IDENTIFYING PROBABLE FRAUDULENCE IN FINANCIAL STATEMENTS OF SELECTED AUTOMOBILE COMPANIES

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ABSTRACT
A deliberate misstatement of material facts by management in the books of accounts of the companies with a view to deceive investors, creditors and other stakeholders is known as Financial Statements Fraud. Some of the common techniques for financial statement fraud include overstatement of assets, sales and profits while understatement of liabilities, expenses or losses. Due to such kind of falsification, sometimes the elements of financial statements do not represent the true picture of the companies. The main objective of this study is to identify the probabilities of financial statement fraud and the determinants discriminating the selected automobile companies between possible fraud and possible non-fraud companies for the period of ten years (2008-09 to 2017-18) using the Beneish Model and Discriminant Analysis. The findings of the study indicate a 40% chance of Bajaj Auto Ltd. being possibly fraudulent for the selected time periods. This study reveals that Total Accruals to Total Assets Index and Day's Sales Receivable Index are the most important determinants for discriminating the selected automobile companies between possible fraud and possible non-fraud companies.

Keywords: Financial Statement Fraud, Beneish Model, Discriminant Analysis, Total Accruals to Total Assets Index, Day's Sales Receivable Index

1. INTRODUCTION:
Financial statements are reports that summarize a company's operations and financial performance. Financial statements are a key tool, which provides information about the companies to different stakeholders for taking their decisions. As ownership and management are different in the corporate form of business, there are possibilities that figures of financial statements may have been manipulated. If there is any manipulation in the figures of financial statements, then it creates a harsh impact on the decision of respective stakeholders. A deliberate misstatement of material facts by management in the books of accounts of the companies with a view to deceive the investors, creditors and other stakeholders is known as Financial Statements Fraud (Omoye & Eragbhe, 2014). Some of the common techniques for financial statement fraud include overstatement of assets, sales and profits while understatement of liabilities, expenses or losses. Such kind of Manipulation in the financial statements leads to disagreement between the company's financial and non-financial measures like employee headcount, number of retail outlets and warehouse space, which creates an inconsistency. It represents the red flag for gatekeepers in suspecting fraud in financial statements prepared (Brazel, Jones & Zimbelman, 2009). Due to falsification in the financial statements, sometimes the elements of financial statements do not represent the true picture of the companies. Thus, there are a severe impact of these kinds of frauds on the economy of the country and various stakeholders of the companies (Omoye & Eragbhe, 2014). Due to this reason, now a days financial statement fraud is becoming the most important research topic among researchers. In this study, an attempt is made to identify the probabilities of financial statement fraud for the selected Automobile Companies.

2. LITERATURE REVIEW:

- **Marvadi & Savani (2020)** made an attempt to identify probable fraudulence for selected pharmaceutical companies. This study aimed to demystify the earnings management practices of selected pharmaceutical companies in India using M Score and Discriminant Analysis. It was found that the majority of the selected companies confirm the results of the Beneish M Score Model for being possible fraudulent companies for almost all the years of study. From the result of the M Score Model and Discriminant Analysis, it was also suggested that investors and stakeholders should take care of themselves while investing in Lupin Ltd. and Divis Lab Ltd.
- **MacCarthy (2017)** conducted a case study with a view to detecting the Financial Fraud and Corporate Failure of Enron Corporation. The Altman Z Score and Beneish M Score Models were used for this purpose. Five years (1996-2000) financial information was collected from the US SEC Edgar database. In this study, the Beneish model revealed that the financial statements of the selected five years were manipulated by management. On the basis of the analysis, it was suggested that stakeholders would be better protected when these two models were used simultaneously than when only the Altman Z Score was used.
- **Omar et al. (2014)** examined the case of Megan Media Holdings Berhad (MMHB) for the purpose of identifying financial statement fraud using the Beneish Model and Ratio Analysis. The study concluded that an M Score value greater than negative 2.22 showed that MMHB had manipulated its earnings. In addition to this, the operating efficiency ratio also showed that the company had recorded fictitious revenue.
- **Bhavani & Amponsah (2017)** evaluated the M score and Z score for the detection of Accounting Fraud. The purpose of this study was to compare the results of two forensic accounting tools i.e. Beneish M Score Model and the Altman Z Score Model in the detection of the malfeasance of Toshiba. The result showed that Beneish M Score was not able to detect any fraud while some indication of fraud was provided by the Altman Z Score Model. The study concluded that the selection of the right forensic tool could influence the outcome of fraud detection.
- **Arman & Sharmin (2019)** conducted an Empirical Analysis of the likelihood of the company's manipulation of its financial statements using the Beneish M Score Model. 105 companies of Dhaka Stock Exchange covering the period of the years 2016-2018 were selected for the study. The findings revealed Age, short-term loans and the percentage of shares owned by the general public were significant factors affecting the likelihood of fraud. It was suggested that matured companies were more likely to manipulate their earnings but when the companies were listed, these chances were decreased because of increased disclosure.

3. RESEARCH METHODOLOGY:

3.1 Research Designs:

The present study is based on Descriptive and Causal Research Designs, which is an attempt to identify the possible fraud and non-fraud for the selected Automobile companies of India.

3.2 Objectives of the study:

The followings are the major objectives of this study.

1. To identify the possible fraud and non-fraud for the selected Automobile companies of India using Beneish M Score Model.
2. To identify the highest contributing variable affecting probable fraudulence for the selected Automobile Companies.
3. To compare the companies as being possible fraud and non-fraud based on Beneish M Score Model and Discriminant Analysis.
4. To predict the probabilities of probable fraudulence based on possible fraudulent cases over a period of time.

3.3 Sample Size:

Five listed companies from the Automobile sector of India have been selected for the study, which is as follows.

1. TATA Motors Ltd.
2. Bajaj Auto Ltd.
3. Ashok Leyland Ltd.
4. TVS Motors Ltd.

5. Sundaram Clayton Ltd.

3.4 Data Collection and Time Period of Study:

The study is based on secondary data collected from the annual reports of respective selected companies for the time period of the year 2008-09 to 2017-18.

3.5 Tools and Techniques:

3.5.1 Beneish M Score Model:

Professor Messod Beneish developed Beneish M-score Model in 1999 as a complementary forensic tool to Altman Z Score Model with the aim of protecting stakeholders in their analysis.

The following formula is used to calculate M-Score.

M - Score = - 4.84 + 0.920*DSRI + 0.528*GMI + 0.404*AQI + 0.892*SGI + 0.115*DEPI –0.172*SGAI + 4.679*TATA – 0.327*LEVI

By using the above formula, if the obtained M-score is greater than negative 2.22, it indicates that the company's financial statements may have been manipulated.

3.5.2 Discriminant Analysis:

In order to classify the selected companies as possibly fraudulent and possibly non-fraudulent over a period of study, a Discriminant analysis has been carried out. The following Discriminant Analysis Model has been used in this study.

Fraud (dummy variable) = $\beta_0 + \beta_1$ **DSRI** + β_2 **GMI** + β_3 **AQI** + β_4 **SGI** + β_5 **DEPI** + β_6 **SGAI** + β_7 **TATA** + β_8 **LVGI** + ε

Here, $\beta_0, \beta_1, \beta_2$......... are coefficients

The description of variables, which are used in the Beneish Model and Discriminant Analysis Model has been given below.

Variables	Formula
1. DSRI: Day's Sales Receivable Index	$\frac{\frac{\text{Accounts Receivables (t)}}{\text{Sales(t)}}}{\frac{\text{Accounts Receivables(t}-1)}{\text{Sales(t}-1)}}$
2. GMI: Gross Margin Index	$\frac{\frac{\text{Sales(t}-1) - \text{Cost of goods sold (t}-1)}{\text{Sales(t}-1)}}{\frac{\text{Sales(t)} - \text{Cost of goods sold (t)}}{\text{Sales(t)}}}$
3. AQI: Assets Quality Index	$\frac{\frac{[1 - \text{Current assets (t)} + PP\&E]}{\text{Total Assets(t)}}}{\frac{[1 - \text{Current assets(t}-1) + PP\&E]}{\text{Total Assets(t}-1)}}$
4. SGI: Sales Growth Index	$\frac{\text{Sales (t)}}{\text{Sales (t}-1)}$
5. DEPI: Depreciation Index	$\frac{\frac{\text{Depreciation (t}-1)}{\text{Depreceaition (t}-1) + \text{PP} + \text{E(t}-1)}}{\frac{\text{Depreciation (t)}}{\text{Depreceaition (t)} + \text{PP} + \text{E(t)}}}$
6. SGAI: Sales, General and Administrative Expenses Index	$\frac{\frac{\text{Sales, General and Administration expense (t)}}{\text{Sales(t)}}}{\frac{\text{Sales, General and Administration expense (t}-1)}{\text{Sales(t}-1)}}$
7. LVGI: Leverage Index	$\frac{\frac{[\text{Long term debt (t)} + \text{Current liabilities(t)}]}{\text{Total assets(t)}}}{\frac{[\text{Long term debt (t}-1) + \text{Current liabilities (t}-1)]}{\text{Total assets (t}-1)}}$

8. TATAI: Total Accruals to Total Assets Index	$\dfrac{\Delta Current\ assets(t) - \Delta Cash\ (t) - \Delta Current\ liabilities(t) - \Delta Current\ maturities\ of\ LTD(t) - \Delta Income\ tax\ payable(t) - Depreciation\ and\ amortization\ (t)}{\text{Total assets (t)}}$
9. Fraud (dummy variable used in Discriminant Analysis)	1= if the value of the M score is above negative 2.22 0= if the value of the M score is below negative 2.22

4. DATA ANALYSIS AND INTERPRETATION:

4.1. Beneish M Score Model:

The following table 1 shows the result of the M Score for the selected Automobile companies for the ten-year time periods (2008-09 to 2017-18).

Table 1 M-score for Selected Automobile Companies

Year	TATA Motors Ltd.	Bajaj Auto Ltd.	Ashok Leyland Ltd.	TVS Motors Company Ltd.	Sundaram Clayton Ltd.	Average
2009	-1.3175	-3.1265	0.1100	-1.7095	-2.2627	-1.6612
2010	-3.2693	-5.5684	1.7882	-2.7086	-3.4797	-2.6476
2011	-2.4749	-1.1850	-2.5535	-2.1953	-3.3054	-2.3428
2012	-2.8863	-2.6176	-4.2204	-2.9786	-2.4384	-3.0283
2013	-2.8038	-1.0295	-2.6142	-2.1921	-2.6608	-2.2601
2014	-2.7315	-3.0349	-2.4180	-2.7347	-2.7870	-2.7412
2015	-3.2025	-1.6487	-2.9412	-2.1832	-2.5644	-2.5080
2016	-1.9010	-3.6920	-2.6794	-2.7628	-1.9213	-2.5913
2017	-2.6285	-1.1386	-2.8664	-2.7031	-2.9599	-2.4593
2018	-2.2857	-2.5068	-2.5128	-2.7912	-2.1910	-2.4575
Average	-2.5501	-2.5548	-2.0908	-2.4959	-2.6571	-2.4697

The value of the M Score is greater than negative 2.22 for Tata Motors Ltd. in the years 2009 and 2016; for Bajaj Auto Ltd. in the years 2011, 2013, 2015 and 2017; for Ashok Leyland Ltd. in the years 2009 and 2010, for TVS Motor Ltd. in the years 2009, 2011, 2013 and 2015, for Sundaram Clayton Ltd. in the year 2016 only. Thus, all these companies show the possibility of fraudulence in these year's financial statements while the financial statements of the remaining years of these companies indicate no possibility of fraudulence. According to ten years average value of M Score, only Ashok Leyland Ltd. shows possibilities of fraudulence in its financial statements.

4.2 Discriminant Analysis:

In order to classify the selected companies as possibly fraudulent and possibly non-fraudulent over a period of study, a Discriminant analysis has been carried out.

The following table shows the result of the Discriminant Analysis.

Table 2: Group Statistics

FRAUD CRITERIA		Mean	Std. Deviation	Coefficient of Variation
Possible Non Fraudulent companies	DSRI	0.9592	0.19426	0.2025
	GMI	0.9476	0.19783	0.2088
	AQI	0.9017	0.52841	0.5860
	SGI	1.1556	0.18451	0.1597
	DEPI	0.9689	0.14421	0.1489
	SGAI	0.9897	0.11036	0.1115

	LVGI	0.9918	0.11609	0.1171
	TATAI	-0.0994	0.10781	-1.0846
	M SCORE	-2.9103	0.60402	-0.2076
Possible Fraudulent companies	DSRI	1.3966	0.63459	0.4544
	GMI	1.0571	0.20755	0.1963
	AQI	1.8375	3.31066	1.8017
	SGI	1.1031	0.17403	0.1578
	DEPI	1.0759	0.31484	0.2926
	SGAI	1.0802	0.32192	0.2980
	LVGI	0.8701	0.22084	0.2538
	TATAI	0.0599	0.12455	2.0793
	M SCORE	-1.3368	1.10338	-0.8254
Total	DSRI	1.0817	0.41610	0.3847
	GMI	0.9782	0.20458	0.2091
	AQI	1.1637	1.81314	1.5581
	SGI	1.1409	0.18144	0.1590
	DEPI	0.9989	0.20858	0.2088
	SGAI	1.0151	0.19463	0.1917
	LVGI	0.9578	0.16004	0.1671
	TATAI	-0.0548	0.13282	-2.4237
	M SCORE	-2.4697	1.04545	-0.4233

The above table 2 shows that Because of having the least value of the coefficient of variation, SGAI and SGI is the most consistent variable for the possible Non-fraudulent companies and possible fraudulent companies respectively while TATAI is the least consistent variable for both the possible Non-Fraudulent and possible fraudulent companies due to its higher value of the coefficient of variation. However, in terms of variability, the standard deviation of AQI seems to vary a lot between Possible Non Fraudulent companies and Possible Fraudulent companies.

The following table 3 shows the result of Eigenvalues.

Table 3: Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.324[a]	100.0	100.0	0.755

a. First 1 canonical discriminant functions were used in the analysis.

The last column of the above table 3 indicates the canonical correlation, which is the simple correlation coefficient between the discriminant score and their corresponding group membership. The square of the canonical correlation of function 1 is $(0.755)^2 = 0.5700$, which means 57.00% of the variance in the discriminant model between the two categories of Companies is due to the changes in the above predictor (independent) variables.

The following table 4 shows the result of Wilks' Lambda.

Table 4: Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1	0.430	37.100	8	0.000

From above table 4, it has been found that the value of Wilk's Lambda for function 1 is 0.430, which indicates the significance of the discriminant function 1, which is tested using the Chi-square test with 8 degrees of freedom at a 5% level of significance. Since; the p-value is less than 0.05, it can be inferred that the discriminant function 1 is significant and hence, it can be used for further interpretation of the results.

The following table 5 shows the result of Standardized Canonical Discriminant Function Coefficients.

Table 5: Standardized Canonical Discriminant Function Coefficients

Function	DSRI	GMI	AQI	SGI	DEPI	SGAI	LVGI	TATAI
1	0.935	0.153	0.705	0.321	-0.368	0.087	-0.425	0.603

The above table 5 shows that Day's Sales Receivable Index is the most important variable followed by the Assets Quality Index, Total Assets to Total Accrual Index, Leverage Index, Depreciation Index, Sales Growth Index, Gross Margin Index and Sales and General Administration Index for the function 1.

The following table 6 shows the result of the Structure Matrix.

Table 6: Structure Matrix									
Function	M Score	TATAI	DSRI	LVGI	GMI	AQI	DEPI	SGAI	SGI
1	0.812	0.564	0.471	-0.319	0.218	0.209	0.208	0.188	-0.115

Above table 6 of structure matrix indicates the correlation between the discriminant score and each of the independent variables. The above table indicates the correlation coefficient between the discriminant score and TATA is 0.564 whereas the correlation with DSRI, LVGI, GMI, AQI, DEPI, SGAI and SGI is 0.471, -0.319, 0.218, 0.209, 0.208, 0.188, -0.115 respectively for the function 1. Thus, TATAI and DSRI are the most important determinants in discriminating between the two categories of Possible Non-Fraudulent companies and Possible Fraudulent companies in the case of function 1.

The following table 7 shows the result of the Canonical Discriminant Function Coefficients.

Table 7: Canonical Discriminant Function Coefficients									
Function	DSRI	GMI	AQI	SGI	DEPI	SGAI	LVGI	TATA	Constant
1	2.529	0.764	0.396	1.766	-1.793	0.455	-2.799	5.353	-1.656

The Unstandardized Discriminant Function from the above table can be written as:

Score 1 = -1.656 + 2.529 DSRI + 0.764 GMI + 0.396 AQI + 1.766 SGI – 1.793 DEPI + 0.455 SGAI – 2.799 LVGI + 5.353 TATA

TATA followed by LVGI, DSRI, DEPI, SGI, GMI, SGAI, AQI is found to be the best predictors of the Beneish M score of above discriminating function 1.

The following table 8 shows the result of the Classification Results.

Table 8: Classification Results					
		FRAUD CRITERIA	Predicted Group Membership		Total
			Possible Non-Fraudulent	Possible Fraudulent	
Original	Count	Possible Non Fraudulent	36	0	36
		Possible Fraudulent	5	9	14
	%	Possible Non Fraudulent	100.0	0.0	100.0
		Possible Fraudulent	35.7	64.3	100.0
Cross-validated	Count	Possible Non Fraudulent	35	1	36
		Possible Fraudulent	8	6	14
	%	Possible Non Fraudulent	97.2	2.8	100.0
		Possible Fraudulent	57.1	42.9	100.0

This table 8 of Classification Results is also called confusion table or classificatory table. It indicates that out of 36 observations of possible Non-Fraudulent, 36 are correctly classified as possible Non-Fraudulent Category-0, whereas, 0 is wrongly classified as possible Fraudulent. Similarly, out of 14 observations of possible Fraudulent, 9 are correctly classified as possible Fraudulent, whereas, 5 are wrongly classified as possible Non-Fraudulent. Thus, out of total of 50 observations, 45 observations are correctly classified by the discriminant function.

Therefore, the Hit ratio = $\frac{\text{No.of correct predictions}}{\text{total number of cases}}$

Hence, the Hit ratio is $= \frac{45}{50} = 0.900 = 90.0\%$

From the above Discriminant Analysis, it is found that all 36 observations of possible non-fraudulent are correctly classified. From the 14 observations of possible fraudulent, 9 are correctly classified but 5 are wrongly classified. It is revealing that these are possible non fraudulent observations, which are as follows: TVS Motors Ltd. in the years 2011, 2013 and 2015 and Sundaram Clayton Ltd. in the years 2016 and 2018.

❖ In order to find out whether both the models give the same result or not, a comparison of results of the M Score Model and Discriminant Analysis has been carried out as follows:

Table 9: Results of M Score and Discriminant Analysis

		Years										
Company Name	**Membership**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**Remarks**
1.TATA Motors ltd.	M Score	PF	NF	NF	NF	NF	NF	NF	PF	NF	NF	NF
	Discriminant Analysis	PF	NF	NF	NF	NF	NF	NF	PF	NF	NF	NF
2.Bajaj Auto ltd.	M Score	NF	NF	PF	NF	PF	NF	PF	NF	PF	NF	NF
	Discriminant Analysis	NF	NF	PF	NF	PF	NF	PF	NF	PF	NF	NF
3.Ashok Leyland ltd.	M Score	PF	PF	NF	NF	NF	NF	NF	NF	NF	NF	NF
	Discriminant Analysis	PF	PF	NF	NF	NF	NF	NF	NF	NF	NF	NF
4.TVS Motors ltd.	M Score	PF	NF	PF	NF	PF	NF	PF	NF	NF	NF	NF
	Discriminant Analysis	PF	NF	NF”	NF	NF”	NF	NF”	NF	NF	NF	NF
5.Sundaram Clayton ltd.	M Score	NF	NF	NF	NF	NF	NF	NF	PF	NF	PF	NF
	Discriminant Analysis	NF	NF	NF	NF	NF	NF	NF	NF”	NF	NF”	NF

Here, PF = Possible Fraudulent and NF = Possible Non-Fraudulent

Above table 9 indicates that all of the selected companies are found to be possibly non-fraudulent in most of the years of study according to both Beneish M Score Model and Discriminant Analysis. The above table also indicates that TVS Motors Ltd. has changed in the possibility of being converted to non-fraudulent company in the years 2013, 2014 and 2015 and Sundaram Clayton Ltd. in the years 2016 and 2018.

- To predict the probabilities of the selected automobile companies being possibly fraudulent based on fraudulent cases, the following group membership table has been used over the period of time.

Table 10: Comparison of Beneish M Score and Discriminant Analysis

Company Name	**Beneish M Score Model**		**Discriminant Analysis**	
	No. of time incurring Fraud	**Probabilities**	**No. of time incurring Fraud**	**Probabilities**
1.TATA Motors Ltd.	2	0.20	2	0.20
2.Bajaj Auto Ltd.	4	0.40	4	0.40
3.Ashok Leyland Ltd.	2	0.20	2	0.20
4.TVS Motors Ltd.	4	0.40	1	0.10
5.Sundaram Clayton Ltd.	2	0.10	0	0.10

The above table 10 indicates the result of predicted probabilities of probable fraudulence for the selected companies. As per Beneish M Score Model, Bajaj Auto Ltd. and TVS Motors Ltd. Have 40% chance of fraudulence while Tata Motors Ltd., Ashok Leyland Ltd. and Sundaram Clayton Ltd. have only 20% chance of fraudulence while Discriminant Analysis shows that Bajaj Auto Ltd. have 40% chance; Tata Motors Ltd. and Ashok Leyland Ltd. have 20% chance; TVS Motors Ltd. have 10% chance and Sundaram Clayton Ltd. have no chance of fraud. According to the results of both the Beneish M Score Model and Discriminant Analysis, the Predicted probability of fraudulence is 0.40 for Bajaj Auto Ltd., which is the highest probability from the selected companies for the selected time period.

The predicted probabilities of fraudulence are too lower in the case of Sundaram Clayton Ltd. as per the results of both models.

5. FINDINGS

- Based on the Beneish M Score, Bajaj Auto Ltd. and TVS Motor Ltd. are likely fraudulent companies in a four-year from the selected ten years of study. The Day's Sales Receivables Index and Sales Growth Index are contributing variables to the possibility of fraudulence for Bajaj Auto Ltd. while the Assets Quality Index, Sales Growth Index and Day's Sales Receivables Index are contributing variables to the possibility of fraudulence for TVS Motor Company Ltd.
- Total Accrual to Total Assets Index and Day's Sales Receivables Index are the most important determinants in discriminating the selected companies between possible Non-Fraudulent companies and possible Fraudulent companies.
- Beneish M Score Model and Discriminant Analysis reveal that almost all the observations are correctly classified as possible fraud and possible non-fraud.
- Probability prediction based on Beneish M Score Model and Discriminant Analysis indicates a 40% chance of Bajaj Auto Ltd. being possibly Fraudulent for selected time periods.
- As the calculated value of predicted probabilities is smaller than 0.50 for each of the selected companies, all the selected companies are probable Non-Fraudulent companies according to the results of both Beneish M Score and Discriminant Analysis.

6. CONCLUSION:

This study is an attempt to identify the possibility of fraudulence for the selected five Automobile Companies of India for the selected ten years (2008-09 to 2017-18) using the Beneish M Score and Discriminant Analysis. This study reveals that Total Accruals to Total Assets Index and Day's Sales Receivable Index are the most important determinants in discriminating the selected automobile companies between possible fraudulent and possible non-fraudulent companies. Except for Bajaj Auto Ltd., all the selected Automobile Companies indicate possible non-fraudulence. Thus, hardly any of the selected Automobile Companies show possible fraudulence.

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