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Pricing Efficiency of Convertible Bonds in China

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Abstract: The paper examines the pricing efficiency of convertible bonds in China by calculating the relative cheapness of the Chinese convertible bonds from 2012 to 2019. Relative cheapness is measured by the difference between the convertible bond's implied volatility in conversion options and the stock's look-back annualized volatility. The results show that cheaper convertible bonds significantly outperform more expensive convertible bonds regarding risk-adjusted performance indicators such as the Sharpe ratio, annualized Sortino ratio, and Return-over-Maximum-Drawdown. A simple long-short strategy sorting bonds using this measure can produce an average monthly return of 1.54%.

Keywords: convertible bonds; conversion options; efficiency

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1. Background and Rationale

Convertible bonds are hybrid financial instruments containing both debt and equity characteristics. They are also generally seen as an effective way of raising capital for most financial institutions. These organizations can pay lower coupons than regular bonds and avoid capital repayment in maturity if investors convert the bonds into stocks under certain conditions. On the other hand, investors prefer investing in convertible bonds for income-generating properties, downside protection, and capital appreciation potential [1].

Convertible bonds contain parameters for their pricing, such as par value, coupon rate, terms of issue, conversion price, maturity date, and special clauses. The special provisions include the Conversion Clause, the Mandatory Redemption Clause, the Forced Put Provision Clause, and clauses such as the Downward Adjustment Clause in China and Japan that lowers the conversion price.

Throughout history, there were many convertible bond issuances in the developed financial markets each year, and the pricing for those convertible bonds was effective from extensive analyst coverage. As a result, organizations frequently rely on convertible bonds in developed financial markets as an effective way to raise capital, while investors also invest and trade convertible bonds to enhance market efficiency and generate returns. In addition, [2] demonstrated that convertible bond issuance, pricing, and term design are important factors that influence convertible bond investors' demand in the developed market.

However, it is generally believed that convertible bonds' pricing is less efficient in emerging markets such as China, where the number of issuances in convertible bonds is relatively low, and the market is perceived to be quite inefficient since there are a lot of retail investors and market manipulation activities [3]. Therefore, by studying the pricing efficiency of convertible bonds in China and analyzing if the market is genuinely inefficient, the research can offer both organizations and investors fresh insights and provide hints on effective trading strategies for the emerging market convertible bonds for fruitful returns.

2. Literature Review

The research for the pricing of convertible bonds can be dated back to the 1970s, when the single-factor model of enterprise value or stock value was used to determine the pricing of convertible bonds [4-6]. However, it is not until several years later that [7] developed a model that factors the addition of interest rates to price convertible bonds correctly. Furthermore, factors such as credit risk have been incorporated, and the binomial interest rate tree model was used for the pricing of convertible bonds to account for the probability of default and loss given default in the pricing process [8].

However, to determine the pricing of convertible bonds in China, it is believed that the research should consider country-specific factors to determine relevant variables in the pricing model. For example, for a public company's general issuance of convertible bonds in China, it must satisfy a particular debt rating before being allowed to raise money on the stock market by the China Securities Regulatory Commission, and the regulator usually requires the company's bond to be ranked above AA-. Since a higher rating means less probability of default, this generally indicates that the default risk for the issuing company is low. In addition, the convertible bonds in China usually have a much shorter maturity time than convertible bonds in the developed market such as US or UK, which is typically six years in China compared to twenty years in the developed market, making the interest rate factor less relevant for the pricing model [9]. Therefore, the behaving of underlaying stock and the convertible bond's stock option weighs more in the pricing of the convertible bonds in China. In addition, researchers have broken the pricing of an individual convertible bond in China into different parts and priced each part accordingly to arrive at a fair value for the convertible bond to indicate the individual convertible bond's pricing efficiency [10].

In the simplest form for the pricing of convertible bonds, it is often viewed as the pure straight bond plus the value of a call option to convert into stock [11]. The value of the pure straight bond of the corporation is derived relatively straightforward and can often be valued using the risk-free rate plus a credit spread. Regarding the pricing of call options in the convertible bonds, the value of the options depends not only on the special clauses such as the Mandatory Redemption Clause in convertible bonds but also on the option pricing model that is being used. For example, researchers have priced the value of the options in convertible bonds based on discounting the risk-free rate only since the company can always issue additional stock without default risk to satisfy the conversion request [12]. A more popular and widely used model in China for pricing options in convertible bonds is the direct application of the Black-Scholes Model [13]. The options' implied volatility in convertible bonds is a crucial element in pricing both options and convertible bonds [3]. However, the Black-Scholes-Merton Model does not automatically account for the special clauses in convertible bonds. Therefore, this research will perform further qualitative analysis to determine the effects of those special clauses on the pricing issues.

The Black-Scholes model was developed by Fischer Black, Myron Scholes, and Robert Merton. This model is widely used in option pricing and valuation, taking into account factors such as volatility, stock price, exercise price, time to expiration, and risk-free interest rates. The implied volatility of options can be calculated by using the market price of the options and back-solving for the volatility [13].

$$C = S_t N(d_1) - Xe^{-rt} N(d_2) \tag{1}$$

$$d_1 = \frac{ln\frac{S_t}{X} + \left(r + \frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}} \tag{2}$$

$$d_2 = d_1 - \sigma\sqrt{t} \tag{3}$$

Where C is the convertible bond call option price, S_t is the underlying stock price, X is the exercise price of the option, r is the risk-free interest rate, t is the time to maturity of the option, σ is the volatility of the asset, and the model follows the Cumulative Distribution Function (CDF) pattern of the normal distribution. In addition, the pricing of options in convertible bonds is often seen as the indicator of "cheapness", and therefore, the higher the implied volatility for the convertible bonds' options, the more expensive for those convertible bonds overall [14].

Interestingly, some additional findings have been extracted from the Chinese convertible bond market. Empirically, demonstrated that the main purpose for a company to issue convertible bonds is to raise money and push the investors as quickly as possible to convert the bond into stocks. By doing so, the company can avoid capital repayment to mitigate the risks, and the company would also shorten the timeframe for the enforcement of the Mandatory Conversion Clause and the Downward Revision Clause to quicker the conversion process [9].

It is also worth noting that convertible bonds are often classified based on three stages: the busted stage, the hybrid stage, and the equity stage, and the pricing of convertible bonds is more likely to be explored in the hybrid stage as the securities have strong characteristics that are both in debt and equity, and the options are at-the-money. In contrast, the convertible bonds would behave like a pure straight bond in the busted stage, while the convertible bonds would behave like a stock in the equity stage. In both the busted and the equity stages, the implied volatility in the convertible bonds would fail to indicate the cheapness of the convertible bonds because there will be less volatility for both the in-the-money and the out-of-the-money options (Figure 1).

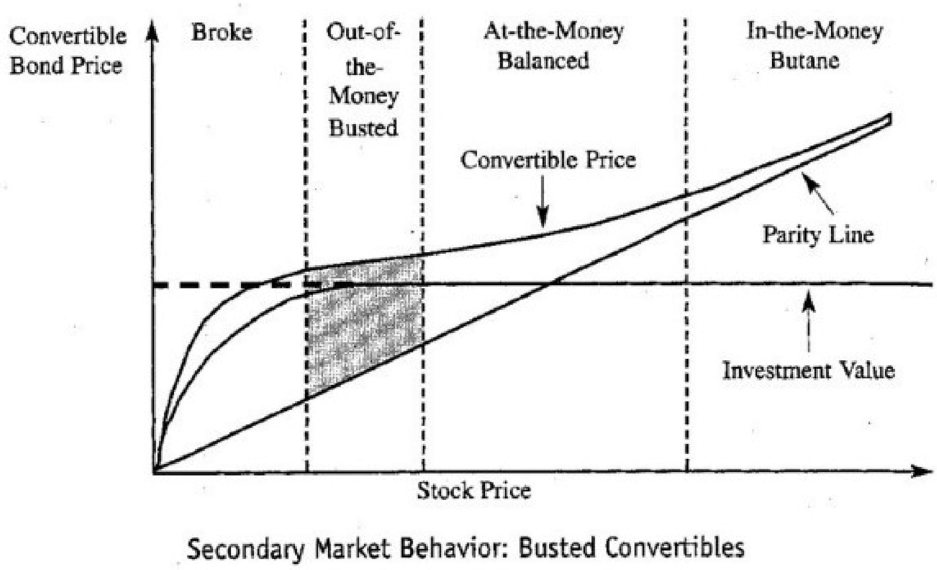

Figure 1. Convertible Bond Stages.

By examining the relevant literature and particularly literature related to the pricing of Chinese convertible bonds, most papers deal with creating a pricing model or analyzing pricing efficiency for the single or a group of convertible bonds. Therefore, this research would make meaningful contributions to the existing literature by examining the pricing efficiency of convertible bonds in the Chinese market as a whole. Also, this research has benefitted from the increasing use of convertible bonds to raise money by the Chinese public companies since 2018, thanks to the initiative of opening the Chinese financial market by the China Securities Regulatory Commission.

3. Aims and Objectives

The study has the following aims:

1) To investigate the pricing efficiency of convertible bond in China from 2012-2019 to analyze whether the market for the convertible bond is efficient.

2) Based on the results above, this article further uses the data matrix acquired and created to develop feasible trading strategies and compare their performance with other strategies at one point and over time.

In support of these aims, the objectives are to:

1) Obtain convertible bond and stock market data in China from 2012-2019 to acquire data matrixes such as general information, price, and bond implied volatilities. Then, use programming software to match all China convertible bonds' data with their corresponding stock peers from 2012-2019.
2) Construct daily stock returns, looked-back stock volatilities, and the differences between stock volatilities with their corresponding convertible bonds' implied volatilities to determine the cheapness of convertible bonds.
3) Create five groups based on convertible bonds' cheapness and calculate equal-weighted returns to determine the market pricing efficiency. Also, control data outliers from special clauses by forming alternative control groups.
4) Perform necessary ratio calculations and compare performances over time.

4. Research Methodology

4.1. Research Philosophy

The research philosophy for the study is primarily empirical, as data from financial data terminals and China Securities Regulatory Commission is heavily used as empirical data to be manipulated and analyzed. The data acquired is valid historical data based on the historical market events observed between 2012-2019 in the bond and stock markets. Thus, based on the research aims and objectives, the research is based on heavy quantitative analysis and historical observations of the financial markets for the bonds and stocks. In addition, the data that the study to use is empirical daily market data, and the information belongs to the vital part for the project to derive the differences between convertible bonds' implied volatility in options and stocks' annualized volatility to indicate the cheapness of convertible bond to analyze the pricing efficiency. If the implied volatility for the convertible bonds' options is too high against the corresponding stocks' annualized volatility, it means the convertible bonds are mostly overvalued. Therefore, the data is primarily being analyzed to derive the cause-and-effect relationships [15].

In addition, realism philosophy would be used for further analysis since special clauses in convertible bonds often make them candidates for potential outliers or noises. For example, the Mandatory Redemption Clause will deem the company that issues the convertible bond right to call them back for bonds that are priced over a threshold [16]. Also, the Forced Put Conversion Clause will enable the investors to sell convertible bonds back to the issuers if the price is too low [17]. In addition, the Downward Adjustment Clause will enable the issuers to make the out-of-the-money convertible bonds more likely to be converted to stocks by lowering the conversion price [18]. Thus, these events require further analysis qualitatively instead of quantitatively and will result in data adjustments to reveal an accurate picture. Specifically, for the Mandatory Redemption Clause, often, if the convertible bond is priced over CNY 130 for 15 trading days over 30 trading days, the issuing company will call the bonds back at a lower price or face value to force the investors to convert bonds into stocks, thereby creating noises in the data [19]. In such a case, those convertible bonds that triggered the Mandatory Redemption Clause are counted as outliers and should be excluded to adjust and enhance the integrity of quantitative data.

The research would not use the interpretivism methodology. The investigations are not concerned with analyzing the interactions of different peoples in an organization or how other people interact with objects in a specific phenomenon to arrive at valuable conclusions.

4.2. Research Approach

This research approach is based on the induction method as a bottom-up approach rather than the deduction method as top-down. The intuition for bottom-up analysis is that there is no specific guidance for the particular ways of Chinese convertible bonds and stocks data collection, the calculation for the cheapness of convertible bonds, and the establishment of profitable trading strategies. In addition, the research conducted is specific and relevant to the Chinese convertible bond market only for regional market analysis, in which there was scarce research conducted in this area for convertible bonds [9]. A general statement or theory can then be inducted from the completed bottom-up analysis by working closely with the data, calculating equal-weighted return for the five groups, and deriving feasible trading strategies.

4.3. Research Type

The final explanatory studies would be conducted after descriptive analysis using the eight-year data matrixes for the research study type: after getting the equal-weighted returns with controlled variables for noise reductions and calculating the ratios, further explanatory studies can be conducted to study the ratios and form meaningful conclusions about performance comparisons.

4.4. Research Strategy

Extensive quantitative data manipulation and analysis is conducted to test the hypothesis of whether Chinese convertible bonds' pricing is efficient. Also, a series of experiments are conducted in the study, and noise reduction techniques are strictly enforced to calculate the equal-weighted return for five groups over eight years based on cheapness. Once this process is done, the groups of monthly returns can be annualized by multiplying them by twelve to derive the annualized return for different groups. Also, suggested performing other return calculations such as the yearly return to derive the arithmetically and geometrically return over one year. In addition, trading strategy performance based on long-short can be calculated, and the research can then compute the financial ratios such as annualized Sharpe ratio, annualized Sortino ratio, maximum drawdown, and return-to-drawdown ratio to aid the further analysis [20].

4.5. Research Techniques

The research will use both quantitative and qualitative techniques to derive meaningful conclusions. Quantitative techniques will be primarily implemented to derive the data matrixes for analysis, while qualitative techniques will be employed to guide the quantitative analytical process to understand the reasons behind specific actions of the issuing companies and financial markets. For example, when the convertible bonds are priced too high because of the market anomaly and heating, the issuer may forcefully call back the convertible bonds and retire them. This behavior will create two consequences. The first is that the convertible bonds would have no return in the current month and should be excluded from the further calculation. Conversely, even if the issuer does not call back the bond straight away, the bond's implied volatility for the equity option would be deemed too low since the price is too high, rendering the analysis ineffective. Therefore, this sample should also be eliminated from the analytical process. The impact of these specific events can only be assessed with careful qualitative analysis, and both quantitative and qualitative techniques are vital for this study.

5. Data and Sample

5.1. Data Access

The data needed for this project is mainly quantitative in nature and readily available through the WIND terminal. Thus, the data is easily accessible by using institutional access through colleges or organizations. The data will be primarily used and manipulated for research purposes only.

The project will use data from the China Securities Regulatory Commission website for the qualitative data. It would be easier to access the database because it is entirely open and accessible for the public companies' disclosures and annual reports.

5.2. Sampling Strategies

Table 1 illustrates the sampling strategies of convertible bonds from the Chinese A-stock market, including the convertible bond population, sampling time-stamp, and sampling size versus the stock counterparts.

Table 1. Sampling strategies.

	Convertible Bond	**Stock**
Population	427	Around 3500
Sampling time-stamp	Daily	Daily
Sampling size	427	427

Sampling for this project is limited as it is believed the study for the whole population of the convertible bond would be conducted for the country analysis in China. Therefore, sampling of stocks is limited, and it only needs to match the corresponding population of convertible bonds one-on-one.

5.3. Data Collection and Manipulation

The study accessed, manipulated, and derived time-series data for convertible bonds and stocks. In addition, the convertible bonds' implied volatility data was acquired from WIND, and the implied volatility was precalculated by the system according to the market price and ready to be used. Conversely, the research obtained eight years of Chinese Financial Market stocks' closing price. Therefore, the daily return and the annualized volatilities for stocks should be computed based on the stocks' closing prices for the required analysis.

$$R_t = \frac{P_1}{P_0} - 1 \tag{4}$$

In which P_1 is the closing price of the stock for today, and P_0 is the closing price of the stock for yesterday.

$$\sigma_{annual\ stock} = \sigma_{daily}\sqrt{252} \tag{5}$$

$$\sigma_{daily\ stock} = \sqrt{\frac{\sum(x_i - \bar{x})^2}{n-1}} \tag{6}$$

Where σ represents the standard deviation of stocks in the daily and annual interval, 252 represents the number of trading days in a year, xi and x bar represent sample return, and sample mean return, respectively, and n represents the look-back period.

The data collected is in secondary data format from a financial data terminal called WIND, a localized and specialized data platform for Chinese stock and bond markets. Also, data from the China Securities Regulatory Commission will be collected for specific qualitative studies, such as why certain actions would cause the convertible bonds' implied volatilities to jump and why convertible bonds were not called back after reaching the price target as over CNY 130. In addition, the study collected eight-year convertible bonds' data in China from 2012 to 2019 to include variables such as index and ticks, dates of trading, daily closing prices, and daily implied volatility. For stocks, eight-year of stocks' data from the Chinese Financial Market from 2012 to 2019 were collected to contain index and ticks, dates, and daily closing prices for computation.

After data collection, the research conducted extensive data manipulations to first match convertible bonds' data with corresponding stock' data by using computations from the programming software to create a data matrix. Then, a calculation was performed to derive the time-series data for eight years for both convertible bonds and corresponding stocks' daily returns. Furthermore, with those stocks' daily return on file, the research further computed looked back daily standard deviations for stocks of 60 days to indicate realized short-term volatilities in the stock market. Finally, with those data on file, the research can derive the cheapness of convertible bonds by taking the differences between the implied volatility of convertible bond options and stocks' annualized volatilities.

$$\alpha = IV_{convertible\ bond\ option} - \sigma_{annual\ stock} \quad (7)$$

Where α represents the relative cheapness or mispricing of the convertible bond, and Implied Volatility (IV) is calculated by deriving volatility of options from market data by applying the Black-Scholes option pricing model [13]. With the above calculation, the research further interpreted the calculated result as the lower the figure, the cheaper the convertible bond compared to the corresponding stock, and the hypothesized better performance for the convertible bond in the Chinese Market.

To better compare the results of the relative cheapness of different convertible bonds, this research further divides the calculated results into five groups based on cheapness. The study also ensures a sufficient number of bonds in each group for the computation since there was a relatively low volume of convertible bonds issued in the early years of the Chinese Convertible Bond Market. After this step, those five groups' monthly, annualized, arithmetic, and geometric annual returns were computed to provide further ratio analysis to indicate performance. Then, the research plots and analyzes the return results of the long-short strategy to see if group one outperforms other groups, especially group five, to indicate the pricing efficiency of the Chinese Convertible Bond Market. In the end, the research computes other valuable figures such as annualized Sharpe ratio, annualized Sortino ratio, maximum drawdown, maximum drawdown by year, and return-to-drawdown ratio.

6. Result

6.1. Return

The research chooses to exclude data in 2015 for the Chinese Convertible Bond Market since there was an over 40% drop from the stock market crash from June 2015, making the convertible bonds that were still outstanding in the market less than five [21]. The study yielded the following yearly arithmetic and geometric annual returns for five groups, with group one, outperforming other groups during the 2012-2019 period.

Table 2 computes annualized returns arithmetically and geometrically for five groups of convertible bonds based on relative cheapness, as measured by the differences between the implied volatility of convertible bonds minus the looked back daily standard deviations of stocks for 60 days.

Table 2. Annualized Arithmetic and Geometric Returns for Five Groups of Convertible Bonds (2012-2019).

Arithmetic Annual Return	2012	2013	2014	2016	2017	2018	2019
Group 1	15.43%	0.10%	39.34%	45.11%	18.36%	5.24%	44.82%
Group 2	13.33%	-5.80%	63.29%	-2.20%	6.29%	1.27%	27.02%
Group 3	8.57%	-10.45%	44.80%	3.44%	-7.61%	-6.70%	27.26%
Group 4	12.86%	5.98%	35.96%	0.37%	-5.49%	-6.90%	27.10%
Group 5	0.90%	-2.38%	40.90%	-8.36%	-6.53%	-3.15%	17.43%

Geometric Annual Return	2012	2013	2014	2016	2017	2018	2019
Group 1	16.31%	-0.89%	45.42%	52.04%	18.87%	5.00%	53.38%
Group 2	13.61%	-6.48%	80.55%	-2.79%	6.07%	0.93%	29.45%
Group 3	8.52%	-10.31%	53.98%	2.99%	-8.11%	-6.79%	29.94%
Group 4	13.33%	5.68%	41.54%	-0.09%	-5.85%	-6.96%	30.23%
Group 5	0.59%	-2.62%	48.22%	-8.56%	-6.95%	-3.32%	18.34%

6.2. The Annualized Sharpe Ratio and the Annualized Sortino Ratio

The annualized Sharpe ratio and the annualized Sortino ratio were also conducted to aid the further analysis. The study utilized the annual arithmetic return, the average yield of the ten-year Chinese government bond as the proxy for the risk-free rate, and annualized standard deviation for the denominator. The standard deviation for the annualized Sortino ratio, on the other hand, only considers downside deviation where the return is less than the risk-free.

$$Sharpe\ Ratio_{annual} = \frac{(R_{annual} - R_f)}{\sigma_{annual}} \quad (8)$$

In which R_{annual} represents the annual arithmetic returns from groups, R_f is proxied by using the average yield of the ten-year Chinese government bond, and σ_{annual} represents the annualized standard deviation of group returns.

$$Sortino\ Ratio_{annual} = \frac{(R_{annual} - R_f)}{\sigma_{downside}} \quad (9)$$

Where $\sigma_{downside}$ considers only downside deviation if $R_{annual} < R_f$. This criterion is to avoid penalizing the portfolio's upside performance.

Table 3 computes the annualized Sharpe ratio according to formula, with the annualized arithmetic return, the standard deviation of annualized return, and risk-free rate as proxied by the yearly average yield of ten-year Chinese government bond yield.

Table 3. Annualized Sharpe ratio.

Annualized Return	2012	2013	2014	2016	2017	2018	2019	
Group 1	15.43%	0.10%	39.34%	45.11%	18.36%	5.24%	44.82%	
Group 2	13.33%	-5.80%	63.29%	-2.20%	6.29%	1.27%	27.02%	
Group 3	8.57%	-10.45%	44.80%	3.44%	-7.61%	-6.70%	27.26%	
Group 4	12.86%	5.98%	35.96%	0.37%	-5.49%	-6.90%	27.10%	
Group 5	0.90%	-2.38%	40.90%	-8.36%	-6.53%	-3.15%	17.43%	
	2012	2013	2014	2016	2017	2018	2019	
Rf	3.47%	3.83%	4.18%	2.89%	3.59%	3.66%	3.20%	
Annualized SD	2012	2013	2014	2016	2017	2018	2019	
Group 1	24.53%	50.24%	60.34%	82.93%	50.19%	30.65%	59.54%	
Group 2	36.66%	47.13%	88.77%	39.51%	31.52%	30.03%	50.22%	
Group 3	31.85%	31.51%	48.27%	35.69%	45.90%	28.83%	46.39%	
Group 4	27.44%	34.33%	43.94%	34.06%	36.91%	27.70%	32.65%	
Group 5	28.58%	26.83%	49.76%	37.67%	41.18%	24.13%	35.26%	
Annualized Sharpe	2012	2013	2014	2016	2017	2018	2019	Average
Group 1	48.78%	-7.43%	58.28%	50.91%	29.42%	5.17%	69.91%	36.43%
Group 2	26.90%	-20.44%	66.58%	-12.88%	8.54%	-7.95%	47.44%	15.46%
Group 3	16.04%	-45.32%	84.14%	1.56%	-24.41%	-35.91%	51.87%	6.85%
Group 4	34.25%	6.27%	72.31%	-7.40%	-24.62%	-38.11%	73.19%	16.56%
Group 5	-8.98%	-23.13%	73.80%	-29.84%	-24.59%	-28.22%	40.35%	-0.09%

Table 4 computes the annualized Sortino ratio based on formula (9), with the same calculation methodology as formula (8), except only downside deviation is included where $R_{annual} < R_f$.

Table 4. Annualized Sortino Ratio.

Annualized Return	2012	2013	2014	2016	2017	2018	2019	
Group 1	15.43%	0.10%	39.34%	45.11%	18.36%	5.24%	44.82%	
Group 2	13.33%	-5.80%	63.29%	-2.20%	6.29%	1.27%	27.02%	
Group 3	8.57%	-10.45%	44.80%	3.44%	-7.61%	-6.70%	27.26%	
Group 4	12.86%	5.98%	35.96%	0.37%	-5.49%	-6.90%	27.10%	
Group 5	0.90%	-2.38%	40.90%	-8.36%	-6.53%	-3.15%	17.43%	
	2012	2013	2014	2016	2017	2018	2019	
Rf	3.47%	3.83%	4.18%	2.89%	3.59%	3.66%	3.20%	
Annualized Downside SD	2012	2013	2014	2016	2017	2018	2019	
Group 1	5.44%	42.32%	27.12%	44.78%	31.44%	13.32%	23.38%	
Group 2	15.23%	42.10%	25.69%	44.90%	9.74%	14.41%	15.79%	
Group 3	12.42%	22.82%	4.16%	28.61%	30.58%	12.08%	10.67%	
Group 4	4.85%	22.89%	near 0%	33.89%	17.56%	17.62%	7.49%	
Group 5	10.78%	17.34%	7.33%	40.80%	25.40%	9.55%	24.45%	
Annualized Sortino Ratio	2012	2013	2014	2016	2017	2018	2019	Average
Group 1	219.75%	-8.82%	129.64%	94.28%	46.97%	11.89%	177.98%	95.96%
Group 2	64.73%	-22.89%	230.12%	-11.33%	27.63%	-16.58%	150.82%	60.36%
Group 3	41.09%	-62.56%	975.97%	1.95%	-36.63%	-85.69%	225.56%	151.38%
Group 4	193.66%	9.40%	∞	-7.44%	-51.75%	-59.92%	318.85%	67.13%
Group 5	-23.87%	-35.78%	500.69%	-27.55%	-39.87%	-71.28%	58.21%	51.51%

Group one performed better than other groups in terms of risk-adjusted return in the annualized Sharpe ratio. However, surprisingly, groups three and four, after taking into consideration positive infinity in ratio calculation, performed relatively well in annualized Sortino ratio, indicating that those two groups have relatively higher downside risk-adjusted returns.

6.3. Maximum Drawdown and Return-over-Maximum Drawdown (ROMAD)

In the next step, the research calculated maximum drawdown, maximum drawdown by year, and return-to-drawdown ratio. In terms of maximum drawdown and maximum drawdown by year, a lower number indicates lower volatility and spread, while a higher return-to-drawdown ratio indicates a higher risk-adjusted performance for the group. The return-to-drawdown ratio result can complement the existing Annualized Sharpe- and Annualized Sortino Ratio.

$$Maximum\ Drawdown = V_{peak} - V_{trough} \quad (10)$$

Where V_{peak} is the portfolio's highest value, and V_{trough} is the portfolio's lowest value.

$$Return\ over\ Maximum\ Drawdown\ (ROMAD) = \frac{R_{annual}}{Maximum\ Drawdown} \quad (11)$$

In which the higher ratio indicates the better performance.

Table 5 computes the Maximum Drawdown according to formula (10) and ROMAD according to formula (11) with the peak and trough cumulative value and the arithmetic return and drawdown.

Table 5. Maximum drawdown and ROMAD.

Maximum Drawdown	Geo	Ari						
Group 1	-486.45%	-244.56%						
Group 2	-218.67%	-154.33%						
Group 3	-146.94%	-125.17%						
Group 4	-217.68%	-143.78%						
Group 5	-261.34%	-166.87%						
Maximum Drawdown Yr Ari	2012	2013	2014	2016	2017	2018	2019	
Group 1	-17.80%	-18.38%	-48.65%	-66.71%	-24.68%	-14.83%	-47.41%	
Group 2	-16.95%	-18.40%	-66.57%	-15.00%	-13.12%	-11.12%	-32.69%	
Group 3	-13.91%	-10.71%	-45.73%	-19.06%	-18.35%	-11.60%	-31.08%	
Group 4	-16.15%	-11.14%	-42.96%	-14.76%	-15.65%	-10.16%	-28.35%	
Group 5	-15.11%	-7.96%	-43.60%	-10.33%	-9.76%	-8.15%	-23.58%	
ROMAD Ari	2012	2013	2014	2016	2017	2018	2019	Average
Group 1	86.68%	0.52%	80.87%	67.62%	74.38%	35.33%	94.53%	62.85%
Group 2	78.65%	-31.55%	95.08%	-14.68%	47.92%	11.40%	82.66%	38.49%
Group 3	61.64%	-97.58%	97.97%	18.06%	-41.47%	-57.74%	87.72%	9.80%
Group 4	79.64%	53.70%	83.69%	2.48%	-35.10%	-67.94%	95.60%	30.30%
Group 5	5.94%	-29.84%	93.82%	-80.87%	-66.96%	-38.72%	73.90%	-6.10%

The table above indicates that group one has the most significant arithmetic and geometric maximum drawdown but the most significant risk-adjusted performance for the over 50% average ROMAD ratio. However, group four performed better than group three in terms of ROMAD.

6.4. Long-Short Return

The study also conducts long-short returns as the group one return minus group five return for a feasible trading strategy. The result shows that the long-short trading strategy can generate a fruitful average double-digit percentage return yearly of 18.51%, with a monthly return of 1.54%.

Table 6 demonstrates the long-short return as indicated by the average of annualized monthly return differences over one year between group one and group five.

Table 6. Long-short return.

Date	Annualized Difference
2012	14.54%
2013	2.47%
2014	-1.56%
2016	53.47%
2017	24.89%
2018	8.39%
2019	27.39%
-	Monthly Return: 1.54%
-	Yearly Return: 18.51%

6.5. Caveat

The above result looks promising, but it should be mindful that convertible bond contains special clauses which could jeopardize the above analysis. For example, if the convertible bond is priced over CNY 130 over a continuous 15 trading days in 20 regular trading days, the bond would trigger the Mandatory Redemption Clause as the issuer would typically call the bond back at a lower price to retire the bond completely. Therefore, these events should be considered outliers and excluded from our sample. This logic is the same for the puttable bond if the price is too low, and investors would sell those bonds back. Thus, an alternative analysis is conducted to exclude certain convertible bonds from the sample if they are priced over CNY 150, and the result can be seen in the Appendix A. The research gives a grace range from CNY 130 to CNY 150 to consider the fact that the convertible bond may have price swings, and the issuing company may not choose to call the bond back if the price rise is only 30% from CNY 100 to CNY 130.

6.6. Control Group Result

After controlling outliers from the trigger of special clauses, the paper derived results for the controlled group. Similarly, group one yields the largest return both arithmetically and geometrically, indicating the pricing efficiency of convertible bonds from the Chinese market. Also, group one has the highest average annualized Sharpe ratio, followed by group four and group two. In terms of annualized Sortino ratio, groups one, two, and three performed better than others. Group one also has the highest risk-adjusted performance from average ROMAD, followed by groups two and four. Interestingly, after controlling for outliers, the annualized long-short return from the long-short strategy increases, and the result turns positive in the year 2014, suggesting profit opportunities for implementing the trading strategy.

7. Conclusion

This paper examines the convertible bonds from the Chinese Financial Market from 2012 to 2019 to examine the pricing efficiency of the market overall:

The research utilizes the relative cheapness of convertible bonds from their corresponding stocks by taking the difference between the convertible bond's implied volatility in conversion options and the stocks' look-back annualized volatility.

The research divides those convertible bonds into five groups based on their cheapness and calculates the equal-weighted return from each group to examine the pricing efficiency, with the hypothesis that underpriced convertible bonds should outperform overpriced convertible bonds.

The paper utilizes ratios to analyze risk-adjusted performance and investigates the long-short strategy based on cheapness.

In addition, outliers are also controlled, and alternative results from the controlling group are calculated for data robustness.

The results show that the cheapest group consistently outperformed other groups in arithmetic and geometric returns. In addition, it performed best in terms of annualized Sharpe ratio, annualized Sortino ratio, and ROMAD as risk-adjusted performance indicators. An average double-digit percentage return can also be extracted from long the cheapest group and short the most expensive group strategy in the observing period.

Surprisingly, the research finds that fair-valued convertible bonds in group three, where the implied volatility from options in convertible bonds and corresponding annualized volatility from stock are relatively equal, yielded a lower risk-adjusted performance than group four. This may imply that convertible bonds in this range are more volatile than other groups.

The research also provides valuable insights for further research on this topic. First, future papers can examine annualized volatilities from stocks in the longer look-back period, such as 120 days and 200 days, to examine the pricing efficiency. Secondly, further studies can examine the reasons for relative underperformance in risk-adjusted ratios from the fair valued convertible bond groups. Thirdly, other trading strategies based on pricing efficiency can be developed and tested to earn higher risk-adjusted performance in the Chinese Convertible Bonds Market. Lastly, further research can also examine other special clauses such as the Downward Adjustment Clause on the pricing efficiency for convertible bonds in China.

Appendix A

Table A1 computes annualized returns arithmetically and geometrically for five groups of convertible bonds based on relative cheapness, with the same methodology as Table 2 but considering the call-back decision by corporations.

Table A1. Control group return information.

			Arithmetic Annual Return Group		
Year	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**Group 5**
2012	15.43%	13.33%	8.57%	12.86%	0.90%
2013	0.10%	-5.80%	-10.45%	5.98%	2.38%
2014	53.63%	57.01%	41.93%	38.84%	41.41%
2016	45.11%	-2.20%	3.44%	0.37%	8.36%
2017	18.36%	6.29%	-7.61%	-5.49%	-6.53%
2019	45.97%	27.53%	27.52%	27.93%	17.79%
			Geometric Annual Return Group		
Year	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**Group 5**
2012	16.31%	13.61%	8.52%	13.33%	0.59%
2013	-0.89%	-6.48%	-10.31%	5.68%	-2.62%
2014	67.11%	71.39%	49.77%	45.71%	48.95%
2016	52.04%	-2.79%	2.99%	-0.09%	-8.56%
2017	18.87%	6.07%	-8.11%	5.85%	6.95%
2019	55.04%	30.19%	30.29%	31.24%	18.78%

Table A2 computes the control group annualized Sharpe ratio according to formula (5), after considering the call-back decision by corporations.

Table A2. Control group annualized Sharpe ratio.

			Annualized Return		
Year	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**Group 5**
2012	15.43%	13.33%	8.57%	12.86%	0.90%
2013	0.10%	-5.80%	10.45%	5.98%	-2.38%
2014	53.63%	57.01%	41.93%	38.84%	41.41%
2016	45.11%	-2.20%	3.44%	0.37%	-8.36%
2017	18.36%	6.29%	-7.61%	-5.49%	-6.53%
2018	4.78%	1.54%	-7.11%	-7.24%	-3.08%
2019	45.97%	27.53%	27.52%	27.93%	17.79%
			Rf		
	Year			**Value**	
	2012			3.47%	
	2013			3.83%	
	2014			4.18%	
	2016			2.89%	
	2017			3.59%	
	2018			3.66%	
	2019			3.20%	

		Annualized SD			
Year	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**Group 5**
2012	24.53%	36.66%	31.85%	27.44%	28.58%
2013	50.24%	47.13%	31.51%	34.33%	26.83%
2014	57.60%	74.49%	48.48%	40.95%	49.72%
2016	82.93%	39.51%	35.69%	34.06%	37.67%
2017	50.19%	31.52%	45.90%	36.91%	41.18%
2018	32.69%	30.52%	28.34%	28.37%	24.06%
2019	60.26%	48.35%	45.68%	33.98%	34.39%
		Annualized Sharpe			
Year	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**Group 5**
2012	48.76%	26.89%	16.02%	34.22%	-9.01%
2013	-7.43%	-20.44%	-45.32%	6.27%	-23.13%
2014	85.85%	70.93%	77.88%	84.65%	74.88%
2016	50.91%	-12.88%	1.56%	-7.40%	-29.84%
2017	29.42%	8.54%	-24.41%	-24.62%	-24.59%
2018	3.45%	-6.93%	-37.99%	-38.40%	-28.01%
2019	70.98%	50.32%	53.24%	72.77%	42.41%
		Average			
	40.28%	16.63%	5.85%	18.21%	0.39%

Table A3 calculates the control group annualized Sortino ratio according to formula (6), after considering the call-back decision by corporations.

Table A3. Control group annualized Sortino ratio.

		Annualized Return			
Year	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**Group 5**
2012	15.43%	13.33%	8.57%	12.86%	0.90%
2013	0.10%	-5.80%	-10.45%	5.98%	-2.38%
2014	53.63%	57.01%	41.93%	38.84%	41.41%
2016	45.11%	-2.20%	3.44%	0.37%	-8.36%
2017	18.36%	6.29%	-7.61%	-5.49%	-6.53%
2018	4.78%	1.54%	-7.11%	-7.24%	-3.08%
2019	45.97%	27.53%	27.52%	27.93%	17.79%
		Rf			
	Year			**Value**	
	2012			3.47%	
	2013			3.83%	
	2014			4.18%	
	2016			2.89%	
	2017			3.59%	
	2018			3.66%	
	2019			3.20%	
		Annualized Downside SD			
Year	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**Group 5**
2012	5.44%	15.23%	12.42%	4.85%	10.78%
2013	42.32%	42.10%	22.82%	22.89%	17.34%
2014	near 0%	near 0%	1.16%	3.78%	5.98%
2016	44.78%	44.90%	28.61%	33.89%	40.80%
2017	31.44%	9.74%	30.58%	17.56%	25.40%
2018	14.68%	14.39%	14.96%	18.68%	9.46%

2019	15.27%	14.41%	11.01%	69.38%	22.53%
			Annualized Sortino Ratio		
Year	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**Group 5**
2012	219.75%	64.73%	41.09%	193.66%	-23.87%
2013	-8.82%	-22.89%	-62.56%	9.40%	-35.78%
2014	∞	∞	3250.65%	916.37%	622.38%
2016	94.28%	-11.33%	1.95%	-7.44%	-27.55%
2017	46.97%	27.63%	-36.63%	51.75%	-39.87%
2018	7.68%	-14.71%	-71.96%	-58.31%	-71.22%
2019	280.05%	168.86%	220.94%	356.35%	64.75%
			Average		
	106.65%	35.38%	477.64%	194.04%	69.83%

Table A4 calculates the control group Maximum Drawdown and ROMAD according to formula (7) and (8), after considering the call-back decision by corporations.

Table A4. Control group maximum drawdown and ROMAD.

			Maximum Drawdown		
Group		**Ari**		**Geo**	
Group 1		-277.60%		-1073.29%	
Group 2		-131.68%		-205.62%	
Group 3		-92.69%		-104.60%	
Group 4		-132.74%		-190.03%	
Group 5		-93.13%		-115.72%	
			Maximum Drawdown Yr Ari		
Year	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**Group 5**
2012	-17.80%	-16.95%	-13.91%	-16.15%	-15.11%
2013	-18.38%	-18.40%	-10.71%	-11.14%	-7.96%
2014	-55.26%	-58.92%	-43.22%	-38.95%	-43.81%
2016	-66.71%	-15.00%	-19.06%	-14.76%	-10.33%
2017	-24.68%	-13.12%	-18.35%	-15.65%	-9.76%
2018	-15.29%	-10.88%	-11.96%	-10.47%	-8.08%
2019	-49.09%	-32.08%	-31.45%	-29.12%	-23.34%
Average	-35.32%	-23.62%	-21.24%	-19.46%	-16.91%
			ROMAD Ari		
Year	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**Group 5**
2012	86.68%	78.65%	61.64%	79.64%	5.94%
2013	0.52%	-31.55%	-97.58%	53.70%	-29.84%
2014	97.05%	96.76%	97.03%	99.73%	94.51%
2016	67.62%	-14.68%	18.06%	2.48%	-80.87%
2017	74.38%	47.92%	-41.47%	-35.10%	-66.96%
2018	31.28%	14.15%	-59.47%	-69.12%	-38.16%
2019	93.65%	85.82%	87.49%	95.91%	76.19%
Average	64.46%	39.58%	9.39%	32.46%	-5.60%

Table A5 computes the control group long-short return based on the average of annualized monthly return differences over one year between group one and group five, after considering the call-back decision by corporations.

Table A5. Control group long-short return.

Date Annualized Difference	
Year	**Annual Return**
2012	14.54%
2013	2.47%
2014	12.22%
2016	53.47%
2017	24.89%
2018	7.87%
2019	28.18%
Monthly Return	
1.71%	
Yearly Return	
20.52%	

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