



## **Indicators of Financial Distress - An Empirical Study of Indian Textile Sector**

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### **Introduction**

Businesses across the globe faces challenges to ensure stability, growth and sustainability. Macroeconomic volatility in developed nations can have spiraling effect on developing nations. Companies have to deal with not only changes in economic environment but also adapt to changes in social, cultural, political and technological environment. Companies have to constantly devise strategies to cope up with the dynamism of business environment. Failure to do so will lead to financial distress and bankruptcy. This adversely affects the interests of all corporate stakeholders. Identification of indicators of financial distress becomes very crucial in order to take remedial measures to avoid bankruptcy and prevent wealth destruction of stakeholders.

Research has shown that financial statements can provide important information about financial distress in companies (Kane et al, 2006). Financial statements contains data which can give valuable insights to all stakeholders. Ratios calculated using financial data reflects the inter relationships between business numbers (Mondal and Roy, 2013). Appropriate ratios can help the management to analyse the performance and take suitable steps to achieve profitability and growth.

### **Indian textile sector**

India is the second largest producer of textiles in the world. It boasts of 63% of world's market share in textiles and garments. This sector contributes 14% to industrial production and 27% to Gross Domestic Product of the country. It provides employment to over 45 million skilled and non-skilled labour. Availability of raw materials and labour has made this sector an important sourcing hub.

However the sector is challenged by scarcity of trained manpower, increasing cost of energy, high transport costs, low economies of scale and obsolete labour laws. Of the 388 listed companies in textile industry, around 35% have reported net losses for the year ended March 2015 (source: Capitaline Data base). This indicates widespread

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distress in this sector. This paper aims to examine financial distress in textile sector in India and important indicators of financial distress using financial ratios.

### **Research Objective**

The objective of this paper is to:

- a) Identify financial ratios that can indicate financial distress in listed companies in Indian textile industry.
- b) Develop a model which can predict financial distress in listed companies in Indian textile industry.

### **Literature Review**

Numerous studies have been conducted in the area of financial distress and development of distress prediction models. Beaver's (1966) was one of the earliest work in this field. He used univariate analysis to predict bankruptcy. Later Altman (1968) developed the very popular 'z' score model using Discriminant Analysis.

Ohlson (1980) used Logistic Regression to develop 'o'score for predicting bankruptcy. Most of the subsequent studies focused on identifying the most powerful indicators of financial distress and bankruptcy.

Ganesalingam and Kumar (2001) studied 42 successful and 29 failed companies using financial ratios as predictors of financial distress. Principal Component Analysis, Factor Analysis, Discriminant Analysis and Cluster Analysis techniques were adopted to comment upon financial distress. Multivariate analysis was found to be effective in classification of bankrupt and non- bankrupt companies.

Li-Jen Ko et al (2001) analysed financial ratios of 53 companies during the period 1981-85 to develop a distress prediction model., five financial ratios viz TL/TA, QA/CL, Sales /FA, Margin/Sales and Cash dividend/ share were observed to be important indicators of distress.

Platt & Platt (2002) developed an early warning system to predict financial distress using 82 companies having net losses for several years. Logit regression was used to establish the parameters of the model. It was concluded that variables indicating profit margin, leverage, liquidity and growth were strong indicators of financial distress. Murty and Misra (2004) used cash flow ratios as variables to identify sickness in Indian companies ranging across 13 sectors. 9 cash flow ratios were studied of which 5 ratios were found to be significant viz Cash flow / TA, Cash flow / TL, Cash flow / CA, Cash flow /CL, Cash flow / Capital employed. Cash flow ratios were identified as good indicators of corporate health.

Becerra et al (2005) used linear discriminant models, neural networks and wavelet networks for corporate financial distress prediction. 60 failed and non-failed UK firms were selected for the study for the period 1997-2000. Financial ratios were used as variables. It was observed that non-linear models are an alternative to linear models in

developing distress prediction models. Wavelets networks were found to be more advantageous over neural networks. Kane et al (2006) studied the usefulness of financial reporting data to predict the probability of a firm recovering from financial distress is reviewed. It was observed that cash flow has the most predictive ability. Altman's model and logit regression were used as statistical tools for the study. Sharpe and Stadnik (2007) studied Australian general insurers experiencing financial distress. 69 general insurers were studied for the period 1998-2001. Financial ratios like profitability ratios, underwriting expense ratio, cession ratio, scale, growth, asset composition and insurance lines were used as variables. It was observed that holding of property, reinsurance assets, and mix of insurance lines influences financial distress.

Wang and Li (2007) used a rough set model to construct a distress prediction model for Chinese companies. 212 healthy companies and 212 failed companies were selected for study for the period 1998-2005. 34 financial variables and 5 non-financial variables indicating corporate governance were observed. Growth ratio per equity share, net return on assets, EPS, interest coverage, net profit margin, corporate governance coefficient were found to be most significant variables in identifying distress. Coyne et al (2008) analysed financial ratios of 13 bankrupt health care systems and 7 solvent health care systems. Ratios like Operating cash flow percentage change, OCF/ Net revenues, days of cash on hand, Cash flow / Total Liabilities, D/E, DSCR; Days of receivables were reviewed. OCF changes, OCF/Net revenues and Cash flow / Total Liabilities emerged as distinct indicators of financial distress. It shows the sensitivity of health care systems to cash management. Mahdi and Bizhan (2009) reviewed 30 failed and 30 non-failed companies in Tehran Stock Exchange. Multi variate discriminant analysis was used to construct distress prediction model. Working capital / Total Assets, Current Assets/Current Liabilities, Earnings before Interest and Tax/Total Assets, Total Earnings/Total Assets, Sales/Total Assets were found to be important indicators of financial distress. Zaki (2011) developed distress prediction models for commercial and Islamic banks in UAE during the period 2000-08. 16 financial institutions were studied for the period 2000-08. The objective was to establish fundamental and external factors leading to financial distress. Panel discrete choice models were used to analyse the variables. It was observed that Cost to Income ratio, Equity to Total Assets, Total Asset growth were significant indicators of financial distress. Macroeconomic factors did not impact the probability of financial distress.

Bhunja and Sarkar (2011) studied 64 companies in pharma sector in India. A discriminant function was modelled with 7 ratios. It was observed that MDA is still a reliable statistical tool for financial distress prediction. It was observed that financial ratios have a predictive ability to identify a failed company and a non-failed company. Ratios measuring liquidity and profitability are most important in identifying a failed company and a successful company.

Mondal and Roy (2013) developed models for predicting business sickness in Indian Steel sector using financial ratios as variables. Cluster Analysis and stepwise logistic regression analysis were used as statistical tools for the same. It was observed

that Growth rate of PAT and Debt Equity ratio are important variables to predict corporate sickness. Lakshan and Wijekoon (2013) reviewed 70 failed and 70 non- failed companies listed in Colombo stock exchange. Logit regression was used to construct corporate failure prediction model. It was observed that cash flows, leverage, liquidity were important indicators of corporate failure.

Researchers have used different statistical methods to develop bankruptcy prediction models. Multivariate Discriminant Analysis, Logistic Regression, Artificial Neural Networks have emerged as the most popular tools in the field of distress studies.

### **Research Methodology**

Financial distress has been defined differently in different studies. Negative net worth, default in payment of debt, filing for bankruptcy, continuous losses, delisting from stock exchanges are some of the definitions used in past studies. For the current study, a distressed company is defined as one which has incurred continuous net losses for 3 consecutive years.

63 listed companies from textile sector incurring continuous net losses for 3 years were selected for study. These distressed companies are matched with 74 non- distressed listed companies from the same sector to develop the distress prediction model. Logistic regression has been used to identify the most important factors differentiating a distressed company from a non -distressed company and develop the model. The dependent variable is the distress factor i.e 0 for a distressed company and 1 for a non-distressed company. The independent variables are the selected financial ratios.

The logistic regression equation for the above can be derived as:

$$\text{Log}(P/1-P) = b_0 + b_1x_1 + b_2x_2 + \dots + b_nx_n$$

Where  $x_1 - x_n$  are the independent variables

$b_0 - b_n$  are the coefficients of the independent variables

If  $b_0 + b_1x_1 + b_2x_2 + \dots + b_nx_n$  is denoted by 'z', then the probability (P) of distress can be calculated as under:

$$\text{Log}\left(\frac{P}{1-P}\right) = z$$

$$P/1-P = \text{antilog } z$$

$$P = \frac{e^z}{1+e^z}$$

The value of P will lie between 1 and 0. Hence if  $P > 0.50$ , the firm will be identified as non- distressed.

### **Independent variables**

Financial ratios convey information about the profitability, efficiency in operations, solvency, leverage and working capital management of the company. For

this study, 10 financial ratios are selected. Each of these ratios are explained in the following paragraphs:

1. Return on capital employed (ROCE):-  $\text{EBIT} / \text{Total Capital employed}$

ROCE is a measure of overall profitability of a company. It measures the operating return earned by the company on its total capital.

2. Net profit Margin (NPM):  $\text{Net profit} / \text{Net Sales}$

NPM shows the relationship between the net profits and Sales. It is a measure of operational profitability and also efficiency of the company in controlling its costs.

3. Debt Equity (D/E):  $\text{Total Debt} / \text{Total Shareholders' Funds}$

It indicates the proportion of borrowed funds to owner's funds invested in the business. It is an important indicator of a company's long term solvency and financial risks.

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

This ratio is a measure of liquidity of a business. Current ratio indicates the extent of current assets available to meet current liabilities.

5. Fixed Asset Turnover Ratio (FATR):  $\text{Net Fixed Assets} / \text{Net Sales}$

FATR is an indicator of efficiency in utilization of fixed assets to generate sales.

6. Net profit to Total Assets (NTA):  $\text{Net Profit} / \text{Total Assets}$

This ratio indicates performance efficiency by establishing the relationship between net profits earned to total assets.

7. Working Capital Turnover (WCTR):  $\text{Net Current Assets} / \text{Net Sales}$

This ratio is a measure of working capital management of the business. It indicates liquidity position in a business.

8. Debt to Total assets (DTA):  $\text{Total Debt} / \text{Total Assets}$

DTA is an indicator of long term solvency of a company. It shows the extent of assets available in relation to total debt.

9. Sales to Total Assets (STA);  $\text{Net Sales} / \text{Total Assets}$

STA is a measure of efficiency in utilizing assets to generate sales.

10. Working capital to Total Assets (WCTA):  $\text{Net Current Assets} / \text{Total Assets}$

WCTA measures the relationship between working capital and total assets employed by the company.

All the above ratios can be categorized as under:

Ratios indicating profitability – ROCE, NPM

Ratios indicating long term solvency – D/E

Ratios indicating short term solvency – CR, WCTA

Ratios indicating efficiency in operations – FATR, NTA, WCTA, DTA, STA

### **Data Analysis and interpretation**

The financial ratios of 137 selected companies were analysed using logistic regression in SPSS. The results of data analysis is discussed in the following paragraphs.

1. The correlation matrix as given in Table 1 shows that ROI is highly correlated to NTA and WCTA. NPM is highly correlated to FATR.

**Table 1: Correlation Matrix**

		ROI	NPM	CR	DE	FATR	NTA	WCTA	DTA	STA	WCS
ROI	Pearson Correlation	1	.136	.014	.017	-.108	.981**	.750**	-.348**	-.347**	.018
	Sig. (2-tailed)		.113	.869	.843	.207	.000	.000	.000	.000	.836
	N	137	137	137	137	137	137	137	137	137	137
NPM	Pearson Correlation	.136	1	-.005	.022	-.718**	.143	.072	-.029	.121	-.264**
	Sig. (2-tailed)	.113		.950	.796	.000	.096	.406	.733	.160	.002
	N	137	137	137	137	137	137	137	137	137	137
CR	Pearson Correlation	.014	-.005	1	.006	.000	.025	.048	-.034	-.102	.029
	Sig. (2-tailed)	.869	.950		.946	.996	.772	.579	.695	.234	.734
	N	137	137	137	137	137	137	137	137	137	137
DE	Pearson Correlation	.017	.022	.006	1	-.024	.017	.014	-.015	-.034	-.007
	Sig. (2-tailed)	.843	.796	.946		.779	.842	.872	.865	.694	.931
	N	137	137	137	137	137	137	137	137	137	137
FATR	Pearson Correlation	-.108	-.718**	.000	-.024	1	-.122	-.137	.057	-.201*	.256**
	Sig. (2-tailed)	.207	.000	.996	.779		.156	.111	.510	.019	.003
	N	137	137	137	137	137	137	137	137	137	137
NTA	Pearson Correlation	.981**	.143	.025	.017	-.122	1	.784**	-.423**	-.440**	.035
	Sig. (2-tailed)	.000	.096	.772	.842	.156		.000	.000	.000	.682
	N	137	137	137	137	137	137	137	137	137	137
WCTA	Pearson Correlation	.750**	.072	.048	.014	-.137	.784**	1	-.475**	-.397**	.081
	Sig. (2-tailed)	.000	.406	.579	.872	.111	.000		.000	.000	.346
	N	137	137	137	137	137	137	137	137	137	137
DTA	Pearson Correlation	-.348**	-.029	-.034	-.015	.057	-.423**	-.475**	1	.296**	-.060
	Sig. (2-tailed)	.000	.733	.695	.865	.510	.000	.000		.000	.487
	N	137	137	137	137	137	137	137	137	137	137
STA	Pearson Correlation	-.347**	.121	-.102	-.034	-.201*	-.440**	-.397**	.296**	1	-.117
	Sig. (2-tailed)	.000	.160	.234	.694	.019	.000	.000	.000		.173
	N	137	137	137	137	137	137	137	137	137	137
WCS	Pearson Correlation	.018	-.264**	.029	-.007	.256**	.035	.081	-.060	-.117	1
	Sig. (2-tailed)	.836	.002	.734	.931	.003	.682	.346	.487	.173	
	N	137	137	137	137	137	137	137	137	137	137

*computed using SPSS*

\*\* Correlation is significant at the 0.01 level (2-tailed).

\* Correlation is significant at the 0.05 level (2-tailed).

**Table 2 Model Summary**

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	60.981 <sup>a</sup>	.607	.811

a. Estimation terminated at iteration number 10 because parameter estimates changed by less than .001.  
*computed using SPSS*

- The pseudo R squares as given by Cox & Snell R Square and Nagelkerke R square in Table 2 indicate that model is a good fit and independent variables explain 81% of the variations between distressed and non- distressed companies.
- The Hosmer and Lemeshow test results as given in Table 3 indicates that the model is a good fit for the data since the significance > 0.5.

**Table 3 Hosmer and Lemeshow Test**

Step	Chi-square	df	Sig.
1	6.617	8	.578

*computed using SPSS*

**Table 4. Variables in the Equation**

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Step 1 <sup>a</sup> ROI	6.42 9	3.5 28	3.3 21	1	.068	619.531	.615	623869.070
NPM	10.4 51	4.3 59	5.7 49	1	.016	34583.1 08	6.73 9	177473185.7 74
CR	- .002	.00 9	.07 1	1	.790	.998	.979	1.016
DE	- .015	.02 7	.30 0	1	.584	.985	.933	1.040
FATR	.598	.37 4	2.5 66	1	.109	1.819	.875	3.783
NTA	18.4 59	6.7 67	7.4 40	1	.006	103859 302.437	180. 371	5980313540 4222.020
WCTA	- 2.421	1.1 75	4.2 47	1	.039	.089	.009	.888
DTA	.198	.18 8	1.1 11	1	.292	1.219	.844	1.761
STA	.282	.44 8	.39 7	1	.528	1.326	.551	3.193
WCS	.149	.07 7	3.8 03	1	.051	1.161	.999	1.349
Constant	.546	.95 4	.32 8	1	.567	1.726		

a. Variable(s) entered on step 1: ROI, NPM, CR, DE, FATR, NTA, WCTA, DTA, STA, WCS.

4. Table 4 gives the coefficients of the independent variables to form the logistic regression equation. As seen from the Table, NTA is significant at 1% level and NPM and WCTA are significant at 5% level. NTA, NPM and WCTA are important indicators of financial distress. Profitability as denoted by NPM and efficiency as denoted by NT and WCTA have emerged as two very significant factors influencing financial distress.

5. Using the coefficients of the independent variables as given in Table 4 above, the probability of a company not in distress can be modeled as:

$$P = \frac{e^z}{1+e^z}$$

Where  $z = 0.546 + 6.429 \text{ ROI} + 10.451 \text{ NPM} - 0.002\text{CR} - 0.015\text{DE} + 0.598\text{FATR} + 18.459\text{NTA} - 2.421\text{WCTA} + 0.198\text{DTA} + 0.282\text{STA} + 0.149\text{WCS}$

A value of  $P > 0.5$  indicates non- distress and a value of  $P < 0.5$  indicates distress.

1. Table 5 summarizes the classification accuracy of the developed model. 92.7% of the companies selected was classified correctly by the model.



**Table 5. Classification results**

DF Observed	DF Predicted		Percentage correct
	0	1	
0	55	8	87.3
1	2	72	97.3
Overall percentage			92.7

**Conclusion and scope for future study**

Two factors which have clearly come as very important indicators of distress are profitability and efficiency in operations. Profitability as measured by Net Profit margin (NPM) can serve as very good measure of financial health of companies. Profitability is influenced by sales and pricing strategies, cost structure and taxes. Another strong indicator is Net Profit to Total Assets (NTA) and Working Capital to Total Assets (WCTA). These two ratios measures the efficiency of asset utilization. NTA measures a company’s ability to use its fixed and current assets in an optimum manner for profit generation. WCTA indicates the working capital level in relation to total assets thereby highlighting the effectiveness of working capital management.

Firms facing financial distress can turnaround themselves if appropriate and timely remedial measures are adopted. Regular review and monitoring of the probability of distress can provide insight into the strategies required for turnaround since recovery strategies have to be temporal in nature to be effective. (Sudarsanam and Lai, 2001).Continuous monitoring of the accounting variables can aid company’s management in assessing the financial health of the business. This would also enable other stakeholders like investors, employees, customers, suppliers to review the performance of the company and safeguard their interests.

Our study has emphasized on accounting variables to develop distress prediction model. This may not capture the all the factors causing distress in companies. Non accounting factors like interest rates, inflation, corporate governance, industry scenario can also lead to financial downfall in companies. Future research can include these factors. Also this study has focused on one sector viz. textiles. It can be extended to other sectors to develop a generic model for forecasting financial distress.

Annexure

**List of companies**

	<b>Distressed</b>		<b>Non Distressed</b>
1	Malwa Cotton Spinning Mills Ltd	1	Arvind Ltd
2	Garware Marine Industries Ltd	2	Blue Blends (India) Ltd
3	NRC Ltd	3	Bombay Dyeing & Manufacturing Company Ltd
4	Priyadarshini Ltd	4	Century Enka Ltd
5	STI India Ltd	5	DCM Ltd
6	Garden Silk Mills Ltd	6	Garware-Wall Ropes Ltd
7	Gupta Synthetics Ltd	7	Grasim Industries Ltd
8	Eskay K`nIT (India) Ltd	8	Indian Card Clothing Company Ltd
9	SM Energy Teknik & Electronics Ltd	9	Aditya Birla Nuvo Ltd
10	Birla Transasia Carpets Ltd	10	Singer India Ltd
11	Prashant India Ltd	11	JCT Ltd
12	Uniworth Ltd	12	Lakshmi Machine Works Ltd
13	United Leasing & Industries Ltd	13	Mafatlal Industries Ltd
14	Suryajyoti Spinning Mills Ltd	14	Raymond Ltd
15	Jaybharat Textiles & Real Estate Ltd	15	Shri Dinesh Mills Ltd
16	Veena Textiles Ltd	16	SRF Ltd
17	GTN Industries Ltd	17	Siyaram Silk Mills Ltd
18	Vardhman Polytex Ltd	18	Stovec Industries Ltd
19	Perfect-Octave Media Projects Ltd	19	Swadeshi Polytex Ltd
20	Jyoti Overseas Ltd	20	RSWM Ltd
21	Ashima Ltd	21	Himatsingka Seide Ltd
22	Manor Estates & Industries Ltd	22	Vardhman Textiles Ltd
23	Amit Spinning Industries Ltd	23	Nahar Spinning Mills Ltd
24	Spentex Industries Ltd	24	Addi Industries Ltd
25	Winsome Yarns Ltd	25	Loyal Textile Mills Ltd
26	Sri Malini Spinning Mills Ltd	26	Bluechip Tex Industries Ltd
27	Gem Spinners India Ltd	27	PBM Polytex Ltd
28	Uniworth Textiles Ltd	28	Ashnoor Textile Mills Ltd
29	Nylofils India Ltd	29	Deepak Spinners Ltd
30	Oxford Industries Ltd	30	Super Sales India Ltd
31	Gangotri Textiles Ltd	31	Shiva Texyarn Ltd
32	Haria Exports Ltd	32	Konark Synthetic Ltd

33	Cityman Ltd	33	Ruby Mills Ltd
34	Sri Ganapathy Mills Company Ltd	34	Bonanza Industries Ltd
35	Faze Three Ltd	35	Reliance Chemotex Industries Ltd
36	KSL and Industries Ltd	36	Suryalata Spinning Mills Ltd
37	Shreeyash Industries Ltd	37	Jamshri Ranjitsinghji Spg & Wvg Mills Co Ltd
38	LN Industries India Ltd	38	T T Ltd
39	Flora Textiles Ltd	39	Betex India Ltd
40	Alps Industries Ltd	40	Lakshmi Mills Company Ltd
41	Alka India Ltd	41	Ginni Filaments Ltd
42	GSL Nova Petrochemicals Ltd	42	Suryalakshmi Cotton Mills Ltd
43	Sri Ramakrishna Mills (Coimbatore) Ltd	43	Indo Count Industries Ltd
44	Thambbi Modern Spinning Mills Ltd	44	Welspun Syntex Ltd
45	Bijlee Textiles Ltd	45	Donear Industries Ltd
46	Jarigold Textiles Ltd	46	Binayaka Tex Processors Ltd
47	Rosekamal Textiles Ltd	47	Maral Overseas Ltd
48	Wheel & Axle Textiles Ltd	48	Rajapalayam Mills Ltd
49	Golden Carpets Ltd	49	Welspun India Ltd
50	Hari Govind International Ltd	50	Premier Synthetics Ltd
51	Amit International Ltd	51	Ganesh Ecosphere Ltd
52	Lloyd Rock Fibres Ltd	52	VTM Ltd
53	Rainbow Denim Ltd	53	Poddar Developer Ltd
54	Kanco Enterprises Ltd	54	Sangam (India) Ltd
55	STL Global Ltd	55	Trident Ltd
56	Runeecha Textiles Ltd	56	Banswara Syntex Ltd
57	Simplex Mills Company Ltd	57	Zenith Fibres Ltd
58	Abhishek Corporation Ltd	58	Bhilwara Spinners Ltd
59	Gokak Textiles Ltd	59	Sanrhea Technical Textile Ltd
60	First Winner Industries Ltd	60	K G Denim Ltd
61	Birla Cotsyn India Ltd	61	Aarvee Denims & Exports Ltd
62	Pradip Overseas Ltd	62	Bengal Tea & Fabrics Ltd
63	Thomas Scott India Ltd	63	Dhanalaxmi Roto Spinners Ltd
		64	Bhandari Hosiery Exports Ltd
		65	Tatia Global Venture Ltd
		66	Asahi Industries Ltd
		67	Orbit Exports Ltd

		68	Sunil Industries Ltd
		69	Uniroyal Industries Ltd
		70	Kitex Garments Ltd
		71	Sambandam Spinning Mills Ltd
		72	Kandagiri Spinning Mills Ltd
		73	Sarla Performance Fibers Ltd
		74	Cheviot Company Ltd

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