FORECASTING FINANCIAL TURBULENCE: AN EVALUATION OF CORPORATE BANKRUPTCY RISK IN BANKING FIRMS

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Abstract

In a volatile financial environment, the early identification of bankruptcy risk is critical for maintaining economic stability, particularly in the banking sector. This study evaluates the financial health of Indian banking firms using Altman's Z-score model, a time-tested tool for forecasting corporate bankruptcy. By analyzing financial data from 138 public and private banks over the period 2014–2023, the research reveals considerable fluctuations in asset quality, profitability, and capital adequacy. Public sector banks have shown improved financial stability in recent years, attributed to reforms and better risk governance, while private sector banks displayed greater variability in financial health. These findings support the relevance of sector-specific and regionally adapted models for risk assessment (Agarwal & Patni, 2019; Kumar & Ravi, 2007). Furthermore, the study contributes to the broader discourse on business failure by integrating insights from recent literature on legal and organizational determinants in emerging markets (Arzou & Kobiyh, 2025). This research underscores the importance of robust financial metrics and predictive tools in shaping informed policy decisions and investor strategies, especially in emerging economies where regulatory frameworks and market dynamics pose unique challenges.

Keywords: Bankruptcy Risk, Financial Distress, Banking Sector, Altman's Z-Score, Financial Stability

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1. INTRODUCTION

In the contemporary global economy, financial distress and bankruptcy have emerged as critical areas of concern for investors, stakeholders, and policymakers (Arzou & Kobiyh, 2025; Budhidharma et al., 2023; Eyalsalman et al., 2024; Swain et al., 2025). The unpredictability of economic cycles, coupled with the complex interplay of internal and external financial variables, necessitates robust tools and methodologies for assessing and predicting the financial health of entities. Companies across industries are increasingly vulnerable to market fluctuations, operational inefficiencies, and regulatory challenges, making it essential to monitor their financial stability proactively. The Indian banking sector, a pivotal contributor to the country's economic development, is no exception. With its diverse structure encompassing public and private sector banks, the sector represents a significant portion of India's financial infrastructure, warranting a deeper understanding of its financial resilience (Reserve Bank of India, 2021). Bankruptcy, defined as the inability of an entity to meet its financial obligations, has far-reaching implications. It not only affects creditors, investors, and employees but also poses risks to broader economic stability. Edward I. Altman's Z-score model, introduced in the late 1960s, has proven to be one of the most effective tools for predicting corporate bankruptcy. The model combines various financial ratios into a single score, categorizing companies into zones that reflect their financial health or distress (Altman, 1968). Despite its widespread adoption in academic research and practical financial analysis, the model's application to sector-specific contexts, such as Indian banking, remains underexplored (Agarwal & Patni, 2019).

India's banking sector is characterized by a dual challenge of balancing profitability and maintaining asset quality amidst regulatory pressures and economic uncertainties. Public sector banks, in particular, have historically faced issues related to non-performing assets (NPAs) and governance inefficiencies, while private sector banks have grappled with heightened competition and market volatility (Daniel et al., 2025). These challenges underscore the need for a systematic approach to evaluating bankruptcy risk in the sector. The roots of bankruptcy can be traced back to ancient civilizations, where early legal systems provided mechanisms for debt resolution. Roman and medieval laws laid the groundwork for modern bankruptcy proceedings, evolving into frameworks that address corporate and institutional insolvency in today's context (Ogachi et al., 2020). Over the years, the study of bankruptcy risk has transitioned from qualitative assessments to sophisticated quantitative models. The Altman Z-score, complemented by advancements in statistical and machine learning techniques, has emerged as a preferred methodology for forecasting financial turbulence (Toudas et al., 2024).

Despite the availability of models like Altman's Z-score, there exists a gap in the literature regarding their sectoral application and regional customization. While existing research highlights the efficacy of these models, their specific application in the Indian banking sector remains limited (Kumar & Ravi, 2007). This study addresses that gap by evaluating the bankruptcy risk of Indian banking firms using a comprehensive, decade-long financial dataset. It aims to answer the core research question:

RQ: How effective is the Altman Z-score model in predicting financial distress across public and private sector banks in India?

The theoretical framework of this research is grounded in Altman's financial distress prediction model, adapted to fit the specific characteristics of banking institutions. Methodologically, this study employs a quantitative approach, incorporating descriptive statistics and non-parametric tests to analyze differences between public and private sector banks. The significance of this study lies in its ability to inform policymakers, investors, and banking professionals about evolving financial vulnerabilities, thereby supporting more resilient banking strategies. Among the main findings, the research identifies considerable differences in financial stability between the two banking categories across the observed years, with a noteworthy convergence in risk profiles emerging only in the most recent period.

The rest of this paper is structured as follows. Section 2 reviews the relevant literature on bankruptcy prediction models and sector-specific applications, particularly in emerging markets. Section 3 outlines the research design and methodology, including data sources, variable construction, and the application of the Altman Z-score model. Section 4 presents the empirical results. Section 5 discusses the research results. Section 6 concludes the paper with a summary of key findings, implications, and directions for future research.

2. LITERATURE REVIEW

The assessment of financial distress and bankruptcy prediction has been extensively explored through various models and methodologies across different sectors and countries. Agarwal and Patni (2019) analyzed the Altman Z-score model's applicability for predicting financial distress among Bombay Stock Exchange (BSE) public sector undertakings (PSUs), classifying companies into 'safe', 'gray', and 'distress' zones, thus emphasizing proactive financial management. Similarly, Hasan and Fatama (2020) applied the Altman Z-score to evaluate the bankruptcy risks of commercial banks in Bangladesh, offering policy recommendations to mitigate financial challenges. In Vietnam, Tung et al. (2019) assessed multidisciplinary enterprises, demonstrating the utility of Altman's Z-score in evaluating financial stability. A broader industry-specific focus was provided by Daniel et al. (2025), who developed tailored bankruptcy models for the construction sector, significantly improving predictive accuracy compared to traditional models like Altman's. This need for customization was further underscored by Dragotă and Delcea (2019), who incorporated financial and non-financial parameters to enhance bankruptcy prediction models in Indian listed companies, achieving high accuracy rates. Recent studies have reinforced these findings by incorporating legal, financial, and organizational determinants of business failure in emerging markets (Arzou & Kobiyh, 2025).

The effectiveness of advanced predictive techniques has also been explored. Rangoonwala and Bhatia (2020) employed artificial neural networks (ANN) to forecast wilful defaults among Indian commercial banks, revealing the significance of integrating multiple financial indicators. Similarly, Charalambous et al. (2000) highlighted the superior accuracy of neural networks over traditional models in bankruptcy prediction for Indian firms. Meanwhile, Mishra et al. (2024) compared logistic regression, linear discriminant analysis (LDA), and ANN models, demonstrating that both traditional and advanced methods are effective in predicting financial distress in Indian banks. Further emphasizing the need for multifaceted approaches, Asgarnezhad Nouri and Soltani (2016) incorporated both accounting and market variables into their models, achieving high accuracy rates and underscoring the importance of comprehensive risk assessment. Supporting this trend, Budhidharma et al. (2023) applied random forest and logit models to detect early warning signs of financial distress.

Studies focusing on specific sectors provide valuable insights into bankruptcy risks. Murthy et al. (2018) applied Altman's Z-score to Heritage Foods Ltd., confirming the model's utility in assessing financial soundness in the manufacturing sector. Similarly, Matturungan et al. (2017) evaluated financial distress in Indonesian manufacturing firms, highlighting the relevance of specific financial ratios in predicting bankruptcy. Kumar et al. (2023) extended the evaluation to India's public sector banks using capital, assets, management, earnings, liquidity, sensitivity (CAMELS), and Z-score methodologies, revealing improvements in solvency and profitability. Exploring agricultural companies, Kiaupaite-Grushniene (2016) found Altman's model effective in categorizing firms into financial health zones in Lithuania. In the hospitality sector, Matejić et al. (2022) demonstrated the relevance of Altman's Z-score for evaluating financial stability among Serbian hotel companies. Region-specific studies further enrich the literature. Ong et al. (2011) examined corporate failure in Malaysia's government-linked companies (GLCs) using the Altman Z-score, highlighting significant relationships between financial distress and performance variables. Mohammed (2017) applied Altman's model to Raysut Cement Company in Oman, confirming its financial stability. In Kenya, Ogachi et al. (2020) used the Z-score to predict bankruptcy among listed companies, identifying key financial indicators. In India, Ray (2011) and Shisia et al. (2014) focused on financial distress in the automobile industry and Kenyan retail chains, respectively, emphasizing the importance of proactive measures for financial stability. Further contributions by Eyalsalman et al. (2024) examined the impact of International Financial Reporting Standard (IFRS) 9, liquidity, and credit risk on banks' performance.

Additionally, corporate governance and regulatory implications have been linked to financial distress prediction. Ezejiofor and Okerekeoti (2021) explored the Altman model's impact on corporate governance in Nigerian banks, revealing its potential to influence board size and independence. Kumar et al. (2023) employed Recursive PLS-SEM to analyze bankruptcy trends in India, highlighting regulatory and economic implications for bankruptcy reforms. Aspal and Nazneen (2014) examined capital adequacy in Indian private banks, revealing significant factors influencing solvency requirements. In a broader legal context, Swain et al. (2025) explored cross-border insolvency regimes, adding depth to the legal perspective on bankruptcy prediction.

Recent research further expands the discourse. Arzou and Kobiyh (2025) examined the legal, financial, and organizational determinants of business failure in emerging markets, reinforcing the multidimensional nature of financial distress. Budhidharma et al. (2023) advanced predictive accuracy by applying Random forest and logit models to detect early warning signs of financial distress, showing promise for artificial intelligence (AI)-based approaches in financial analytics. Eyalsalman et al. (2024) analyzed the effects of IFRS 9 implementation and liquidity, credit, and capital risks on bank performance, highlighting regulatory challenges and financial impacts. Swain et al. (2025) discussed cross-border insolvency regimes in the aviation sector, contributing to the understanding of legal dimensions in bankruptcy risk evaluation across sectors.

Collectively, these studies highlight the importance of tailored, multidimensional, and context-specific approaches to financial distress prediction and management. The literature underscores the utility of traditional models like Altman's Z-score while advocating for advanced techniques such as ANN and sector-specific adaptations, thereby offering valuable insights into the dynamics of financial risk assessment across diverse sectors and regions. However, the literature on forecasting financial turbulence and evaluating corporate bankruptcy risk in Indian banking firms highlights several research gaps. While Altman's Z-score model has been widely applied, specific studies on its effectiveness in Indian banking institutions remain limited. There is also no consensus on the most suitable financial ratios or variables to include, necessitating standardized criteria for consistency and comparability. Additionally, research on the dynamic nature of financial distress, including early warning systems for identifying and mitigating risks in Indian banks, is scarce. Addressing these gaps could enhance bankruptcy prediction models and provide valuable insights for risk management strategies.

In today's rapidly evolving financial landscape, the stability and resilience of the banking sector are crucial for sustained economic growth and development. The Indian banking sector, being a cornerstone of the nation's financial infrastructure, plays a pivotal role in facilitating economic activities, supporting businesses, and promoting financial inclusion. However, with increasing market volatility, regulatory changes, and global economic uncertainties, banks face heightened risks of financial distress and potential bankruptcy. This necessitates a comprehensive understanding of the factors contributing to financial instability and the development of effective predictive models to assess bankruptcy risks. Moreover, traditional qualitative assessments are no longer sufficient in predicting financial distress. Quantitative models, such as Edward I. Altman's Z-score, have proven effective in forecasting bankruptcy risks in various industries. However, their application in the Indian banking sector remains underexplored, creating a significant gap in academic research and practical financial analysis. This study addresses the pressing need to evaluate the applicability of the Altman Z-score model within the Indian banking context. By analyzing the financial metrics of both public and private sector banks over a ten-year period (2014–2023), the research aims to provide valuable insights into the financial resilience of these institutions. The findings will aid policymakers, investors, and banking professionals in making informed decisions to mitigate risks, enhance governance, and promote economic stability.

3. RESEARCH METHODOLOGY

This study employs an inferential quantitative research design to evaluate bankruptcy risk among listed Indian banking firms over the period of 10 years, from 2014 to 2023. Inferential design was chosen to go beyond simple observation and measure differences across categories using statistical reasoning. The primary model used in this research is Altman's Z-score, which combines five key financial ratios into a single score that helps identify whether a firm is in the safe, grey, or distress zone of financial stability. The model is especially effective in bankruptcy prediction due to its integration of profitability, liquidity, solvency, and operational efficiency measures. The data for this study was collected from annual reports and financial statements of 138 listed Indian banks, both public and private, retrieved via the ProwessIQ database managed by the Centre for Monitoring Indian Economy (CMIE). This database is widely recognized for its reliability and breadth, providing comprehensive firm-level data across time. The financial variables used in the Z-score calculation include working capital to total assets (X_1), retained earnings to total assets (X_2), EBIT to total assets (X_3), market value of equity to total liabilities (X_4), and sales to total assets (X_5). Each of these indicators serves a specific evaluative purpose: 1) liquidity (X_1), 2) profitability trends (X_2), 3) operational performance (X_3), 4) leverage control (X_4), and 5) efficiency of asset use (X_5). To ensure consistency, all financial variables were normalized on a per-year basis. The Altman Z-score was calculated for each bank for each year within the dataset. These scores were then used to classify firms into risk categories: 1) safe (Z > 2.6), 2) grey (1.1 < Z < 2.6), and 3) distress (Z < 1.1), as per the model for non-manufacturing firms. Descriptive statistical techniques such as mean, median, standard deviation (SD), minimum, and maximum were used to evaluate central tendency and dispersion of the Z-scores. For inferential analysis, the Kolmogorov-Smirnov (K-S) and Shapiro-Wilk (S-W) tests were used to assess the normality of the Z-score distribution. Upon confirming non-normality, the Mann-Whitney U test was selected as the appropriate non-parametric alternative to the independent sample t-test to examine differences in bankruptcy risk between public and private banks.

Alternative methodologies that could have been used include logistic regression analysis, which is suitable for binary classification problems such as predicting whether a firm will go bankrupt. This method allows interpretation of odds ratios and can incorporate both financial and non-financial predictors. Another powerful alternative is the use of machine learning algorithms, which have gained popularity in recent years for financial distress prediction due to their ability to model complex, non-linear relationships and handle multicollinearity. Additionally, survival analysis techniques like Cox proportional hazards models could be used to model the time until bankruptcy, offering insights into the longevity of financial stability. Panel data econometric models, such as fixed effects or random effects regressions, could capture unobserved heterogeneity across banks and over time, offering greater explanatory depth. The choice of Altman's Z-score in this study is justified due to its proven accuracy, simplicity, transparency, and widespread acceptance in both academia and industry. It provides clear thresholds that make it easier for practitioners to interpret results without requiring advanced statistical training. However, recognizing that the banking sector is distinct from manufacturing firms for which the original Z-score was developed, this study adopted the revised Z model, specifically designed for non-manufacturing and service-based industries.

Future studies may benefit from integrating these alternative methodologies with Altman's model to improve the robustness and adaptability of bankruptcy prediction tools, especially in the face of volatile economic conditions or regulatory transitions. Moreover, the inclusion of macroeconomic variables such as *inflation*, *gross domestic product (GDP) growth*, *interest rates*, and *regulatory shifts* could offer more dynamic insights. Mixed-methods approaches combining quantitative indicators with qualitative inputs, such as managerial interviews or case studies, may enrich the predictive framework and contextual interpretation of distress signals.

The Altman Z-score is a financial model used to predict the probability of a company going bankrupt within two years. It incorporates multiple financial ratios to generate a single score that indicates the likelihood of bankruptcy. Edward Altman developed different versions of the Z-score model for different types of firms, including manufacturing and non-manufacturing firms. Below is a detailed framework for calculating the Altman Z-score for both types of firms.

Altman Z-score for manufacturing firms:

$$Z = 1.2\,X_1 + 1.4\,X_2 + 3.3\,X_3 + 0.6\,X_4 + 0.999\,X_5 \quad (1)$$

Altman Z-score for non-manufacturing firms (including service firms):

$$Z = 6.56\,X_1 + 3.26\,X_2 + 6.72\,X_3 + 1.05\,X_4 \quad (2)$$

where:
- X_1 = working capital to total assets ratio;
- X_2 = retained earnings to total assets;
- X_3 = earnings before interest and taxes (EBIT) to total assets;
- X_4 = market/book value of equity to total liabilities;
- X_5 = sales to total assets.

The variables of the study are listed below:

Working capital to total assets (X_1): This ratio measures the liquidity of the firm, reflecting its ability to cover short-term obligations with short-term assets, which is calculated by dividing the net working capital by the total assets of the firm. The net working capital is the difference between current assets and current liabilities. A higher ratio indicates better liquidity, meaning the company can more easily meet its short-term obligations. Firms with higher working capital relative to their total assets are generally considered less risky.

Retained earnings to total assets (X_2): Retained earnings represent the cumulative profits that have been reinvested in the company rather than paid out as dividends. This ratio, measured by dividing retained earnings by total assets, indicates the extent to which a company has funded its assets through retained earnings. A higher ratio suggests a strong, self-financing company that relies less on external debt and more on internally generated funds. It reflects the firm's ability to sustain growth and weather financial difficulties over time.

Earnings before interest and taxes (EBIT) to total assets (X_3): This ratio assesses a company's profitability and efficiency in generating earnings from its assets before the influence of interest and taxes. It is calculated by dividing the EBIT and total assets of the firm. A higher EBIT to total assets ratio indicates that the company is effectively using its assets to generate operating profits. It is a measure of operational efficiency and profitability.

Market value of equity to total liabilities (X_4): This ratio compares the market value of the company's equity to its total liabilities, providing insight into the leverage and financial structure of the firm. This ratio is measured by the market value of equity divided by total liabilities of the company, whereas, market value of equity is measured by the total market capitalization of the company. A higher ratio indicates a strong equity cushion relative to liabilities, suggesting that the company is less leveraged and has a lower risk of insolvency. It reflects the firm's ability to cover its liabilities through its market-valued equity.

Sales to total assets (X_5): This asset turnover ratio measures the company's ability to generate sales from its asset base, indicating how efficiently the firm is using its assets to produce revenue. A higher ratio implies that the company is effectively utilizing its assets to generate sales, which is a sign of operational efficiency. It shows the firm's capability to generate income from its asset investments.

Table 1. Interpretation of the Z-score into different zones for manufacturing firms

Manufacturing firms			*Non-manufacturing firms*		
Score	*Zone*	*Remarks*	*Score*	*Zone*	*Remarks*
Z > 2.99	Safe zone	Low bankruptcy risk	Z" > 2.6	Safe zone	Low bankruptcy risk
1.81 < Z < 2.99	Gray zone	Moderate bankruptcy risk	1.1 < Z" < 2.6	Gray zone	Moderate bankruptcy risk
Z < 1.81	Distress zone	High bankruptcy risk	Z" < 1.1	Distress zone	High bankruptcy risk

4. RESULTS

4.1. Overall bankruptcy analysis

Table 2 presents the descriptive statistics of the Altman Z-score from 2014 to 2023 and provides insights into the financial stability and bankruptcy risk of select Indian listed banks over the study period. The minimum Z-score fluctuates significantly, with the lowest value recorded in 2023 (-6.894), indicating severe financial distress in at least one bank during that year. Over the years, multiple instances of negative Z-scores suggest that some banks consistently faced financial instability. The maximum Z-score values remain relatively stable, ranging from 4.841 in 2020 to 6.244 in 2014. This suggests that the best-performing banks maintained financial stability throughout the period, with some banks achieving a strong financial position despite overall industry challenges. The average Z-score exhibits a cyclical pattern, with the highest value (1.331) in 2023 and the lowest (0.915) in 2022. The relatively low averages suggest that many banks operated close to financial distress zones, as per the Altman Z-score classification. The decline in the average Z-score in 2022 could reflect the residual impact of the COVID-19 pandemic on bank stability, while the recovery in 2023 indicates improvement in financial performance. The SD measures the dispersion of Z-scores, with the highest value in 2014 (1.347) and the lowest in 2020 (0.839).

Table 2. Descriptive statistics of Altman Z-score for the study period from 2014–2023

Year	*2023*	*2022*	*2021*	*2020*	*2019*	*2018*	*2017*	*2016*	*2015*	*2014*
Min	-6.894	-2.938	-2.587	-1.804	-3.430	-1.793	-4.557	-2.104	-2.941	-4.181
Max	5.858	5.502	5.160	4.841	5.364	5.130	5.380	5.032	5.160	6.244
Average	1.331	0.915	1.184	1.071	1.162	1.305	1.180	1.198	1.217	1.296
SD	1.311	0.961	0.975	0.839	0.954	0.892	1.200	1.017	1.191	1.347

Source: Authors' calculation based on secondary data.

4.2. Bankruptcy analysis of public sector banks

Table 3 presents the descriptive statistics of public sector banks from 2014 to 2023, based on the Altman Z-score, and reveals significant variations in financial stability over the years. The minimum Z-score, which indicates the lowest financial stability among public sector banks, ranged from 0.166 in 2020 to 0.690 in 2023. This suggests that at least one bank was at a high risk of financial distress in 2020, but the situation improved significantly by 2023. The maximum Z-score, which represents the best-performing bank each year, varied from 0.423 in 2020 to 5.220 in 2023, highlighting a sharp contrast in financial health among banks. The average Z-score fluctuated over the years, reaching its lowest value of 0.324 in 2020 and peaking at 2.058 in 2023. This indicates that public sector banks experienced their weakest financial position during the COVID-19 pandemic, which severely impacted their stability. However, a strong recovery is observed in 2023, possibly due to improved economic conditions, recapitalization efforts, and better risk management practices. The SD, which measures the variability in financial stability among banks, ranged between 0.054 in 2021 and 0.913 in 2023. Overall, public sector banks faced significant financial stress between 2014 and 2020, particularly in 2020, when both minimum and average Z-scores were at their lowest. However, post-2020, there has been a consistent upward trend, culminating in a strong recovery in 2023. The widening gap between the best- and worst-performing banks in 2023 suggests that while some banks have strengthened their financial position, others continue to struggle, requiring targeted interventions for sustained sectorial stability.

Table 3. Descriptive statistics of public sector banks for the study period from 2014–2023

Year	*2023*	*2022*	*2021*	*2020*	*2019*	*2018*	*2017*	*2016*	*2015*	*2014*
Min	0.690	0.203	0.245	0.166	0.178	0.333	0.304	0.322	0.317	0.257
Max	5.220	0.557	0.518	0.423	0.441	0.545	0.589	0.689	0.645	0.858
Average	2.058	0.384	0.370	0.324	0.341	0.411	0.406	0.423	0.399	0.442
SD	0.913	0.069	0.054	0.058	0.056	0.062	0.060	0.087	0.071	0.142

Source: Authors' calculation based on secondary data.

4.3. Bankruptcy analysis of private banks

Table 4 presents the descriptive statistics of private sector banks from 2014 to 2023, providing valuable insights into their financial stability and risk exposure, as measured by the Altman Z-score. The minimum Z-score fluctuates significantly across the years, indicating periods of financial distress for certain banks. Notably, in 2023, the minimum Z-score reached a record low of -21.904, suggesting severe financial instability in at least one bank. This sharp decline in 2023 is a stark contrast to previous years, where the minimum Z-score ranged from -1.847 (2014) to -0.010 (2018), indicating relatively better financial health in earlier years. The maximum Z-score, which represents the highest financial stability recorded in each year, also exhibits variability. The highest Z-score was recorded in 2023 at 17.109, a sharp increase compared to the previous years, where values remained below 2.5. This significant variation between the minimum and maximum values in 2023 suggests increased heterogeneity in financial performance among private banks.

The average Z-score, which represents the overall financial stability of private banks, remained relatively stable over the years, fluctuating between 0.419 (2020) and 0.499 (2016). This consistency indicates that, on average, private sector banks have maintained a moderate level of financial stability. However, the steep drop in the minimum value in 2023 suggests that while most banks remained stable, a few experienced extreme distress. SD measures the dispersion of financial stability scores among banks. The SD values remained relatively low (around 0.2 to 0.3) until 2023, when it spiked to 3.332, indicating an unprecedented increase in variability. This suggests that while some banks experienced strong financial health, others faced severe challenges, leading to greater instability in the sector. Overall, the findings suggest that while private banks maintained stability over the years, 2023 witnessed significant volatility, necessitating further investigation into underlying economic or regulatory factors affecting financial health.

Table 4. Descriptive statistics of private sector banks for the study period from 2014–2023

Year	*2023*	*2022*	*2021*	*2020*	*2019*	*2018*	*2017*	*2016*	*2015*	*2014*
Min	-21.904	-0.66	-0.690	-0.315	-0.920	-0.010	-0.786	-0.164	-1.369	-1.847
Max	17.109	2.118	1.218	1.079	1.206	1.153	1.712	2.034	1.076	1.247
Average	2.489	0.451	0.449	0.419	0.445	0.491	0.491	0.499	0.477	0.488
SD	3.332	0.302	0.247	0.210	0.247	0.210	0.278	0.279	0.279	0.335

Source: Authors' calculation based on secondary data.

4.4. Bifurcation of firms based on level of bankruptcy (2023)

Table 5 highlights the bifurcation of firms based on their bankruptcy risk in 2023, reveals significant variations between public and private sector banks. Among the 138 firms analyzed, 51 (36.96%) fall into the safe zone, indicating strong financial stability, with private banks (39) outnumbering public banks (12). The grey zone, representing moderate risk, comprises 62 firms (44.93%), with private banks (53) significantly exceeding public banks (9). The stress zone, indicating high bankruptcy risk, includes 25 firms (18.12%), with private banks (21) again outnumbering public banks (4). This suggests that while private banks dominate all categories, they also exhibit higher financial instability compared to public banks.

Table 5. Bifurcation of firms based on level of bankruptcy (2023)

	Safe zone			*Grey zone*			*Stress zone*		
	Public	*Private*	*Total*	*Public*	*Private*	*Total*	*Public*	*Private*	*Total*
No. of firms	12	39	51	9	53	62	4	21	25

Source: Authors' calculation based on secondary data.

4.5. Test of hypothesis

4.5.1. Test of normality

The year-wise normality tests of the Altman Z-scores for Indian listed banking companies from 2014 to 2023, summarized in Table 6, utilized both the K-S and S-W tests to evaluate the distribution patterns. The K-S test results consistently show significance values (Sig.) of 0.000 across all years, indicating that the Z-scores do not follow a normal distribution. Similarly, the Shapiro-Wilk test reports significance values of 0.000 for each year, further confirming the non-normality of the data. Since both tests reject the *H0* of normality at a conventional threshold of 0.05, this necessitates the use of non-parametric statistical methods in further analyses. Consequently, the Mann-Whitney U test was applied to compare the median Altman Z-scores between public and private sector banks in India.

Table 6. Result of year-wise tests of normality of Altman Z-score

Year	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
2014	0.189	137	0.000	0.749	137	0.000
2015	0.149	137	0.000	0.816	137	0.000
2016	0.170	137	0.000	0.797	137	0.000
2017	0.150	137	0.000	0.850	137	0.000
2018	0.117	137	0.000	0.939	137	0.000
2019	0.148	137	0.000	0.832	137	0.000
2020	0.133	137	0.000	0.915	137	0.000
2021	0.148	137	0.000	0.873	137	0.000
2022	0.217	137	0.000	0.707	137	0.000
2023	0.240	137	0.000	0.599	137	0.000

Source: Authors' calculation based on secondary data.

4.5.2. Analysis and interpretation of hypothesis testing results

The results presented in Table 7 summarize the outcomes of hypothesis testing conducted using the independent samples Mann-Whitney U, a non-parametric alternative to the independent t-test, to test whether there is a statistically significant difference in the financial health, as measured by the Altman Z-score, between public and private sector banks in India for the years 2014 to 2023. For nine out of the ten years analyzed (2014 to 2022), the p-values are consistently below the commonly accepted significance level of 0.05. Specifically, the p-values for these years range from as low as 0.000 to 0.042. This indicates strong evidence against the *H0*, leading to its rejection for these years. The *H0* in this context posits that there is no significant difference in the Altman Z-scores between public and private sector banks. Therefore, the rejection of the *H0* suggests that there were statistically significant differences in the financial health of public and private banks during these years.

In 2014, the p-value is 0.042, slightly below the 0.05 threshold, indicating a significant difference in that year. This trend continues and becomes even more pronounced in subsequent years, with p-values dropping to 0.002 in 2015 and 0.010 in 2016, reflecting an increasing divergence in the financial health of public and private banks. The consistent rejection of the *H0* from 2014 to 2022 suggests that external factors such as economic reforms, regulatory changes, or macroeconomic conditions may have differently impacted the two banking sectors during this period. The years 2019 and 2020 are particularly noteworthy, with p-values of 0.000, indicating extremely strong evidence of significant differences in financial health. This period coincides with significant disruptions in the Indian banking sector, including the aftermath of the NPAs crisis, the implementation of the Insolvency and Bankruptcy Code (IBC), and the broader economic slowdown, which may have had varying impacts on public and private sector banks. Public sector banks, traditionally burdened with higher NPAs, may have struggled more compared to their private counterparts, which generally maintained healthier balance sheets and better asset quality.

The trend of significant differences continues into 2021 and 2022, with p-values of 0.001 and 0.009, respectively. These years mark the recovery phase following the COVID-19 pandemic, during which banks faced challenges related to loan moratoriums, credit growth, and provisioning requirements. The persistent differences in financial health could reflect the varying capacities of public and private banks to manage these challenges, with private banks potentially demonstrating greater resilience and quicker recovery. However, in 2023, the p-value rises sharply to 0.348, well above the 0.05 threshold, leading to the acceptance of the *H0*. This indicates that, for the first time in the analyzed period, there is no statistically significant difference in the financial health of public and private sector banks. The convergence in financial health could be attributed to several factors, including comprehensive banking sector reforms, improved asset quality across the board, and uniform regulatory measures that have leveled the playing field between public and private banks. Additionally, the stabilization of macroeconomic conditions and the resolution of legacy NPAs in public sector banks may have contributed to this convergence. The acceptance of the *H0* in 2023 suggests a potential shift in the dynamics of the Indian banking sector. It implies that the historical disparities in financial health between public and private sector banks may be diminishing, leading to a more homogenized banking environment. This could be a positive development, indicating that public sector banks have successfully addressed some of their structural weaknesses and are now on a more equal footing with private banks in terms of financial stability.

In conclusion, the hypothesis testing results reveal significant differences in the financial health of public and private sector banks in India from 2014 to 2022, with a notable convergence observed in 2023. These findings highlight the evolving landscape of the Indian banking sector and underscore the impact of economic, regulatory, and institutional factors on the financial performance of banks. The results also suggest that while historical disparities were evident for most of the study period, recent developments have led to greater alignment in the financial health of public and private banks, reflecting broader improvements in the sector's overall stability and resilience.

Table 7. Result summary of hypothesis testing

No.	*Year*	*Test*	*P-value*	*Decision*
1	2014	Independent samples Mann-Whitney U test	0.042	Rejection of *H0*
2	2015	Independent samples Mann-Whitney U test	0.002	Rejection of *H0*
3	2016	Independent samples Mann-Whitney U test	0.010	Rejection of *H0*
4	2017	Independent samples Mann-Whitney U test	0.011	Rejection of *H0*
5	2018	Independent samples Mann-Whitney U test	0.013	Rejection of *H0*
6	2019	Independent samples Mann-Whitney U test	0.000	Rejection of *H0*
7	2020	Independent samples Mann-Whitney U test	0.000	Rejection of *H0*
8	2021	Independent samples Mann-Whitney U test	0.001	Rejection of *H0*
9	2022	Independent samples Mann-Whitney U test	0.009	Rejection of *H0*
10	2023	Independent samples Mann-Whitney U test	0.348	Acceptance of *H0*

Source: Authors' calculation by using MS Excel based on secondary data.

5. DISCUSSION

The present study evaluated the financial health of Indian banking firms over a decade (2014–2023) using the Altman Z-score model. The results demonstrated significant variation in bankruptcy risk between public and private sector banks, which gradually converged by 2023. This convergence supports the findings of Kumar et al. (2023), who reported improved solvency and profitability in Indian public sector banks using CAMELS and Z-score methodologies, validating the impact of government-led reforms and restructuring policies. The volatility in private sector banks' Z-scores echoes the concerns raised by Eyalsalman et al. (2024), who showed how liquidity and credit risk, especially under IFRS 9, affect banks' financial performance. The present findings reinforce their conclusions and underline the need for private banks to adopt more dynamic and responsive risk management mechanisms.

The rise in public sector Z-scores can also be linked to strategic recapitalization, consolidation, and regulatory oversight. These patterns parallel the observations by Budhidharma et al. (2023), who highlighted the predictive strength of machine learning models like random forests in identifying early warning signals of financial distress. These findings imply that policymakers and financial analysts should consider hybrid models combining Z-scores with advanced analytics. Moreover, the multidimensionality of bankruptcy risk was echoed in this study and is supported by Arzou and Kobiyh (2025), who emphasized the interplay of legal, financial, and organizational determinants in emerging market failures. The complexity of Indian banking operations suggests the importance of a holistic approach that considers structural, legal, and macroeconomic indicators alongside financial ratios.

The statistical methodology used, including non-parametric tests like the Mann-Whitney U, aligns with the work of Mishra et al. (2024), who combined Altman's Z-score with logistic regression and ANN for distress prediction in Indian banks. This affirms that statistical rigor enhances the accuracy and reliability of traditional models. Region-specific studies, such as those by Ong et al. (2011) in Malaysia and Mohammed (2017) in Oman, found Altman's model effective in identifying firms with weak fundamentals. These findings corroborate our study's validation of the Z-score's utility in the Indian context. Similarly, Murthy et al. (2018) and Matturungan et al. (2017) showed the model's adaptability in non-financial sectors, reinforcing its robustness across industries. The observed sectoral differences in distress levels also resonate with the findings of Matejić et al. (2022) and Kiaupaite-Grushniene (2016), who applied the Z-score to hotels and agriculture firms, respectively. Their sector-specific insights align with the Indian banking sector's heterogeneity in financial practices. The insights by Swain et al. (2025) on the legal dimensions of insolvency contribute to understanding broader regulatory implications. In a highly interconnected financial ecosystem, coordinated insolvency regimes are essential for stability, especially relevant for Indian banks engaged in cross-border lending or operating under diverse legal jurisdictions.

Finally, the governance implications discussed by Ezejiofor and Okerekeoti (2021) further validate our findings. Their study showed how bankruptcy risk models influence board decisions and corporate governance structures, which is increasingly critical in India amid rising compliance requirements and shareholder activism. Thus, the discussion affirms the importance of integrating traditional and advanced analytical frameworks while considering legal, organizational, and sectoral complexities. Future studies should explore hybrid and AI-based approaches while deepening cross-sectoral and cross-national comparisons for a more comprehensive risk assessment framework.

6. CONCLUSION

This study provided a comprehensive evaluation of the bankruptcy risk in Indian banking firms using Altman's Z-score model, focusing on 10 years, from 2014 to 2023. The main findings reveal significant differences in financial health between public and private sector banks throughout most of the study period. Public sector banks exhibited gradual improvement in stability, especially in the post-pandemic period, while private sector banks displayed higher volatility, with some institutions showing extreme distress. A noteworthy finding is the convergence in financial health between the two sectors in 2023, indicating a potential shift in risk profiles and performance equilibrium across the Indian banking landscape. The average Z-scores and variability in the Altman index also highlighted the asymmetric recovery paths followed by different banks, revealing the influence of regulatory reforms, risk management strategies, and capital adequacy initiatives implemented over the years.

The implications of these results are significant for investors, regulators, and policymakers. For investors, the Z-score analysis provides a valuable tool for assessing institutional risk and making informed portfolio decisions. Understanding the bankruptcy risk helps in designing appropriate investment strategies, especially in emerging markets where sectoral fragility often affects overall market performance. Policymakers and regulators may leverage these insights to identify vulnerabilities, enhance governance frameworks, implement targeted policy interventions, and ensure early intervention in distressed banks. The study also underscores the importance of robust credit risk assessment, early warning systems, and capital adequacy planning within the banking system to prevent systemic collapse and promote sustainable financial development.

Despite its contributions, this research has certain limitations. It relies exclusively on secondary data and applies only the Altman Z-score model, which may not capture non-financial factors such as management quality, market sentiment, corporate governance practices, or political influences. Moreover, the model, while reliable, is static in nature and may not account for abrupt shifts in macroeconomic variables or exogenous shocks such as geopolitical crises, pandemics, or regulatory overhauls. Additionally, it does not incorporate dynamic modeling techniques like Monte Carlo simulations, survival analysis, or real-time market sentiment analytics, which could enhance the predictive robustness and applicability of the findings across various market scenarios.

Future research could explore hybrid bankruptcy prediction models that integrate machine learning algorithms with traditional financial metrics for improved accuracy and real-time applicability. Such models could also incorporate macroeconomic indicators, sentiment analysis, and qualitative data to capture multi-dimensional risk factors. Studies can also be extended to other financial institutions such as NBFCs, cooperative banks, and fintech firms, offering comparative institutional perspectives. Cross-country panel analyses between emerging and developed economies may yield insights into structural differences in bankruptcy causality. By addressing these aspects, future investigations can contribute more holistically to the discourse on financial stability in emerging economies like India and support evidence-based interventions to safeguard institutional soundness and systemic resilience.

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