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The Debt Default Prediction of Real Estate Enterprises Based on the Modified KMV Model

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Abstract: *In order to accurately measure corporate default risks of Chinese real estate enterprises and to solve the problem of insufficient adaptability of traditional KMV model, this paper takes 111 Shenwan real estate enterprises in 2020-2024 as samples and combines the "Three Redlines" regulatory framework. Firstly, the optimal correction logic is determined by using the ROC curve analysis method, which compares the multi-group measurement schemes of the expected asset growth rate and the default point, i.e. the expected asset growth rate is estimated by "the historical average asset growth rate of the previous two periods", and the default point is set as "short-term debt (DS) + 0.45 × long-term debt (DL)".At this time, the model prediction accuracy (AUC value) reaches 0.875, and the overall prediction accuracy is improved to 85.8%, which is significantly better than the traditional model and other schemes. Further comparing the effect of the model before and after the correction, it is found that the mean difference of the default distance between the "red orange grade (high risk)" and the "yellow green grade (low risk)" enterprises after the correction is expanded by 0.315, and the model's discrimination of risk identification is significantly enhanced. The empirical results of 17 representative China Securities real estate enterprises show that the average default distance of the industry in 2020-2024 decreased from 0.515 to 0.432 year by year, which confirms the trend of rising credit risk in the real estate industry. The research conclusions show that the modified KMV model is more suitable for the characteristics of Chinese real estate enterprises, and can provide quantitative tools and practical references for risk management and control of regulatory authorities, credit decision-making of financial institutions and risk management of real estate enterprises.*

Keywords: *Real Estate Enterprises; KMV Model; Default Prediction*

1. Introduction

As a pillar industry of the national economy, the real estate industry runs through dozens of upstream and downstream fields such as steel, building materials, and home appliances, and has a profound impact on the growth of the national economy. The input-output table shows that the real estate industry accounts for 9.6% of the total GDP in 2024. While the real estate industry promotes economic growth, it also carries the housing needs of urban residents. According to the National Bureau of Statistics, by the end of 2024, the national urban resident population had reached 944 million, and the urbanization rate was 67.00%. With the continuous advancement of urbanization, housing demand is still growing. The dual positioning of this economic attribute and social attribute determines the special significance of its stable development. The report of the 20th National Congress of the Communist Party of China clearly points out that it is necessary to "adhere to the positioning that the house is used for living, not for speculation, and accelerate the establishment of a multi-agent supply, multi-channel security, rent and purchase housing system." This positioning not only anchors the transformation direction of the industry from "scale expansion" to "quality improvement", but also implies the underlying requirements for "risk prevention". The Central Economic Work Conference held in the same year further pointed out that real estate has a "far-reaching" impact on economic growth, employment, fiscal and taxation income, residents' wealth, and financial stability. We must "adhere to overall development and security, and achieve high-quality development and high-level security. The benign interaction". This discussion directly points to the core contradiction of the industry: real estate is deeply bound to the financial system, and its debt scale accounts for more than 20% of the credit balance of the entire financial industry, and forms a complex risk transmission network through channels such as trusts, bonds, and pre-sale funds. Once the risk of debt default is out of control, it will not only impact the quality of bank credit, but also spread to the real economy through financial products, supply chain accounts and other paths, and even

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affect social stability.

In order to curb the accumulation of debt risk in the real estate industry from the source and solve the development dilemma of "high leverage", the regulatory authorities issued the "Three Redlines" financing supervision policy in August 2020, and constructed a targeted risk constraint framework: the three core indicators of "asset-liability ratio ≤ 70%, net debt ratio ≤ 100%, and cash short-debt ratio ≥ 1" after excluding pre-paid accounts are taken as the yardstick, and the number of red lines touched by enterprises is divided into four grades of red, orange, yellow and green. Corresponding to the growth control of differentiated interest-bearing liabilities, the interest-bearing liabilities of enterprises in the red grade (touching the Three Redlines) should not be added. The growth rate of orange gear (touch 2) is strictly controlled within 5%, the upper limit of yellow gear (touch 1) is 10%, and the green gear (no touch line) can be moderately relaxed to 15%. This policy directly cuts off the disorderly financing path of high-debt housing enterprises, becomes a key turning point in the industry's risk exposure, and also provides an authoritative regulatory basis for risk stratification. Under the dual constraints of "Three Redlines" and "no speculation in housing", the traditional "high leverage - high debt - high turnover" model of the industry has accelerated its failure, and structural problems have erupted in the transition period: housing companies generally face multiple pressures such as narrowed financing channels, low sales returns, and depleted liquidity reserves. The risk of default is accelerating and spreading. Over the past two decades, real estate enterprises have expanded rapidly through the cycle of "taking land-financing-preselling-retaking land". The average asset-liability ratio has remained above 80% throughout the year, and some enterprises have even exceeded 90%, far exceeding the 60% safety line of manufacturing [1]. This model can cover the cost of debt through rising house prices during the market's upswing, but when the "Three Redlines" policy tightens the financing gate in 2020, and the continued downturn in the sales side since 2021 has blocked returns, the vulnerability of the capital chain has exploded instantaneously, superimposing the concentrated outbreak of default risk since 2021 - from the successive defaults of the top 100 housing companies to the year-on-year increase in the number of defaults in 2022 by 68.2%, and the surge in the amount of tax arrears in 2023 by 65.2%, which has promoted the deepening of academic exploration of default risk measurement methods. Three mainstream paradigms of traditional statistical model, numerical simulation model and modern structured model are gradually formed.

From the early point of view, the risk measurement takes the traditional statistical model as the core, focusing on the financial indicators and macro variables to describe the financial vulnerability of real estate enterprises before default. Hu Sheng et al. (2018) [2] screened indicators from the five dimensions of debt repayment, profitability, operation, development and macroeconomics, and constructed a Logistic model to predict the default of listed housing enterprises. The accuracy rate was 82.7%; Wang Junzi et al. (2017) [3] further focused on the perspective of commercial bank credit, confirming the inhibitory effect of indicators such as the proportion of shareholders' equity and net operating cash flow on credit default, which echoes the reality that the average asset-liability ratio of real estate enterprises exceeds 80% and high leverage aggravates liquidity risk. However, such models rely on lagging financial statement data, and it is difficult to capture dynamic risks such as off-balance-sheet liabilities and limited pre-sale funds under the "Three Redlines" policy. The Logit stress test of An Qiangshen et al. (2016) [4] shows that when house prices fall and GDP growth slows, the traditional model has a prediction deviation of default rate of 15.3%, which cannot effectively adapt to the risk transmission chain of "sales downturn-repayment obstruction-capital chain rupture". In order to make up for the static defects of the traditional model, the numerical simulation model attempts to describe the risk through dynamic cash flow deduction. Chen Yang et al. (2009) [5] took "net cash flow is negative" as the default standard, and used Monte Carlo simulation to find that when house prices fell by more than 15%, the default probability of housing enterprises jumped from 5% to 32%, which provided a quantitative explanation for the surge in the number of industry defaults in 2022. Zhao Xin et al. (2014) [6] further introduced Wiener process to simulate the randomness of sales revenue and buyers' credit status, and improved the ability to identify the hidden risks of "high inventory and low turnover" housing enterprises. However, this kind of model requires high data frequency, needs monthly cash flow data support, is limited in the application of non-listed real estate enterprises, and the I2 model proposed by Yi Chuanhe et al. (2010) [7] does not include policy variables such as "Three Redlines", which is difficult to adapt to the new environment of deepening industry regulation after 2020. With the gradual improvement of the capital market, the KMV model based on option pricing theory has become a research hotspot in the measurement of default risk of real estate enterprises because it can reflect market expectations in real time. Yin Zhao et al. (2015) [8] compared the three models of Credit Metrics, KMV and Credit Portfolio View, and found that the KMV model has the best discrimination for the risk of real estate enterprises. The average default distance difference between high-performance and low-performance real estate enterprises is 2.64, and the fit

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between the prediction results and the credit rating of commercial banks is 78%. Zou Jin et al. (2012) [9] further constructed a hybrid model of "financial indicators + KMV variables", and the accuracy of early warning was 12.3% higher than that of a single financial model, which confirmed the complementary value of KMV model and financial data. Aiming at the problem that the standard KMV model adapts to mature markets and does not match the characteristics of "short-term debt pressure" of Chinese real estate enterprises, Wang Hui et al. (2018) [10] calibrated the default point with 147 listed real estate enterprises data, and found that the setting of "short-term debt + 0.42 × long-term debt" was 9.6% higher than the accuracy of the standard model; Zou Jin et al. (2012) [9] also tried to add industry-specific indicators such as inventory turnover rate and proportion of accounts received in advance to enhance the model's ability to identify hidden risks; Zheng Yong (2018) [11]confirmed through the dynamic stochastic general equilibrium model that the influence coefficient of macro variables such as house price and GDP on the asset value of housing enterprises is 0.35, suggesting that the KMV model needs to include policy impact factors. However, the existing amendments focus on a single parameter, do not form a system optimization framework of "default point + asset growth rate", and do not connect the regulatory logic of the "Three Redlines", which is difficult to meet the refined needs of industry risk prevention and control.

On the whole, although the existing research provides a methodological basis for the measurement of default risk of real estate enterprises, there are still four major gaps: First, the KMV model parameter correction is fragmented, and the two-dimensional optimization is not carried out for the characteristics of "short debt pressure and stable asset growth "of real estate enterprises; second, the sample grouping follows the "default / non-default" dichotomy, and does not combine the "Three Redlines" to solve the sample imbalance problem, making it difficult to achieve early risk warning; third, the cross-sectional data in the short term of three years are mostly used, which cannot describe the dynamic trend of increasing risk year by year from 2021 to 2023. Fourth, the application of the model is out of touch with the practical risk control, and the data bottlenecks such as insufficient disclosure of off-balance-sheet liabilities have not been solved, and the closed loop of "risk prediction-practical prevention and control" has not been formed. Based on these gaps, combined with the new characteristics of industry risk and the "Three Redlines" regulatory framework, the KMV model is systematically revised and applied to form the following possible marginal contributions: Firstly, this study constructs a two-dimensional localization optimization framework for the core parameters of the KMV model, combines the debt structure and growth characteristics of Chinese real estate enterprises, and simultaneously corrects the default point and the expected asset growth rate measurement method to improve the model industry suitability; secondly, it relies on the "Three Redlines" regulatory system to reconstruct the sample grouping logic, breaks through the limitations of the traditional dichotomy, solves the problem of scarcity and category imbalance of default samples, and strengthens the forward-looking nature of risk early warning. thirdly, using multi-period long-term panel data, the dynamic characterization path of industry credit risk is established to make up for the shortcomings of static cross-section data in trend analysis and provide support for long-term risk prevention and control; fourthly, this study builds a "model correction-risk prediction-practical prevention and control" connection mechanism, proposes solutions to the model's actual operation data requirements, and promotes the research results to the supervision and financial institutions' risk control scenarios.

2. Research Methods

2.1 KMV Model

In the real estate industry, corporate credit risk has significant cyclical and leverage amplification effects. Traditional static analysis methods based on financial indicators are often difficult to reflect the dynamic impact of market changes on default probability in time. Therefore, this paper introduces the KMV model derived from Merton's (1974) [12] option pricing idea, constructs a structured risk measurement framework with enterprise market asset value as the core and dynamic default probability as the output, and embeds it into the default prediction system. The core idea of the KMV model is to regard the assets of the enterprise as a basic asset and the equity of the enterprise as a European call option on the assets of the enterprise. By estimating the asset value and asset volatility of the enterprise, the KMV model can calculate the default distance DD of the enterprise, and then calculate the expected default probability EDF for a period of time in the future.

The KMV model assumes that the asset value V_t of the enterprise follows a lognormal distribution over time, which follows the following stochastic differential process:

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$$dV_t = \mu V_t dt + \sigma_V V_t dW_t \tag{1}$$

Among them, μ represents the expected return rate of assets, σ_V is the volatility of assets, and W_t is the standard Brownian motion, which is used to reflect the uncertainty and continuity of asset prices. When the enterprise faces a debt that will expire at the future time T and the face value is D, if $V_t < D$, the enterprise's assets are insufficient to cover the debt, and the enterprise defaults at this time.

The shareholders of the enterprise can exercise the residual claim only when the asset value is greater than the debt level, and their rights and interests are essentially equivalent to a European call option with a due execution price of D and a target of V_t. Under the risk-neutral pricing framework, the value of the European call option at the current time point (t = 0) is the market value of the company's equity, which can be further expressed as:

$$E_0 = V_0 N(d_1) - De^{-rT} N(d_2) \tag{2}$$

$$d_1 = \frac{\ln\left(\frac{V_0}{D}\right) + \left(r + \frac{1}{2}\sigma_V^2\right)T}{\sigma_V\sqrt{T}}, d_2 = d_1 - \sigma_V\sqrt{T} \tag{3}$$

In the formula, E_0 is the equity value, V_0 is the asset value of the current enterprise, r is the risk-free interest rate level, T is the maturity time, and N (·) is the cumulative distribution function of the standard normal distribution.

In fact, V_0 and σ_V cannot be directly observed in reality, so the KMV model introduces the estimation relationship of equity volatility as a supplementary condition. At this time, according to the Ito lemma, the relationship between the equity volatility σ_E and the asset volatility satisfies the following relationship:

$$\sigma_E E_0 = \frac{\partial E_0}{\partial V_0} \cdot \sigma_V V_0 \tag{4}$$

According to Eq. (2), the partial derivative can be obtained:

$$\frac{\partial E_0}{\partial V_0} = N(d_1) \tag{5}$$

Substitute into the above formula to get:

$$\sigma_E E_0 = N(d_1) \cdot \sigma_V V_0 \tag{6}$$

At this time, the formula (2) and (6) together constitute a nonlinear equation group, and further combine the market observable stock price and volatility (E_0, σ_E) to carry out numerical iteration, and reversely derive the estimated values of V_0 and σ_V. After obtaining the asset value parameter, combined with the solution of the geometric Brownian motion, the asset value of any time t in the future can be expressed as:

$$V_t = V_0 \cdot \exp\left[\left(\mu - \frac{1}{2}\sigma_V^2\right)t + \sigma_V\sqrt{t} \cdot \varepsilon\right], \varepsilon \sim N(0,1) \tag{7}$$

Further, we can derive the default probability of the enterprise at the maturity point T, that is, the probability that the asset value falls below the debt face value D:

$$EDF = P(V_t < D) = P\left(\varepsilon < \frac{\ln\left(\frac{D}{V_0}\right) - \left(\mu - \frac{1}{2}\sigma_V^2\right)T}{\sigma_V\sqrt{T}}\right) \tag{8}$$

In order to standardize the expression, the default distance (DD) is introduced and defined as:

$$DD = \frac{\ln\left(\frac{D}{V_0}\right) - \left(\mu - \frac{1}{2}\sigma_V^2\right)T}{\sigma_V\sqrt{T}} \tag{9}$$

The probability of default at this time can be further rewritten as:

$$EDF = N(-DD) \tag{10}$$

In the formula, DD represents the standard deviation multiple of the current asset value exceeding the default point, which is the core index to measure the enterprise credit safety margin. EDF is the final output variable of the KMV model, which is used to measure the probability of default of enterprises in

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a certain period of time in the future. Compared with the static scoring model based on book financial data, the KMV model is based on market data and can timely reflect the risk exposure changes of credit risk in the real estate industry due to policy tightening, changes in the financing environment or fluctuations in market expectations. In this paper, the EDF calculated by the KMV model will be used as one of the core input variables, combined with policy constraints (three red lines), financial indicators, etc., to jointly build a multi-modal default prediction system to improve the sensitivity and forward-looking recognition ability of the model to the credit risk of real estate enterprises.

2.2 Default Distance Correction

2.2.1 Selection of Default Group and Control Group

This paper selects 111 listed real estate enterprises in the Shenwan Real Estate Index constituent stocks from January 1,2020 to December 31,2024 as research samples. According to the regulatory standards of the "Three Redlines" in the real estate industry (excluding the asset-liability ratio, net debt ratio and cash short-term debt ratio after pre-collection), it is initially divided into four grades of "red, orange", "yellow and green" according to the number of "stepping on the line" of the enterprise, and then the samples are merged and grouped based on the principle of homogeneity of risk characteristics. From the perspective of risk attributes, "red and orange" real estate enterprises have formed systematic financial vulnerability because they trigger two or more red lines: such enterprises generally face the common dilemma of strictly limited financing growth (orange ≤ 5%, red file cannot be added), weakened cash flow generation ability and narrowed debt rolling space. The default risk stems from the fundamental contradiction between high leverage mode and financing constraints, and the risk characteristics are highly convergent; However, "yellow and green" housing enterprises (yellow grade stepping on a red line, green grade zero stepping line) retain a certain financing elasticity (yellow grade ≤ 10%, green grade ≤ 15%), which can buffer short-term pressure through sales refund or new financing, and the underlying logic of financial robustness is more consistent. In summary, this study finally merged the samples into two categories: "red orange grade (high risk group)" and "yellow green grade (low risk group)".

2.2.2 Parameter Determination

▪ Equity value: The average value of the daily stock closing price of listed companies during the study period is multiplied by the total equity, that is, equity value = the average daily closing price × the total equity of listed companies.

▪ Risk-free interest rate: the arithmetic mean of long-term treasury bond interest rate in the past ten years is selected as the benchmark, and the risk-free interest rate is determined to be 5% (0.05).

▪ Asset value and asset volatility: the calculation is completed by Matlab software. The specific steps are as follows: the asset value is calculated according to the formula of "equity value + book liability";

1) Calculate the logarithmic return rate based on the daily closing price of the stock (using the LN function, that is $ln(Pt/Pt-1)$), and derive the asset return rate through the Taylor series expansion;

2) Using the sample standard deviation method (std function in Matlab) to calculate the daily volatility of assets;

3) The daily volatility is annualized by the square root method (SQRT function) (multiplied by the square root of the number of trading days in the year) to obtain the annual volatility of the asset.

2.2.3 Modification of Default Distance (DD)

In order to optimize the calculation logic of the expected asset growth rate in the KMV model and improve the accuracy of the risk characterization of the real estate enterprise by the default distance (DD), this study designs three estimation schemes of the expected asset growth rate and carries out the effect test. The specific process is as follows: combined with the correlation characteristics of the real estate enterprise's asset growth and historical operating performance and profit level, three types of measurement paths are set: Firstly, the expected asset growth rate is set to 0 by using the simplified hypothesis, and the default distance is calculated based on this and recorded as DD_0. The scheme is the conventional setting of the traditional KMV model for reference; secondly, the expected value is estimated by the historical average asset growth rate. Taking the current period as the t period, the arithmetic average of the book asset growth rate of the first two periods (t-1 period, t-2 period) is selected as the expected asset growth rate, and the corresponding default distance is recorded as DD_1. This scheme aims to incorporate the historical inertia of enterprise asset growth and adapt to the industry

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attributes of stable project development cycle and continuous asset growth of real estate enterprises. Thirdly, the expected asset growth rate is fitted with the net income growth rate (net income growth rate = current retained earnings increase / initial net assets), and the default distance is calculated and recorded as DD_2, trying to indirectly reflect the asset expansion expectation through the profit growth potential of the enterprise. Then, in order to test the effectiveness of the three types of schemes, the default distance measured in three cases (the default point DP is uniformly set by the traditional setting, that is, DPT = short-term debt DS + 0.5 × long-term debt DL) is used as the input variable. The ROC curve analysis method is used to evaluate the prediction accuracy of the model, and the AUC value (area under the curve) is used as the core evaluation index (the closer the AUC value is to 1, the stronger the risk discrimination ability of the model). The empirical results show that (see Fig.1), the AUC values of, DD_1, $DD_2$are 0.857, 0.875 and 0.761, respectively. Among them, the scheme of estimating the expected asset growth rate with the historical average asset growth rate of the previous two periods (DD_1) performs best, and the AUC value is significantly higher than the other two schemes. The net income growth rate fitting scheme (DD_2) is disturbed by short-term profit fluctuations (such as project settlement rhythm differences, temporary effects of policy subsidies, etc.), and the fitting degree of the long-term growth trend of assets is low, resulting in the worst prediction effect.

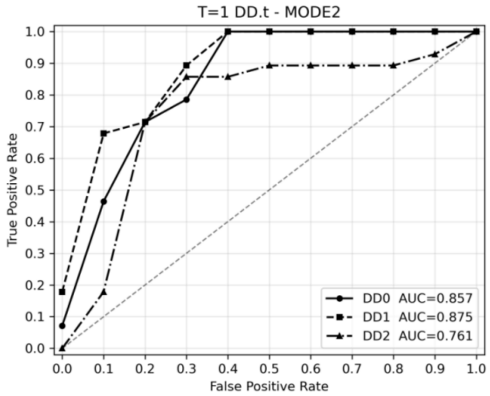

Figure 1: The Accuracy (AUC) of the Model under Three Asset Growth Rates.

On the basis of determining the expected asset growth rate based on the historical average asset growth rate of the first two periods, this study further modifies the default point (DPT). The default point of the traditional KMV model is “short-term debt (DS) + 0.5 × long-term debt (DL)” , but the debt structure of Chinese real estate enterprises’ short-term debt pressure concentration and long-term debt rollover limitation may lead to this setting deviation. Therefore, the long-term debt coefficient is optimized by traversal test. The specific process and results are as follows: Firstly, the test interval of long-term debt coefficient is set to be 0.05-1.0. Twenty values (0.05,0.1,0.15... 1.0) were selected at an interval of 0.05, and substituted into the default point formula ($DPT = DS + \lambda \times DL$, λ is the long-term debt coefficient). Combined with the determined “historical average asset growth rate” , the AUC values corresponding to each coefficient under the five time dimensions of 2020 (T = 1), 2020-2021 (T = 2), 2020-2022 (T = 3), 2020-2023 (T = 4), 2020-2024 (T = 5) were calculated (model prediction accuracy). The results are shown in Table 1.

Table 1 Accuracy under Different Default Points

T=1	Point of default	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5
	AUC under historical average growth rate	0.745	0.794	0.827	0.836	0.843	0.851	0.853	0.856	0.858	0.859
	Point of default	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95	1.00
	AUC under historical average growth rate	0.858	0.858	0.858	0.861	0.86	0.859	0.86	0.86	0.86	0.86
T=2	Point of default	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5
	AUC under historical average growth rate	0.715	0.76	0.788	0.796	0.807	0.811	0.813	0.814	0.812	0.812
	Point of default	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95	1
	AUC under historical average growth rate	0.812	0.809	0.809	0.809	0.806	0.806	0.805	0.805	0.804	0.803
T=3	Point of default	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5
	AUC under historical average growth rate	0.699	0.74	0.762	0.774	0.776	0.782	0.785	0.785	0.785	0.787
	Point of default	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95	1

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	AUC under historical average growth rate	0.786	0.787	0.786	0.785	0.787	0.787	0.788	0.787	0.786	0.787
T=4	Point of default	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5
	AUC under historical average growth rate	0.706	0.744	0.765	0.769	0.774	0.775	0.778	0.778	0.777	0.775
	Point of default	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95	1
	AUC under historical average growth rate	0.776	0.777	0.774	0.773	0.772	0.769	0.768	0.767	0.766	0.766
T=5	Point of default	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5
	AUC under historical average growth rate	0.716	0.743	0.752	0.757	0.757	0.721	0.718	0.718	0.716	0.713
	Point of default	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95	1
	AUC under historical average growth rate	0.714	0.714	0.71	0.711	0.709	0.707	0.707	0.704	0.703	0.703

From a single period of time, in the data of T = 1 (2020), the AUC value reaches 0.861 when the long-term debt coefficient is 0.7, which is the highest in this period; however, the cross-period stability analysis shows that the optimal coefficients in different periods are different (for example, the optimal coefficient of T = 2 is 0.4, and that of T = 3 is 0.85), which needs to be further screened by the mean stability of the comprehensive 5-year data. After averaging the AUC values of each coefficient in the period of T = 1-T = 5, it is found that when the long-term debt coefficient is 0.45, the 5-year AUC values are 0.858 (T = 1), 0.812 (T = 2), 0.785 (T = 3), 0.777 (T = 4), 0.716 (T = 5), respectively. The mean value is significantly higher than other coefficients, and the annual AUC value fluctuates less, reflecting better cross-cycle stability.

Combined with the test results of the previous expected asset growth rate (the historical average asset growth rate corresponds to the highest AUC value), the core parameters of the revised KMV model are finally determined: the expected asset growth rate is measured by the historical average asset growth rate of the previous two periods, and the default point is set as "short-term debt + 0.45 × long-term debt". Sexuality.

In order to verify the effect of parameter correction on the risk identification ability of KMV model, this study takes 111 Shenwan real estate enterprises as samples to compare the difference of default distance (DD) between "red orange file (high risk group)" and "yellow green file (low risk group)" under the original model (default point $\lambda = 0.5$) and the modified model (default point $\lambda = 0.45$, expected asset growth rate taking the historical average of the first two periods). In the original model, X_0 denotes the mean value of the default distance of the red and orange companies, and X_1 denotes the mean value of the default distance of the yellow and green companies. In the modified model, Y_0 represents the mean of the default distance of the red and orange companies, and Y_1 represents the mean of the default distance of the yellow and green companies. From the descriptive statistical results (as shown in Table 2), it can be seen that both models can initially identify the differences between high and low risk groups. Whether it is the original model or the modified model, the average default distance of yellow-green companies (the original model X_1= 3.913, the modified Y_1= 4.604) is significantly higher than that of red-orange companies (the original model X_0= -0.848, the modified Y_0= -0.471), and the average default distance of red-orange companies is negative. This result conforms to the core logic of "the smaller the default distance, the higher the default risk". It is confirmed that the KMV model can effectively distinguish the credit status differences between the two types of risk groups through the data of the year before the default of the enterprise.

Table 2 Statistical Analysis of Four Groups of Default Distance

Variable	Amount of Observations	Mean Value	Standard Deviation	Minimum Value	Maximum Value
X_0	111	-0.848	1.91	-5.475	2.41
X_1	111	3.913	4.93	-4.706	21.946
Y_0	111	-0.471	1.971	-5.108	3.011
Y_1	111	4.604	4.925	-2.924	22.847

By further comparing the effects of the model before and after the correction, the core differences are reflected in the "difference of default distance between high and low risk groups" and "standard deviation": under the original model, the average difference of default distance between yellow-green and red-orange is 4.761 (3.913- (-0.848)), while the difference of the revised model is expanded to 5.075 (4.604- (-0.471)), and the difference is 0.314 higher than that before the correction, indicating that the revised model has a clearer risk stratification of "low risk (yellow-green)" and "high risk (red-orange)" enterprises. The discrimination of risk identification is significantly improved; at the same time, the standard deviation of the default distance of the modified model has been expanded (the red and orange

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file has increased from 1.91 to 1.971, and the yellow and green file has been fine-tuned from 4.93 to 4.925), which means that the model is more accurate in depicting the individual credit status differences of enterprises in the same risk group, reducing the “average” masking of enterprise risks by the original model.

In summary, whether it is from the change of the mean difference of the default distance between the high and low risk groups, or from the change of the standard deviation reflecting the individual risk difference, the modified KMV model (default point λ = 0.45 + the historical average asset growth rate of the first two periods) is superior to the original model, which effectively improves the measurement and identification ability of credit risk of real estate enterprises.

3. Using the Modified KMV Model to Measure the Credit Risk of Real Estate Enterprises

In order to further verify the practical application value of the modified KMV model, this study selects 17 representative enterprises in the CSI real estate index component as samples (including Poly Development, Vanke A and other head real estate enterprises and * ST Zhongdi and other risk-based enterprises). The expected asset growth rate is estimated by using the historical average asset growth rate of the first two periods, and the default point is set by “DPT = DS + 0.45DL” to measure the default distance (DD) of each enterprise from 2020 to 2024. The results are shown in Table 3.

Table 3 China Securities Refer to the Default Distance of Listed Companies in the Real Estate Industry

Observation Number	Enterprise Name	DD				
		2020	2021	2022	2023	2024
1	Everbright Jiabao Co., Ltd	0.667	0.529	0.555	0.498	0.492
2	Grandjoy Holdings Group Co., Ltd	0.472	0.475	0.400	0.376	0.364
3	Shenzhen New Nanshan Holding (Group) Co.,Ltd	0.433	0.434	0.468	0.436	0.443
4	Shenzhen Overseas Chinese Town Co.,Ltd	0.454	0.455	0.375	0.376	0.367
5	Poly Developments And Holdings Group Co., Ltd	0.421	0.419	0.390	0.389	0.375
6	Cinda Real Estate Co., Ltd	0.549	0.550	0.548	0.490	0.464
7	5I5J Holding Group Co., Ltd	0.702	0.702	0.543	0.507	0.489
8	Gemdale Corporation	0.571	0.570	0.494	0.488	0.467
9	China Vanke Co., Ltd	0.447	0.446	0.382	0.380	0.365
10	Seazen Holdings Co., Ltd	0.499	0.499	0.494	0.483	0.458
11	Hangzhou Binjiang Real Estate Group Co., Ltd	0.523	0.522	0.496	0.451	0.425
12	Shanghai Wanye Enterprises Co., Ltd	0.524	0.526	0.494	0.510	0.529
13	Guangzhou Pearl River Industrial	0.524	0.525	0.494	0.484	0.466
14	Zhuhai Huafa Properties Co., Ltd	0.438	0.436	0.456	0.424	0.398
15	China Merchants Shekou Industrial Zone Holdings Co.,Ltd	0.464	0.461	0.411	0.394	0.376
16	China City Investment Holdings Limited	0.493	0.495	0.371	0.332	0.316
17	Cred-Chongshi Real Estate Co.,Ltd	0.577	0.578	0.631	0.576	0.552

From the calculation results, the default distance of 17 sample real estate enterprises shows a significant annual trend: the average default distance in 2020 is 0.515, which is the highest in 5 years; in 2021, it will be slightly reduced to 0.507; in 2022, it will further fall to 0.47; in 2023 and 2024, it continued to decline, with 0.447 and 0.432 respectively, showing a decreasing trend year by year. According to the core logic of the KMV model-the smaller the default distance, the higher the probability that the value of the enterprise’s assets falls below the default point, that is, the greater the credit risk. This trend shows that the credit risk of the sample housing enterprises continues to rise from 2020 to 2024, and the financial robustness gradually deteriorates. It should be noted that the selected samples are large listed companies with market influence in the real estate industry, and their operating conditions and risk changes are highly representative of the overall situation of the industry. Therefore, it can be inferred from the decreasing default distance of sample housing enterprises that the credit risk situation of China’s real estate industry has deteriorated in the past five years, which is consistent with the tightening of financing under the “Three Redlines” policy. The fact that the continuous downturn in the sales side leads to the accumulation of liquidity pressure in the industry is consistent with the reality, which further confirms the effectiveness of the modified KMV model in depicting the risk trend of the industry.

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4. Main Conclusions and Policy Recommendations

4.1 Main Conclusions

In this study, 111 real estate enterprises in China are taken as samples, and the localization optimization of KMV model and the measurement of default risk of real estate enterprises are studied. The core conclusions are as follows: Through the ROC curve analysis method, the expected asset growth rate measurement scheme and the default point setting are compared and tested in multiple dimensions, and the optimal scheme of the modified KMV model is finally determined: The expected asset growth rate is estimated by the "historical average asset growth rate of the first two periods", and the default point is set as "DPT = short-term debt (DS) + 0.45 × long-term debt (DL)" , under this correction scheme. The prediction accuracy of the model is 85.8%. Compared with the traditional KMV model and other measurement schemes, the recognition ability of credit risk of real estate enterprises is significantly improved, which effectively solves the problem that the traditional model adapts to the debt characteristics and growth attributes of Chinese real estate enterprises. Further, taking 17 representative listed companies in the China Securities Real Estate Index as the research object, using the modified KMV model to measure their default distance in 2020-2024, it is found that the average default distance of the sample enterprises has decreased from 0.515 in 2020 to 0.432 in 2024 year by year. Combined with the negative correlation between default distance and credit risk, it can be clear that the credit risk of China's real estate industry continued to rise from 2020 to 2024. This conclusion is consistent with the realistic background of industry financing tightening and sales repayment pressure under the "Three Redlines" policy, which provides a quantitative basis for grasping the risk dynamics of the industry and formulating targeted prevention and control measures.

4.2 Policy Recommendations

Based on the empirical conclusion of the modified KMV model and the credit risk characteristics of the real estate industry, in order to accurately prevent and control risks and promote the steady development of the industry, the following suggestions are put forward from the three core dimensions of regulatory authorities, financial institutions and real estate enterprises:

- Strengthen risk stratification control and improve the data disclosure system.

Establish a "red-orange-yellow-green" dynamic monitoring mechanism, take the default distance of the revised KMV model as the core indicator, and build a real estate enterprise risk rating system combined with the "Three Redlines".Regulatory authorities intensify monitoring of debt rollover and pre-sale fund use for "red-orange" high-risk enterprises, and intervene in advance in liquidity-stressed enterprises.

- Optimize the logic of credit approval and strengthen the application of risk early warning.

Incorporate the revised KMV model into the entire credit approval process. Financial institutions may refer to the logic of "default point = short-term debt + 0.45 × long-term debt + historical average asset growth rate" as an important basis for credit line approval and interest rate pricing. Financial institutions strictly limit new credit to "red-orange" high-risk enterprises and reasonably determine the credit scale for "yellow-green" enterprises. They regularly update industry risk indicators to support dynamic risk control strategy adjustments.

- Optimize the debt structure and enhance the ability to resist risks.

Guide "red-orange" high-risk enterprises to adjust their debt structure through debt extension, debt-to-equity swaps and asset disposal, reduce the proportion of short-term debt, and replace it with long-term low-interest funds to bring the asset-liability ratio closer to the "Three Redlines" safe range. Real estate enterprises may refer to the "historical average asset growth rate of the previous two periods" to rationally plan land acquisition, construction and sales rhythms, avoid blind expansion, and improve default distance and risk resistance through stable asset growth.

References

[1] ZHANG Xinmin, HAN Zixuan. Debt-to-Asset Ratio and Corporate Debt Repayment Risk —Based on Debt Structure and Asset Quality[J]. Research on Economics and Management, 2025,46(04): 134-144.
[2] HU Sheng, LEI Huan-huan, HU Hua-qiang. Research on Credit Risk Measurement of China's Real

ISSN 2616-5902 Vol. 7, Issue 11: 1-10, DOI: 10.25236/AJBM.2025.071101

Estate Enterprises Based on Logistic Model[J]. China Soft Science, 2018, (12): 157-164.

[3] WANG Junzi, LIU Lantao. Research on Real Estate Credit Risk of Commercial Banks in China Based on Logistic Model[J]. Review of Economy and Management, 2017, 33(02): 86-95.

[4] AN Qiang-shen, JIANG Zhan-ying .Risk Controllable or Eve-of-Crisis?———Social Financing Risk Pressure Test of Real Estate Based on Logit Model [J]. Journal of Yunnan University of Finance and Economics, 2016, 32(02): 119-127.

[5] CHEN Yang, CHEN Shuang jie. Stress Testing on Default Probability of Real Estate Development Enterprises ———The Application of Monte Carlo Simulation of Cash Flow in Commercial Banks[J]. Journal of Modern Finance, 2009, 14(04): 37-42.

[6] ZHAO Xin, LI Ming-bao. Measuring the Default Rate of Chinese Listed Real Estate Companies Based on Cash Flow Simulation [J]. Systems Engineering, 2014, 32(09): 19-27.

[7] Yi Chuanhe, Xue Shan. Measurement of Expected Default Rate of China 's Real Estate Listed Companies by I2 Model [J].Seek, 2010, (08): 20-22.

[8] YIN Zhao, HAN Jia-fei. An Empirical Analysis and Comparative Study of Credit Risk Models [J]. Journal of Central University of Finance & Economics, 2015, (S2): 23-30.

[9] Zou Jin, Wang Dabo. Research on Credit Risk Evaluation of China 's Real Estate Listed Companies-Empirical Analysis Based on Mixed Model [J]. Journal of Southwest Minzu University (Humanities and Social Sciences Edition), 2012,33 (11): 109-114.

[10] WANG Hui, ZHANG Guo-jun. The Application of KMV Model in Chinese Listed Real Estate Companies Credit risk Measurement [J]. On Economic Problems, 2018, (03): 36-40.

[11] ZHENG Yong. Credit risk, Housing Price and Macroeconomic Fluctuation [J]. Jinan Journal (Philosophy & Social Science Edition), 2018, 40(07): 24-37.

[12] ROBERT C MERTON. On the pricing of corporate debt: The risk structure of interest rates [J]. The Journal of finance, 1974, 29(2): 449-470.