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# Credit Default Risk Assessment of Listed Real Estate Firms Using the KMV Model

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**Abstract**

This study examines the credit default risk of Chinese listed real estate firms using the KMV structural credit risk model, with particular attention to market-based risk assessment and the limitations of conventional credit ratings. Drawing on data from 261 real estate firms listed on mainland China's A-share markets and the Hong Kong Stock Exchange between 2010 and 2023, the study estimates distance to default (DD) from equity market information and financial statement data. A logistic regression approach is employed to translate DD into estimated default probabilities, while receiver operating characteristic (ROC) analysis and firm-level case studies are used to evaluate risk discrimination and early-warning performance. The results reveal a substantial deterioration in the creditworthiness of mainland-focused property developers during the industry downturn, particularly in 2022–2023, alongside pronounced differences between mainland and non-mainland firms. The DD measure achieves an area under the ROC curve (AUROC) of 0.760, indicating moderate discriminatory ability within the evaluated sample. Comparative case studies further suggest that market-based risk indicators can provide more frequent signals of financial deterioration than conventional credit ratings, although their predictive reliability depends on appropriate calibration and validation. The findings highlight the potential of the KMV model as a supplementary instrument for credit risk monitoring while emphasizing the need for improved probability calibration, rigorous out-of-sample validation, and integration with firm-level and macroeconomic indicators.

**Keywords:** KMV Model, Credit Default Risk, Real Estate Firms, Distance to Default (DD), Expected Default Frequency (EDF), Credit Risk Early Warning, China

## 1. Introduction

Over the past two decades, the real estate sector has been one of the major pillars of China's economic growth. Hong (2023), China's Minister of Housing and Urban-Rural Development, highlighted the sector's economic significance through the "40–50–60" figures: real estate-related loans account for approximately 40% of total bank credit, real estate-related revenues contribute around 50% of local governments' comprehensive fiscal resources, and housing assets constitute approximately 60% of Chinese households' wealth. These figures underscore the systemic importance of the real estate sector, suggesting that developments in this industry can have far-reaching implications for the broader economy.

Real estate serves not only as an essential component of household consumption but also as an investment asset, with strong linkages to the credit system. Since the implementation of China's housing system reform in 1998, the commercial housing market has experienced rapid expansion. During this period, real estate developers increasingly relied on business models characterized by housing presales, intensive cash flow management, and highly leveraged financing, thereby creating conditions conducive to the accumulation of speculative pressures and potential asset price bubbles. In response to growing concerns over housing market speculation and financial instability, the Chinese government introduced the principle that "housing is for living in, not for speculation" at the Central Economic Work Conference in late 2016. Subsequently, in 2020, the People's Bank of China and the China Banking and Insurance Regulatory Commission, together with other relevant authorities, introduced the "Three Red Lines" policy to impose stricter financial constraints on real estate developers. These regulatory measures were intended to curb speculative activities in the property market, contain the accumulation of housing market bubbles, and mitigate systemic financial risks.

Since 2021, however, numerous real estate developers in China have experienced widespread debt defaults, resulting in the failure to deliver a substantial number of presold residential properties and generating

far-reaching socioeconomic consequences (Ronghao, 2022). Drawing on historical experiences of real estate bubbles, Qushi et al. (2022) conducted a statistical analysis of 22 real estate bubble episodes across 15 countries over the past five decades. Their findings indicate that more than 40% of these episodes were associated with the transmission of financial risks to the banking sector, ultimately triggering systemic banking crises. Against this backdrop, assessing the credit default risk of real estate firms is of critical importance for monitoring and preventing real estate crises and mitigating the transmission of financial risks to the banking system.

Existing credit rating agencies in China exhibit considerable delays in adjusting their credit ratings, often downgrading firms only after a default has occurred (Figure 1). Compared with traditional credit scoring models that primarily rely on financial indicators, the KMV model incorporates equity market information into the assessment of credit risk, offering a more forward-looking and dynamic perspective. Using the KMV model, this study estimates the distance to default (DD) of real estate developers listed on the Chinese mainland A-share and Hong Kong stock markets, evaluates the model's ability to rank firms according to their credit risk, and compares its early warning performance with that of domestic credit rating agencies.

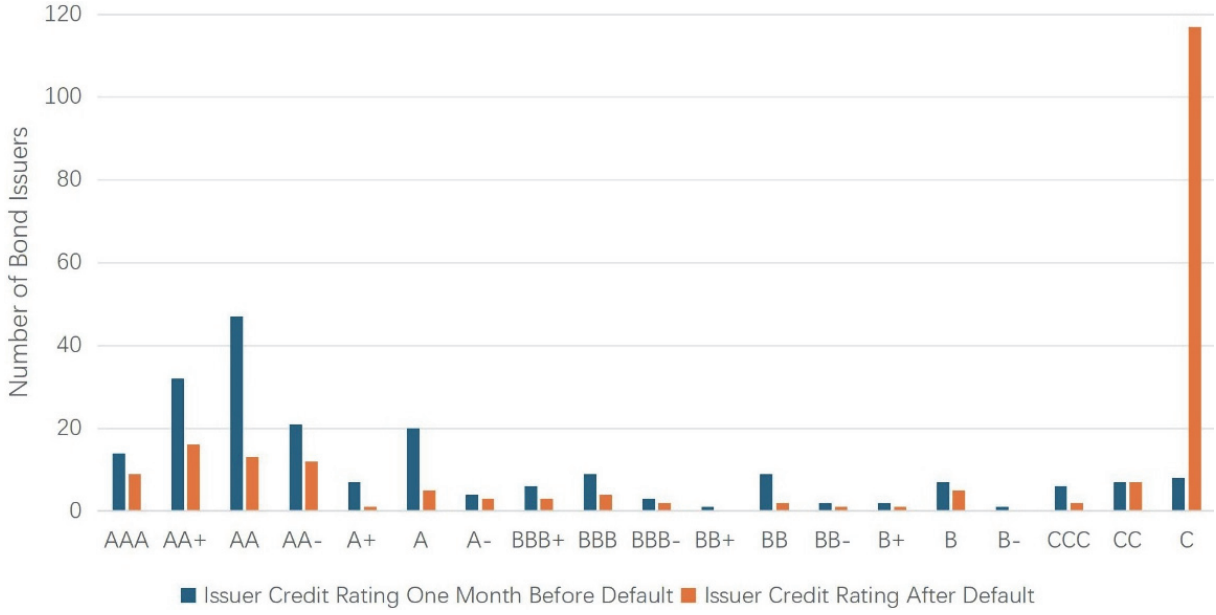



Figure 1. Distribution of Issuer Credit Ratings Before and After Bond Defaults (January 1, 2014–December 15, 2025)

Note. Figure 1 illustrates a comparison of the credit ratings of 206 bond issuers one month prior to their first bond default and after the default over the past decade (excluding issuers lacking pre- and post-default rating records).

Data source: East Money Choice database and authors' compilation.

## 2. Literature Review

### *2.1 Credit Risk Assessment Models*

With the rapid development of capital markets and advances in information technology, big data analytics, and artificial intelligence, credit risk assessment has undergone substantial methodological development. Earlier approaches relied heavily on expert judgment and conventional credit scoring, whereas subsequent studies increasingly incorporated financial statements, market information, macroeconomic indicators, and large-scale multidimensional data into quantitative risk assessment. A variety of models have consequently been developed, including KMV, CreditMetrics, Credit Portfolio View, CreditRisk+, Logistic regression, and more recent machine learning methods. These approaches differ considerably in their theoretical foundations, information requirements, modeling mechanisms, interpretability, and predictive performance.

Among the most influential credit risk assessment approaches, the KMV model provides a market-based framework for estimating corporate default risk. Building on the Black–Scholes–Merton option-pricing framework, the model treats a firm's equity as a contingent claim on the value of its underlying assets and relates default risk to asset value, asset volatility, and the firm's liability structure. A central concept of the KMV framework is the distance to default, which measures the distance between the estimated market value of a firm's assets and its

default point. This distance is subsequently mapped into an expected default frequency (EDF) using empirical default information (Dwyer et al., 2004).

Compared with approaches relying primarily on accounting information, the KMV model incorporates forward-looking market information, particularly equity values and stock-price volatility, and can therefore capture changes in corporate creditworthiness more dynamically. This enables the model to identify deteriorating credit conditions that may not yet be fully reflected in financial statements. However, its effectiveness depends heavily on the availability and reliability of market information. The model is therefore more readily applicable to publicly listed firms with actively traded securities, whereas its application to private firms and small and medium-sized enterprises is more challenging because their market values and asset volatility are not directly observable. Despite these limitations, the KMV model remains one of the most influential approaches to corporate default risk measurement.

CreditMetrics provides a different perspective by focusing on changes in the value of credit-sensitive instruments caused by default and credit-rating migration. The model uses information on credit ratings, transition probabilities, recovery rates, credit spreads, and correlations among borrowers to estimate the distribution of future portfolio values and corresponding credit risk measures (J.P. Morgan, 1997). Its major advantage lies in its ability to incorporate changes in credit quality before default occurs. However, its results are sensitive to the accuracy of transition matrices, recovery assumptions, and correlation estimates, while the calculation process may become relatively complex for large portfolios.

Credit Portfolio View places greater emphasis on the relationship between credit risk and macroeconomic conditions. Wilson (1998) argues that default probabilities and credit-rating transitions vary with the business cycle rather than remaining constant over time. Accordingly, the model links credit migration probabilities to macroeconomic variables and simulates their evolution under different economic scenarios. This approach is particularly useful for capturing cyclical variations in credit risk. Nevertheless, its performance depends on the appropriate selection of macroeconomic variables and the accuracy with which their relationships with default risk are specified.

CreditRisk+ adopts an actuarial perspective and concentrates primarily on the frequency and severity of default losses. It models the occurrence of defaults using Poisson-type processes and aggregates individual exposures to derive the overall portfolio loss distribution (Credit Suisse Financial Products, 1997). The framework is relatively straightforward and computationally efficient, making it suitable for portfolio loss estimation. However, its simplifying assumptions may limit its ability to represent complex dependence structures and changes in borrower credit quality prior to default (Gordy, 2000).

Logistic regression has also been widely employed in credit scoring and default probability estimation. It estimates the probability of default or non-default based on a set of borrower characteristics and provides an explicit relationship between explanatory variables and credit outcomes (Hosmer et al., 2013). Its main advantages are computational simplicity, transparency, and ease of interpretation, which are particularly important in financial applications requiring model validation and explanation. Nevertheless, conventional Logistic regression may be less effective when default risk is driven by complex nonlinear relationships or high-order interactions that are not explicitly specified in the model.

As the volume and dimensionality of available credit data have increased, machine learning techniques have become increasingly prominent in credit risk assessment. Support vector machines (SVM), for example, can employ kernel functions to capture nonlinear relationships in high-dimensional feature spaces and have demonstrated strong classification performance (Cortes & Vapnik, 1995). Their effectiveness, however, can be sensitive to kernel selection and parameter tuning, while their results are less straightforward to interpret than those of conventional regression models.

Artificial neural networks (ANN) use multilayer nonlinear transformations to identify complex relationships among predictors and outcomes (Hill et al., 1994). Their flexible structure allows them to model patterns that may be difficult to capture with traditional statistical specifications. However, ANN models generally require substantial model tuning and computational resources, and their limited interpretability may constrain their application in credit decisions that require clear explanations.

Random forests (RF) improve predictive stability by combining multiple randomized decision trees and aggregating their predictions (Breiman, 2001). They are capable of handling high-dimensional data and capturing nonlinear relationships and interactions without requiring these relationships to be specified in advance. Although RF can provide measures of variable importance, its ensemble structure makes the overall decision process less transparent than that of simpler statistical models.

XGBoost similarly exploits an ensemble of decision trees but employs gradient boosting, regularization, and computational optimization to enhance predictive performance (Chen & Guestrin, 2016). It has demonstrated particularly strong performance on structured and tabular data and is capable of capturing complex nonlinearities and interactions among credit risk factors. However, its performance depends on appropriate hyperparameter selection, and its predictions are generally less directly interpretable than those produced by Logistic regression.

Empirical comparisons further demonstrate that the advantages of different models depend on the characteristics of the dataset and the objective of the assessment. Baesens et al. (2003) found that advanced classification methods such as SVM and neural networks can achieve strong predictive performance in credit scoring, while Logistic regression remains competitive because of its robustness and interpretability. Lessmann et al. (2015), in a large-scale comparison of 41 classification methods across multiple credit scoring datasets, further showed that advanced and ensemble-based approaches frequently achieve superior predictive performance, although no single method consistently dominates under all conditions. Similarly, Barboza et al. (2017) reported that ensemble learning techniques, including boosting and random forests, can outperform several conventional approaches in bankruptcy prediction.

Overall, existing credit risk assessment models differ substantially in terms of their information sources, assumptions, predictive mechanisms, and practical applicability. KMV provides a theoretically grounded and forward-looking measure of corporate default risk but depends strongly on observable market information. CreditMetrics captures both default and credit migration, whereas Credit Portfolio View explicitly incorporates macroeconomic fluctuations, and CreditRisk+ provides a relatively parsimonious approach to modeling portfolio default losses. Logistic regression offers strong transparency and interpretability but has limited flexibility in capturing complex nonlinear relationships. In comparison, machine learning methods such as SVM, ANN, RF, and XGBoost can more effectively exploit nonlinear and high-dimensional information, although such predictive flexibility is generally accompanied by greater model complexity and reduced interpretability.

Therefore, the evolution of credit risk assessment should not be understood as a simple replacement of conventional models by increasingly complex techniques. Rather, each approach addresses different dimensions of credit risk and involves trade-offs among predictive accuracy, interpretability, data availability, computational requirements, and practical implementation. With the growing availability of heterogeneous financial and nonfinancial information, an increasingly important research question is how to exploit the predictive advantages of advanced data-driven methods while retaining sufficient robustness, transparency, and explanatory power for credit risk management.

### *2.2 Applications and Limitations of Credit Risk Assessment Models in China*

The KMV model has been increasingly applied in China to assess corporate default risk and to support the development of credit risk early-warning systems. Weiting et al. (2017) applied the KMV framework to bond default risk assessment in the Chinese market and explored its use in constructing an early-warning system for corporate bonds. Focusing on the real estate sector, Zhen et al. (2022) employed the KMV model to examine corporate credit risk in the context of real estate regulation and changing policy conditions. Taken together, these studies demonstrate the practical application of the KMV model in different Chinese credit risk settings, while also providing a basis for evaluating its effectiveness and limitations under market- and industry-specific conditions.

These two studies provide useful settings for examining the practical applicability of the KMV framework in the Chinese market. The bonds evaluated in the 2017 Shanghai Stock Exchange report have now all matured, meaning that their ultimate repayment or default outcomes are observable and can therefore be used to retrospectively evaluate the effectiveness of the early-warning model (Weiting et al., 2017). By contrast, the 2022 report issued by the National Institution for Finance & Development focused specifically on the real estate sector and was conducted shortly after the introduction of major regulatory policies affecting the industry (Zhen et al., 2022). It therefore provides an important context for examining the performance of credit risk models under substantial policy and macroeconomic changes.

Compared with conventional credit scoring models that rely primarily on financial indicators, the KMV model is dynamic and incorporates market information by converting changes in a borrowing firm's equity value into information about its credit condition. Since equity prices tend to respond relatively quickly to changes in firm quality and market expectations, the model has a certain degree of forward-looking capacity. However, this market-based feature also restricts the direct application of the standard KMV model to publicly listed firms for which market-based equity information is observable, creating difficulties when the credit risk of non-listed

firms needs to be assessed.

To address this limitation, Weiting et al. (2017) first calculated the distance to default (DD) of listed firms and used it as the dependent variable. They then identified five significant firm-level indicators reflecting profitability, liquidity, debt-servicing capacity, and leverage and employed these indicators as explanatory variables in a multiple regression model. The estimated regression equation was subsequently applied to the corresponding financial indicators of non-listed firms to predict their DD values (Weiting et al., 2017). This approach extends the applicability of the KMV framework beyond listed firms by establishing an indirect relationship between observable fundamentals and market-based default-distance measures.

Nevertheless, the predictive accuracy of this extension warrants further examination. Among the 21 bonds identified as being at high risk of default in the early-warning list generated by the Shanghai Stock Exchange study, only one bond (122683.SH, "12 Chunhe Bond") subsequently experienced an actual default, while the remaining bonds fulfilled their repayment obligations as scheduled. Meanwhile, according to Eastmoney Choice data, as many as 479 bond defaults occurred during the period from 2019 to 2021. Although these figures cannot by themselves establish the overall predictive performance of the model without a complete out-of-sample evaluation framework, they raise questions regarding its ability to discriminate between high- and low-risk bonds and identify defaults that were not included in the original warning list.

The treatment of non-listed firms also presents several methodological limitations. Weiting et al. (2017) did not report sufficient evidence regarding the explanatory power of the multiple regression model used to infer DD for non-listed firms. More importantly, the explanatory variables were largely derived from firms' financial statements. Such an approach may overlook the effects of macroeconomic conditions, industry cycles, and policy shocks, which can be particularly important for firms operating in highly cyclical sectors. Consequently, estimating the DD of non-listed firms solely through a multiple regression equation based on firm-level financial indicators may require further methodological improvement.

Another important issue concerns the relationship between DD and the expected default frequency (EDF). Under the theoretical normal-distribution mapping, EDF can be expressed as:

$$EDF = 1 - N(DD),$$

where $N(\cdot)$ denotes the cumulative distribution function of the standard normal distribution. Under this specification, when DD exceeds approximately four standard deviations, the theoretical EDF rapidly approaches zero. Such behavior may not adequately reflect the fat-tailed characteristics commonly observed in actual financial markets.

In practice, the KMV framework does not rely exclusively on this theoretical normal-distribution mapping. Instead, it uses extensive historical default data to establish an empirical relationship between DD and EDF (Crosbie & Bohn, 2003). This empirical calibration is one of the important features of the KMV approach because firms with the same theoretical DD may exhibit different realized default frequencies under different market conditions. However, this also raises several questions regarding model transferability. In particular, whether a DD–EDF relationship identified from large historical databases of U.S. firms remains stable across different periods and institutional environments is open to further investigation. Similarly, whether market-determined equity values always provide an adequate representation of firms' underlying economic value remains an important empirical issue.

These challenges are particularly relevant in the Chinese market because sufficiently large and long-term historical default databases remain relatively limited. Consequently, many domestic applications of the KMV model have focused primarily on DD rather than establishing a robust empirical mapping between DD and EDF. Weiting et al. (2017), for example, determined a critical DD threshold by referring to a limited number of historical default cases and low-credit-rating observations. They subsequently employed a Probit model based on fundamental indicators to estimate the probability that a bond's future DD would fall below this critical threshold. Thus, the resulting probability represents the likelihood of a bond entering the predefined high-default-risk region rather than a directly observed empirical default probability.

Although this approach achieved relatively strong predictive results for certain observed default entities, its robustness requires further examination. The critical DD threshold was itself calibrated partly on the characteristics of the available default observations, while the number of default cases used for calibration was relatively limited. This may increase the sensitivity of the resulting threshold to the specific sample and introduce potential sample-selection or calibration bias. Therefore, further validation using larger and more representative default samples is necessary before the estimated threshold can be generalized more broadly. The application of

the KMV framework to China's real estate sector reveals another issue relevant to credit risk assessment. Zhen et al. (2022) employed DD as the dependent variable and included total assets, total liabilities, inventory turnover, net profit margin, the cash-to-short-term-debt ratio, and real estate regulatory policies as explanatory variables in a multiple regression analysis. Their results suggested that firms with larger total assets tended to exhibit greater DD values and, consequently, lower estimated default risk. This finding is broadly consistent with conventional credit-rating practices, under which larger firms tend to receive higher credit ratings. An examination conducted in the present study of the relationship between corporate asset size and credit ratings assigned by rating agencies similarly indicates that firms with larger asset bases are more likely to obtain higher credit ratings (Figure 2).

However, the experience of large-scale corporate distress, exemplified by the Evergrande case, suggests that firm size should not necessarily be interpreted solely as a risk-reducing factor. Although larger firms may benefit from stronger financing capacity, diversified operations, and greater access to external resources, the failure of a systemically important large enterprise can generate considerably broader spillover effects through financial institutions, suppliers, investors, and the real economy. Accordingly, from the perspective of financial stability, larger firms may warrant more intensive monitoring rather than mechanically being assigned lower levels of risk. This distinction highlights an important limitation of credit risk models that focus primarily on the probability of default while giving insufficient consideration to the potential systemic consequences and loss severity associated with default.

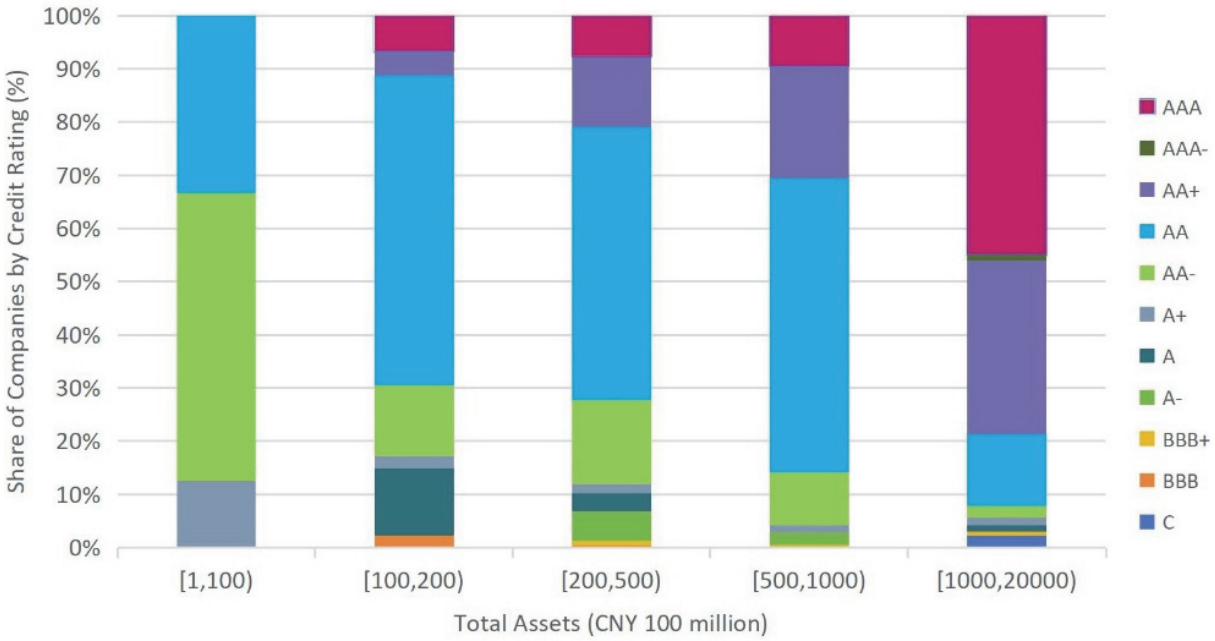



Figure 2. Distribution of Credit Ratings by Total Asset Size of Real Estate firms

Data source: East Money Choice database and authors' compilation.

## 3. KMV Model and Credit Risk Assessment Method

### *3.1 Framework of the KMV Model*

The KMV model evaluates corporate default incentives from the perspective of equity holders. Within this framework, shareholders' equity is treated as a European call option written on the market value of the firm's assets, with the face value of debt serving as the exercise price. When the market value of the firm's assets exceeds its debt obligations, the firm has an incentive to repay its liabilities, and shareholders retain the residual value of the assets. By contrast, when the market value of assets falls below the relevant debt threshold, the firm is assumed to default.

Accordingly, corporate default risk increases as the market value of the firm's assets approaches the face value of its debt, and default becomes more likely once the asset value falls below the default threshold. Because long-term liabilities generally impose less immediate repayment pressure than short-term liabilities, KMV studies suggest that the default point (DPT) should lie between the book value of current liabilities and the total book value

of debt. The default point is therefore commonly specified as:

Default Point (DPT)= Current Liabilities + 0.5 × Non-current Liabilities

Based on the Black–Scholes–Merton (BSM) option-pricing framework, the market value and volatility of a firm's assets can be inferred from the observed market value and volatility of its equity. The estimated asset value and asset volatility are then used to characterize the distribution of future asset values. By comparing this distribution with the default point, the probability that the firm's asset value will fall below the DPT can be estimated, thereby obtaining the expected default frequency (EDF).

Under the standard KMV framework, the equity value $V_E$ can be expressed as:

$$V_E = V_A N(d_1) - De^{-rT} N(d_2) \tag{3.1}$$

$$d_1 = \frac{\ln\left(\frac{V_A}{D}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \tag{3.2}$$

$$d_2 = d_1 - \sigma_A \sqrt{T} \tag{3.3}$$

$$\sigma_E = \frac{V_A}{V_E} N(d_1) \sigma_A \tag{3.4}$$

where $V_A$ denotes the market value of assets, $\sigma_A$ is the volatility of asset value, $\sigma_E$ is the volatility of equity value, D represents debt (Default Point), r is the risk-free interest rate, T denotes the debt maturity, and N(·) is the cumulative distribution function of the standard normal distribution. By solving the above equations simultaneously, $V_A$ and $\sigma_A$ can be estimated.

Distance to default (DD) measures the number of standard deviations by which the value of a firm's assets exceeds the default point. A larger DD indicates a lower probability of default. Following the empirical specification adopted in this study, the debt maturity is set to (T=1), and the expected growth rate of asset value is assumed to be zero. Accordingly, DD can be expressed as the difference between the expected asset value and the default point, divided by the standard deviation of asset value:

$$DD = \frac{V_A - D}{V_A \times \sigma_A} \tag{3.5}$$

However, this study does not directly employ the theoretical EDF. Instead, a univariate Logistic regression is used to map DD into an empirical expected default probability. A 50% default probability and a BBB− credit rating are jointly adopted as the warning threshold. BBB− represents the median category among the 19 credit rating grades and is assigned a numerical rating score of 10. In standard credit rating frameworks, BBB − typically serves as the boundary between investment and speculative grades, with ratings of BBB − and above classified as investment grade and those below as speculative grade. A default probability of 50% indicates an equal tendency toward default and repayment. Accordingly, firms with an estimated default probability greater than 50% are classified as having a stronger tendency toward default, whereas firms with an estimated default probability below 50% are considered more likely to fulfill their debt obligations.

*3.2 Model Evaluation Methods*

This study evaluates the credit risk assessment performance of the KMV model from two complementary perspectives: the discriminatory ability of distance to default (DD) and the effectiveness of model-based early-warning signals relative to conventional credit ratings. The evaluation combines receiver operating characteristic (ROC) analysis with firm-level comparative case studies.

First, the discriminatory ability of DD is assessed using the ROC curve and the area under the ROC curve (AUROC). The ROC curve illustrates the relationship between the true positive rate (sensitivity) and the false positive rate (1 − specificity) across different classification thresholds. The AUROC summarizes the model's ability to distinguish firms experiencing debt defaults from those without observed defaults. An AUROC of 0.5 indicates discriminatory performance equivalent to random classification, whereas a value of 1.0 represents perfect

discrimination. Because lower DD values indicate higher credit risk, the direction of the DD measure is appropriately considered when constructing the ROC curve.

The empirical evaluation uses the DD estimates of 161 Hong Kong-listed real estate firms for 2021, together with their observed debt default status. The sample includes 77 firms classified as default observations and 84 classified as non-default observations. However, the default group includes firms that experienced defaults before or during the measurement period, as well as firms with subsequent default events. Accordingly, this analysis primarily evaluates the retrospective discriminatory ability of DD rather than establishing its strictly prospective predictive accuracy. A rigorous forward-looking evaluation would require excluding firms already in default at the prediction date and defining a consistent subsequent default observation window.

Second, the early-warning performance of the KMV model is examined through comparative case studies of selected A-share-listed and Hong Kong-listed real estate firms. Changes in estimated expected default frequency (EDF) are compared with adjustments in domestic credit ratings and observed corporate default events. Particular attention is given to the timing, frequency, and persistence of warning signals. The study adopts an estimated default probability of 50% and a BBB− credit rating as reference warning thresholds. These thresholds are used for comparative analysis rather than treated as empirically optimized classification cutoffs.

Finally, the evaluation considers the potential trade-off between Type I errors (false positives) and Type II errors (false negatives). False-positive warnings may generate unnecessary monitoring costs, whereas false-negative assessments may delay the identification of deteriorating creditworthiness. Because the present analysis does not establish an independently validated optimal threshold, its findings are interpreted cautiously. The combined ROC analysis and case-based comparisons provide preliminary evidence regarding the usefulness of the KMV model as a supplementary credit risk assessment instrument, while further out-of-sample validation and probability calibration remain necessary to establish its reliability for prospective default prediction.

## 4. Sample, Data, and Variables

### *4.1 Sample Selection*

This study examines the credit default risk of real estate firms listed on mainland China's Shanghai and Shenzhen A-share markets and the Hong Kong Stock Exchange. The principal sample period covers 2010–2023, encompassing different stages of China's real estate market development, including rapid industry expansion, regulatory tightening, and the widespread financial distress experienced by property developers after 2021. This period provides an empirical setting for investigating changes in corporate creditworthiness under varying market and regulatory conditions.

The sample comprises 261 publicly listed real estate firms, including 161 Hong Kong-listed firms and 100 A-share-listed firms. Hong Kong-listed firms are identified using the Level-4 Global Industry Classification Standard (GICS) categories of Real Estate Development and Diversified Real Estate Activities. To maintain consistency in the sample classification, the selection additionally requires Hong Kong shares to account for 100% of issued ordinary shares and A-shares to account for 0% as of December 31, 2020. A-share-listed firms are selected according to the Level-2 Real Estate Industry classification under the Shenwan Industry Classification System (2021).

Because firms entered and exited the stock markets at different times, and because trading suspensions and data availability varied across firms, a balanced panel could not be established without substantially reducing sample coverage. Accordingly, an unbalanced panel structure is adopted to retain the maximum number of observations for which the required financial and market variables are available. For Hong Kong-listed firms, the final dataset contains 1,990 valid firm-year observations over 2010–2023.

The sample includes firms with different geographical exposures, financing structures, and operating characteristics. For subsequent comparative analysis, Hong Kong-listed firms are further classified into mainland-focused and non-mainland groups according to the principal geographical location of their real estate operations. This distinction allows the study to examine differences in credit risk associated with exposure to mainland China's property market and regulatory environment.

### *4.2 Data Sources and Processing*

The primary financial and market data are obtained from the Eastmoney Choice Financial Terminal, which provides corporate financial statements, historical stock prices, trading information, and other indicators relevant to credit risk assessment. The dataset combines firm-level accounting information with equity market observations to estimate the parameters required by the KMV model.

The principal observation period for Hong Kong-listed firms is 2010–2023. For certain A-share-listed firms, historical market-based information is available from 2006 onward. These earlier observations provide supplementary historical information where relevant, although the main cross-market analysis focuses on the 2010–2023 period.

Equity market value is measured using information from the final trading day of each calendar year. Equity volatility is estimated from daily logarithmic stock returns observed during the corresponding year and subsequently annualized. Corporate liability information is extracted from consolidated financial statements, ensuring consistency between the financial obligations used in the default-point calculation and the broader financial position of the listed entity.

Risk-free interest rates are selected according to the relevant financial market. For Hong Kong-listed firms, the Hong Kong market interest rate series is used as the risk-free rate proxy, while the yield on one-year Chinese government bonds is applied to A-share-listed firms. The model's debt maturity and default prediction horizon are set to one year ($T = 1$), consistent with the empirical specification adopted in this study.

Data availability is affected by differences in listing dates, delisting events, trading suspensions, and financial reporting coverage. Firm-year observations lacking sufficient information for KMV estimation are excluded. Where appropriate, isolated missing observations are supplemented using interim financial statements or adjacent-year averages, as described in the original data-processing approach.

Nevertheless, such supplementation may affect estimated asset values, volatility measures, and subsequent default-risk assessments. In particular, information unavailable at a given prediction date should not be used when evaluating prospective forecasting performance. Therefore, the empirical findings should be interpreted in light of potential sample-selection effects, missing-data treatment, and the limitations associated with retrospective model evaluation.

*4.3 Variable Definitions and Measurement*

The principal variables used in this study are constructed within the Black–Scholes–Merton structural credit risk framework underlying the KMV model. The key variables include equity market value, equity volatility, estimated asset value, estimated asset volatility, the default point, distance to default (DD), and expected default frequency (EDF).

**Equity Market Value (VE).** Equity market value represents the market valuation of shareholders' equity at the end of each observation year. It is obtained from the corresponding equity market information and serves as an observable input for estimating the underlying market value of corporate assets.

**Equity Volatility (σE).** Equity volatility measures fluctuations in the market value of shareholders' equity. It is calculated using daily logarithmic stock returns during each calendar year and annualized to reflect market-based variations in corporate risk.

**Asset Value (VA) and Asset Volatility (σA).** Because the market value and volatility of corporate assets are not directly observable, these variables are inferred from equity market value and equity volatility using the Black–Scholes–Merton option-pricing relationships presented in Section 3.1. They provide the principal inputs for estimating a firm's distance to default.

**Default Point (DPT).** The default point represents the liability threshold against which the estimated asset value is assessed. Following the empirical specification used in this study, it is calculated as:

$$DPT = \text{Current Liabilities} + 0.5 \times \text{Non-current Liabilities}$$

This specification assigns greater weight to current liabilities because they generally impose more immediate repayment obligations than longer-term debt.

**Distance to Default (DD).** DD measures the standardized distance between the estimated asset value and the default point. A higher DD indicates a larger estimated financial buffer against default, whereas a lower or negative DD signals greater financial vulnerability. The calculation follows Equation (3.5), with a one-year horizon and an assumed zero expected growth rate of asset value.

**Expected Default Frequency (EDF).** EDF represents the estimated probability of corporate default. Rather than directly applying the theoretical normal-distribution mapping, this study employs a univariate logistic regression model to establish an empirical relationship between DD and observed default outcomes. The resulting estimates are used to examine variations in corporate credit risk and compare model-based warning signals with conventional credit ratings.

**Default Status.** Default status is a binary indicator distinguishing firms with observed debt default events from those without such events within the relevant observation period. Its construction is important for evaluating the discriminatory ability of DD through ROC analysis. As discussed in Section 3.2, the existing evaluation sample includes firms with defaults occurring before or during the measurement period. Therefore, the corresponding classification results should be interpreted as evidence of retrospective risk discrimination rather than independently validated prospective default prediction.

Together, these variables provide a market-based framework for examining corporate financial vulnerability, identifying differences in credit risk across listed real estate firms, and evaluating the applicability and limitations of the KMV model in China's real estate sector.

## 5. Empirical Results and Analysis

### *5.1 Time-Series Characteristics of Distance to Default for Hong Kong-Listed Real Estate Firms*

Using the KMV model, annual distance-to-default (DD) values were estimated for 161 Hong Kong-listed real estate firms over the period from 2010 to 2023. After excluding firm-year observations with missing values, mainly due to trading suspensions, the final sample contains 1,990 valid firm-year observations.

As shown in Table 1, the mean DD for the full sample over 2010–2023 is 2.49, while the median is 2.35, suggesting that, on average, firms' asset values remained above their estimated default points. However, the distribution of DD exhibits substantial dispersion. The minimum DD declined to −18.57 in 2023, whereas the maximum reached 33.83 in 2022, with an overall standard deviation of 2.34. Such pronounced cross-sectional heterogeneity may partly reflect the diverse composition of Hong Kong-listed real estate firms. The sample includes both developers that rely heavily on the high-leverage and high-turnover business model prevalent in mainland China and long-established Hong Kong developers whose operations are concentrated in Hong Kong or overseas markets and are generally characterized by more conservative operating strategies.

To further examine this heterogeneity, the sample is divided into a mainland group, consisting of firms whose principal real estate development activities are concentrated in mainland China, and a non-mainland group, comprising firms whose operations are primarily concentrated in Hong Kong or overseas markets. Figure 5 compares the evolution of DD between these two groups over the sample period.

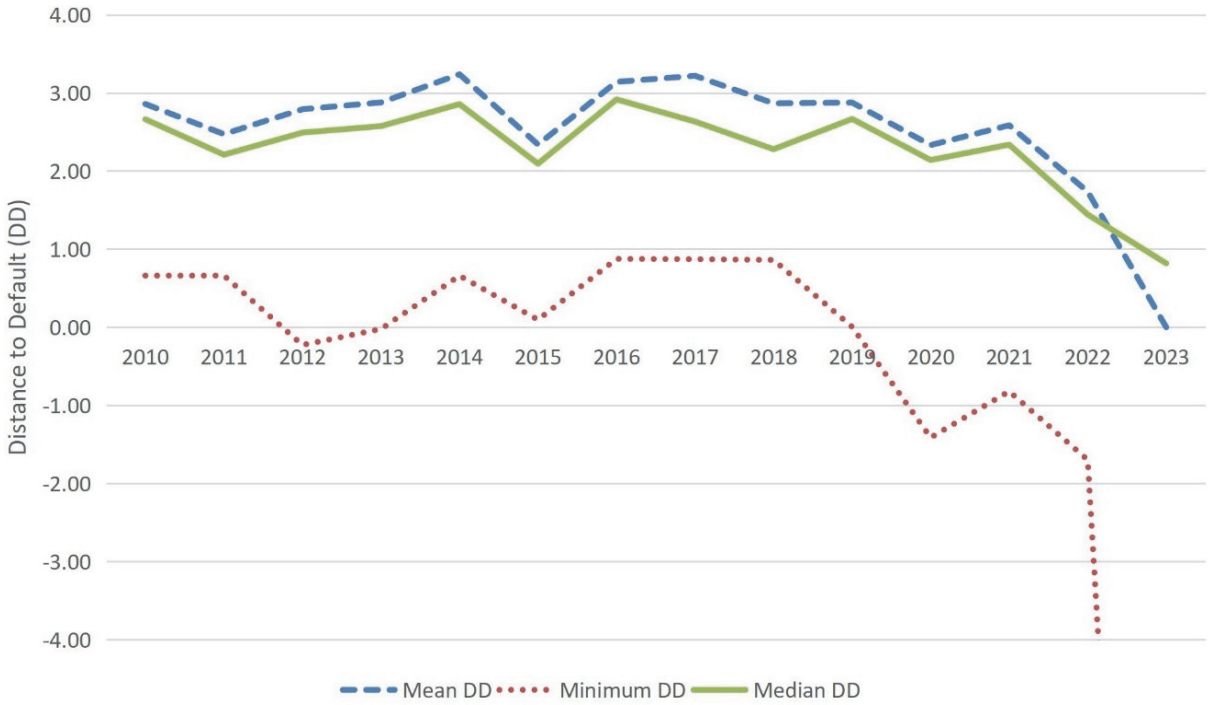



Figure 3. Trends in Distance to Default (DD) for Hong Kong-Listed Real Estate Firms, 2010–2023

Data source: East Money Choice database and authors' compilation.

Table 1. Descriptive Statistics of Distance to Default (DD) for Hong Kong-listed Real Estate Firms, 2010–2023

| Year | Mean DD | Min DD | Median DD | Max DD | SD DD | N |
|---|---|---|---|---|---|---|
| 2010 | 2.86 | 0.66 | 2.66 | 7.89 | 1.23 | 113 |
| 2011 | 2.47 | 0.67 | 2.21 | 9.22 | 1.22 | 116 |
| 2012 | 2.79 | -0.23 | 2.49 | 15.21 | 1.74 | 121 |
| 2013 | 2.88 | -0.02 | 2.58 | 8.67 | 1.53 | 130 |
| 2014 | 3.24 | 0.66 | 2.86 | 11.91 | 1.79 | 138 |
| 2015 | 2.34 | 0.10 | 2.09 | 7.40 | 1.40 | 141 |
| 2016 | 3.14 | 0.88 | 2.92 | 12.74 | 1.63 | 144 |
| 2017 | 3.22 | 0.87 | 2.63 | 19.18 | 2.27 | 144 |
| 2018 | 2.87 | 0.86 | 2.28 | 15.39 | 2.02 | 149 |
| 2019 | 2.88 | 0.01 | 2.67 | 17.69 | 1.92 | 154 |
| 2020 | 2.33 | -1.41 | 2.14 | 20.84 | 1.95 | 157 |
| 2021 | 2.59 | -0.82 | 2.34 | 19.23 | 1.98 | 161 |
| 2022 | 1.74 | -1.70 | 1.44 | 33.83 | 3.00 | 161 |
| 2023 | 0.00 | -18.57 | 0.82 | 9.64 | 4.15 | 161 |
| Overall | 2.49 | -18.57 | 2.35 | 33.83 | 2.34 | 1990 |

Data source: East Money Choice database and authors' compilation.

Based on Figure 3, which illustrates the temporal trends in distance to default (DD), Figure 4, which presents the distribution of DD through box plots, and Figure 5, which provides a comparative analysis across different groups of firms, the evolution of credit risk among Hong Kong-listed real estate firms can be broadly divided into three distinct phases.

Phase I — Relative Stability and Shared Growth Benefits (2010–2014)

During this period, both the mean and median DD of Hong Kong-listed real estate firms remained relatively high, with the mean ranging from 2.47 to 3.24 and the standard deviation fluctuating between 1.22 and 1.79. Although slightly negative minimum DD values were observed in 2012 and 2013, overall credit risk remained relatively contained. Firms primarily operating in the Hong Kong property market, as well as Hong Kong-based developers and mainland Chinese property developers with substantial exposure to mainland China, benefited from accelerating urbanization and the sustained expansion of the mainland Chinese real estate market. Consequently, asset values generally provided substantial buffers against outstanding liabilities, and the sector exhibited limited evidence of pronounced downside tail risk.

Phase II — Policy Constraints and Structural Divergence (2015–2019)

In 2015, amid macroeconomic deleveraging pressures, the mean DD declined to a temporary low of 2.34. A moderate recovery subsequently emerged during 2016–2017, supported by favorable policies aimed at reducing housing inventories. However, following the formal establishment of the policy principle that "housing is for living in, not for speculation" in 2017, financing conditions in mainland China began to tighten. Meanwhile, the standard deviation of DD increased to 2.27 in 2017, with the maximum value reaching 19.18, indicating growing cross-sectional heterogeneity in firms' credit risk profiles. This divergence reflected differences in firms' geographical exposure, business models, and expansion strategies. Property developers with substantial operations in mainland China, particularly those that had pursued aggressive debt-financed expansion, began to exhibit increasing credit vulnerabilities. By contrast, financially conservative Hong Kong-based developers with limited mainland exposure, or those primarily engaged in income-generating investment properties in mainland China, generally maintained relatively high DD values, remaining within the upper and comparatively safer range of the distribution.

Phase III — Regulatory Tightening and the Concentration of Downside Tail Risk (2020–2023)

The introduction of the "Three Red Lines" policy in 2020 imposed substantial financing constraints on property developers that had relied heavily on leveraged expansion in mainland China. Although the mean DD remained at 2.33 in 2020, the minimum value deteriorated sharply to −1.41, suggesting that the estimated asset values of certain highly leveraged developers had fallen below their default thresholds. In 2021, the minimum DD remained negative at −0.82, indicating persistent financial distress among the most vulnerable firms. During 2022–2023, the simultaneous deterioration in mainland China's property sales and financing conditions was accompanied by a pronounced decline in DD. In 2022, the mean DD decreased to 1.74, while the minimum fell to −1.70. By 2023, the mean DD had declined to approximately zero (0.00), accompanied by a sharp decrease

in the minimum value to −18.57 and an increase in the standard deviation to a sample-period high of 4.15. These developments indicate a substantial deterioration in sector-wide credit conditions, together with a marked increase in the dispersion of firm-level credit risk.

The graphical evidence further reinforces these findings. As illustrated in Figure 3, the dashed line representing the mean DD exhibits a particularly sharp downward trajectory during 2022–2023. Similarly, the box plots in Figure 4 reveal a substantial downward shift in the overall DD distribution in 2023, accompanied by an extended lower whisker and numerous extreme negative outliers. These patterns suggest that firms with substantial exposure to mainland China's regulatory environment and property market cycle, particularly financially distressed mainland Chinese developers, experienced severe deterioration in their asset values and a corresponding increase in default risk. For some firms, these financial vulnerabilities were accompanied by actual credit default events. Nevertheless, the maximum DD reached 33.83 in 2022, highlighting considerable heterogeneity in credit risk across the sector. This exceptionally high value suggests that certain Hong Kong-listed real estate firms, particularly those with limited exposure to mainland China's property development market or those that had undertaken deleveraging measures at an earlier stage, maintained relatively strong credit profiles despite the broader industry downturn. Their comparatively high DD values indicate substantial financial resilience and an enhanced capacity to withstand adverse market conditions, underscoring the increasingly differentiated effects of regulatory tightening and market adjustments on firms with distinct geographical exposures and financial structures.

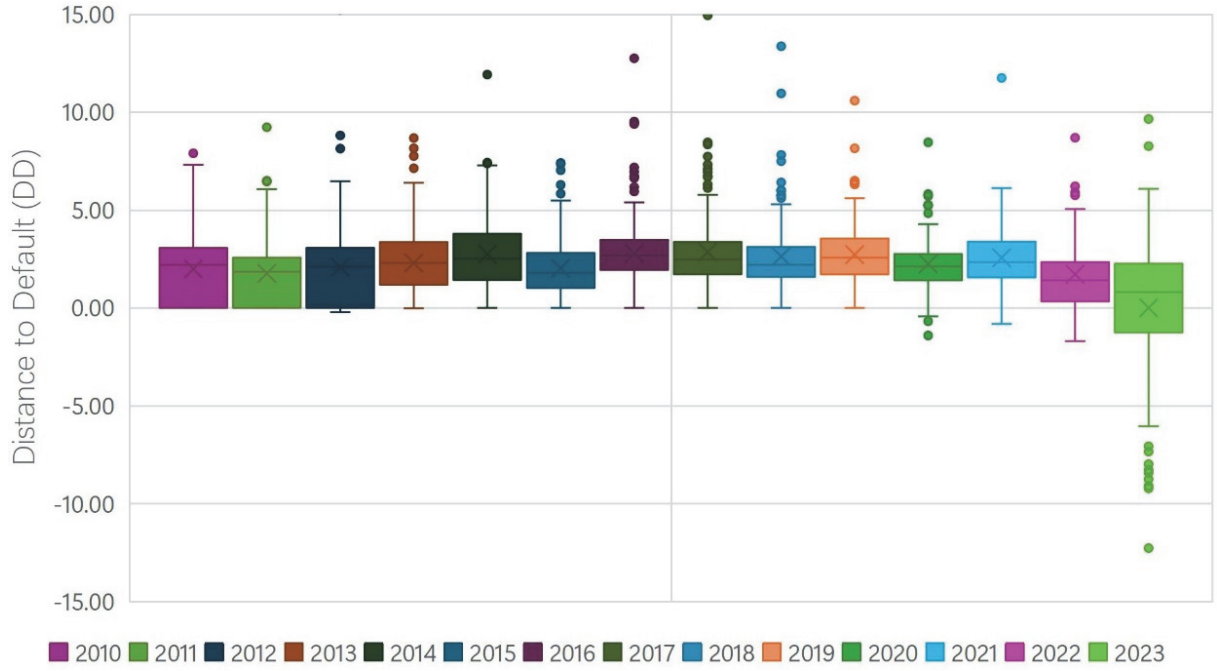



Figure 4. Box Plots of Distance to Default (DD) for Hong Kong-Listed Real Estate Firms, 2010–2023

Data source: East Money Choice database and authors' compilation.

Figure 5 and Table 2 further confirms that the sharp decline in distance to default (DD) was primarily driven by the mainland group, with the two groups exhibiting pronounced divergence in their credit risk trajectories during the crisis period. For the mainland group, which was heavily exposed to mainland China's regulatory policies and property market conditions, the mean DD declined sharply to 0.65 in 2022, while the median fell to 0.32, approaching the default threshold. By 2023, the mean DD had plummeted to −2.32, accompanied by a decline in the median to −1.21, with both measures entering substantially negative territory. These findings indicate that the combined effects of the "Three Red Lines" policy and the prolonged property market downturn were associated with severe erosion of asset values among highly leveraged mainland Chinese property developers, substantially increasing their credit vulnerability and contributing to widespread credit distress and default events. In contrast, the non-mainland group, comprising firms whose primary operations were concentrated in Hong Kong or overseas markets, demonstrated considerably greater resilience despite

facing broader macroeconomic pressures. Specifically, the mean DD decreased from 3.00 in 2021 to 2.40 in 2022 and further to 1.38 in 2023, while the median declined to 1.26 in 2023. Nevertheless, both measures remained above 1.0, indicating that these firms generally maintained a positive buffer against their estimated default thresholds. Furthermore, the maximum DD observed in the overall sample during 2022 – 2023 reached 33.83, highlighting substantial heterogeneity in financial resilience across Hong Kong-listed real estate firms. This pattern suggests that certain Hong Kong-based developers, particularly those with limited exposure to mainland China's property market cycle or those that had implemented deleveraging strategies at an earlier stage, were better positioned to withstand adverse market conditions. Overall, the contrasting trajectories of the two groups underscore the importance of geographical exposure, leverage structures, and regulatory sensitivity in shaping firm-level credit risk during periods of systemic stress.

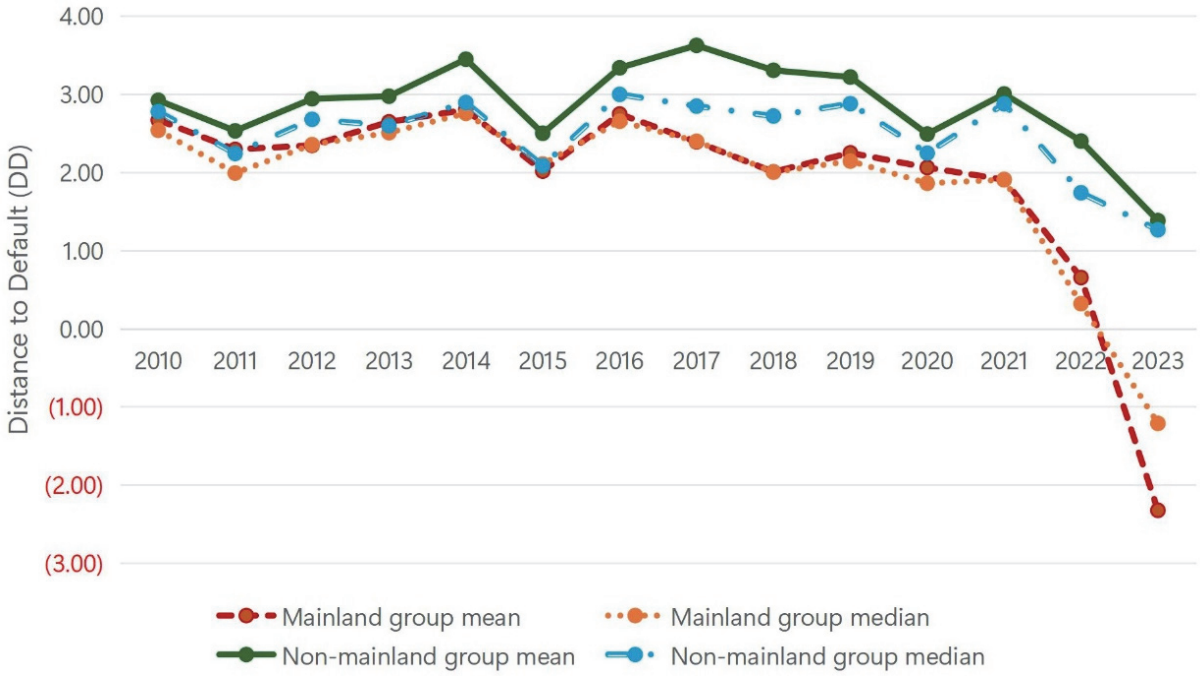



Figure 5. Comparison of Distance to Default (DD) between Mainland and Non-mainland Groups of Hong Kong-listed Real Estate Firms, 2010–2023.

Data source: East Money Choice database and authors' compilation.

Table 2. Comparison of Distance to Default (DD) between Mainland and Non-mainland Groups of Hong Kong-listed Real Estate Firms, 2010 – 2023

| Year | Mainland group mean | Mainland group median | Non-mainland group mean | Non-mainland group median |
|---|---|---|---|---|
| 2010 | 2.67 | 2.54 | 2.92 | 2.77 |
| 2011 | 2.29 | 1.99 | 2.53 | 2.24 |
| 2012 | 2.34 | 2.35 | 2.94 | 2.68 |
| 2013 | 2.64 | 2.51 | 2.97 | 2.60 |
| 2014 | 2.80 | 2.75 | 3.45 | 2.89 |
| 2015 | 2.01 | 2.10 | 2.50 | 2.08 |
| 2016 | 2.74 | 2.65 | 3.33 | 3.00 |
| 2017 | 2.39 | 2.39 | 3.62 | 2.84 |
| 2018 | 2.00 | 2.00 | 3.3 | 2.72 |
| 2019 | 2.25 | 2.14 | 3.22 | 2.88 |
| 2020 | 2.06 | 1.86 | 2.49 | 2.24 |
| 2021 | 1.90 | 1.90 | 3.00 | 2.88 |
| 2022 | 0.65 | 0.32 | 2.40 | 1.74 |
| 2023 | -2.32 | -1.21 | 1.38 | 1.26 |

Data source: East Money Choice database and authors' compilation.

In general, the distance to default (DD) estimated using the KMV model effectively captures the historical evolution of credit risk among real estate firms and exhibits pronounced sensitivity to mainland China's macroeconomic conditions and sector-specific regulatory policies, particularly the principle that "housing is for living in, not for speculation" and the "Three Red Lines" policy. Credit risk among Hong Kong-listed real estate firms exhibits not only significant procyclicality but also substantial cross-sectional heterogeneity. Specifically, mainland Chinese property developers directly exposed to regulatory constraints experienced a rapid deterioration in creditworthiness during the market downturn, accompanied by a pronounced concentration of downside tail risk. In contrast, Hong Kong-based developers with relatively independent business operations demonstrated greater financial resilience, highlighting the differentiated effects of regulatory tightening and market fluctuations on firms with distinct geographical exposures and business structures.

*5.2 Evaluation of the Credit Risk Ranking Ability of Distance to Default (DD)*

To evaluate the ability of distance to default (DD) to discriminate between firms with different levels of credit risk, this study conducts a receiver operating characteristic (ROC) analysis using a sample of 161 Hong Kong-listed real estate firms. The DD values are estimated from financial statement information and equity market data as of the end of 2021, while corporate default status is determined from observed debt default events. As reported in Table 3, the evaluation sample comprises 77 firms classified as default observations and 84 firms classified as non-default observations. Among the default observations, 73 firms experienced debt defaults in 2021 or thereafter, while four had already defaulted before 2021.

The ROC curve evaluates the discriminatory ability of DD across alternative classification thresholds by examining the relationship between the true positive rate and the false positive rate. Since lower DD values indicate greater financial vulnerability, smaller DD estimates are treated as stronger indicators of default risk. Figure 6 presents the ROC curve, and Table 4 reports the corresponding area under the ROC curve (AUROC) and associated statistical results.

The estimated AUROC is 0.760, with a standard error of 0.038 and a 95% confidence interval ranging from 0.686 to 0.833. The result is statistically significant ($p < 0.001$), indicating that DD demonstrates discriminatory performance above the random-classification benchmark of 0.5. An AUROC of 0.760 suggests that, when a default-classified firm and a non-default-classified firm are randomly selected from the evaluation sample, the DD measure assigns a higher risk ranking to the default-classified firm approximately 76% of the time, with appropriate treatment of tied observations. This finding provides evidence that market-based distance-to-default estimates contain useful information for distinguishing firms with different observed credit risk outcomes.

Nevertheless, several methodological considerations should be acknowledged when interpreting these results. First, the classification of default observations includes firms that experienced defaults before or during the measurement year. Consequently, the reported AUROC reflects the ability of DD to distinguish firms according to their observed default status rather than a strictly forward-looking assessment of future defaults. In particular, using end-of-2021 DD estimates for firms that had already defaulted may introduce temporal inconsistencies between risk measurement and default identification. Second, the analysis is conducted within the available evaluation sample without an independently validated out-of-sample forecasting framework. Therefore, the reported discriminatory performance should not be interpreted as direct evidence of prospective default prediction accuracy.

Furthermore, AUROC measures ranking performance but does not establish whether estimated default probabilities are well calibrated or whether a particular warning threshold produces an acceptable balance between false-positive and false-negative classifications. Additional evaluation using sensitivity, specificity, precision, recall, and probability calibration measures would provide a more comprehensive assessment of the model's practical applicability. A temporally structured validation framework, in which firms already in default are excluded at the prediction date and subsequent defaults are assessed over a consistently defined forecasting horizon, would further strengthen the evidence regarding predictive reliability.

Table 3. Case Processing Summary

| Default | Valid N (listwise) |
|---|---|
| Positive[a] | 77 |

| | |
|---|---|
| Negative | 84 |
| Missing | 0 |
| Total | 161 |

Smaller values of the test result variable(s) indicate stronger evidence for a positive actual state.

a. The positive actual state is 1.

Data source: East Money Choice database and authors' compilation.

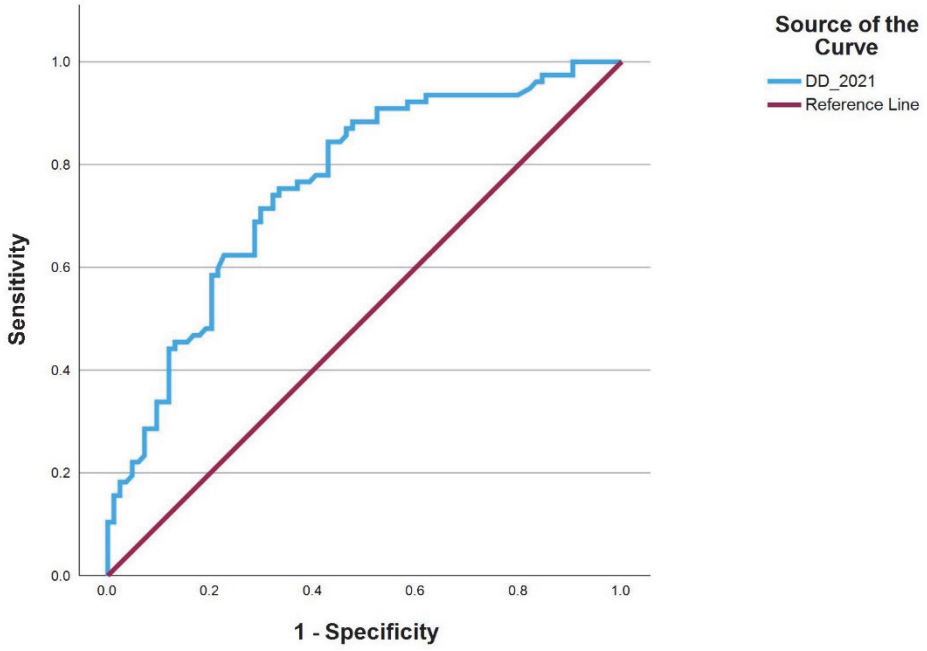



Figure 6. ROC Curve

Table 4. Area Under the ROC Curve

| | | | Asymptotic 95% Confidence Interval | |
|---|---|---|---|---|
| Area | Std. Error[a] | Asymptotic Sig.[b] | Lower Bound | Upper Bound |
| .760 | .038 | .000 | .686 | .833 |

Test Result Variable(s): DD_2021

The test result variable(s): DD_2021 has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a) Under the nonparametric assumption

b) Null hypothesis: true area = 0.5

Data source: East Money Choice database and authors' compilation.

Overall, the empirical findings indicate that DD possesses moderate discriminatory ability in distinguishing between default-classified and non-default-classified Hong Kong-listed real estate firms. The AUROC of 0.760 supports the usefulness of the KMV framework as a supplementary instrument for credit risk ranking and monitoring. However, its effectiveness as a prospective early-warning model requires further validation using temporally consistent default observations, independent testing samples, and appropriately calibrated default probabilities.

*5.3 Comparative Case Analysis of the KMV Credit Risk Model for A-Share-Listed Real Estate Firms*

A comparative analysis of selected A-share-listed real estate firms suggests that default probabilities estimated using the KMV model are generally more responsive to changes in firms' underlying credit risk than

domestic credit ratings, highlighting the model's potential advantages in the timely identification of credit deterioration.

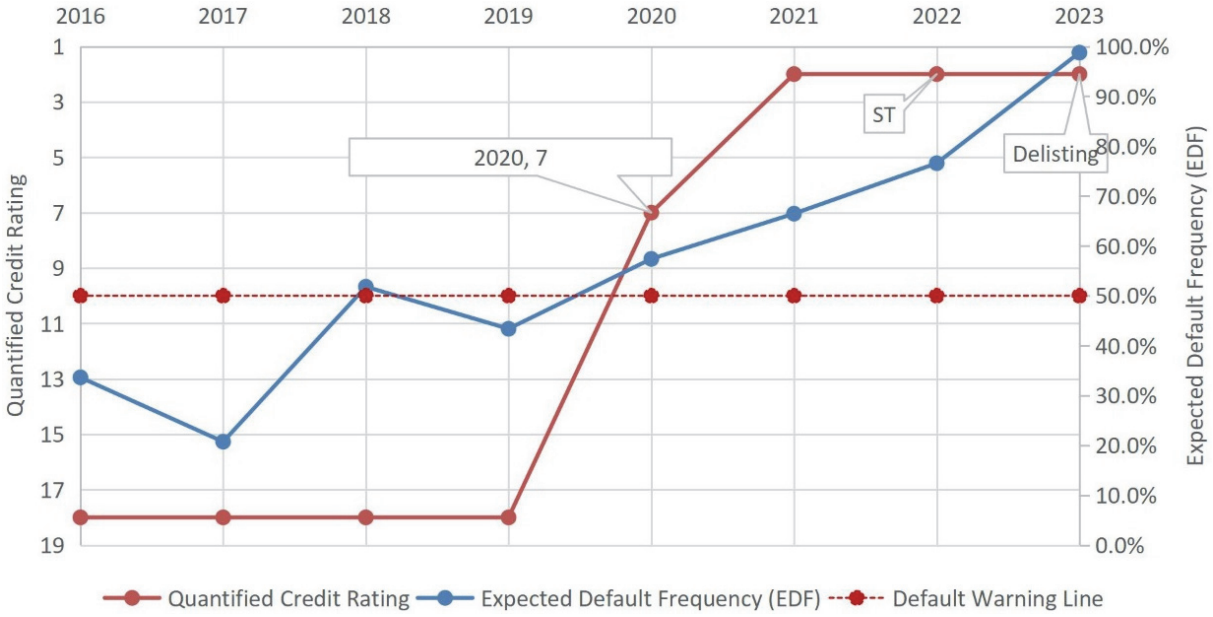



Figure 7. Default Warning of ST Tahoe

Data source: East Money Choice database and authors' compilation.

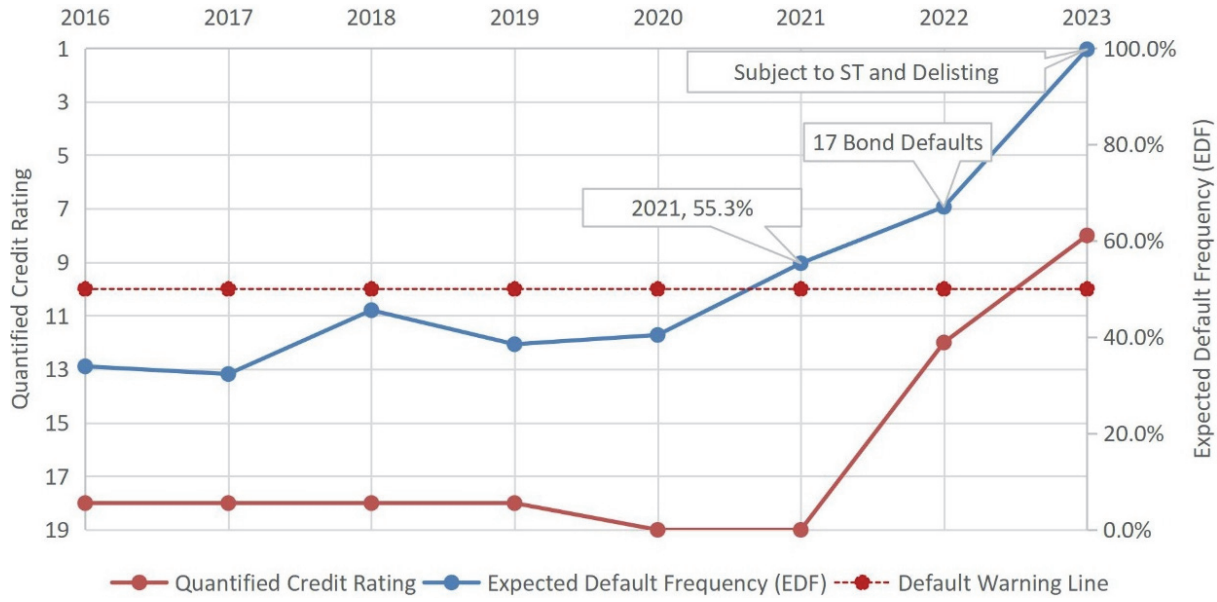



Figure 8. Default Warning of ST Yango

Data source: East Money Choice database and authors' compilation.

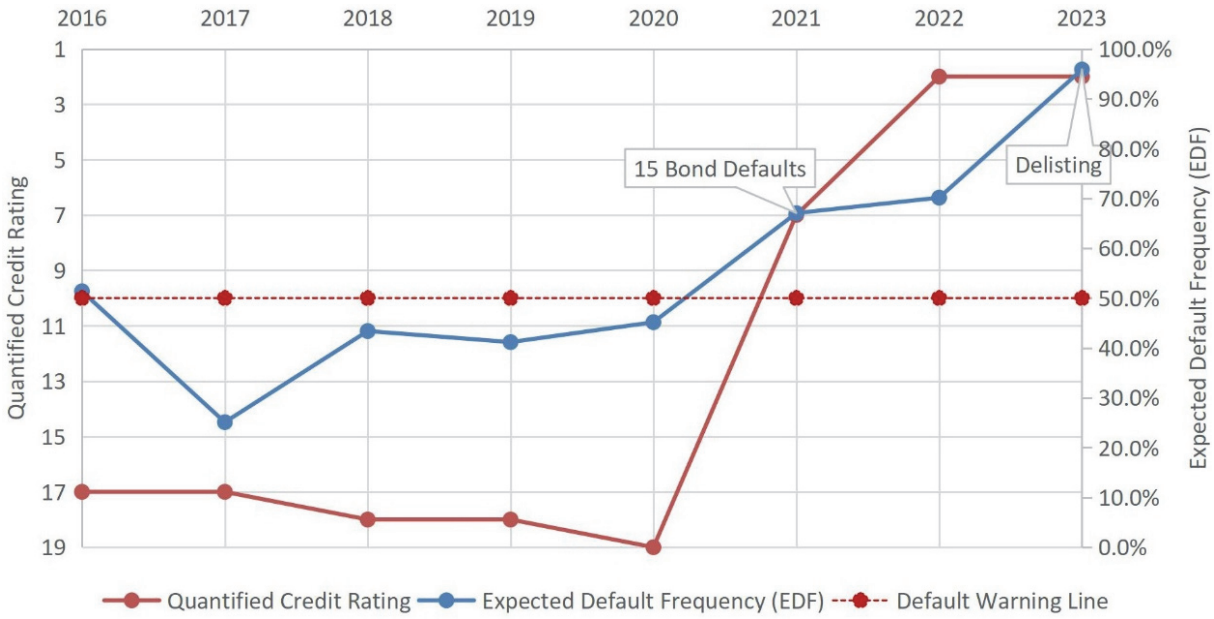



Figure 9. Default Warning of *ST Languang

Data source: East Money Choice database and authors' compilation.

The comparative analysis of the three firms that experienced actual debt defaults, as illustrated in Figures 7–9, reveals a broad temporal alignment between distance to default (DD) and domestic credit ratings in identifying default risk. Specifically, both indicators generally crossed their respective early-warning thresholds in the year of default. Nevertheless, DD provides a more granular assessment of the magnitude of firms' credit risk and, in certain cases, generates early-warning signals ahead of domestic credit rating downgrades, as exemplified by ST Yango. Furthermore, DD tends to generate more frequent risk warnings than domestic credit ratings, suggesting a greater sensitivity to potential default events and a lower tolerance for Type II errors (false negatives), albeit potentially at the expense of more Type I errors (false positives). These findings indicate that DD may serve as a valuable complement to the existing domestic credit rating system by enhancing the timeliness and sensitivity of credit risk identification.

*5.4 Comparative Case Analysis of the KMV Credit Risk Model for Hong Kong-Listed Real Estate Firms*

The time-series patterns of expected default frequency (EDF) estimated using the KMV model are examined for two selected Hong Kong-listed real estate firms. As illustrated in Figure 10, China Evergrande Group breached the KMV model's default early-warning threshold on multiple occasions prior to its actual debt default, suggesting that its underlying credit vulnerabilities had emerged several years before the default event. These findings indicate that the firm's financial fragility had accumulated over an extended period, while subsequent regulatory tightening and the downturn in the real estate market exacerbated existing liquidity pressures and contributed to the eventual materialization of credit risk.

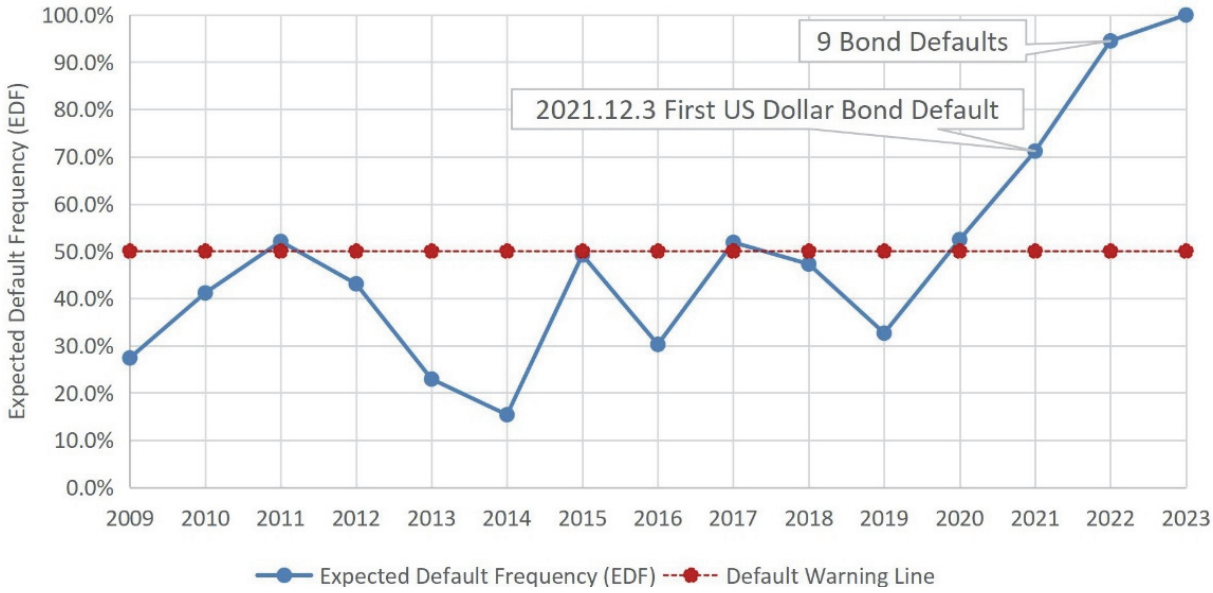



Figure 10. Default Warning of China Evergrande Group

Data source: East Money Choice database and authors' compilation.

As illustrated in Figure 11, Sun Hung Kai Properties approached the KMV model's default early-warning threshold during the 2008 global financial crisis but exhibited a relatively stable credit risk profile throughout the remaining sample period, with no subsequent breaches of the early-warning threshold. Overall, the KMV model estimates suggest that Sun Hung Kai Properties maintained a sound credit profile and demonstrated considerable resilience to adverse market conditions.

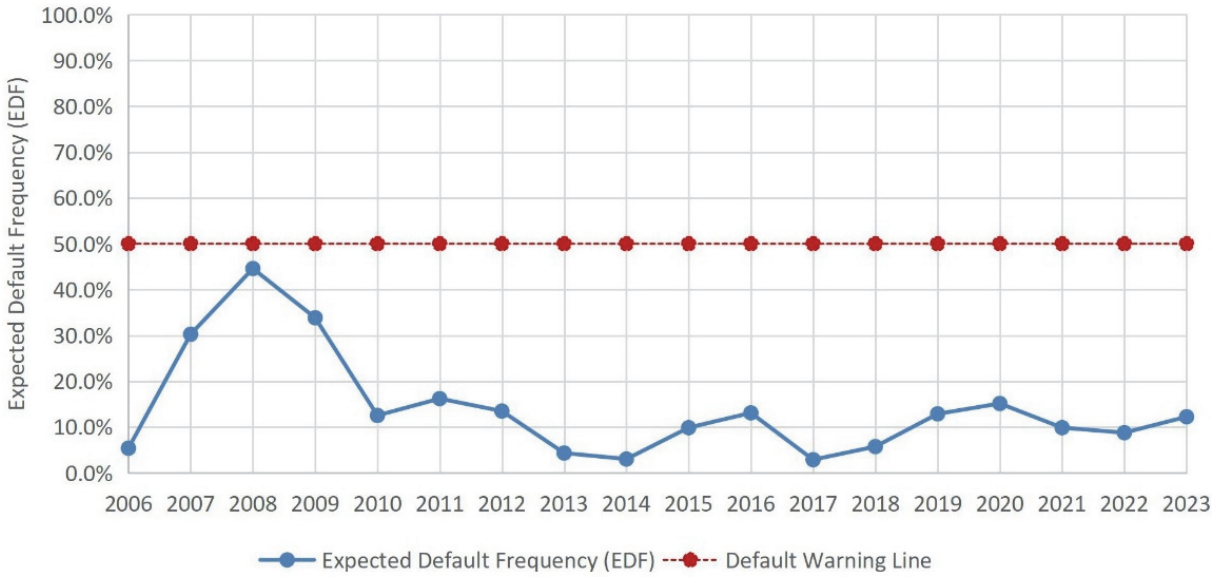



Figure 11. Default Warning of Sun Hung Kai Properties

Data source: East Money Choice database and authors' compilation.

## 6. Limitations and Potential Improvements of the KMV Model in Assessing Credit Risk among Listed Real Estate Firms

### *6.1 Major Limitations*

Despite its usefulness in assessing credit risk, the application of the KMV model to listed real estate firms is subject to several limitations.

First, the KMV model relies on market-based information and is therefore primarily applicable to publicly listed firms, limiting its direct applicability to unlisted entities. Given that a considerable number of Chinese real estate developers remain unlisted or operate through corporate structures in which the listed entity differs from the principal operating entity, the model's coverage and applicability are inevitably constrained.

Second, the theoretical relationship between distance to default (DD) and expected default frequency (EDF) typically relies on distributional assumptions that may not adequately capture the fat-tailed characteristics of actual asset returns. Under the conventional normal distribution assumption, the estimated default probability approaches zero rapidly when DD exceeds 4, potentially leading to an underestimation of extreme credit risk. Moreover, the limited availability of historical default data in China makes it difficult to establish a stable and empirically calibrated mapping between DD and EDF.

Third, although DD serves as the primary credit risk indicator in this study and enables meaningful comparisons and rankings across firms, the determination of appropriate early-warning thresholds remains challenging. In particular, the trade-off between false positives (Type I errors) and false negatives (Type II errors) requires further empirical investigation to establish the reliability and practical effectiveness of the model's early-warning signals.

Fourth, the current model does not fully incorporate non-market information that may significantly influence corporate creditworthiness, including macroeconomic conditions, regulatory policy announcements, financial misreporting, corporate governance quality, and related-party transactions. The exclusion of these factors may limit the model's ability to capture firm-specific vulnerabilities and credit risk arising from institutional and regulatory changes.

Finally, the AUROC value of 0.760 obtained in this study indicates that DD possesses moderate discriminatory power in distinguishing between defaulting and non-defaulting firms, although its predictive performance remains subject to improvement. This finding suggests that reliance on a single structural credit risk model may be insufficient to meet the increasingly stringent requirements of regulators and financial institutions for accurate and timely default prediction. Consequently, integrating the KMV framework with additional financial, macroeconomic, and qualitative indicators may offer a promising approach to enhancing credit risk assessment and early-warning performance.

### *6.2 Directions for Future Improvement*

To enhance the accuracy and reliability of credit risk early-warning systems for listed real estate firms, several potential improvements to the KMV framework warrant further investigation.

First, the KMV model could be extended by incorporating a broader range of explanatory variables, including macroeconomic indicators such as GDP growth, interest rates, inflation, unemployment, and population growth; regulatory policy indicators derived from policy documents; market indicators such as the Shanghai Composite Index and the Dow Jones Industrial Average; and firm-level financial indicators reflecting profitability, operational efficiency, and leverage. Expert assessments could also be incorporated into the indicator selection process to ensure the economic relevance and industry-specific applicability of the selected variables.

Second, statistical techniques, including correlation analysis, principal component analysis (PCA), sensitivity analysis, and analysis of variance (ANOVA), could be employed to identify relevant predictors and reduce potential redundancy among explanatory variables. Particular attention should be paid to the effects of monetary policy adjustments, including interest rate increases and decreases, as well as firm ownership structure and asset size, on default probabilities. Furthermore, potential interaction effects among these factors could be examined to better understand the heterogeneous responses of real estate firms to changing economic and regulatory conditions.

Third, integrating the KMV framework with alternative credit risk assessment approaches, including logistic regression, machine learning algorithms, Altman's Z-score model, CreditMetrics, and CreditRisk+, could improve predictive performance and model robustness. Comparative evaluations and ensemble modeling approaches could be employed to identify complementary strengths across different methodologies. In particular, machine learning techniques could facilitate parameter calibration, variable selection, and the identification of nonlinear relationships, thereby potentially enhancing the model's ability to capture complex patterns of credit risk.

Fourth, a comprehensive evaluation framework should be established to assess the discriminatory power and predictive performance of alternative models. Performance metrics could include receiver operating characteristic (ROC) curves, the area under the ROC curve (AUROC), the Kolmogorov–Smirnov (KS) statistic,

and the frequencies of Type I and Type II errors. Particular emphasis should be placed on examining false-negative (FN) and false-positive (FP) cases to identify the underlying causes of missed defaults and false alarms, thereby improving the calibration of early-warning thresholds and the practical effectiveness of credit risk monitoring.

Fifth, quantitative model evaluation could be complemented by firm-level case studies and regulatory policy text analysis. Detailed investigations of corporate default events, ownership structures, governance mechanisms, business models, abnormal related-party transactions, and potential financial irregularities could provide additional insights into the underlying determinants of credit deterioration. Moreover, incorporating stress-testing scenarios into the early-warning framework would enable a more systematic assessment of firms' resilience under adverse macroeconomic, financial, and regulatory conditions.

Finally, the development of a more comprehensive historical default database for Chinese real estate firms is essential for improving the empirical calibration of the KMV model. As additional default observations become available, a market-specific mapping between distance to default (DD) and expected default frequency (EDF) could be progressively established, reducing reliance on restrictive theoretical distributional assumptions and improving the accuracy of default probability estimation in the Chinese market. Together, these improvements could contribute to the development of a more comprehensive and robust credit risk assessment framework, providing more reliable early-warning information for financial institutions, investors, and regulatory authorities.

## 7. Conclusions

This study applies the KMV structural credit risk model to assess the financial vulnerability of 261 real estate firms listed on mainland China's A-share markets and the Hong Kong Stock Exchange, with particular emphasis on the evolution of credit risk among Hong Kong-listed developers during 2010–2023. By combining market-based distance-to-default (DD) estimates, receiver operating characteristic (ROC) analysis, and firm-level comparative case studies, the study examines the applicability of the KMV framework to credit risk assessment in China's real estate sector. The empirical findings lead to several conclusions.

First, the results reveal substantial temporal variation and cross-sectional heterogeneity in corporate credit risk. The overall mean DD of Hong Kong-listed real estate firms is 2.49, with a pronounced deterioration in credit conditions during 2022–2023. Mainland-focused developers experienced a substantially sharper decline in DD than firms operating primarily in Hong Kong or overseas markets. These contrasting trajectories suggest that geographical exposure, financing structures, and differences in business models are important considerations in understanding corporate financial vulnerability. The observed deterioration coincided with regulatory tightening and the broader property market downturn, although the descriptive analysis does not establish a causal relationship between specific policies and changes in default risk.

Second, the ROC analysis indicates that DD possesses moderate discriminatory ability in distinguishing firms according to their observed default status. The estimated AUROC of 0.760, with a 95% confidence interval of 0.686–0.833, demonstrates that market-based DD estimates contain useful information for credit risk ranking. However, because the evaluation sample includes firms that defaulted before or during the measurement period, this finding primarily supports retrospective risk discrimination rather than independently validated prospective default prediction. Consequently, the predictive reliability of the model requires further investigation using temporally consistent default definitions and out-of-sample validation.

Third, the comparative case studies suggest that market-based credit risk indicators can complement conventional credit ratings by providing more frequent information about changes in corporate financial conditions. The experiences of financially distressed developers, including China Evergrande Group, illustrate the potential usefulness of DD and estimated expected default frequency (EDF) in monitoring deteriorating creditworthiness. In contrast, the case of Sun Hung Kai Properties demonstrates the model's ability to reflect relatively stable financial conditions. Nevertheless, these selected cases do not establish the model's overall superiority in forecasting defaults, particularly given the potential trade-off between early detection and false-positive warnings.

The findings have several implications for financial institutions, investors, and regulatory authorities. First, market-based structural credit risk measures may be incorporated into existing monitoring systems as supplementary indicators rather than substitutes for conventional ratings and financial statement analysis. Second, risk assessment should account for differences in corporate leverage, geographical exposure, and business models, particularly during periods of sector-wide financial stress. Third, the development of comprehensive historical default databases and empirically justified warning thresholds would strengthen the practical application of structural credit risk models in the Chinese market.

Despite these contributions, the study has several limitations. The KMV framework relies on observable equity market information, restricting its direct applicability to unlisted firms. Its estimates are sensitive to assumptions concerning asset values, volatility, and default thresholds. Moreover, the present evaluation does not provide independently validated out-of-sample forecasting results, while the empirical mapping between DD and EDF requires further documentation and calibration. Future research should address these limitations through temporally structured validation, alternative model specifications, probability calibration, and systematic evaluation of false-positive and false-negative classifications. Integrating firm-level financial characteristics, macroeconomic conditions, regulatory indicators, and appropriately validated machine learning methods may further improve the robustness and practical usefulness of credit risk assessment.

Overall, this study provides empirical evidence that the KMV framework can capture important differences in the financial vulnerability of listed real estate firms, particularly during periods of substantial market adjustment. Its principal contribution lies in demonstrating the usefulness of market-based distance-to-default measures for credit risk discrimination and monitoring, while identifying the methodological improvements necessary to establish reliable prospective early-warning performance.

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