# The Saga of Ruchi Soya Industries Limited : Could Credit Risk Models Predict Bankruptcy?

Nidhi Gupta<sup>1</sup> Vandana Gupta<sup>2</sup>

### Abstract

Purpose : The primary objective of this study was to examine the efficacy of credit risk models in predicting bankruptcy and evaluating the firm's post-acquisition performance.

Design/Methodology : Ruchi Soya Industries Limited, an Indian listed firm that went into bankruptcy in 2018, was identified for back-testing and evaluating the predictive ability of four models: three accounting-based (Altman Z-score, Altman's emerging market score, and Zmijewski) and the market-based KMV model. In the second stage of analysis, the operating and financial performance of the company was evaluated for pre-bankruptcy and post-acquisition by Patanjali Foods using *t*-tests on financial parameters of solvency, profitability, and efficiency.

Findings : The findings of this study revealed that while all the models were accurate in predicting default accurately for up to 1 year before bankruptcy, they failed to do so accurately beyond that. The predictive ability of the models was highest for the KMV model, followed by Zmijewski and Altman's Z-score. The performance of the firm improved significantly post-acquisition on profitability and solvency parameters.

Practical Implications : According to the findings of this research, credit risk models are accurate at predicting financial trouble and bankruptcy up to 1 year in advance. These findings can be used for credit appraisal by lenders to assess any financial trouble and enable effective risk management. These models can also be used to avoid business failure to develop proactive and preventive financial and managerial decisions. The impact on performance parameters post-acquisition can help consultants and advisors evaluate the restructuring process to see whether there has been value creation post-restructuring.

Keywords : accounting-based models, bankruptcy, market-based models, predictive

JEL Classification Codes : C52, G33, G13

Paper Submission Date : January 24, 2023 ; Paper sent back for Revision : February 18, 2023 ; Paper Acceptance Date : March 5, 2023 ; Paper Published Online : March 15, 2023

redit risk management has received increasing significance over the years in India, with the alarming rise in the non-performing assets (NPA) of banks over the last several years, which has been an outcome of the inability of businesses to repay the loans taken from banks. This led the Central Bank to come up with several schemes to reduce the debt exposure of corporates facing financial distress. Before 2016, institutional debt defaults were handled through different laws and regulations, such as the Sick Industrial Companies Act (SICA), 1985; Debt Recovery Act, 1993; Corporate Debt Restructuring (CDR); Strategic Debt Restructuring (SDR);

#### DOI: https://doi.org/10.17010/ijf/2023/v17i3/172673

64 Indian Journal of Finance • March 2023

<sup>&</sup>lt;sup>1</sup> Student, FORE School of Management, Adhitam Kendra, B-18, Qutub Institutional Area, New Delhi - 110 016. (Email:044029@fsm.ac.in)

<sup>&</sup>lt;sup>2</sup> Professor – Finance and Accounting, FORE School of Management, Adhitam Kendra, B-18, Qutub Institutional Area, New Delhi - 110 016. (Email : vandana.gupta@fsm.ac.in); ORCID iD : https://orcid.org/0000-0002-1723-1951

SARFAESIAct, 2002; and Company Law, 2013 (amendments to Companies Act). However, these schemes failed to resolve the twin balance sheet problem, which resulted from the inability of the borrowers to repay the banks on time, which in turn caused the banks' standard assets (loans) to turn sub-standard and ultimately into NPAs. The continuing surge in NPAs promoted the need to conceptualize and implement a uniform code for resolving and recovering stressed assets. Thus, the Bankruptcy Code (IBC) in 2016 empowers both operational and financial creditors to register insolvency. This code warrants that the companies in financial crisis would have the resolution routed through the National Company Law Tribunal (NCLT) as the legal body and insolvency professionals (IP) managing these companies. The end result of this process would either be restructuring the stressed assets or liquidating the company under trial. It has been determined that several companies are IBC members and are thus insolvent or in liquidation.

## **Corporate Insolvency Resolution Process (CIRP)**

According to the code, an operational creditor can initiate an application for insolvency against a corporate debtor before an adjudicator. A clear procedure has been established under the code for an operational creditor to apply for insolvency, which is as follows:

(1) When a corporate debtor defaults on commitments, the operational creditor sends a notice under the code to the corporate debtor. Demand notices serve as legal notices that require payment of the defaulted payment.

(2) If the corporate debtor continues to fail to make payments to the operational creditor, the creditor may file a court application. Under Section 9 of the Code, the operational creditor has the authority to apply for the application.

After the adjudicating authority accepts the case, the CIRP process is the same for financial and operational creditors.

The Basel II and its advanced internal rating-based models (AIRBs), which enable banks to assess risk and computation of PDs, as well as the gaps in credit risk evaluation by external credit rating agencies that emerged during the global financial crisis, all contributed to the explosive growth of several credit risk models, including accounting-based and market-based models. The credit risk models are broadly on default prediction, which has been phrased interchangeably as insolvency and bankruptcy prediction or financial distress prediction. Against this backdrop, this study has two main goals:

Solution to the predictive ability of the four models for up to 1 year, 2 years, and 4 years before the bankruptcy.

Solution To analyze the acquisition impact on the operating and financial performance of the firm for post-acquisition by Patanjali Foods.

## **Review of Literature**

The forerunners of accounting-based models are Altman (1968), Altman et al. (1977), and Beaver (1966). Other works on these models have been conducted by Abdelsalam (2008), Agarwal and Taffler (2008), Ahuja and Singhal (2014), Altman et al. (2017), Bandyopadhyay (2006), Chitta et al. (2019), Hussain et al. (2014), Jayadev (2006), Kumar and Kumar (2012), Ohlson (1980), Taffler (1983, 1984), Viswanatha Reddy (2012), and Zmijewski (1984).

A study by Ahmed and Govind (2018) emphasized the efficacy of time-varying coefficients of the Altman *Z*-score on listed firms in Canada. In their study, Al-Manaseer and Al-Oshaibat (2018) also reaffirmed that Altman

Z-score showed strong predictive ability for insurance firms listed on the Amman Stock Exchange (ASE). Chandra and Awasthi (2019) examined the insolvency risk of four commercial banks in India using the z-score and found that the percentage of non-performing assets to total advances of the industrial sector was found to be an important determinant that aggravated the insolvency risk of banks. Other similar works by Agarwal and Patni (2019) corroborated the predictive ability of the Altman Z-score on public sector units in India; whereas Kapil and Agarwal (2019) focused on the Altman Z-score and its correlation to various financial performance indicators and compared the traditional models with new methods such as decision tree framework and neural network framework to predict bankruptcy.

Kittur (2019) evaluated the effectiveness of Altman's Z-score and identified NPA as a benchmark stability indicator. Kittur's study showed mixed results, with Z-scores capturing the financial distress marginally during the distress period while failing to capture the future NPAs. Kaur's (2019) study tested the Altman Z-score on the banking sector in India for the period from 2012–2017. The study also used Tobin's Q as the performance measure. The findings revealed that during times of market upturns, the stocks of firms that were financially distressed outperformed stocks of firms that were non-distressed. Tung and Phung (2019) tested the Altman Z-score on Vietnamese firms and found that both financial and non-financial factors impacted bankruptcy prediction. They applied the Altman model to firms in Vietnam.

In their research, Shetty and Vincent (2021) developed a default prediction model for the Indian industrial sector by using binary logistic regression analysis. Their analysis found that the return on assets, current ratio, debt-to-total assets ratio, sales-to-working capital ratio, and cash flow-to-total assets ratio were significant. Arora and Saurabh (2022) investigated the financial distress among Indian companies listed on the Bombay Stock Exchange (BSE). The relevance of the market capitalization/debt ratio was discovered in accordance with previous research.

Several research studies focused on the impact of the resolution process of IBC and the subsequent impact on firms' financial and operating performance. Among these include those by Kattadiyil and Umarov (2021) on Alok Industries that went into IBC. Studies on firms' performance post-restructuring included those by Joshi and Desai (2019) on the energy sector.

### **Research Design and Methodology**

The two main objectives of this study are as follows:

Solution To evaluate the predictive ability of four accounting-based and market-based models on Ruchi Soya Industries Limited, which went bankrupt in 2018. The models are back-tested for up to 4 years before bankruptcy.

♥ To evaluate and compare the company's performance for pre- and post-acquisition on different ratios.

### Scope of the Study

This study focuses on Ruchi Soya Industries Limited, which filed for bankruptcy under the IBC in 2018 and was later acquired by Patanjali Foods. To perform the study, secondary data were utilized. The financial data for the analysis were taken from the company's annual reports. To get at the relevant interpretation and analysis, data from the financial years 2013–2014 to 2021–2022 were evaluated. Financial data were taken from the EIKON database for additional research, and information on the NCLT and CIRP processes was obtained from Ruchi Soya Industries Limited's FPO report. Furthermore, the remaining data were accessed from Prowess CMIE (Centre for Monitoring Indian Economy).

### Models Used for the Study

This study has identified three original accounting-based models and the KMV market model for further analysis. The models chosen for this study are as follows:

- ♦ Altman's Z-score model
- ♦ Altman's emerging market scoring model
- Szmijewski score model
- ♦ KMV model

### Altman's Original Z-Score Model

The Altman *Z*-score model was developed by Edward Altman in 1968, which is a bankruptcy predictor model using multivariate discriminant analysis (MDA). This model generates a *Z*-score, representing the likelihood of a company filing for bankruptcy in the next 2 years. This model uses the financial statements (balance sheet and income statement) to measure the financial status and is based on the combination of five key financial ratios, weighted with coefficients. These five calculated ratios will then be multiplied by the coefficient developed by Altman to calculate the *Z*-score.

Altman's statistically derived discriminant function takes the form as follows:

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

where,

 $X_1 =$  working capital/total assets

 $X_2 =$  retained earnings/total assets

 $X_3 = \text{EBIT/total assets}$ 

 $X_4$  = market capitalization/book value of total liability

$$X_5 = \text{sales/total assets}$$

The firm is classified as follows:

"Financially sound" if Z > 2.99, and

"Financially distressed" or "bankrupt" if Z < 1.81,

1.81 < Z < 2.99 = grey zone

### Altman's Emerging Market Scoring Model (EMS)

The emerging market-scoring model is used to rate emerging market credit and is based on the following two factors:

- ✤ Financial evaluation using a qualitative risk model.
- An evaluation of unique credit risk in the emerging market to arrive at a final modified rating.

Indian Journal of Finance • March 2023 67

Although the basic foundation of this model remains the original Altman *Z*-score model, which was published in 1968, it can be applied to nonmanufacturing companies and other factors such as firm fragility to exchange rate, industry relatedness, and profitable position in the industry.

The equation for the model is given below:

$$EMScore = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 + 3.25$$
<sup>(2)</sup>

where,

 $X_1 =$  working capital/total assets

 $X_2$  = retained earnings/total assets

 $X_3 = \text{EBIT/total assets}$ 

 $X_4 =$  book value of equity/book value of the total liability

The constant term enables us to standardize the analysis so that default equivalent zones of discrimination are:

Z > 2.6 = safe zone 1.1 < Z < 2.6 = grey zone

Z < 1.1 =distress zone

### Zmijewski Score

The *X*-score model, developed by Zmijewski (1984), is the most widely used model among researchers and practitioners. It uses an approach to predict bankruptcy and uses financial measures to measure the firm's performance, leverage, and liquidity. The ratios were chosen based on their performance in earlier research.

 $Zmijewski's Score = -4.336 - 4.513X_1 + 5.679X_2 - 0.004X_3$ (3)

where,

 $X_1 =$  net income/total assets

 $X_2 =$ total liabilities/total assets

 $X_3 = \text{current assets/current liabilities}$ 

The cut-off point = 0

♥ If the *X*-score is below the cut-off point, the company is in a healthy condition.

b However, if the X-score is above the cut-off point, the company is in financial distress.

### KMV Model (1993)

The KMV model is the market-based model and is an extension of the Merton model (1974). Merton pioneered the market models using the application of Black and Scholes (1973). Merton (KMV) implemented the VK model to calculate an expected default frequency (EDF) credit measure, which is the probability of default during the

68 Indian Journal of Finance • March 2023

forthcoming year or years for firms with publicly traded equity. There are essentially three steps in the determination of the default probability of a firm, which are as follows:

Setimate the value of asset and asset volatility : In this step, the asset value and asset volatility of the firm are estimated from the market value and volatility of equity and the book value of liabilities.

Solution the distance to default (DD): The DD is calculated from the asset value and asset volatility (step-1) and the book value of liabilities.

Scalculate the default probability : The default probability is determined directly from the DD and the default rate for given levels of DD.

The model assumes that the company's equity is a call option on the company's underlying value with a strike price equal to the face value of the company's debt under the KMV model.

$V_{E} = V_{A} \Phi(d_{1}) - D_{E}^{-r.T} \Phi(d_{2})$	(4)
$\sigma_{E} = (V_{A}/V_{E}) \Phi(d_{1}) \sigma_{A}$	(5)

The KMV–Merton model basically uses two non-linear equations (4) and (5) to translate the value and volatility of a firm's equity into an implied probability of default. The value of the option is observed as the overall value of the firm's stock in the KMV–Merton model, but the value of the underlying asset (the firm's worth) is not immediately observable. Although  $V_A$  must be calculated,  $V_E$  can be calculated in the marketplace by multiplying the firm's shares outstanding by the current valuation.

#### **Operating and Financial Performance**

For analyzing the second objective of our research, the following hypotheses have been set to investigate the financial performance of sample units:

𝔄 H₁: There is no significant difference between the net profit margin of post-acquisition and pre-acquisition.

♣ H₂: There is no significant difference between the return on equity of post-acquisition and pre-acquisition.

⇔ H<sub>3</sub>: There is no significant difference between the earnings per share of post-acquisition and pre-acquisition.

 $\mathfrak{B}$   $H_4$ : There is no significant difference between the return on capital employed post-acquisition and pre-acquisition.

⇔ H<sub>5</sub>: There is no significant difference between sales asset turnover post-acquisition and pre-acquisition.

𝔅 H<sub>6</sub>: There is no significant difference between the debt-equity ratio post-acquisition and pre-acquisition.

𝔅 H<sub>7</sub>: There is no significant difference between the interest coverage ratio post-acquisition and pre-acquisition.

⇔ H<sub>8</sub>: There is no significant difference between the EBITDA margin post-acquisition and pre-acquisition.

Paired sample *t*-test is used to investigate the significant differences in financial ratios in pre-and post-restructuring periods (Joshi & Desai, 2019).

Table 1. Findings on Altman's Z-Score								
2014	2015	2016	2017	2018	2019	2020	2021	2022
2.51	2.50	2.19	0.91	-3.15	-0.88	3.20	5.28	7.18
Table 2. Findings on Altman's EMS Model								
2014	2015	2016	2017	2018	2019	2020	2021	2022
4.51	4.24	3.26	0.26	-12.15	-7.45	7.06	10.71	13.84
Table 3 Findings on the Zmijewski Model								
2014	2015	2016	2017	2018	2019	2020	2021	2022
	2014 2.51 Tabl 2014 4.51 Tabl	2014       2015         2.51       2.50         Table 2. Fine         2014       2015         4.51       4.24	2014         2015         2016           2.51         2.50         2.19           Table         2. Findings or           2014         2015         2016           4.51         4.24         3.26           Table         3. Findings or	2014         2015         2016         2017           2.51         2.50         2.19         0.91           Table 2. Findings on Altma           2014         2015         2016         2017           4.51         4.24         3.26         0.26           Table 3. Findings on the Zn	2014         2015         2016         2017         2018           2.51         2.50         2.19         0.91         -3.15           Table 2. Findings on Altman's EMS           2014         2015         2016         2017         2018           4.51         4.24         3.26         0.26         -12.15           Table 3. Findings on the Zmijewski	2014         2015         2016         2017         2018         2019           2.51         2.50         2.19         0.91         -3.15         -0.88           Table 2. Findings on Altman's EMS Model           2014         2015         2016         2017         2018         2019           4.51         4.24         3.26         0.26         -12.15         -7.45           Table 3. Findings on the Zmijewski Model	2014       2015       2016       2017       2018       2019       2020         2.51       2.50       2.19       0.91       -3.15       -0.88       3.20         Table 2. Findings on Altman's EMS Model         2014       2015       2016       2017       2018       2019       2020         4.51       4.24       3.26       0.26       -12.15       -7.45       7.06         Table 3. Findings on the Zmijewski Model	2014         2015         2016         2017         2018         2019         2020         2021           2.51         2.50         2.19         0.91         -3.15         -0.88         3.20         5.28           Table 2. Findings on Altman's EMS Model           2014         2015         2016         2017         2018         2019         2020         2021           4.51         4.24         3.26         0.26         -12.15         -7.45         7.06         10.71           Table 3. Findings on the Zmijewski Model

Year	2014	2015	2016	2017	2018	2019	2020	2021	2022
Emerging markets	0.35	0.43	0.92	1.43	4.80	3.17	-4.57	-1.19	-1.68

### **Analysis and Results**

It can be observed from Table 1 that when the company filed for bankruptcy in 2018, it was in the distress zone and also for 1 year before bankruptcy. The company was in the grey zone for 2 years to 4 years before the bankruptcy. If we observe the Altman Z-score for post-acquisition, the company was close to 3.88 in the score, which is in solvency; thereafter, the Z-score was >3.88, implying the company was in a safe zone. Thus, as per the Altman Z-score, the company was in the safe zone after being acquired by Patanjali Foods, and the strategy of restructuring could successfully turnaround the company into solvency status.

For Altman's emerging market score, FY2018 is the year for the firm to enter into bankruptcy, and it is observed from Table 2 that the company was in the financial distress zone in the year of bankruptcy and 1 year before bankruptcy. However, for up to 4 years before 2018, the year of entering IBC, the company was depicted in the safe zone. Thus, this model could accurately predict the company in a distress zone up to 1 year before bankruptcy. Post-acquisition, the score was >2.66, indicating that the company was in the safe zone. Thus, this model also corroborates that restructuring of the company led to the company being in solvency status. We conclude that the Altman EMS model could also predict bankruptcy and financial distress for Ruchi Soya for 1 year before being under IBC.

As evident from Table 3, the Zmijewski X-score for 1 year before entering into IBC was greater than 0 and depicted that the firm will default in the next 2 years. However, for up to 2 years and up to 4 years before IBC, this model could not accurately predict the company in the distress zone. After the acquisition, the score was less than 0, showing that the company was in solvency status and was in the safe zone. Thus, this model could also predict financial distress up to 1 year before being filed for bankruptcy.

All three accounting-based models are tested for validity for post-acquisition by Patanjali Foods and clearly show consistent findings in the company entering into solvency status and being in a "safe" zone. Also, there is a common pattern with all three models: financial distress could be predicted for 1 year before filing for bankruptcy.

#### Testing the KMV Model on Ruchi Soya Industries Limited

The inputs taken for this model are market capitalization, outstanding debt, risk-free rate  $(R_t)$ , and risk premium  $(R_m - R_t)$ . For the KMV model, the equity volatility was calculated using the firm's annualized daily volatility, and

Table 4. Data jor the Rive Model				
Variables	Values			
r	0.069			
Market capitalization	531.22			
Sigma_equity	0.195			
Book value of debt	72274.3			
Maturity period	5			
Beta	0.87			
Market return	0.136			

for the stock prices, 1-year before the CIRP process is taken (from July 27, 2017 – July 26, 2018). Returns, standard deviation, and beta were calculated using these values in Excel. The standard deviation of equity is computed as 19.5%. Treasury bond yield 10Y (2017) has been taken into consideration as a risk-free rate.  $R_f$  is taken as 6.69%, and  $R_m$  is taken as 13.6%. Therefore, the risk premium  $(R_m - R_f)$  is taken as 6.91%. At last, the figures of market capitalization and outstanding debt for 2018 are being taken. The KMV approach will allow for estimating the market value of assets and volatilities of assets and then using this to measure the probability of default (Table 4).

By solving the two simultaneous non-linear equations, the probability of default is computed, which is 0.99 for Ruchi Soya Industries Limited. The PD of the defaulted firm is 99.09%. The PD for 5 years is 0.43, which is 43%; depending on a firm's default probability, the lenders decide the rate of interest applicable for the debt. Hence, our model could predict the insolvency of Ruchi Soya Industries Limited.

#### Findings on Post-Acquisition by Patanjali Foods in 2019 on Operating and Financial Performance

The findings from the ratios and *t*-test in Table 5 show that the acquisition strategy helped the company in improving its operating and financial performance. The resolution process of IBC emphasizes restructuring and turnaround through acquisition. This is reflected in the improved financial parameters of the firm. The company's performance in the year ending on March 31, 2018, alongside the EPS and the EBITDA margin, went on to become unfavorable, leading to a decline in the key financial parameters. The unanticipated rapid decline and persistent low pricing of castor oil, adverse global demand conditions, and the market environment — all had a

Activities	t calculated	t table value	<i>p</i> -value	Hypotheses Accepted or Rejected			
Net profit margin	-2.5511	4.302653	0.125397	Rejected			
ROE	-3.168266913	3.182446305	0.050548083	Rejected			
EPS	-2.24888597	4.30265273	0.153469992	Rejected			
ROCE	-3.67911907	4.30265273	0.066583668	Rejected			
Sales turnover	-1.132908033	3.182446305	0.339609174	Rejected			
Debt-equity ratio	0.008344351	3.182446305	0.99386612	Rejected			
Interest c	-7.266779257	3.182446305	0.00537777	Accepted			
EBITDA margin	-4.866808823	2.776445105	0.008238654	Accepted			

#### Table 5. Findings of t-test for Ratios Pre- and Post-Acquisition

#### Indian Journal of Finance • March 2023 71

substantial influence on the performance of the company's castor business and contributed considerably to its poor performance. The results show a significant difference in three financial parameters in the pre-and post-restructuring periods as per the paired *t*-test.

The null hypothesis (H<sub>1</sub>) is rejected, implicating a significant difference in the net profit margin for the company in the two periods of pre-acquisition and post-acquisition. Considering the *p*-value calculated for ROE, the null hypothesis (H<sub>2</sub>) will not be accepted, and there is a significant difference between the two time periods based on the sample taken. The *p*-value for the EPS is calculated as 0.15346, which is more than the significance value of 0.05, and the null hypothesis (H<sub>3</sub>) is stated to be rejected. The null hypothesis (H<sub>4</sub>) gets rejected for return on capital employed as the *p*-value shows a significant difference between the ratio for pre-acquisition and post-acquisition periods.

The sales turnover ratio significantly differs in the pre-acquisition and post-acquisition periods considering the p-value; hence, the null hypothesis H<sub>5</sub> is rejected. The debt-to-equity ratio for the corporation in the two periods of pre-acquisition and post-acquisition is significantly different, suggesting that the null hypothesis H<sub>6</sub> is rejected. The interest coverage ratio does not show a significant difference in both periods inferring from the p-value, indicating that we will fail to reject the null hypothesis H<sub>7</sub>. The p-value suggests we cannot reject the null hypothesis H<sub>8</sub> because the EBITDA margin does not differ significantly between the two periods.

## Conclusion

This study has been conducted on Ruchi Soya Industries Limited, an Indian-listed firm that entered into bankruptcy in 2018 under the IBC. Three accounting-based models and one market-based KMV model are tested for up to 4 years before bankruptcy in the first stage of analysis. In the second stage of analysis, the company's performance is evaluated for post-acquisition by Patanjali Foods. Although the accounting models could predict financial distress up to 1 year before default, the KMV model could depict a high probability of default and is thus the most robust. Our *t*-test on ratios clearly indicates that the company's overall performance improved on several parameters after Patanjali Foods was acquired in 2019.

### **Managerial and Theoretical Implications**

Credit risk models have practical applications for a wide set of end users: management, investors, and lenders. There has been a growing emphasis on these models in the last few decades, with growth in derivatives, the Basel framework, and risk management techniques. These models can provide a framework to lenders and help them evaluate the financial risk profile of client borrowers. Lenders can use the models to define credit limits for different borrowers and also set credit limits for different sectors. They can help mitigate firms' business failure by developing proactive and preventive financial and managerial decisions. The change in financial parameters after the resolution of distressed firms and their subsequent acquisition can help consulting firms evaluate the restructuring process to see if there has been value creation post-restructuring. This would pave the way for better decision-making in future advisory roles. Although accounting models are based on financial information that can be accessed in the public domain, the market models are continuously evaluating the risk and can monitor the risk profiles more frequently as compared to the accounting models.

## Limitations of the Study and Suggestions for Future Research

The study is based on financial information from annual reports that are likely to be subject to "creative accounting practices" or window dressing. The scope of the study can be enhanced by factoring in business risks,

industry-specific factors, macro variables, and management quality in addition to financial variables, as these parameters also play a crucial role in the firm's overall risk profile. A wider study with a larger sample size would allow us to identify and create a more robust model. It is also felt that data mining techniques such as decision tree, random forest, and support vector machines can substantiate our findings further, and although no one method can be 100% accurate, a combination of models could best define the default prediction for firms. These models can serve to mitigate the financial risk of lenders by pre-empting default risk and evaluating the solvency status of firms. Early identification of financial distress would enable the respective company to take immediate steps to work on the firm's survival. Many large firms face financial distress, but with efficient strategies, they can tide over being bankrupt in the near future. Thus, a combination of models (parametric and non-parametric) and additional variables could provide a better insight into the credit risk for firms.

## **Authors' Contribution**

Dr. Vandana Gupta conceived the idea of analyzing the company and testing the reliability of accounting-based models and the market-based model on the bankruptcy of Ruchi Soya. Dr. Gupta has done extensive research on bankruptcy prediction models and identified the models to be used for analysis. Nidhi Gupta did her summer internship at Ruchi Soya (now Patanjali Foods) and was keen to work on a research project. She downloaded data from Prowess CMIE and the company's website. Dr. Gupta wrote the manuscript with initial inputs from Nidhi Gupta.

## **Conflict of Interest**

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

## **Funding Acknowledgement**

The authors received no financial support for this article's research, authorship, and/or publication.

## Acknowledgement

The infrastructural support provided by FORE School of Management, New Delhi, in completing this paper is gratefully acknowledged.

## References

- Abdelsalam, H. M. (2008). A credit assessment model for small businesses in Egypt. *Indian Journal of Finance*, 2(4), 3–16. https://www.indianjournaloffinance.co.in/index.php/IJF/article/view/71660
- Agarwal, A., & Patni, I. (2019). Applicability of Altman Z-score in bankruptcy prediction of BSE PSUs. *Journal of Commerce & Accounting Research*, 8(2), 93–103. http://publishingindia.com/jcar/
- Agarwal, V., & Taffler, R. (2008). Does financial distress risk drive the momentum anomaly? *Financial Management*, 37(3), 461–484. http://dx.doi.org/10.1111/j.1755-053X.2008.00021.x

Indian Journal of Finance • March 2023 73

- Ahmed, M. A., & Govind, D. (2018). An evaluation of the Altman Z-score model in predicting corporate bankruptcy for Canadian publicly listed firms. *Summit Research Repository*. http://summit.sfu.ca/item/18342
- Ahuja, B. R., & Singhal, N. (2014). Assessing the financial soundness of companies with special reference to the Indian textile sector: An application of the Altman Z score model. *Indian Journal of Finance*, 8(4), 38–48. http://dx.doi.org/10.17010/ijf/2014/v8i4/71922
- Al-Manaseer, S. R., & Al-Oshaibat, S. D. (2018). Validity of Altman Z-score model to predict financial failure: Evidence from Jordan. *International Journal of Economics and Finance*, 10(8), 181–189. https://doi.org/10.5539/ijef.v10n8p181
- Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4), 589–609. https://doi.org/10.2307/2978933
- Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., & Suvas, A. (2017). Financial distress prediction in an international context: A review and empirical analysis of Altman's Z-score model. Journal of International Financial Management & Accounting, 28(2), 131-171. https://doi.org/10.1111/jifm.12053
- Altman, E. I., Haldeman, R. G., & Narayanan, P. (1977). ZETA<sup>™</sup> analysis a new model to identify bankruptcy risk of corporations. *Journal of Banking & Finance*, 1(1), 29–54. http://doi.org/10.1016/0378-4266(77)90017-6
- Arora, P., & Saurabh, S. (2022). Predicting distress : A post insolvency and bankruptcy code 2016 analysis. *Journal of Economics and Finance*, 46, 604–622. https://doi.org/10.1007/s12197-022-09582-y
- Bandyopadhyay, A. (2006). Predicting probability of default of Indian corporate bonds: Logistic and Z-score model approaches. *Journal of Risk Finance*, 7(3), 255–272. https://doi.org/10.1108/15265940610664942
- Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, 4, 71–111. https://doi.org/10.2307/2490171
- Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, 81(3), 637–654. https://doi.org/10.1086/260062
- Chandra, S., & Awasthi, R. (2019). Insolvency risk: Issues and challenges for public sector commercial banks of India. *Indian Journal of Finance, 13*(12), 19–33. https://doi.org/10.17010/ijf/2019/v13i12/149266
- Chitta, S., Jain, R. K., & Sriharsha, R. (2019). Financial soundness of Maharatna companies: Application of Altman Z s c o r e m o d e l . In dian Journal of Finance, 13(10), 22-33. https://doi.org/10.17010/ijf/2019/v13i10/147745
- Hussain, F., Ali, I., Ullah, S., & Ali, M. (2014). Can Altman Z-score model predict business failures in Pakistan? Evidence from textile companies of Pakistan. *Journal of Economics and Sustainable Development*, 5(13), 110–115.
- Jayadev, M. (2006). Predictive power of financial risk factors: An empirical analysis of default companies. *Vikalpa, 31*(3), 45–56. https://journals.sagepub.com/doi/pdf/10.1177/0256090920060304
- Joshi, N. A., & Desai, J. (2019). Financial restructuring and its impact on operating performance in the energy sector in India. *Indian Journal of Finance*, 13(1), 37–54. http://doi.org/10.17010/ijf/2019/v13i1/141047
- 74 Indian Journal of Finance March 2023

- Kapil, S., & Agarwal, S. (2019). Assessing bankruptcy of Indian listed firms using bankruptcy models, decision tree and neural network. *International Journal of Business and Economics*, 4(1), 112–136. https://doi.org/10.5281/zenodo.2596723
- Kattadiyil, B., & Umarov, I. (2021). Alok industries, pre & post corporate insolvency resolution process. *Economics* and Innovative Technologies, 6, 38-48. https://inlibrary.uz/index.php/economics and innovative/article/view/12177
- Kaur, J. (2019). Financial distress and bank performance: A study of select Indian banks. *International Journal of Financial Management*, 9(3), 26–35. http://www.publishingindia.com/ijfm/30/financial-distress-and-bank-performance-a-study-of-select-indian-banks/828/5761/
- Kittur, A. H. (2019). Effectiveness of the Altman Z-Score model: Does the Altman Z-Score model accurately capture the effects of non-performing assets (NPA) in the Indian banking sector? (Dissertation). http://urn.kb.se/resolve?urn=urn:nbn:se:lnu:diva-86144</div>
- KMV Corporate. (1993). Credit monitor overview. San Francisco California, 60-66.
- Kumar, R. G., & Kumar, K. (2012). A comparison of bankruptcy models. *International Journal of Marketing, Financial Services and Management Research, 1*(4), 76–86.
- Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, 29(2), 449–470. https://doi.org/10.2307/2978814
- Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, 81(1), 109–131. https://doi.org/10.2307/2490395
- Shetty, S., & Vincent, T. N. (2021). Corporate default prediction model: Evidence from the Indian industrial sector. *Vision*. https://doi.org/10.1177/09722629211036207
- Taffler, R. J. (1983). The assessment of company solvency and performance using a statistical model. *Accounting and Business Research*, *13*(52), 295–308. https://doi.org/10.1080/00014788.1983.9729767
- Taffler, R. J. (1984). Empirical models for the monitoring of UK corporations. *Journal of Banking & Finance*, 8(2), 199–227. https://doi.org/10.1016/0378-4266(84)90004-9
- Tung, D. T., & Phung, V. T. (2019). An application of Altman Z-score model to analyze the bankruptcy risk: Cases of multidisciplinary enterprises in Vietnam. *Investment Management & Financial Innovations*, 16(4), 181–191. http://dx.doi.org/10.21511/imfi.16(4).2019.16
- Viswanatha Reddy, C. (2012). Analysis of liquidity, profitability, risk and financial distress: A case study of Dr. Reddy's Laboratories Ltd. Indian Journal of Finance, 6(12), 5-17. https://www.indianjournaloffinance.co.in/index.php/IJF/article/view/72358
- Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research*, 22, 59–82. https://doi.org/10.2307/2490859

#### **About the Authors**

Nidhi Gupta is a second-year student with a specialization in finance at FORE and has been placed with HCL Tech. She did her summer internship at Ruchi Soya Industries Limited and collaborated with her mentor at FORE, Prof. Vandana Gupta, to undertake this research on the company. She did extensive research on the company and also on the various credit risk models being applied for default prediction.

Dr. Vandana Gupta is a Professor of Finance at FORE School of Management, Delhi, India. She has done her PGDM from IIM Ahmedabad and PhD in credit risk. Her experience spans 30 years that includes academics and industry. She has worked with some leading corporates like Infosys, ICRA (India's leading Credit Rating Agency), Religare Securities Limited (equity research), and Telstra (Telecom). Her teaching areas are financial reporting and analysis, corporate finance, credit risk, project appraisal and financing, and business valuations. She has to her credit several research papers in national and international journals and has presented her research at national and international conferences. She is also a corporate trainer.