

Analysis of China's A-share Market Based on Implied Volatility

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Abstract. Market volatility is the focus of investors in the process of investment research. It is not only related to investors' judgment of market trends, but also has an important impact on the results of investment returns. The implied volatility of the market is a kind of volatility that is obtained with the Black-Scholes model, which has been widely recognized as well as applied in market analysis. Taking China's A-share market investment as an example, this paper analyzes and forecasts the market situation based on its implied volatility by Monte Carlo simulation, and compares the relevant results with the volatility calculated in the traditional way. This paper uses the Black-Scholes model and MATLAB soft solution to solve the implied volatility of China's A-share market represented as of the HS300 Index by numerical method. At the same time, the actual volatility of the HS300 index is calculated based on historical data. It is found that the results of the two are relatively close during the study period. After that, this paper takes the calculated implied volatility as the input parameter and combines the historical data to conduct Monte Carlo simulation of the trend of the HS300 Index in the next year (select different time points as the simulation starting point).

Keywords: Implied volatility, black-scholes model, A-share market, monte carlo simulation.

1. Introduction

1.1. Background

Analysis of market conditions is an essential part of investment activities. Effective market conditions analysis can help investors predict the future trend of the market more accurately and make more reasonable investment decisions. For a long time, investors have been skilled in using various quantitative methods to study and predict market conditions, such as time series [1], Monte Carlo simulation, etc. One of the most critical parameters in the quantitative model is earnings and the other is volatility. Investors usually calculate the expected return of assets based on the average of historical data, and calculate the volatility based on the standard deviation of historical data. However, volatility based on historical data is often difficult to represent future volatility, because uncertainty itself is highly uncertain. So how can we better get the market volatility as the model input? If you believe that the information reflected by the market is valuable, and if you believe that the market has reference value for the pricing of all assets, you may as well find the pricing of volatility in the market and deduce the volatility from it. Fortunately, implied volatility is such a kind of market recognized volatility reflected in the option price. This paper will study and forecast China's A-share market based on bank volatility, and related matters will be explained in detail below.

1.2. China's A-share Market

Strictly speaking, the scientific name of China's A-share is called RenMinBi (Chinese Official currency) common stock. A-shares are ordinary shares issued by listed companies in Chinese Mainland, and RMB is the official legal currency for A-share transactions.

Generally speaking, China's stock market can be recognized and analyzed from three different sections: The first section is A-share market, the second section is B-share market and the remaining section is H-share market. Among all the different markets, the A-share market established in the beginning of 1990s is a broadly representative asset of China's financial market, not only from the perspective of the amounts of listed companies but also the hudge market size in total [2].

The HS300 index is the first full-market index in China that focuses on the Shanghai and Shenzhen markets. It is composed of the largest, most liquid and most representative 300 listed stocks in the

stock exchange markets of Shanghai as well as Shenzhen. Therefore, such kind of index can best exhibit the whole performance of the listed companies' securities in the A-share markets. The HS300 Index was officially released on April 8, 2005, with a base date of December 31, 2004 and a base start line of 1000 dots. As of December 31, 2022, the overall market value of the index sample accounted for about 50% of the total market value of the A-share market, which has a good market value characterization. For research in this paper, the HS300 index is applicable because it has corresponding option contracts. On December 23, 2019, Shenzhen Stock Exchange listed Harvest HS300 ETF option contracts [3]. This asset is a exchange contract designed by Huatai Securities HS300 ETF index fund with HS300 of subject matter.

1.3. Volatility and Implied Volatility

The risk and return of assets are the attributes that investors focus on when analyzing the stock market. Volatility is an indicator to measure the uncertainty of returns of different assets, which is also regarded as the risk extent of asset returns. The standard deviation of the return on assets is usually used as its calculation formula. This volatility is calculated based on historical data, so it is also called historical volatility. Just as its name implies, this volatility mainly contains past information rather than future information.

When analyzing the stock market, investors tend to pay more attention to the future because they need to make predictions. This requires investors to find a volatility that can reflect the future expectations of the market. Implied volatility is just such a tool. It is the result of inputting the trading price of options in the market into the Black-Scholes model, and then extrapolating it. On theory, implied volatility is the expectation of the volatility of related assets in the future from the opinion of market investors. Based on the implied volatility, investors can further analyze the future market situation, such as applying it to simulation.

The concept of implied volatility in this paper comes from the Black-Scholes Model. Its derivation and calculation cannot be separated from the analysis and introduction of the Black-Scholes Model. Specific details will be explained in the second part of this paper.

1.4. Literature Review

Fisher Black and Myron Scholes first proposed the Black-Scholes option pricing model [4]. Based on the Black-Scholes model, Robert C. Merton deduced the option pricing formula in a more general case [5]. Steven Manaster and Gary Koehler used the Black-Scholes model, a method for calculating the implied volatility of assets is provided and explained in detail [6]. There are also research achievements in the application of implied volatility. Nikolaos, Ioannis, George studied the time-varying correlation between the returns of financial markets, implied volatility and policy uncertainty. Their research outcomes tell us that the correlation is indeed time-varying and very sensitive to the impact of oil demand and the United States economic recession [7]. Some other researchers study implied volatility backed out from option prices and the compare it with realized volatility in different assets [8].

In combination with the above content, previous literature studies mainly derive implied volatility based on theory, or observe the relationship between implied volatility and relevant market factors and record the observed conclusions. However, the scenarios for further application of implied volatility are relatively limited. The main innovation of this topic is to expand the application scenarios of implied volatility (used to analyze and predict market conditions). At the same time, another innovation of this topic is to focus on a specific market/asset for research, rather than focusing on the Black-Scholes model theory itself as in previous literature.

2. Methodology

2.1. The Black-Scholes Model

Although the relevant formula of Black-Scholes model is highly complex, there are many easily accessible channels to query the specific details, and the research purpose of this paper is mainly to take advantage of the Black-Scholes model as a tool to calculate the implied volatility, rather than to study the theory and derivation of the model itself, so this paper will only show the relevant conclusive information of the Black-Scholes model.

The option pricing (European option, in which the right cannot be exercised before the expiration date) formulas derived from the Black-Scholes model are

$$c = S_t N(d_1) - K e^{-r(T-t)} N(d_2) \quad (1)$$

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

$$d_1 = \frac{\ln(S_t/K) + (r + \sigma^2/2)(T-t)}{\sigma\sqrt{T-t}} \quad (3)$$

$$d_2 = d_1 - \sigma\sqrt{T-t} \quad (4)$$

Where

c - price of the call option (European type ones)

p - price of the put option (European type ones)

S_t - price of the stock at time t

K - options contract's strike price

r - risk-free rate

T - the maturity time point

t - time point between starting and the maturity time

σ - implied volatility

$N(d)$ - the cumulative probability which means the standard normal random variable is no larger than d.

The above formulas can be said to be the foothold of the follow-up research work of this paper. There are two different methods to calculate implied volatility according to the Black-Scholes formulas. The first method is to derive the analytical solution based on the above formula. The advantage of this method is that it can obtain a complete analytical form and observe the role of various parameters in the analytical solution, but the disadvantage is that the calculation process is extremely complex and the results are difficult to understand. The second method is to use the above formula to obtain the numerical solution. The advantage of this method is that it does not need complex mathematical derivation, and the calculation ability of professional software is sufficient to support the results. However, it must be admitted that the numerical solution cannot provide specific formulas, which makes it impossible for this result to directly reflect the role of various parameters. In this research, in order to balance the time cost and the results sought, we decided to use the numerical method to calculate the implied volatility after evaluation. In mathematical form, it is expressed as following

$$\Delta = |P_o - P_c| \quad (5)$$

$$\text{identify the } \sigma \text{ to Min} \Delta \quad (6)$$

$$s. t. \Delta \geq A \quad (7)$$

Δ - absolute value of the difference between P_o and P_c

P_o - the observed (in the market) price of the option

P_c - the price of the option calculated from the Black-Scholes model

A - the largest acceptable error of the numerical solution of implied volatility.

Specifically, possible sigma of an identified range with an identified step is listed firstly, and then the Black-Scholes model formulas are applied to calculate the corresponding option price. The sigma which has the closest option price to price of that option which is observed (in the market) in the market is chosen to be the implied volatility.

It should be noted that basic assumptions and premise of the Black-Scholes model include: not taking all sorts of costs into consideration; all securities are perfectly separable; short selling is allowed; do not consider asset dividends; there is no risk-free arbitrage opportunity (that is, the assumption of market effectiveness is established); transactions occur continuously in time; the expected return, risk and risk-free interest rate are constant parameters. These assumptions are also the premise of the research work of this paper.

If we ignore these favorable interference factors here, it will be beneficial for us to work more at home in the limited time.

2.2. Monte Carlo Simulation

Monte Carlo simulation is a numerical simulation method based on probability and statistics. The basic idea is to abstract a specific problem into a probability model, set the corresponding random variables, use the computer to generate a series of random numbers, input the model for a large number of repeated calculations, and obtain the simulated predicted value of the variables. Since each input obeys a specific distribution, the computer will randomly select any value of each input in the range according to the probability distribution, and finally calculate the probability distribution result of the desired variable through a large number of repeated simulations [9].

The reason why this method is named Monte Carlo simulation is mainly because Monte Carlo is a famous gambling city in Europe, and gambling is intrinsically related to the calculation of probability, so it is named after this gambling city.

Monte Carlo simulation uses computer to realize simulation based on probability and statistics theory. When conducting analysis and research, investors often want to know the probability of an event or the predicted value of a variable. Monte Carlo simulation is to simulate the event or variable when analyzing through a large number of "experiments" by computer, calculate the corresponding probability of the event, or obtain the simulated predicted value of the random variable. From the perspective of modeling ideas, Monte Carlo modeling can be summarized into three main parts: first, construct or describe the probability process; Then the corresponding estimators are established based on the sampling from the known probability distribution; Finally, the simulation prediction results of variables are formed through a large number of repeated experiments.

A core assumption in the Black-Scholes model is that at time t the fluctuation of asset price S_t follows geometric Brownian motion. Meanwhile the distribution of the price of assets just follows closely a semi-lognormal distribution. In other words, the change of the price of asset is nondiscrete, namely:

$$dS_t = \mu S_t dt + \sigma S_t dw_t \quad (8)$$

μ - expected return rate of asset price

σ - expected volatility of asset price (equivalent to implied volatility in this paper)

dw_t - standard Wiener process.

The above formula is converted by Ito formula:

$$S_t = S_0 \exp \left[\left(\mu - \frac{1}{2} \sigma^2 \right) t + \sigma \sqrt{t} x \right] \quad (9)$$

x - random variable subject to standard normal distribution.

After obtaining each of the above parameters, the expected trend distribution of the stock market in the future can be obtained by taking these parameters as input and using computer software for simulation calculation.

2.3. Research Steps and Methods

The research in this paper will combine theoretical introduction and empirical research, with empirical research as the main part and necessary theoretical explanation and elaboration as appropriate. In the part of theoretical introduction, literature review and comparison methods are used to summarize the relevant concepts of implied volatility and introduce the principle of Black-Scholes model. In the empirical research part, MATLAB software is used to calculate the implied volatility of the A-share market based on the Black-Scholes model as well as analyze the A-share market. On this basis, Monte Carlo simulation is taken advantage to predict the future market of A-share market with implied volatility as the input to characterize uncertainty. Finally, the simulation results are compared with the actual situation.

In terms of specific implementation steps, the first step is to collect data, including the market data of the HS300 index, the option price data of the HS300 Index, and the risk-free interest rate data. The specific data selection criteria will be detailed in the third part of this article. The second step is to take advantage of the Black-Scholes model to calculate the implied volatility of the HS300 Index based on the collected data. The third step is to use the calculated implied volatility as the input, and analyze and forecast the future market of A-share market represented by the HS300 Index through Monte Carlo simulation. Finally, compare the predicted results of Monte Carlo simulation with the actual trend of A-share, test the matching degree between the simulated results with the actual situation, and consider the further optimization direction [10].

3. Implementation and Results

3.1. Implementation

As mentioned above, if the implicit volatility is calculated by analytical method, the analytical calculation process is extremely complex, and the most centered target of study in this report is to focus on the application of the implicit volatility rather than the demonstration of its theoretical derivation process. Therefore, we use numerical method to solve here.

The following part calculates the price of options in a positive order with the help of the Black-Scholes model. Before that, the paper list all parameters required for calculation and collect corresponding information.

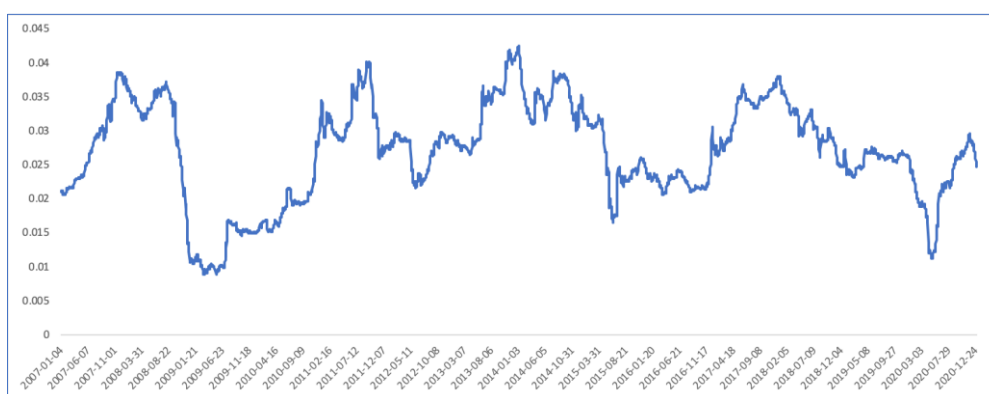


Figure 1. One-year spot bond yield trend

First, we need to introduce risk-free rate in the empirical process (see Fig. 1). Referring to relevant literature and research records, when determining the risk-free rate, researchers mainly take advantage of the treasury bond yield and interbank disassembly rate. In this paper, we choose the one-year spot bond yield as the risk-free yield. The relevant historical data can be obtained from the "yield curve of Chinese bonds" in Wind database. The following figure shows the risk-free yield based on the yield data of Chinese government bonds from January 4, 2007 (the first market trading day in 2007) to December 31, 2020. It can be seen that it fluctuates between 0.01 and 0.04 in most

time periods. In this paper, combining the historical yield of one-year treasury bonds and the information of Wind database, the risk-free yield is determined as 0.0216. That is

$$r = 0.0216$$

Then, by querying the market information of the HS300 index option contracts in the wind database, we learned that the latest price of the European call option contracts expiring in March 2023 was 0.52. That is

$$c_{\text{observed}} = 0.52$$

The option price information obtained from the market data will be used as the benchmark for comparing the price of the same option which is calculated by the above implied volatility. In other words, after using the Black-Scholes model to compute the theoretical prices of the option corresponding to a series of implied volatility, compare these prices with the actual observed option prices (in the market). The closer the volatility is to the actual observed price, the closer the numerical solution of the implied volatility we require.

In addition to the option price, we also collected exercise price of that option contract as well as the contemporaneous price of asset from Wind database information.

$$K = 3.70$$

$$S_t = 4.20$$

At the same time, the time interval is 52 days according to the calculation of the actual time point from the expiration time of the contract. That is

$$T - t = 52/360$$

After collecting the information of these relevant parameters, we can take a step to compute the price of the option contract with the help of Black-Scholes model. The research in this paper starts with 0.0001 as the starting point, 0.0001 as the step length, and 1 as the end point, as the value range of the assumed implied volatility. With the help of MATLAB, a series of option prices are calculated (the calculation process is conducted with the guidance of the Black-Scholes model, and more further specific code can be found in the attachment).

Due to the accuracy of the calculation results, there are five groups of data worthy of attention after comparison. These five groups of data are input by different implied volatility (0.2195, 0.2196, 0.2197, 0.2198, 0.2199), but the theoretical price of options calculated by them is 0.52, which is just equal to the exact observed price (in the market) of the option contract from Wind database.

Considering that the range of this group of data is still small, the impact on the accuracy of the overall results is very limited. Therefore, this paper decides to take the average of five groups of numbers (the same median) as the final result of implied volatility. That is

$$\sigma = 0.2197$$

So far, the implied volatility of the HS300 index calculated based on the option market information has been obtained (see Fig. 2). Next, we will calculate the actual volatility of the HS300 Index. We first collected the market information of the HS300 Index in the past year, as shown in the figure below.



Figure 2. HS 300 Index

It can be observed from the above figure that in the past year (2022), the HS300 Index showed a downward trend of shock. From nearly 5000 at the beginning of the year to less than 4000 at the end of the year, it fell by about 1000. The main reason behind this is that under the influence of the COVID-19, a series of epidemic prevention measures in Chinese Mainland have had a certain impact on economic activities. As a barometer of the economy, the stock market reflects that people's optimism about the future economic situation has continued to weaken in the past year. Of course, fundamental analysis is not the focus of this study. Therefore, there will be no more detailed analysis and elaboration of the trend of A-share market in China represented as the HS300 Index. However, there is no denying that the understanding of the background information related to fundamentals can help us better analyze the results of this research process and help us more effectively quote the research conclusions of this paper. From the intuitive observation, the volatility of the HS300 Index in 2022 is not very high as a whole, because the whole year shows a consistent trend.

It should be noted that the object of our research is not just the realized volatility of the HS300 Index value itself, but the asset return's volatility which is reflected by the HS300 Index (see Fig. 3). We process the historical data of the HS300 Index to obtain its daily return on assets in the past year.

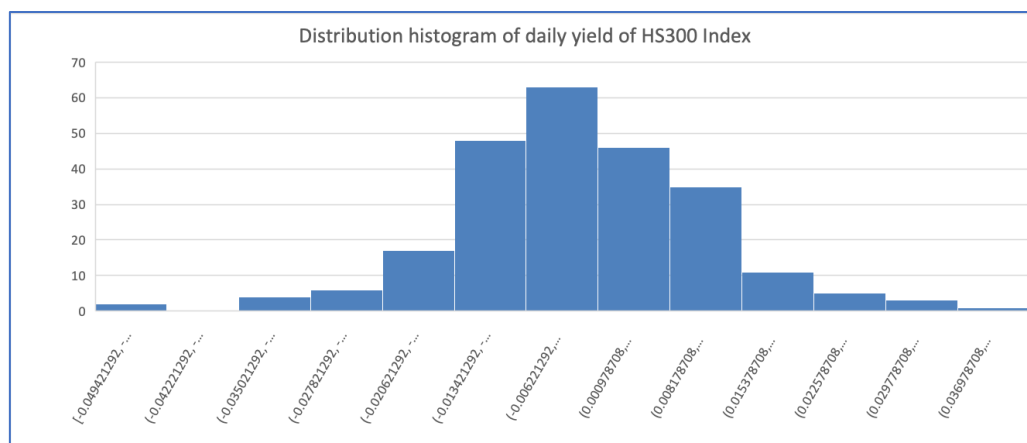


Figure 3. Distribution histogram of daily yield of HS300 Index

From the distribution histogram, we can see that the distribution of the daily yield of the HS300 Index basically presents a symmetrical distribution, and the position of the symmetry axis is about -0.00622.

According to the above data, the volatility of the yield is 0.01285 (which is on a daily base). The volatility of a daily base is annualized, and the annualized volatility result is 0.2032. That is

$$\sigma_{\text{observed}} = 0.2032$$

It is found that the implied volatility calculated above seems to be very close to the observed actual volatility (in the market). As for why the two are so close, we will make a more specific analysis later.

In the next part, we will use Monte Carlo simulation to predict the future trend of China's A-share market, represented by the HS300 Index, with volatility as input and historical data information.

This paper takes the HS300 index at the beginning and end of 2022 as the starting point of Monte Carlo simulation, calculates the mean value of the yield based on historical data, and uses the implied volatility calculated above as the input parameter, and simulates it using MATLAB.

3.2. Results

By using the Black-Scholes model and taking the market data of the HS300 Index and the option price information as input, we calculate the numerical solution of the implied volatility. Then we use the implied volatility as the input parameter, combined with the historical data of the HS300 Index in 2022, to simulate the development path of the A-share market in the next year through Monte Carlo. The results are shown in the Fig. 4 and Fig. 5. Each line in the figure shows the change path of the HS300 Index in the next year.

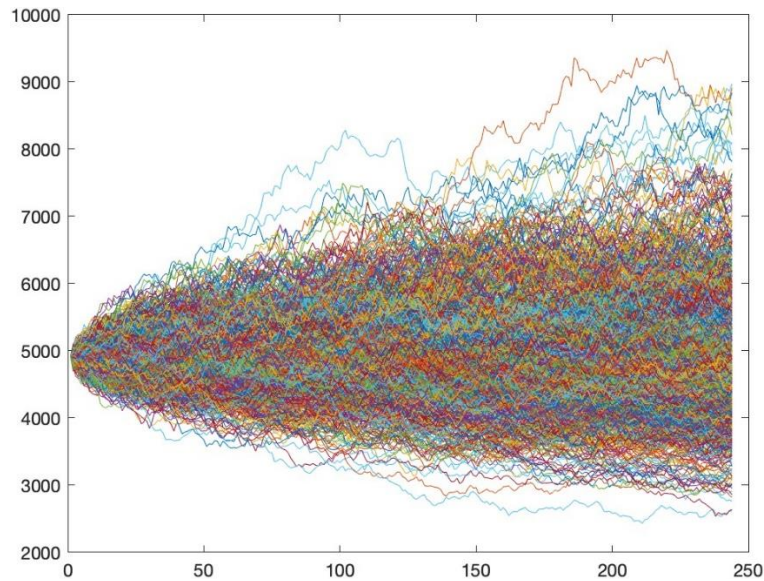


Figure 4. Development path of the A-share market (starting point: the beginning of 2022)

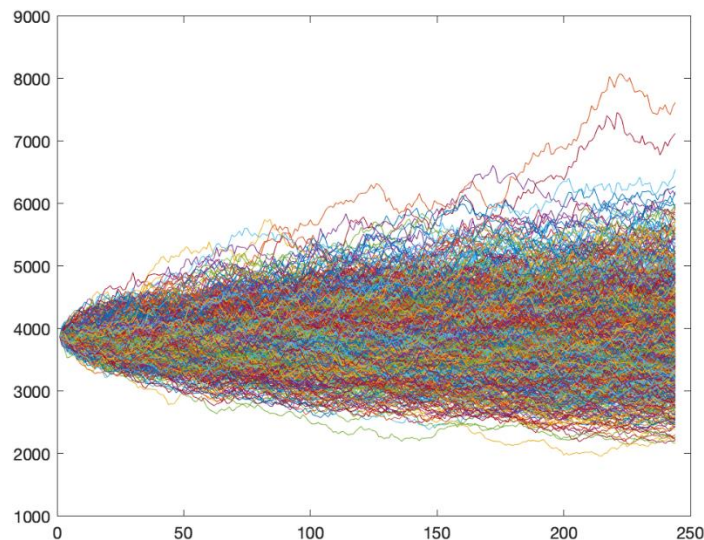


Figure 5. Development path of the A-share market (starting point: the end of 2022)

The Fig. 4 takes the index at the beginning of 2022 as the simulation starting point, and Fig. 5 takes the index at the end of 2022 as the simulation starting point. By observing the first figure, we can find that the actual situation of the index at the end of 2022 is covered in all the simulated index change paths. In addition, the distribution of path density up and down is relatively symmetrical. By observing the second figure, it can be observed that with the index at the end of 2022 as the starting point and the implied volatility as the parameter as the input of Monte Carlo simulation, the distribution and concentration of the HS300 index will be higher in the next year. At the same time, the number of upward development paths is more than the number of downward development paths. In particular, the upper boundary of the index path is higher, reflecting the simulation results that the upside space of the A-share market in the next year is larger than the downside space.

Another point worth mentioning here is that the actual volatility and implied volatility mentioned above are very close to each other. Through consulting the literature, we have not found any special analysis and explanation for this situation. It can be seen that the close value of the two does not constitute a significant anomaly. This is a coincidence to some extent. From the perspective of the gap of exact volatility and implied volatility, the exact volatility is according to the statistical analysis historically. Here if we just believe that the future is an extension of the history, using the historical analysis to forecast the volatility is close to the standard deviation of the return of the target asset. The implied volatility is the volatility value inferred by replacing the market price of the contract by

the price in theory. When the two are relatively close in value, and it reflects that the derivatives market believes that the future market volatility is highly likely to continue its historical development. If we look at the real relationship from the perspective of the gap between the exact volatility from the implied volatility, it also has been observed that the actual volatility and the implied volatility have a certain mutual regression relationship, that is, they are not completely independent of each other, and there will be deviation, regression, re-difference and re-regression with the development of time.

4. Conclusion and Prospect

4.1. Conclusion

This paper uses the BSM model and MATLAB soft solution to solve the implied volatility of China's A-share market represented as of the HS300 Index by numerical method. At the same time, the actual volatility of the HS300 index is calculated based on historical data. It is found that the results of the two are relatively close during the study period. After that, this paper takes the calculated implied volatility as the input parameter and combines the historical data to conduct Monte Carlo simulation of the trend of the HS300 Index in the next year (select different time points as the simulation starting point). It is found that if the index at the starting point of the previous time period is the simulation starting point, the simulation results can cover the actual index at the tail end of the previous time period; If the index at the end of the previous time period is the simulation starting point, it shows a certain bullish trend. In general, using implied volatility as input and Monte Carlo simulation can form a series of path-visible distribution of A-share market change results, which can help us more intuitively observe the possibility of different results. In this respect, this research has achieved some expected results. However, there are still some areas to be optimized in this study.

Since the output of Monte Carlo simulation is a series of possible development paths rather than a single simulation result, it is more appropriate to understand it as a result of probability distribution. According to our simulation results, the distribution range is often a large range, so it is difficult to guarantee the accuracy of the prediction. Its main value is to observe the probability distribution of the future trend of the market, that is, the path with high density means that the probability of occurrence is higher, and the path with low density means that the probability of occurrence is lower. Through visual observation of this probability, we can judge the future changes and development of the market. Especially important, when we use the implied volatility as the input parameter of Monte Carlo simulation, it itself carries the information from all the investors trading in that derivatives market about the forecasted volatility of the market (this information is priced through option trading), which is beneficial to optimize our decision-making judgment.

4.2. Prospect

Due to time constraints, this study only selects the past year (2022), and the relevant parameters are calculated based on the historical data of this year, so it is impossible to exclude the contingency under a specific time. If more in-depth research is carried out, on the basis of the above research work, it is necessary to collect more time periods as observation objects, eliminate the impact of this contingency as much as possible, and verify the applicability of implied volatility in a longer time dimension.

In this study, the gap of the calculated implied volatility and the actual volatility according to the historical information is very small, so it is not possible to carry out further comparison and observe the potential impact on the forecast results caused by the difference between the two. In the future, more time needs to be devoted to in-depth research, such as observing the linkage between the implied volatility and the actual item of different indexes and different times, further confirming the changes in the size of the difference between the two, and trying to analyze the reasons for the difference, so as to form a dynamic analysis chain.

The Monte Carlo simulation method has some shortcomings, such as: the simulation result is only another form of probability expression, not a specific definite answer; generally, more computation processing steps are required. Therefore, if time permits, in addition to Monte Carlo simulation, more forecasting methods can also be considered to judge the future trend of the market. For example, time series method can be considered. This method can also combine historical data and calculated implied volatility as input parameters of the model to predict the future trend of the index. Although other methods have their own advantages and disadvantages, if we can get the prediction results through more methods, we can carry out more in-depth comparison and analysis.

In addition, in the future, when conducting in-depth research, more complex factors can be taken into account, such as the dividend of stocks in the index, the dynamic change of risk-free return, etc., so that the calculation results of implied volatility are closer to the actual situation.

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Appendix

MATLAB code of Calculation of implied volatility	MATLAB code of Monte Carlo simulation
<pre> clc; clear; close all; S=4.2; K=3.7; T=52/360; r=0.0216; sigma=(0.0001:0.0001:1)' a=ones(10000,1); S=S*a; K=K*a; </pre>	<pre> T0=readtable('HS300.xlsx') assetNames=["index"] retnsT=tick2ret(T0(1: 242, "index")); assetRetns=retnsT(:, "index"); arimaT=assetRetns(1, "index") Er=arimaT.Variables/243 Varr=var(assetRetns.Variables) T=1; nSteps=243; nSims=1000; S=T0(242, "index") </pre>

```
T=T*a;
r=r*a;
d1=(log(S./K)+(r+sigma.^2/2).*T)./(sigma.*T.^0.5);
d2=d1-sigma.*T.^0.5;
N_d1=normcdf(d1)
N_d2=normcdf(d2)
c=S.*N_d1-K.*exp(-r.*T).*N_d2
c_observed=0.5200

S=table2array(S)
Dt=T/(nSteps);
sigma=(Varr/Dt)^0.5;
sigma=0.2197;
u=Er/Dt+1/2*sigma^2
mat=randn(nSteps, nSims);
mat=exp((u-
sigma^2/2)*Dt+sigma*sqrt(Dt).*mat);
mat=cumprod(mat, 1);
mat=[repmat(S, 1, nSims); mat.*S];
figure;
plot(mat);
mat=mat-S
csvwrite('MCS.csv', mat)
```
