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Article

Credit Risk Evaluation of Real Estate Industry Based on GA-GARCH-KMV Model

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Abstract: Credit risk assessment in the real estate industry has garnered significant attention from government regulators, investors, and business scholars. However, the evaluation of credit risk in this sector poses numerous challenges, primarily due to the intricate interplay of economic cycles and political landscapes. In this study, we propose a novel method that leverages the GARCH(1,1) model in conjunction with the Genetic Algorithm (GA) to enhance the KMV model's performance. By refining the default point and equity value volatility in the KMV model, our approach offers more accurate credit risk evaluations in the real estate industry. Empirical results demonstrate the superior accuracy of our improved KMV model, providing valuable insights for early credit risk warning in the real estate sector.

Keywords: Credit Risk; GARCH(1,1); Genetic Algorithm; KMV Model; Real Estate Industry

1. Introduction

In every one the global pandemic's relentless sweep and the ongoing conflict between Russia and Ukraine, the likelihood of credit risk emanating from enterprises is on the rise. The subprime mortgage crisis in 2008 was caused by the default on subprime mortgages and the credit risk problems, which eventually led to the global financial crisis. This crisis reveals the importance of real estate credit risk assessment, as low-quality real estate loans and poor credit practices can trigger turbulence in the financial system. It involves significant investment, borrowing, and consumption. When the housing market is hit by credit risk, it has a ripple effect on the construction industry, financial institutions, household finances and consumer confidence. These effects could spread to other sectors, leading to overall economic instability. Credit risk in the real-estate sector Evaluation is not only related to the security of individual real estate transactions, but also related to the health of the entire financial system and the economy. Given its significance as one of the most critical financial risks in the capital market, evaluating credit risk has become paramount. Leveraging sophisticated mathematical calculations, credit risk assessment plays a pivotal role not only in helping enterprises enhance their management and optimize debt structures to reduce capital-raising costs but also in aiding financial institutions in gauging loan risk and efficiently managing credit assets.

The real estate industry exhibits distinctive features, characterized by immense capital requirements and prolonged capital return cycles. Many enterprises face difficulties in bridging the substantial capital gap. Liu Xiangli and Gu Shuting (2014) [1] highlighted that banks view real estate as the second-largest investment sector after manufacturing, with real estate loans constituting approximately 20% of total loans. However, Cai Zhen, et al. (2023) [2] and others pointed out that from a long-term perspective, the real estate regulation policy is conducive to reducing the risk of default of real estate enterprises, but also conducive to the healthy and stable development of the real estate market. The risk associated with this 20% of loans is comparable to the systemic risk faced by the entire financial system. Concurrently, China's real estate industry has witnessed a persistent rise in the asset-liability ratio since 2009, with occasional minor fluctuations that quickly revert to an upward trend. The extended capital occupation cycle and slow fund return in real estate ventures intensifies capital pressures for companies in the sector. Failure in achieving diversified transformation poses a severe risk to the daily operations of real estate enterprises and even jeopardizes their capital chain. A prime example is Evergrande, where unsuccessful diversification played a critical role in its tumultuous journey.

Ke Konglin and Zhou Chunxi (2005) [3] presents an overview of international research on credit risk assessment, highlighting prominent models such as Credit Metrics by JP. Morgan Bank, CreditRisk+ by CSFP, KMV model by KMV Corporation, and Credit Portfolio View by McKinsey & Company. Among these models, the KMV model stands out for its ability to incorporate not only financial data but also leverage stock price fluctuations of listed companies to compute credit risk assessment indicators, such as the default distance of listed firms, through complex iterative operations. This characteristic enhances the model's timeliness and predictability in risk assessment.

However, given the delayed inception of China's capital market compared to Europe and the United States, the absence of a unified database for defaulting enterprises, and disparities in shareholding and trading regulations among listed companies, direct application of the traditional KMV model poses certain challenges for credit risk assessment in China. Therefore, adapting the traditional KMV model to align with China's national conditions becomes imperative.

The adaptation of the KMV model by Chinese scholars has been approached from two significant angles. Firstly, improvements to the Black-Scholes-Merton (BSM) model have been made. For instance, Wang Jia and Cao Qiongyu (2022) [4] enhanced the traditional KMV model by introducing a jump factor into risky asset prices. They argued that utilizing the jump-diffusion KMV model for measuring the credit risk of listed companies yields more consistent and accurate results in the context of China's market dynamics. Similarly, Xie Chi, et al. (2014) [5] built the JD-KMV model on the foundation of KMV by employing maximum likelihood and least squares methods to estimate model parameters and explore the jump characteristics of stock prices. Their findings indicate that both the JD-KMV and KMV models offer better credit risk measurement for listed companies, with the JD-KMV model exhibiting significantly superior performance.

Secondly, scholars have made enhancements regarding the default point in the KMV model. Feng Jinghai and Tian Jing (2016) [6] utilized an overall optimal genetic algorithm to determine the optimal default point, thus creating a risk measurement model tailored to China's specific circumstances. Additionally, they explored the significance of the KMV model in industry-level empirical research. In another study, Zhang Jiantong, et al. (2019) [7] compared cross-sectional default points, using 0.75 as the long-term default point in the calculation formula. The validation concluded that the KMV model demonstrated the most robust risk identification capabilities at this specific point in time.

Overall, the revised KMV model, enriched by these scholarly contributions, proves to be a more effective and tailored approach to credit risk assessment within the Chinese context.

In recent years, Hovakimian Armen, et al. (2012) [8] integrated leverage effects into the empirical EDF of the KMV model to measure firms' credit risk, highlighting the central role played by the probability of default in the static trade-off theory of capital structure. Additionally, Chinese scholars Zhang Nengfu and Zhang Jia (2010) [9] utilized an improved version of the KMV model to measure credit risk in Chinese listed companies, demonstrating significant advantages over previous models for credit risk quantification. Leveraging the classical Merton model as the theoretical basis, this improved model addressed the limitations of prior quantitative credit risk models, utilizing financial data and market prices as input data, and exhibiting enhanced predictive capabilities in weakly efficient markets.

Building upon this context, this paper focuses on further refining the KMV model by modifying the default point. The real estate industry heavily relies on capital raising to sustain its capital chain, closely following market cycles. Moreover, most real estate companies experience low or even negative net cash flow, resulting in widening capital gaps and serving as underlying risks in every one frequent market fluctuations. As such, this study selects real estate companies that have faced suspension of trading (ST) in the past five years, along with 33 other companies exhibiting sound performance, as the research subjects. By employing the GARCH(1,1) model and the GA genetic algorithm, the KMV model is enhanced to assess the risk of this sample set.

Through these refinements, this research seeks to contribute to a more robust credit risk assessment framework for the real estate industry, providing valuable insights into the sector's vulnerability to market uncertainties and capital challenges.

2. Improved KMV Model Construction

The KMV model, developed by KMV in 1993, is a corporate credit monitoring model based on the theoretical foundation of the Black-Scholes-Merton (BSM) option pricing model. The fundamental concept of the KMV model can be succinctly summarized as follows: Credit risk on a loan arises from the risk that the debtor's market value of assets may not cover its liabilities. However, since the assets are not actively traded in the market, their market value cannot be directly observed. To address this challenge, the model takes an innovative approach by viewing the bank's lending problem from the perspective of the borrowing firm's owner. At the debt's maturity, if the market value of the company's assets exceeds the value of its debt (known as the established default point), the equity value of the company is the difference between the market value of its assets and the debt. On the other hand, if the market value of the assets is lower than the debt at that point, the company is required to sell all its assets to repay the debt, resulting in an equity value of zero.

2.1. KMV Model

KMV posits that a firm's likelihood of default hinges on the value of its assets. A default event is deemed not to occur when the calculated total value of debt is lower than the value of assets. Conversely, a default event is triggered when the total value of debt surpasses the value of assets. Additionally, the KMV model establishes a company's default threshold as its debt value and subsequently calculates the expected default rate based on the relationship between default distance and the probability of default risk occurrence. The schematic diagram of the model is illustrated in Figure 1:

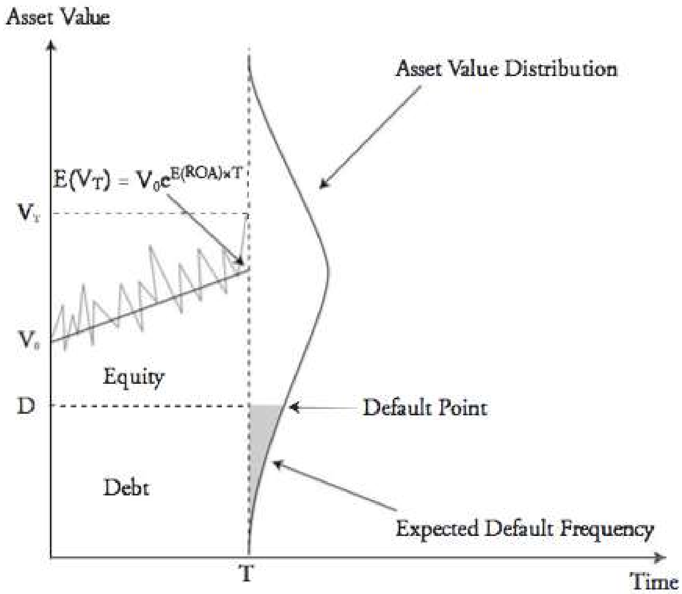

Figure1. KMV model schematic diagram.

The ultimate metrics of the KMV model encompass the computation of default distance and the expected probability of default, which serve to gauge the credit risk level of listed companies. These calculations can primarily be undertaken through the following steps:

① Compute the market value of assets (V_A) and the volatility of asset market value (σ_A) for the listed companies.

Per the model definition, the functional relationship between the market value of assets (V_A) and the volatility of asset market value (σ_A) for listed companies adheres to the following constraints.

$$V_E = V_A N(\mathrm{d}_1) - DE^{-\mathrm{rt}} \mathrm{N}(\mathrm{d}_2) \tag{1}$$

$$\mathrm{d}_1 = \frac{\ln \frac{V_A}{D} + (r + \frac{1}{2}\sigma^2{}_{\mathrm{A}})\mathrm{t}}{\sigma_{\mathrm{A}}\sqrt{\mathrm{t}}} \tag{2}$$

$$\mathrm{d}_2 = d_1 - \sigma_{\mathrm{A}}\sqrt{\mathrm{t}} \tag{3}$$

$$N(\mathrm{d}) = \int_{+\infty}^{d} \frac{1}{\sqrt{2\Pi}} \mathrm{e}^{-\frac{\mathrm{x}^2}{2}} dx \tag{4}$$

where V_E represents the market value of the listed company's equity, V_A represents the market value of the listed company's total assets, D represents the value of the listed company's debt, *r* represents the market risk-free interest rate, t represents the repayment term of the underlying debt of the listed company, and N(d) represents the standard cumulative normal distribution function.

The relationship between the volatility of the total asset value and the volatility of the equity value of a listed company satisfies the following:

$$\sigma_{\mathrm{E}} = \frac{V_A}{V_E} N(d_1)\sigma_{\mathrm{A}} \tag{5}$$

where, σ_E denotes the volatility of the equity value of the listed company.

In this paper, we will solve the asset value VA and asset value volatility σ_A by iterative algorithm using MATLAB 2018a software associating equations (1) to (5).

② Calculate the default point DP for listed companies.

The expression for calculating the default point (DP) as presented by KMV when introducing the KMV model is DP = 1×STD + 0.5×LTD, wherein the default point is determined by the summation of 1 times the short-term liabilities (STD) and 0.5 times the long-term liabilities (LTD). KMV derived these coefficients from extensive empirical analysis of more than 3,400 listed companies and over 40,000 non-listed companies in the European and American markets, based on numerous instances of defaults spanning several years. Consequently, this default point has gained widespread recognition and adoption in countries with well-developed capital markets.

③ Calculation of default distance DD.

The default distance (DD) is an evaluative indicator utilized to assess the extent of credit default risk associated with a listed company. It represents the relative difference between the expected value and the default trigger (DP). A higher DD value signifies a larger disparity between the company's asset value and its liabilities, leading to a lower probability of default, as per option pricing theory.The public representation of the default distance can be expressed as follows:

$$DD = \frac{E(V_A) - DP}{E(V_A) * \sigma_A} . \tag{6}$$

2.2. GA-GARCH-KMV Model Construction

2.2.1. GARCH Model

According to the premise assumptions of the KMV model, the fluctuations in equity value of listed companies are assumed to follow a normal distribution. However, in reality, most companies exhibit a spiky thick-tailed volatility aggregation distribution of equity value volatility. Additionally, the stock market is sensitive and volatile, and unexpected events can significantly impact the accuracy of the method. To address these challenges, this study employs the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model for volatility analysis of financial data.The GARCH model is widely recognized in the field of finance for its applicability in risk assessment and forecasting of financial asset returns. Many finance scholars concur that the GARCH(1,1) model aligns closely with the characteristics of China's stock market. For instance, Wang Xiuguo and Xie Youhuang (2012) [10] conducted empirical testing using the GARCH model and found that the extended KMV model for credit risk assessment yielded favorable results, providing effective early warning for credit risk situations in the market. Similarly, Zhou Shuyuan (2019) [11] demonstrated the superiority of the KMV model with GARCH for credit risk assessment in industries with overcapacity, proving its ability to accurately evaluate the credit risk of seven industries prone to overcapacity. Given the successful applications of the GARCH(1,1) model in prior research, this paper adopts the GARCH(1,1) model to optimize equity value volatility, enhancing the overall robustness of credit risk assessment in the study. The GARCH(1,1) model is:

$$\sigma_t^2 = \alpha_0 + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} \tag{7}$$

where α is the return coefficient, β is the lagging coefficient, and $\alpha_0 \neq 0$, $\beta \geq 0$, $\alpha + \beta < 1$.

2.2.2. GA-KMV Model

GA Genetic Algorithm is an optimization technique inspired by natural evolutionary theory, seeking high-quality solutions by emulating the process of natural selection and reproduction. It proves particularly effective for model optimization and learning, especially in complex problems with numerous parameters and intricate mathematical representations. By employing a superior selection process, it can derive optimal solutions with exceptional adaptability.

Compared to traditional optimization methods and algorithms, genetic algorithms offer four key attributes:

(1) They commence the search for global optimization with a set of potential solutions, avoiding the limitation of local optima often associated with single starting points.

(2) Genetic algorithms exhibit self-adaptation and self-learning capabilities, allowing them to autonomously discern the underlying laws of external conditions once the coding method and fitness function are established.

(3) They demonstrate extensive applicability, necessitating only the specification of an appropriate fitness function.

(4) Genetic algorithms employ probabilistic search mechanisms, imparting flexibility and adjustability to their approach.

As a result, genetic algorithms stand out as a powerful tool for solving optimization challenges, providing efficient and robust solutions for problems with complex landscapes and a diverse range of applications.

In this paper, the following steps are calculated using the GA-KMV model:

The first step involves computing the asset value (V_A) and the volatility of the asset value (σ_A) for the sampled firms.

Moving on to the second step, the default point parameters (short-term debt coefficient α and long-term debt coefficient β) are encoded using a binary coding method.

In the third step, the initial population is generated. Each individual within the population corresponds to a set of potential solutions, represented as a set of values for the violation point parameters (α, β) that signify a feasible violation point.

In the fourth step, the default distance (DD) is computed by setting the maturity time (T) as 1 year and the risk-free rate (μ) as the yield of the underlying Treasury bond. For each default point (α, β), the default distance DD of the sample companies is calculated using equation (6).

Moving to the fifth step, the fitness function value is determined for each individual (α, β) within the population. The average misclassification rate 1-((m+n)/N) at the occurrence of situations in the third and fourth steps is calculated as the fitness value for that breach point.

In the sixth step, the corresponding selection operation, crossover operation, and variation operation are performed.

Proceeding to the seventh step, the algorithm checks whether the termination condition is met. If the termination condition is satisfied, the algorithm concludes, and the optimal solution for the default point parameters (α, β) and the default distance DD are output. Conversely, if the termination condition is not met, the algorithm returns to step 4 for further iterations.

3. Parameter Design

The traditional KMV model has many limitations and the original parameters of the KMV model are not fully applicable to the Chinese Shanghai and Shenzhen stock markets compared to the foreign stock markets.

3.1. Calculation of Equity Value of Listed Companies

The total number of shares of listed companies in China comprises outstanding shares and restricted shares (non-marketable shares). For the calculation of the equity value of listed companies, this study adopts the sum of the share price of outstanding shares and the share price of restricted shares as the enterprise's equity value.

The specific calculation is as follows: Equity value = Number of outstanding shares × price of outstanding shares + Number of non-marketable shares × price of outstanding shares.

3.2. Total Asset Value Volatility and Risk-free Interest Rate

In this paper, we utilize the GARCH model to assess the equity value volatility of listed companies. We select a sample with stock trading data spanning every unit trading day to determine the annual stock price volatility (σ_E). The annual volatility of the company's asset value (σ_A) is estimated through equations (1) to (4) to calculate the implied total asset value (V_A) of the company per year. The stock price volatility (σ_E) is employed as the initial value to estimate the rate of the company's asset value volatility, and iterative loops are conducted until convergence is achieved for the total company asset value and total company asset value volatility.

In the calculations, T is set as 1 year, and for the risk-free rate, we generally use the one-year time deposit rate from the benchmark interest rate for RMB deposits in financial institutions published by the Monetary Policy Department of the People's Bank of China. The risk-free rates applied in this paper for the period of 2016 to 2020 are 2.25%, 1.75%, 1.75%, 1.9%, and 1.75%, respectively.

3.3. Estimated Default Point (DPT)

In the traditional KMV model, the default point is set as DPT=1×STD+1/2×LTD, where STD represents the short-term liabilities, and LTD represents the long-term liabilities of the enterprise. However, existing studies and model analysis have identified limitations in utilizing the KMV model to measure Chinese listed companies due to substantial differences between the Chinese capital market and the European and American markets. As a result, the accuracy of the model can be enhanced through modifications.

Empirical research conducted by Zhang Dabin, et al. (2015) [12] on credit risk measurement of A-share listed companies demonstrated that the improved KMV model significantly enhances the accuracy of credit risk measurement for A-share listed companies. The average accuracy of the GA-KMV model, incorporating the genetic algorithm (0.7825), is notably higher than that of the QR-KMV model based on regression analysis (0.6931) and substantially outperforms the average accuracy of the traditional KMV model (0.4224). In this study, the GA genetic algorithm is employed to optimize the default points, leading to a certain improvement in the model's evaluation accuracy.

4. Empirical Results and Analysis

4.1. Source of Sample Data

The research subjects chosen for this study are Chinese A-share listed real estate companies, totaling 44 in number. The sample selection satisfies the following two requirements:

(1) The sample consists of both non-ST (no suspension of trading) or ST* (previously suspended but currently trading) listed companies, and the selection ensures a roughly equivalent size of enterprises between the two categories. The sample size is determined based on the approach employed by Ma Ruowei, et al. (2014) [13], where the ratio of ST listed companies to non-ST listed companies is set as 1:3. This selection approach aims to avoid issues of over-sampling and self-selection biases.

(2) The ST companies are chosen from the data of the year immediately preceding the year in which they became ST, or from the data of the year in which they were ST if they had already been listed for more than 200 trading days. In the process of sample selection, companies simultaneously listed in A, B, and H shares are excluded to prevent their influence on the subsequent calculation of daily equity value volatility.All data in this article are from the CSMAR Financial Terminal database.

4.2. Calculation of Equity Value Volatility

Taking ST Honggao 002504 as an example, a total of 243 sample points were selected for the year 2020. Firstly, the daily return per share was subjected to the J-B test in Eviews software. the J-B statistic was calculated as 135.9499, significant at the 1% significance level. This result indicates that the data rejects the original hypothesis of conforming to a normal distribution. Moreover, the kurtosis value of 6.6634 is higher than the standard kurtosis value of 3, and the skewness value of 0.040401 indicates right-skewness. These observations imply that the data exhibit characteristics of sharp peaks, thick tails, and a right-skewed distribution.

In order to further construct the GARCH model, the time series data must undergo a smoothness test. Continuing with the example of ST Honggao 002504.The Augmented Dickey-Fuller (ADF) value for the sample data is -13.88436, which is significantly lower than the critical value of -2.574593 at the 1% confidence level. This result suggests that the daily stock return of ST Honggao exhibits significant smoothness at the 1% significance level.

After successfully passing the ADF test, an ARCH test is performed on the data to determine the presence of the ARCH effect, which is essential for further constructing the GARCH model. The ARCH test conducted on the daily stock price return of ST Honggao 002504 reveals a lagged first-order P value of 0.0001, which is lower than the critical value of 0.05 at the 5% confidence level. This result indicates the presence of the ARCH effect in the data, warranting the construction of a GARCH model as follows:

$$\sigma_t^2 = 0.000281 + 0.35486\mu^2_{t-1} + 0.354631\sigma^2_{t-1} \tag{8}$$

where the stock daily return lagged first-order ARCH value is 0.35486 and GARCH value is 0.354631, and $\alpha + \beta = 0.709491 < 1$, satisfying the constraints of the GARCH model, from which the ST Honggao 002504 equity value volatility is

$$\sigma = \sqrt{Vt * n} = \sqrt{0.0009672 * 250} = 0.493711945.$$

Similarly, by the above process to calculate the remaining 43 sample companies, so the volatilities of equity value of the 44 sample companies are shown in Table1.

Table1. Volatilities of equity value of sample companies.

Sample Name	σ_A	Sample Name	σ_A	Sample Name	σ_A	Sample Name	σ_A
002781 The World Show	0.820409529	000560 I love my home	0.379126715	000926 Fuxing shares	0.210667371	000909 Digital Source Technic	0.275846514
000616 ST Haitou	0.598908804	000615 Ao Yuan Meigu	0.651261861	002285 WorldLink	0.535682754	000928 Sinosteel International	0.704560345
002482 ST Guangtian	0.324913035	000620 Xinhualian	0.542009938	600658 Electronic City	0.534502935	002051 CIGI	0.28080649
600807 Jinan High-Tech	0.477469896	000631 Shunfa Hengye	0.380986024	600665 Tiandiyuan	0.408512218	002061 Zhejiang Jiaoke	0.202598776
600239 ST Yuncheng	0.779819724	000656 Jinke Co.	0.436900239	000014 Shahe shares	0.551824985	002062 Hongrun Construction	0.448998886
Sample Name	**σ_A**	**Sample Name**	**σ_A**	**Sample Name**	**σ_A**	**Sample Name**	**σ_A**
603007 ST Kao	0.43205851	000667 Beautiful Homes	0.640191341	000507 Zhuhai Port	0.698312573	002116 China Haicheng	0.35857508
000732 ST Taihe	0.472260604	000797 China Wuyi	0.343543577	000553 Andromeda A	0.47143542	002564 Tianwo Technology	0.577157336
002504 ST Honggao	0.493711945	000838 Caixin Development	0.550294959	000608 Sunshine shares	0.53824364	002628 Chengdu Road and Bridge	0.352340075
002586 ST Weihai	0.47340116	000863 Sanxiang Impression	0.435159355	000628 High-tech Development	0.418697049	002663 Pupang Stock	0.608793246
002781 *ST Chisin	0.492623064	000886 Hainan Expressway	0.212756275	000668 Rongfeng Holdings	0.420998647	600094 Daimyo City	0.208507208
000505 Beijing Grain Holdings	0.768791253	000918 Cascade City	0.66487462	000718 Suning Global	0.674419004	000711 Jinglan Technology	0.624533954

4.3. GA-KMV Algorithm to Calculate the Optimal Default Point

Due to the GA genetic algorithm's rapid and highly accurate convergence rate in seeking the global optimal solution, this study employs the genetic algorithm toolbox in MATLAB software to optimize the default point parameters. The coding method used is binary coding, with a population size set to 50. The crossover probability is set at 0.8, while the mutation probability is set at 0.01. The maximum number of iterations is limited to 200, and the function tolerance is set to 10-6, indicating convergence is achieved when the weighted average change of the fitness function value is less than 10-6. The intervals of α and β are defined as [0, 5] and [0, 5], respectively. The algorithm is applied to 44 sample companies and repeated multiple times, resulting in stable iterations. The values of the fitness function converge to 0.272727272 within 51 generations. The algorithm terminates at the 51st generation, satisfying the termination condition where the weighted average change in the value of the fitness function becomes less than 10-6. The results of multiple runs show that the default point parameter values fluctuate up and down between 1.013 and 1.834, yielding the formula for calculating the default point for listed companies in the real estate industry, as shown in Equation:

$$DPT=1.013\times STD+1.834\times LTD \tag{9}$$

4.4. Comparative Analysis of Model Prediction Effects

Table 2. Distance to default for sample companies.

Sample Name	DD value	Corrected DD	Sample Name	DD value	Corrected DD	Sample Name	DD value	Corrected DD
002781 The World Show	1.3319	-0.0520	000560 I love my home	2.5638	2.2176	000926 Fuxing shares	3.7294	22.1319
000616 ST Haitou	0.3267	-21.4186	000615 Ao Yuan Meigu	1.5255	1.0932	002285 WorldLink	1.8312	1.8141
002482 ST Guangtian	3.0256	0.9411	000620 Xinhualian	1.3583	-6.2771	600658 Electronic City	1.7695	0.5201
600807 Jinan High-Tech	1.3407	-4.6935	000631 Shunfa Hengye	2.6175	2.5115	600665 Tiandiyuan	1.3457	2.0833
600239 ST Yuncheng	1.1931	0.9926	000656 Jinke Co.	1.6281	-2.9111	000014 Shahe shares	1.5064	0.9306
603007 ST Kao	2.0990	-0.2021	000667 Beautiful Homes	1.3475	-0.0150	000507 Zhuhai Port	1.4204	0.9830
000732 ST Taihe	2.0296	-0.0469	000797 China Wuyi	2.6418	1.6085	000553 Andromeda A	2.0292	1.7796
002504 ST Honggao	1.0791	-5.8070	000838 Caixin Development	1.7181	0.9677	000608 Sunshine shares	1.8239	1.1381
002586 ST Weihai	1.9750	-2.5012	000863 Sanxiang Impression	2.2373	1.6561	000628 High-tech Development	2.2883	1.9706
Sample Name	**DD value**	**Corrected DD**	**Sample Name**	**DD value**	**Corrected DD**	**Sample Name**	**DD value**	**Corrected DD**
002781 *ST Chisin	1.9967	-1.6404	000886 Hainan Expressway	4.6900	4.6846	000668 Rongfeng Holdings	2.3270	1.4230
000505 Beijing Grain Holdings	0.8513	-0.0802	000918 Cascade City	1.3651	0.3668	000718 Suning Global	1.4595	1.3083
000909 Digital Source Technology	3.5805	2.3575	000092 Sinosteel International	1.3412	1.2990	002051 CIGI	3.4554	3.3322
002061 Zhejiang Jiaoke	4.4681	0.5472	000206 Hong Run Construction	2.0643	1.0501	002116 China Haicheng	2.7170	2.6759
002564 Tianwo Technology	1.7172	1.6432	002628 Chengdu Road and Bridge	2.1985	1.3141	002663 Pupang Stock	2.3962	1.9925
600094 Daimyo City	4.5221	0.6077	000711 Jinglan	1.4679	1.4235	--	--	--

By utilizing GARCH(1,1) to enhance the equity value volatility of the KMV model and GA genetic algorithm to improve the default points of listed companies in the sample, the goodness of fit is then tested. The α and β parameters of the modified KMV model, as well as the parameters given in the traditional KMV model (α=1, β=0.5), are substituted into the KMV model for the two groups of samples, respectively. Table 2 presents the statistical values of the default distance (DD) for the ST group, and the DD values before and after the correction for the non-ST group, along with the correctness level of judgments made on the samples before and after the correction.

Through a direct comparison of the above data, it is observed that when the default points are calculated using the traditional KMV model, the DD values of the default group are all greater than 0, resulting in an assessment accuracy rate of 0%. Conversely, for the healthy group, all DD values are also greater than 0. In contrast, considering the actual situation in 2021, the losses occurred for Xinhualian, Wonderful Property, Caixin Development, Cascade, and Shilian in the healthy group, yielding a comprehensive assessment correct rate of 84.8%. After the modification, the accuracy of the model for the default group reaches 81.8%, and for the healthy group, the assessment accuracy reaches 90.9%. The comparison demonstrates that the modified KMV model effectively distinguishes the varying levels of credit default risk between ST and non-ST enterprises. Additionally, the mean values of default distance for the ST class sample and non-ST class sample before the correction are 1.5680 and 2.2773, respectively. After the model correction, the mean values of default distance for the ST class sample and non-ST sample become -3.3171 and 1.8250, respectively, indicating significant differences between the two.

5. Conclusions

An accurate evaluation of credit risk in the real estate industry can offer valuable insights for government decision-makers and investors. This paper conducts an empirical study by selecting sample data from a total of 44 listed real estate companies spanning from 2016 to 2020. The study improves the equity value volatility in the KMV model using the GARCH model and simulates the optimal default point using the GA genetic algorithm.

The enhanced KMV model indicates that the credit risk assessment of the real estate industry becomes more accurate when the short-term debt coefficient is set to 1.013 and the long-term debt coefficient is set to 1.834. This improved model aids in better identifying the current credit risk status of enterprises and facilitates a more accurate evaluation of credit risk in the real estate industry. The new default point is more suitable for the credit risk analysis of the listed real estate enterprises in China. Moreover, it can be found that under the same conditions, the new default point of China's listed real estate enterprises is higher than the default point set by KMV companies, and the proportion of long-term liabilities in the default point is higher. The reasons are as follows:

First, the default point set by KMV companies ignores the characteristics of the industry. The real estate industry has the characteristics of large capital occupation and high debt level. Due to the real estate project, long development cycle, long cycle of capital recovery, the real estate enterprises are more biased and have good long-term liabilities. Therefore, the enterprises make more decisions on whether to default Long-term liabilities will be considered, and the short-term liabilities of real estate enterprises are a large amount of advance payment, which do not belong to the liabilities that need to be paid and pay interest.

Second, China's listed real estate enterprises have the implicit endorsement of the government and can bear higher risks. When the real estate enterprise cash flow problems, especially the large real estate enterprise capital problems, the government to reduce the impact on the society, through bank loans, mergers, and acquisitions to help enterprises through the crisis, which makes the real estate enterprises, less consider the default risk, and choose higher financial leverage to get higher returns.

Given the current economic recovery, the central government has recognized real estate as a "pillar industry of the national economy," and financial institutions continue to support the property market in China through investments. In this context, the real estate industry should exercise caution in addressing risk-related issues while moving forward. Only by maintaining steady development while effectively managing risks can the healthy growth of the market be promoted. Real estate is closely related to people's livelihood, and the government and related enterprises must pay attention to it.

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