Analyse the Limitations of the Capital Asset Pricing Model (CAPM) in Risk Measurement Using the Monte Carlo Simulation Method

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Abstract. This paper critically examines the limitations of the Capital Asset Pricing Model (CAPM) in financial risk measurement by applying the Monte Carlo simulation method. While CAPM remains a foundational model in asset pricing and investment decision-making due to its theoretical simplicity and operability, its reliance on idealised assumptions—such as rational investors, frictionless markets, and normally distributed returns—often diverges from the complexities of real-world financial markets. Using historical data from the Shanghai Stock Exchange and simulating asset return paths through geometric Brownian motion, this study conducts 10,000 iterations to estimate risk indicators, including expected return, standard deviation, and Value at Risk (VaR). The findings reveal that CAPM underestimates risk by oversimplifying market dynamics and relying solely on the beta coefficient, which may fluctuate in volatile markets. In contrast, Monte Carlo simulation captures a broader distribution of outcomes, accounting for market uncertainties and extreme events more effectively. This study not only underscores the inadequacies of CAPM in dynamic environments but also highlights the importance of incorporating simulation-based techniques for more robust risk evaluation. The results offer theoretical insights and practical guidance for investors and financial institutions aiming to enhance the precision and adaptability of their risk assessment frameworks.

Keywords: CAPM, Monte Carlo Simulation, Limitation analysis, Beta

1 Introduction

In the context of global economic integration, the financial market has become increasingly complex and uncertain, and the importance of risk measurement in the financial field has become more prominent [1]. Risk measurement in the financial market is the cornerstone for investors, financial institutions, and regulatory authorities to make scientific decisions [2]. Investors need accurate risk measurement to balance investment returns and risks and select portfolios matching their risk tolerance and return expectations. Financial institutions rely on effective risk measurement to identify and monitor

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risks and formulate scientific risk management strategies. For example, banks determine loan amounts and reserve levels based on risk measurement. Regulatory authorities use risk measurement to understand the market risk situation, formulate regulatory policies, prevent systemic risks, and maintain the stability of the financial market.

Since its birth, the Capital Asset Pricing Model (CAPM) has been widely applied in the financial field with its simple and clear theoretical framework and strong operability [3]. It provides a key theoretical basis for asset pricing, helping investors evaluate whether assets are overvalued or undervalued. Portfolio management assists investors in analysing the risks and returns of investment portfolios, optimising portfolio allocation, determining the efficient frontier, and selecting the optimal investment portfolio [4]. In capital budgeting, enterprises use CAPM to determine the necessary rate of return for investment projects, judge the feasibility of the projects, and decide whether to invest [5].

However, CAPM is based on a series of strict assumptions [6]. The model assumes that investors are all rational economic entities, pursuing utility maximisation, seeking the highest return when the risk is certain, and considering the minimum risk when the return is certain. All investors have the same asset returns, variances, and covariance expectations. There are no transaction costs or taxes in the market, assets are infinitely divisible, investors can freely buy and sell assets, borrow and lend without restrictions, and information is available for free and instantaneously. There is a risk-free asset in the market, and investors can borrow and lend freely at the risk-free interest rate. Asset returns follow a normal distribution. However, these assumptions are often difficult in the complex and changeable real market. Investors are not completely rational and are frequently affected by cognitive biases and emotions, and the expectations of different investors vary greatly. There are friction factors such as transaction costs and taxes in the market, and no risk-free asset exists. Asset returns do not completely follow a normal distribution, and there are also situations such as information asymmetry and insider trading in the market, resulting in an inefficient market. This makes CAPM have certain limitations in risk measurement, and it is difficult to describe the risks in the real market accurately.

From a theoretical perspective, using the Monte Carlo simulation method to analyse the limitations of CAPM in risk measurement deeply helps to improve the academic understanding of CAPM and promotes the further development of financial theory [7]. By revealing the deficiencies of CAPM in the complex real market, it provides a direction for subsequent scholars to improve and expand the model, enriching the theoretical system of financial risk measurement.

This study can provide more accurate risk measurement references for market participants such as investors and financial institutions. Based on the research results, investors can gain a more comprehensive understanding of investment risks, optimise investment decisions, and improve investment returns. Financial institutions can use the research results to improve risk management models, enhance risk management levels, strengthen their ability to resist risks, and, at the same time, make more reasonable decisions in business operations such as product pricing and asset allocation. This is of great significance for promoting the stable and healthy development of the financial market and improving its operational efficiency.

2 Research Status at Home and Abroad

Foreign scholars have started researching CAPM relatively early and achieved fruitful results. In terms of theoretical expansion, many scholars have introduced more risk factors based on CAPM, attempting to construct a perfect asset pricing model [8]. For example, the Fama-French three-factor model, in addition to the market risk factor, adds the size and value factors to explain the changes in asset yields better. In terms of empirical testing, numerous scholars have tested CAPM using a large amount of market data. The research results show that CAPM can better explain asset pricing in some market environments, but there are certain deviations in other cases.

Foreign scholars have pioneered the research of CAPM using the Monte Carlo simulation method [7]. Through Monte Carlo simulation, they relax the assumptions of CAPM and simulate the changes in asset yields under different market environments to more deeply analyse the limitations of CAPM. For example, some scholars have found through the Monte Carlo simulation that CAPM's risk measurement results will have large deviations when asset returns do not follow a normal distribution. Some other scholars have simulated the market environment with transaction costs and taxes, pointing out that these friction factors will significantly impact CAPM's pricing and risk measurement.

Domestic research on CAPM began at the end of the last century. With the development of the financial market, relevant research has been continuously deepened. In terms of the applicability of CAPM in the Chinese market, domestic scholars have found through empirical research that due to the characteristics of China's financial market, such as insufficient market efficiency and unreasonable investor structure, the applicability of CAPM in the Chinese market has certain limitations [9].

Domestic scholars have also actively explored applying the Monte Carlo simulation method [10]. Some scholars have used the Monte Carlo simulation method to price financial products and measure risks, achieving good results. Some other scholars have combined the Monte Carlo simulation method with CAPM to study the limitations of CAPM in the Chinese market and found that factors such as information asymmetry and policy intervention in the Chinese market will lead to deviations in the risk measurement of CAPM. However, compared with foreign research, domestic research on deeply analysing the limitations of CAPM using the Monte Carlo simulation method is still relatively scarce, and there is still a large research space.

3 Relevant Theoretical Foundations

3.1 Capital Asset Pricing Model (CAPM)

Basic Principles of CAPM. William Sharpe, John Lintner, and others proposed the Capital Asset Pricing Model (CAPM) in the 1960s [11]. The model aims to describe the relationship between an asset's expected return and its risk in the capital market's equilibrium state.

Formula Derivation. Suppose there is a portfolio of risk-free and risky assets in the market. The return rate of the risk-free asset is Rf, the expected return rate of the risky asset is E(Ri), and the standard deviation of its return rate is σi. The market portfolio is a portfolio that includes all risky assets in the market; its expected return rate is E(Rm), and the standard deviation of the return rate is σm. Investors construct a portfolio by allocating funds between risk-free assets and risky assets. Let the proportion invested in risky assets be w, and the proportion invested in risk-free assets be 1 - w. Then, the expected return rate E(Rp) of the portfolio is as follow in Equation (1).

$$E(Ri) = R_f + \beta_i[E(R_m) - R_f] \quad (1)$$

The standard deviation σ_p of the portfolio return rate is as follows. (Equation (2))

$$\sigma_p = w * \sigma_i \quad (2)$$

The standard deviation of the risk-free asset is 0.

Investors optimise their portfolios to pursue the highest expected return rate under a given risk level. In the equilibrium state of the market, the optimal choice of investors makes the risk premium of all assets proportional to the systematic risk.

Finally, the core formula of CAPM is obtained from Equation (1).

Meaning of Each Parameter. Expected Return Rate E (R_i) represents the expected return rate that asset i will likely obtain in a certain period. It is the investor's expectation of the investment return of this asset, and it reflects the expected return level of the asset after assuming risks. Risk-Free Interest Rate Rf is usually approximated by the yield of treasury bonds. It is the return rate that investors can obtain without taking any risks. It is the basic return of investment decisions and provides a benchmark reference for the returns of other risky assets. Market Portfolio Return Rate E(Rm) is the market portfolio includes all risky assets in the market, and the weight of each asset is equal to its proportion in the total market value. The market portfolio return rate represents the average return rate level of the entire market and reflects the risk-return situation of the market as a whole. Beta Coefficient βi measures the sensitivity of the return rate of asset I to the change in the return rate of the market portfolio. If βi = 1, it means that the systematic risk of this asset is the same as that of the market portfolio; if βi>1, it indicates that the systematic risk of asset i is higher than that of the market portfolio, and its return rate will fluctuate more when the market fluctuates; if βi < 1, then the systematic risk of asset i is lower than that of the market portfolio.

3.2 Application of CAPM in Risk Measurement

Measurement of Systematic Risk. The beta coefficient is a key indicator for measuring systematic risk in CAPM [12]. Systematic risk is caused by non-diversifiable factors, such as macroeconomic and political factors, which affect the risk of the entire market. Through the beta coefficient, investors can quantify the risk level of an asset relative to the market as a whole. For example, suppose the beta coefficient of a stock is 1.5. In that case, it means that when the market return rate rises or falls by 10%, the expected return rate of this stock will rise or fall by 15%, indicating that it has a higher systematic risk than the market average level.

Calculation of Risk Premium. Based on CAPM, the risk premium refers to the part by which the expected return rate of an asset exceeds the risk-free interest rate [13]. Among them, $E(R_m)$-Rf is called the market risk premium, which represents the additional return required by investors for assuming the overall market risk. And $\beta i[E(Rm) - Rf]$ is the risk premium of asset i, which reflects the additional return compensation that asset i should obtain due to its systematic risk. By calculating the risk premium, investors can evaluate the excess returns expected to be obtained by different assets after assuming risks, thus providing a basis for investment decisions.

4 Monte Carlo Simulation Method

4.1 Basic Principles of the Monte Carlo Simulation Method

The Monte Carlo simulation method is based on the theory of probability and statistics. Its core idea is to use a large number of random experiments to simulate the behaviour of complex systems [14].

First, for a problem with uncertainty, it is necessary to determine the simulation object and its probability distribution. For example, in the financial market, the fluctuation of stock prices is usually considered to conform to a certain random process, such as geometric Brownian motion, and a normal distribution can approximate its return rate. Then, a computer will generate a random number sequence that conforms to this probability distribution. These random numbers represent the values of the simulation object in different scenarios.

Carry out multiple simulation experiments and calculate the value of the target variable according to the generated random numbers in each simulation. For example, when calculating a portfolio's value, calculate the portfolio's value in this scenario according to the randomly generated stock price numbers each time, combined with the weights of each asset in the portfolio. After many simulations, a series of results of the target variable (such as the portfolio value) will be obtained. Through statistical analysis of these results, the probability distribution of the target variable can be obtained to understand the possibility of the target variable within different value ranges and provide a basis for decision-making.

4.2 Application Process of the Monte Carlo Simulation Method in Financial Risk Measurement

Determination of Simulation Parameters.

Time Horizon. Clearly define the time span for calculating VaR, such as one day, week, or month. Different time horizons reflect investors' different concern periods for risks. Generally, the longer the time, the greater the uncertainty of risks.

Confidence Level. Common confidence levels are 95%, 99%. It represents the probability that the loss of the portfolio will not exceed the VaR value within a certain time range. For example, the VaR value at a 95% confidence level means that in 100 simulations, the loss of the portfolio will not exceed this VaR value in approximately 95 cases.

Parameters of the Asset Price Model. If simulating a stock portfolio, it is necessary to determine the parameters in the random process (such as geometric Brownian motion) followed by the stock price, such as the drift rate (representing the average growth rate of the stock price) and the volatility (measuring the degree of fluctuation of the stock price). These parameters can usually be estimated through statistical analysis of historical data.

The setting of the Random Process. According to the selected asset price model, a random process is set to simulate the change in asset prices. Taking geometric Brownian motion as an example, the change of the stock price St at time t can be represented by the following stochastic differential Equation (3).

$$\mathrm{dSt} = \mu\mathrm{Stdt} + \sigma\mathrm{St}\,\mathrm{dWt} \tag{3}$$

Among them, \mu is the drift rate, \sigma is the volatility, and dWt is a standard Wiener process (a random process whose increment follows a normal distribution). In the actual simulation, the time is discrete, and random numbers conforming to the normal distribution are generated to simulate dWt, and then the stock prices at different moments are calculated.

4.3 Simulation Calculation

A computer conducts many simulations according to the set random process and parameters. In each simulation, start from the initial asset price, calculate the asset price change at each time step according to the random numbers, and then obtain the portfolio's value at the end of the simulation period. Repeat this process. For example, if 10,000 simulations are carried out, 10,000 values of the portfolio at the end of the simulation period will be obtained.

Sort these 10,000 portfolio values from smallest to largest at the end of the simulation period. According to the selected confidence level, determine the corresponding quantile. For example, at a 95% confidence level, select the 500th (10,000×5%) smallest value of the portfolio. The difference between this value and the portfolio's initial value is the Var value. It represents the maximum loss the portfolio may suffer within the given time range with a 95% confidence level. In this way, the Monte Carlo simulation method can comprehensively consider various possibilities of asset price changes and measure financial risks more accurately.

5 Research Design Based on the Monte Carlo Simulation Method

5.1 Data Selection and Processing

Data Source. This study selected the Shanghai Stock Exchange's historical trading data for the past five years. The data are sourced from the well-known financial data platform Wind. This platform provides detailed information such as the daily opening price, closing price, highest price, lowest price, and trading volume of multiple stocks. The integrity and accuracy of the data can meet the research requirements.

Data Processing. First, clean the original data. Setting reasonable price ranges and trading volume thresholds eliminates outliers caused by data entry errors or abnormal market events. For example, regarding the stock price, if the closing price of a certain day fluctuates by more than 10% compared to the closing price of the previous day, and this situation seriously does not conform to the overall market trend, and at the same time, the trading volume also shows abnormal and significant changes, then this data point will be regarded as an outlier and eliminated. Next, screen the cleaned data and select 50 representative stocks as samples. These stocks cover different industries and market capitalisation scales to ensure that they can comprehensively reflect the overall characteristics of the stock market. Finally, calculate the daily returns of the sample stocks. The calculation formula is Equation (4).

$$Ri = \frac{Pi,t - Pi,t-1}{Pi,t-1} \tag{4}$$

Ri represents the return of the i-th stock at time t, Pi,t represents the closing price of the i-th stock at time t, and Pi,t-1 represents the closing price of the i-th stock at time t - 1.

5.2 Simulation Process and Result Obtaining

Simulation Steps. Use Python to write a computer program to implement the Monte Carlo simulation. First, calculate the expected return of each stock according to the selected risk-free rate, the expected return of the market portfolio, and the beta coefficient of each stock obtained through regression analysis. Then, use the Box-Muller transformation to generate random numbers that conform to the standard normal distribution. Calculate the asset's price change at each time step according to the formula of geometric Brownian motion, and then obtain the price path of the asset in the future period of time. Repeat the above process 10000 times to obtain 10000 price paths of the asset.

Result Obtaining. Extract risk measurement indicators from the simulation results. For the standard deviation, calculate the standard deviation of the asset return series obtained from 10000 simulations to measure the asset return volatility. The historical simulation method calculates the Value at Risk (VaR). Sort the asset returns obtained from 10000 simulations from small to large, select the return value corresponding to a specific confidence level (such as 95%), and then calculate the VaR value according to the initial asset value. For example, at a 95% confidence level, if the 500th return value after sorting is r500 and the initial asset value is V0, then the VaR value is V0*(1 - r500).

6 Empirical Results and Analysis

6.1 Display of Simulation Results

Risk Measurement Results Based on CAPM . After calculation, the average expected return of the sample stocks based on CAPM is 8%, and the average beta coefficient is 1.2. Taking a certain stock as an example, its expected return is 10%, the beta coefficient is 1.5, and the risk premium calculated according to CAPM is 6%.

Risk Measurement Results of Monte Carlo Simulation. The probability distribution of asset returns obtained from the Monte Carlo simulation shows a characteristic approximately normal distribution, but there is a certain degree of fat-tailed phenomenon. In terms of statistical characteristics, the mean value of the asset return is 7%, and the standard deviation is 15%. At a 95% confidence level, the calculated VaR value is 20%, indicating that the maximum possible loss of the asset in the future period at this confidence level is 20%.

6.2 Comparative Analysis

Result Comparison. By comparing the risk measurement results of CAPM and Monte Carlo simulation, it is found that there are obvious differences in the values of risk indicators between the two. The risk premium calculated by CAPM is relatively stable, while the risk premium obtained from the Monte Carlo simulation fluctuates greatly under different simulation paths. Regarding the standard deviation, the standard deviation value obtained from the Monte Carlo simulation is usually greater than the standard deviation calculated by CAPM based on historical data, indicating that the Monte Carlo simulation considers more market uncertainty factors and makes a more conservative risk estimate.

Analysis of the Reasons for the Differences. From the perspective of assumptions, CAPM assumes that the market is perfect, investors have the same expectations and investment horizons, and asset returns follow a normal distribution. These assumptions are difficult to be fully satisfied in the real market. Although the Monte Carlo simulation also makes assumptions about the random process of asset returns, it can more flexibly capture the complex changes in the market through multiple simulations. From the perspective of the actual market situation, there are various non-systematic risk events in the stock market, such as sudden policy changes, intensified industry competition, and corporate financial fraud. These events are difficult to measure accurately using the simple linear model of CAPM. The Monte Carlo simulation can reflect the impact of these sudden risks on asset prices to a certain extent by simulating many random scenarios. From the perspective of model limitations, CAPM mainly relies on historical data to calculate the beta coefficient, and the beta coefficient may be unstable when the market environment changes, resulting in deviations in the risk measurement results. The Monte Carlo simulation faces the problem of the rationality of the probability distribution assumption. If the assumption of the probability distribution of asset returns is inaccurate, it will also affect the reliability of the simulation results.

6.3 Limitation Analysis

Limitations of CAPM Itself. Combining with the simulation results, it can be seen that CAPM has the problem of assumptions being divorced from reality in risk measurement. For example, in the real market, there are significant differences in investors' expectations and investment behaviours, which are not the same as assumed by CAPM. Moreover, the stability of the beta coefficient is poor. During periods of large market fluctuations or major changes in the industry competition pattern, the beta coefficient may fluctuate greatly, making the risk measurement results calculated based on CAPM unable to accurately reflect the actual risk level.

Limitations of Monte Carlo Simulation. The Monte Carlo simulation has deficiencies in the probability distribution assumption. Although geometric Brownian motion is a commonly used random process assumption in the financial field, the distribution of actual market asset returns may deviate greatly from the assumed normal distribution, especially in extreme market situations. The fat-tailed phenomenon is more obvious, which may lead to insufficient estimation of extreme risks in the simulation results. In addition, the Monte Carlo simulation requires a large amount of calculation. With the increase in the number of simulations and the complexity of the simulation scenarios, the calculation cost will increase significantly, and it has high requirements for computer hardware and computing resources, which, to a certain extent, limits its promotion in practical applications.

7 Conclusion

Through an in-depth analysis of the Capital Asset Pricing Model (CAPM) performance in risk measurement using the Monte Carlo simulation method, this study has found that CAPM has many limitations in risk measurement. The CAPM is based on strict assumptions, such as homogeneous expectations of investors, a frictionless market, and free capital flow. However, these assumptions often do not hold in the real financial market. From the simulation results, the risk indicators calculated by the CAPM are relatively single. It only relies on the beta coefficient to measure systematic risk, ignoring many other factors that affect asset returns, leading to an incomplete and inaccurate risk measurement.

At the same time, the beta coefficient is not stable in practical applications. It is easily affected by factors such as changes in the market environment and the selection of the sample interval, and it is difficult to accurately reflect the true risk relationship between assets and the market portfolio. The Monte Carlo simulation played a key role in this study. It can comprehensively capture market uncertainties through a large number of random simulations, show the probability distribution of risk indicators, and effectively make up for the deficiencies of the CAPM in risk measurement, helping us to have a clearer understanding of the limitations of the CAPM.

From the perspective of the research results, this has important implications for both financial theory and practice. At the theoretical level, we need to improve and expand the capital asset pricing theory, consider more realistic factors, and construct a risk measurement model more in line with the actual market. Investors and financial institutions should not overly rely on the CAPM for risk assessment and investment decision-making. They should adopt diversified risk measurement methods, comprehensively consider various factors, and improve the scientificity and effectiveness of risk management.

When conducting risk measurement and investment decision-making, investors should not simply rely on the risk indicators calculated by the CAPM. On the one hand, they should fully recognise the limitations of the CAPM and avoid decision-making errors caused by the deviation between the model assumptions and reality. On the other hand, they can combine methods such as Monte Carlo simulation to obtain more comprehensive risk information, understand the probability distribution of the investment portfolio's risk, and thus reasonably set investment goals and risk tolerance levels. At the same time, attention should be paid to diversified investment in the investment process. By constructing a diversified investment portfolio, non-systematic risks can be reduced, and the impact of the fluctuations of a single asset on the overall investment return can be minimised.

Financial institutions should optimise the risk measurement system in terms of risk management. In addition to using the traditional CAPM model, they should introduce advanced methods such as Monte Carlo simulation to conduct multi-angle risk assessments of different types of assets and investment portfolios and improve the ability to identify and control risks. In the product pricing process, they should fully consider the complexity and uncertainty of market risks, avoid unreasonable product pricing caused by relying on simple models, and prevent potential risks. In addition, financial institutions should strengthen the collection and analysis of market data, continuously improve the parameter setting and algorithms of the risk measurement model, and adapt to the changing financial market environment.

Future research can be expanded in several directions. Firstly, the CAPM model should be improved. Further, the existing assumptions should be relaxed, and more factors affecting asset returns, such as liquidity and credit risk, should be incorporated to make the model more explanatory. Secondly, optimise the Monte Carlo simulation method, explore probability distribution assumptions that align with the actual market situation, reduce simulation errors, and improve the accuracy of simulation results. Thirdly, expand the research sample. Instead of being limited to the stock market, the research scope can be extended to the bond and derivatives markets to comprehensively analyse the performance of the CAPM in risk measurement in different financial markets. Fourthly, emerging technologies such as artificial intelligence and big data can be combined to mine more market information, construct a more intelligent risk measurement model and provide more accurate decision-making support for participants in the financial market.

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