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Credit Risk Research on Chinese Real Estate Enterprises Based on Modified KMV Model

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ABSTRACT: This paper first analyses the current situation of credit risk in China's real estate industry, and then compares the traditional and modern credit risk measurement models. On this basis, the KMV model is selected, and the artificial intelligence model Genetic Algorithm (GA) and GARCH model are introduced to improve the accuracy of the KMV model. Secondly, the annual financial data and stock trading data of 24 real estate listed companies for 2018 - 2022 are selected for empirical research. By analyzing the total default distance of the 24 companies and the actual economic development of China, it is proved that the results of the GA-GARCH-KMV model are 8% more correct than the classical KMV model, which indicates that the model has better applicability.

KEYWORDS: Default distance, KMV model, GARCH model, GA model, Real Estate Industry.

I. INTRODUCTION

China's real estate industry has a relatively extended development cycle, real estate companies have a relatively low proportion of their own capital, and due to policy sensitivities, this industry is subject to government monopolies on both the supply side and the demand side. In recent years, the vast majority of real estate companies have experienced negative sales growth and declining net profits, exposing real estate companies to increasingly prominent credit risks. The malformed financing situation in the industry has seriously constrained the sustainable and stable development of the real estate industry. The default of credit bonds of the top 100 real estate companies has become a warning signal for the real estate industry, and as defaults continue to occur, the subject of the defaults has shifted from typical but unrepresentative real estate companies to more dominant companies in the industry. The industry's willingness to repay debt continues to weaken, and as defaults gradually climb, this highlights the importance of examining corporate credit risk methodologies. In order to better address this challenge, we need to thoroughly explore and adopt appropriate credit research methodologies to effectively assess and respond to rising debt risks.

At present, the more mature international credit risk measurement methods mainly include credit measurement model, CreditRisk+ model, credit portfolio view and credit monitoring model KMV model. The KMV model was first proposed as a credit risk prediction model by Kealhofer, Mcquown and Vasicek (1974). Tudela and Young (2003) used metrics such as ROC curves and AUC metrics to assess the predictive ability of the Merton model for the default risk of UK public companies and compared it with other commonly used default prediction models, and concluded that the results obtained by the KMV model are more accurate and forward-looking, and that the out-of-sample predictive performance of the KMV model is better than that of other models. The KMV model is able to calculate a company's credit risk directly from stock market data and company financial data, which makes the KMV model the most widely used, and the use of the KMV model can dynamically reflect a company's present credit status (2003) . Nyambuu and Bernard (2015) applied the KMV model to assess the sovereign default risk of emerging economies and verify the reasonableness of using the KMV model to measure the sovereign default risk of developing countries. Capasso et al (2020) uses the KMV model to measure a company's credit risk and to analyses the relationship between that risk and climate change exposure, the study shows that a company's credit risk is negatively correlated with the total amount of the company's carbon emissions and carbon intensity. The KMV model can also be used for firms to predict their bankruptcy, Altman (1968) and Ohlson (1980) conducted a study on calculating the probability of firms' bankruptcy by applying the Z-score and O-score in combination with the KMV model for financial ratios, respectively. Hillegeist et al. (2004) used the KMV model to combine multiple factors including financial ratios, market data, and corporate governance to more accurately predict the probability of a firm's bankruptcy. Bharath and Tyler (2008) use the KMV model to explain the difference between CDS (credit default swap) premiums and bond yields, apply the KMV-Merton model to investment decisions in practical situations, and show that the model can be used to help investors make risk management and investment decisions. Zhang and Shi (2016) introduce particle swarm optimization and fuzzy clustering to improve the price estimation of non-circulating stocks and the calculation parameters of default points based on the KMV model, and the results show that the improved hybrid KMV model is more accurate in predicting credit risk. Zhang and Li (2018) use the KMV model and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to measure the credit risk and market risk of six commercial banks involved in carbon financing in China. Wang et al. (2018) state that short-term and long-term liabilities play a decisive role in measuring the level of real estate credit risk and have a significant impact on the credit risk of real estate firms. Yu et al. (2020) randomly sampled listed companies that had bond issues in China, divided the sample into groups with good credit status and groups with poor credit status, and re-measured the coefficient values based on genetic algorithms.

The purpose of this study is to examine the changes in credit risk in China's property sector in recent years. In this study, the KMV model is chosen as a measure of credit risk, and the distance to default is used to quantify the change in credit risk in the real estate industry. Meanwhile, the GARCH (1,1) model and genetic algorithm are used to correct the stock value volatility and default points that need to be used in the KMV model in order to improve the accuracy of the model.

II. MODIFIED KMV MODEL

A. Classic KMV model

The KMV model is an extension and application of the BSM option pricing model (Black-Scholes-Merton). A corporate creditor is equivalent to holding a risk-free bond denominated in debt, interpreting the market value of a call option as the market value of equity. D denotes the number of loans for which the enterprise is indebted, T denotes the maturity of the debt, V_A represents the market value of the enterprise's assets, the volatility of enterprise asset values is σ_a,the equity value of the business is V_E， σ_E denotes the volatility of the firm's equity value.

$$V_E(T) = \max\left[V_A(T) - D, 0\right] \tag{1}$$

The KMV model assumes that asset values follow standard geometric Brownian motion:

$$dV_A = rV_A d_t + V_A \sigma_A d_{W_t} \tag{2}$$

Where W_t is a standard Brownian motion and the call option at a given moment t can be calculated by the BSM pricing formula:

$$V_E = V_A N(d_1) - De^{-r(T-t)} N(d_2) \tag{3}$$

$$d_1 = \frac{Ln(\frac{V_A}{D}) + (\text{r} + \frac{\sigma_A^2}{2})(T-t)}{\sigma_A \sqrt{T-t}} \tag{4}$$

$$d_2 = d_1 - \sigma_A \sqrt{T-t} \tag{5}$$

where r denotes the risk-free rate, d_1 and d_2 denote intermediate variables. In equations (3)(4) and (5), V_A and σ_A are variables that are not directly observable in the market and must be used to build the following equations using the known equity value V_E and the volatility of the equity value σ_E:

$$\sigma_E = \frac{N(d_1) V_A \sigma_A}{V_E} \tag{6}$$

Combining equation (3) and (6), V_A and σ_A can be obtained. The default point (DPT) in the formula is defined as the tipping point for public companies using a linear combination of short-term debt (SD) and long-term debt (LD), with DPT defined as:
DPT = SD + 0.5LD. Default distance (DD) is the distance between the value of a firm's assets and the firm's default threshold. When the default distance is greater, it means that the distance to the company's default point is farther and the probability of default is smaller, indicating that the company's credit risk is lower (2003). The methodology is the analytical basis and conclusion support for the subsequent empirical results. The distance to default for the KMV model is given by:

$$DD = \frac{V_A - DPT}{V_A \sigma_A} \tag{7}$$

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B. Equity value volatility modification: based on the GARCH model

In this paper, the GARCH model (1986) is used to address the uncertainty in the volatility of firms' market value thus correcting the traditional KMV model. The classic KMV model uses historical stock prices from the previous period to estimate stock value volatility for the next period. In actuality, price changes in the Chinese stock market tend to show the phenomenon of "Heavy-Tailed", which is not in line with the assumption of the KMV model on the normal distribution of stock prices. Therefore, the accuracy of calculations using estimation methods based on historical data is not great. To address this issue, this paper uses the GARCH model to determine the volatility of stock values with a modification of the KMV model. The expression for the GARCH (p, q) model is as follows：

$$\alpha_t = \sigma_t \varepsilon_t \tag{8}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \alpha_{t-i}^2 + \sum_{j=1}^{q} \beta_j \alpha_{t-j}^2 \tag{9}$$

$$\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j \leq 1, \alpha_0 > 0, \alpha_i \geq 0, \beta_j \geq 0 \tag{10}$$

Where α_t is the set of time series, ε_t is a random sequence with mean 0, variance 1 and independently and identically distributed, ${\sigma_t}^2$ is the conditional variance, α_0 is the constant term, α_i and β_j are the parameters to be estimated. Equation (10) is the constraints of the GARCH model and an important determination of the applicability of the model to the given data. Since the time series model is based on white noise that follows a normal distribution, it is necessary to use the Jarque-Bera (JB) test to determine the distribution of the data, followed by the ADF test to verify the stability of the data, followed by the autocorrelation test of the data to test the relationship between the variables, and finally to determine the ARCH effect. Once the sample data has passed all the above operations, we can construct a GARCH (1,1) model as in equation (11) to determine the volatility of the stock. This approach can correct the shortcomings of the standard KMV model in calculating the volatility of stock values and improve the accuracy of the calculations.

$$\sigma_t^2 = C + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{11}$$

According to the GARCH (1,1) model daily volatility of stock price is calculated as follows:

$$\sigma_n^2 = \frac{C}{1-\alpha-\beta} \tag{12}$$

The relationship between annual stock price volatility σ and daily volatility σ_n is given in the following equation:

$$\sigma = \sigma_n * \sqrt{n} \tag{13}$$

where n is the number of trading day days per year.

C. Default point parameter modification: based on genetic algorithm model

Genetic Algorithm (2003) is an algorithm that seeks the global optimum by modelling the natural selection process of superiority and inferiority, guided by a fitness function. Since the calculation of the default point is related to long-term and short-term debts, we have two decision variables α and β to define the DPT in this case:

$$DPT = \alpha * SD + \beta * LD \tag{14}$$

N companies are selected from the study data, where the number of ST and non-ST companies is N/2. ST (Special Treatment) category companies are companies in the Chinese stock market that indicate specific risks or financial problems. We determine the firm attributes by judging the default distance DD, and judge the default of the firms based on the result of DD, if DD>0, the firms are judged not to be in default (non-ST firms); if DD<0, the firms are judged to be in default (ST firms). So there are four possible scenarios and the number of firms as shown in Table 1.

The number of two types of classification errors are N/2-m and N/2-n, respectively, and the optimal default point parameter is sought by modifying the KMV model with genetic algorithm so that the two types of errors are least under this parameter. It means seeking the optimal values of α and β so that the average error probability G (m, n) =1- (m + n)/N is minimum. To find the optimal default point of the KMV model by genetic algorithm, α and β in equation (14) are regarded as chromosomes required by the genetic algorithm, which can be calculated with the known asset value and the modified volatility of the equity value to get the default distance of the bonds at each moment during the optimization process; and using the default distance as a criterion to update α and β in the

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direction of the better direction until the algorithm terminates, and the optimal default point of the KMV model is outputted. The design flowchart is shown in Figure 1.

Table1. Possible cases

Possible cases	***Number of judgements***
ST companies judged to be ST companies	m
ST companies judged to be non-ST companies	N/2-m
Non-ST companies judged to be non-ST companies	n
Non-ST companies judged to be ST companies	N/2-n

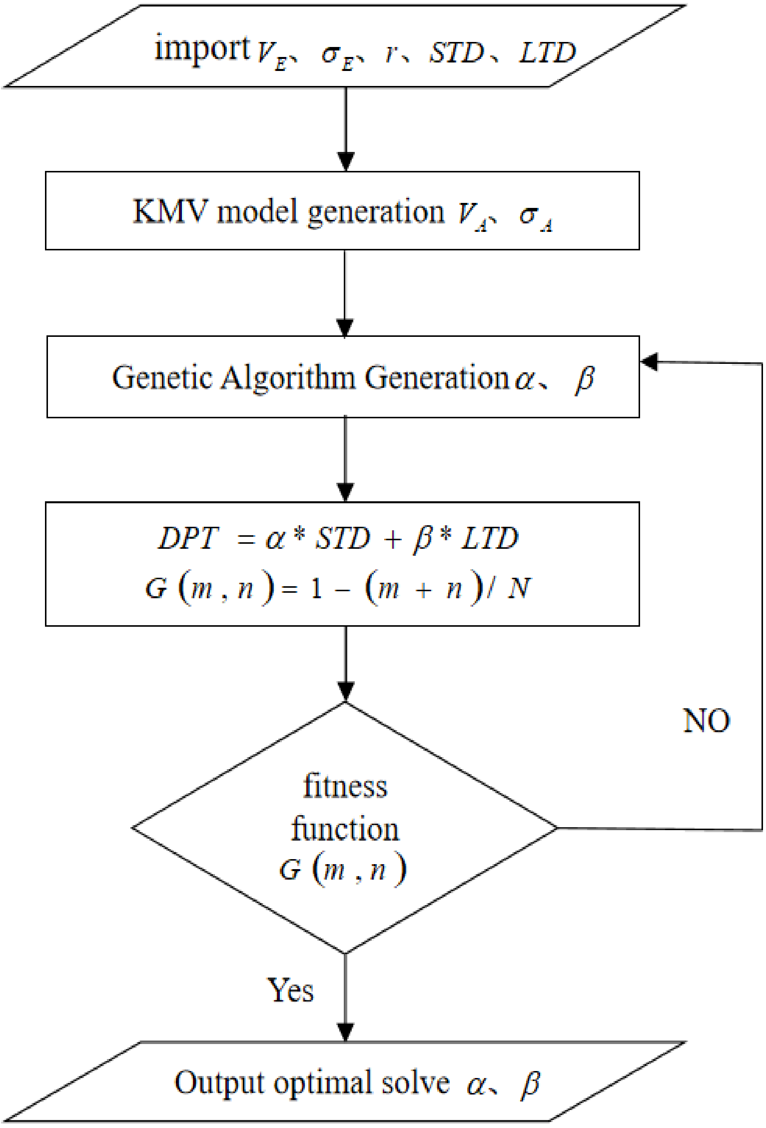

Figure 1.GA-GARCH-KMV Design Flowchart

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III. EMPIRICAL RESEARCH

A. Data selection

Based on the availability and comparability of data, we have selected the real estate sector in China's A-share market for 2018-2022. Based on the model used, we divided the data into ST class and non-ST class and selected 12 listed real estate companies in the ST category. As a reference for ST companies, in order to avoid the hardness of variable differences due to time differences and enterprise size differences, 12 real estate companies with corresponding years and comparable market capitalization sizes were selected as non-ST samples, as shown in Table 2.

Table 2. Sample group information

group	*ST Company Stock Code*	*ST implementation date*	*Selected year*	*Selected non-ST Company Stock Codes*
A	000007.SZ	2021.04.30	2020	000886.SZ
B	000616.SZ	2021.05.06	2020	000797.SZ
C	000620.SZ	2021.04.29	2021	000558.SZ
D	000671.SZ	2018.09.16	2018	000608.SZ
E	000732.SZ	2019.07.05	2019	600082.SH
F	000909.SZ	2023.04.28	2022	900928.SH
G	000918.SZ	2018.04.26	2018	600503.SH
H	600077.SH	2019.08.30	2019	002016.SZ
I	600239.SH	2021.04.28	2020	000882.SZ
J	600393.SH	2019.10.31	2019	000718.SZ
K	600568.SH	2018.02.01	2018	000631.SZ
L	600823.SH	2021.03.25	2021	600604.SH

Based on the data required for the GA-GARCH-KMV model, our selected frequencies and sources are shown in Table 3.

Table3. Data used for research

<table>
<tr><th></th><th>variable</th><th>time range</th><th>frequency</th><th>source</th></tr>
<tr><td rowspan="4">individual stock</td><td>closing price on a trading day</td><td rowspan="4">2018.01.01-2022.12.31</td><td>per trading day</td><td rowspan="4">Choice Financial Terminal</td></tr>
<tr><td>equity value of stocks (V_E)</td><td rowspan="4">per year</td></tr>
<tr><td>short-term debt (SD)</td></tr>
<tr><td>long-term debt (LD)</td></tr>
<tr><td>risk-free rate</td><td>Interest rates on one-year treasury bonds (r)</td><td>2018-2022</td><td>www.chinabond.com.</td></tr>
</table>

B. empirical results

Based on the 5 years dataset from 2018 to 2022, the GA-GARCH-KMV model calculated the values of model coefficients α and β as 1.5291 and 1.1270 respectively. Compared with the original KMV model, it can be seen that the coefficients of short-term debt (SD) and long-term debt (LD) are larger, and it can be seen from the selection of default points that the main component of credit risk in China's A-share real estate industry is still short-term debt. Table 4 shows the DD values of the distance to default before and after the correction for the ST and non-ST groups, as well as the number of correct judgements made on the samples before and after the modification.

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Table 4. Empirical Default Distance (DD) results before and after modification of the GA-GARCH-KMV model

Group	*ST (KMV)*	*ST (GA-GARCH-KMV)*	*Non-ST (KMV)*	*Non-ST (GA-GARCH-KMV)*
A	2.3508	2.1852	1.9307	1.8531
B	1.5716	1.4372	-3.8403	-8.4459
C	-12.6303	-3.6911	1.8127	1.6444
D	-17.0736	-30.0003	1.9162	1.2360
E	-9.3925	-11.1830	1.4094	0.2757
F	0.5266	-0.0674	1.9310	0.2272
G	0.0557	-1.2596	1.1749	0.5975
H	-17.1445	-30.4873	0.9794	-0.0624
I	-27.7749	-48.2090	1.2899	0.0565
J	-0.3682	-0.4660	1.3281	0.1158
K	0.7375	-0.0930	1.4764	0.4379
L	-15.1866	-28.4849	0.9377	0.3057
Number of correct judgments	7	10	11	10

Compared to the classical KMV model, the GA-GARCH-KMV model improved the overall accuracy by 8%, but the identification of ST firms improved the outcome rate by 25%, the results of which are shown in Table 5.

Table 5. Results

Model	*total*	*Number of successful ST company recognition*	*Number of successful non-ST company identifications*	*recognition success rate*	*ST company recognition success rate*	*Non-ST company recognition success rate*
KMV	24	7	11	0.75	0.58	0.92
GA-GARCH-KMV	24	10	10	0.83	0.83	0.83

As can be seen from Table 5, the GA-GARCH-KMV model shows a significant improvement in the identification accuracy of ST companies over the original model, while the identification accuracy of non-ST companies decreases slightly. This suggests that the GA-KMV model is more rigorous than the original KMV model in determining default risk. This suggests that the GA-KMV model is more rigorous than the original KMV model in determining default risk. However, it is undeniable that the GA-KMV model is more accurate in predicting firms that are vulnerable to default.

IV. CONCLUSIONS & RECOMMENDATIONS

A. Conclusions

In this paper, the GARCH(1,1) model and genetic algorithm are used to modify the volatility of equity value and the selection of default points in the KMV model, and the overall accuracy of the GA-GARCH-KMV model is improved by 8% compared with the classical KMV model. Among the 12 ST companies, the classical KMV model obtained 7 correct ones, while the GA-GARCH -KMV model reached 10 correct ones, and the GA-GARCH-KMV model increased the success rate of identifying ST companies by 25%.

Acceptably, the success rate of identifying non-ST companies decreased by 9%, and the number of successes of the GA-GARCH-KMV model in the 12 non-ST groups was 10 less than the number of correct ones in the original KMV model. The reason for this comparison is because the coefficients on both short-term debt (SD) and long-term debt (LD) are larger in the GA-GARCH-KMV model than in the original model. From the perspective of risk control, the modified KMV model can judge the default distance of the enterprise in a timely manner according to its debt situation, which is more conducive to the enterprise's timely adoption of self-management measures and methods to ensure the normal operation of the enterprise.

B. Recommendations

The sample selected for this paper is the 2018-2022 A-share real estate data for the study of China's real estate industry, the sample size is relatively small, and there is no further research on the credit impact of the external environment on enterprises.

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