



Student Research Group 'Stochastic Volatility Models'

Methods of Simulation of the Heston Model: A Review

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Heston Model Definition

Assume that the spot asset at time t follows the diffusion

$$dS(t) = \mu S(t)dt + \sqrt{v(t)}S(t)dZ_1(t), \quad (1)$$

$$dv(t) = \left(\delta^2 - 2\beta v(t) \right) dt + 2\delta \sqrt{v(t)}dZ_2(t), \quad (2)$$

where Z_1, Z_2 are the correlated Wiener processes with $dZ_1 dZ_2 = \rho dt$.



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Statistical Estimation

Let X, X_1, X_2, \dots, X_n be a series of independent and identically distributed random variables with a distribution function $F(x)$. Unbiased consistent estimators of $\mathbb{E}[X]$ and $\text{var}[X]$ are:

- The sample mean is the average of the sample values:

$$\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i \quad (3)$$

- The sample variance is the average squared deviation from the mean:

$$S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2 \quad (4)$$

Statistical Estimation



Lemma 1

Let X_1, X_2, \dots, X_n be a series of independent and identically distributed random variables, and $h : \mathbb{R} \rightarrow \mathbb{R}$ be a borel function. Then $h(X_1), h(X_2), \dots, h(X_n)$ is a series of independent and identically distributed random variables.

Thus, we could write the unbiased consistent estimator of $\mathbb{E}[h(X)]$ as follows:

$$\widehat{\mathbb{E}[h(X)]} = \frac{1}{n} \sum_{i=1}^n h(X_i). \quad (5)$$



Random and Pseudo-Random Numbers

Definition 2

A random sequence of numbers is a sequence (in time or in space) with no discernable pattern.

Definition 3

Pseudorandom number generator is an algorithm that generates a sequence of numbers that has no internal pattern. However, the series requires a starting seed, and if the algorithm is started repeatedly with the same seed, it will go through precisely the same sequence of numbers.

Check out the lecture by A.N.Shiryaev (Probability Theory Department x Vega Institute Foundation Seminar, Oct 19) for more details.



Law of Large Numbers

Theorem 4 (Khinchin)

Let X_1, X_2, \dots, X_n be a sequence of independent and identically distributed random variables with a distribution function $F(x)$ and $\mathbb{E}X_i = \mu$. Then

$$\mathbb{P}\text{-}\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n X_i = \mu. \quad (6)$$

Theorem 5 (Kolmogorov)

Let X_1, X_2, \dots, X_n be a sequence of independent and identically distributed random variables with a distribution function $F(x)$ and $\mathbb{E}X_i = \mu$. Then

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n X_i \stackrel{a.s.}{=} \mu. \quad (7)$$



Central Limit Theorem

Theorem 6 (Lindeberg-Lévy)

Let X_1, \dots, X_n be a sequence of i.i.d. random variables with $\mathbb{E}[X_i] = \mu$ and $\text{var}[X_i] = \sigma^2$. Then as n approaches infinity, the random variables $\sqrt{n}(\bar{X}_n - \mu)$ converge in law to a normal distribution $\mathcal{N}(0, \sigma^2)$, i.e.

$$\sqrt{n} (\bar{X}_n - \mu) \xrightarrow{d} \mathcal{N}(0, \sigma^2). \quad (8)$$



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Conclusion

We introduced the three most common simulation methods for dynamics of the two-factor Gaussian diffusion model:

1. Euler scheme;
2. Broadie-Kaya scheme;
3. Andersen scheme.

Using these methods we simulated the dynamics of the Heston model and computed the price of the European call options with different strikes and maturities.

