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Management

FINANCIAL DISTRESS INDICATORS OF INDIAN MANUFACTURING COMPANIES– A FACTOR ANALYSIS APPROACH

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ABSTRACT Manufacturing sector is critical for any developing economy. Indian manufacturing sector, contributing to around 17% to country's GDP is witnessing widespread distress. Many companies are reporting losses for continuous years. The Banking sector is heavily stressed due to bad loans to manufacturing sector. Insolvency proceedings are being initiated against many large companies in manufacturing sector. A distressed company adversely affects its stakeholder's viz. investors, lenders, employees and government leading to wealth and capital erosion. In such times, it is important to capture early indicators of distress to develop measures to overcome the situation thereby preventing bankruptcy. This study seeks to examine and identify factors indicating financial distress in listed manufacturing companies in India. Financial ratios reflecting profitability, solvency, efficiency and cash flows are used as variables. Factor Analysis and Logistic Regression is adopted to identify significant variables. It is observed that efficiency in operations is a key factor influencing a company's profitability and survival.

KEYWORDS : Manufacturing sector, Financial Distress, Financial ratios, Factor Analysis, Logistic Regression

Introduction

Manufacturing sector is a critical sector for Indian economy. Ambitious projects for boosting manufacturing has been always a top priority for the Government. The sector contributes to around 16.57% to Indian GDP. In December 2016, the yoy growth was pegged at 0.6%. The period April to June 2017 saw a growth of 1.6%/. As per RBI Financial Stability Report, 2017, Gross NPAs of banking sector was 10.2% of which 25% was stressed advances to industry. Metals, chemicals, textiles, food processing have shown increasing bad loans. RBI has identified 488 companies for possible insolvency proceedings. 12 large companies, accounting for bad loans of over 251,000 crores, identified for immediate bankruptcy proceedings are all from manufacturing sector. This points out to wide spread financial distress in Indian manufacturing sector. Financial distress and bankruptcy depresses the investment climate of the economy and erodes the wealth of investors. Thus, it becomes very important to identify the signals which can indicate financial distress so that appropriate remedial measures can be taken by all concerned stakeholders to protect their wealth. This information should be derivable from the financial reports made available by the company. This study is an attempt to identify factors indicating financial distress in manufacturing companies in India using financial information provided by the company. This study seeks answers to the following research questions:

(I) Can ratios calculated from financial reports identify financial distress?
(ii) Which are the most significant ratios which signals financial distress?

2. A Brief Review of Literature

Studies on corporate distress and bankruptcy gained prominence in 1960's when Beaver (1966) and Altman (1968) used financial ratios to predict bankruptcy. Since then academicians and researchers across the globe have experimented with various ratios, statistical tools and methods to identify the most important variables which can predict bankruptcy and most effective method to identify the same. Financial ratios were found to be most useful in distress and bankruptcy prediction. Some of the most popular ratios used were Net Income/Net Assets, Current Assets/Current Liabilities, Working Capital /Total Assets, Operating Profits /Total Liabilities, Cash flow/Total Assets, Cash flow/Total Liabilities, Growth rate in earnings, growth rate in revenues, [Murty and Misra, (2004), Hossari and Rahman, (2005), Wang and Li, (2007), Gepp and Kumar, (2008), Bredart, (2014), Senapati and Ghosal, (2016)]. Non-financial ratios also gained importance as influencers of corporate distress. Macro-economic factors like Gross Domestic Product, Net national Income, Exchange Rate, Interest Rate were some of the popular non-accounting ratios used in studies on corporate distress and bankruptcy, [Tirapat and Aekkachai, (1999) , Smith and Liou, (2007), Bhattacharjee et al, (2009), Tsai and Chang, (2010)]. Factor like Board size, auditors opinion, behavioural pattern of managers, proportion of independent managers, credit cycle , market risks were also observed as important variables affecting corporate distress, [Turetsky and McEwen, (2001), Hui and Jing-Jing, (2008), Yazdipour and Constand, (2010), Tsai and Chang, (2010), Xie et al, (2011)]. Different techniques and methods were applied to validate and improve the effectiveness of the existing models. Jones and Hensher,(2004) used a mixed logit method, Fitzpatrick, (2004) used Option Pricing model, Li-Jen Ko et al, (2001) used Composite Rate Induscton System to develop bankruptcy prediction models. An innovative Sliced Average Variance Estimate (SAVE) was used by Wang Zheng, (2004) to identify ratios. The author used Generalised Smoothing Spline model and Recursive Partition Tree Model to predict bankruptcy in Taiwanese companies. Gepp and Kumar, (2008) constructed bankruptcy prediction model using hybrid method combining Survival Analysis with Discriminant and Logit Analysis. However Discriminant Analysis, Logistic Regression and Artificial Neural Network emerged as most popular methods due to their effectiveness in identifying discriminating factors.

Most of the above studies were focused on developed economies in US, Europe and Asia. Very few studies focused on developing countries especially India. Research in India was limited to application of existing models to Indian companies. This study aims to fill this gap. The objective of this study is to examine financial distress in manufacturing companies in India and identify factors that signal distress.

3. Research Methodology

The present study follows an empirical approach. The research methodology is discussed in the following paragraphs.

3.1 Sample selection – Manufacturing companies listed in Indian stock exchanges reporting net losses for three consecutive years during the period 2005-2015 were identified as distressed companies. Companies with incomplete data and very small companies with a turnover of less than 10 crores have been excluded from the study. Thus 287 manufacturing companies formed the initial sample. For each of these companies, a matching non-distressed company from the same industry was identified giving 574 companies for final review and analysis. Capitaline Database was used to select the companies.

3.2 Variable selection – Financial ratios are used as independent variables. Eighteen ratios indicating profitability, solvency, efficiency and cash flows are used (Refer Annexure 1). Variables are selected based on literature survey and general consensus on ability

of a ratio to indicate a particular aspect of business. The dependent variable is Distress, coded as 0 for distress and 1 for non-distress. The financial ratios were computed using the financial statements of the selected companies provided in Capitaline Database.

3.3. Statistical technique used – The data has been analysed using Factor Analysis and Logistic Regression. Factor analysis is used to derive the significant factors from the independent variables and Logistic Regression with factor scores is used to develop the model.

4. Results of Data Analysis

Factor Analysis is used to identify the most important factors which explains the maximum variance between the two groups i.e distressed and non -distressed companies.

(I) KMO and Bartlett's Test is used to evaluate the assumptions of factor analysis namely adequacy of sample and correlation matrix. The Kaiser-Meyer-Olkin value measures sampling adequacy. The value ranges from 0 to 1. Kaiser (1974) recommend 0.5 as minimum acceptance level. The Bartlett's test of Sphericity tests the null hypothesis that the correlation matrix is an identity matrix. An identity matrix is one in which all the diagonal elements are 1 and all the off diagonal elements are near zero. This hypothesis has to be rejected. A low significance level rejects the null hypothesis. Table 1 shows a KMO value of 0.566 which is greater than 0.5 and Bartlett's test of Sphericity is significant with a p value < 0.01. Hence the assumptions of factor analysis is satisfied and the data is suitable for factor analysis.

Table 1 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.566
Bartlett's Test of Sphericity	Approx. Chi-Square	8906.071
	df	153
	Sig.	.000

source: SPSS output

(ii) Table 2 shows the proportion of each variable's variance that is accounted by the factors. It is the sum of factor loadings for the variables. The values have to be more than 0.5 to be considered for further analysis. Thus 91.7% of the variance in GPM and 67.1% of the variance in EBITM is accounted by the extracted factors.

Table 2 Communalities

	Initial	Extraction
GPM	1.000	.917
EBITM	1.000	.671
NPNW	1.000	.891
NPTA	1.000	.836
DE	1.000	.877
OPI	1.000	.754
DTA	1.000	.766
FATO	1.000	.520
CTO	1.000	.596
INVTO	1.000	.710
DTO	1.000	.799
WCTO	1.000	.940
CR	1.000	.933
QR	1.000	.943
WCTA	1.000	.732
FATA	1.000	.810
CFOTA	1.000	.793
CFOS	1.000	.817

Extraction Method:
Principal Component Analysis.

source: SPSS output

(iii) able 3 is divided into three blocks. Block (a) gives the Eigen values and the percentage of variance accounted by each factor. Block (b) gives the Eigen values and the percentage of variance accounted by each factor after extraction and Block (c) gives the Eigen Values and the percentage of variance accounted by each factor after rotation. viz. 20.37% of the variance in variables is accounted by the first extracted factor, 19.8% of the variance in variables is accounted by second extracted factor and so on. Cumulatively 79.4% of the variance is accounted by seven factors. All these factors have an Eigen value > 1. Hence it is found appropriate to retain seven factors for further analysis.

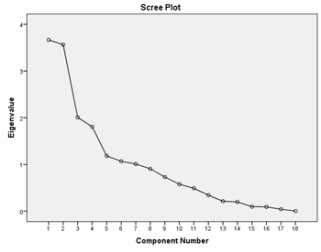
Table 3 Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.667	20.372	20.372	3.667	20.372	20.372	3.613	20.075	20.075
2	3.565	19.805	40.177	3.565	19.805	40.177	3.542	19.677	39.752
3	2.008	11.153	51.330	2.008	11.153	51.330	1.946	10.813	50.565
4	1.807	10.039	61.369	1.807	10.039	61.369	1.868	10.376	60.941
5	1.182	6.566	67.935	1.182	6.566	67.935	1.180	6.557	67.499
6	1.068	5.933	73.868	1.068	5.933	73.868	1.138	6.323	73.821
7	1.009	5.607	79.475	1.009	5.607	79.475	1.018	5.654	79.475
8	.907	5.039	84.515						
9	.731	4.062	88.576						
10	.577	3.208	91.785						
11	.490	2.722	94.506						
12	.343	1.904	96.410						
13	.214	1.186	97.597						
14	.197	1.096	98.693						
15	.098	.542	99.235						
16	.093	.517	99.752						
17	.042	.235	99.987						
18	.002	.013	100.000						

Extraction Method: Principal Component Analysis.

(iv) The scree plot produced in Figure 1 graphs the Eigen values against the factors. The first break in the line is after seventh factor. It can be observed all these factors have an Eigen value > 1.

FIGURE 1 SCREE PLOT



source: SPSS output

(v) Rotated Component matrix shows the loadings of the eighteen variables on the seven factors extracted. All factors with a loading of less than 0.5 is suppressed As seen in Table 4, GPM, EBITM, INVTO, DTO and CFOS are heavily loaded on Factor 1. Similarly NPTA, DTA, CTO, WCTA and FATA are loaded on Factor 2. The empty spaces in the Table represents loadings < 0.5.

Table 4 Rotated Component Matrix[a]

	Component						
	1	2	3	4	5	6	7
GPM	-.957						
EBITM	.635						
NPNW				-.943			
NPTA		-.891					
DE				.935			
OPI						.863	
DTA		.847					
FATO					-.615		
CTO		.745					
INVTO	.834						
DTO	.885						
WCTO							.967
CR			.965				
QR			.969				
WCTA		-.809					
FATA		.841					
CFOTA					.793		
CFOS	.899						

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]a. Rotation converged in 6 iterations. *source: SPSS output*

After rotation, the seven factors can be interpreted as under:

(a) Profitability and Efficiency: Factor 1 comprises 5 variables with loadings of more than 0.5. viz GPM, EBITM, INVTO, DTO and CFOS. These variables represent profitability and efficiency.

(b) Productivity: Factor 2 has NPTA, DTA, CTO, WCTA and FATA as important variables. This factor represents productivity w.r.t capital employed.

(c) Liquidity: Factor 3 is made up of CR and QR. Both these variables measure liquidity or short term solvency of the business.

(d) Leverage: Factor 4 includes NPNW and DE. Both these variables represent two different aspects of business viz. capital productivity and leverage.

(e) Efficiency: Factor 5 has FATO and CFOTA as the important variables. These ratios are linked to efficiency in managing the business.

(f) Solvency: Factors 6 has only one variable i.e. OPI. OPI reflects the impact of leverage i.e the operating margin coverage for interest outgo.

(g) Working capital: Factor 7 comprise of Working Capital to Turnover ratio. This indicates the productivity of working capital.

(vi) Table 5 gives the correlation of the factors after rotation.

Table 5 Component Transformation Matrix

Component	1	2	3	4	5	6	7
1	.858	.504	-.078	.063	-.014	.012	-.010
2	.501	-.851	.056	.066	.104	.084	.016
3	-.015	.085	.835	.518	-.110	.116	.044
4	.101	.013	.516	-.844	-.100	-.034	-.004
5	-.005	-.047	-.164	-.036	-.764	.613	.102
6	-.055	.113	.015	-.099	.615	.730	.252
7	.017	-.008	-.024	.002	-.077	-.263	.961

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

source: SPSS output

(vii) The factor scores obtained for the seven factors are used as variables for Logistic Regression to identify the most significant set of variables signalling distress.

(viii) Omnibus Test of Model Coefficients (Chi square test) is a 'Goodness of Fit' test of the model with independent variables. The chi square has significant p value. The chi-square value (df=7) = 277.495 with a p value <0.01 in Table 6 indicates that model with seven factors can distinguish between distressed and non-distressed companies.

Table 6 Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	277.495	7	.000
	Block	277.495	7	.000
	Model	277.495	7	.000

source: SPSS output

(ix) Cox & Snell R square and Nagelkerke R square values indicates the amount of variance in the dependent variable explained by the independent variables. As given in Table 7, 51.1% of the variation is explained by the independent variables.

Table 7 Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	518.238[a]	.383	.511

a. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

source: SPSS output

(x) Table 8 gives the coefficients of the independent variables and the significance levels of each variables in the model. The Wald statistic and the corresponding significance level test the importance of each variable in the model. Factors 1, 3, 5, 6 and 7 are significant factors. Factor 3 indicating solvency and Factor 6 indicating leverage are very critical for survival of the business.

Table 8 Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)
FAC1_1	.428	.196	4.768	1	.029	1.534
FAC2_1	-.470	.260	3.257	1	.071	.625
FAC3_1	1.094	.150	53.269	1	.000	2.986
FAC4_1	.104	.557	.035	1	.852	1.109
FAC5_1	3.933	.487	65.340	1	.000	51.070
FAC6_1	9.842	.965	104.109	1	.000	18815.308
FAC7_1	.993	.196	25.558	1	.000	2.699

a. Variable(s) entered on step 1: FAC1_1, FAC2_1, FAC3_1, FAC4_1, FAC5_1, FAC6_1, FAC7_1.

source: SPSS output

Of the seven factors retained, Factor 1, Factor 3, Factor 5, Factor 6 and Factor 7 have emerged significant with a p value < 0.05. Factor 1 represents profitability and efficiency in operations. GPM and EBITM reflects the ability of a company to generate profits from its operations. INVTO and DTO indicates the efficiency of a company in managing its inventory and debtors both are which are critical for short term solvency. CFOS is the ultimate measure of company's ability to generate cash from its Sales. Factor 3 is a measure of short term solvency CR and QR indicates whether the company is able to meet its short term obligation through its current assets. Factor 5

has FATO and CFOTA. FATO indicates efficiency in utilising fixed assets to generate sales and CFOTA measures the quantum of cash generated from operating activities in relation to total investment. OPI in Factor 6 is an important indicator of long term solvency. It reflects the profit cover available for interest outflows. Factor 7 with WCTO measures the sales generated in relation to working capital employed. Factor 2 which includes ratios measuring profits, current assets and fixed assets in relation to total assets and factor 4 comprising of NPNW and DE is not observed to be significant. The quantum of fixed assets, current assets, working capital held is not as important as the ability of the company to use these assets to generate profit as represented by Factors 1,3,5,6 and 7. This clearly highlights the relevance of efficiency in operations for long term survival and growth.

(xi) Using the coefficients as above the model can be constructed as : Log (p/1-p) = 0.428*Factor1 - 0.470*factor 2 + 1.094*Factor 3 +0.104*Factor4 + 3.993*Factor 5 + 9.842*Factor 6 + 0.993* Factor 7

(xii) The classification results are shown in Table 9. Of the 574 cases 85.5% cases have been correctly classified as distressed and non-distressed.

Table 9 Classification Table[a]

	Observed		Predicted		
			Distress		Percentage Correct
		.000000	1.000000		
Step 1	Distress	.000000	209	78	72.8
		1.000000	7	280	97.6
	Overall Percentage				85.2

a. The cut value is .500

5. Conclusion and Recommendation

Corporate financial distress is an adversity which can be combated if identified at an early stage. If not identified, it leads to further decay and probable bankruptcy. It would be of immense value to all the stakeholders especially to managers, lenders and investors to arrest wealth erosion by adopting suitable remedial measures. An analysis of financial ratios of distressed and non-distressed manufacturing companies in India highlights the important factors which can signal distress in companies. Profitability is always critical for success and survival of a business, but profitability depends on the efficiency with which assets are utilised for generating revenues. The efficiency in managing inventories and debtors have emerged as very critical factors which in turn will lead to long term sustainability. The ability of a company to control and manage its operating assets to generate revenues and cash extremely important for its survival. The proposed model can easily indicate the probability of distress. Managers and lenders should continuously review and monitor these factors for suitable intervention.

Annexure 1

Financial Ratios and their Formulae

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): $\frac{\text{Reported Net Profit} * 100}{\text{Total Assets}}$

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): $\frac{\text{Total Debt}}{\text{Total Assets}}$

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. Current Ratio (CR): $\frac{\text{Current Assets}}{\text{Current Liabilities}}$

14. Quick ratio (QR): $\frac{\text{Current Assets} - \text{Inventories}}{\text{Current Liabilities}}$

15. Working Capital to Total Assets (WCTA): $\frac{\text{Net Current Assets}}{\text{Total Assets}}$

16. Fixed Assets to Total Assets (FATA): $\frac{\text{Net Block of Fixed Assets}}{\text{Total Assets}}$

17. Cash Flow to Total Assets (CFOTA): $\frac{\text{Cashflow from Operations}}{\text{Total Assets}}$

18. Cash Flows to Sales (CFOS): $\frac{\text{Cashflow from Operations}}{\text{Net Sales}}$

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