

The α -Hypergeometric Stochastic Volatility Model

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The Positivity Problem in Finance (and other fields)

Two simple ways to have positivity

$$x^2 \quad e^x$$

Positivity is important in finance for:

- Volatility.
- Interest rates.
- Stock price.

and **Noise** is given by the Gaussian distribution, hence in \mathbb{R} .

Positivity in Econometrics

The GARCH:

$$r_t = \sigma_t \epsilon_t$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \beta_1 \epsilon_{t-1}^2$$

The EGARCH:

$$r_t = \sigma_t \epsilon_t$$
$$\ln \sigma_t^2 = \alpha_0 + \alpha_1 g(\epsilon_{t-1}) + \beta_1 \ln \sigma_{t-1}^2$$

Positivity in Interest rates

Zero coupon bond

$$B(t, T) = \mathbb{E}_t^{\mathbb{Q}} \left[e^{-\int_t^T r_u du} \right]$$

Vasicek (Ornstein-Uhlenbeck):

$$dr_t = \kappa(\theta - r_t)dt + \sigma dw_t$$

easy but **Gaussian!**

Dothan:

$$dr_t = \kappa r_t dt + \sigma r_t dw_t$$

positive but much more complicated.

Equity Derivatives

For the stochastic volatility models:

$$ds_t = s_t \sigma_t dw_t^1 \quad (1)$$

and

$$d\sigma_t = a\sigma_t dt + b\sigma_t dw_t^2 \quad (2)$$

$$d \ln \sigma_t = a(b - \ln \sigma_t) dt + \alpha dw_t^2 \quad (3)$$

$$d\sigma_t = a(b - \sigma_t) dt + \alpha dw_t^2 \quad (4)$$

- Hull & White (2): volatility non stationary but exponential so positive!
- Chesney & Scott (3): logarithm of volatility Ornstein-Uhlenbeck so Gaussian but volatility is exponential so positive!
- Stein & Stein (4): volatility is Ornstein-Uhlenbeck so Gaussian, volatility is **negative**.

but

- Hull & White not good because volatility is a geometric Brownian motion.
- Chesney & Scott, we don't know the stock density or its characteristic function. Cannot calibrate the model.
- Stein & Stein (4), we don't know the stock characteristic function (option pricing by FFT) but volatility is Gaussian!

Equity Derivatives

$$ds_t = s_t \sqrt{\sigma_t} dw_t^1$$

and

$$d\sigma_t = a(b - \sigma_t)dt + \alpha \sqrt{\sigma_t} dw_t^2 \quad (5)$$

- The volatility is positive and we know the characteristic function of the stock.
- The **Feller** condition $2ab > \alpha^2$ ensures that $\sigma_t > 0$.

Option contains **integrated** volatility

$$E_t^Q \left[\left(s_t e^{-\frac{1}{2} \int_t^T \sigma_u du + \int_t^T \sigma_u dw_u^1} - K \right)_+ \right]$$

Whether the volatility oscillates a lot (large α) or not (small α) option convey little (no) information on that aspect.

Equity Derivatives

The **Feller** condition is not satisfied in practice:

1. The volatility can touch 0.
2. The volatility distribution is too close to 0.

In fact the square root process is positivity using the x^2 function.

Positivity using e^x doesn't work but the exponentiation is **appealing**.

The Hypergeometric Stochastic Volatility Model

The forward price dynamic:

$$df_t = f_t e^{v_t} dw_{1,t} \quad (6)$$

$$dv_t = (a - b e^{\alpha v_t}) dt + \sigma dw_{2,t} \quad (7)$$

with $dw_{1,t} \cdot dw_{2,t} = \rho dt$ (controls the **leverage**).

- Volatility v_t looks like an OU process.
- Stock volatility e^{v_t} is positive by construction.

For $\alpha = 1$ we know how to compute the Mellin transform of the stock (so option pricing is possible).

The Hypergeometric Stochastic Volatility Model

$$\begin{aligned}\mathbb{E} \left[\left(\frac{f_t}{f_0} \right)^\lambda \right] &= \mathbb{E} \left[\exp \left(-\frac{\lambda}{2} \int_0^t e^{2v_u} du + \lambda \int_0^t e^{2v_u} dw_{1,u} \right) \right] \\ &= e^{-\frac{\lambda\rho}{\sigma} e^{v_0}} \mathbb{E} \left[\exp \left(\alpha_0 e^{v_t} + \alpha_1 \int_0^t e^{v_s} ds - \frac{\alpha_2^2}{2} \int_0^t e^{2v_s} ds \right) \right]\end{aligned}$$

with

$$\alpha_0 = \frac{\lambda\rho}{\sigma} \quad \alpha_1 = -\frac{\lambda\rho}{\sigma} \left(a + \frac{\sigma^2}{2} \right) \quad \alpha_2^2 = -\lambda^2(1 - \rho^2) - \frac{2b\rho\lambda}{\sigma} + \lambda.$$

and $dv_t = (a - be^{v_t})dt + \sigma dw_{2,t}$.

Girsanov's theorem to cancel the drift of the volatility

$$\mathbb{E} \left[\left(\frac{f_t}{f_0} \right)^\lambda \right] = e^{-\frac{a}{\sigma^2} v_0 + (\frac{b}{\sigma^2} - \frac{\lambda\rho}{\sigma}) e^{v_0}} e^{-\frac{a^2 t}{2\sigma^2}} \mathbb{E}^Q \left[\exp \left(\frac{av_t}{\sigma^2} + \beta_0 e^{v_t} + \beta_1 \int_0^t e^{v_s} ds - \frac{\beta_2^2}{2} \int_0^t e^{2v_s} ds \right) \right]$$

with

$$\beta_0 = \frac{\lambda\rho\sigma - b}{\sigma^2} \quad \beta_1 = (b - \lambda\rho\sigma) \left(\frac{a}{\sigma^2} + \frac{1}{2} \right) \quad \beta_2^2 = -\lambda^2(1 - \rho^2) + \lambda \left(1 - \frac{2b\rho}{\sigma} \right) + \frac{b^2}{\sigma^2}.$$

and $dv_t = \sigma d\tilde{w}_{2,t}$

The Hypergeometric Stochastic Volatility Model

$$F(t, v) = \mathbb{E}^Q \left[\exp \left(\frac{avt}{\sigma^2} + \beta_0 e^{vt} + \beta_1 \int_0^t e^{v_s} ds - \frac{\beta_2^2}{2} \int_0^t e^{2v_s} ds \right) \right] \quad (8)$$

and $F(0, v) = \exp \left(\frac{av}{\sigma^2} + \beta_0 e^v \right)$. $F(t, v)$ solves the PDE:

$$\begin{aligned} \partial_t F &= \frac{\sigma^2}{2} \frac{d^2 F}{dv^2} - \frac{\beta_2^2}{2} e^{2v} F + \beta_1 e^v F, \\ &= -HF \end{aligned}$$

so $F(t) = e^{-Ht} F(0)$ and in integral form:

$$F(t, v_0) = \int_{-\infty}^{+\infty} q(\sigma^2 t, v_0, y) F(0, y) dy$$

- q is the heat kernel.
- $-\frac{\beta_2^2}{2} e^{2v} + \beta_1 e^v$ is the potential (well known): **Morse** potential.

The Hypergeometric Stochastic Volatility Model

The Laplace transform of the HK is known

$$\begin{aligned} G(v, y; s^2/2) &= \int_0^{+\infty} e^{-\frac{s^2}{2}t} q(t, v, y) dt = \int_0^{+\infty} e^{-\frac{s^2}{2}t} e^{-Ht} dt. \\ &= \left(\frac{s^2}{2} + H \right)^{-1} \end{aligned}$$

G is the fundamental solution (the Green function, or the resolvent) of $H + \frac{s^2}{2} = 0$ that is to say G solves:

$$-\frac{\sigma^2}{2} \frac{d^2 G}{dv^2} + \frac{\beta_2^2}{2} e^{2v} G - \beta_1 e^v G + \frac{s^2}{2} = \delta_y \quad (9)$$

$$G(v, y; \eta^2/2) = \frac{\Gamma\left(\eta - \frac{\nu_1}{\nu_2} + \frac{1}{2}\right)}{\nu_2 \Gamma(1 + 2\eta)} e^{-(v+y)/2} W_{\frac{\nu_1}{\nu_2}, \eta}(2\nu_2 e^{y_>}) M_{\frac{\nu_1}{\nu_2}, \eta}(2\nu_2 e^{y_<})$$

with ν_1, ν_2 related to β_1, β_2, η to s and $y_> = \max(v, y)$, $y_< = \min(v, y)$, $W_{\kappa, \eta}$ and $M_{\kappa, \eta}$ are the Whittaker functions (related to confluent hypergeometric functions):

$$\begin{aligned} W_{\kappa, \eta}(z) &= z^{\eta + \frac{1}{2}} e^{-z/2} \Psi\left(\eta - \kappa + \frac{1}{2}, 1 + 2\eta; z\right) \\ M_{\kappa, \eta}(z) &= z^{\eta + \frac{1}{2}} e^{-z/2} \Phi\left(\eta - \kappa + \frac{1}{2}, 1 + 2\eta; z\right). \end{aligned}$$

The Hypergeometric Stochastic Volatility Model

1. G is known.
2. q is the inverse Laplace transform of G .
3. We integrate q over $F(0, v)$ it gives the Mellin transform of the spot.
4. We compute the inverse Mellin transform of the spot to get the option price.

Conclusions

- we develop a stochastic volatility model with positive volatility
- we provide the main results to perform option pricing

Open Problems

- all the problems are open....