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# Bankruptcy Prediction Models


### Abstract

This paper provides a comprehensive review of the evolution of bankruptcy prediction and financial distress models, tracing the transition from traditional accounting-based static models to dynamic, market-driven, and artificial intelligence-enhanced approaches. Key milestones include the discrete-time hazard model, which corrects biases in classical logit models by using multi-year panel data, and structural models rooted in the Black–Scholes–Merton framework, which consistently outperform accounting-based benchmarks by exploiting forward-looking market information. The review highlights the growing importance of firm structural characteristics (size, diversification) and, particularly in emerging markets such as China, the need for regional systemic risk early-warning systems. Recent literature demonstrates that deep learning and big-data techniques achieve superior accuracy and earlier detection by capturing complex non-linear patterns across accounting, market, macroeconomic, and alternative data sources. The synthesis concludes that the most effective contemporary bankruptcy prediction frameworks integrate the theoretical foundation of structural models, the dynamic richness of hazard specifications, market-based signals, and the representational power of deep neural networks, paving the way for real-time, interpretable, and contagion-aware systems in the future.


***Keywords:*** *bankruptcy prediction, distance to default, Merton model, BSM-Prob, KMV model, hazard model, Shumway model, deep learning, financial risk early-warning, China financial regulation*

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# İflas proqnozlaşdırma modelləri


### Xülasə

Bu məqalə iflas proqnozlaşdırılması və maliyyə çətinliyi modellərinin təkamülünə dair hərtərəfli icmal təqdim edir və ənənəvi mühasibatlıq əsaslı statik modellərdən dinamik, bazaya söykənən və süni intellektlə gücləndirilmiş yanaşmalara keçidi izləyir. Əsas mərhələlər arasında çoxillik panel məlumatlarından istifadə etməklə klassik loqit modellərindəki qərəzləri aradan qaldıran diskret-zamanda təhlükə modeli və qabaqlayıcı bazar məlumatlarından istifadə edərək hesabata əsaslanan meyarları ardıcıl şəkildə üstələyən Black–Scholes–Merton çərçivəsinə əsaslanan struktur modellər yer alır. İcmal həmçinin şirkətin struktur xüsusiyyətlərinin (ölçü, diversifikasiya) artan əhəmiyyətini və xüsusilə Çin kimi inkişaf etməkdə olan bazarlarda regional sistemik risklər üçün erkən xəbərdarlıq sistemlərinə ehtiyacı vurğulayır. Son ədəbiyyat göstərir ki, dərin öyrənmə və böyük data texnikaları mühasibat uçotu, bazar, makroiqtisadi və alternativ məlumat mənbələri üzrə kompleks qeyri-xətti nümunələri tutmaqla daha yüksək dəqiqlik və daha erkən aşkarlama imkanı yaradır.

Ümumi nəticə ondan ibarətdir ki, müasir iflas proqnozlaşdırma çərçivələrinin ən effektiv forması struktur modellərinin nəzəri əsasını, təhlükə modellərinin dinamik tutumunu, bazar siqnallarını və dərin neyron şəbəkələrinin təqdimedici gücünü birləşdirən inteqrasiya olunmuş yanaşmadır. Bu isə gələcəkdə real vaxt rejimində işləyən, izah olunan və yoluxma effektlərini nəzərə alan sistemlərin yaranmasına yol açır.

***Açar sözlər:*** *iflas proqnozlaşdırılması, defolt məsafəsi, Merton modeli, BSM-Prob, KMV modeli, təhlükə modeli, Shumway modeli, dərin öyrənmə, maliyyə risklərinə erkən xəbərdarlıq, Çin maliyyə tənzimləməsi*

## Introduction

In recent years, more advanced methods have been developed in the field of bankruptcy prediction models compared to traditional accounting-based approaches. As alternatives to classical models such as Altman (1968) and Ohlson (1980), the discrete-time hazard model proposed by Shumway (2001) and the market-based BSM-Prob model developed by Hillegeist and colleagues (2004) have gained prominence (Altman, 1968; Ohlson, 1980; Shumway, 2001; Hillegeist et al., 2004).

Shumway's model aims to predict firms' bankruptcy risk by using both accounting and market data. The most important difference between this model and the classical logit model is that, instead of relying on a single observation year, it uses a dataset covering all years for each firm during the estimation process. This allows the model to more accurately capture the effects of changes in a firm's financial structure over time, in contrast to static logit models.

**Research**

In the market-based prediction literature, the BSM-Prob model developed by Hillegeist and colleagues, which is based on the Black–Scholes–Merton option-pricing framework, stands out. It has been demonstrated that this model outperforms both the Altman and Ohlson models in in-sample and out-of-sample tests. These results indicate that the dynamic nature of market data enables the development of more sensitive and predictive models (Wu et al., 2010).

In addition, there are studies suggesting that various firm characteristics may serve as additional determinants in bankruptcy prediction. For example, Rose (1992) proposed a model showing that managers attempt to reduce bankruptcy risk through diversification when firm-specific human capital is high (Rose, 1992). Denis and colleagues (1997) measured corporate diversification by the number of business segments (Denis et al., 1997), while Beaver and colleagues (2005) argued that large firms have lower bankruptcy probabilities, partly due to corporate diversification (Beaver et al., 2005). These findings show that firm size and the level of diversification are important structural features that should be taken into account in bankruptcy prediction.

**Models Based on Financial and Legal Indicators**

Throughout China's decades-long process of social and economic development, the financial sector has played a vital role as the cornerstone of the market economy and has occupied a central position within the economic system. As the laws and regulations governing the financial system have been improved, the traditional financial risk early-warning model has also been optimized within the construction of these regulatory frameworks. The implementation of legally safeguarded financial prevention and control measures, along with the early detection of financial risks, plays an important role both in shaping the legal structure of financial markets and in establishing regulations aimed at preventing financial risks.

From time to time, the financial market experiences functional disruptions, which significantly increase the likelihood of risk. Financial risks, characterized by high danger and crisis potential, have the capacity to inflict substantial damage on the market economy. In particular, regional financial risks tend to have strong linkages and spillover effects; therefore, they carry a high probability of triggering nationwide financial crises and even global financial crises through ripple effects. Under the pressure of rapid economic growth, numerous uncertain factors emerge. As a result, the early warning, prevention, and control of regional financial risks have become important tasks of macroeconomic regulation in China.

Although national legal supervision mechanisms are capable of effectively monitoring risks, the implementation of efficient financial risk early-warning systems ensures a more harmonious and orderly development of financial markets, contributes to the smoother functioning of the overall market economy, and provides greater economic benefits to society. Strengthening early-warning mechanisms for regional financial risks carries significant practical value in preventing financial crises and stabilizing regional economic growth. Since financial behaviour is directly linked to the economy and society, all sectors are increasingly paying attention to risks in the financial domain.

Deep learning, a widely used technology in the field of artificial intelligence, can model complex data by means of its multilayered processing structure and nonlinear transformation mechanisms, allowing it to extract abstract and high-level features. At the same time, deep learning can process large-scale data, identify suitable and effective features, and learn them through training, using multilayer perceptron models for supervised or unsupervised learning. As the depth of the model increases, the representation of features becomes more accurate.

Chen et al. (2020) used a deep neural network to model evacuation processes in metro stations and conducted simulation experiments (Chen et al., 2020). They classified datasets with a convolutional neural network model and a pretrained model, verifying the proposed model's accuracy and training speed. Chen et al. (2021) applied deep learning technology to model cybersecurity systems in smart cities, successfully reducing network security risks (Chen et al., 2021). Deep learning can also be used in financial analysis; for example, it can be effective in predicting commodity prices, forecasting financial events, detecting financial risks, and analysing other current issues. Zhou et al. (2021) applied deep learning to the financial risk early-warning system for real-estate companies, providing concrete analysis and demonstration (Zhou et al., 2021).

Within the context of electronic early-warning systems for regional financial risks, researchers have also conducted studies on the causes of risks, transmission channels, indicators, and model selection. Du et al. (2021) established a scientific and effective electronic early-warning system based on big-data technology, integrating large volumes of information and incorporating relevant risk indicators into the system (Du et al., 2021).

The evaluation index systems used for selecting financial risk early-warning indicators mostly focus on foreign exchange crises, bond crises, or banking crises; however, they remain insufficient for fully capturing systemic financial risk. Moreover, traditional financial risk early-warning systems rely heavily on linear models, which fail to adequately capture the dynamics of complex economic systems.

**Merton Model and Its Derivatives**

The Merton Model and its derivatives are among the structural credit-risk models developed to estimate the probability of corporate default. Introduced in 1974 by Robert C. Merton, this model assesses financial risk—particularly through capital structure and market value—to measure a firm's likelihood of bankruptcy (Aywak, 2022). The foundation of the model is the Black–Scholes option-pricing theory, and it interprets a firm's equity as a European call option.

According to the Merton Model, the value of a company's assets determines whether it can meet its obligations (Merton, 1974). If the firm is unable to repay its debts at maturity—that is, if the value of its assets falls below the value of its liabilities—this signifies default. Using this approach, the firm's probability of default is calculated based on the stochastic behaviour and volatility of its assets.

**The core components of the model are:**

– Total asset value of the firm;
– Volatility of the firm's assets;
– Maturity structure and magnitude of debt;
– Risk-free interest rate;
– Equity value and market observations.

In the Merton Model, the probability of default is treated as the likelihood that a firm's asset value will fail to cover its liabilities. Within this framework, concepts such as Default Distance (DD) and Default Probability (DP) have been developed. Default Distance measures how far a firm's asset value is from the default threshold, while Default Probability expresses the likelihood of default based on the statistical distribution of this distance.

One major advantage of the Merton Model is that it provides a market-based and statistically sophisticated estimation of default risk (Abdullah, 2016). However, it also has several limitations. For instance, asset value and asset volatility are not directly observable, requiring indirect estimation. In addition, the model assumes a single debt maturity and a constant risk-free interest rate, which may not adequately represent more complex capital structures.

Among the best-known advanced derivatives of the Merton Model are the KMV Model, the Black–Cox Model, and the Longstaff–Schwartz Model.

The KMV Model, developed by Moody's and built upon the Merton framework, is widely applied for estimating the default probabilities of private firms (Septiana et al., 2025). In this model, the default threshold is defined more flexibly using historical data.

The Black–Cox Model extends the Merton Model by introducing a "default barrier" that is monitored continuously over time, allowing the calculation of dynamic default probabilities.

The Longstaff–Schwartz Model incorporates interest-rate risk into the structural framework, jointly evaluating both debt and interest-rate components.

These models are effectively used in many areas, including modern credit-risk management, credit default swap (CDS) pricing, and corporate debt analysis.

## Conclusion

In summary, bankruptcy and financial distress prediction has progressed from static, backward-looking, accounting-centric models → dynamic hazard/market-based structural models → AI-augmented, big-data-driven, non-linear systems. The most effective contemporary frameworks combine:

• the theoretical rigor of structural (Merton-type) models,
• the time-series richness of hazard/panel approaches,
• the forward-looking information content of market variables, and
• the representational power of modern deep learning architectures.

Future advances are likely to focus on interpretability of deep models, real-time prediction using high-frequency and unstructured data, integration of climate and geopolitical risk factors, and the development of truly systemic early-warning systems capable of detecting contagion across firms, sectors, and regions before traditional indicators signal distress. In an increasingly interconnected and fast-moving financial environment, models that can continuously learn and adapt from market and alternative data streams will dominate bankruptcy and financial risk prediction in the coming decade.

## References

1. Abdullah, A. M. (2016). Comparing the reliability of accounting-based and market-based prediction models. *Asian Journal of Accounting & Governance, 7*.
2. Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance, 23*(4), 589–609.
3. Aywak, B. O. (2022). *Structural credit risk modelling and valuation based on the Merton model* (Doctoral dissertation, University of Nairobi).
4. Beaver, W. H., McNichols, M. F., & Rhie, J. W. (2005). Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy. *Review of Accounting Studies, 10*(1), 93–122.
5. Chen, L., Han, Q., Qiao, Z., & Stanley, H. E. (2020). Correlation analysis and systemic risk measurement of regional, financial and global stock indices. *Physica A: Statistical Mechanics and Its Applications, 542*, 122653.
6. Denis, D. J., Denis, D. K., & Sarin, A. (1997). Agency problems, equity ownership, and corporate diversification. *The Journal of Finance, 52*(1), 135–160.
7. Du, G., Liu, Z., & Lu, H. (2021). Application of innovative risk early warning mode under big data technology in Internet credit financial risk assessment. *Journal of Computational and Applied Mathematics, 386*, 113260.
8. Hillegeist, S. A., Keating, E. K., Cram, D. P., & Lundstedt, K. G. (2004). Assessing the probability of bankruptcy. *Review of Accounting Studies, 9*(1), 5–34.
9. Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance, 29*(2), 449–470.
10. Ohlson, J. A., & Garman, M. B. (1980). A dynamic equilibrium for the Ross arbitrage model. *The Journal of Finance, 35*(3), 675–684.
11. Rose, D. C. (1992). Bankruptcy risk, firm-specific managerial human capital, and diversification. *Review of Industrial Organization, 7*, 65–73.
12. Septiana, N. I., Katri, F. S. B. H., Ideris, A. B., & Noryatim, N. (2025). Estimating expected default probability and credit risk spread using the KMV Merton model: A case study of Bank Islam Malaysia Berhad. *Jihbiz: Jurnal Ekonomi, Keuangan dan Perbankan Syariah, 9*(1), 93– 105.
13. Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *The Journal of Business, 74*(1), 101–124.
14. Wu, Y., Gaunt, C., & Gray, S. (2010). A comparison of alternative bankruptcy prediction models. *Journal of Contemporary Accounting & Economics, 6*(1), 34–45.
15. Zhou, W., Chen, M., Yang, Z., & Song, X. (2021). Real estate risk measurement and early warning based on PSO-SVM. *Socio-Economic Planning Sciences, 77*, 101001.

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