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A Comparative Analysis of Three Quantitative Pricing Frameworks for SSE 50ETF Options: BS Analytical Model, CRR Binomial Tree Model and Monte Carlo Simulation

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Abstract. This study compares the effectiveness and feasibility of the Black-Scholes (BS) analytical model, the Cox-Ross-Rubinstein (CRR) binomial-tree model and Monte Carlo simulation of SSE 50 ETF European call contracts. With the help of the no-arbitrage condition, risk-neutral valuation and geometric Brownian motion are used to create these three models in Python with the same benchmark parameters and later compare their pricing accuracy, convergence rate and algorithmic efficiency, and their applicability to various applications. The numerical data shows that the three methods give almost the same option price: 0.0846 to the BS model, 0.0847 the 200-step CRR model, and 0.0843 the Monte Carlo simulation of 100, 000 paths. The BS approach is by nature simple and easy to use, but has some limitations. As the number of iterations increases, the CRR framework is inclined to the BS value and thus can be used in American style options. High-dimensional and path-dependent derivatives are best modeled using Monte Carlo simulation, whose accuracy depends on the number of simulated paths and the traditional model is not able to price American contracts directly. These results explain the tradeoff between accuracy, flexibility and computational cost in option pricing model selection.

Keywords: SSE 50 ETF options, Black–Scholes model, CRR binomial-tree model, Monte Carlo simulation, option pricing

1. Introduction

As the Chinese derivatives sector advanced over recent times, the SSE 50ETF options were implemented to assist traders in hedging exposures. Accurate pricing of options serves as the foundation for portfolio selection and risk control choices. Given that market disruptions and analytical flaws exist, the costs might deviate from the genuine market value.

Three prominent option valuation techniques are frequently utilized: the Black-Scholes (BS) theoretical framework, the Cox-Ross-Rubinstein (CRR) discrete tree approach, and Monte Carlo simulation. While overseas investigation has evaluated the efficacy across mature markets, limited research has utilized SSE 50ETF futures information from China's developing sectors for a comprehensive horizontal assessment.

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This research evaluates the pricing outcomes of the three strategies for SSE 50ETF options, and investigates their merits, drawbacks and suitable scenarios. It offers empirical proof for the conventional valuation framework of China's option sector and offers a basis for traders.

2. Literature review

Option valuation constitutes a fundamental field within financial engineering. Following the introduction of classical option pricing frameworks, Chinese researchers have performed theoretical derivation and empirical evaluations regarding the Chinese equity market using three primary valuation instruments: the Black-Scholes analytical framework, the CRR binomial tree method, and Monte Carlo simulation, offering benchmarks for the pricing activities of SSE 50ETF options.

2.1. Foreign research status

2.1.1. Research on the Black-Scholes analytical model

Black and Scholes initially established a closed-form pricing framework for European non-dividend-paying stock options [1]. Within the framework of frictionless markets, geometric Brownian motion of the underlying asset, constant volatility, arbitrage-free replicating strategies were derived to use in the computation of option values and, thereby, to form the foundation of the modern option valuation. Merton also extended the Black-Scholes model and also included continuous dividend payments as well as varying risk-free rates [2]. He strengthened the theoretical framework of Black-Scholes-Merton and confirmed the rationality of risk-neutral valuation.

Continued studies have shown the shortcomings of Black-Scholes framework [3]. Real-world financial markets have characteristics of fluctuation pattern, price spikes and transaction cost, and non-uniform volatility levels. Several scholars have extended the Black-Scholes to develop jump-diffusion and stochastic volatility models. However, due to its simplified nature of computation and ease of calculation, the original Black-Scholes paradigm has remained in use to approximate European options.

2.1.2. Research on the CRR binomial tree model

The CRR binomial tree option valuation framework was proposed by Cox, Ross and Rubinstein [4]. The model represents the price of assets on frequent intervals in a grid, and assumes that every time period has two possible outcomes of the primary securities: upward or downward. The process is reversed to obtain option values in a risk-neutral environment. The method is an effective way of managing the early-exercise possibility of the American derivatives, and it also addresses the weakness of the Black-Scholes model, which is limited to the European contracts. The longer the time intervals, the closer the pricing outputs of the binomial tree algorithm are to the value obtained via the Black-Scholes closed-form solution, and hence there has been a bridge between finite-precision algorithms and continuous mathematical methods.

Subsequently, a series of studies have sought to hasten the convergence of binomial models and integrate models of exotic instruments, such as barrier options [5]. Previous studies have further recognized the following challenges. An increased time interval can increase the computational load in a quadratic manner, thus this method is inefficient with high-dimensional derivative instruments.

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2.1.3. Research on the Monte Carlo simulation

The first application of Monte Carlo simulation to option pricing theory was the adoption of Boyle method of averaging discounted payoffs across a large number of simulated paths in the risk-neutral distribution of market factors [6]. It is particularly suitable to path-dependent derivatives whose value is determined by the overall price path, and not only by the end value. This was followed by an analysis by Jasra and Del Moral of the applications of SMC in this context which have proven useful in computing arithmetic Asian securities, and in the calculation of sensitivities in the context of stochastic volatility [7]. The primary merit of Monte Carlo is its versatility, yet it possesses a cost – it is extremely "heavy" in terms of processing and the quantity of paths that are simulated constitutes a crucial variable in the precision of the algorithm.

2.1.4. Comparative research on the three types of models

Previous international investigations have performed a direct comparison among these three frameworks [8-10]. Several practical researches demonstrate that these three methodologies are remarkably similar regarding outcomes for simple European contracts. A binomial tree for CRR can be employed to value American securities. Monte Carlo simulations are highly potent for path-dependent derivatives. The Black-Scholes paradigm is suitable for deriving swift analytical outcomes of European contracts but cannot be utilized for intricate elements like American-style rights and path-dependent characteristics. Various investigations have identified that model discrepancies stem from abstract assumptions, fragmented time intervals and the magnitude of simulation trials. Precision and execution expense frequently clash in real-world applications.

3. Theoretical foundations

This segment establishes the core principles of option valuation and offers a comprehensive theoretical basis for the design and evaluation of the Black-Scholes formula, the Cox-Ross-Rubinstein (CRR) binomial tree framework, and Monte Carlo techniques. Introduce essential notions, no-arbitrage valuation, risk-neutral pricing, geometric Brownian motion and various tools of stochastic analysis.

3.1. Basic concepts of options

Moreover, various derivative agreements exist. The option holder finances the option to obtain the privilege, yet not the duty, to purchase or sell the primary asset at a particular reference price by the maturity date. The issuer receives the premium and shall execute delivery.

Based on the principles governing option trading, two categories exist: European contracts (executable solely at maturity) and American contracts (permitted for execution throughout the entire duration). Call agreements anticipate asset value rises, whereas put contracts anticipate asset value falls.

Terminal Payoff Formulas are shown as follows:

Call option: $$\max(S-K,0)_T \quad (1)$$

Put option: $$\max(K-S,0)_T \quad (2)$$

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S is the price at maturity and K is the strike price. Option prices are in fact the present values of uncertain future payoffs.

3.2. No-arbitrage pricing principle

Arbitrage-free valuation represents the fundamental concept of derivative valuation. Arbitrage refers to a risk-free gain with no initial outlay. Within an arbitrage-free market, securities possessing identical risk and reward ought to have the identical price; otherwise, by modifying the discrepancy between these values, one might find an arbitrage chance.

Both the Black-Scholes framework and the CRR binomial model adhere to replication portfolio principles; a portfolio of underlying securities plus risk-free instruments is established to match the option reward structure. At present, this replication cost corresponds exactly to the theoretical option value. According to the no-arbitrage criterion, option prices remain unaffected by risk levels and therefore can be calculated via risk-neutral valuation.

3.3. Risk-neutral pricing principle

Theoretically, the three pricing models can be derived from risk-neutral pricing. In a hypothetical risk-neutral world, all investors are indifferent to risk, and all assets yield the risk-free rate r.

Basic pricing formula under the risk-neutral measure:

$$V_0 = E^{-rT} E^{Q}[V_T] \tag{3}$$

V_0 is the current derivative price, V_T is the terminal payoff, T is time-to-maturity. The current price is the expected discounted future payoff under the risk-neutral measure.

The Black–Scholes model provides a closed-form analytical solution for the expectation.

The CRR binomial tree framework determines option premiums via descending computation utilizing risk-neutral expectations in finite periods.

Monte Carlo techniques estimate expectations via the summation of returns from numerous randomly generated trajectories, grounded in the principle of large numbers.

Risk indifference represents a useful methodology. These financial figures remain realistic within genuine trading environments provided they adhere to the no-arbitrage principle.

3.4. Geometric Brownian motion of underlying assets

Under the Black-Scholes model, the stock price S_t will follow a Geometric Brownian Motion (GBM).

$$dS_t = \mu S_t dt + \sigma S_t dW_t \tag{4}$$

μ is the drift rate, σ is constant volatility, and W is a Wiener process. Under riskneutral measure, drift μ is replaced by risk-free rate r. Log-returns of the underlying assets are normally distributed.

GBM represents a fundamental stochastic premise for these three frameworks, binomial schemes partition GBM, whereas Monte Carlo provides sample trajectories via this probabilistic mechanism. Ito's Lemma serves as a calculus instrument for stochastic analysis used to derive the Black-Scholes PDE.

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3.5. Black-Scholes partial differential equation

Utilizing no-arbitrage replication and Ito's theorem, the Black-Scholes PDE is expressed as:

$$\frac{\partial V}{\partial t} + rS\frac{\partial V}{\partial S} + \frac{1}{2}\sigma^2 S^2 \frac{\partial^2 V}{\partial S^2} = rV \tag{5}$$

Notably, the PDE excludes the real-world drift μ. Together with the terminal payoff boundary condition, the closed-form Black-Scholes formula for European options can be obtained. The two numerical methods to solve the PDE are the CRR binomial tree and Monte Carlo simulation.

4. Model construction and comparative analysis

Establish the Black-Scholes theoretical framework, CRR binomial tree technique and Monte Carlo simulation methodology consecutively within this chapter. Utilize SSE50 ETF options as the analytical object and construct a shared benchmark. Python is employed to implement these three frameworks. The four metrics of evaluation include market price, convergence properties, computational duration and practical applicability.

4.1. Sample and parameter setting

The SSE 50 ETF is chosen as the primary asset, and actual Shanghai Stock Exchange-based SSE 50 ETF derivatives are utilized.

The regular parameters are shown in Table 1:

Table 1. Parameter settings for SSE 50 ETF option pricing

Parameter	Symbol	Value
Current underlying price	S_0	2.600
Strike price	K	2.650
Time-to-maturity (year)	T	0.25 (3 months)
Continuously-compounded risk-free rate	r	0.022
Volatility of underlying asset	σ	0.20
Dividend yield	q	0.01

4.2. Construction of the Black-Scholes analytical model

Within the valuation formula for a European call contract, N(x) signifies the integrated distribution function of the conventional normal distribution, and qq symbolizes the continuous cash dividend rate of the primary underlying stock.

$$C_{BS} = S_0 e^{-qT} N(d_1) - K e^{-rT} N(d_2) \tag{6}$$

$$d_1 = \frac{\ln(S_0/\mathrm{K}) + (r - q + \sigma^2/2)T}{\sigma\sqrt{T}} \tag{7}$$

$$d_2 = d_1 - \sigma\sqrt{T} \tag{8}$$

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Black-Scholes represents a theoretical straightforward technique which operates extremely rapidly. It remains restricted to European instruments and lacks support for the early-exercise options of American variants.

4.3. Construction of the CRR binomial tree model

In the Cox–Ross–Rubinstein (CRR) binomial tree model, the time to maturity T is divided into nn equal intervals, each with a length of $\Delta t = \frac{T}{n}$.

At each time step, the underlying asset price either increases by a factor u or decreases by a factor d, where $u = e^{\sigma\sqrt{\Delta t}}, \quad d = e^{-\sigma\sqrt{\Delta t}} = \frac{1}{u}$.

Here, σ denotes the volatility of the underlying asset. These factors determine the upward and downward movements in the CRR binomial tree.

For an underlying asset paying a continuous dividend yield q, the risk-neutral probability of an upward movement is $p = \frac{e^{(r-q)\Delta t} - d}{u - d}$, where r denotes the continuously compounded risk-free interest rate. The corresponding probability of a downward movement is $1 - p$. Option valuation proceeds by backward induction, starting from maturity. For a European call option, the terminal payoff at each final node is

$$C_{n,j} = \max(S_{n,j} - K, 0) \tag{9}$$

The value of each preceding node is subsequently computed as the risk-neutral expected value of its two potential outcomes at the subsequent period:

$$C_{i,j} = e^{-r\Delta t}[pC_{i+1,j+1} + (1-p)C_{i+1,j}] \tag{10}$$

Here, K is the strike price, while $S_{i,j}$ and $C_{i,j}$ denote the underlying asset price and the call option value, respectively, at time $i\Delta t$ after j upward movements.

Under identical model parameters, the CRR price tends toward the corresponding Black–Scholes value as the number of time intervals n expands. For American options, early exercising is accounted for by selecting the maximum of the discounted anticipated continuation gain and the instantaneous exercise reward at every node.

4.4. Construction of the Monte Carlo simulation model

Within the risk-neutral framework, the dividend-receiving primary asset is modeled to adhere to geometric Brownian motion with fixed coefficients. Its final value in simulation iteration *i* is created as

$$S_{T,i} = S_0 \exp[(r - q - \tfrac{1}{2}\sigma^2)T + \sigma\sqrt{T}Z_i] \tag{11}$$

where S_0 is the initial asset price, r is the continuously compounded risk-free rate, q is the continuous dividend yield, σ is volatility, and T is time to maturity. The variables Z_i are independent standard normal random variables, with Z_i ~ $N(0,1)$.

To estimate the European call option price, N terminal asset prices are simulated, and the payoff for each simulation is calculated as

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$$H_i = \max(S_{T,i} - K, 0) \tag{12}$$

where K is the strike price and H_i denotes the payoff in simulation i. The simulated payoffs are then averaged and discounted at the risk-free rate to obtain the Monte Carlo estimator:

$$\widehat{C_{MC}} = \frac{e^{-rT}}{N} \sum_{i=1}^{N} \max(S_{T,i} - K, 0) \tag{13}$$

Here, N denotes the number of simulations, and $\widehat{C_{MC}}$ is the estimated call option price. Increasing N reduces the estimator's standard error and improves its statistical precision.

This terminal-payoff strategy is appropriate for European instruments. Regarding American securities, the computational framework should likewise incorporate early termination, such as via the least-squares Monte Carlo (LSMC) technique, which calculates continuation worths to aid in execution selections.

4.5. Reproduction with Python

```python
import numpy as np
from scipy.stats import norm
import time

# SSE 50 ETF parameters
S0 = 2.600        # Current underlying asset price
K = 2.650         # Option strike price
T = 0.25          # Time to maturity in years (3 months)
r = 0.022         # Continuously-compounded risk-free rate
sigma = 0.20      # Annualized volatility of underlying asset
q = 0.01          # Continuous dividend yield of ETF

def bs_call(S0, K, T, r, sigma, q):
    d1 = (np.log(S0/K)+(r - q + 0.5*sigma**2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma*np.sqrt(T)
    c = S0*np.exp(-q*T)*norm.cdf(d1) - K*np.exp(-r*T)*norm.cdf(d2)
    return c

def crr_eu_call(S0, K, T, r, sigma, q, n):
    dt = T / n                          # Time interval per step
    u = np.exp(sigma * np.sqrt(dt)) # Up multiplier
    d = np.exp(-sigma * np.sqrt(dt)) # Down multiplier
    p = (np.exp((r - q) * dt) - d) / (u - d)  # Risk-neutral up probability

    S = np.zeros(n + 1)
    for j in range(n + 1):
        S[j] = S0 * (u ** j) * (d ** (n - j))

    C = np.maximum(S - K, 0)

    # Backward recursion from maturity to present
    for i in range(n - 1, -1, -1):
        for j in range(i + 1):
            C[j] = np.exp(-r * dt) * (p * C[j + 1] + (1 - p) * C[j])
    return C[0]

def mc_call(S0, K, T, r, sigma, q, N_path):
    Z = np.random.normal(0, 1, size=N_path)
    ST = S0 * np.exp((r - q - 0.5 * sigma ** 2) * T + sigma * np.sqrt(T) * Z)
    payoff = np.maximum(ST - K, 0)
    c = np.exp(-r * T) * np.mean(payoff)
    return c

if __name__ == "__main__":
    bs_price = bs_call(S0, K, T, r, sigma, q)
    print(f"BS analytical price: {bs_price:.4f}")

    n_step = 200  # Number of time steps for binomial tree
    t1 = time.time()
    crr_price = crr_eu_call(S0, K, T, r, sigma, q, n_step)
    t_crr = time.time() - t1
    print(f"CRR binomial tree(n={n_step}): {crr_price:.4f}, time cost:{t_crr:.4f}s")

    N_sim = 100000  # Number of simulation paths for Monte Carlo
    t2 = time.time()
    mc_price = mc_call(S0, K, T, r, sigma, q, N_sim)
    t_mc = time.time() - t2
    print(f"Monte-Carlo simulation(N={N_sim}): {mc_price:.4f}, time cost:{t_mc:.4f}s")
```

```
BS analytical price: 0.0846
CRR binomial tree(n=200): 0.0847, time cost:0.0490s
Monte-Carlo simulation(N=100000): 0.0843, time cost:0.0050s
```

Figure 1. Python implementation and comparison of european call option pricing methods

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As shown in Figure 1, the Black–Scholes framework provides a theoretical European call premium of 0.0846. The CRR binomial tree featuring 200 intervals generates a price of 0.0847, accompanied by a computed duration of 0.0490 seconds. The Monte Carlo technique with 100,000 iterations predicts the option valuation at 0.0843, alongside a recorded execution time of 0.0050 seconds.

4.6. Comparative analysis of models

4.6.1. Pricing performance

When given the required time intervals of the CRR binomial tree and enough simulation paths of Monte Carlo simulations, these three models produce strikingly the same values of SSE 50 ETF European call options. Black-Scholes closed-form formula is the optimal theoretical benchmark in risk-neutral pricing models.

CRR binomial tree is based on discrete backward. The few time intervals create large temporal discrepancies, and the estimations of the time intervals introduce discretization errors resulting in it not converging to Black-Scholes values. As the number of steps is greater, the number of steps decreases and the CRR results eventually converge to the BS price. However, the lack of precision arithmetic still has small numerical errors.

Statistical variations will have an effect on Monte Carlo results. According to the law of large numbers, increasing the number of simulated paths decreases estimation dispersion and makes estimated prices converge towards the Black Scholes target. However, such improvements in sampling are not able to eliminate underlying inconsistencies that occur due to core assumptions such as constant volatility.

Prices of non European items differ in efficiency. Black Scholes model does not manage early exercise payouts of Americans. CRR tree has the inherent ability to support American contracts by comparing continuation value with immediate payoff at each level. Monte Carlo Monte Carlo does not include facilities to represent the American instruments and requires other methods, e.g. the least squares Monte Carlo. In the case of path dependent exotic securities, Monte Carlo is better than binomial models which face the problem of dimensionality.

4.6.2. Computational efficiency

This Black Scholes model gives the quickest valuation since it is a closed form mathematical representation that does not require any iteration or stochastic processes. Whenever inputs are entered the option values can be computed in real time. Its main disadvantage however is that it only takes the European contracts and cannot estimate the exotic derivatives without coming up with specific formulae.

The computation of the CRR binomial tree grows quadratically with time intervals. An increase in the number of steps increases the lattice points, which increase memory requirements and execution time. Though it works well with American early exercise, it is inefficient with high-dimensional derivatives. In the case of path-dependent contracts, some extra path data are required at every node, which increases computational requirements. In Python execution, CRR is executed quickly and with few steps, but reduces significantly in speed when accuracy is crucial.

Monte Carlo simulation is ideal with path-dependent and high-dimensional derivatives. Its implementation costs are mainly associated with the path volume, but not with the overall risk factors. But American options cannot be directly valued using traditional Monte Carlo. Increased

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accuracy requires additional samples of simulations, increasing the computational time. There is an open trade-off between smaller samples which execute faster and have high sampling variability and larger samples which have less processing speed and high accuracy. In cases where least-squares regression has been integrated in American option valuation, additional overhead is added through additional regression tasks.

4.6.3. Applicable scenarios

Table 2 provides a qualitative evaluation of the Black–Scholes framework, the CRR binomial tree, and Monte Carlo simulation regarding their suitability for various option categories and computational velocity. The Black–Scholes model is showcased as being highly appropriate for European contracts and providing extremely rapid pricing, yet its conventional execution fails to support American or path-sensitive instruments. The CRR binomial tree handles both European and American contracts, but its performance is inferior for path-dependent contracts, and its processing duration grows with the quantity of time periods. Monte Carlo simulation is primarily suited for path-sensitive contracts and can also value European contracts, whereas American pricing necessitates an extra algorithm. Its execution load depends on the quantity of simulated trajectories. In summary, this analysis demonstrates distinctions in computational performance and versatility among these three techniques.

Table 2. Evaluation of option pricing techniques based on suitability and execution efficiency

Table	European Options	American Options	Path-Dependent Options	Computation Speed
Black–Scholes	Optimal	Not Available	Not Available	Extremely fast
CRR Binomial Tree	Available	Optimal	Low efficiency	Moderate, degrades with more steps
Monte Carlo simulation	Available	Requires extra algorithm	Optimal	Slow, sample-dependent

5. Conclusions

The primary subject of investigation within this work involves SSE 50 ETF options: the Black Scholes fundamental framework, the Cox Ross Rubinstein binomial tree technique, and Monte Carlo simulation. In accordance with these experiments, the outcome of the three frameworks is consistent in case of European options when all parameters are set to an ideal outcome. When model validity conditions hold, the results of high-order step CRR binomial-tree computations as well as huge-sample Monte-Carlo computations are astonishingly similar to the fundamental benchmarks of Black Scholes, demonstrating conceptual consistency between no arbitrage based approaches to valuing options and the binomial-tree.

The Black-Scholes framework is relatively straightforward to apply and provides almost instant execution speed, rendering it extremely useful for rapid market evaluation and sensitivity assessments for European-style SSE 50 ETF options. However, it is based on a set of ideal market conditions: a steady volatility, a steady risk free interest rate, smooth markets and the trading of assets constantly. In real Chinese ETF option markets, implied volatility swings between different strike prices and different durations forming volatility smile patterns; risk free yield changes across different macroeconomic periods; bid ask spreads, trading costs as well as position limits all present real financial impediments. Such practical market failure deviations of theoretical bases are bound to

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result in systematic valuation errors between theoretical Black Scholes valuation and actual SSE 50 ETF option marketplace valuation. Moreover, its closed form equations are unable to deal with the American early exercise and most of the complex derivative cashflows which restricts its functioning range.

The CRR binomial tree methodology presents a straightforward and transparent architecture. Reverse induction from maturity effectively illustrates the risk-neutral pricing rationale, while it inherently supports American-style early-exercise assessments by comparing the continuation value against the immediate-exercise outcome at every lattice point. It is more accurate in its computations with respect to increasing step count; otherwise exceptionally large time scales can create substantial numerical discretization errors. Nonetheless, the quadratic growth of node density creates feasibility constraints. In very high-dimensional multi-asset derivatives or other instruments with path dependence, the binomial-tree approach suffers the curse of dimensionality and has prohibitive computational and storage costs. Therefore, the CRR technique is most suitable for low-dimensional European or American single-underlying securities like equity and ETF options.

Monte Carlo analysis is especially useful in high-dimensional, path-dependent derivatives because its performance is mostly determined by the volume of the simulation path, rather than risk factor dimensions, enabling it to have unique benefits when pricing Asian derivatives, barrier contracts and other instruments whose payoffs are determined by full historical price patterns. However, to obtain high accuracy and reduce sampling variations requires a large number of sample paths, which greatly augment the cost of computation. Moreover, traditional vanilla Monte Carlo is not able to price American options or would have to be adjusted through least-squares regression or other optimal-stopping methods, introducing more implementation complexities and extra processing overheads.

Pragmatically, model selection should strike a balance between the price precision requirements, exact target contract features, and available computational resources. The Black Scholes analytical model remains the most cost-conscious of the options to the rapid valuation of basic SSE 50 ETF options. The CRR binomial tree is a reliable numerical alternative provided the elements of American options are required and the principal asset is small. Monte Carlo simulation is the most preferred method in cases where the security dimension is high or path dependent irrespective of the comprehensive algorithmic intensity.

The current study has some limitations. First, using the theoretically computed constant parameters instead of the rolling market-implied volatility may limit the ability of the models to reflect the changing market dynamics. Second, the exploration relies largely on numerical experiments and is not empirically verified using actual SSE 50 ETF option market quotes. Third, model parameterization does not consider transaction costs, liquidity differences and volatility-smile effect observed in the ETF option market in China. Future studies may combine market implied volatility indices, apply actual high-frequency trading data, and market-friction corrections to evaluate the true usefulness of these three pricing models in the Chinese ETF option market in more depth. Besides, further studies may also compare refined model versions like stochastic volatility models and least-squares Monte Carlo computing of American options, to explore development avenues of pricing in the context of realistic market constraints.

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