^2$ . Then

$$\pi_f = \langle f, \ell \rangle_w = \sum_{n \geq 0} f_n \ell_n \quad (5)$$

for the **Fourier coefficients** and **Hermite moments**

$$f_n = \langle f, H_n \rangle_w, \quad \ell_n = \langle \ell, H_n \rangle_w = \int_{\mathbb{R}} H_n(x) g_T(x) dx$$

# Price and Density approximation

## Price approximation

$$\pi_f \approx \pi_f^{(N)} = \sum_{n=0}^N f_n \ell_n = \sum_{n=0}^N \langle f, \ell_n H_n \rangle_w = \int_{\mathbb{R}} f(x) g_T^{(N)}(x) dx \quad (6)$$

## “Gram-Charlier A expansion”

$$g_T^{(N)}(x) = w(x) \sum_{n=0}^N \ell_n H_n(x)$$

# European calls and puts - Fourier coefficients

- Consider the discounted payoff function for a call option with log strike  $k$

$$f(x) = e^{-rT} (e^x - e^k)^+$$

- Its **Fourier coefficients**  $f_n$  are given by

## Fourier coefficients call option

$$f_0 = e^{-rT+\mu_w} I_0 \left( \frac{k - \mu_w}{\sigma_w}; \sigma_w \right) - e^{-rT+k} \Phi \left( \frac{\mu_w - k}{\sigma_w} \right)$$

$$f_n = e^{-rT+\mu_w} \frac{1}{\sqrt{n!}} \sigma_w I_{n-1} \left( \frac{k - \mu_w}{\sigma_w}; \sigma_w \right) \quad n \geq 1$$

# European calls and puts - Fourier coefficients (cont)

- The functions  $I_n(\mu; \nu)$  are defined recursively by

$$\begin{aligned} I_0(\mu; \nu) &= e^{\frac{\nu^2}{2}} \Phi(\nu - \mu); \\ I_n(\mu; \nu) &= \mathcal{H}_{n-1}(\mu) e^{\nu\mu} \phi(\mu) + \nu I_{n-1}(\mu; \nu), \quad n \geq 1 \end{aligned}$$

where  $\mathcal{H}_n(x)$  are the standard Hermite polynomials,  $\Phi(x)$  denotes the standard Gaussian distribution function, and  $\phi(x)$  its density

- To prove this representation of Fourier coefficients it is sufficient to establish the following identity

$$I_n(\mu; \nu) = \int_{\mu}^{\infty} \mathcal{H}_n(x) e^{\nu x} \phi(x) dx, \quad n \geq 0.$$

- This can be **shown using integration by parts and the identity**

$$\mathcal{H}_n(x) = x\mathcal{H}_{n-1}(x) - \mathcal{H}'_{n-1}(x).$$



# Calculation of the Hermite-moments $\ell_n$

- Let  $\pi : \mathcal{E} \rightarrow \{1, \dots, M = (N+2)(N+1)/2\}$  be an enumeration of the set of exponents

$$\mathcal{E} = \{(m, n) : m, n \geq 0; m + n \leq N\}$$

- The polynomials

$$h_{\pi(m,n)}(v, x) = v^m H_n(x), \quad (m, n) \in \mathcal{E}$$

form a basis of  $\text{Pol}_N$

- The  $(M \times M)$ -matrix  $G$  representing the infinitesimal generator of  $(V_t, X_t)$  on  $\text{Pol}_N$  is sparse in view of the elementary property

$$H'_n(x) = \frac{\sqrt{n}}{\sigma_w} H_{n-1}(x)$$

which is a consequence of

$$\mathcal{H}'_n(x) = n \mathcal{H}_{n-1}(x)$$

# The matrix of the generator

The matrix  $G$  has at most 7 nonzero elements in column  $\pi(m, n)$

$$G_{\pi(m-2, n), \pi(m, n)} = -\frac{\sigma^2 m(m-1)v_{\max}v_{\min}}{2(\sqrt{v_{\max}} - \sqrt{v_{\min}})^2}, \quad m \geq 2$$

$$G_{\pi(m-1, n-1), \pi(m, n)} = -\frac{\sigma \rho m \sqrt{n} v_{\max} v_{\min}}{\sigma_w (\sqrt{v_{\max}} - \sqrt{v_{\min}})^2}, \quad m, n \geq 1$$

$$G_{\pi(m-1, n), \pi(m, n)} = \kappa \theta m + \frac{\sigma^2 m(m-1)(v_{\max} + v_{\min})}{2(\sqrt{v_{\max}} - \sqrt{v_{\min}})^2}, \quad m \geq 1$$

$$G_{\pi(m, n-1), \pi(m, n)} = \frac{r \sqrt{n}}{\sigma_w} + \frac{\sigma \rho m \sqrt{n} (v_{\max} + v_{\min})}{\sigma_w (\sqrt{v_{\max}} - \sqrt{v_{\min}})^2}, \quad n \geq 1$$

$$G_{\pi(m+1, n-2), \pi(m, n)} = \frac{\sqrt{n(n-1)}}{2\sigma_w^2}, \quad n \geq 2$$

$$G_{\pi(m, n), \pi(m, n)} = -\kappa m - \frac{\sigma^2 m(m-1)}{2(\sqrt{v_{\max}} - \sqrt{v_{\min}})^2}$$

$$G_{\pi(m+1, n-1), \pi(m, n)} = -\frac{\sqrt{n}}{2\sigma_w} - \frac{\sigma \rho m \sqrt{n}}{\sigma_w (\sqrt{v_{\max}} - \sqrt{v_{\min}})^2}, \quad n \geq 1$$

# Calculation of the Hermite-moments $\ell_n$ (cont.)

## Theorem 3

The coefficients  $\ell_n$  are given by

$$\ell_n = [h_1(V_0, X_0), \dots, h_M(V_0, X_0)] e^{TG} \mathbf{e}_{\pi(0,n)}, \quad 0 \leq n \leq N$$

where  $\mathbf{e}_i$  is the  $i$ -th standard basis vector in  $\mathbb{R}^M$ . In particular,

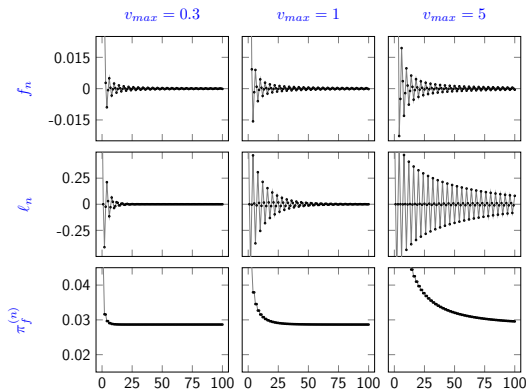
$$\ell_0 = 1;$$

$$\ell_1 = \frac{1}{\sigma_w} \left( rT - \frac{\theta}{2} \left( T + \frac{e^{-\kappa T} - 1}{\kappa} \right) + \frac{e^{-\kappa T} - 1}{2\kappa} V_0 + X_0 - \mu_w \right)$$

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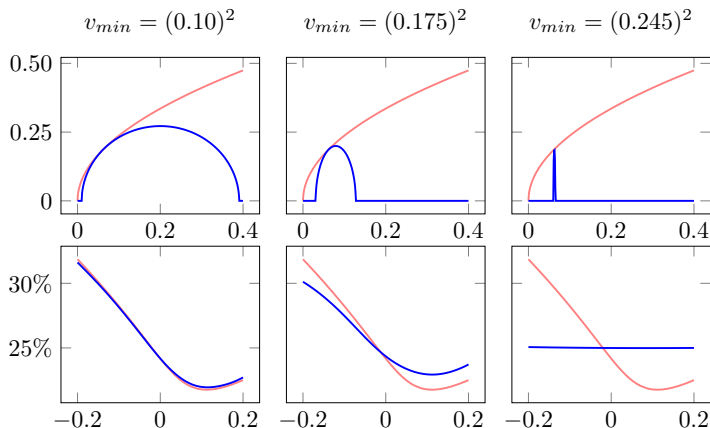
# Example: Call option pricing



**Figure:** The Fourier coefficients (first row), the Hermite moments (second row), and the price expansion (third row) as a function of the order  $n$ . The parameters values are  $T = 1/12$ ,  $X_0 = k = 0$ ,  $\kappa = 0.5$ ,  $\theta = V_0 = (0.25)^2$ ,  $\sigma = 0.25$ ,  $v_{min} = (0.10)^2$ ,  $\rho = -0.5$ , and  $v_{max} \in \{0.3, 1, 5\}$ ,  $\mu_w = \mathbb{E}[X_T]$  and  $\sigma_w^2 = v_{max}T/2 + \epsilon$

# Volatility smiles - Call option

Fix  $\theta = \sqrt{v_{\min} v_{\max}} = v_*$  and scale up  $v_{\min}$



Diffusion function  $\sigma\sqrt{Q(v)}$  (1<sup>st</sup> row) and implied volatility smile (2<sup>nd</sup> row)