Predicting Earnings Manipulation Using Beneish M - Score of Selected Companies in India

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Abstract

In the field of global competition, the corporate world is witnessing manipulation of financial statements to achieve the desired outcomes. According to India Forensic Consultancy Services, at least 1200 companies listed on domestic stock exchanges counterfeited their financial statements. The increasing rate of such undesired acts laid path for the investigation into such practices. This empirical research work was conducted to predict the signs of earnings manipulation of companies listed with the BSE 100 index by using the probabilistic Beneish M score eight variable model. Time frame for the investigation of financial statements' data was confined to 2011 to 2016 to calculate the M score. Based on M score results of each year, the companies were classified into two groups: likely manipulator and non-likely manipulator. Then multinomial regression technique was used to find the most significant variables that affected manipulation. The outcomes of the results revealed that three ratios, namely *TATA* (total accruals to total assets), *DSRI* (daily sales in receivables index), and *SGI* (sales growth index) variables could be considered as signals of earnings manipulation by companies. The present work contributes to the literature through identification of probable earnings manipulators in BSE 100 index companies which investors prefer the most for their equity investments. The research findings may be an eye-opener for regulators /policy makers to implement stringent checks on auditing of financial results of the companies. Furthermore, the research would be useful for the investors to go for face validation of companies instead of relying on misrepresentation of their true value.

Key words : **earnings manipulation, Beneish M - score, Indian companies**

JEL Classification : G30, M40, M41

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Accounting fraud, earnings management, or "cooking the books" means using accounting techniques to show financial reports that give a positive scenario or view of a company's business activities and financials. A large number of companies in India are believed to indulge in these illegal practices. As per the report by Pune - based India Forensic Consultancy Services (ICS), at least 1200 companies listed on domestic stock exchanges had counterfeited their financial statements, which also included 20 - 25 firms of benchmarks such as Sensex and Nifty. The ICS inspected 4,867 and 1,288 companies listed on the BSE & NSE, respectively and gave some shocking revelations about the earnings manipulation. The results showed that the manufacturing

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sector, which contributes about 28% of India's GDP, has the most fraudulent activities due to the distinct nature of business.

According to a survey conducted by KPMG India in 2008, more than 80% of the respondents accepted fraud as a problem and 70% believed that it will increase in the years to come. Considering the results of the survey and increase in the number of frauds, we tried to predict the earnings manipulators in Indian listed companies.

In the present research work, we used two widely accepted methods : Beneish M - Score model (eight variables) and logistic regression. Previous researchers have applied the M-Score on companies which were declared as manipulators and those research papers were more focused on the validation of Beneish M-Score - whether is it a proficient statistical tool to predict the manipulator or not. In our research paper, we apply the Beneish M-Score on Indian listed companies to predict whether they did the earnings manipulations or not. M score is a probabilistic model, and we can predict if there is a probability of earnings manipulations in the financial statements of companies.

Review of Literature

Razali and Arshad (2014) analyzed the relationships between corporate governance structure and the possibility of fraudulent financial reporting. They analyzed annual reports of 227 public listed companies in Malaysia using Beneish M-score and Altman's Z score on data for the year 2010 - 2011. They found that the effectiveness of corporate governance structure reduced the likelihood of earnings management in financial reporting.

Mahama (2015) worked on to determine how early investors, regulators, and the other stakeholders can detect the financial stress of a company. This research paper primarily focused on the case of Enron Corp. They used two models - Altman's Z-Score and Beneish M-Score on the 10K reports of Enron drawn from the U.S. SEC Edgar database. They found that the fraudulent activities of the company could have been detected as early as in 1997, long before its actual filing in 2011.

Tarjo and Herawati (2015) analyzed the application of Beneish M - Score models and data mining to detect earnings manipulation to know the ability of Beneish M-Score in detecting the manipulation in their earnings. They worked on data released by the financial services authority for the period of 2001 - 2014 using the Beneish M-score model (1999) and data mining (Zaki & Theodoulidis, 2013) on this problem. Their results showed that overall, the Beneish M - score was capable of detecting earnings manipulation.

Roy and Debnath (2015) analyzed the earnings management practices in financial reporting of public enterprises in India using M-Score. The study explored how the companies were manipulating their financials to give a positive image of their financial health to investors, but in reality, their financials were unsteady. The authors worked on financial statements over the period of 2002 - 03 to 2012 - 13. They analyzed data for 25 enterprises using Beneish's five variable M-score model. The study found that earnings manipulation had a negative relation with profitability and positive relation with liquidity.

Anh and Linh (2016) detected earnings management using the M-score model for non- financial Vietnamese listed companies. This paper examined earnings manipulations among Vietnamese listed companies on Hochiminh Stock Exchange by using Beneish M-score on a sample of 229 non-financial listed companies during the period from 2013 to 2014. They found that 48.4% of the companies on the HOSE were involved in earnings manipulation. This study suggested that the M-score model is one of the known techniques in detecting earnings manipulations, and it can also be useful for improvement in financial reporting quality and the protection of the investors.

Aris, Arif, Othman, and Zain (2015) worked on detection of the fraudulent financial statement using statistical techniques. This paper examined the possibility of the fraudulent financials in a small and medium scale enterprise using three tools namely Beneish model, Altman's Z-score, and financial ratios for the earnings forecasting models ratio. Ahuja and Singhal (2014) also came out with a framework for understanding of the Altman's Z-score and applied it on selected companies of the Indian textile industry for the period from 2006 to 2011.

Ahmed and Naima (2016) investigated the signs of earnings management of earnings in non-financial firms in Bangladesh. They collected the data of 102 publicly listed and non-financial enterprises from the years 2010 to 2013 using Beneish model as a statistical tool to analyze the collected data. The findings of M-score showed that the proportion of likely manipulators have declined over the years. The results of independent *t* - test revealed that inflated revenues and capitalizing expenses served as a signal of earnings manipulation.

Kamal, Salleh, and Ahmad (2016) assessed whether the Beneish M-Score is reliable in detecting earnings manipulation by Malaysian listed companies before making announcement to the public. The sample consisted of 17 public listed companies from 1996 to 2014. The results suggested that the Beneish M-score model was capable of detecting earnings manipulation, and earnings manipulation by 82% was detected in 14 out of 17 listed companies.

Mavengere (2016) analyzed the validity of Altman's Z score and the Beneish M score as statistical models that can be used to detect earnings manipulation and can be a useful tool for the stakeholders. They obtained data from entity Z's website for the period from 2011 to 2014. The results showed the firm in the "Grey Zone" ; whereas, the Beneish M-Score revealed Z to be a company who was manipulating its financials.

Mehta and Bhavani (2017) focused on the detection of fraud in the financial statements of Toshiba Corporation of Japan using Beneish model, the Altman's Z-score, and Benford's Law for the year from 2008 to 2014. Repousis and Repousis (2016) aimed to investigate the Beneish M-model (8-variables) to identify the occurrence of financial manipulation and earnings manipulation. They analyzed a data of 25,468 companies in Greece for the period of 2011-2012 excluding financial institutions. They found that 8,486 companies or approx. 33% of the samples were greater than -2.22, which means they were likely to be manipulators.

Roshchina (2016) explored the earnings management level of Finnish & German companies using the Beneish M-Score model. The objective was to know whether Beneish M-score model is capable of predicting earnings manipulations in Finland and Germany. They found a significant relationship between days' sales in receivables index : DSRI, gross margin index (GMI), total accruals to total assets (TATA), the sales growth index (SGI), and other variables of Beneish M-score. They also concluded that the Finnish market was more stable and applicable for trustworthy investments.

Kaur, Sharma, and Khanna (2014) analyzed the levels of earnings management in the various sectors of the economy. They classified the best five and bottom five performers of each sector by sales turnover for the year 2013 and ascertained whether they lied as earnings manipulator. A total of 332 companies were studied using two popular methods namely, modified Jones model and Beneish M-Score. The results showed that the IT sector, which is the top performer in India, had its topmost three performers engaged in earnings management.

Phua, Lee, Smith, and Gayler (2010) aimed to highlight a new direction from data mining such as epidemic detection, insider trading, and intrusion detection. They worked on 40 different fraud detection papers within a common fraud type over a period of 10 years. They found adversary, types and sub types of fraud, the technical nature of data, performance metrics, and methods and techniques.

Lobo and Zhou (2001) studied the relationship between disclosure quantity and earnings management. They used the ratings published by Association for Investment Management and Research. They analysed 1444 firms using data spanning over the period from 1990-1995. To determine the earnings management, they used the modified Jones model. They found that corporate disclosure and earnings management were significantly negatively related, which means firms with lower disclosure ratings gravitated to engage more in earnings management and those firms which were engaged more in earnings management tended to have lower quality disclosure.

Selim (2006) collated the methods for evaluating and determining the earnings management activities done by companies listed in the Istanbul Stock Exchange (ISE). The model used by the author was modified Jones model. He analyzed 58 companies spanning from 1990-2003. They found that manipulation pertaining to income or expenses were expected to be correlated with discretionary accruals and if there was no manipulation, such correlation was not expected.

Beneish, Lee, and Nichols (2013) examined the investment of detailed financial analysis associated with the detection of earnings manipulation. They worked on determining the prediction of returns with the help of M - score spanning from 1982-1988. They found out that forensic accounting had the significant out-of-sample ability not only to detect fraud, but also to predict future stock returns.

Beneish (1999) suggested a model for detecting manipulation. He analysed 74 companies which had done some manipulation. After subjecting the companies to Accounting and Auditing Enforcement Releases (AAERs), it was found that 49 companies violated GAAP. The model for detection of manipulation is :

$$M_i = \beta' X_i + \bar{\varepsilon}_i,$$

where, M is dichotomous variable coded 1 for manipulator and 0 otherwise, X is the matrix of explanatory variables. They took a sample between 1982-1992. He took a sample between 1982 - 1992. He found out that manipulation consisted of artificial inflation of revenues or deflation of expenses and high sales due to which manipulation was in force.

Wyrobek and Stanczyk (2015) investigated the usefulness of external audit of financial statements in detecting manipulation in Poland. They prepared questionnaires & directed interviews conducted by 15 certified external auditors spanning from 2010-2015. They concluded that audit of financial statements was not sufficient to detect techniques.

Dechow, Ge, Larson, and Sloan (2011) analyzed the characteristics of misstating firms. They obtained the sample that was alleged to have misstated financial statements. A model was developed to predict accounting misstatements termed as F-score. The period of examining was from 1982 - 2005. They found that at the time of misstatement, accrual quality was low, off-balance sheet activities were more, and managers of misstating firms appeared to be sensitive to their firms' stock price.

Dikmen and Küçükkocaoğlu (2010) proposed a mathematical algorithm to detect earnings management practices. They worked on traditional statistical models used as a benchmark. The algorithm went through 126 listed Turkish manufacturing firms spanning from 1992-2002. Finally, they found out a mathematical algorithm which proved that increase in growth margin index, sales growth increase, and leverage index led to earnings management.

Dechow, Sloan, and Sweeney (1996) analyzed a new approach to test accrual-based earnings management which is applicable in every sample period. They worked on an econometric framework and traditional t - test model to develop such a model that is useful for all common models and which does not change in one period to another. Their results indicated that incorporate reversals could increase the test power by 40% and also provided a robust solution.

Kaur, Mehra, and Khanna (2015) analysed 1027 companies from seven sectors for a period of four years (2010-2013). They also used the modified Jones model for detecting the earnings management in each sector. Pustylnick (2011) introduced a new approach to detection of manipulations in the data of financial statements. He used Altman Z-score and compared it with P - score over a period of 5 years. He found that the rate of change of P-score and rate of change of Z-score coincided with each other over a period when a company was manipulating their earnings.

Mollik, Mir, McIver, and Bepari (2013) examined Australian firms which were engaged in a high level of earnings management during the global financial crisis. They worked on the methods to analyze the impact of GFC and industry effect on a sample that comprised of 149 firms considering the time period from 2006 to 2009.

They found that firms were engaged in income - decreasing earnings management during GFC (2008 and 2009) and that was due to discretionary accruals.

Persons (1995) analyzed whether financial leverage, capital turnover, asset composition, and firm size were factors associated with fraudulent financial reporting. With the help of Jack-Knife Method and Z-score, he obtained the predicted fraudulent financial reports spanning a time period from 1982-1991 in which fraudulent financial reporting firms and non-fraudulent reporting firms were examined.

Ravisankar, Ravi, Rao, and Bose (2011) analyzed the data mining techniques to identify fraud detection. They worked on financial ratios and variables that can lead to fraud using data mining techniques such as multilayer feed forward neutral network (MLFF), support vector machine (SVM), genetic programming (GP), logistic regression, and probabilistic neural network (PNN). They took 202 listed companies in Chinese stock exchange in which 101 were fraudulent and 101 were non-fraudulent. They noticed that PNN outperformed all techniques.

Summers and Sweeney (1998) investigated the relationship between insider trading and fraud. They worked on determining whether insider trading activity was a useful indicator of the incidence of fraud by using Cascade logit analysis over a span of 1980 to 1987 in which they examined 184 companies. They found that in the presence of fraud, insiders reduced their holding of companies' stocks by selling the same.

Alleyne and Howard (2005) investigated how auditors perceived responsibilities for uncovering fraud in Barbados. They prepared a survey which supported quantitative and qualitative approach. A total of 43 respondents were surveyed regarding the perception and experience of fraud. They found that auditors strongly disagreed that they were responsible for uncovering fraud and fraud was not a big issue in Barbados.

Apparao, Singh, Rao, Bhavani, Eswar, and Raajani (2009) analyzed a large amount of data like fraudulent financial statements and they worked on data mining algorithm using logit regression analysis. Majorly, they used five techniques to detect the earnings manipulation such as regression, neural network, decision tree, Bayesian, and SVM methodology. Finally, they examined the usefulness of each method in detecting earnings manipulation.

Objectives of the Research

(1) To predict the earnings manipulation of the Indian listed companies using Beneish M - score.

(2) To identify the variables that have a significant influence on earnings manipulation.

(3) To give stakeholders the early signals of earnings manipulations in the financial statement of the companies for the purpose of making investments/ lending into such companies.

Methodology

Pune - based ICS reported that approx. 1200 companies listed on domestic stock exchanges have manipulated their financials, which also included some 20-25 firms of indices like Sensex and Nifty. From this report, we got a lead for our research paper. The study population is companies listed on BSE 100 index for the period of 2011-2016. The sample was selected using purposive sampling method.

The following was the criteria to determine the sample size :

(i) Data of financial statements/ eight variables of Beneish M score were collected with the help of Prowess IQ of BSE 100 companies for 5 years starting from 2011-2016.

(ii) The companies belonging to the banking sector for which M score calculation was not possible and also the companies for which eight variables data were not available for all 5 years were excluded.

(iii) The final sample of companies considered for calculation of M score was 65 out 100 companies listed on the BSE 100 index.

Beneish M-score is the model developed by Messod D. Beneish for detecting or predicting companies with a potential to do earnings manipulations. It uses financial ratios and is somewhat similar to Z score, but Z score helps in predicting bankruptcy ; whereas, M score helps in predicting manipulation earnings. It is important to note that it is a probabilistic model and one of its major limitations is that the ability to detect fraud is not with 100% accuracy.

The formula of Beneish M-Score is as follows:

$$M = -4.840 + 0.920 * DSRI + 0.528 * GMI + 0.0404 * AQI + 0.892 * SGI + 0.115 * DEPI - 0.172 * SGAI + 4.679 * TATA - 0.327 * LVGI$$

If the M - score > -2.22 & > -1.78, it shows indications of earnings manipulation within companies.

The eight variable model :

$$M = -4.84 + 0.92*DRSI + 0.528*GMI + 0.404*AQI + 0.892*SGI + 0.115*DEPI - 0.172*4.679*TATA - 0.327*LVGI$$

As per the formula, it is important to apply the eight variables to compute the Beneish M-Score. The formula and significance of the variables are as follows :

DSRI (Days' Sales in Receivable Index) = (Receivables Current Year/ Sales Current Year)/ (Receivables Prior Year/ Sales Prior Year)

The day sales in receivable of the current and previous year are compared with the aim of disclosing aerated revenue (Beneish, 1999).

GMI (Gross Margin Index) = [(Sales Prior Year - Cost of Goods Sold Prior Year)/Sales Prior Year]/ [(Sales Current Year - Cost of Goods Sold in Current Year)/Sales Current Year]

This ratio measures the gross margin or current and compares with previous year. A poor growth prospect entity is likely to manipulate (Beneish, 1999).

AQI (Asset Quality Index) = (Current Assets + Property, Plant, & Equipment)/ Total Assets

Non - current assets deducting property plant and equipment are compared with total assets with an *AQI* greater than 1, which reveals that the entity has cost deferral or has increased its intangibles which created earnings manipulation (Beneish, 1999).

SGI (Sales Growth Index) = Sales Current Year/ Sales Prior Year

This ratio measures current sales with previous year's sales (Beneish, 1999).

DEPI (Depreciation Index) = [Depreciation Previous Year/ (Depreciation + PPE Previous Year)]/ [Depreciation Current Year/ (Depreciation+ PPE Current Year)]

This ratio measures the depreciation rate of the current year compared to the previous year. Slow moving rates of depreciation may indicate a company is espousing an income friendly method of depreciation or reconsidering useful life upwards (Beneish, 1999).

SGAI (Sales, General and Administrative Expenses Index) = (Sales, General and Administrative Expenses Current Year/ Sales Current Year)/ (Sales, General and Administrative Expenses Prior Year/ Sales Prior Year)

This ratio compares current sales, general, and administrative expenses with previous year (Beneish, 1999).

LVGI (Leverage Index) = [(Long-term debt + Current Liabilities Current Year)/ Total Assets Current Year]/ [(Long-term debt + Current Liabilities Prior Year)/ Total Assets Prior Year]

Total debt is compared with current total assets to previous year's total assets (Beneish, 1999).

TATA (Total Accruals to Total Assets) = (Net Income - Cash Flow from Operating Activities)/ Total Assets

The ratio measures the extent of discretionary accounting policies undertaken by the management that translate into earnings alteration (Beneish, 1999).

Here, we are considering both the values of -2.22 and -1.78 as the indications of earnings manipulations. This means that if the M-Score of a company is above -2.22/-1.78, then that company is likely to be a manipulator. When it is below/ less than -2.22/-1.78, then that company is not likely to be a manipulator.

➪ **Data Mining :** The data mining technique used in this research paper is logistic regression or logit regression. Data mining starts with testing the principle component analysis(PCA) to the variables of Beneish M-Score. PCA helps in determining which variables of M-Score Beneish model is predictor of earnings manipulation.

The logistic regression model of this study is :

$$\text{Earnings Manipulation} = \beta_0 + \beta_1 DSRI + \beta_2 GMI + \beta_3 AQI + \beta_4 SGI + \beta_5 DEPI + \beta_6 SGAI + \beta_7 TATA + \beta_8 LVGI + \varepsilon i$$

where,
Earnings manipulation = dummy variable (1 for manipulator and 0 for non-manipulator),
DSRI = daily sales receivable index,
GMI = gross margin index,
AQI = asset quality index,
SGI = sales growth index,
DEPI = depreciation index,
SGAI = Sales and general administration expenses index,
TATA = Total accrual to total assets,
LVGI = Leverage index,
εi = Residual.

Analysis and Results

The data were obtained from Prowess IQ database spanning the time period from 2011 - 2016 for 65 companies representing BSE 100 index. Beneish M score results of all 65 companies for the past 5 years reveals that 11 companies are found be earnings manipulator in one or more years from their respective financial results. So, it

Table 1. Descriptive Statistics of Probable Earnings Manipulator Companies

Variables	*DSRI*	*GMI*	*AQI*	*SGI*	*DEPI*	*SGAI*	*TATA*	*LVGI*
Mean	1.032	0.777	1.059	0.963	0.988	1.328	0.079	0.979
Median	0.916	0.901	1.016	0.999	0.994	1.111	0.082	0.994
Standard Deviation	0.462	0.593	0.140	0.270	0.266	0.723	0.054	0.133
Skewness	1.100	-2.332	1.794	-0.732	-0.054	1.522	0.098	-0.211
Kurtosis	1.245	6.724	3.871	-0.070	1.231	2.977	-1.066	0.904
Range	1.951	2.956	0.621	1.037	1.269	3.166	0.183	0.618
Minimum	0.342	-1.348	0.901	0.344	0.369	0.501	-0.006	0.665
Maximum	2.293	1.608	1.523	1.380	1.638	3.667	0.177	1.283

Notes: *DSRI* = Daily Sales Receivable Index, *GMI* = Gross Margin Index, *AQI* = Asset Quality Index, *SGI* = Sales Growth Index, *DEPI* = Depreciation Index, *SGAI* = Sales and General Administration Expenses Index, *TATA* = Total Accrual to Total Assets, and *LVGI* = Leverage Index

Table 2. Descriptive Statistics Summary of Non-Manipulator Companies

Variables	*DSRI*	*GMI*	*AQI*	*SGI*	*DEPI*	*SGAI*	*TATA*	*LVGI*
Mean	1.21	1.05	1.34	1.16	1.04	1.03	0.89	1.00
Median	1.05	1.01	0.98	1.11	1.02	1.00	0.71	0.99
Standard Deviation	1.35	0.40	3.68	0.68	0.32	0.55	0.68	0.22
Skewness	10.77	9.10	13.21	14.62	8.74	12.23	1.79	5.97
Kurtosis	128.53	112.31	190.71	237.44	115.15	186.35	3.44	63.95
Range	18.88	6.21	59.40	11.93	4.99	9.50	3.63	3.09
Minimum	0.12	0.16	-1.81	0.39	0.36	0.05	0.00	0.48
Maximum	19.00	6.38	57.59	12.32	5.35	9.55	3.64	3.57

Notes: *DSRI* = Daily Sales Receivable Index, *GMI* = Gross Margin Index, *AQI* = Asset Quality Index, *SGI* = Sales Growth Index, *DEPI* = Depreciation Index, *SGAI* = Sales and General Administration Expenses Index, *TATA* = Total Accrual to Total Assets, and *LVGI* = Leverage Index

can be predicted that around 20% of the companies from BSE 100 index are found be indulging in manipulation of financial statements as per Beneish M score model. This finding is again in line with the report of ICS consultancy firm, which revealed the facts of earnings manipulation of Indian listed companies.

The Table 1 provides the descriptive statistics of companies that are found to be indulging in earnings manipulation. The results show that the highest standard deviation and range is shown by *SGAI* followed by *GMI* and *DSRI*. Highest negative skewness is observed for *GMI, SGI, LVGI,* and *DEPI*. Maximum kurtosis is observed for *GMI* followed by *AQI* and *SGAI*.

The Table 2 provides the descriptive statistics of companies that were not indulging in earnings manipulation. The results show that the highest standard deviation is observed for *AQI* followed by *DSRI*. All the variables show positive skewness. Highest positive skewness is shown by *SGI* followed by *AQI* and *SGAI*. The highest range is shown by *AQI* followed by *DSRI* and *SGI*. Maximum kurtosis is observed for *SGI* followed by *AQI* and *SGAI*.

The Table 3 shows the correlation amongst the variables. The highest correlation is observed between *SGI* and *TATA* (0.733), followed by *SGI* and *DSRI* (0.675), and *TATA* and *DSRI* (0.626). *AQI* has a negative linear relationship with a majority of the variables. The maximum negative correlation is observed between *DSRI* and *LVGI* (-0.527), followed by *SGAI* and *TATA* (-0.437), and *SGI* and *SGAI* (-0.375).

Table 3. Correlation Matrix Amongst the Variables

	DSRI	*GMI*	*AQI*	*SGI*	*DEPI*	*SGAI*	*TATA*	*LVGI*
DSRI	1.000							
GMI	0.428	1.000						
AQI	-0.069	-0.043	1.000					
SGI	0.675	0.119	-0.101	1.000				
DEPI	0.025	0.021	-0.038	-0.075	1.000			
SGAI	-0.314	0.063	0.089	-0.375	-0.107	1.000		
TATA	0.626	0.207	-0.164	0.733	-0.006	-0.437	1.000	
LVGI	-0.527	-0.321	0.021	-0.206	0.194	0.038	-0.232	1.000

Notes: *DSRI* = Daily Sales Receivable Index, *GMI* = Gross Margin Index, *AQI* = Asset Quality Index, *SGI* = Sales Growth Index, *DEPI* = Depreciation Index, *SGAI* = Sales and General Administration Expenses Index, *TATA* = Total Accrual to Total Assets, and *LVGI* = Leverage Index

Table 4. Logistic Regression Test Results

Omnibus Tests of Model Coefficients

Variables of M score in equation	**Chi-square**	***df***	**Sig.**
DSRI, GMI, AQI, SGI, DEPI, SGAI, TATA, LVGI	157.786	8	.000

Model Summary

Variables of M score in the equation : *(DSRI, GMI, AQI, SGI, DEPI, SGAI, TATA, LVGI)*	-2 Log likelihood	Cox & Snell *R* Square	Nagelkerke *R* Square
	23.912[a]	.382	.898

a. Estimation terminated at iteration number 13 because parameter estimates changed by less than .001.

Variables in the Equation

Variables	**Beta Coefficient**	**Wald**	**Sig.**
DSRI	-7.547	5.368	0.021**
GMI	-3.787	1.756	0.185
AQI	0.291	0.181	0.670
SGI	-9.789	3.564	0.059*
DEPI	-3.423	1.094	0.296
SGAI	2.738	2.996	0.083
TATA	-37.896	9.669	0.002***
LVGI	0.939	0.030	0.863
Constant	25.554	6.701	

***significant at 1%, **significant at 5%, *significant at 10%

Notes: *DSRI* = Daily Sales Receivable Index, *GMI* = Gross Margin Index, *AQI* = Asset Quality Index, *SGI* = Sales Growth Index, *DEPI* = Depreciation Index, *SGAI* = Sales and General Administration Expenses Index, *TATA* = Total Accrual to Total Assets, and *LVGI* = Leverage Index

MLR analysis and log likelihood tests appears as 'Sig' in the 'Final' row in the 'Model Fitting Information'. A well-fitting model is significant at the .05 levels or lesser than that. In this study, the 'Sig' value in the 'Final' row in the 'Model Fitting Information' is .000, which proves the analysis to be a well-fitting model (Table 4).

The chi-square statistic is the difference in -2 log-likelihood between the final model and a reduced model. Cox/Snell, Nagelkerke coefficients are 38.2% and 89.8%. If the chi-square statistic shows a small p- value ($p <= 0.05$), it is assumed a good model fit. In the present study, the results show that *DSRI, SGI*, and *TATA* are the variables that most significantly affect the predictability of the organizations which are doing manipulation in earnings management. The results also show that the coefficients for these variables are negative, the highest being the *TATA* followed by *SGI* and *DSRI*.

The total accruals to total assets ratio has often been used as proxies for earnings management (Kumari & Pattanayak, 2015; Kaushal, 2013). Higher *TATA* (total accruals to total assets) signifies for accounting not supported by cash which serves as a sign of possible ways of manipulation by recognizing future revenues or inflating accruals. Significant *SGI* (sales growth index) suggests that higher sales growth is good, but growth firms are more likely to commit fraud because their financial position and capital needs put pressure on managers to achieve earnings targets. Declining value of *SGI* may have a significant impact on value of stock ; thus, higher *SGI* becomes a sign of manipulation (Beneish, 1999). Third *DSRI* variable is also found to be significant in the study, which indicates a disproportionate increase in accounts receivable relative to sales by inflating revenues (Harrington, 2005 ; Warshavsky, 2012). Thus, it can be concluded that the increase might have resulted from revenue inflation by manipulating reporting of earnings.

Discussion and Conclusion

This study aimed to find out the probability of earnings manipulations in financial statements of Indian companies. In order to examine the likelihood of manipulation, financial statements data of BSE 100 index companies from the years 2011 to 2016 were collected. It was found that11 companies indulged in earnings manipulations, while 54 companies did not indulge in earnings manipulations using the Beneish M Score. Besides the above findings, the results of the study reveal that out of eight variables, three variables : *TATA* (total accrual), *DSRI* (sales index), and *SGI* (sales growth index) are the variables that mainly cause the probable manipulation. Such an indication is in line with the findings of Tarjo and Herawati (2015) who also found that Beneish M score was capable of detecting earnings manipulation with four significant variables : *TATA, SGAI, DEPI,* and *GMI*. Ahmed and Naima (2016) also proved that *DSRI, AQI, TATA,* and *SGAI* were the ratios that had mainly caused the probable manipulation in Bangladesh firms. In a nutshell, these results highlight the evidence of earnings manipulation by recognizing future revenues, thus inflating accruals and capitalizing expenses that lead to high expenses in later years (Harrington, 2005; Warshavsky, 2012).

Implications

The empirical results of the present study point out a number of implications. First, it will provide an early signal to the prospective investors. Secondly, detection of earnings manipulation in financial statements becomes useful for banks and creditors during due diligence or entering a new business relationship. Finally, such indications will be an eye-opener for regulators /policy makers for implementing stringent checks on auditing of financial results of the companies to avoid such earnings manipulation. In addition, this study also contributes to the current literature by extending the findings of the M-Score to Indian companies listed on the BSE 100 index, which was not studied in the past.

Limitations of the Study and Scope for Future Research

Beneish M score is a probabilistic model based on ratios to predict earnings manipulation. In the present research, efforts are made to analyze companies representing only BSE 100 index. It can be used for various other indices with a sample of more companies as well and further investigations can be done. Along with M score, the books of accounts can be checked with other models and methods as well to check with 100% accuracy whether these companies are indulging in earnings manipulations or not. This will safeguard the interest of stakeholders and will assist the existing and prospective shareholders in their investment decisions.

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