DOI: https://doi.org/10.36719/2663-4619/123/69-75

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Financial Failure Prediction Models

Abstract

The stable economic and social development of modern states hinges on uninterrupted financial inflows, operational profitability, and sustained investment. Within this framework, the timely analysis and prediction of corporate bankruptcy emerge as pivotal mechanisms for identifying internal vulnerabilities and enabling pre-emptive interventions. This study examines classical bankruptcy prediction models—ranging from Beaver's univariate ratio tracking and Altman's Z-Score discriminant analysis to Ohlson's logistic regression, Springate's simplified MDA, Zmijewski's probit-based probability estimation, and the market-augmented CHS framework. By synthesizing their methodologies, strengths, and contextual limitations, the research underscores their collective role in transforming financial diagnostics into proactive economic safeguards. Bankruptcy is revealed not as an abrupt event but as a detectable, progressive decline—affording critical windows for recovery if early signals are heeded. The integration of accounting-based and market-driven indicators, tailored to local economic realities, is proposed as essential for enhancing predictive accuracy and supporting macroeconomic resilience.

Keywords: *bankruptcy prediction, financial distress, Altman Z-Score, Beaver model, Ohlson O-Score, Springate model, Zmijewski model, CHS model, financial ratios, early warning systems, economic stability, corporate failure, discriminant analysis, probit regression, market-based indicators*

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Maliyyə uğursuzluğunu proqnozlaşdırma modelləri

Xülasə

Müasir dövlətlərin sabit iqtisadi və sosial inkişafı fasiləsiz maliyyə axınları, əməliyyat mənfəətliliyi və davamlı investisiya qoyuluşları üzərində qurulur. Bu çərçivədə korporativ iflasın vaxtında təhlili və proqnozlaşdırılması daxili zəifliklərin müəyyənləşdirilməsi və qabaqlayıcı müdaxilə tədbirlərinin həyata keçirilməsi baxımından xüsusi əhəmiyyət daşıyır. Tədqiqatda klassik iflas proqnozlaşdırma modelləri – Biverin tək göstəricilər sistemindən, Altmanın Z-skoruna əsaslanan diskriminant analizindən, Ohlsonun logistik reqressiya modelindən, Sprinqeytin sadələşdirilmiş MDA yanaşmasından, Zmijevskinin probit əsaslı ehtimal qiymətləndirməsindən və bazar göstəriciləri ilə inteqrasiya olunmuş CHS modelindən istifadə təhlil edilir. Bu modellərin metodoloji əsasları, üstünlükləri və məhdudiyyətlərinin müqayisəli şəkildə öyrənilməsi onların maliyyə diaqnostikasını proaktiv iqtisadi təhlükəsizlik vasitəsinə çevirdiyini göstərir. İflasın qəfil deyil, mərhələli şəkildə inkişaf edən proses olduğu və erkən siqnallar vaxtında aşkarlandığı halda bərpa imkanlarının mövcud olduğu vurğulanır. Mühasibat uçotu göstəriciləri ilə bazar yönümlü göstəricilərin birgə tətbiqi və yerli

iqtisadi şəraitə uyğunlaşdırılması proqnoz dəqiqliyinin artırılması və makroiqtisadi dayanıqlığın gücləndirilməsi üçün vacib hesab edilir.

Açar sözlər: *iflasın proqnozlaşdırılması, maliyyə çətinliyi, Altman Z-skoru, Biver modeli, Ohlson O-skoru, Sprinqeyt modeli, Zmijevski modeli, CHS modeli, maliyyə əmsalları, erkən xəbərdarlıq sistemləri, iqtisadi sabitlik, korporativ uğursuzluq, diskriminant analiz, probit reqressiyası, bazar yönümlü göstəricilər*

Introduction

The stable economic and social development of any state in today's conditions is built upon the regular flow of financial resources into budgets, the stable operation of profitable enterprises, and the uninterrupted inflow of investments. In this context, the task of analysing and evaluating the financial condition of enterprises becomes particularly important. This makes it possible to identify internal problems in a timely manner and to develop and implement the most appropriate intervention measures in advance (Tokhirovna, 2024).

Predicting corporate bankruptcies is of great importance for every economic sector. This is further confirmed by the constant emergence of global financial crises and the increase in credit risk. The diagnosis of instability within enterprises can serve as the basis for an objective assessment of the current state of an economic entity in this context (Rayevnyeva et al., 2021).

It should also be noted that corporate bankruptcy is a global issue. In different countries around the world, various methods are used to address the problems of companies facing bankruptcy. However, business collapse is not a sudden event; the process goes through several stages. If early warning signals are detected in time, work on solutions can begin at an early stage.

Research

Classical financial forecasting models have been developed to evaluate the future financial conditions of enterprises and to predict potential risks of financial failure. These models are generally based on the analysis of ratios derived from financial statements.

One of the most widely used models is Altman's Z-Score model, which determines the bankruptcy risk of firms based on five different financial ratios. The Altman model was introduced to the world in 1968. Edward Altman published what has become the most well-known model aimed at predicting bankruptcy. The model represents a Z-score calculated using various groups of financial performance indicators. Through this model, it is possible to forecast the financial condition of an economic entity for the next 2–3 years (Altman et al., 2017).

Altman introduced several models; among them, the most comprehensive and accurate one is a statistical model composed of five financial ratios that together form the Z-score. The assessment in this model is based on comparing the resulting Z-score with specific threshold values. A score below 1.81 indicates a high risk of bankruptcy, and as the score increases, the probability of bankruptcy decreases proportionally (Asif et al., 2024).

Research on the objectivity of models based on multivariate discriminant analysis (MDA) also occupies an important place in the evaluation of financial conditions. At this point, the emphasis is placed on how accurately the financial condition of economic entities can be assessed using MDA models, and examples of such models have been discussed previously. The accuracy of these models is particularly significant for Russian companies, as in practice it has been observed that these models are often idealized and contain a margin of error. Therefore, it is necessary to determine the most accurate model. Since the 1960s, research has been conducted to develop quantitative models capable of predicting critical financial conditions and high probabilities of bankruptcy.

Another important model is Beaver's approach based on single-ratio analysis, in which the behaviour of certain ratios over time—particularly cash flow, total liabilities, and assets—is monitored. In 1966, the well-known financial analyst William Beaver proposed an indicator system for evaluating the financial condition of enterprises with the aim of determining the likelihood of bankruptcy (Beaver, 1966). This system includes the following key financial indicators: return on assets (ROA), the share of debt in total liabilities, the current ratio, the ratio of net working capital to total assets, and the Beaver coefficient (the ratio of the sum of net profit and depreciation to total debt).

Beaver's evaluation system, based on these ratios, aims to detect potential bankruptcy risks at an early stage by analysing a company's financial stability. The fundamental feature of this model is that it makes predictions by tracking the behaviour of specific individual ratios over time (Tıryaki, 2021). William Beaver's indicator system for diagnosing bankruptcy is usually presented in tabular form with the basic ratios (Table 1).

Table 1. Financial Indicators According to Beaver's Bankruptcy Prediction System.

№	Indicator Name	Calculation Formula	Healthy Companies (Group I)	Companies 5 Years Before Bankruptcy (Group II)	Companies 1 Year Before Bankruptcy (Group III)
1	**Beaver Coefficient (Profitability Ratio)**	(Net Profit + Depreciation) / Total Debt	0.40 – 0.45	≤ 0.30	≈ 0.06
2	**Current Ratio (Liquidity Ratio)**	Current Assets / Short-Term Liabilities	≥ 3.2	0.17 – 0.15	≤ 0.15
3	**Return on Assets (ROA)**	(Net Profit × 100) / Total Assets	6 – 8	≤ 2	≤ 1
4	**Financial Leverage**	(Total Debt × 100) / Total Assets	4 – 22	≤ 37	Higher than Group II
5	**Equity-to-Assets Coverage Ratio** (Support of Assets by Equity)	(Equity – Fixed Assets) / Total Assets	≤ 50	≤ 80	Very low

Source: Matyukhin, 2012, p. 348.

This model aims to monitor a company's bankruptcy risk over time by observing the decline and deterioration of various financial ratios. In particular, the Beaver coefficient is a critical indicator, as it reflects the company's ability to repay its debts. A deterioration in these values indicates an increase in bankruptcy risk. Since weighting coefficients are not assigned to the indicators in Beaver's model, no final aggregate bankruptcy score is calculated. Instead, the obtained indicator values are compared with the normative values calculated by Beaver for financially healthy companies, companies one year prior to bankruptcy, and companies five years prior to bankruptcy.

In contrast, Ohlson's O-Score model is based on a logistic regression approach and was developed primarily for publicly traded companies, using a broader set of financial variables. In 1980, James A. Ohlson introduced the "Ohlson Model (O-Model)" in his study titled "Financial Ratios and the Probabilistic Prediction of Bankruptcy" (Ohlson & Garman, 1980).

This model is fundamentally based on the same approach as Altman's model; however, Ohlson developed a more robust and statistically reliable model by using statistical data from more than 2,000 companies in his analysis. The O-Model consists of a total of nine variables. These variables are presented in the table below.

Table 2. Variables Included in the Ohlson Model.

Variable	Description
AS (Firm Size)	Size adjusted for inflation: AS = log(Total Assets / GDP Price Index)
LM (Financial Leverage)	LM = Total Debt / Total Assets
WCM (Net Working Capital Ratio)	WCM = Net Working Capital / Total Assets
ICR (Inverse Current Ratio)	ICR = Short-Term Liabilities / Current Assets
ROA (Return on Assets)	ROA = Net Profit / Total Assets — typically negative for firms close to bankruptcy
Debt > Assets Adjustment	Binary variable: assigned 1 if total debt exceeds total assets; otherwise 0
FTDR (Debt Service Capacity)	FTDR = Funds from Operations (FFO) / Total Debt
FFO (Funds from Operations)	FFO = Profit Before Tax + Depreciation
ROA Adjustment	Binary variable: assigned 1 if the company has posted net losses for the last two consecutive years
CINI (Net Income Change)	CINI = [Net Profit (t) – Net Profit (t–1)] / [Net Profit (t) + Net Profit (t–1)]

Source: Barchuk, 2019, p. 22.

Ohlson used data from 2,000 industrial firms that had been publicly traded for at least three years during the period 1970–1976. Among these firms, 135 had gone bankrupt, which provided a sufficient statistical basis for testing the model. The CHS Model was developed in 2010 at Harvard University to predict financial bankruptcy and credit risk by combining accounting data with market-based indicators. The model incorporates both balance sheet variables and market performance measures in order to more accurately reflect the behaviour of firms that are prone to financial distress (Ståhle & Ståhle, 2012). The variables included in the CHS Model are summarized in the table below:

Table 3. Variables Used in the CHS Model.

Variable	Description
Weighted Profitability Measure (WPM)	WPM = Weighted Average (Quarterly Net Income / MTA), where MTA = Market-Valued Total Assets = Book Value of Debt + Market Capitalization. More recent quarters are assigned higher weights.
Leverage Ratio (LM)	LM = Total Debt / MTA, indicating the firm's indebtedness relative to its market-valued assets.
Short-Term Liquidity (STL)	STL = Cash and Cash Equivalents / MTA, measuring the firm's short-term payment capacity.
Weighted Relative Return Performance (WRRP)	WRRP = Weighted Average [log(Gross Stock Return) – log(Gross FTSE Index Return)], evaluating how the firm's stock performs relative to the market index. More weight is assigned to recent quarters.
Recent 3-Month Return Volatility (RV)	RV = Standard Deviation of Stock Prices over the Last 3 Months, based on the observation that distressed firms typically exhibit higher volatility.
Relative Firm Size (RS)	RS = log(Market Capitalization / Total Market Capitalization of FTSE100). Smaller firms are generally more vulnerable due to limited access to financing.
Overvaluation Factor (OF)	OF = MTA / Adjusted Book Value, where Adjusted Book Value = Book Value + 0.1 × (Market Value – Book Value). This indicator is used to identify potentially overvalued firms that have recently experienced large losses.

Variable	Description
Stock Price Logarithm (SPL)	SPL = log(Last Stock Price). Distressed firms often have low stock prices. An upper threshold of $15 is applied, since higher values showed no significant effect on model accuracy.

Source: Latisheva, 2017, p. 24.

The Springate model follows a structure similar to the Altman model, but it was developed using data from Canadian companies. The Springate model takes into account the following four key financial ratios:

1. The ratio of working capital to total assets – this ratio reflects the company's ability to cover its short-term liabilities.
2. The ratio of earnings before interest and taxes (EBIT) to total assets – this indicator shows how efficiently the company uses its assets and its operating profitability.
3. The ratio of earnings before interest and taxes (EBIT) to short-term debt – this measures the company's capacity to meet short-term obligations using its operating income.
4. The ratio of sales revenue to total assets – this is an efficiency ratio that evaluates sales performance relative to the company's asset base.

The Springate model calculates a Z-score by applying specific weights to these ratios. If this score falls below a certain threshold ($Z < 0.862$), the company is considered to be at potential risk of bankruptcy. The model was developed particularly for assessing bankruptcy risk in medium-sized firms and is noted for its simplicity (Husein, 2015).

Additionally, the Zmijewski model aims to evaluate the probability of corporate financial failure using the probit regression method. In 1984, M. Zmijewski developed a model based on probit regression analysis to predict the bankruptcy risk of companies. The model was constructed using data from 840 firms for the period 1972–1978, of which 40 had gone bankrupt and 800 were financially healthy (Muzani & Yuliana, 2021).

The Zmijewski model measures the probability of financial failure in companies by using three key financial ratios:

1. ROA (Return on Assets) = Net Profit / Total Assets
2. Financial Leverage = Total Debt / Total Assets
3. Liquidity Ratio = Current Assets / Short-Term Liabilities

The general form of the model is as follows:

$$Z = \beta_0 + \beta_1(\text{ROA}) + \beta_2(\text{Financial Leverage}) + \beta_3(\text{Liquidity Ratio})$$

Due to its probit regression structure, the output of the model provides a direct probability value associated with the likelihood of bankruptcy. If the calculated value exceeds a certain threshold, the company is considered to be at risk of financial failure.

The advantage of this model is that, unlike earlier models which rely on fixed threshold values, it generates a statistical probability, allowing for a more flexible prediction of financial distress. Moreover, because it can be applied with only a few variables, it is suitable for use in cases where data accessibility is limited.

The common feature of these models is that they combine statistical methods for measuring bankruptcy risk with historical data, thereby supporting forward-looking decision-making processes.

Conclusion

The prediction of corporate bankruptcy transcends mere financial diagnostics; it constitutes a strategic imperative for safeguarding macroeconomic stability, protecting stakeholder interests, and sustaining societal welfare in an interconnected global economy. Far from being isolated corporate failures, bankruptcies ripple outward—eroding tax revenues, triggering unemployment, disrupting supply chains, and amplifying systemic credit risk. In this light, robust bankruptcy forecasting models serve not only as early warning systems for individual enterprises but as critical instruments of national economic resilience.

The classical models reviewed—from Beaver's univariate vigilance to Altman's discriminant precision, Ohlson's probabilistic rigor, and the market-augmented CHS framework—collectively affirm a foundational truth: financial distress is detectable, measurable, and, if identified early, often mitigable. These tools transform raw accounting signals into actionable intelligence, enabling creditors, investors, regulators, and managers to intervene before collapse becomes inevitable. Their shared reliance on financial ratios underscores a universal language of solvency: liquidity sustains operations, profitability validates efficiency, and leverage defines vulnerability.

Yet the true power of these models lies not in their mathematical elegance but in their preventive potential. Bankruptcy is not a sudden catastrophe but a progressive deterioration—one that begins years in advance through gradual erosion of cash buffers, shrinking margins, and mounting obligations. By illuminating these trajectories, predictive models shift the paradigm from reactive crisis management to proactive stabilization, allowing corrective measures—restructuring, divestiture, or policy support—to be deployed at stages where recovery remains viable.

In an era of heightened volatility, where geopolitical shocks, technological disruption, and climate-related risks routinely destabilize corporate foundations, the role of bankruptcy prediction evolves from academic exercise to societal safeguard. For emerging economies like Russia, where institutional trust and data transparency may lag, adapting these models with local calibration is essential to overcome idealized assumptions. For global markets, integrating real-time market signals (as in CHS) anticipates distress that balance sheets alone conceal.

Ultimately, the enduring value of bankruptcy prediction lies in its capacity to protect the future by decoding the present. When enterprises thrive, societies prosper; when they falter undetected, collective progress stalls. By institutionalizing systematic financial surveillance—grounded in proven models, enriched by contextual insight, and applied with disciplined foresight—policymakers and business leaders can transform the spectre of corporate failure into a manageable, and often avertable, risk. In doing so, they uphold the stable flow of resources, confidence, and opportunity upon which modern states depend.

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Received: 05.06.2025
Accepted: 14.09.2025