

Exploring Pricing Biases in Chinese Convertible Bonds Market: The Influence of Green Bond Policies

Yuchi Cheng¹⁺, Zhan Huang²⁺, Yue Yu³⁺, Ziqing Zhou^{4*+}

*Corresponding author email: qing79236@gmail.com

¹Faculty of Science, The University of Melbourne, Melbourne, 3010, Australia, yuchi.cheng@student.unimelb.edu

²Aberdeen Institute of Data Science and Artificial Intelligence, South China Normal University, Foshan, 528225, China, 20223803002@m.scnu.edu.cn

³Economics School, Jilin University, Changchun, 130015, China, yueyu0713@gmail.com

⁴School of International Economics and Trade, Central University of Finance and Economics, Beijing, 102206, China

+These authors contributed equally to this work and should be considered co-first authors.

Abstract. This study employed the Black-Scholes model, Binomial Tree model, and Monte Carlo simulation to price convertible bonds in the Chinese market, and on this basis, developed trading strategies and tested the effectiveness of the pricing. The results indicated that the pricing through the Monte Carlo model was the most efficient, offering the highest level of accuracy. Building on this, the study focused on the differences between the theoretical prices calculated by these models and the actual market prices. With the aid of Propensity Score Matching (PSM), convertible bonds were categorized into "green" and "ordinary" and were assessed systematically using the Difference-in-Difference (DID) method to evaluate the impact of the Green Bond Policy introduced in China in July 2021. The conclusion drawn from the empirical analysis was that the policy reduced the deviation between the theoretical and actual prices of the green convertible bonds, which was beneficial to the development of the green convertible bond market.

Keywords: Convertible Bonds, Pricing Bias, Backtesting, Regression Analysis.

1 Introduction

Convertible bonds, fully known as “convertible bonds of listed companies”, are a type of bond with embedded options issued by listed companies. In the bond status, like ordinary bonds, the issuer is required to make regular interest payments according to the contract. However, investors of convertible bonds have the right to convert the bonds into company stocks at a pre-agreed price, which is known as the conversion provision. Convertible bonds are distinguished from other bonds due to their embedded option of conversion provision and the provisions as follows. The redemption provision allows the issuing company to redeem the convertible bond at a pre-determined price when specific conditions are met, which can limit investors' returns and is often exercised by rational companies to reduce debt and mitigate equity dilution risk. The put option provision enables investors to sell the bond back to the issuer at a specified price if the stock price remains low, preventing losses and positively impacting the convertible bond's value. The downward adjustment provision allows the issuing company to adjust the conversion

price under certain conditions when the stock price remains low, impacting the convertible bond's value based on specific terms and the company's credit rating. Starting from 2017, the Securities and Futures Commission (SFC) issued new regulations on refinancing, followed by the implementation of the credit subscription system, which ushered in a boom in both supply and demand in the convertible bonds market. In March 2020, the revised Securities Law was implemented, relaxing the refinancing requirements. Afterwards, 2022 saw the release of the three new regulations. The system related to convertible bonds market has been improved continuously, and the market scale has continued to expand. According to Wind data, the recent situation of convertible bonds in the past five years is shown in Figure 1, both showing a steady growth trend in terms of the balance of convertible bonds and the number of surviving bonds.

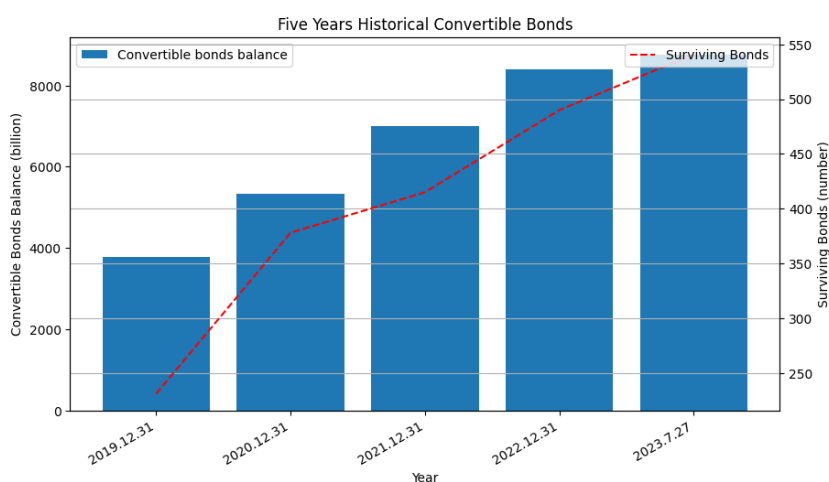


Fig. 1. Recent Situation of Convertible Bonds Market [Owner-draw].

As of July 27, 2023, the stock of convertible bonds in the whole market amounted to 874.888 billion yuan. Since 2023, 71 convertible bonds have been issued with a combined size of 88.193 billion yuan. The primary market of convertible bonds has been active in the past year. According to Wind data, over the past year, 147 convertible bonds were listed, with an increase of 25.64% [1,2].

2 Literature Review

2.1 Review of Pricing Research on Convertible Bonds

Since the 1970s, the pricing mechanism of convertible bonds has been a significant focus in the field of finance. Early studies concentrated mainly on basic concepts and value characteristics of convertible bonds. In the late 1970s and 1980s, Fischer Black, Myron Scholes and Robert Merton introduced the renowned Black-Scholes model, providing a closed-form analytical solution for the pricing of European options. Recently, Tsvetelin et al. derived a partial differential equation for the price of defaultable derivatives based on the B-S model by considering stochastic time and adding a jumping process, then obtained a closed formula for the price of convertible bonds [3]. Xie et al. found that the price estimated by the B-S model was close to the market

price [4]. John Cox and Stephen Ross and Mark Rubinstein introduced the Binomial Tree model in 1979 as a discrete-time based option pricing method, which further remedied the shortcomings of the Black-Scholes model. In 2001, Longstaff and Schwartz introduced an innovative approach to pricing financial derivatives, the Least Squares Monte Carlo (LSM) simulation model. This method combines the stochastic nature of Monte Carlo simulation with the deterministic nature of least squares regression, providing a more powerful and flexible tool for pricing complex financial derivatives. Researchers also came up with some new findings in recent years. Viva and Hefnawy use Monte Carlo simulation to examine the incentives of firms to issue convertible bonds and find that convertible bonds may be more susceptible to significant undervaluation due to market conditions and sentiment than natural pricing errors [5]. Han considered that the biggest drawback of the Monte-Carlo simulation method lies in its inability to solve the execution problem in advance and its relatively low efficiency in numerical operations. However, it is undeniable that it can handle the complex path problem properly when facing the pricing of American options [6].

2.2 Research Review of China's Convertible Bond Market

Over the recent years, as China's financial market continues to open and mature, researchers have begun to focus on China's unique market environment, empirical analysis and the impact of policies on convertible bond pricing. Wang and Zhang utilized the binomial tree model to analyze the value of convertible bonds with Guo convertible bonds as a case study [7]. Using the Monte Carlo method, Luo and Zhang presented an innovative method for pricing convertible bonds with downward adjustment provisions of the conversion price, finding that the new method yields higher pricing accuracy [8]. Tian's study empirically analyzed the pricing of convertible bonds using the Black-Scholes model, attributing the discrepancies between theoretical and market prices to several factors [9]. Zhao investigated the impact of changes in subscription policies on the underpricing of convertible bond issuances in the Chinese market, focusing on the moderating effect of information asymmetry [10]. Furthermore, the emergence of green bonds, financial instruments designed to fund environmentally sustainable projects, has become a new area of focus. Fan analyzed the development of green bond markets both domestically and internationally, examining the value of green bonds [11].

2.3 Direction and Contribution of the Study

Based on the review of historical literature and analysis of existing studies, this article aims to further deepen the understanding of China's convertible bond market, especially in the context of the green bond policy launched in China in 2021. We will employ the Black-Scholes model, Binomial Tree model and Monte Carlo simulation, which are three pricing models for a comprehensive pricing performance assessment. Based on this, we combine Bootstrap and regression analysis techniques to test the robustness of the pricing model and quantify the impact of economic and financial variables on the price of convertible bonds. To assess the market effect of the 2021 green bond policy, we categorize convertible bonds into "green" and "non-green" groups through propensity score matching and systematically evaluate the policy effect using the difference-in-differences method. Preliminary results show that the new policy significantly reduces the deviation between the theoretical and actual prices of "green" convertible bonds, further confirming the market's positive response to the green finance policy. In the complex and multifaceted context of China's convertible bond market, investors are facing increasing

investment and decision-making challenges. This study aims to provide insights into the pricing, risk assessment, and market impact of convertible bonds, providing practical insights and strategies for investors and policy makers.

3 Theoretical Framework

3.1 Pricing Models

In the Black-Scholes model, we first divide the value of convertible bonds into two parts: the value of the regular bond component and the value of the option component (the conversion option). The Black-Scholes formula mainly focuses on the option component. Firstly, we calculate the value of the pure bond component, whose discount rate can be taken as the same as the discount rate of regular bonds with similar credit rating, listing time, and maturity. Secondly, we use the Black-Scholes formula to calculate the value of the option component. Finally, we sum up the results from the previous two steps to obtain the theoretical price of the convertible bond based on the Black-Scholes model.

When using the Black-Scholes model to price the convertible bonds, we have to consider the impact of conversion provision, redemption provision, put option provision, and downward adjustment provision.

(1) For the conversion provision, it grants investors the right to transform convertible bonds into stock during the conversion period. This provision can be conceptualized as a non-dividend-bearing American call option. Since a non-dividend-bearing American call option do not exercise prematurely in theory, its pricing can be done by using the Black-Scholes formula for European call options.

(2) For the redemption provision, it provides the issuer with the right to redeem the convertible bonds at a lower cost when the market price of the underlying stock exceeds a predefined threshold. If the issuer acts rationally, promptly exercises this provision upon fulfillment of redemption criteria, it can be construed as investors selling a non-dividend-bearing American call option. Analogously, the valuation of this option can be done by employing the Black-Scholes formula for European call options.

(3) For the put option provision, it safeguards investor interests by giving them the right to vend convertible bonds at a predetermined price when the market price of the underlying stock remains persistent poor performance. From the investor's perspective, this provision may be similar to an American put option. Given that American put options have the possibility of early exercise, the pricing of option is executed using the Binomial Tree model.

(4) For the downward adjustment provision, it comes into effect when the stock price undergoes sustained depreciation, thereby triggering the conditions stipulated for the adjustment of the conversion price. Since in China, listed companies generally do not easily execute downward adjustment provisions, this research paper won't delve further into this aspect.

The Binomial Tree model is another suitable method for pricing European and American options. The main idea of this pricing model is to simulate the stock price during the convertible bond's remaining term through the Binomial Tree model. After obtaining the simulated stock prices at each node, the value of the convertible bond at each node is determined based on the

conversion provision, redemption provision, and put option provision, and finally, the initial convertible bond pricing is derived based on the risk-neutral pricing principle.

Let $V_{i,j}$ represent the value of the convertible bond at time (i,j) , where i indicates the number of time steps in the Binomial Tree model, and j refers to the branching of the tree at each time step, k be the conversion ratio of the convertible bond, B_r be the redemption price from the issuer, B_c be the put value for the investor, $S_{i,j}$ be the stock value and $C_{i,j}$ be the holding value at time (i,j) . The determination of convertible bond value at different time points is as follows:

(1) Convertible bond at maturity: At maturity, the convertible bondholder can choose between conversion and redemption by the issuer. Therefore, the investor will execute the option with the higher value.

$$V_{i,j} = \max(S_{i,j} * k, B_r) \quad (1)$$

(2) Convertible bond in conversion, redemption, and put periods: When the convertible bond can be held, redeemed, put, and converted, rational investors will choose the path that maximizes the value. Additionally, the redemption right is usually exercised by the issuer when the stock price rises. Thus, when the benchmark stock price exceeds the conversion price, the issuer will choose redemption.

$$V_{i,j} = \max(\min(C_{i,j}, B_r), S_{i,j} * k, B_c) \quad (2)$$

(3) Convertible bond in conversion and redemption periods: Most convertible bonds specify that put can only occur in the last two years. Therefore, during this period, usually around 3-5 years, investors can only choose between redemption, conversion, or holding.

$$V_{i,j} = \max(S_{i,j} * k, B_r, C_{i,j}) \quad (3)$$

(4) Convertible bond issued but not in the conversion period: Generally, the redemption period and conversion period of convertible bonds are the same length. During the six months after issuance, investors can only hold the bonds.

$$V_{i,j} = C_{i,j} \quad (4)$$

The principle of Monte Carlo simulation is to produce a great number of random sample results through computer simulations when a problem involves probabilistic characteristics. Its main focus is on multiple simulations of future price paths of financial securities and specialized analysis of specific paths and options. Generally, Monte Carlo simulation involves the following steps: similar to the Binomial Tree model, it first divides the time interval into n sub-intervals. However, the Monte Carlo simulation does not fix the price increase and decrease in each interval but follows a certain probability distribution. Then, the price of the option corresponding to each price path change is calculated and discounted based on the risk-free rate. By repeating the above steps m times, we obtain a large number of discounted values of option payoffs, and the initial option price can be obtained.

Following the simulation of price trajectories for the underlying stocks, each trajectory is subjected to a comprehensive evaluation. This evaluation considers whether the trajectory falls within the temporal boundaries stipulated by the provisions and examines whether historical paths of the underlying stock adhere to the conditions for execution. These evaluations collectively determine the eligibility for execution. Considering the characteristics of American call options governed by conversion provisions, it is assumed that early exercises do not occur. Moreover, once the provisions are met, rational investors and issuers will promptly exercise the

options, as mentioned earlier in the introduction section. Therefore, the following principles apply:

- (1) If neither redemption nor put option provisions are activated due to the stock's performance, investors choose the strategy that generates higher returns between conversion and redemption at maturity, and they receive the corresponding benefits.
- (2) Regarding redemption provisions, execution takes place if, during the preceding 15 days, the underlying stock's price has continuously exceeded 130% of the conversion price.
- (3) Concerning put option provisions, execution occurs if, during the preceding 15 days, the underlying stock's price has fallen below 70% of the conversion price.

It is essential to note that these criteria are commonly employed in the terms of almost all convertible bonds in China, providing a reasonable and well-founded basis for their application. By applying these criteria to evaluate the performance outcomes of each underlying stock price trajectory at the convertible bond's maturity, calculating the average performance outcomes across all trajectories, and discounting these outcomes to the first day of the convertible bond's listing using the risk-free rate, the price of the convertible bond can be determined.

3.2 Empirical Models

3.2.1 Data Description

In this study, we obtained a total of 465 convertible bonds from Wind for all Chinese markets through July 27, 2023. We also query data on other variables required to price convertible bonds, such as the yield to maturity of Chinese treasury bonds and the price series of the underlying stocks corresponding to convertible bonds. We have done the following data processing procedures:

- (1) For the financial data of the issuing company, due to a high number of missing values, we have filled in the missing values using data from adjacent years of the company. If the issuing company did not have any observations on any of the financial data, we excluded this sample.
- (2) For the financial data, we also deal with the data below the 5% quartile and above the 95% quartile by replacing them with data from the corresponding quartile in the same industry.
- (3) In order to reduce the variance of the samples, we took log for variables with all positive observations and performed Box-cox transformation for variables containing negative observations, using the function from Scipy library in Python.

After completing the above process, we organize the data into a panel data format, at which point 283 convertible bonds remain.

3.2.2 Propensity Score Matching

In this study, we'll identify the policy impact using the Difference-in-Difference (DID) method. Since this method requires matching of the samples in the treatment group (green convertible bonds) and control group (ordinary convertible bonds), we will first process the samples using Propensity Score Matching (PSM) method, which makes the samples in two groups more comparable. For the covariates, this essay drew upon Zhou's research on green bond pricing as a

reference for identifying several variables that have a significant impact on pricing bias [2]. The variable details are provided as Appendix A.

3.2.3 Difference-in-Difference

Categorized and screened by the PSM model, the panel data is subjected to a series of regression analyses. These analyses aim to determine the impact of different variables on $bias_{MC}$. The variables included in these regression models, each with detailed descriptions, are presented in Appendix B.

The study conducts regression analyses on all variables with data after PSM. For Difference-in-Difference method, we use *green* variable to distinguish treatment group and control group, and *period* to distinguish periods before from after policy implementation. The analysis employs $bias_{MC}$ as the dependent variable, the interception term $green * policy$ as the core explanatory variable, and all other variables as control variables.

$$bias_{MC} = \beta_0 + \beta_1 green * policy + Controls + fe \quad (5)$$

A total of four regressions were performed, some of these regressions consider individual fixed effects or time fixed effects.

4 Empirical Analysis

4.1 Pricing on the Convertible Bonds Market

We price the convertible bonds in the Wind database with the three models by rolling window method. In order to make the sample more comparable, we selected convertible bonds with data available for 274 trading days since listing (assuming 252 trading days in a year and 22 trading days in a month) to synthesize into the panel data, with a total of 279 convertible bonds.

4.1.1 Pricing Bias on the First Trading Day

First, we calculated the pricing bias of the three models on the first day of listing for all the convertible bonds in the sample, the pricing bias is defined in the way of $(theoretical\ price / actual\ price) * 100\%$, and the results are shown in Figure 2.

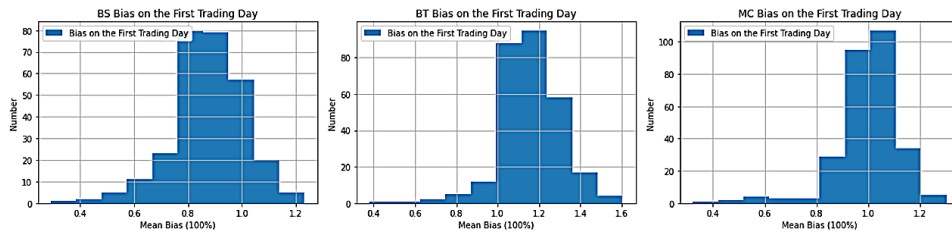


Fig. 2. Result of Pricing Bias [Owner-draw].

From Figure 2, it can be found that the Black-Scholes model tends to underestimate the price of convertible bonds on the listing date of convertible bonds, making the theoretical price of convertible bonds lower than actual price, which results in the mean of bias significantly less than 1. In contrast, the two numerical models tend to overestimate the price of convertible bonds on

the listing date of convertible bonds. Among them, the magnitude of overestimation in the Binomial Tree model is larger than that in the Monte Carlo simulation.

4.1.2 Pricing Bias over Security Tenure

Then, we calculated the theoretical prices of the three models for all the convertible bonds for 274 trading days after the listing date and obtained the following images. The result is shown in Figure 3.

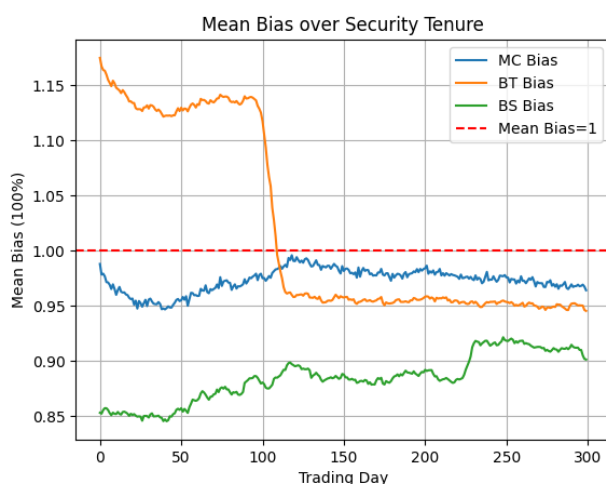


Fig. 3. Mean Bias over Security Tenure [Owner-draw].

It can be found that when $t=0$ (listing date), the mean bias of the three pricing methods is the correspondent to the findings above. We can find that the Black-Scholes model has always underestimated the convertible bonds, and its theoretical price has always been lower than the actual price. The Binomial Tree model overestimated the convertible bonds at the beginning, and then fell back rapidly around the 100th trading day until it became underestimating the value of convertible bonds. There is a steep decline. Based on the assumption of 22 trading days in a month, around the 100th trading day is when the conversion and redemption provisions of most convertible bonds start. Probably this steep decline can be explained by the effect of two provisions. Because in Binomial Tree model, once it reaches the redemption period or the put option period, regardless of whether the stock price meets the requirements for 15 trading days within the 30-day period, as long as the stock price reaches the specified price, we consider it satisfies the condition. The Monte Carlo simulation has the most stable performance among the three models and is the closest to the actual price. It can be found to underestimate convertible bonds and have a decreasing trend over time consistently and slightly.

4.1.3 Pricing Bias over Natural Time

Finally, we also plot the trend of pricing bias for all the convertible bonds in our sample over natural time using the three models, as shown in Figure 4.

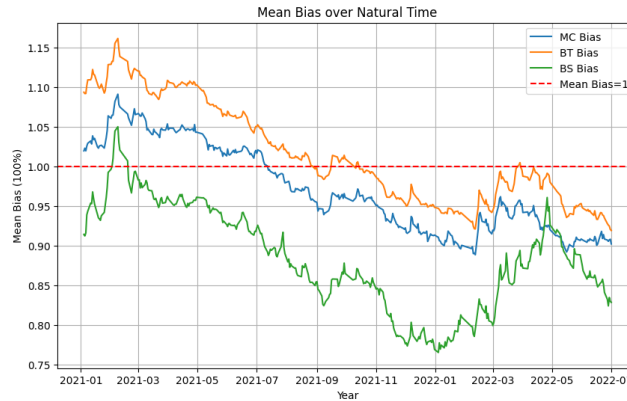


Fig. 4. Mean Bias over Natural Time [Owner-draw].

From Figure 4, we can find that the pricing bias of the Black-Scholes model changes with smaller fluctuations over time, but there is no obvious trend. In contrast, the pricing bias of the two numerical models shows a clear downward trend from overestimation to underestimation.

4.2 Backtesting

For each convertible bond, we have obtained three theoretical prices through three models. However, we need a standard to compare these models. The most difficult part of designing a criterion is that the issue price of convertible bonds in China is fixed at 100 CNY. Therefore, it makes little sense to study the bias of the price on the listing date, and we have to introduce the factor of time. Here, we might as well make the following assumption based on the no-arbitrage principle: the actual trading price of convertible bonds in the market may fluctuate due to short-term factors, but as long as there is sufficient liquidity, it will converge to the theoretical price in the long run. Under the above assumption, we can study the bias of the price in the period after listing. Through panel data we can verify the validity of pricing.

4.2.1 Strategy

Our validation methodology is as follows: for each convertible bond, we compute their theoretical prices over the two years following the listing date, and measure the bias in pricing using $bias = (theoreticalprice/actualprice) * 100\%$ again.

If we can observe that the actual price returns to the theoretical price in the long run, we can validate our hypothesis and thus show that our pricing is valid.

We simulate quantitative trading with the following strategy: on the first trading day of each month, we adjust our portfolio. If the number of tradable convertible bonds in the market on that day is greater than 10, a position is opened. Since the Chinese convertible bond market basically does not allow short trades, we only consider long trades. We choose to buy the top 25% of convertible bonds with the largest pricing bias on that day to form the portfolio. The actual prices of these convertible bonds are lower than the theoretical prices, and if the hypothesis is true, they should rise to converge to the theoretical prices. We can therefore hold these convertibles until the next month's adjustment date when we sell them. If we have a positive

return on the trade, we can show that the hypothesis is valid. In order to simulate a more realistic market trading environment, we assume a transaction fee of 0.1% and a stamp duty of 0.1%. The entire time period of the backtesting is from January 2017 to June 2023, and the number of convertible bonds in the backtesting is 455 in total.

4.2.2 Backtesting Result

We first use the theoretical prices obtained from Monte Carlo simulation and obtained the following results. Here, the vertical coordinate of the Figure 5 is the return on the portfolio of assets in percent, while the vertical coordinate of the Figure 6 is the value of the assets, where we have assumed an initial asset value of 1, with the aim of exploring how many times that value will eventually be by the investment strategy.



Fig. 5. Return on portfolio in percent [Owner-draw].



Fig. 6. Value of the assets [Owner-draw].

Since most of the convertible bonds provided in the Wind database were issued after 2017, the number of convertible bonds at the beginning of 2017 is very small and hardly traded. Using this simple strategy, we can get positive returns from the backtesting.

Next, we compare the results of Monte Carlo simulation with the results from the backtesting using the theoretical prices obtained from the Binomial Tree model and the Black-Scholes model, as shown in Table 1.

Table 1. Results by using two different methods [Owner-draw].

	Annual Return	Annual Volatility	Maximum Draw-down	Sharpe Ratio
Monte Carlo	0.18545	0.18020	-0.14388	1.02913
Binomial Tree	0.15614	0.18573	-0.13706	0.84068
Black-Scholes	0.07274	0.11610	-0.13573	0.62651

It can be found that the Monte Carlo simulation yields the largest annualized return, but also the largest annualized volatility and maximum drawdown. In contrast, the Black-Scholes model yields the smallest annualized return, annualized volatility, and maximum drawdown. We compare the three models using Sharpe ratios that combine return and volatility and conclude that the Monte Carlo simulation performs the best, the Binomial Tree model the second best, and Black-Scholes the worst. This may be due to the fact that the Black-Scholes model is unable to solve the path dependence problem, the Binomial Tree model can only solve the weak path dependency problem, and the Monte Carlo simulation can handle the strong path dependency problem. Based on the above results, we can conclude that the theoretical prices derived from the Monte Carlo simulation perform best in the backtesting, which indicates that the pricing effectiveness of the Monte Carlo simulation is the best among the three models.

4.2.3 Robustness Testing

4.2.3.1 Parameter Selection

During the backtesting process, we purchase the top 25% of convertible bonds with the largest pricing bias as the portfolio. If we change this percentage, we can get different results. Therefore, we used the Grid Search method to traverse different ratios from 0.05 to 1 for every 0.05 and got the following results. Only the results of annualized returns are shown in Figure 7.

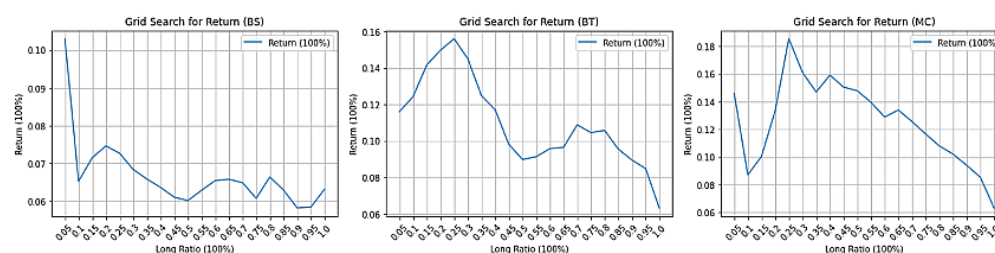


Fig. 7. Annualized return of different pricing models [Owner-draw].

It can be found that the annualized return of the Monte Carlo simulation and the Binomial Tree model exhibit a quadratic pattern and are highest at a scale of 25%, which is just the result shown above. At the same time, the results of both are highly similar, except that the Monte Carlo simulation is slightly better than the Binomial Tree model. In contrast, the Black-Scholes model is highest at a ratio of 5%, but only achieves an annualized return of about 10%. Even when the

optimal parameters of Black-Scholes are chosen, the backtesting results are not as good as the two numerical models.

4.2.3.2 Bootstrap Testing

Considering the price regulation in Chinese convertible bond market, the fact that the strategy can earn positive return does not necessarily prove that the strategy is effective. Therefore, we use the Bootstrap method to test the strategies. Instead of selecting the top 25% of convertible bonds with the largest deviation, we randomly select 25% of convertible bonds to form a portfolio, and record the annualized return, annualized volatility, maximum drawdown, and Sharpe ratio of the backtesting results for each sample. The above samples are conducted a total of 500 times to obtain the sampling distribution, and then we observe whether the backtesting obtained by the strategy belong to the extremes of the distribution. We first show the results of the Monte Carlo simulation in Figure 8.

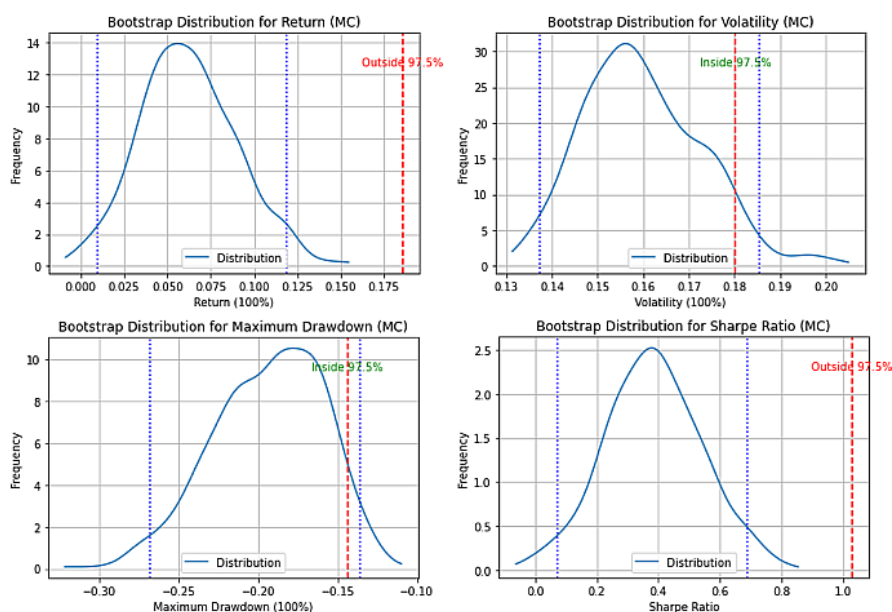


Fig. 8. Results of the Monte Carlo simulation [Owner-draw].

It can be found that after 500 times of Bootstrap sampling, the shape of the distribution is close to a normal distribution according to the central limit theorem. Using the theoretical prices obtained from Monte Carlo simulation, the annualized return and Sharpe ratio are greater than the 97.5% quartile of the distribution, which are significantly higher than the parameters obtained from random sampling. The annualized volatility and maximum retracement are both greater than the 2.5% quartile and less than the 97.5% quartile, which are not significantly different from the results of random sampling. Therefore, we can consider the strategy using the theoretical prices obtained from the Monte Carlo simulation to be effective, because it performs better than random sampling in terms of returns, but does not underperform random sampling in terms of risk. Next, we show the results of the Bootstrap test using the theoretical prices from the

Binomial Tree model and the Black-Scholes model, as shown in the following figure, where only the annualized return is shown in Figure 9.

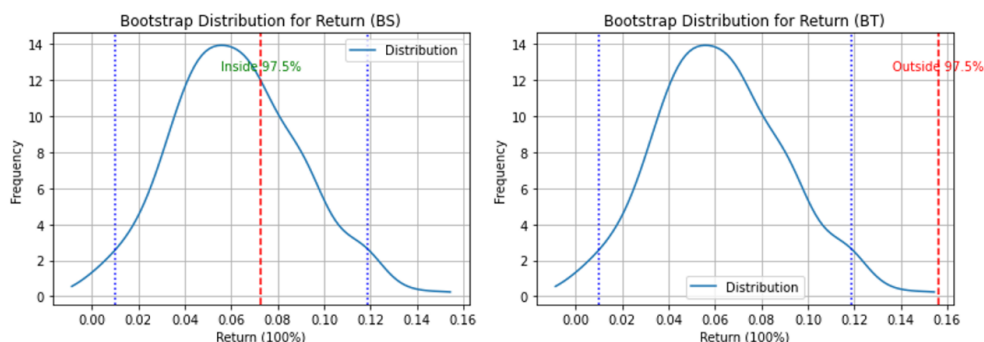


Fig. 9. Bootstrap Distribution for Return [Owner-draw].

It can be found that the strategy based on the theoretical price of the Binomial Tree model can still be considered valid, while the Black-Scholes model cannot, as it falls within the 2.5% quantile and 97.5% quantile. In summary, after backtesting and robustness testing, we can conclude that the Monte Carlo simulation is the best model among these three models.

4.3 Regression Results

On July 1, 2021, the Catalogue of Projects Supported by Green Bonds (2021 Edition) issued by the People’s Bank of China, the Development and Reform Commission, and the Securities and Futures Commission came into effect. For the issuance of green bonds, the government holds an encouraging attitude. Convertible bonds, as a special kind of bond, may also be affected by this policy. Therefore, we check the fund-raising purposes of the convertible bonds in our sample and mark the convertible bonds whose fund-raising purposes are to support environmental improvement, resource saving and efficient utilization, sustainable social development and green and low-carbon transformation, etc. as green convertible bonds, and try to investigate whether this policy has a different impact on the pricing bias of green convertible bonds and other convertible bonds. As we have shown above, the pricing bias obtained from Monte Carlo simulation gradually changes from overvaluation to undervaluation over time. To control heterogeneity at the time level between the two types of convertible bonds themselves, we use the Difference-in-Difference method to conduct a quasi-natural experiment using July 1, 2021, as the date of policy implementation, with green convertible bonds as the treatment group and other convertible bonds as the control group.

4.3.1 Propensity Score Matching

Before the Difference-in-Difference method, we first conduct the PSM method to make the samples in two groups more comparable. When conducting the PSM model, the study firstly applied a 1-to-1 nearest neighbor matching method. The results of the logistic regression, indicating an Average Treatment Effect (ATT) value of 0.38, corresponding to a t-value of 0.97. Out of a total of 279 observations, 5 observations in the control group fall outside the value

range, while the treatment group has no observations beyond this range. These suggest a substantial overlap in propensity score values between the treatment and control groups, thereby confirming the representativeness of using the filtered sample for subsequent empirical analysis. After matching, we employed the “pstest” to assess the degree of data balance achieved by this matching. As shown in Table 2, all variable standard deviations have significantly decreased after matching, and each is below 10%. Furthermore, the results of the corresponding t-tests do not reject the null hypothesis of no systematic differences between the treatment and control groups. This underscores that the data selected using the PSM are well-balanced, attesting to the high quality of the matching.

Table 2. Pstest of PSM [Owner-draw].

Variable	Un-matched/Matched	Mean			T-test		V(T)/V(C)
		Treated	Control	%bias	t	p> t	V(C)
year	U	2020.3	2020.2	4.0	0.23	0.819	1.01
	M	2020.3	2020.3	-4.3	-0.19	0.853	0.99
industry	U	4.026	3.880	6.4	0.36	0.720	0.90
	M	4.026	4.132	-4.6	-0.20	0.846	0.82
credit	U	3.763	3.689	5.9	0.32	0.747	0.80
	M	3.763	3.790	-2.1	-0.10	0.922	1.09
owner	U	0.158	0.237	19.7	-1.08	0.283	*
	M	0.158	0.184	-6.6	0.30	0.764	*
volatility	U	0.476	0.490	-9.5	-0.54	0.593	0.90
	M	0.476	0.467	6.4	0.32	0.751	1.63

* if variance ratio outside [0.52; 1.92]

4.3.2 Heterogeneity Analysis.

Since the "Difference-in-Differences" approach assumes that trends in the treatment and control groups were parallel before the policy was implemented, we used data from after the PSM. Also, we plotted the images of pricing bias over time obtained by the Monte Carlo simulation between the two samples after PSM to visualize the trend of the two samples more intuitively, as shown in Figure 10.

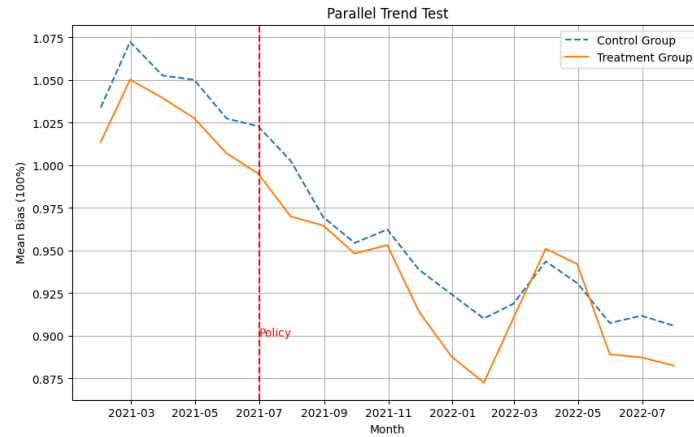


Fig. 10. Parallel Trend Test [Owner-draw].

It can be seen that the two groups have essentially the same trend prior to the policy, with the pricing bias of control group being slightly higher than the treatment group. After the policy, the relative relationship between two groups changes significantly, with the pricing bias of two groups first approaching each other and then fluctuating significantly. Next, we generated the *Policy* variable in the panel data by taking the *Policy* variable to be 0 before July 1, 2021 and 1 thereafter, and then generated an interaction term between the *Policy* and *Green* variables, using $Policy * Green$. Then, we include the interaction term into the regression, and obtained the following results. Due to the large number of control variables, only the important ones are shown in Table 3.

Table 3. Results of DID (by interaction) [Owner-draw].

	(1)	(2)	(3)	(4)
credit	0.0169	0	0.0176	0
	(1.83)	(.)	(1.90)	(.)
volatility	0.102***	0.125***	0.116***	0.121***
	(13.80)	(16.83)	(15.45)	(16.17)
treat_policy	-0.0587***	-0.0482***	-0.0550***	-0.0450***
	(-22.26)	(-18.06)	(-20.94)	(-16.76)
_cons	0.0729	-1.237***	0.522***	-0.937***
	(0.91)	(-10.37)	(5.64)	(-6.35)
N	17136	17136	17136	17136
r2		0.185		0.210
r2_a		0.181		0.206
Individual Fixed Effect	No	Yes	No	Yes
Time Fixed Effect	No	No	Yes	Yes

As can be seen in the Table 3, the coefficients on the interaction term are negative and significant, at least at the 1% level, regardless of whether we control individual fixed effects or time fixed effects. Next, we use the “diff” command in Stata to obtain more intuitive results.

Table 4. Results of DID (by ‘diff’) [Owner-draw].

Policy	Group	bias MC	Standard Error	t	P>t
Before	Control	1.627			
	Treated	1.623			
	Diff(T-C)	-0.004	0.001	-3.00	0.003***
After	Control	1.551			
	Treated	1.528			
	Diff(T-C)	-0.023	0.001	15.31	0.000***
Difference-in-Difference		-0.018	0.002	8.59	0.000***

From the Table 4 above, we can find that the pricing bias of green convertible bonds is lower than that of other convertible bonds before the policy. After the policy, the pricing bias of both types of convertible bonds decreases, but since we found in the previous section that the pricing bias obtained from the Monte Carlo simulation shows a downward trend from overestimation to underestimation in time, this result does not necessarily indicate that the policy leads to a decline in the pricing bias of convertible bonds. However, after the policy, the decline in the pricing bias of green convertibles is significantly greater than that of other convertibles, and the gap between the pricing bias of the two is even greater. Therefore, from the above analysis of the results of the Difference-in-Difference method, we can conclude that the impact of the government’s support policy for green bonds on July 1, 2021 is greater for green convertible bonds than for other convertible bonds. Under the impact of the policy, the ratio of the theoretical price to the actual price of green convertible bonds is smaller. This may be due to the fact that investors’ expectations for green convertible bonds rise more and are more willing to buy them. This result suggests that the government’s supportive policy for green bonds has played a role in the convertible bond market, making the market move in a more favorable direction for green convertible bonds.

5 Conclusion

This study focuses on analyzing how convertible bonds are priced in China, particularly exploring the differences between their theoretical value and the actual market price. Mainly three models, which are the Black-Scholes model, the Binomial Tree model, and the Monte Carlo simulation, are used to estimate bond prices. After assessing bootstrap method, we find that the Monte Carlo simulation provides the most reliable pricing estimates. Therefore, the study investigates the bias between the theoretical bond prices calculated through the Monte Carlo simulation and the real market prices. To ensure robustness testing, convertible bonds are categorically divided into “green” and “non-green” groups using Propensity Score Matching. Using this groundwork, the Difference-in-Difference approach is employed to systematically examine the effects of China’s policy initiatives to promote green bonds, introduced in July 2021. The

subsequent findings highlight a noticeable reduction in the bias between the theoretical and actual prices of “green” convertible bonds, indicating a closer convergence between theoretical expectations and real market outcomes.

Appendix

Due to space constraints, the appendix portion of the article was uploaded to Github for readers to check out, at <https://github.com/Zixuanqin1897/Convertible-Bonds>.

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