Pricing Analysis of Drop-Back Certificate: Comparison between Monte-Carlo Simulation and Generative Artificial Intelligence-Assisted Pricing

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Abstract. With the increasing complexity of structured financial products, traditional numerical pricing methods face significant challenges in computational efficiency and practical application. The advancement of generative artificial intelligence technology offers new approaches for financial pricing. This study takes the USD Drop-Back Certificate issued by Credit Suisse as the research subject. Methodologically, it begins by simulating the path of the S&P 500 index under the geometric Brownian motion (GBM) assumption. Subsequently, a subset of Monte-Carlo results is used to train a generative Artificial Intelligence (GenAI) model, enabling it to learn the mapping relationship between model parameters and the expected present value of the product. The model is then deployed to perform pricing predictions on out-of-sample data. Finally, the accuracy, stability, and efficiency of the AI-assisted pricing outcomes are evaluated. The findings reveal that AI-assisted pricing achieves a high degree of consistency with Monte-Carlo results while substantially reducing single-instance pricing computation time, with efficiency improvements reaching several orders of magnitude. This research indicates that GenAI can serve as an effective augmentation to Monte-Carlo simulation, offering a more efficient and equally reliable technical pathway for the rapid pricing of complex structured products.

Keywords: Financial Instruments, Pricing, Monte-Carlo simulation, GenAI.

1 Introduction

With the continuous development of the financial market, structured products, due to their customizable nature that can meet various needs, have seen a significant expansion in market size. However, products like Credit Suisse's 463340-USD Drop-Back Certificate, due to their complex mechanisms, are difficult to price using traditional

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methods, which makes the pricing analysis of such back-reference certificates an important research direction in the field of financial engineering.

Currently, the financial industry typically employs the "Monte Carlo simulation" method to address such issues. In their research, Ajay Jasra and Pierre Del used path-dependent products as an example to thoroughly explore how the sequential Monte Carlo method can be applied to option pricing [1]. However, Monte Carlo simulation has drawbacks such as slow convergence speed and high computational cost. Relevant studies have pointed out the disadvantages of low computational efficiency and large result volatility of Monte Carlo simulation, especially when dealing with multi-period path-dependent products, such as Bermuda options [2].

Meanwhile, the rapid development of emerging technologies represented by GenAI has opened up new possibilities for pricing of financial derivatives: Relevant scholars have systematically expounded that GenAI can integrate multi source information to assist pricing decisions in financial product pricing analysis, and relevant studies have also shown that GenAI has the characteristics of technological and economic complementarity, intellectualization, integration and innovation [3,4].However, whether financial practitioners will accept and trust AI pricing models is an important issue. Relevant research has found that AI anxiety, hallucination concerns and privacy concerns significantly hinder users from adopting GenAI [5].

Therefore, both traditional and new pricing methods have corresponding problems. In response to numerous issues with Monte-Carlo simulations, scholars in the past have proposed various improvement methods, such as efficient grid algorithms and variance reduction techniques for addressing jump risks [6,7]. In terms of GenAI, relevant scholars believe that strict benchmarking and robustness evaluation must be carried out for the output results of GenAI [8]. However, the valuation accuracy, model stability and practical advantages of the two methods over mature numerical methods are still lacking systematic comparative empirical tests.

In order to reveal the complementarity and conflict between the two simulation methods in financial modeling, this study takes Credit Suisse USD drop-back certificate as the research object to compare the performance differences between Monte-Carlo simulation and GenAI assisted pricing. The results of Monte-Carlo are used to evaluate the accuracy of GenAI pricing, so as to make up for the research gap that the reliability and accuracy of GenAI have not been strictly verified and the lack of comparison with Monte-Carlo simulation methods in unified and complex scenarios.

2 Method

2.1 Data Sources and Explanation

In financial engineering research, the core boundary between empirical research and numerical method research lies in whether the parameters of the Monte-Carlo simulation and GBM model rely on real data.

In real-world pricing scenarios, the volatility of GBM is derived from historical or implied volatility, the risk-free rate is taken from market interest rates, and the expected

return is based on long-term expectations. These parameters must be calibrated using real data to answer the question of "the reasonable value of an asset in the real market".

However, in numerical experimental research, the research objective is not to reproduce actual prices but to test "the performance characteristics of algorithms given a model". In this case, parameters do not need to be estimated from real data but instead serve as input variables set for the experiment.

It is important to emphasize that "no need for real data" does not mean that the analytical logic for all financial assets is the same. Although all types of assets are based on the GBM model and have consistent parameter forms, the essential differences between assets are determined by their payoff structures. For example, even when using the same volatility, interest rate, and expected return parameters, the price distributions, trigger probabilities, and path sensitivities of vanilla options, barrier options, and Drop-Back Certificates are significantly different. The differentiation of assets does not depend on GBM but on differences in payoffs.

Meanwhile, in this type of research, parameters play the role of "control variables". The core of the research is to analyze the performance differences between Monte-Carlo and AI algorithms as parameters change from low to high, which belongs to structural sensitivity analysis rather than point estimation of the true values of parameters.

In summary, there is a strict distinction between numerical experiments and empirical research in financial scientific research: in real-world pricing and risk management, parameters must come from real data; when testing computational efficiency, stability, etc., parameters are experimental settings and do not rely on real data.

2.2 Indicator Selection and Description

In order to systematically compare the traditional Monte-Carlo simulation method with the emerging GenAI-assisted pricing method, this paper took the price calculated by Monte-Carlo simulation method as the core and selects evaluation indicators in the two dimensions of error accuracy and computing efficiency.

First of all, the selection of benchmark was the pricing result obtained through a large number of path simulations using Monte-Carlo pricing method. At the same time, standard error (SE) was selected to measure the uncertainty of Monte-Carlo method and explain whether the error of AI assisted pricing method is reasonable.

On this basis, this paper used average absolute error (MAE) and root mean square error (RMSE) to measure the deviation between GenAI pricing results and benchmark values. MAE reflects the average pricing error level, while RMSE is sensitive to larger errors. The combination of the two can comprehensively measure the accuracy and stability of AI assisted pricing methods [9]. At the same time, the efficiency of single simulation pricing for the two methods was compared using computation time (Runtime).

2.3 Method Description

This study used both Monte Carlo simulation and generative AI to price a product issued by Credit Suisse called "USD Drop-Back Certificate" and compared these two pricing methods.

Although in current public discussions, generative AI is often narrowly understood as large language models such as ChatGPT, in the academic definitions of machine learning and artificial intelligence, the connotation of generative AI is much broader. Generally speaking, generative models refer to models that can learn the data generation mechanism or conditional distribution and thereby generate new samples or numerical results. The objects of their generation are not limited to text or images.

The AI pricing model in this paper is not a language generation model, but a numerical generative AI. This model learns the implicit structure of the Monte Carlo random pricing process and directly generates the corresponding pricing results when given new model parameters, thereby achieving a generative substitution for the traditional random simulation method.

Firstly, this study selects the output values obtained through Monte Carlo simulation as the pricing benchmark. The price of the S&P 500 can be simulated using geometric Brownian motion. For all parameters except the volatility, this study sets fixed values based on the product issuance terms and the market environment at the time of issuance (for example, the risk-free interest rate is 2%, the dividend rate is 1.8%, and the product term is 3 years). Volatility is the independent variable, within the range of (15%, 45%], after weighing the calculation cost and data size, it is sampled with a step size of 0.01, resulting in a total of 3,000 values.

For each volatility value, the future three-year index paths are simulated using a daily time step. According to Glasserman's error analysis, the error of Monte Carlo simulation needs to be increased by 100 times to reduce by 10 times [9]. To control the error within 1%, a total of 50,000 independent paths are simulated. The discounted present value at the current time for each path's maturity income is calculated using the risk-free interest rate, and the expected value is taken as the present value under this volatility.

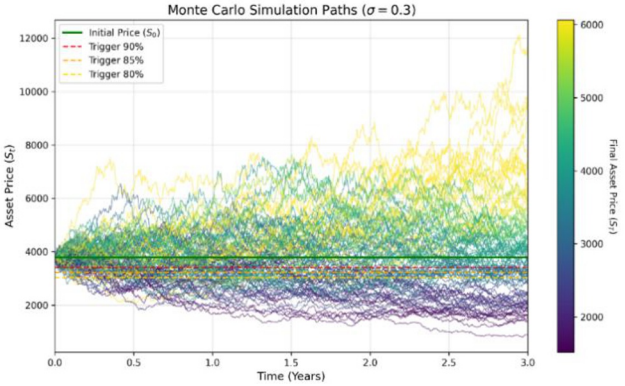


Fig. 1. Monte Carlo simulation of the price path of the underlying asset (volatility = 0.30)

The figure1 shows 100 representative sample paths generated based on an annualized volatility of 30% under the geometric Brownian motion assumption.

Finally, 3000 sets of data $\{\sigma, P_{\mathrm{MC}}(\sigma)\}$ were obtained, where $P_{\mathrm{MC}}(\sigma)$is the Monte Carlo benchmark price corresponds to the given volatility. Subsequently, the data set was divided into a training set and a test set. The stratified random sampling method was used to randomly select two out of every three consecutive volatility points as training data, and the remaining one was reserved for testing. In total, 2000 samples were used to train the AI agent model, and the remaining 1000 samples were used for subsequent comparative evaluation.

During the training phase, the AI model was parameterized as a family of adjustable functions to approximately describe the mapping relationship between model parameters and the expected present value of the product. In this paper, the 2000 training samples generated by Monte Carlo simulation with high precision pricing were used as supervisory signals to input the model. The training objective was to minimize the deviation between the generated prices and the Monte Carlo benchmark prices, using loss functions such as mean squared error for measurement. Through numerical optimization methods (such as gradient descent and its variants), the model parameters were continuously updated during the training process, allowing the generated pricing results to gradually approach the true pricing implied by the random simulation.

The essence of this training and optimization process lies in that the AI model does not directly replicate a single random path or a local numerical calculation step but learns the global structural characteristics corresponding to the Monte Carlo pricing problem from the overall sample. Once the training is completed, the model parameters are fixed, and subsequent pricing with new input parameters no longer requires explicit execution of random path simulation or repetitive numerical integration but rather generates pricing results directly through the optimized model. From a numerical calculation perspective, this process is equivalent to performing an offline optimization and compression on the Monte Carlo pricing operator, converting the high computational cost of random simulation into a one-time training expense, thereby improving future pricing efficiency.

Finally, in this paper, two methods are compared based on two key indicators: error accuracy and computational efficiency.

3 Results

3.1 Monte-Carlo Benchmark Pricing Results

Under the framework of risk-neutral pricing mentioned above, this paper used Monte-Carlo simulation method to generate a large number of target index price paths under given model parameters and executed the path dependent return rules of product contracts on each path. Finally, the due return was discounted and expected, and the theoretical price of the product was obtained as the benchmark pricing result.

Under the setting of benchmark parameters (the risk-free interest rate is 2%, the dividend rate is 1.8%, and the contract term is 3 years), the expectation of the present value of the earnings due from each path was taken as the price under this volatility.

Finally, 3000 sets of volatility and the present value under this volatility were obtained. Another 2000 samples were allocated to train the AI-assisted pricing model, and the other 1000 samples were used for the calculation of the benchmark price and subsequent comparative evaluation.

The price of the product obtained by Monte-Carlo method is about $992.8847, which would be used as a benchmark for comparison with AI assisted pricing. At the same time, based on 50000 simulation paths, the corresponding Monte-Carlo estimation standard error was 0.4718. This shows that under the current setting of the number of simulation paths, the Monte-Carlo pricing results are negligible relative to the overall price scale of the product, and the estimates have converged to a stable range. Therefore, the Monte-Carlo pricing result as the training and comparison benchmark of AI assisted pricing method has good stability and reliability.

3.2 GenAI Pricing Results

After obtaining the pricing results of Monte-Carlo, this paper further constructed the AI-assisted pricing model. The selected 2000 samples were used as training labels to learn the relationship between model parameters and product prices to build AI-assisted pricing models. After the model training, the pricing was repeated three times in 1000 groups of test parameters that did not participate in the training.

In view of the fact that three repeated pricing experiments have been carried out in this paper, and all the results are not feasible to show one by one in the text, this paper uses the equal interval sampling method. A set of pricing results was selected every 100 times from the experimental results, a total of 10 representative groups of samples were selected for display, and the variance of three pricing under each volatility was calculated to reflect the stability of AI-assisted pricing results in different experimental stages. The results are shown in Table 1:

Table 1. Three repeated pricing results of 10 representative samples

Number	Sigma	Price-1	Price-2	Price-3	Three-price variance
1	0.1501	1018.3952	1018.3952	1018.3952	0
101	0.1803	1013.2560	1013.2560	1013.2560	0
201	0.2102	1008.1858	1008.1858	1008.1858	0
301	0.2402	1003.0896	1003.0896	1003.0896	0
401	0.2701	998.0104	998.0104	998.0104	0
501	0.3001	992.9142	992.9142	992.9142	0
601	0.3302	987.8011	987.8011	987.8011	0
701	0.3603	982.6879	982.6879	982.6879	0
801	0.3901	977.6257	977.6257	977.6257	0
901	0.4203	972.4955	972.4955	972.4955	0

According to the above table 1, the variance of the three AI repeated pricing results is 0, mainly due to the sufficient training data (2000 groups of samples cover the full volatility range) and the good convergence of the model, and the loss function has converged to a smaller order of magnitude (below 0.001) to ensure that the same input corresponds to the same output, which verifies the stability of the model [10,11]. It should be noted that the strong stability of GenAI pricing in this study is due to the standardized data training based on Monte Carlo simulation and the single scenario (only volatility changes); If the pricing mechanism is further improved, such as adding more factors, the stability of AI may decline, which needs to be dealt with through cross verification and other means.

After evaluating its pricing performance and taking the expected value as the pricing result, the product price obtained by GenAI-assisted pricing model is about $992.9226.

3.3 Comparison of Monte-Carlo Simulation and GenAI Pricing Methods

In order to systematically compare the differences in accuracy and efficiency between the two pricing methods, Monte-Carlo simulation and GenAI-assisted pricing are used to price the same product under the same parameter settings, and the results are compared and analyzed.

In terms of pricing accuracy, the MAE and RMSE of the two indicators selected in this paper are 1.9776 and 2.3295 respectively. Compared with the benchmark value, both are in a very low proportion range of the overall price level of the product and have higher pricing accuracy in the average sense. At the same time, RMSE is only slightly higher than MAE, indicating that the pricing error distribution is relatively concentrated, which further verifies the reliability of GenAI assisted pricing method in numerical accuracy and stability.

In terms of computational efficiency, the computational cost of Monte Carlo simulation is positively correlated with the number of paths (50000 paths need to traverse the income calculation and discount of each path), and the expectation of single pricing is about 16.6616 seconds. The AI model learns the mapping relationship between sigma and present value through training. A single prediction only needs to perform forward propagation operation without repeating path simulation. The single prediction time is only 0.00000076 seconds, so the efficiency is improved by several orders of magnitude.

Based on the comparison results of pricing accuracy and computing efficiency, it can be seen that once the AI model is trained, the use of AI assisted pricing requires little additional computing cost in a single forecast and can give price estimates in a very short period of time. This feature has obvious advantages when it needs frequent repeated pricing or scenario analysis, especially for application scenarios that need rapid and repeated pricing.

4 Conclusion

This study is based on a risk-neutral pricing framework, comparing Monte-Carlo simulation with AI-assisted modeling in the pricing of financial products, and provides a new solution for rapid pricing.

In terms of accuracy, the benchmark price derived from Monte-Carlo simulation is $992.8847, while the AI-assisted pricing outputs $992.9226, with an extremely small deviation. The AI model's MAE is 1.9776 and RMSE is 2.3295, with error levels comparable to the sampling error of Monte-Carlo, proving that its pricing results are stable and reliable and can effectively replace traditional methods.

In terms of efficiency, a single Monte-Carlo pricing run takes approximately 16.6616 seconds, whereas AI-assisted pricing only requires 0.0000076 seconds, representing an efficiency improvement of several orders of magnitude. This is because Monte-Carlo relies on extensive path generation and backtracking, with computational costs growing linearly with the number of paths; in contrast, after the AI model is trained, it only needs to perform forward inference with no additional overhead, demonstrating significant advantages in high-frequency pricing scenarios.

In conclusion, AI-assisted pricing can substantially improve efficiency while ensuring accuracy, providing an efficient and precise technical solution for financial value determination, and its future applications and technical potential warrant continuous exploration. Especially in the future, if further calculations of Greek values or more frequent and complex simulations are performed, its efficiency advantages will become even more prominent.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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