Research on Pricing of SSE STAR 50ETF Options Based Monte Carlo Simulation

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Abstract. The SSE STAR 50ETF options, as pivotal financial derivatives in China's capital market, are critical for investors and regulators. Traditional pricing models (e.g., Black-Scholes) assume market efficiency and log-normal asset returns, often failing to capture the high volatility and risks of the STAR market. This study proposes an enhanced pricing framework using Monte Carlo simulation to address these gaps. This paper analyze the market traits of SSE STAR 50ETF options and highlight the limitations of conventional models. To better reflect the underlying asset's volatility, we integrate stochastic volatility (HESTON) and jump-diffusion models. Our experimental design compares Monte Carlo-simulated Black-Scholes (BS), HESTON, and GARCH models (treatment group) against standard BS, HESTON, and GARCH models (control group). By simulating STAR 50ETF price paths under no-arbitrage principles, we derive option prices and validate them empirically. Results show that Monte Carlo-based models outperform the control group in fitting market prices, offering investors more accurate pricing and risk management tools. This research contributes to the understanding of derivatives pricing in emerging high-volatility markets.

Keywords: SSE STAR 50ETF option pricing; Monte Carlo simulation; GARCH; HESTON; Black-Scholes (BS).

1 Introduction

The SSE, launched in 2019, is a key platform in China for supporting innovative and high-tech enterprises. The introduction of SSE STAR 50ETF options in 2022 further enhanced market tools for risk management and speculation. However, the 's unique characteristics, such as high volatility, rapid price fluctuations, and frequent jumps in asset prices, present significant challenges for accurate option pricing.

Traditional option pricing models, such as the Black-Scholes (BS) model, are widely used but rely on assumptions like constant volatility and continuous price paths, which do not align with the 's behavior. While advanced models like the HESTON (stochastic volatility) and GARCH (time-varying volatility) models address some limitations, they still struggle to fully capture the market's extreme price movements and jumps.

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To overcome these challenges, this study employs the Monte Carlo simulation method, a flexible numerical technique that can model complex financial processes, including stochastic volatility and jumps. By simulating numerous potential price paths, Monte Carlo methods provide a more realistic framework for option pricing. This paper compares Monte Carlo-based versions of the HESTON, BS, and GARCH models (experimental group) with their standard counterparts (control group) to evaluate their performance in pricing SSE STAR 50ETF options.

BS model is the most classical partial differential analysis method, which obtains the theoretical price of option by solving the partial differential equation. However, constant volatility and frictionless market model assumptions are difficult to fully satisfy in reality, resulting in pricing results that may deviate from the actual market conditions. It applies only to European options. The model also assumes no dividends, leading to inaccuracies for dividend-paying stocks. Other simplifications, like frictionless markets and no transaction costs, further limit its practical accuracy. These constraints have spurred the development of advanced models incorporating stochastic volatility, dividends, and market frictions. Despite its shortcomings, the B&S model remains a key theoretical benchmark in finance. While the B-S model provides a foundational framework for option pricing, its assumptions of constant volatility and risk-free interest rates have been widely criticized for failing to capture the complexities of real-world markets [1]. Recent studies further demonstrate that jump risks and stochastic premiums significantly affect pricing accuracy in high-volatility markets [2]. As a result, numerous extensions and modifications to the B-S model have been proposed to address these limitations.

Researchers developed stochastic volatility models to overcome BS model limitations. D'Uggento compared B&S model and ANN, and proved through indicator analysis and performance indicators that the results obtained by BS model were not as accurate as those predicted by machine algorithm [1]. The HESTON model is one of the most widely used, introducing a mean-reverting stochastic process for volatility. Studies by Mutinda have demonstrated that stochastic volatility models improve pricing accuracy, particularly for options with longer maturities [3]. A comprehensive comparison by Bakshi et al. confirms that stochastic volatility models consistently outperform constant-volatility assumptions across multiple asset classes [4]. However, these models still struggle to fully capture sudden price jumps observed in markets. GARCH models, model time-varying volatility and have been widely applied in option pricing.

Wang used Monte Carlo method to price SSE 50ETF and found that the pricing effect of call option was better than that of put option [5]. Monte Carlo simulation has emerged as a powerful tool for option pricing, particularly for complex models that lack closed-form solutions. Yuan used the volatility data predicted by the Garch model was substituted into the B-S equation, and the Monte Carlo method and quasi-Monte Carlo method were used for several simulations respectively, and since then, advancements in computational power have made these methods more accessible [6]. Zhang combined the Markov chain Monte Carlo (MCMC) method with the GARCH model for the study of European option pricing. Through the empirical analysis of the data of S&P100 European index options, it is found that the improved model improves the pricing accuracy [7]. Huang proposed two options pricing model simulation solutions of HESTON and

BS, combined with variance reduction method, and found that Monte Carlo method can improve the simulation accuracy [8].

In the context of Chinese financial markets, research on option pricing has gained momentum with the development of derivative markets. Studies by Liang and Zhang have explored the applicability of traditional BS Model in the Chinese market, highlighting the need for adaptations to account for unique characteristics [9]. This research builds on these foundations by applying Monte Carlo simulation to the pricing of SSE STAR 50ETF options, addressing the unique challenges posed by the and contributing to the growing body of research on option pricing in emerging markets.

This research aims to develop an advanced options pricing framework for SSE STAR 50ETF options on the SSE using Monte Carlo simulation, which compares the performance of traditional models (e.g. BS, HESTON, GARCH) with Monte Carlo-based models by enhancing the stochastic fluctuation and jump diffusion process. Empirical analysis using historical data to assess pricing accuracy and the impact of parameters. The results of the study are intended to provide investors with more accurate risk management tools and support regulatory decisions in China's evolving financial markets.

2 Theoretical Model and Algorithm of Option Pricing

In the study of financial derivatives pricing, this study selects three representative pricing models. These instruments have been selected based on their respective strengths to effectively address the complex volatility characteristics and risk management needs of financial markets. The BS model is simpler and is a closed solution, which is suitable for the lognormal distribution of the underlying asset prices. GARCH model can capture the volatility aggregation effect in the financial market. HESTON model can better reflect the random characteristics of volatility in the real market. In view of the limitations of the traditional BS model, two improved models, GARCH model and HESTON model, are investigated in this chapter.

2.1 Traditional BS Model

BS model derived the pricing formula for European options, which is used to calculate the theoretical price of options. For European call options and put options, the pricing formula is

$$C = N(d_1)\, S_t - N(d_2) K e^{-r(T-t)} \tag{1}$$

$$P = N(-d_2) K e^{-r(T-t)} - N(-d_1) S_t \tag{2}$$

For the coefficients d_1 and d_2

$$d_1 = \frac{ln(S_0/K)+(r+\sigma^2/2)T}{\sigma\sqrt{T}} \tag{3}$$

$$d_2 = d_1 - \sigma\sqrt{T-t} \tag{4}$$

Where C is the call option price, P is the put option price, S_t is the current price of the underlying asset, K is the exercise price, T is the remaining expiration time of the option (in years), σ represents the volatility of the subject matter, and $N(\cdot)$is the standard normal cumulative distribution function.

2.2 GARCH Model

GARCH is an extension of the ARCH model, which is specifically used to model the volatility clustering phenomenon of financial time series. The model is built on two key assumptions:

(1) The model believes that the volatility of time series is time-varying, which can be effectively predicted based on historical data.

(2) The forecast value of volatility at the current point depends on the previous volatility level and the square term of historical residual. The form of the GARCH Model is

$$\gamma_t = c_1 + \sum_{i=1}^{R} \phi_j \gamma_{t-1} + \sum_{j=1}^{M} \phi_j \varepsilon_{t-j} + \varepsilon_t \tag{5}$$

$$\varepsilon_t = \mu_t \sqrt{h_t} \tag{6}$$

$$h_t = k + \sum_{i=1}^{q} G_i h_{t-1} + \sum_{i=1}^{p} A_i \varepsilon^2{}_{t-i} \tag{7}$$

h_t is the conditional variance process, u_t is the process of standard normal distribution, and u_t and h_t are independent of each other and represent the operation process of conditional mean.

2.3 HESTON Model

The HESTON model is one of the representatives of Stochastic Volatility models. By introducing the stochastic volatility process, HESTON model more truly reflects the market volatility characteristics which improves the assumption of constant volatility of the traditional BS model, and more accurately describes the volatility characteristics of financial markets (such as volatility clustering and leverage effect) by introducing the stochastic volatility process. The form of the HESTON Model is

$$dS_t = \mu S_t dt + \sqrt{v_t} S_t dW_t^1 \tag{8}$$

$$dv_t = \kappa(\theta - v_t)dt + \delta\sqrt{v_t} dW_t^2 \tag{9}$$

$$dW_t^1 dW_t^2 = \rho\, dt \tag{10}$$

S_t is the price process, representing the underlying asset price of ETF options in China at time t; v_t is the variance process. v_t is the state variable and follows the CIR process. Where μ represents the mean value of the stock price; The parameters κ,θ,δ are nonnegative constants. Ω is the long-run variance; μ is the rate of reversion to the mean; δ is the variance of volatility; W_t^1 and W_t^2 denote the Brownian motion process; denotes the correlation coefficient of the 2 Brownian motions.

The pricing formula of call option can be obtained by solving HESTON model

$$C(t, T, S, K) = S_t P_1 (S_t) - Ke^{-r(T-t)} P_2 S_t \tag{11}$$

The analytical solution of the HESTON model involves five key parameters whose parameter set can be expressed as $\Omega = [V_0, \kappa, \theta, \sigma, \rho]$. The calibration of these parameters critically impacts volatility surface fitting, as discussed in the research [10]. Due to the complexity of the model structure, the estimation process of these parameters often faces great computational difficulty and accuracy challenges.

3 Monte Carlo Simulations of Three Option Pricing Models

3.1 Monte Carlo Simulations

Traditional option pricing models like BS and GARCH face limitations in complex markets due to their inability to fully capture volatile and unpredictable implied volatility. This study employs Monte Carlo simulation to address these challenges by modeling stochastic financial paths through random sampling, thereby enhancing pricing accuracy.

Monte Carlo simulation has the advantage of flexibility and adaptability, and can optimize the pricing effect of BS, GARCH and HESTON models in 50ETF options [11]. Its core is to generate random data by constructing a probability model and approximate the true solution with statistical results. In the research, we should focus on the selection of data volume and model adaptation to ensure the accuracy and reliability of the results.

3.2 Monte Carlo simulation of BS-Model

The Monte Carlo simulation procedure for European options under the BS framework involves: (1) specifying key parameters - underlying price (S), strike price (K), risk-free rate (r), volatility (σ), and time to maturity (T). The geometric Brownian motion model is used to simulate the future path of the price of the underlying asset according to the assumptions of the BS model. It is completed by the following formula:

$$S_t = S_0 \, exp((r - \frac{\sigma^2}{2})T + \sigma\sqrt{T}\, Z) \tag{12}$$

S_T is the stock price at time t, $S0$ is the initial stock price, σ is the volatility, and T is to period time, r is the risk-free interest rate, and Z is a random variable with standard normal distribution. For each simulated stock price path, calculate the payoff of the European option. For call options, the payment price of the option is $\max(S_T\text{-}K,0)$， For put options, the payment price of the option The lattice is $\max(K-S_T,0)$. Take the average of all simulated option payment prices and multiply by the discount factor to obtain the Monte Carlo estimated price of the option price

$$\text{option price} \approx e^{-rT} \frac{\sum \text{price paid}}{\text{Number of simulations}} \tag{13}$$

Multiple simulation trials are conducted to ensure estimation robustness.

3.3 Monte Carlo Simulation of GARCH-Model

When Monte Carlo simulations are performed using the GARCH model, the parameters of the GARCH model are mainly involved. GARCH model needs to be fitted to obtain the parameter estimates. The GARCH model usually takes the form

$$h_t = k + \sum_{i=1}^{q} G_i h_{t-1} + \sum_{i=1}^{p} A_i \mu_{t-i}^2 \tag{14}$$

h_t is the conditional variance process, u_t is the process with standard normal distribution, and u_t and ht are independent of each other. Represents the operation process of the conditional mean.

(1) Calculate standardized residuals.

(2) Simulating future standardized residuals.

(3) Calculate future volatility.

(4) Generate future volatility

$$h_{t+1} = k + \sum_{i=1}^{q} G_i h_{t-1} + \sum_{i=1}^{p} A_i \mu_{t-i}^2 \tag{15}$$

μ_{t-i} is the standardized residual at time t - i.

(5) Calculate the option price. For each stochastic path, the option pricing formula is used to calculate the price of the option based on its payoff function and the conditional asset price at maturity.

(6) Obtain the option price expectation.

3.4 Monte Carlo Simulation of HESTON Model

The steps are as follows:

(1) Determine the model parameters.

(2) Initialization: The total number of simulation paths is set as N, and the time step is set as Δt.

(3) Stochastic differential equation of HESTON model is used to simulate the future path of volatility.

(4) The underlying asset's price trajectory is generated using geometric Brownian motion.

(5) Calculate the payment price of European option.

4 The Empirical Part

4.1 Data Analysis

This study selects the Choice financial terminal option data, a total of 96 groups of data, 48 groups of call options, 48 groups of put options, the time span from April 23 to September 24. The strike price of all contracts ranges from 1.4 to 0.8. Initial price of the subject matter, the Shibor closing price of each trading day is selected as the initial price of the subject matter. The strike price K is the strike price on the trading day. For example, the strike price of SSE STAR 50 ETF buying May 1000 put option and the strike price of SSE STAR 50 buying May 1000 call option are both 1.

In order to describe the price fluctuation of financial products, this paper chooses the logarithmic return rate of options for representation, and this paper will further analyze the logarithmic return rate of options.

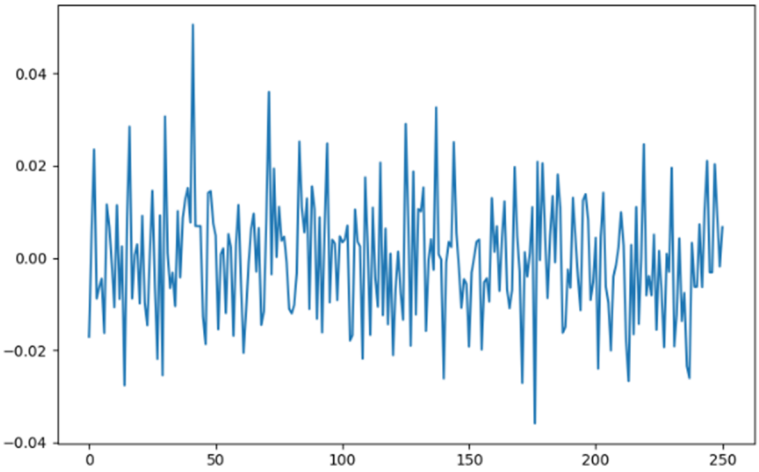

Fig. 1. Distribution of log returns of SSE STAR 50ETF.

It can be clearly observed from Fig. 1 that the SSE STAR 50ETF return series presents a typical volatility agglomeration effect. Specifically, the volatility of this series is obviously time-varying, which is manifested by significant differences in the amplitude of fluctuations in different periods.

Further analysis reveals that the dynamic evolution process of volatility is self-reinforcing (Table 1). When the market enters a state of high volatility, the volatility levels at adjacent time points will affect each other, resulting in a trend of rising volatility. It is worth noting that this agglomeration effect is positively correlated with the level of volatility, that is, as the underlying volatility increases (regardless of extreme outliers), the volatility agglomeration phenomenon becomes more significant. This feature fully reflects the long memory and persistence of volatility in financial time series, and also provides intuitive evidence for the existence of risk contagion mechanism (Fig.2 and Fig. 3).

Table 1. Statistical characteristics of log return series.

Statistical Magnitude	Data	Statistical Magnitude	Data
Maximum value	0.0521	P value	0.0000
Minimum value	-0.0440	J-B statistics	19.3278
Mean value	0.0025		
Standard deviation	0.0166		
Coefficient of skew	-0.1648		
Kurtosis coefficient	5.1618		

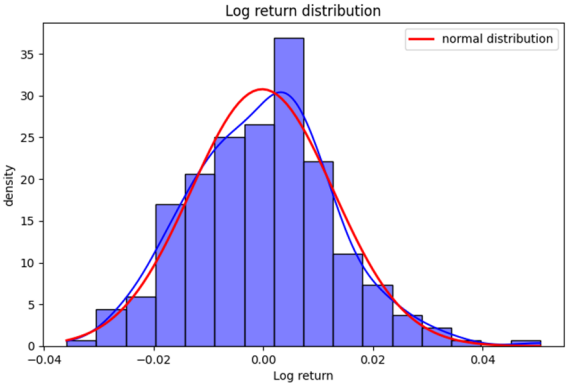

Fig. 2. Normality test for the log-return series.

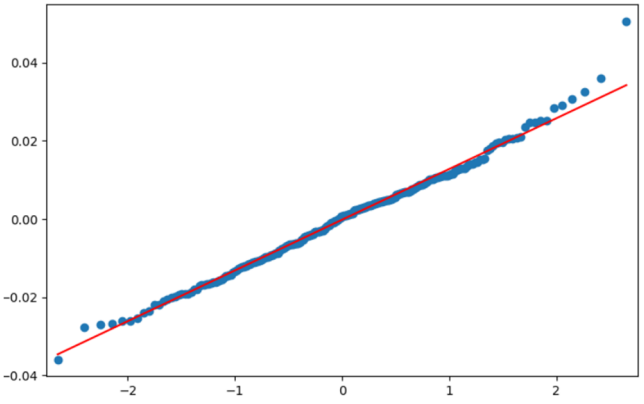

Fig. 3. Q-Q plot of the normality test for the log-return series.

The log return series of STAR 50ETF is skewed to the right as a whole, with the skewness coefficient of -0.1648 and the peak coefficient of 5.1618, which are significantly higher than the kurtosis value of the normal distribution. The p value of the normality test is much less than 0.05. To verify the uncertainty of the BS model assuming that the subject matter follows a normal distribution. The results of this analysis verify

the inapplicability of the assumption that the subject matter follows the normal distribution in the BS model. Then, the unit root test is used to judge the series stationarity.

Table 2. Distribution of return series data of SSE STAR 50ETF.

-	-	T value	Probability
ADF Statistic	-	-16.6215	0.0000
Critical Values	1%	-3.4568	-
-	5%	-2.8732	-
-	10%	-2.5730	-

According to Table 2, the value of the test statistic T is 16.6215, which is far below the critical value at each confidence level value, the p-value of the simultaneous test is very close to 0, which indicates to reject the null hypothesis of the existence of a unit root, that is, the series.

Therefore, based on the stability of this rate of return series, the mode in the time series analysis method can be used type carries out regression analysis on it. The ACF and PACF of this sequence are plotted, as shown in Fig. 4.

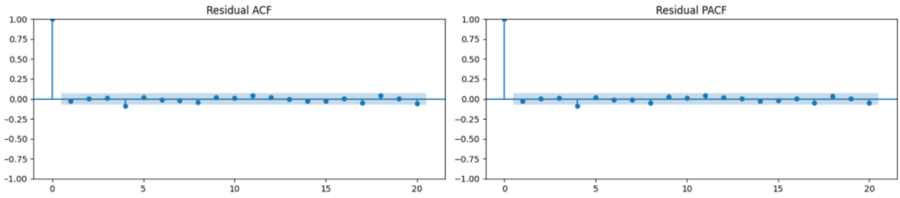

Fig. 4. Plot of ACF and PACF of SSE STAR 50ETF return series.

As can be seen from the above observation, the PACF chart of the series shows that the fluctuation is relatively stable without obvious fluctuation tailing feature. Then, this research uses Python to conduct L-M test on the return series of 50ETF, and the test results are shown in Table 3.

Table 3. L-M test results of the series.

	T value	Probability
L-M test statistic	34.8446	0.0000
Test critical value: 5%	11.0705	

At the third and fourth lags, ARCH-LM test is significant ($p<0.05$), indicating that there is a high-order ARCH effect (volatility aggregation) in the return series, which is suitable for GARCH models. In order to improve the prediction accuracy, AIC and BIC methods are used to confirm the best GARCH model parameters p and q, and finally confirm the use of GARCH (1, 1) Model.

The optimal values of p and q are 1 and 1, respectively. It can get the result of the model at this time.

Table 4. GARCH(1,1) model parameters

	Coefficient	Std.Error	T Statistic	Prob
omega	3.6154e-06	1.010e-10	3.581e+04	0.000
Alpha[1]	1.0000e-02	0.158	6.321e-02	0.0000
Beta[1]	0.6623	5.536e-02	11.965	0.0000

Table 4 show that the P values of the parameters of the conditional mean equation as well as the variance equation are highly significant, and the P values of each parameter are highly significant the p-values are all below 0.05.This aligns with Hansen and Lunde's conclusion that GARCH(1,1) remains a robust benchmark for volatility forecasting [12].

Fig. 5 displays the residuals of the SSE STAR 50ETF return series fitted by the GARCH(1,1) model. The residual series exhibits random fluctuations around the mean without apparent trends or periodicity, approximating a stationary sequence. This observation supports the validity of the model specification.

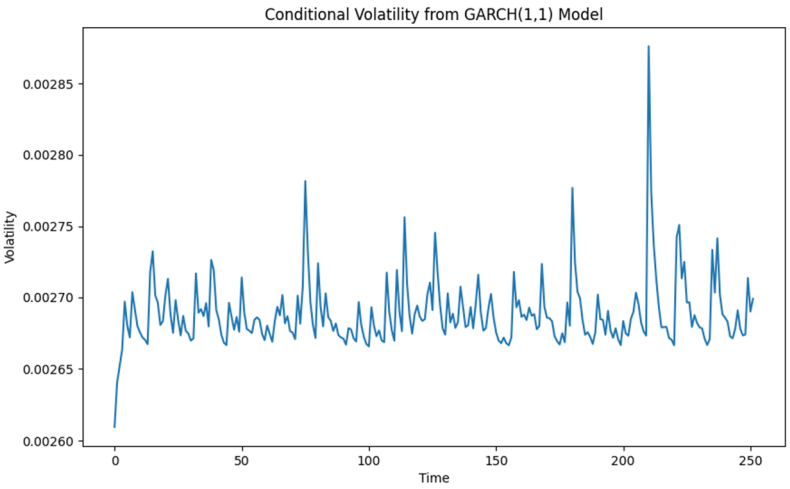

Fig. 5. SSE STAR 50ETF return series fitted GARCH(1,1) residuals.

4.2 Selection and Estimation of Parameters

Parameter estimation of BS model. (1)Risk-free interest rate r: The one-year SHIBOR is selected as the risk-free interest rate. (2) Underlying asset S0: The closing price of each trading day within the option trading range is selected as the initial price. (3) Volatility is calculated using real-time implied volatility.

The GARCH model parameters determined. The parameter estimation of the GARCH model was implemented in Python through the following procedure: First, the logarithmic returns $R_t=\ln(S_t/S_{t-1})$ of the underlying asset were calculated and subjected

to descriptive statistical analysis.Unit root tests confirmed return series stationarity prerequisite before LM tests uncovered volatility clustering patterns. Then, the model order was determined by analyzing ACF/PACF plots along with information criteria (AIC and BIC), leading to the establishment of a GARCH(1,1) model. Finally, an iterative algorithm was applied to estimate the daily asset price volatility σt^2.

HESTON Model parameters determined. Following the methodology demonstrated by Yan for Chinese financial derivatives , this research employ the simulated annealing method to calibrate the five parameters of the HESTON model [13]. By constantly adjusting the parameters to better reflect the actual market data, the algorithm using the initial value may not be accurate enough, and more accurate parameter estimation can be obtained as the process goes on. Here we set the set of initial values to be $\Omega_0 = \{V_0, \theta_0, \kappa_0, \rho_0, \sigma_0\} = \{0.01,0.1,2,0.5,0.1\}$,

The maximum number of iterations is 5000 to prevent excessive consumption of computing resources. Termination condition: the absolute difference between the optimal value and the most original solution for 100 consecutive iterations is less than 0.001, and the temperature cycle is terminated. The following Fig. 6 shows the simulation results.

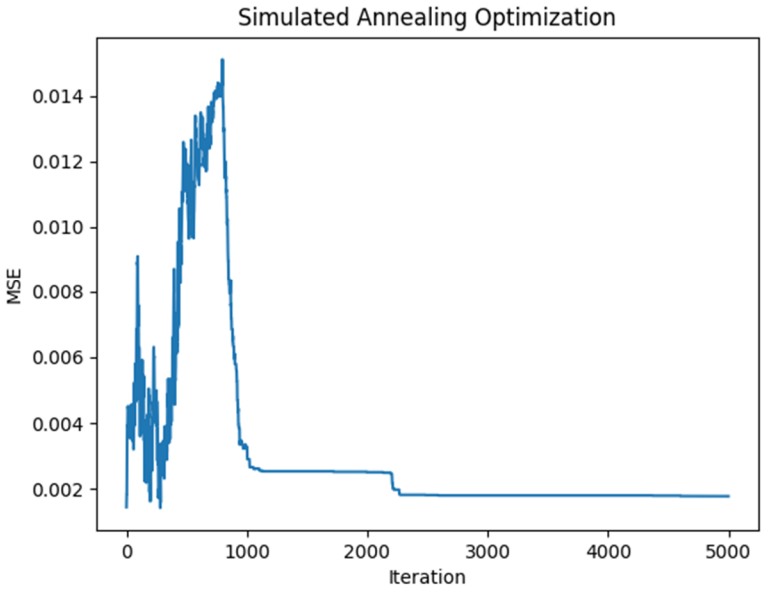

Fig. 6. Error convergence of simulated annealing.

It can be seen that the fluctuation is large from 0 to 1000 iterations, and the error gradually decreases after 1000 iterations. Stable parameter estimation results can be obtained after 2200 iterations. Finally, the results after the calibration of these parameters are obtained:

$$\Omega_0 = \{V_0, \theta_0, \kappa_0, \rho_0, \sigma_0\} = \{0.0204, 0.0876, 0.8316, 0.8690, 0.4267\}$$

In this study, MAE (mean absolute error) and MAPE (mean absolute relative error) were used to measure the error level of each group.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|P_t - C_t| \tag{16}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|P_t - C_t|}{P_t} \tag{17}$$

Where N is the total sample, is the actual option price, and is the theoretical price simulated by the pricing model.

The option price calculated by each model is substituted into MAE and MAPE formulas to calculate the error of each model.

Among them, the control group is the ordinary HESTON, BS and GARCH model, and the experimental group is the group after Monte Carlo simulation.

Table 5. In-sample call option pricing errors

Model	MAE	MAPE
BS	0.0068	0.3783
GARCH	0.0164	0.6130
HESTON	0.0025	0.0754
MC-BS	0.0067	0.3765
MC-GARCH	0.0020	0.5062
MC-HESTON	0.0131	0.0396

Table 6. In-sample put option pricing errors

Model	MAE	MAPE
BS	0.0120	0.3181
GARCH	0.0210	0.5627
HESTON	0.0398	0.1278
MC-BS	0.0118	0.3138
MC-GARCH	0.0008	0.5024
MC-HESTON	0.0029	0.0649

It can be seen from the results of Table 5 and Table 6 that the Monte Carlo simulation model option error performs better than the traditional model out of sample, and the performance of MC-BS, MC-GARCH and MC-HESTON is better than that of the control group than BS, GATCH and HESTON models.

The experimental group is better at pricing put options relative to call options. GARCH and BS models have larger errors in call options, but the Monte Carlo simulation method does improve the model and the overall degree of fit is better.

5 Conclusion

This study evaluates the pricing performance of Monte Carlo-based models (MC-HESTON, MC-BS, MC-GARCH) against traditional models for SSE STAR 50ETF options. Empirical results demonstrate that the MC-HESTON model achieves the highest accuracy in pricing call options, with lower MAE (0.0131) and MAPE (0.0396) compared to control groups, validating its adaptability to China's high-volatility market. However, put option pricing exhibits larger errors, suggesting a need for further model calibration.

The Monte Carlo method enhances pricing accuracy by addressing stochastic volatility and path dependency, though computational complexity remains a challenge. Recent advances in machine learning suggest potential pathways to accelerate Monte Carlo simulations. This research provides a practical framework for pricing derivatives in emerging markets, while highlighting the trade-off between model sophistication and parameter estimation efficiency.

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