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INSOLVENCY AND BANKRUPTCY CODE: A STUDY OF INDIAN BANKS WITH REFERENCE TO ALTMAN Z SCORE

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ABSTRACT

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The implementation of the Insolvency and Bankruptcy Code 2016, which has been carried out in phases since August 5, 2016, was instituted with the aim of revamping the antiquated and intricate corporate insolvency regulations in India. This legislative measure was designed to tackle the pervasive issue of non-performing loans, which has had far-reaching consequences for the banking industry and the availability of credit within the broader economy. However, the unusual and surprising actions taken by the Reserve Bank of India, the central bank of India, to list delinquent borrowers and instruct banks to commence insolvency procedures against them, demonstrate a remarkable level of speed and determination. One notable illustration is the case of Essar Steel, which has encountered a default on loans amounting to around $6.9 billion and is presently undergoing a distressed sale in accordance with the Code. In light of the proactive implementation of the Code by Indian banks, as mandated by the Reserve Bank, and the commendable quality of available assets, it becomes imperative for foreign debt and equity investors to have a comprehensive understanding of the Code, along with the attendant obstacles and prospects it presents. The current investigation employed the Altman-Z score model to forecast the level of safety exhibited by banks in India with respect to potential insolvency and bankruptcy. The banks that were chosen for this study were picked based on specific criteria. The analysis conducted to assess the safety of these banks relied on information that was published in their respective Annual Reports. The research indicates that a significant proportion of Indian banks exhibit a higher level of safety in relation to insolvency and bankruptcy. The Altman-Z score analysis revealed that the performance of banks in India was strong during the first eight years of the study period. However, notable variations were observed during the latter two years of the study period. It is recommended that bank management proactively address these substantial disparities to minimise the risk of insolvency and bankruptcy.

KEY WORDS: ***Banking Governance, Banking Regulation, Banking Sustainability***

INTRODUCTION

The implementation of the Insolvency and Bankruptcy Code 2016 in India had a significant impact on the rates of default in debt repayments. According to the Insolvency and Bankruptcy Board of India, the implementation of the Code has resulted in the return of approximately USD 14.2 billion in previously unpaid loans during the past two years. To put it another, the improvement in repayment rates can be attributed to the apprehension felt by controlling shareholders of Indian debtors regarding the potential loss of control over their predominantly family-owned enterprises in the event of insolvency. Hence, it is of equal significance for current creditors and shareholders to acknowledge the alteration in the relationship between debtors and creditors brought about by the Code. This is due to the fact that creditors now have the ability to effectively assert their entitlements, potentially leading to a transfer of ownership of debtors.

BANKRUPTCY PREDICTION MODELS

The literature study reveals various methodologies that have been employed in the prediction of bankruptcy. The Scoring model is considered as one of the methodologies employed in the examination of bankruptcy. The Scoring model is formulated as a linear combination of accounting variables, wherein the coefficients assigned to each variable determine its respective weightage in generating a meaningful score. The scoring model's output is utilised in conjunction with a benchmark value to assess the financial well-being of the banks. The utilisation of score value derived from models is of significance to public sector banks in their pursuit of loan acquisition from the Reserve Bank of India (RBI) or other financing agencies (Pradhan, 2014). The scoring model possesses the capacity to categorise banks into distinct pre-established groupings by means of a suitable tool that supplants human evaluation. The utilisation of scoring models in credit risk applications has gained significant popularity over the past four decades, resulting in a substantial and rapidly expanding body of research. The fundamental premise underlying scoring models involves the identification of elements that have the potential to impact the likelihood of default, and subsequently amalgamating these factors into a meaningful score. The aforementioned factors consist of accounting variables that are assigned weights and included into a multivariate model. Imanzadeh (2011) posits that the bankruptcy prediction model is a method employed to forecast the future state of a corporation. This model assesses the likelihood of bankruptcy by aggregating a set of financial parameters.

Numerous alternative models exist for the purpose of predicting bank failures, including the employment of financial ratios from Standard and Moody's, the utilisation of the Beaver model, the application of the Altman Z-score model, the implementation of Ohlson's model, the adoption of the CAMEL model, the utilisation of the Grover model, the application of the Springate model, the employment of neural networks, and the utilisation of Zmijewskis model. These models serve the purpose of assessing the overall financial well-being of a bank. A comprehensive review of the literature reveals that the Altman-Z score model, Grover model, Springate model, and Zmijewski model are the most commonly utilised models in worldwide failure prediction studies for evaluating the financial performance of banks. Previous studies conducted by Vaziri (2012) and Warastuti (2014) employed scoring models to assess the predictability of financial institution failure. These models were observed to have a substantial degree of predictive accuracy. Due to its strong predictive capacity, the model exhibits a high level of accuracy.

Altman Z-Score Model

The Altman Z-Score Model is a widely used financial tool for predicting the likelihood of a company's bankruptcy. Edward Altman is credited as being the pioneer in use ratios as a means of assessing the financial distress of a corporation. The initial occurrence of this event took place in 1968, thereby leading to the individual being recognised as the progenitor of bankruptcy.

The utilisation of multivariate discriminant analysis (MDA) in the prediction of corporate failure was pioneered by E. Altman in 1968. Altman (year) employed an initial sample consisting of 66 firms, with an equal distribution of 33 enterprises in each of the two groups, namely the failure and non-failure groups. The bankruptcy group comprised of corporations who submitted bankruptcy petitions under Chapter 11 of the United States Bankruptcy Act between the years 1946 and 1965. All the businesses that were utilised in the study were only manufacturing firms, and those classified as small firms with assets valued at less than $1 million were excluded from the analysis. A comprehensive investigation was conducted utilising multiple factors, and those that exhibited negligible influence or relevance in isolation were excluded from the calculation.

From the initial set of variables, a total of five variables were chosen as the most effective in predicting financial distress. To determine the final set of variables, the following procedure was employed: firstly, the statistical significance of different alternative functions was examined, including the determination of the relative contributions of each independent variable. Secondly, the inter-correlation between relevant variables was evaluated. Lastly, the predictive accuracy of various profiles was observed, and the judgement of the analyst was taken into consideration.

The initial Z-score model, as part of the MDA framework, incorporates five financial ratios: Working Capital to Total Assets, Retained Earnings to Total Assets, Earnings before Interest and Taxes to Total Assets, Market Value of Equity to Book Value of Total Liabilities, and Sales to Total Assets.The original Z-score model, established in 1968, incorporated five variables and has demonstrated its efficacy in bankruptcy prediction. This model is particularly reliable due to its comprehensive assessment of crucial financial indicators, including assets, revenue, working capital, and earnings.

However, the initial Z-score model was shown to possess certain limitations as it solely encompassed publicly owned manufacturing enterprises that had their shares listed in the stock market. The model fails to consider extraordinary situations, such as recessions, during which non-liquid assets like inventories become superfluous due to low demand in relation to the amount of inventories maintained.

The model was constructed using the market value of the firm as its foundation, hence limiting its applicability exclusively to publicly traded companies. Altman further expanded his research by developing two additional formulas that could be used to private and non-manufacturing firms. In order to be relevant for private companies, Altman (2000) proposed a modification to the model by replacing the book value with the market value of equity. This adjustment was made using the same dataset employed in the original study conducted in 1968. This revised estimation suggests that a comprehensive adjustment of all coefficients is necessary, along by the introduction of new values to establish the boundaries of safety and risk.

The calculation of the market value of equity to book value of total liabilities is not feasible in cases where a company's stock is not publicly traded. In order to rectify this issue, it is possible to recalculate the Z score by utilising the book value of equity. The accuracy of Altman's (2000) updated Z-Score prediction model in correctly predicting bankruptcy was demonstrated. The accuracy of Type I is marginally lower compared to the model that incorporates the market value of equity, while the accuracy of Type II remains the same.

The sales to total assets ratio is expected to exhibit variation among non-manufacturing enterprises, potentially influenced by industry-specific factors. The probability of being higher is expected to be greater for service firms in comparison to other manufacturing firms. Given that the service industry is generally characterised by a high level of capital intensity. As a result, it is probable that the non-manufacturing firm will exhibit a greater level of assets turnover, thereby leading to a higher Z score. Therefore, it is probable that the model will underestimate specific types of bankruptcy. Altman proposed the removal of this ratio from the formula as a means of rectifying this issue.The accuracy of the model in accurately identifying the complete sample one year before to failure (-1 year) was found to be highly accurate, with a classification rate of 95%. However, as the forecast time rose, the misclassification of failed enterprises showed a considerable increase. Specifically, the misclassification rate was observed to be 28% at -2 years, 52% at 3 years, and 71% at 4 years. In the year 2000, enhancements were made to the Altman model specifically tailored for the emerging markets, resulting in the development of an emerging market scoring model.

A score below 1.8 indicates a high probability of insolvency for the company, whilst companies with scores beyond 3 demonstrate a low likelihood of facing bankruptcy. Investors may employ Altman Z-scores as a tool for assessing the viability of purchasing or divesting from a stock, particularly when apprehensive about the underlying financial robustness of the company. Investors may opt to acquire a stock when its Altman Z-Score value approaches 3, while they may choose to divest or engage in short selling when the value approaches 1.8.

Working capital / Total asset: Working capital is a common measure of a company's liquidity, efficiency, and overall health. Total assets show the overall assets of banks including both short and long-term. The WC/TA ratio is a sign of a bank's liquidity and ability to meet creditors' short-term obligations.

Retained earnings / Total assets: Retained earnings are the amount carried out to the coming years from net earnings. Accumulated Retained Earnings to Total Asset (TA) is the ratio that measures the accumulated profitability of the banks.

Operating earnings / Total assets: Earnings before Interest and Taxes (EBIT) show the operating profit of banks. EBIT to Total Asset measures the operating efficiency of an organization. The value of this ratio indicates the capacity of the firm to generate satisfactory earnings to pay off its fixed obligation like interest.

Book value of equity / Total liabilities: This is the ratio of the Book value of shareholder's Equity to total liabilities. This ratio indicates the long-term financial soundness of the banks. Having a 1:1 equity debt mix is considered quite good, whereas excessive debt represents the danger of insolvency.

Sales/Total Assets ratio: This is the standard capital-turnover ratio illustrating the sales-generating ability of the assets of a firm. It refers to the capability of management to deal with competitive conditions. This ratio was dropped in the Z”-Score model.

Cut Off Limits

Z-Score	Zone	Result
$Z > 2.9$	Safe	Safe
$1.23 < Z > 2.9$	Grey	Stable
$Z < 1.21$	Distress	Likely to be Bankruptcy

LITERATURE REVIEW

According to Dhama (2020), The primary objective of this study is to forecast the likelihood of bankruptcy in Indian private banks by employing financial parameters, including Return on Assets (ROA), Gross Non-Performing Assets (GNPA), Earnings per Share (EPS), Profit After Tax (PAT), and Gross National Product (GNP) of the country. This research elucidates the significance of Ohlson's number, Graham's number, and Zmijewski number as prominent indicators of bankruptcy within the framework of constructing a neural network-based model. The prediction involves an analysis of financial data pertaining to private sector banks in India, specifically HDFC, ICICI, AXIS, YES Bank, Kotak Mahindra Bank, Federal Bank, IndusInd Bank, RBL, and Karur Vysya. The data spans a period of ten years, from 2010 to 2019. The model that was built during the course of this research will provide assistance to financial institutions and banks in India in comprehending the economic state of the banking industry. The neural network has demonstrated more stability when applied to smaller sample numbers compared to the discriminating technique of analysis. The objective of this study is to establish a connection between the theoretical advancements of artificial neural networks (ANNs) and their practical applications in real-world scenarios. From a variable standpoint, it has been demonstrated that Ohlson's score and Graham's number exhibit considerable strength in relation to other variables when it comes to predicting bankruptcy.

According to Pradhan (2014), The utilisation of Z score values for the purpose of predicting bankruptcy has been a consistent practise, as indicated by researchers from historical periods. This paper presents the Z score value for public sector banks. This metric holds significance in situations where banks seek loans from the Reserve Bank of India (RBI) or any other financial institution. The purpose of employing a backpropagation neural network is to predict the internal parameters associated with the Z score, and thereafter utilise these internal parameters to anticipate the Z score value until the year 2020. This research highlights the application of BPNN (Backpropagation Neural Network) in predicting insolvency for public sector banks in India. The results of the Z score validation indicate that the neural network is capable of making accurate predictions. The customised back-propagation neural network aims to forecast the internal variables of a company in order to manage bankruptcy and evaluate creditworthiness when a bank seeks credit. Additionally, it may be employed to strategize the repayment durations for the borrowed funds.

According to Joshi (2020), The objective of this study is to evaluate the financial performance of specific public sector banks that exhibit the highest degree of gross non-performing assets, employing Altman's Z-Score model. The analysis revealed that all of the chosen banks were classified within the safe zone, as indicated by an average Altman's Z-Score value exceeding the designated threshold of 2.9. There were considerable differences seen in the Altman's Z-Score values among the banks, which could perhaps be attributed to variations in their asset sizes. However, upon individual examination of each bank, it was found that the Altman's Z-Score did not display statistically significant fluctuation across the years throughout the ten-year study period. The Altman's Z-Score value shown statistically significant differences between the first five-year period and the last five-year period when considering all banks as a collective group. Therefore, it is imperative for public sector banks to effectively manage their non-performing assets and develop novel strategies to enhance their profitability. A notable disparity in Altman's Z-Score value was identified during the initial and latter halves of the study period, during which all banks were aggregated. The observed phenomenon could potentially be attributed to the rise in the magnitude of Gross Non-Performing Assets (GNPAs) during the latter portion of the specified time period.

According to the study conducted by Shrivastava et al. (2020), The objective of this research article is to develop a machine learning-based prediction model that is both efficient and suitable for an early warning system designed to detect bank failure. This study employs a novel methodology known as the Synthetic Minority Oversampling Technique (SMOTE) to address the issue of imbalanced data by transforming it into a balanced distribution. The findings of this study have implications for multiple stakeholders, including shareholders, lenders, and borrowers, as they pertain to the assessment of banks' financial stress. This study presents an analytical methodology that encompasses several steps. Firstly, it employs lasso regression to identify the most significant indicators for bank failure. Secondly, it utilises the SMOTE technique to transform imbalanced data into a balanced form. Lastly, it employs suitable machine learning techniques to accurately predict bank failure. This study presents a methodical methodology that encompasses several steps. Firstly, it employs lasso regression to identify the most significant indicators relevant to bank failure. Secondly, it utilises the Synthetic Minority Over-sampling Technique (SMOTE) to balance the unbalanced data. Lastly, it selects suitable machine learning approaches to accurately predict bankruptcy.

RESEARCH SCOPE

The scope of the investigation encompasses the time frame spanning from 2011 to 2020. This inquiry pertains to the concealment of several financial and operational performance metrics, including but not limited to working capital, total assets, retained earnings, earnings before interest and taxes, book value of equity, and book value of total liabilities. The utilisation of Z scores for the assessment of solvency status.This study aims to investigate the concerns pertaining to financial stability and operating performance by analysing a set of selected operating and financial ratios. An endeavour is also undertaken to ascertain the association between these factors.

RESEARCH OBJECTIVES

The research objectives for addressing the issues described above are as follows:

- To evaluate the financial soundness of select Indian public sector banks based on the Altman's Z-Score model.
- To estimate the predictor value of Z-Score

HYPOTHESIS FOR THE STUDY

The following hypothesis has been developed for the study

- H1: There is a significant difference between the Altman's Z-Score Values of the selected banks

DATA SET

The Model used in the study tried to predict the Bankruptcy of selected Indian banks. Therefore, the study used an empirical research design. In this Study, secondary data was collected from various website. The data were collected from Annual reports, the Reserve Bank of India (RBI) website, the Money Control website, the Capital Line website and Bombay Stock Exchange (BSE) website. Excel was used to handle the data and perform econometric analyses. The data was taken for ten ten-year period from the year 2010-11 to 2019-20. The sample of the study comprises 16 Indian banks, out of which 11 banks are public sector banks, and 5 are private banks. The type and the number of banks are selected based on the availability of data and the consequences of time limitations.

This study applied Altman Z-score bankruptcy model on the above banks. The reason for the selection of these models amongst various models available for evaluating the financial performance of banks, as a literature survey shows that the majority of international failure prediction studies employed this model.

RESEARCH METHODOLOGY

The present study is a combination of both theoretical as well as analytical works. In the research work, the procured data have been analyzed in as many ways as possible by using various statistical tools and techniques with a view to evaluating the comparative financial performance of selected Public and Private Sector Banks operating in India during the period of 2011-2020. To analyze the data, various arithmetical and statistical tools like Percentage, Mean, Standard Deviation, etc. have been used to have an idea of the general profile of the variables. Besides these, depending on the need of the study Regression and Z-Score Model have been conducted.

Altman Z-Score Model

The model developed a following equation with zones of discrimination

$Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 1.0X5$

Were,

X1 = Working capital/Total assets,

X2 = Retained earnings/Total assets,

X3= Earnings before interest and taxes/Total assets,

X4 = Market value equity/Book value of total liabilities and

Z= overall index

<u>Zones of discrimination</u>

$Z > 2.99$ = "Safe" Zone

$1.81 < Z < 2.99$ = "Gray"

Zone $Z < 1.81$ = "Distress" Zone

Z-score was re-estimated based on the other databases for private manufacturing companies, non-manufacturing companies, and service companies. The Z-score model for the service companies uses four variables to discriminate between obligors. These variables are – liquidity, leverage, profitability, and solvency. These variables are measured with the help of the following ratios:

An equation for service industries as per Z-score Model -1993

$Z = 6.56X1+ 3.26\ X2+6.72\ X3+1.05\ X4$

Were,

X1= Working capital/Total assets,

X2 = Retained earnings/Total assets,

X3= Earnings before interest and taxes/total assets,

X4 = Market value equity/Book value of Total liabilities and

Z= overall index.

An Altman Z-score close to 1.21 suggests a Bank might be headed for bankruptcy, while a score closer to 2.9 suggests a company is in solid financial positioning.

To predict the bankruptcy and profitability that is to calculate Z-Score

Z-Score	Zone	Result
Z > 2.9	Safe	Safe
1.23 < Z > 2.9	Grey	Stable
Z < 1.21	Distress	Likely to be Bankruptcy

RESULTS AND ANALYSIS

PUBLIC SECTOR BANK									
Bank Name	Year	Input Parameters				Z Score	Zone	Z Score	Zone
		(CA-CL)/TA	Retained Earnings/TA	EBIT/TA	Equity/TL				
ALLAHABAD BANK	2020	0.000	0.000	0.000	0.000	3.250	Safe	0.000	Distress
	2019	0.926	0.028	-0.037	0.008	9.181	Safe	5.931	Safe
	2018	0.931	0.037	-0.026	0.003	9.307	Safe	6.057	Safe
	2017	0.937	0.057	-0.003	0.003	9.571	Safe	6.321	Safe
	2016	0.927	0.056	-0.005	0.003	9.484	Safe	6.234	Safe
	2015	0.955	0.053	0.007	0.003	9.735	Safe	6.485	Safe
	2014	0.955	0.051	0.007	0.002	9.736	Safe	6.486	Safe
	2013	0.962	0.053	0.008	0.002	9.790	Safe	6.540	Safe
	2012	0.961	0.055	0.012	0.003	9.812	Safe	6.562	Safe
	2011	0.951	0.053	0.013	0.003	9.753	Safe	6.503	Safe
BANK OF BARODA	2020	0.898	0.061	-0.002	0.001	9.330	Safe	6.080	Safe
	2019	0.917	0.058	0.001	0.001	9.462	Safe	6.212	Safe
	2018	0.918	0.060	-0.004	0.001	9.439	Safe	6.189	Safe
	2017	0.923	0.057	0.004	0.001	9.514	Safe	6.264	Safe
	2016	0.915	0.059	-0.010	0.001	9.380	Safe	6.130	Safe
	2015	0.946	0.055	0.008	0.001	9.687	Safe	6.437	Safe
	2014	0.949	0.054	0.008	0.001	9.711	Safe	6.461	Safe
	2013	0.951	0.058	0.009	0.001	9.736	Safe	6.486	Safe
	2012	0.946	0.061	0.013	0.001	9.747	Safe	6.497	Safe
	2011	0.950	0.058	0.016	0.001	9.776	Safe	6.526	Safe
BANK OF INDIA	2020	0.907	0.352	-0.007	0.005	10.306	Safe	7.056	Safe
	2019	0.911	0.352	-0.014	0.004	10.285	Safe	7.035	Safe
	2018	0.927	0.358	-0.014	0.003	10.403	Safe	7.153	Safe
	2017	0.919	0.299	-0.004	0.002	10.233	Safe	6.983	Safe
	2016	0.924	0.235	-0.013	0.001	9.995	Safe	6.745	Safe
	2015	0.942	0.206	0.003	0.001	10.124	Safe	6.874	Safe
	2014	0.922	0.205	0.006	0.001	10.009	Safe	6.759	Safe
	2013	0.944	0.217	0.007	0.001	10.197	Safe	6.947	Safe
	2012	0.929	0.217	0.009	0.001	10.111	Safe	6.861	Safe
	2011	0.921	0.183	0.010	0.002	9.955	Safe	6.705	Safe
CANARA BANK	2020	0.912	0.053	-0.002	0.001	9.391	Safe	6.141	Safe
	2019	0.904	0.051	-0.003	0.001	9.327	Safe	6.077	Safe
	2018	0.904	0.057	-0.011	0.001	9.298	Safe	6.048	Safe
	2017	0.919	0.057	0.003	0.001	9.481	Safe	6.231	Safe

	2016	0.921	0.056	-0.006	0.001	9.435	Safe	6.185	Safe
	2015	0.926	0.057	0.006	0.001	9.554	Safe	6.304	Safe
	2014	0.932	0.059	0.006	0.001	9.599	Safe	6.349	Safe
	2013	0.938	0.059	0.009	0.001	9.656	Safe	6.406	Safe
	2012	0.946	0.059	0.011	0.001	9.722	Safe	6.472	Safe
	2011	0.945	0.058	0.015	0.001	9.740	Safe	6.490	Safe
CENTRAL BANK OF INDIA	2020	0.882	0.044	-0.003	0.016	9.176	Safe	5.926	Safe
	2019	0.897	0.045	-0.025	0.012	9.126	Safe	5.876	Safe
	2018	0.891	0.047	-0.024	0.008	9.095	Safe	5.845	Safe
	2017	0.902	0.046	-0.011	0.006	9.253	Safe	6.003	Safe
	2016	0.892	0.052	-0.009	0.006	9.221	Safe	5.971	Safe
	2015	0.916	0.051	0.003	0.005	9.451	Safe	6.201	Safe
	2014	0.913	0.044	-0.003	0.005	9.365	Safe	6.115	Safe
	2013	0.933	0.047	0.005	0.004	9.561	Safe	6.311	Safe
	2012	0.925	0.044	0.003	0.003	9.489	Safe	6.239	Safe
	2011	0.920	0.033	0.008	0.002	9.443	Safe	6.193	Safe
INDIAN BANK	2020	0.927	0.069	0.004	0.002	9.586	Safe	6.336	Safe
	2019	0.928	0.068	0.001	0.002	9.564	Safe	6.314	Safe
	2018	0.929	0.071	0.004	0.002	9.604	Safe	6.354	Safe
	2017	0.914	0.076	0.008	0.002	9.549	Safe	6.299	Safe
	2016	0.925	0.077	0.005	0.002	9.606	Safe	6.356	Safe
	2015	0.927	0.074	0.008	0.002	9.626	Safe	6.376	Safe
	2014	0.926	0.072	0.008	0.002	9.614	Safe	6.364	Safe
	2013	0.928	0.068	0.011	0.003	9.638	Safe	6.388	Safe
	2012	0.935	0.071	0.016	0.003	9.722	Safe	6.472	Safe
	2011	0.939	0.071	0.022	0.004	9.792	Safe	6.542	Safe
STATE BANK OF INDIA	2020	0.876	0.058	0.006	0.000	9.228	Safe	5.978	Safe
	2019	0.877	0.060	0.000	0.000	9.204	Safe	5.954	Safe
	2018	0.874	0.063	-0.004	0.000	9.162	Safe	5.912	Safe
	2017	0.870	0.069	0.005	0.000	9.219	Safe	5.969	Safe
	2016	0.868	0.061	0.006	0.000	9.185	Safe	5.935	Safe
	2015	0.878	0.062	0.009	0.000	9.279	Safe	6.029	Safe
	2014	0.917	0.066	0.009	0.000	9.541	Safe	6.291	Safe
	2013	0.904	0.063	0.013	0.000	9.471	Safe	6.221	Safe
	2012	0.896	0.062	0.014	0.001	9.422	Safe	6.172	Safe
	2011	0.874	0.053	0.012	0.001	9.240	Safe	5.990	Safe
PUNJAB NATIONAL BANK	2020	0.932	0.073	0.001	0.002	9.610	Safe	6.360	Safe
	2019	0.930	0.057	-0.020	0.001	9.405	Safe	6.155	Safe
	2018	0.924	0.053	-0.026	0.001	9.315	Safe	6.065	Safe
	2017	0.942	0.058	0.003	0.001	9.636	Safe	6.386	Safe
	2016	0.940	0.057	-0.009	0.001	9.546	Safe	6.296	Safe
	2015	0.946	0.064	0.007	0.001	9.707	Safe	6.457	Safe

	2014	0.951	0.065	0.009	0.001	9.754	Safe	6.504	Safe
	2013	0.941	0.067	0.014	0.001	9.736	Safe	6.486	Safe
	2012	0.942	0.060	0.015	0.001	9.730	Safe	6.480	Safe
	2011	0.937	0.056	0.017	0.001	9.699	Safe	6.449	Safe
SYNDICATE BANK	2020	0.000	0.000	0.000	0.000	3.250	Safe	0.000	Distress
	2019	0.930	0.045	-0.010	0.008	9.441	Safe	6.191	Safe
	2018	0.944	0.042	-0.014	0.004	9.494	Safe	6.244	Safe
	2017	0.948	0.044	0.002	0.003	9.631	Safe	6.381	Safe
	2016	0.947	0.038	-0.003	0.002	9.564	Safe	6.314	Safe
	2015	0.949	0.041	0.007	0.002	9.656	Safe	6.406	Safe
	2014	0.937	0.045	0.007	0.002	9.589	Safe	6.339	Safe
	2013	0.945	0.046	0.007	0.003	9.655	Safe	6.405	Safe
	2012	0.950	0.046	0.008	0.003	9.692	Safe	6.442	Safe
	2011	0.955	0.041	0.008	0.004	9.707	Safe	6.457	Safe
UCO BANK	2020	0.857	0.039	-0.010	0.042	8.975	Safe	5.725	Safe
	2019	0.864	0.036	-0.019	0.024	8.935	Safe	5.685	Safe
	2018	0.863	0.035	-0.020	0.011	8.896	Safe	5.646	Safe
	2017	0.882	0.043	-0.008	0.007	9.132	Safe	5.882	Safe
	2016	0.900	0.043	-0.011	0.004	9.223	Safe	5.973	Safe
	2015	0.934	0.047	0.006	0.004	9.575	Safe	6.325	Safe
	2014	0.938	0.043	0.007	0.004	9.598	Safe	6.348	Safe
	2013	0.940	0.036	0.003	0.004	9.562	Safe	6.312	Safe
	2012	0.941	0.034	0.006	0.004	9.583	Safe	6.333	Safe
	2011	0.941	0.030	0.006	0.004	9.565	Safe	6.315	Safe
UNION BANK OF INDIA	2020	0.924	0.055	-0.007	0.006	9.449	Safe	6.199	Safe
	2019	0.926	0.050	-0.008	0.004	9.435	Safe	6.185	Safe
	2018	0.931	0.049	-0.014	0.002	9.430	Safe	6.180	Safe
	2017	0.933	0.050	0.001	0.002	9.540	Safe	6.290	Safe
	2016	0.933	0.055	0.004	0.002	9.583	Safe	6.333	Safe
	2015	0.950	0.050	0.007	0.002	9.696	Safe	6.446	Safe
	2014	0.954	0.050	0.006	0.002	9.714	Safe	6.464	Safe
	2013	0.955	0.053	0.010	0.002	9.757	Safe	6.507	Safe
	2012	0.950	0.053	0.010	0.002	9.728	Safe	6.478	Safe

The validation process encompassed all internal parameters associated with the Z-score value. The Z-score internal parameter estimates obtained from the years 2011 to 2020 were utilised in the training of the back propagation algorithm. The aforementioned numbers were subsequently utilised as replacements in the Z-score calculation for market credits, resulting in the computation of Z-score values spanning the years 2011 through 2020. The market has experienced fluctuations within the given time frame. In order to estimate the Z-score values in close proximity to the actual values, it is necessary to consider the predictive capacity of the Z-score parameters for financial ratios. The table presents information regarding the percentage error observed at the designated degree of tolerance. Upon utilising the Z-Score, it has been determined that the majority of banks own Z-Scores that surpass the threshold for safety, with the exception of Allahabad Bank and Syndicate Bank in the year 2020. Subsequently, these institutions were amalgamated with Canara Bank.

PRIVATE SECTOR BANK									
Bank Name	**Year**	**Input Parameters**				**Z Score**	**Zone**	**Z Score**	**Zone**
		(CA-CL)/TA	**Retained Earnings/TA**	**EBIT/TA**	**Equity/TL**				
JAMMU AND KASHMIR BANK	2020	0.869	0.058	-0.010	0.001	9.070	Safe	5.820	Safe
	2019	0.915	0.065	0.007	0.001	9.507	Safe	6.257	Safe
	2018	0.916	0.068	0.004	0.001	9.508	Safe	6.258	Safe
	2017	0.901	0.069	-0.018	0.001	9.261	Safe	6.011	Safe
	2016	0.891	0.079	0.009	0.001	9.414	Safe	6.164	Safe
	2015	0.942	0.080	0.011	0.001	9.766	Safe	6.516	Safe
	2014	0.954	0.072	0.022	0.001	9.894	Safe	6.644	Safe
	2013	0.958	0.067	0.021	0.001	9.900	Safe	6.650	Safe
	2012	0.955	0.067	0.020	0.001	9.869	Safe	6.619	Safe
	2011	0.954	0.068	0.018	0.001	9.856	Safe	6.606	Safe
IDBI BANK	2020	0.785	0.079	-0.030	0.035	8.489	Safe	5.239	Safe
	2019	0.784	0.093	-0.071	0.024	8.243	Safe	4.993	Safe
	2018	0.797	0.052	-0.036	0.009	8.415	Safe	5.165	Safe
	2017	0.835	0.057	-0.024	0.006	8.758	Safe	5.508	Safe
	2016	0.853	0.068	-0.013	0.005	8.984	Safe	5.734	Safe
	2015	0.937	0.064	0.004	0.005	9.636	Safe	6.386	Safe
	2014	0.939	0.067	0.005	0.005	9.667	Safe	6.417	Safe
	2013	0.943	0.062	0.008	0.004	9.697	Safe	6.447	Safe
	2012	0.947	0.063	0.009	0.004	9.731	Safe	6.481	Safe
	2011	0.945	0.054	0.009	0.004	9.687	Safe	6.437	Safe
YES BANK	2020	0.802	0.075	-0.113	0.010	8.003	Safe	4.753	Safe
	2019	0.893	0.069	0.006	0.001	9.376	Safe	6.126	Safe
	2018	0.914	0.081	0.020	0.001	9.645	Safe	6.395	Safe
	2017	0.885	0.100	0.023	0.002	9.543	Safe	6.293	Safe
	2016	0.891	0.081	0.023	0.003	9.511	Safe	6.261	Safe
	2015	0.900	0.083	0.021	0.003	9.574	Safe	6.324	Safe
	2014	0.881	0.062	0.021	0.003	9.381	Safe	6.131	Safe
	2013	0.894	0.055	0.019	0.004	9.430	Safe	6.180	Safe
	2012	0.865	0.059	0.020	0.005	9.250	Safe	6.000	Safe
	2011	0.917	0.058	0.019	0.006	9.586	Safe	6.336	Safe
HDFC BANK	2020	0.918	0.111	0.024	0.000	9.795	Safe	6.545	Safe
	2019	0.913	0.119	0.026	0.000	9.803	Safe	6.553	Safe
	2018	0.919	0.099	0.025	0.000	9.771	Safe	6.521	Safe
	2017	0.881	0.103	0.026	0.001	9.540	Safe	6.290	Safe
	2016	0.851	0.097	0.025	0.001	9.322	Safe	6.072	Safe
	2015	0.907	0.104	0.026	0.001	9.717	Safe	6.467	Safe
	2014	0.859	0.087	0.026	0.001	9.345	Safe	6.095	Safe
	2013	0.859	0.089	0.024	0.001	9.339	Safe	6.089	Safe

	2012	0.818	0.087	0.022	0.001	9.051	Safe	5.801	Safe
	2011	0.835	0.090	0.021	0.002	9.163	Safe	5.913	Safe
ICICI BANK	2020	0.879	0.105	0.013	0.001	9.448	Safe	6.198	Safe
	2019	0.868	0.111	0.004	0.001	9.332	Safe	6.082	Safe
	2018	0.875	0.118	0.008	0.001	9.434	Safe	6.184	Safe
	2017	0.864	0.128	0.015	0.002	9.438	Safe	6.188	Safe
	2016	0.861	0.123	0.017	0.002	9.417	Safe	6.167	Safe
	2015	0.905	0.123	0.024	0.002	9.753	Safe	6.503	Safe
	2014	0.879	0.121	0.023	0.002	9.569	Safe	6.319	Safe
	2013	0.877	0.122	0.021	0.002	9.548	Safe	6.298	Safe
	2012	0.883	0.121	0.018	0.002	9.562	Safe	6.312	Safe
	2011	0.909	0.133	0.017	0.003	9.759	Safe	6.509	Safe

FINDINGS

1) All the select sixteen banks reported Altman's Z-Score value (both the version), well above the safe zone cut-off standard of 2.9. However, there was statistically significant difference between the sixteen banks, with regard to the Z-Score values. There was statistically significant difference between the Altman's Z-Score values, for the first eight years and the last two years of the study period, when all the banks were pooled together. The component variable, X3 recorded the maximum contribution to the Altman's Z-score, such that a 1% increase in X3 increased the Altman's Z-score by nearly 6.72%.

2) Empirical studies show that the emerging market model is used less frequently in the Indian context and this paper tested both the models on the same set of data. This paper finds that, as regards to the solvency categorization of the banks, both the Altman's models that were used resulted in similar findings despite having different cut off limits, because the Z scores classified all the banks as Safe from bankruptcy

CONCLUSION

The present study conducted an analysis of the financial performance of a total of eleven public sector banks and five private sector banks. This analysis was carried out using the Altman's Z-Score model. The findings of the study revealed that with the exception of Allahabad bank and Syndicate bank, all other banks were deemed to be in a secure financial position. This determination was made based on the comparison of their average Altman's Z-Score values, which were found to be double the established cut-off of 2.9 for the safe zone. The variation in the Altman's Z-Score values among the banks could potentially be attributed to the disparity in their asset sizes. A notable disparity in the Altman's Z-Score value was noted during the initial and latter halves of the study period, during which all banks were aggregated. The utilisation of the emerging market model in the Indian setting is seen to be rather infrequent according to empirical studies. This study aims to compare the performance of both models using identical data sets. This study demonstrates that the application of Altman's models to determine the solvency categorization of banks yielded consistent results, despite the utilisation of varied cut-off thresholds. Specifically, the Z scores assigned all institutions a classification of being secure from bankruptcy.

All sixteen banks that were selected reported Altman's Z-Score value, both versions, which exceeded the established safe zone cut-off criterion of 2.9. Nevertheless, a statistically significant difference was seen among the sixteen banks in terms of their Z-Score values. A statistically significant variation was observed in the Altman's Z-Score values between the initial eight-year period and the last two-year period of the study, when considering all banks collectively. The variable X3, which represents a component, was shown to have the most impact on the Altman's Z-score. Specifically, a 1% increase in X3 resulted in an approximate 6.72% rise in the Altman's Z-score.

The likelihood of bankruptcy would be significantly higher if the management company failed to promptly do an assessment of the company's financial state. Furthermore, it is imperative for any financial institution that has experienced bankruptcy to prioritise performance enhancement measures in order to minimise the likelihood of future occurrences. Subsequent research endeavours may employ existing bankruptcy prediction models as a basis for their investigations. This can be utilised as a comparative tool for the purpose of forecasting bankruptcy. Furthermore, research may also be conducted within other corporations that are publicly traded on the stock exchange.

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