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IDENTIFYING POSSIBLE FRAUDULENCE IN FINANCIAL STATEMENTS OF SELECTED TEXTILE COMPANIES

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Abstract

Fraud is an intentional act committed by the perpetrator with a view to securing the unfair and unlawful advantage. A deliberate misstatement of material facts by management in the books of company with a view to deceive the investors, creditors and other stakeholders of company are known as the Financial Statements Fraud. The Elements of financial statements are manipulated by overstating assets, sales and profit or understating liabilities, expenses or losses. Sometime the percentage of financial statements that contain false information are quite high regardless of the type of the company. Thus, researchers, management, lenders, workers, suppliers, clients and the community at large have demonstrated a great interest in the detection of financial statements fraud. The study employed pooled data of the selected five leading companies of Textile sector, which are listed in the National Stock Exchange, covering a period of 10 years (2008-09 to 2017-18). The objectives of study are to identify the highest contributing factor affecting Financial Statements Fraud (FSF) for the selected Textile companies and to predict the probability of fraudulence for the selected five leading Textile companies. The study reveals that there is a positive significant effect of LEV on the prediction of the probability of FSF for the selected Textile companies and Debt to Equity, Debt to Assets and Interest Coverage ratios contribute significantly to the possible FSF for the selected Textile companies. Hardly any of the selected Textile companies show the possible fraudulence.

Key Words: *Financial Statement Fraud, Accounting ratios, Fraud Detection Models, Logistic Regression*

1.INTRODUCTION:

Fraud is an intentional act committed by the perpetrator with a view to securing the unfair and unlawful advantage (KPMG, 2006). Any act designs to deceive others is a Fraud, which is resulting into suffering the loss of victim's investments (John Maccarthy, 2017). Financial Statements Fraud (FSF) is a deliberate misstatement of material facts by management in the books of the company with a view to deceive the investors, creditors and other users of financial statements. (Alade Sule Omoye; Emmanuel Eragbhe, 2014). The Elements of financial statements are manipulated by overstating assets, sales and profit or understating liabilities, expenses or losses. Sometimes the percentages of financial statements that contain false information are quite high regardless of the type of the company (T. Spathis, 2002). Thus, the elements of financial statements no longer represent the true picture of the company. This kind of illegitimate task of management has a severe impact on the entire economy because it significantly dampens the confidence of investors (Alade Sule Omoye; Emmanuel Eragbhe, 2014). Such kind of Manipulations in the financial statements lead to disagreement between the company's financial and non-financial measures like employee head count, number of retail outlets and warehouse space. This creates an inconsistency, which represents a red flag for gatekeepers for suspecting fraud in financial statement prepared (Brazel, Jones & Zimbelman, 2009). Thus, researchers, management, lenders, workers, suppliers, clients and the community at large have demonstrated a great interest in the detection of financial statements fraud (T. Spathis, 2002). There are strong research concerns for detecting the financial statements fraud in developed countries, but in India, very little attention has been given to this area in accounting research, especially the use of accounting ratios in detection of financial statement fraud (Ifeanyi, Olagunju & Adeyanju, 2011, Faboyede & Mukoro, 2012).

2.LITERATURE REVIEW:

- **Alade Sule Omoye and Emmanuel Eragbhe (2014)** investigated the financial statements fraud based on the Accounting Ratios in the selected companies of the Nigerian Stock Exchange. For this purpose, accounting data were collected from the reported financial statements of 30 sample firms for the periods of five years (2007-2011). The statistical instrument employed was Pooled Data Binary Logit Regression Model. The findings revealed that investment and liquidity ratios were significantly related to financial statements fraud. It was recommended that accounting ratios should be critically examined by investors, stakeholders and Governments.
- **Ch. T. Spathis (2002)** had detected false financial statements using published data of 76 firms of Greece, which included 38 firms with false financial statements and 38 firms with not false financial statements. Logistic Regression was used to develop the model to identify the factors associated with false financial statements. The findings revealed that the logistic regression model was accurate in classifying the total sample correctly with accuracy rates exceeding 84 percent and Inventories to Sales, Total Debt to Total Assets, Working Capital to Total Assets, Total Net Profit to Total Assets and Financial Distress (Z Score) were the possible indicators of Fraud.
- **Yasmine Magdi Ragab (2017)** studied on the detection of fraudulent financial statements with the help of the financial ratios. The main objective of this study was to identify the significant factors associated with fraudulent financial statements. 66 companies of Egypt covering seven-year time periods (2009-2015) had been selected for the study. The findings revealed that the selected model had correctly classified financial statements approximately at 66.4% and Net Sales to Total Assets, Operating Profit to Net Sales, Total Liabilities to Total Assets were the possible indicators of fraudulent financial statements. The author concluded that financial ratios had the ability to examine the detection of fraudulent financial statements.
- **Normah Omar, Ridzuan Kunji Koya et al. (2014)** examined a case of Megan Media Holdings Berhad (MMHB) for the purpose of identifying the financial statement fraud using Beneish Model and Ratio Analysis. The study revealed that the M Score value greater than negative 2.22 indicating earning manipulation. In addition to this, operating efficiency ratio also showed that the company had recorded fictitious revenue. The paper concluded that both techniques were efficient in detection of the financial statement fraud.
- **Somayyeh Hosseini Nia (2015)** studied Financial ratios of 134 firms of Tehran Stock Exchange to check whether there was the difference between the means of some financial ratios between fraudulent and non-fraudulent firms. For testing the hypothesis, data were collected for the years 2009 to 2014. The study indicated that there was a significant difference between the means of Current Assets to Total Assets, Inventory to Total Assets and Revenue to total assets while insignificant difference between the means of Total Debt to Total Equity, Total Debt to Total Assets, Net Profit to Revenue, receivables to revenue and Working Capital to Total Assets ratio.
- **Rasa Kanapickiene and Zivile Grundiene (2015)** used a ratio-based model for the purpose of fraud detection in the financial statements of the selected companies. The aim of this research was to distinguish financial ratios, the values of which could indicate the frauds in financial statements. Logistic regression was used. The findings showed that Inventories to Total Assets, Sales to Fixed Assets, total liabilities to Total Assets and Cash to Current Liabilities were the most important variables, which revealed statistically differences in fraudulent and non-fraudulent financial statements and in the most of cases, fraud was committed to show that the companies keep growing and to fulfill obligation condition. The study concluded that value of financial ratios could indicate about the financial statement fraud and the designed model could be used by the external users of financial statement information when making decisions for investment and company evaluation.

3. RESEARCH METHODOLOGY:

3.1 Objectives of the study:
1.To identify the highest contributing factor affecting the Financial Statements Fraud (FSF) for the selected five Textile companies.
2.To predict the probability of fraudulence for the selected five Textile companies.

3.2 Research Design:
The study is based on Descriptive and Causal Research Designs.

3.3 Sampling Design:
In all, five leading companies covering the ten-year period (2008-09 to 2017-18) have been selected from Textile Sector of India for this study. This study is based on secondary data collected from the annual reports of

the respective selected companies. Arvind Ltd., Grasim Industries Ltd., Raymond Ltd., Vardhman Textiles Ltd. and Vijay Textiles Ltd. are selected for the study.

3.4 Variables Under Study:

The following ratios have been selected for this study.

Table 1: Variables Under Study

Variables	Proxy	Ratios
Financial Statements Fraud	FSF	Dichotomous Variable taking value "1" for the companies with possible fraud and "0" for the companies with possible non fraud
Leverage ratios	LEV	Debt to Equity, Debt to Asset and Interest Coverage ratio
Profitability ratios	PROF	Return on Assets, Return on Equity, Gross Profit and Net Profit ratio
Investment ratios	INVR	EPS
Asset Management ratios	ASSTU	Inventory ratio and Fixed Assets Turnover
Liquidity ratios	LIQD	Current Ratio and Quick acid test ratio

(Source: Alade Sule Omoye; Emmanuel Eragbhe, 2014)

3.5 Tools and Techniques:

A: Descriptive Statistics
B: Pearson Correlation Coefficient
C: Logistic Regression

3.6 Model Specification:

The Logistic Regression formula is the same used in the study of (Alade Sule Omoye; Emmanuel Eragbhe, 2014), as follows:

$\text{Log}\,(p/(1-p)) = \beta_0 + \beta_1\,\text{LEV} + \beta_2\,\text{PROF} + \beta_3\,\text{ASSTU} + \beta_4\,\text{INVR} + \beta_5\,\text{LIQD} + \mathcal{E}$

Where,

p = Pr (FSF) = Probability of Financial Statements Fraud.

FSF_{ij} =1 when i^{th} company found fraudulent in j^{th} year

= 0 when i^{th} company found Non-Fraudulent in j^{th} year

α = Constant

$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ are the Regression Coefficients

$\mathcal{E}$ = Error term.

In developed countries, SEC provides the list of fraudulent companies every year but in India, SEBI does not provide such information. There is no proper database for classification and identification of possible fraudulence in the financial statements of the companies. Therefore, fraudulence is measured based on fraud detection prediction models and integrating the results of three models which are; Beneish M Score Model, Dechow F Score Model and Pustylnick P Score Model. If the value of M Score is greater than negative 2.22, it indicates that the financial statements of the company may have been manipulated (Beneish, 1999), the value of F Score greater than 1 indicates possibility of material misstatements in the financial statements of the company (Dechow et al. 2011) and If ΔP Score is greater than ΔZ Score, it means the possible existence of fraud in the financial statements of the company (Pustylnick I, 2011). If the result of any two models indicates the presence of fraud in these financial statements, the financial statements are considered fraudulent (Zaki, N. M. 2016). Integrated result of this three fraud detection prediction models is taken as dependent variable and LEV, PROF, INVR, ASSTU and LIQD are taken as independent variables.

4. DATA ANALYSIS AND INTERPRETATION:

In order to find out Mean, Standard Deviation and Coefficient of Variation for the selected companies, Descriptive Statistics have been used.

The following table 2 shows the results of Descriptive Statistics.

Table 2- Descriptive Statistics

	Mean	Standard Deviation	Coefficient of Variation (C.V.)
LEV	2.9790	3.6814	1.2358
PROF	16.3542	6.3242	0.3867
ASSTU	38.8744	57.2157	1.4718
INVR	1.8937	0.8838	0.4667
LIQD	1.3792	1.1226	0.8864

The above table 2 shows Mean, Standard Deviation and Coefficient of Variation for each variable considering 10 years. Here, Coefficient Variation is calculated by dividing mean with the Standard Deviation. Generally, less value of C.V. gives better measure of performance. In our case, PROF has the least value of C.V. and it is only 0.3867. It indicates that PROF is the most consistent variable. In contrast ASSTU has the highest value of C.V. and it is 1.4718, which denotes the least consistent variable.

The following table 3 shows the result of Pearson's Correlation Coefficient.

Table -3 Pearson's Correlation Coefficient

	FSF	LEV	PROF	INVR	ASSTU	LIQD
FSF	1					
LEV	0.419* (0.001)	1				
PROF	0.048 (0.370)	0.538* (0.000)	1			
INVR	0.135 (0.175)	0.689* (0.000)	0.662* (0.000)	1		
ASSTU	0.061 (0.338)	0.625* (0.000)	0.600* (0.000)	0.689* (0.000)	1	
LIQD	-0.040 (0.391)	0.033 (0.409)	-0.194 (0.089)	-0.064 (0.330)	-0.171 (0.118)	1

The Pearson's coefficient as shown in above table 3 is used to verify the existence or non-existence of linear correlation between and among the quantitative variables as indicated above. LEV, PROF, INVR and ASSTU have positive correlation with Financial Statements Fraud, meaning that Fraud will increase with an increase in these four variables and vice versa. LIQD, on the other hand is negatively correlated with the Financial Statements Fraud, meaning that an increase in the value of LIQD will result into decrease in chances of Fraud and vice versa. LEV is a positive significant variable related with the FSF.

The following table 4 shows the result of Model Summary.

Table -4 Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	37.333[a]	0.224	0.355

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Above table 4 of The Model Summary provides the -2LL and pseudo-^{R2} values for the model. Nagelkerke's R^2 suggests that the new model explains roughly 35.5% of the variation in the outcome i.e. prediction of the probability of FSF are being predicted by the LEV, PROF, ASSTU, INVR and LIQD. The Cox and Snell R square is 0.224. Thus, it can interpret that 22.4% predictability of the probability of FSF are explained by the logistic variables. All of the Pseudo R-squares reported are smaller than 0.50 generally agree that the estimated model is a good fit to data.

The following table 5 shows the result of Hosmer and Lemeshow test.

Table -5 Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	4.577	8	0.802

A Small Chi-squared values with a larger p-value closer to 1 indicate a good logistic regression model fit. The Hosmer & Lemeshow test of the goodness of fit suggests the model is a good fit to the data as p=0.802 is greater than 0.05.

The following table 6 shows the result of Classification.

Table -6 Classification Table

	Observed		Predicted		
			FRAUD		Percentage Correct
			Non-Fraud	Fraud	
Step 1	Probability of fraud	Non-Fraud	39	1	97.5
		Fraud	7	3	30.0
	Overall Percentage				84.0

a. The cut value is .500

The above Classification Table 6 shows that the model is accurate in classifying the total sample correctly with accuracy rate of 84.0%. Out of the 40 non fraud observations, the model identified 39 of them as not likely to have fraud observations. Similarly, out of 10 fraud observations, the Model identified correctly 3 as likely to have fraud observations.

The following table 7 shows the result of variables in the Equation.

Table-7 Variables in the Equation

		B	S.E.	Wald	Df	Sig.	Exp(B)
Step 1	LEV	0.525*	0.204	6.623	1	0.010	1.690
	PROF	-0.057	0.089	0.417	1	0.518	0.944
	INVR	-0.003	0.012	0.057	1	0.812	0.997
	ASSTU	-1.198	0.924	1.683	1	0.194	0.302
	LIQU	-0.491	0.652	0.568	1	0.451	0.612
	Constant	0.687	1.661	0.171	1	0.679	1.988

a. Variable(s) entered on step 1: LEV, PROF, ASSTU, INVR, LIQU.

The Prediction equation is as follow:

Log (p/(1-p)) = 0.687 + 0.525 LEV - 0.057 PROF - 0.003 INVR – 1.198 ASSTU - 0.491 LIQD

This table provides the regression coefficient (β), the Wald statistic and the all-important Odds Ratio Exp (β) for the variables. The logistic regression analysis shows that LEV is having positive and PROF, INVR, ASSTU and LIQD are having negative impact on the prediction of the probability of FSF. In addition to this, there is a positive significant effect of LEV and insignificant effect of PROF, INVR, ASSTU and LIQD on the prediction of the probability of FSF. The Wald Chi-Square statistics tests the null hypothesis that the constant equals 0. This hypothesis is rejected because the p-value is greater than the critical p-value of 0.05. Hence, the constant is not 0. Exp (β) column represents the odds ratio for the individual variable. LEV is 1.690 times more likely to affect the predictability of the probability of FSF in compared to other independent variables and ASSTU is 0.302 times less likely to affect the predictability of FSF.

If the predicted probability of financial statement fraud (FSF) is greater than cut off 0.50, it indicates likelihood of fraudulence in that respective company's financial statements.

The following table 8 shows the predicted probability of FSF for the selected leading Textile companies.

Table-8 Predicted probability of FSF for the selected Textile Companies

Year	Arvind Ltd.	Grasim Industries Ltd.	Raymond Ltd.	Vardhman Textiles Ltd.	Vijay Textiles Ltd.
2009	0.1284	0.0512	0.1303	0.1266	0.0490
2010	0.0735	0.0161	0.0705	0.1194	0.0219
2011	0.1079	0.3214	0.1652	0.1409	0.3017
2012	0.0754	0.7961	0.1248	0.1092	0.3568
2013	0.0828	0.9045	0.1468	0.1042	0.2801
2014	0.0594	0.6081	0.1013	0.1086	0.2546
2015	0.0629	0.4691	0.0207	0.0888	0.3896
2016	0.0777	0.1502	0.0241	0.1731	0.1915
2017	0.0768	0.9467	0.0275	0.3228	0.1765
2018	0.0693	0.4660	0.0591	0.0786	0.1923

The above table 8 indicates that the predicted probabilities of FSF are greater than 0.50 in the financial statements of the years 2012, 2013, 2014 and 2017 in Grasim Industries Ltd., which indicate the possibilities of fraudulence in the financial statements of that respective years of Grasim Industries Ltd. while all other selected companies have the predicted probabilities smaller than 0.50 in each year indicating non fraudulence of the companies.

- Predicted probabilities of fraudulence for each of the selected five textile companies have been obtained by averaging the values of the independent variables over the periods of ten years, and estimating the predicted probabilities using logit function p= **log (p/1-p).**

  If the predicted probability of fraudulence is greater than cut off 0.50, it indicates likelihood of fraudulence in that respective company.

The following table 9 shows the probability of fraudulence for the selected leading Textile Companies.

Table- 9 Probability of Fraudulence of selected Textile Companies

Sr. No.	Name of Company	Probability of Fraudulence
1	Arvind Limited	0.080049
2	Grasim Industries Limited	0.431005
3	Raymond Limited	0.070263
4	Vardhman Textiles Limited	0.128636

5	Vijay Textiles Limited	0.181906

From the above table 9, it is clear that the predicted probabilities of fraudulence for each of the selected company are smaller than cut off point 0.50. Thus, all these companies are non-fraudulent. Thus, even though the year wise probability predictions indicate Grasim Industries Ltd. to be the possible fraudulent company in four years, but over the entire duration, none of the selected Textile companies show the possible fraudulence.

5. FINDINGS:

- ✓ According to the result of Descriptive Statistics, PROF is the most consistent variable and ASSTU is the least consistent variable for the selected Textile companies.
- ✓ From the result of Pearson's Correlation Coefficient, Leverage is positive significantly correlated with FSF for the selected Textile companies.
- ✓ Result of Logistic Regression Analysis shows that LEV is having positive significant impact on the prediction of probability of FSF. Thus, the companies having higher the amount of leverage is more likely to indulge in the fraudulent practices. LEV and ASSTU are main determinants of probability of FSF for the selected textile companies. LEV is the highest contributing factor affecting the probability of FSF for the selected textile companies.
- ✓ Year wise probability prediction indicates 40% chances of Grasim Industries Ltd. being possible fraudulent.
- ✓ As the calculated value of predicted probabilities are smaller than cut off 0.50, All the selected Textile companies are non-fraudulent. Thus, shareholders can invest in these companies without the fear of possible fraudulence.

6. CONCLUSION:

This study attempts to identify the major accounting ratios contributing to possible fraudulence in the financial statements of the selected leading Textiles companies of India. The study reveals that Debt to Equity, Debt to Assets and Interest Coverage ratios contribute significantly to the possible Financial Statements fraud in the selected Textile companies. Except Grasim Industries Ltd., all the selected Textile companies indicate the possible non fraudulence. Thus, hardly any of the selected Textile companies show the possible fraudulence.

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