Proceedings of ICFTBA 2026 Symposium: Digital Government, Finance, Accountability, and Sustainable Economic Development
DOI: 10.54254/2754-1169/2026.AB38103

A Review of Monte Carlo Simulation in the Field of Financial Credit Risk Prediction

Zhehao Xu

Hangzhou Foreign Language School, Hangzhou, China
Davidxu0622@gmail.com

Abstract. In recent years, global economic volatility has intensified, and rising market uncertainties have continuously exacerbated, the international situation has shifted, and the uncertainty of the market environment continues to rise. So the operating pressure on small and medium-sized enterprises is constantly increasing. Consequently, the transmissibility and complexity of credit risk have significantly increased. The complexity of credit risk renders traditional static financial risk prediction methods incapable of coping with the complex scenarios involving multiple factors interacting with each other. As a numerical analysis method based on random sampling, Monte Carlo simulation, with its core advantages of being capable of handling multiple variables and supporting dynamic simulation, is increasingly widely applied in the field of financial risk assessment. This essay takes credit risk prediction as the starting point, outlining the core principles of Monte Carlo simulation and the implementation process for risk analysis, and elaborate on their application pathways and modeling logic in three specialized financial fields: real estate investment appraisal, insurance actuarial risk control, and financial derivatives pricing, compare and analyse the adaptability advantages and inherent limitations of this method in different situations. The findings indicate that Monte Carlo simulation can effectively depict the multi-risk resonance effect and the extreme tail loss distribution, addressing the vulnerabilities of traditional single-factor analysis and static rating methods. However, there are also common problems such as weak stability of small samples, high dependence on parameters, and insufficient depiction of heavy-tailed risks. This article summarizes the general characteristics and optimization directions of this method, which can serve as a reference for basic financial risk analysis.

Keywords: Monte Carlo simulation, risk analysis, real estate, insurance industry, financial derivatives

1. Introduction

The COVID-19 pandemic, changes in international situations, and other events have brought persistent uncertainty to the global economy. The slowdown in the growth of major economies, fluctuations in commodity prices, and other changes have made credit risks in the market more complex and difficult to predict. For small and medium-sized enterprises, heightened operational volatility directly impairs debt-servicing capacity. In addition, guarantee relationships between

© 2026 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2754-1169/2026.AB38103

enterprises may allow individual risks to spread to other enterprises, gradually forming network-like risks, which places greater demands on the accuracy of financial risk prediction [1]. Traditional financial risk analysis mostly employs static measurement methods, either examining the impact of individual factors in isolation or conducting research based on fixed corporate network relationships [2]. Although these methods are relatively simple to calculate, they are not very effective in describing real situations where several risk factors influence each other and market conditions change over time. They may also underestimate the probability of extreme events and have difficulty showing how risks are transmitted over time [3]. Therefore, both the academic community and the industry are exploring risk prediction methods that are more in line with the real market conditions. Monte Carlo simulation is one of the widely used types among them.

Monte Carlo simulation is based on probability and statistics theory. It uses computers to generate a large number of random samples and simulate many possible market situations. Finally, it calculates the probability of risks occurring and the distribution of losses. It can effectively handle complex problems involving multiple variables and dynamic changes. Based on this, this article focuses on the application of Monte Carlo simulation in the prediction of financial credit risks: First, we will introduce the basic principles and implementation process of Monte Carlo simulation, secondly, we will analyze the application methods and advantages and disadvantages of it in three typical financial sub-sectors: real estate, insurance industry, and financial derivatives, and finally, summarize the general characteristics and future optimization directions of this method, in order to help understand the logical reasoning of the role of the random simulation method in financial risk management.

2. Relevant theoretical foundations

2.1. Principles and application process of Monte Carlo simulation

2.1.1. The core principles of Monte Carlo simulation

The Monte Carlo simulation method is mainly based on probability and statistics. Based on the mathematical model between the input variables (random variables) and the output variables (such as NPV), with the aid of computer assistance, a large number of random numbers are generated according to the given probability distribution of the input random variables. Through sufficient iterations of the model probability, a large amount of data of the output variables and their distribution functions can be obtained through computer simulation technology [4]. For example, the method of calculating pi using the random point method works as follows: Randomly place points within the square with the range of [-1,1]*[-1,1]. The area of this square is 4, and the area of the unit circle is π. Therefore, the probability of a point falling within the unit circle is $\pi/4$. According to the law of large numbers, when the number of points becomes sufficiently large, the observed frequency will become close to the actual probability. Thus, $\pi \approx 4$*(the number of points within the circle / the total number of points placed).

2.1.2. The specific process of Monte Carlo simulation in risk analysis

In risk quantification analysis, the implementation process of Monte Carlo simulation generally follows this sequence: First, a model needs to be established to describe the main characteristics of the system. In the economic evaluation of investment projects, this model refers to the economic evaluation model that reflects the benefits of the investment project, Secondly, the risk variables and

DOI: 10.54254/2754-1169/2026.AB38103

their probability distributions are determined. Using random numbers, the model is run multiple times, and the estimated values of the economic evaluation indicators of the investment project (such as the internal rate of return on investment, net present value) are statistically calculated, and their probability distributions are given. Finally, the number of simulations is determined to meet the accuracy requirements, and the simulation analysis results are provided [5].

2.2. Definitions related to the financial sector

2.2.1. Credit risk

Credit risk is an important type of risk in financial activities, defined as the scenario where a borrower or counterparty fails to meet contractual payment obligations on a loan or bond, thereby causing economic losses. This risk exists in all kinds of financial institutions. The credit risk of long-term loans or long-term bonds purchased by financial institutions is greater than that of short-term ones. The main characteristics of credit risk are: objectivity, contagiousness, controllability, and periodicity [6]. The traditional definition of credit risk mainly focuses on the risk of default, while the modern definition is broader, and it also considers changes in asset value caused by changes in the debtor's credit condition and repayment ability. Traditional methods (such as VaR) often assume that asset values follow a normal distribution, but the distribution of credit risk returns is non-normal, featuring a limited positive return and a huge negative loss, and presenting a skewed distribution. Monte Carlo simulation can flexibly fit the asymmetric distribution, heavy-tail effect, and nonlinear correlations among assets that actually exist in credit risk. By generating millions of possible future scenario paths, the Monte Carlo simulation can more accurately capture the probability of extreme default events, thereby providing more robust and reliable quantitative results than traditional analytical methods when assessing credit risk exposure and calculating Value at Risk (VaR) [7].

2.2.2. Financial derivatives and pricing risks

The narrow definition of credit asset securitization (ABS, asset-backed securities) falls under bond-type securitization.It mainly refers to the process of reorganizing illiquid but income-generating credit assets held by banks into securities that can be traded in the capital market, with the future cash flows of these assets being used as the basis [8]. Taking the infrastructure credit ABS in the text as an example, banks package multiple infrastructure loans to form an asset pool. The underlying borrowers make regular principal and interest payments, generating cash flows, which are then issued as ABS securities to market investors to achieve the transfer of risks and returns. The traditional weighted average credit rating method only weights the credit rating of a single loan, ignoring the industry and regional default correlations among the loans within the asset pool. This makes it difficult to depict the combined risk of concentrated defaults of multiple loans. Monte Carlo simulation can incorporate the fluctuation of the returns of each loan and the correlation coefficients between assets, conduct multi-period dynamic simulations, set quarterly dynamic default thresholds, and after running tens of thousands of simulations, statistically obtain the overall default probability and loss level of the asset pool, thereby compensating for the shortcomings of traditional static assessment methods and providing quantitative support for the credit risk measurement of ABS products [9].

DOI: 10.54254/2754-1169/2026.AB38103

3. The current application status of Monte Carlo simulation in the financial sub-field

3.1. The real estate sector

In the real estate sector, the investment amount is huge and the cycle is long. There are numerous random disturbances on the income side, cost side, and external policy side. These risks generally do not exist independently, and changes in one factor may also influence other factors. Monte Carlo simulation can consider several uncertain factors at the same time, which makes it possible to simulate the combined effects of different risks in real situations, which cannot be achieved by single-factor sensitivity or break-even analysis.Previous studies have taken typical real estate development projects as the object and established a financial evaluation framework based on net present value (NPV) and internal rate of return (IRR). They have fully demonstrated the application path of Monte Carlo simulation: The research first completed the identification of all risks in the development process through expert interviews and risk checklists. Then, uncertain factors such as land costs, construction costs, sales prices, and financing interest rates were converted into random input variables. Combined with industry experience data, the probability distribution forms and parameter intervals corresponding to each variable were determined. Based on Excel and the Crystal Ball simulation plugin, 10,000 random sampling simulations were carried out. In each round of sampling, the randomly generated parameters were substituted into the established cash flow discount model, and tens of thousands of NPV and IRR calculation results were batch output. Through statistical analysis indicators such as mean value, cumulative probability of achieving revenue targets, and quantification of the distribution characteristics of revenue, the overall risk level of the project was quantified [4].

3.2. Insurance industry

The main business of insurance is closely related to uncertain claim payments, so it has a natural connection with the probabilistic logic of Monte Carlo simulation. Insurance underwriting inherently centers on stochastic claim payouts: whether a policy will result in a claim and the actual loss amount after a claim—are highly uncertain. Traditional static actuarial methods can only calculate expected payout values but fail to capture the fluctuation range of total payouts across a portfolio of policies or the probability of large losses. In contrast, Monte Carlo simulations, through massive scenario sampling, can reconstruct the overall loss distribution resulting from aggregated policies, effectively meeting the risk management needs of insurance actuarial science [10]. Some studies have also constructed a Monte Carlo simulation model for the operational profit risks of life insurance companies in China. In these studies, the net profit of life insurance companies was divided into two main parts: underwriting business profit and investment business profit. Based on historical data from the insurance industry and the capital market, they used the K-S test to fit the probability distributions of input variables such as surrender rates, claim rates, and various asset yields. They then conducted 1000 simulations using Crystal Ball to obtain the distribution of future five-year net profits and the probability of profit occurrence. Through variable contribution analysis, they identified that the return on equity investment is the core factor affecting the profit of life insurance companies [11].

Some studies have applied Monte Carlo simulation to two tasks: one is to artificially set the correlation coefficient between the claim frequency and the average claim amount, generate multiple sets of simulation data, and repeat the simulation 1000 times to test the parameter estimation robustness of the Poisson-Gamma model and the Tweedie model under different levels of risk

DOI: 10.54254/2754-1169/2026.AB38103

correlation, additionally, model parameters were estimated based on actual auto insurance business data. Two sets of models were used to conduct 2000 Monte Carlo simulations respectively, to simulate the probability distribution of the overall total compensation for policy combinations, and to compare the predictive performance of the two models [12]. There are some differences between life insurance simulation and auto insurance simulation. The net profit and net assets of the previous year will be passed on to the next period, and at the same time, factors such as underwriting and surrender risks as well as capital market investments (such as stocks and bonds) are taken into account. The focus is on evaluating the overall operating profit and profit probability of the insurance company.However, auto insurance is a static simulation based on a single policy year. There is no transfer of status across years. The risks mainly come from accident compensation payouts under the policy. The focus is on depicting the interrelationship between claim frequency and average claim amount. The simulation results are mostly used for determining pure premiums, calculating the combined loss of policies, and testing actuarial models.

3.3. Financial derivatives: options, bank credit asset securitization products

Previous studies have focused on American options and used least squares-based Monte Carlo simulation to calculate the pricing of American options. In these studies, geometric Brownian motion was used to simulate many possible price paths of the underlying asset. The calculation then started from the expiration date and moved backward step by step. By using least squares regression, they estimated the expected return conditions for continuing to hold the option at each point in time. The immediate exercise value was then compared with the value of continuing to hold the option, and the better choice was selected. They calculated the average return of all simulated paths based on the initial option price and used the results of the finite difference method as a reference to verify that the pricing accuracy gradually converges as the number of simulations increases. This method not only enables fair pricing but also outputs the quantitative tail loss risk of the return distribution. However, the convergence speed is relatively slow, and the estimation fluctuation is large in small samples. At the same time, the model is difficult to depict the extreme risks of black swan events outside the system, and deviations in parameter settings can also lead to systematic deviations in the overall results [13]. Overall, Monte Carlo simulation can depict the joint default of multiple assets and complex structured cash flows through massive random sampling. It can effectively calculate the credit and tail risks of financial derivatives such as ABS and options. However, due to constraints such as convergence speed, parameter assumptions, and idealization of distributions, it needs to be corrected with other technical methods to improve the reliability of the risk prediction results.

Monte Carlo simulation can be utilized to quantify the credit risk of infrastructure credit ABS asset pools. By addressing the deficiency of traditional weighted ratings in ignoring the correlation of asset defaults, a random path of asset value with correlation is constructed. Multiple time period default determination rules are set. Through thousands of simulations, the overall default probability of the asset pool is statistically calculated, effectively quantifying the credit risk at the portfolio level and allowing the model to deal with correlations between different defaults, capable of handling the correlation of defaults.Meanwhile, the model is highly flexible and scalable. It can gradually incorporate various real-world constraints such as borrowers' early repayment, fluctuations in the value of collateral, random changes in recovery rates, macro pressure scenarios, and concentration limit constraints, and iteratively optimize the risk model. However, there are still some drawbacks: To reduce estimation error, the required number of simulations must increase exponentially. Studies relying on only 10,000 basic simulations may exhibit random fluctuations and insufficient stability

DOI: 10.54254/2754-1169/2026.AB38103

when estimating high-precision tail risks. If high accuracy in tail risk is required, tens of thousands or more samples are needed, which imposes high requirements on computing power and running time. Results in small simulation quantities exhibit random fluctuations and insufficient stability. Moreover, this paper assumes that asset values follow a normal distribution. In reality, credit risk has a significant heavy-tailed characteristic: Under normal circumstances, defaults are rare, and during economic crises, defaults occur in a concentrated manner. The normal distribution assumption may underestimate the probability of extreme systemic defaults. At the same time, it simplifies to daily linear value fluctuations, without depicting jump-type risks such as policy changes, project suspensions, and sudden debt restructurings [9].

4. Conclusion

This essay systematically reviews and conducts a comparative analysis of the application of Monte Carlo simulation in the risk prediction of three major financial sub-sectors: real estate, insurance, and financial derivatives. Based on the empirical results from various fields, it can be observed that Monte Carlo simulation possesses universal core advantages in financial risk prediction: Firstly, it can simultaneously accommodate the simultaneous fluctuations of multiple sets of random risk variables, depicting the joint risks under multi-factor resonance, and compensating for the shortcomings of balance point, static weighted rating, and single-variable sensitivity analysis, which can only calculate risks in isolation, Secondly, relying on the output of complete probability distributions of gains and losses from tens of thousands of random samplings, it not only can obtain expected gains and benchmark default probabilities, but also can quantify the probability of extreme tail losses, meeting the needs of regulatory and institutions for refined risk control and stress testing, Thirdly, the model has strong scalability and is adaptable to differentiated and complex business rules such as long-term cash flows of real estate, batch random claims in insurance, opportunistic exercise of options, and structured cash flows of ABS, and can be easily implemented with lightweight tools like Excel and MATLAB.

However, this method has inherent cross-domain flaws: Monte Carlo simulation has large fluctuations in the calculation results when dealing with small sample simulations, and high-precision simulation requires a significant amount of computing power, the model is highly dependent on the probability distribution, correlation coefficients, default critical values, and other input parameters set by humans, and deviations from the real market laws in these parameters will lead to systematic calculation errors, the conventional normal distribution assumption has inherent limitations, generally underestimating extreme systemic risks such as economic crises and policy shocks, and is unable to inherently capture black swan events that have not occurred in history.The main limitations of this study are as follows: First, the research domain does not cover all branches of the financial field. Future research should be conducted on other branches. Second, most studies only use the Monte Carlo single model alone. The use of quasi-Monte Carlo simulation can be introduced for optimization to enhance computing power. Third, the ability to depict heavy-tailed risks needs to be optimized, and the common problems brought by Monte Carlo simulation should be avoided as much as possible.

References

[1] Zhang, Y. (2021). The COVID-19 pandemic and the world economic situation. *Contemporary World*, (1), 13-20.
[2] Cheng, D., Niu, Z., & Zhang, L. (2020). Delinquent events prediction in temporal networked-guarantee loans. *IEEE Transactions on Neural Networks and Learning Systems, 34*(4), 1692-1704.

DOI: 10.54254/2754-1169/2026.AB38103

[3] Song, L., Ma, Z., Li, Z., & Shang, X. (2024). Survey on temporal graph neural networks for financial risk prediction. *Journal of Software, 35*(8), 3897-3922.
[4] Liao, S. (2019). Research on investment decision risk assessment of real estate projects based on Monte Carlo simulation. *Housing and Real Estate*, (19), 1-3.
[5] Zhang, H., & Zhang, F. (2024). Quantitative risk analysis of investment projects based on Monte Carlo simulation technology. *Construction Economy, 45*(S1), 209-213.
[6] Wang, H. (2015). On the management and prevention of financial credit risk. *Commercial Modernization*, (8), 165.
[7] Wang, L. (2008). *Research on credit risk measurement methods* (Master's thesis, Central South University).
[8] Guan, Q., & Feng, Z. (2004). Measurement of credit default probability: A literature review and comparison. *World Economy*, (11), 40-54.
[9] Wu, K., & Zeng, W. (2015). Monte Carlo simulation analysis of credit risk in bank credit asset securitization products. *Economic Research Guide*, (18), 130-131.
[10] Zhao, Z. (2020). Risk management in insurance industry based on Monte Carlo simulation. *Rural Economy and Technology, 31*(2), 108-110.
[11] Qi, J. (2012). Profitability analysis of Chinese life insurance companies based on Monte Carlo simulation. *Journal of Insurance Professional College, 26*(3), 13-17.
[12] Li, Z., & Meng, S. (2016). Auto insurance pricing model under dependent risk conditions. *Insurance Studies*, (7), 68-77.
[13] Zhang, L. (2015). A Monte Carlo method for American option pricing. *Economic Research Guide*, (27), 95-99.