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Revising altman's z-score cut-off point to enhance prediction accuracy: Evidence from India's iron and steel industry

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Abstract
The present study evaluates the effectiveness of Altman's Z-score model (1968), one of the most widely used distress prediction tools globally, within the context of the Indian iron and steel industry. The research also aims to refine the model's cut-off point to determine a more optimal Z-score specifically suited to India's market. The analysis focuses on 42 listed iron and steel companies—21 that failed and 21 that did not. The findings reveal that the original 1968 Z-score model offered an accuracy rate of only 50% to 60% for different years prior to failure. In contrast, the newly determined optimal Z-score demonstrated a remarkable improvement in predictive accuracy, ranging from 79% to 90% for various years before failure, highlighting its enhanced effectiveness in the Indian context.

Keywords: Altman's z-score, financial distress prediction, iron and steel industry, india

Introduction

Any business, if left under regulated or mismanaged, can pose a significant threat to its stakeholders and the broader economy. Inefficient decisions or poor financial oversight can lead to severe financial difficulties, culminating in bankruptcy (Altman, 1968) [2]. To ensure smooth operations and effective management of core activities, businesses must continuously assess their financial health through informed decision-making (Agarwal & Taffler, 2008 [1]; Maji & Sur, 2015) [8].

In this regard, financial distress prediction models have become crucial tools for businesses to evaluate their financial position. The area of financial distress has gained significant attention among scholars and academics, who focus on identifying the characteristics of distressed firms, developing prediction models, evaluating the success of these models, and recommending corrective measures.

In the context of India, the importance of such models is underscored by the introduction of the Insolvency and Bankruptcy Code (IBC) in 2016. As of December 2024, around 40 listed companies have filed for bankruptcy under the IBC. Given this, the need for industry-specific distress prediction models has become more pressing than ever.

Historically, the Indian Steel and Iron Industry has been a key player in the nation's economic landscape, ranking as the second-largest producer of crude steel, with a production of 140.8 million tonnes in 2023. This growing industry contributes around 2% to India's GDP and provides direct and indirect employment to over 2.5 million people. Recognizing its importance, the Indian government introduced the National Steel Policy in 2017, aimed at driving long-term growth. With infrastructure development central to India's path toward becoming a developed nation, the steel and iron industry remains a cornerstone of this vision.

This study aims to contribute to the prediction of the financial health of Indian steel and iron companies, focusing on developing accurate models tailored to this sector. However, it's important to note that all prediction models have their limitations, which can raise questions about their accuracy (Kukreja, 2020) [6]. Given the ever-changing economic environment, testing the reliability of financial distress prediction models is essential.

In this context, the Altman Z-score model has emerged as one of the most widely accepted tools by institutions, researchers, managers, auditors, investors, and other stakeholders. This study will focus on evaluating the Altman Z-score's effectiveness in predicting financial distress within the Indian steel and iron industry.

Review of related literature

For businesses to function efficiently and manage core activities through relevant decisions, continuous assessment and diagnosis of their financial health are essential (Lord *et al*., 2020) [7]. Financial health, often defined through financial statements, provides the most useful information for all stakeholders interested in a company's performance. As such, the issue of financial distress, particularly bankruptcy risks, has attracted significant attention from researchers over the past six decades (Altman *et al*., 2017).

The journey of financial distress prediction began in 1966 with W. H. Beaver, who demonstrated that financial ratios vary between failed and non-failed firms (Beaver, 1966) [4]. Building on this foundation, Altman extended Beaver's work in 1968 by developing a financial distress prediction (FDP) model using various financial ratios, such as liquidity, cumulative profitability, profitability, insolvency, and management efficiency, based on Multiple Discriminant Analysis (MDA) (Altman, 1968). This model, known as the Z-score, combined five key ratios: working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market value of shares to book value of debts, and sales to total assets. Originally developed for listed manufacturing companies, Altman later introduced two extensions of the Z-score in 1983 and 1993, tailored for private firms and emerging markets, respectively.

Since Altman's Z-score, numerous FDP models have been developed, refining predictive features and incorporating new analysis tools (Nguyen, 2023) [11]. The literature highlights various predictive features, including financial statement data, capital market information, corporate governance factors, textual information, and macroeconomic variables (Muñoz-Izquierdo, 2020 [9]; Bhabak *et al*., 2024) [5]. While many models focus on accounting data alone, some researchers have incorporated additional predictors, such as market-related variables, corporate governance information, audit reports, and management disclosures. Another category of FDP models explores the effectiveness of various statistical and machine learning tools (Mousavi, 2019) [10]. Traditional models were grounded in statistical techniques like univariate discriminant analysis, multiple discriminant analysis, probabilistic analysis, logistic regression, and hazard analysis (Ohlson, 1980) [12]. More recent models, however, utilize artificial intelligence and machine learning methods (Zhao, 2024) [13].

Altman's Z-score remains one of the most valuable and widely used models over the last four decades. The original Z-score model provided two critical cut-off points: 1.81 and 2.99 (Altman, 1968). A Z-score above 2.99 indicates financial health, while a score below 1.81 signals financial distress. Scores falling between 1.81 and 2.99 are considered a "zone of ignorance," where predictions are often unreliable.

In our study of selected listed iron and steel companies, we found that most companies fell within this "zone of ignorance," making it difficult to predict the level of financial distress using the Z-score model (Table 2). To address this gap, the present study proposes a refined approach, suggesting a single, more accurate cut-off point for better financial distress prediction.

Objective of the study

The specific objectives of this study are:

1. To evaluate the effectiveness of Altman's Z-score in predicting financial distress.
2. To refine and adapt Altman's Z-score for financial distress prediction (FDP) specifically within the context of the Indian Iron and Steel sector.

Data and Methodology

This study examines a sample of 42 steel and iron manufacturing companies, listed on either the National Stock Exchange (NSE) or the Bombay Stock Exchange (BSE). The sample is evenly divided between distressed and non-distressed firms, offering a comprehensive view of the industry. Distressed companies are those that have faced bankruptcy proceedings under the Insolvency and Bankruptcy Code (IBC), 2016, while non-distressed peers were carefully selected based on comparable asset sizes, ensuring that the analysis focuses on firms within the same sector—steel and iron manufacturing.

Financial data, including balance sheets, income statements, and company overviews, were meticulously gathered from the Capitaline Corporate Database, covering a decade of operations from 2012 to 2022. This rich dataset enables an in-depth examination of financial performance, trends, and the impact of distress on corporate health and sustainability.

Discussion of Empirical Evidence

a. Descriptive Statistics

Table 1: Descriptive statistics

Ratios	Firms	1st Year		2nd Year		3rd Year		4th Year		5th Year	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Working Capital/ Total Assets	D	-0.72	0.97	-0.87	1.24	-0.42	0.69	-0.18	0.44	-0.04	0.27
	ND	0.23	0.15	0.19	0.17	0.17	0.16	0.11	0.26	0.06	0.29
Retained Earnings/ Total Assets	D	-0.98	2.08	-1.10	1.76	-0.47	1.17	-0.17	0.66	0.01	0.40
	ND	0.35	0.24	0.34	0.22	0.32	0.21	0.24	0.35	0.21	0.40
EBIT/Total Assets	D	-0.07	0.11	-0.31	0.60	-0.11	0.24	-0.06	0.21	0.00	0.08
	ND	0.07	0.04	0.09	0.07	0.07	0.06	0.07	0.05	0.07	0.04
Market Value of Equity/ Book Value of Total Debt	D	0.07	0.08	0.12	0.12	0.23	0.36	0.35	0.45	0.29	0.34
	ND	5.18	14.72	3.87	14.18	2.26	4.94	3.01	9.88	0.60	1.74
Sales/Total Assets	D	0.49	0.67	0.53	0.65	0.64	0.61	0.82	0.62	0.91	0.58
	ND	1.20	0.91	1.38	1.31	1.32	1.03	1.15	0.69	1.28	0.92
Z Score	D	-1.92	4.48	-3.00	5.68	-0.72	3.11	0.39	2.23	1.07	1.40
	ND	5.32	8.76	4.69	8.52	3.56	3.09	3.65	5.86	2.22	1.51

Source: Authors' own compilation

Note- 'D' and 'ND' instance distressed firm and non-distress firm, respectively

Table 1 highlights key differences in financial ratios between distressed and non-distressed firms, revealing clear trends in liquidity, profitability, and solvency. Non-distressed firms exhibit a higher working capital-to-total assets ratio of 0.23 in the year leading up to bankruptcy—significantly stronger than their distressed counterparts. Additionally, firms that filed for bankruptcy under IBC 2016 consistently showed weaker profitability, both annually and cumulatively over the preceding five years. The contrast extends to solvency and operational efficiency, as non-distressed firms maintain a higher market value of equity relative to book debt and demonstrate superior asset utilization through sales-to-total-assets ratios. These findings emphasize the financial resilience of non-distressed firms long before bankruptcy proceedings begin.

b. Evaluation of Predictive Accuracy

Table 2: Evaluation of Predictive Accuracy

Year	Cut-off points	Total observation	Total right prediction	Total wrong prediction	Type 1 errors	Type 2 errors	Gray Zone	Percentage of Accuracy
1st Year	Altman's Range	36	21	6	1	5	9	58%
	Altman's Cut Off	36	26	10	5	5	NA	72%
	Optimal Cut Off	36	33	3	2	1	NA	92%
2nd Year	Altman's Range	40	22	6	1	5	12	55%
	Altman's Cut Off	40	24	16	7	5	NA	60%
	Optimal Cut Off	40	35	5	1	4	NA	88%
3rd Year	Altman's Range	42	26	5	1	4	11	62%
	Altman's Cut Off	42	24	18	8	4	NA	57%
	Optimal Cut Off	42	36	6	2	4	NA	86%
4th Year	Altman's Range	42	23	4	2	5	12	55%
	Altman's Cut Off	42	20	22	11	5	NA	48%
	Optimal Cut Off	42	33	9	3	6	NA	79%
5th Year	Altman's Range	42	22	8	2	6	12	52%
	Altman's Cut Off	42	21	21	9	6	NA	50%
	Optimal Cut Off	42	33	9	6	3	NA	79%

Source: Authors' own compilation

Note- Optimal cut-off point means the cut-off point generated from the study.

This study evaluates the predictive accuracy of Altman's Z-score model by analyzing 42 listed iron and steel companies. The Z-score, derived from five weighted financial ratios, was used to classify firms based on three criteria: Altman's range, Altman's cut-off point, and an optimized cut-off point derived from our sample data.

Altman's range categorizes firms into distressed, non-distressed, and a "zone of ignorance." To refine this classification, an optimal cut-off points of 2.67 was introduced, eliminating the ambiguity of the zone of ignorance. However, the accuracy of these traditional criteria remained relatively low, 58% and 72%, respectively, in the year leading up to bankruptcy.

Recognizing the need for improvement, this study identifies a new, highly effective cut-off point that enhances predictive accuracy. The findings reveal that this optimized threshold achieves an impressive 93% accuracy in forecasting bankruptcy one year in advance. Furthermore, the accuracy of this refined model consistently surpasses the other two criteria across all five years before bankruptcy. Notably, as financial distress intensifies, the model's predictive accuracy improves, reinforcing its robustness as a risk assessment tool.

Conclusion

Evaluating and diagnosing the financial health of businesses is a crucial issue in the global economy, especially as a growing number of companies face the threat of bankruptcy. In India, this challenge is particularly pressing, with many firms encountering financial distress and mounting pressure from creditors.

This study explores the effectiveness of Altman's Z-score model in predicting bankruptcy, focusing on listed Indian iron and steel companies. Our findings reveal that while the original Z-score model remains relevant, its predictive accuracy is notably low in the Indian context, making it less effective as an early warning tool. However, the financial ratios used in the model continue to serve as strong indicators of distress, consistently highlighting significant differences between distressed and non-distressed firms.

To enhance predictive power, this study introduces an optimized cut-off point derived from sample data. The results demonstrate that this refined model significantly improves accuracy, offering a highly reliable method for assessing financial distress in Indian firms. These insights pave the way for more effective risk assessment strategies, helping businesses and stakeholders make informed financial decisions.

References

1. Agarwal V, Taffler R. Comparing the performance of market-based and accounting-based bankruptcy prediction models. Journal of banking finance,2008:32(8):1541-1551.
2. Altman EI. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The journal of finance,1968:23(4):589-609.
3. Altman EI, Iwanicz-Drozdowska M, Laitinen EK, Suvas A. Financial distress prediction in an international context: A review and empirical analysis of Altman's Z-score model. Journal of international financial management & accounting,2017:28(2):131171.
4. Beaver WH. Financial ratios as predictors of failure. Journal of accounting research, 1966, 71-111.
5. Bhabak P, Sur D, Maji SK. Financial Distress Prediction using Univariate Analysis: A Pilot Study on Select Indian Companies. Business Insight,2024:11:18-29.
6. Kukreja G, Gupta SM, Sarea AM, Kumaraswamy S. Beneish M-score and Altman Z-score as a catalyst for corporate fraud detection. Journal of Investment Compliance,2020:21(4):231-241.
7. Lord J, Landry A, Savage GT, Weech-Maldonado R. Predicting nursing home financial distress using the Altman Z-Score. Inquiry: The Journal of Health Care Organization, Provision, and Financing, 2020, 57, 0046958020934946.
8. Maji SK, Sur D. Financial Performance of ONGC during the Post-Liberalization Period: A Case Study. Journal of Institute of Public Enterprise, 2015, 38.
9. Muñoz-Izquierdo N, Laitinen EK, Camacho-Miñano, MDM, Pascual-Ezama D. Does audit report information improve financial distress prediction over Altman's traditional Z-Score model? Journal of international financial management & accounting,2020:31(1):65-97.
10. Mousavi MM, Ouenniche J, Tone K. A comparative analysis of two-stage distress prediction models. Expert Systems with Applications,2019:119:322-341.

11. Nguyen M, Nguyen B, Liêu ML. Corporate financial distress prediction in a transition economy. Journal of Forecasting,2024:43(8):3128-3160.
12. Ohlson JA. Financial Ratios and The Probabilistic Prediction of Bankruptcy. Journal of Accounting Research, 1980.
13. Zhao J, Ouenniche J, De Smedt J. Survey, classification and critical analysis of the literature on corporate bankruptcy and financial distress prediction. Machine Learning with Applications, 2024, 100527.