ISSN (Print Version) 0975-3931
ISSN (On Line Version) 2278-1277

Predictive Modelling for Financial Distress amongst Manufacturing Companies in India

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Abstract

This study develops a model predicting financial distress amongst manufacturing companies in India using logistic regression. Eighteen financial ratios of 574 companies from 34 manufacturing sectors were examined for 2005 – 2019 to develop and validate the model. The study can be considered one of the very few which has examined the financial distress indicators of the manufacturing sector in India. EBIT margin, Interest coverage, quick ratio, Cash flow from operations to Sales, Debtors Turnover, Working Capital to Total Assets, and Fixed Assets to Total Assets are important determinants of the financial health of a business. This study provides useful insights to business managers and lenders to review and monitor the financial soundness of the business. The findings can also help policymakers to design policies and programs to support distressed industries in India. This study also addresses the urgent need for a country-specific distress prediction model. The model developed shows high predictive ability.

1. Introduction

Financial distress is one of the most unique and tangible forms of distress observed in companies which precedes bankruptcy. Huge financial losses are borne by investors, creditors, employees and the government in the event of corporate bankruptcy. The Indian corporate laws provide neither an opportunity for speedy and effective rehabilitation nor an effective exit (H. Jayesh, 2015). *Where does all this leave the investors and other stakeholders of the company?* Without a robust statutory mechanism to address bankruptcy, the stakeholders will have to take the onus of protecting their wealth. Hence it becomes imperative to develop distress prediction models so that timely intervention can be made and wealth erosion minimised. If financial decay can be arrested at an appropriate time through recognition of signs of decay, proper steps

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can be taken to turn around the company, thereby saving investors' wealth. Distress prediction models can be very useful in identifying distress from the early stages. Numerous attempts have been made to explain the phenomenon of financial distress, but no valid theory exists for bankruptcy prediction (Situm Mario, 2015). A theoretically sound, accurate, simple and widely used corporate failure prediction model for stakeholders is yet to be developed (Appiah et al., 2015). Continuous efforts to decipher the factors indicating distress are needed to improve the understanding of corporate distress and bankruptcy, especially in developing countries like India. Financial statements provide a company's monetary value to help users make decisions (Aderemi et al., 2017). Although, through market measures, non-financial and macroeconomic factors have been observed to influence distress, accounting ratios best estimate the probability of corporate distress in India (Charalambakis and Garrett, 2016). However, there is no consensus on the best set of accounting ratios that can serve as distress signals. In this context, this study identifies the firm-specific factors which may lead to financial distress in the manufacturing sector in India.

There are many motivating factors for conducting this study. First, the sector is experiencing widespread distress. A distressed sector adversely affects the investment sentiments in an economy. Reserve Bank of India's Financial Stability Report 2021 pegs the Gross Non-Performing Assets (GNPAs) of scheduled commercial banks for Industries at 11.3% of total advances. Bad loans could hold economic growth for ransom for a developing economy like India. Hence, it is important to identify factors that can indicate companies' financial distress. Early warning signals can help the stakeholders to take remedial measures and minimise investment losses. Secondly, the country-specific model for corporate failure prediction is required due to differences in legal, cultural and regulatory systems. Including country-specific information and regional or industry indicators can improve the accuracy of prediction models' accuracy (Altman et al., 2014). A country-specific model incorporating the unique behavioural factors of Indian companies needs to be developed. Thirdly, most of the studies have focused on developed countries. Most importantly, research in India's corporate distress field has not been very encouraging. Most of the studies focused on the application of existing models to Indian companies to identify sickness [Panda and Bahera, (2015), Nair, (2015) Nair, (2013), Bardia, (2012), Kumar and Kumar, (2012), Sarbapriya Ray, (2011), Reddy and Reddy, (2010)]. Some studies have attempted to identify factors indicating distress in various sectors [Nair and Sachdeva, (2016) – Textile sector, Senapati and Ghoshal, (2016) – Manufacturing sector, Mondal and Roy, (2013) – Steel sector, Bhunia and Sarkar, (2011) – Pharma sector].

Thus, in the wake of the current crisis in the manufacturing sector, a model predicting distress in Indian companies is the need of the hour. An in-depth study of the manufacturing sector to identify early warning signals can add immense value to managers, investors and bankers alike. This study aims to add to the limited body of knowledge addressing financial distress in Indian manufacturing companies and develop a model to predict financial distress.

This study examines 18 accounting ratios for a sample of 574 listed companies from the manufacturing sector for 2005-2019 to identify variables indicating distress. The model is developed using Logistic Regression. The model fit is examined using Nagelkerke R Square (1991) and Cox and Snell R square (1989) test. The model is further examined for robustness using a hold-out sample. The developed model exhibits an overall classification accuracy of 91%.

The remaining part of the article is structured as follows: Section 2 details the literature review. Section 3 outlines the research methodology followed by data analysis and model development. Concluding remarks are presented in the last section.

2. Review of Literature

2.1 Accounting ratios

The literature on bankruptcy studies is enormous. The most important challenge in such studies is selecting potentially informative ratios among more than a hundred. In most corporate distress studies, ratios indicating profitability, efficiency and liquidity have emerged as the most popular ratios, though individual ratios for these parameters are different. Thus, there is no consensus on which ratio is the most important predictor of corporate financial distress. Multiple aspects of the business, viz. profitability, liquidity, solvency, efficiency and cash flows, must be considered to arrive at a robust set of accounting variables.

One of the most popular studies on corporate financial distress is by Altman (1968). Of the 22 potentially helpful ratios, 5 ratios were selected using the following parameters (i) statistical significance and relative contribution of each variable, (ii) intercorrelation between variables, (iii) predictive accuracy of the variables and (iv) analyst's judgment. EBIT/TA was the profitability ratio used in the Z-Score discriminant function (Altman et al., 2014). A formal analysis of the most popular ratios adopted in studies on corporate distress was done to identify the most popular ratios. Profitability, Capital Turnover, Financial Leverage, Short term liquidity, Cash Position and Inventory Turnover were the seven factors identified. An attempt has to be made to understand the unique information provided by each ratio to enable a better selection of ratios (Chen and Shimerda, 1981). In another study, Operating Profit/ Total Assets, Operating Profit/ Fixed assets and Retained earnings/ Total Assets representing profitability, Current Assets/ Total Assets and Quick Assets/ Current Liabilities representing liquidity, Long term Liabilities/Total Assets for leverage, Market Value of Equity/ Total Liabilities to reflect market structure was used to create the model, (Gepp and Kumar, 2008).

Operating cash flow/Total Assets, Cash resources/ Total Assets, Operating cash flow/ Interest payments as measures of profitability and liquidity and Sales/Total Assets Working Capital/Total Assets as measures of efficiency were used in creating a distress prediction model using mixed logit (Jones and Hensher, 2004). Return on equity is also observed as a good estimate of technical efficiency and degree of financial distress (Oberholzer, 2010). Ratios like Cash/Total Assets, Cash/Total Sales, Market Value of

Equity/Total capital Employed, and Standard deviation of EBIT/ Total Assets were used to construct a default rating mode (Wang Zheng, 2004). In an interesting study, a formal ranking of the ratios based on popularity and utility in 53 studies on corporate collapse was done, 5 ratios were found to be useful in more than 25% of the studies done. Net Income/Total Assets, Current Assets/Current Liabilities, Total liabilities/ Total Assets, Working Capital/ Total Assets and EBIT / Total Assets were observed to be the most useful ratios (Hossari and Rahman, 2005). Cash flow ratios were found to be good indicators of corporate health. Cash flow/ Total Assets, Cash flow/ Total Liabilities, Cash flow/ Current Assets, Cash flow/Current Liabilities, and Cash flow/capital Employed were significant in predicting distress (Murty and Misra, 2004).

Along with other ratios, the growth rate in earnings, revenues, total assets, and cash flow per share also had an important bearing on financial distress (Wang and Li, 2007). Ratios like a log of enterprise value and total debt to enterprise value were also used to identify bankrupt companies (Polemis and Gounopoulos, 2012). The ratio of the salary of shareholders to total assets was also used as one of the discriminating factors in research on corporate bankruptcy (Mahdi and Bizhan, 2009). Other important ratios were the log of deflated sales, total assets and the number of employees (Kahya and Theodossiou, 1999), Cash flow to sales and day's sales in receivables (Bhunia et al., 2011). Research has also emphasised long-term solvency ratios like proprietary, debt-equity, and capital gearing ratios as variables to detect financial distress (Bardia, 2012). In a study of small and medium enterprises in Belgium, three ratios which could distinguish a bankrupt company from a non-bankrupt company were identified. Equity / Total Assets representing solvency, Current Assets / Current Liabilities for liquidity and Net Income/ Total Assets for profitability were used to develop the bankruptcy Prediction Model (Brédart, 2014). In a study by the Reserve Bank of India to identify important variables to model corporate distress in India, long-term Liabilities / Total Assets and Operating Profits/ Total Liabilities and Current Assets / Current Liabilities were identified as important ratios (Senapati. and Ghosal, 2016).

Thus ratios indicating Profitability, Financial Leverage, Short term liquidity, Efficiency and Cash Position are most commonly used in distress studies.

2.2 Bankruptcy/Distress Prediction

Exhaustive literature is available on studies on corporate distress and bankruptcy. The quest for developing a bankruptcy prediction model has engaged academicians, researchers and industry experts for decades. Beaver (1966) was one of the earliest propagators of the bankruptcy prediction model using univariate analysis. Subsequently, Altman (1968), Haldeman and Narayanan (1977), Agarwal and Taffler (1983), Mensah (1984), Ohlson (1980), and Zmijewski (1984) all developed bankruptcy prediction models. The above models have been developed using US companies' data. Altman (2014) tested his 'z' score model across 35 European and non-European countries. The model was observed to fit reasonably well in most countries with 75% accuracy. However, new models must be developed incorporating data from relevant countries and industries. The need for country-specific models for corporate failure prediction has been established by empirical research because of differences in legal, cultural and regulatory systems. Also, including country-specific information and regional or industry indicators can improve the accuracy of prediction models (Altman et al., 2014). Studies have recommended developing a predictive model that considers the specific conditions of a particular country using real data on the financial situation (Svabova et al. 2018).

A comprehensive study of the manufacturing sector will add to the existing literature and provide key insights into the behaviour of Indian manufacturing companies. Based on the above discussion, hypotheses are framed as follows:

H1 – Accounting variables can identify financial distress in a company.

H2- Accounting variables can predict financial distress in a company.

3. Methodology

The present study uses empirical and quantitative analysis to identify factors signaling distress.

3.1 Sample

Listed companies in the manufacturing sector reporting net losses for three consecutive years during 2005-2015 were selected as distressed companies. The initial sample comprised 2791 companies from 35 different industries. Small companies with a turnover of less than Rs.100 million and companies with incomplete financial data were excluded from the study. The companies incurring consecutive losses in more than one block of three years within the ten-year review period were retained in the latest block of three years. Two hundred eighty-seven companies formed the final sample. A matching non-distressed company was identified from the same industry for each distressed company. Criteria applied for the selection of matching non-distressed companies are (i) Industry and type of business, (ii) Period (iii) Sales. The final sample comprised 574 distressed and non-distressed companies. Thus, 18 financial ratios were calculated from the financial statements for three years and 30996 observations were analysed for the period under review. Table 1 gives the companies selected and the industry.

Table 1. Number of companies and industry

Sr. No	Nature of Business (Industry)	Number of companies
1	Agro Chemicals	02
2	Alcoholic Beverages	08
3	Auto Ancillaries	26
4	Automobiles	10
5	Cables	12
6	Capital Goods- Electrical Equipment	38
7	Capital Goods – Non Electrical Equipment	28
8	Castings , Forgings and Fasteners	24

9	Cement	12
10	Ceramic Products	10
11	Chemicals	32
12	Consumer Durables	34
13	Diversified	04
15	Edible Oil	16
16	Fertilisers	06
17	FMCG	18
18	Glass & Glass products	10
19	Leather	02
20	Mining and Mineral Products	06
21	Non- Ferrous Metals	08
22	Packaging	26
24	Paper	26
25	Petro chemicals	04
26	Pharmaceuticals	24
27	Plastic Products	14
31	Steel	46
32	Sugar	34
33	Tele Equipment and Infra	06
34	Textiles	86
35	Tobacco Products	02
	Total	**574**

Of the 574 companies selected for the study, 450 companies were used to develop the model. The probability score of each observed company was calculated to examine the model's classification accuracy. The model is tested first on the initial sample (450 companies), then the hold-out sample from the same period (124 companies) and further with additional observations for the period 2014-2019 (68 companies).

3.2 Variables

The dependent variable is the event of distress / non-distress. Distress is coded as 0 and Non-distress as 1. Eighteen accounting ratios representing profitability, liquidity, leverage, efficiency and cash flows are used as explanatory variables. The ratios are computed using the financial statements provided by Bloomberg and Capitaline Database. Table 2 lists ratios and their formulae used in the study.

Table 2 Variables used in the study

Profitability		
1.	Gross Profit Margin (GPM):	$\frac{\text{Gross Profit}*100}{\text{Net Sales}}$
2.	EBIT Margin (EBITM):	$\frac{\text{Earnings before Interest and Taxes}}{\text{Net Sales}}$
3.	Net Profit to Net Worth (NPNW):	$\frac{\text{Reported Net Profit}}{\text{Equity Shareholders Funds}}$

4. Net Profit to Total Assets (NPTA):	$\frac{\text{Reported Net Profit} * 100}{\text{Total Assets}}$
Solvency	
5. Debt to Equity (D/E):	$\frac{\text{Long Term Debts}}{\text{Equity Shareholders Funds}}$
6. Interest Coverage (OPI):	$\frac{\text{Earnings before Interest and Taxes}}{\text{Annual Interest}}$
7. Debt to Total Assets (DTA):	$\frac{\text{Total Debt}}{\text{Total Assets}}$
Efficiency	
8. Fixed Asset Turnover (FATO):	$\frac{\text{Net Sales}}{\text{Net Block of Fixed Assets}}$
9. Capital Turnover (CTO):	$\frac{\text{Net Sales}}{\text{Total Capital Employed}}$
10. Working Capital Turnover (WCTO):	$\frac{\text{Net Sales}}{\text{Net Current Assets}}$
11. Debtors Turnover (DTO):	$\frac{\text{Net Credit Sales}}{\text{Receivables}}$
12. Inventory turnover (INVTO):	$\frac{\text{Inventory}}{\text{Cost of Goods Sold}}$
13. Working Capital to Total Assets (WCTA):	$\frac{\text{Net Current Assets}}{\text{Total Assets}}$
14. Fixed Assets to Total Assets (FATA):	$\frac{\text{Net Block of Fixed Assets}}{\text{Total Assets}}$
Liquidity	
15. Current Ratio (CR):	$\frac{\text{Current Assets}}{\text{Current Liabilities}}$
16. Quick ratio (QR):	$\frac{\text{Current Assets} - \text{Inventories}}{\text{Current Liabilities}}$
Cash flows	
17. Cash Flow to Total Assets (CFOTA):	$\frac{\text{Cashflow from Operations}}{\text{Total Assets}}$
18. Cash Flows to Sales (CFOS):	$\frac{\text{Cashflow from Operations}}{\text{Net Sales}}$

3.3 Model specification

Multivariate Discriminant Analysis is one of the most widely used techniques in corporate distress studies. [Altman, (1968), Altman, Haldeman and Narayanan, (1977), Agarwal and Taffler, (1983)]. Another popular technique viz:- Logit and Probit Analysis, was adopted by Ohlson (1980), Zavgren (1985), Zmijewski, (1984) to construct bankruptcy prediction models. Another method gaining prominence is Artificial Neural Networks reflected in works by Chancharat, (2008), Grunberg and Lukason, (2014), Bredart, Xavier (2014). Support Vector Machine, (Li et al, 2015), Sequential Floating Forward Selection, (Fallahpour, 2017) were also used. It is observed that models developed using contemporary techniques like Discriminant Analysis and Logistic Regression have good predictive accuracy (Gepp and Kumar, 2008). Of the two, Logistic Regression is preferred for predictive analysis as no assumptions are made with regard to the distribution of independent variables, and the results can be easily interpreted. Logistic regression models have better classification abilities than other methods (Suntaruk, 2010; Grünberg and Lukason, 2014). In the present study, logistic regression is used for estimation of distress probability in companies. Logistic regression was significant in this study because the outcome variables in this study were a dichotomy. The variables have a non-linear relationship, which violates one of the assumptions of linear regression. Logistic regression was also vital because it helps in predicting the probabilities of predictor variables influencing the dependent variable.

Equation 1 gives the logit model

$$\text{Log}(p/1\text{-}p) = V \quad \ldots\ldots(1)$$

Where $V = \beta_1 GPM + \beta_2\text{EBITM} + \beta_3 NPNW + \beta_4\ NPTA + \beta_5\ \text{DE} + \beta_6\text{OPI} + \beta_7\text{DTA} + \beta_8\text{FATO} + \beta_9\ \text{CTO} + \beta_{10}\text{INVTO} + \beta_{11}\text{DTO} + \beta_{12}\text{WCTO} + \beta_{13}\text{CR} + \beta_{14}\text{QR} + \beta_{15}\text{WCTA} + \beta_{16}\text{FATA} + \beta_{17}\text{CFOTA} + \beta_{18}\text{CFOS}$

$\beta_1 \ldots .... \beta_{18}$ are coefficients values of independent variables. The log odd score is converted into probability score using Equation 2

$$P(Y) = \frac{e^V}{1+e^V} \quad \ldots\ldots(2)$$

Where:

P (Y) is the probability of non-distress. The event of distress is coded as 0 and the event of non-distress is coded as 1. P (Y) = 1 indicates non-distress and P (Y) = 0 indicates distress. Thus a probability score > 0.50 indicates non-distress, and a probability score < 0.50 indicates distress (Hui Hu, 2011).

4. Results and Discussions

Table 3 reveals variable means of distressed and non-distressed companies

Table 3 Descriptive Statistics (mean) of variables used in the study

Variables	Distressed	Non Distressed
GPM	0.182823	0.288053
EBITM	-0.00953	0.139159
NPNW	-1.33875	0.121499
NPTA	-0.18866	0.065154
DE	9.579902	1.480502
OPI	1.191318	9.671509
DTA	1.33005	0.495293
FATO	2.4185	5.077898

CTO	1.418764	1.546596
INVTO	0.312898	0.262928
DTO	0.314078	0.149167
WCTO	-0.47107	11.62827
CR	3.220292	3.93686
QR	1.614197	1.95284
WCTA	0.211892	0.424081
FATA	0.659284	0.472882
CFOTA	0.070627	0.101779
CFOS	0.047781	0.075727

Means of the variables used in the study

Gross Profit margin, Debt Equity, Debtors Turnover, Fixed Assets Turnover and Cash flow from operations to Sales differ significantly between distressed and non-distressed companies. The results show that distressed companies have large debt in their capital. Also, receivables turnover is poor in distressed companies, which is corroborated by a lower cash flow from operations to sales ratio. Thus, accounting ratios can indicate the financial performance of companies.

Table 4 shows the classification results of the null model (model without any variables) and the initial log-likelihood.

Table 4 Initial Classification Table

	Predicted			Percentage
		Distress	**Non-Distress**	
Observed	**Distress**	0	219	0
	Non-Distress	0	231	100
			450	51.3
Initial log likelihood: -2LL = 623.832				
Cut-off value for classification: 0.5				

Adding independent variables to the null model has reduced the -2 log-likelihood from the initial value of 623.832 to 212.696, indicating that the model is a good fit. The final

ISSN (Print Version) 0975-3931
ISSN (On Line Version) 2278-1277

model is statistically significant, with Nagelkerke R Square and Cox & Snell R Square values indicating that the model can distinguish a distressed company from a non-distressed one.

Table 5 Omnibus Tests of Model Coefficients

Chi-square	**f**	**Significance**	**-2 Log likelihood**	**Cox & Snell R Square**	**Nagelkerke R Square**
411.136	8	0.00	212.696	.599	.799

Thus Hypothesis 1 that accounting ratios can indicate financial distress cannot be rejected. They can distinguish distressed and non-distressed company.

The findings in Table 6 gives that eight predictor variables are significant to the model.

Table 6 Coefficients of predictor variables and their significance

	B	SE.		Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
Lower	Upper								
Step 1[a]	EBITM	17.910	2.336	58.796	1	.000***	59983810.248	616474.891	5836502902.144
	OPI	0.404	.064	40.218	1	.000***	1.498	1.322	1.698
	DTO	-6.486	.838	59.948	1	.000***	.002	.000	.008
	QR	0.312	.132	5.556	1	.018**	1.366	1.054	1.770
	WCTA	-1.134	.370	9.410	1	.002***	.322	.156	.664
	FATA	-2.054	.404	25.805	1	.000***	.128	.058	.283
	CFOS	2.592	.417	38.621	1	.000***	13.358	5.898	30.252
	NPNW	0.076	.021	13.256	1	.000***	1.079	1.036	1.124
a. variable (s) entered on step 1: EBITM, OPI, DTO, QR, WCTA, FATA, CFOS, NPNW.									

******* statistically significant at 1% level
**statistically significant at 5% level

EBITM, OPI, DTO, FATA and CFOS are significant at 1% significance level, and QR and NPNW are significant at 5% significance level. EBIT margin measures the ratio of operating profits to Sales. EBIT margin is thus positively related to firm performance. Literature on corporate distress has used EBIT/ Total Assets (Hossari and Rahman, 2005). Quick ratio measuring the availability of cash and near cash assets to meet short-term liabilities also positively impacts a firm's performance. A high OPI indicating either low debt servicing needs or high-interest coverage keeps a firm financially healthy. The ability of a firm to generate cash flow from operations also suggests positive financial performance. DTO, WCTA, and FATA has shown a negative relation to non-distress. A high debtor turnover theoretically indicates good fund management.

ISSN (Print Version) 0975-3931
ISSN (On Line Version) 2278-1277

However, this study indicates a negative relation to non-distress. Large amount of working capital and fixed assets in relation to total assets indicates inefficiency and hence negatively affects non-distress.

The logit model is developed as:

Log (p/1-p) = *17.910*EBITM + 0.404*OPI – 6.486*DTO + 0.312*QR - 1.134*WCTA – 2.054*FATA + 2.592*CFOS+ 0.76*NPNW*

Substituting the values from each observation, the log-odd score is determined. The log-odd score is then converted into a probability score by the formula:

$$\text{Probability (y)} = \frac{\exp(\log odd\ score)}{1+\exp(\log odd\ score)}$$

Using the probability scores, the companies (observations) are classified into distressed and non-distressed. A company with a probability score > 0.50 is non-distressed. As seen in Table 7, 91.8% of the observations are correctly classified.

Table 7 Classification results (Estimation Sample)

		Predicted		**Percentage**
Observed		**Distressed**	**Non-Distressed**	
Distress	219	189	30	87.7%
Non-Distressed	231	10	221	95.7%
Overall classification accuracy				91.8%

The model was then tested on a hold-out sample of 124 companies (observations). As seen in Table 7, 83% of the companies were correctly classified as distressed and non-distressed, indicating a high degree of model classification accuracy.

Table 8 Classification results (Hold out sample)

			Predicted		**Percentage**
Observed			**Distressed**	**Non-Distressed**	
Distress	68		51	17	75%
Non-Distressed	56		5	51	91%

	Overall classification accuracy	83%

The model was further examined on 68 additional companies for the three year period 2014-2019. Table 9 gives the classification results. 90.5% of the observed companies were correctly predicted as distressed and non-distressed.

Table 9 Classification results (Additional companies)

		Predicted		Percentage
		Distressed	**Non Distressed**	
Distressed	37	34	3	91%
Non-Distressed	31	3	28	90%
Overall classification accuracy				90.5%

Thus, Hypothesis 2 that accounting ratios can predict financial distress cannot be rejected.

5. Conclusion

The current study analyses listed manufacturing companies in India to identify firm-specific accounting ratios significant in distress identification and prediction. Accounting ratios of 574 companies were studied, and a model was developed to predict financial distress. The model can add immense informative value to the limited studies on corporate distress in the Indian context. Also, the existing models predict bankruptcy, whereas the model proposed in this study predicts financial distress, which precedes bankruptcy. This model can help managers monitor and review, enabling the identification of distress-causing zones in business operations. Also, investors can gain better insights into their portfolios. Likewise, lenders can scrutinise the borrowers' profiles and identify potential bad loans. Information on distress can enable policymakers to implement programs to support such industries. The study adds to the existing literature on corporate distress studies and brings fresh insight into the behaviour of distressed manufacturing companies.

Eighteen accounting ratios were examined for 574 companies. EBIT margin (EBITM), Operating Profit to Interest (OPI), Capital to Turnover (CTO), Debtors to Turnover (DTO), Quick Ratio (QR), Working Capital to Turnover (WCTA) and Cash flow from

Operations to Sales (CFOS) have emerged as significant variables in identifying a distressed company. For a business, operating margins, debtors' management, working capital levels and cash realisation from debtors are critical factors for survival and stability, which is corroborated by the current study. The model developed using these predictor variables exhibits strong predictive ability. Though operating margin as a predictor was included in both Altman's (1968) and Ohlson's (1980) model, cash from operations and debtors turnover as a critical test of a company's survival is brought out very strongly in this study.

The present study offers prospects for future research. The study can be extended to the service sector to gain more insights of factors indicating their performance.

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