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DETECTING EARNING MANIPULATION IN A DEVELOPING ECONOMY: AN EMPIRICAL STUDY USING BENEISH M-SCORE MODEL

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ABSTRACT

Manipulation of financial statements entails the intentional and often ill-motivated manoeuvring of financial records towards a pre-determined target. In such cases, motivations include achieving budgetary targets and rewarding senior managers with generous rewards – a classic instance of conflict of interests. Such manipulations have lately become increasingly frequent and severe in Bangladesh. In this back drop, the concerned board of directors is looking for improved surveillance techniques to better prevent and/or, detect and investigate possible financial frauds. In their quest for proactive approach against manipulation of financial statements, the board of directors look for warning signs and the present empirical study provides a profile of a company that is likely to manipulate its financial statements. In this study, data from 2016-2017 financial reports were utilized that correspond to 105 companies, excluding banks, non-banking financial institutions, insurance companies, and mutual funds listed at the Dhaka Stock Exchange (DSE) and the likelihood of accounting manipulation was quantified applying Beneish M-score model. It revealed that the maximum M-score was 7.06 and the minimum was -8.98, where higher scores indicate increased likelihood of accounting manipulation. Using a cut-off point of -1.78, twenty five companies were found to be suspected of accounting manipulation, while using a cut-off point of -2.22, fifty seven companies were found to be likely manipulator. Later a logistic model was developed to relate the likelihood of accounting manipulation to several company specific variables that were not explicitly considered in the Beneish M-score model. The findings are likely to benefit analysis of profiles of companies prone to accounting manipulation and thus could contribute to better corporate governance practices in emerging economies such as Bangladesh.

Keywords: manipulation of financial statements, Dhaka Stock Exchange (DSE), Beneish M-score.

INTRODUCTION

Fraudulent financial reporting stems mostly from mostly ill-motivated manoeuvring of financial records and such instances abound in both developed and developing economies. Earning manipulations have lately become increasingly frequent as well as sophisticated in emerging economies like Bangladesh. Lack of development in capital market could be attributed to the regulator, Securities and Exchange Commission (SEC) that may have failed to detect possible earning manipulators at the entry level, i.e., Initial Public Offering (IPO) or, at a later stage. Analysis on possible earning manipulation of companies and ways to detect those early could safeguard investors' interest. The primary objective of the current study is to profile companies prone to earning manipulation and thus help regulators such as SEC with vigilant evaluation of the quality of financial reports.

Before beginning any financial analysis, an analyst must clarify the purpose, context, and perspective first. General steps in this regard include developing an understanding of the company as well as its industry, which is followed by learning about management. Identifying significant accounting areas comes next and comparison the company's financial statements, disclosures, and accounting policies follow accordingly. Such

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comparison could be in the context of the company's historical record (time series analysis). Also, comparison could be drawn in the context of peer or, competitor companies (cross sectional analysis) by means of ratio analysis. While evaluating the quality of the financial reports, the analysts look for warnings signs of possible issues. Companies that operate in multiple sector – segments by geography or, by product, the analysis becomes more challenging since accounting line items may be shifted resulting in one segment showing strong performance while the consolidated results worsen. In addition to the qualitative steps described above, at the final stage of evaluation of financial reporting quality, the analyst could apply quantitative tools and techniques. Beneish M-score model is one such empirical model that gained popularity recently, esp. in the context of the developed nations (Beneish, 1999). The current study employs Beneish M-score model to ascertain quality of financial reporting and then profiles the companies prone to reporting manipulation via econometric model such as linear and discrete regression models. Such a two-step approach esp. in the context of a developing nation's capital market renders uniqueness to the study.

LITERATURE REVIEW

The Beneish model was developed by Professor Messod Daniel Beneish, who formulated several analytical ratios and variables in order to detect the possible occurrence of financial fraud. He proposed an eight variable model that utilizes data from financial statements of companies and produce a 'M-score' that shows the degree of earning manipulation. Over the years numerous analysts in industry and researchers in academia have applied the model to perform post facto analysis of corporate scandals in order to shedding more light to the dark world of earning manipulation. Bhabani and Amponsah (2017) enlisted the studies that used M-score while analyzing major corporate scandals involving earning manipulation and those include Impink's (2010) analysis of WorldCom scandal, Omar's (2014) analysis of Megan Media Holdings Berhad (MMHB) scandal, and Mahama's (2015) scrutiny of Enron Corporation. Drabkova (2014) found out that the Altman Z-score model (Altman, 1968) and Beneish models were superior compared to other quantitative models in detecting financial reporting frauds. Additionally, studies conducted by Ofori (2016), Aris et al (2013), and Warshavsky (2012) etc. advocated the use of Beneish model as a quantitative tool to evaluate prospects of manipulating earnings. However, other studies questioned the use of Beneish model as an ultimate detector of fraud. Cynthia (2005) argued that the Beneish model could not consistently discover problems in fraud in financial reporting. Ugochukwu and Azubuike (2013) showed that the traditional eight variable-model could not effectively evaluate the quality of financial statements. Amoa-Gyarteng (2014), opted for Altman Z-score model over Beneish model due to the former's efficiency in predicting bankruptcy and detecting FFR at Anglogoldashanti. The Beneish model has eight variables and these are found from information from financial statements (Beneish, 1999). The model is as follows:

$$\text{M-score} = -4.84 + 0.92 \cdot DRSI + 0.528 \cdot GMI + 0.404 \cdot AQI + 0.892 \cdot SGI + 0.115 \cdot DEPI - 0.172 \cdot SGAI + 4.679 \cdot TATA - 0.327 \cdot LVGI$$

Where,

- M-score = Score indicating probability of earnings manipulation
- DSR (days sales receivable index) = $(Receivables_t/Sales_t)/(Receivables_{t-1}/Sales_{t-1})$.
  The receivable days of the current and prior year are compared with the objective of revealing inflated revenue and change here could be indicative of inappropriate revenue recognition.
- GMI (gross margin index) = $\text{Gross margin}_{t-1}/\text{Gross margin}_t$.
  A company with poor growth potential is more likely to manipulate and deterioration in margins could prompt companies to manipulate earnings.
- AQI (asset quality index) = $[1 - (PPE_t + CA_t)/TA_t]/[1 - (PPE_{t-1} + CA_{t-1})/TA_{t-1}]$, where PPE is property, plant, and equipment; CA is current assets; and TA is total assets.

  Change in the percentage of assets other than in PPE and CA could indicate excessive expenditure capitalization. AQI greater than 1 means the entity has either increased its intangibles or cost deferral, which may indicate signs of earning manipulation.

- SGI (sales growth index) = Salest/Salest–1.

  It measures current sales versus prior year and it may reveal company's intention to manage the perception of continuing growth by manipulating sales and earnings.
- DEPI (depreciation index) = Depreciation ratet–1/Depreciation ratet,

  where Depreciation rate = Depreciation/(Depreciation + PPE).

  Declining depreciation rates could indicate understated depreciation as a means of manipulating earnings.
- SGAI (sales, general, and administrative expenses index) = (SGAt /Salest)/ (SGAt–1/Salest–1).

  It compares current SG&A expenses with that of prior year and an increase in fixed SGA expenses may hint at decreasing administrative and marketing efficiency, which could result in companies' earning manipulation.
- TATA=Total Accruals to Total Assets.

  Higher accruals can indicate earnings manipulation and thus this ratio signals to the extent management is involved in earning manipulation.
- LEVI (leverage index) = Leveraget/Leveraget–1, where Leverage is calculated as the ratio of debt to assets. Increasing leverage could influence companies to manipulate earnings.

Beneish (1999) developed the model in a way to make sure that the M-score is a normally distributed random variable with a mean of 0 and a standard deviation of 1.0. Higher M-scores (i.e., less negative numbers) indicate an increased probability of earnings manipulation. In order to classify the companies as potential manipulators, Beneish (1999) proposed that the cut-off value of M-score should be -1.78. Thus any score more that -1.78 would indicate a company more likely to be an earning manipulator. However, a cut-off score of -2.22 has also been proposed, which means a company that scores more than -2.22 is more likely to be an earning manipulator. Finally, it should be noted that Beneish M-Score is a probabilistic model and it cannot detect companies that manipulate their earnings with 100% accuracy.

METHODOLOGY

The current study utilized data from companies listed at Dhaka Stock Exchange and accordingly the M-scores were calculated using Beneish M-score. Later, a multiple linear regression (MLR) model was also developed using SPSS with the probability of earning manipulation (as obtained from M-score using cumulative normal table) as the dependent variables. The independent variables were extracted from companies' financial statements and those had not been used in Beneish model. Multiple linear regression is a popular statistical technique used to analyze relationship between a single dependent variable continuous in nature, here the probability of earning manipulation, and several independent or, predictor variables. These predictor variables are weighted by the MLR procedure to ensure maximal prediction and the weights indicate relative contributions of the predictor variables to the overall forecasting. Additionally, the weights, also called the coefficients, facilitate interpretation as to the impact of each variable in the process of forecasting.

Further, a binomial logistic regression model was developed using SPSS with the dependent variable to be whether the company is a likely earning manipulator or, not; companies with M-scores greater than −2.22 were classified as likely manipulators. The independent variables included data not already included in the Beneish model. Logistic regression is a special form of regression where the dependent variable is a discrete variable, not a continuous one. In this study we developed a binary logistic model where the dependent variable is a dichotomous one having values of 1 and 0 (1 if the company is a likely manipulator of financial statements; 0 other wise). The interpretation is similar to linear regression, although few differences exist.

DATA COLLECTION

The data to be fed into the Beneish model were collected from annual reports of companies listed in the Dhaka Stock Exchange (DSE). Beneish M-score model was primarily developed in the context of developed nations and studies concerning application of this model mostly center on those nations. Therefore, this study was conducted in the context of a developing nation such as Bangladesh's capital market. Although more than 500 companies are listed in DSE, not all the companies have their data available via annual reports in company websites. Also, banks and non-banking financial institutions were excluded from analysis due to the fact that Beneish M-score model cannot readily be applied to financial companies. Finally, a total of 104 companies' data corresponding to year 2016-2017 were collected and subsequently analyzed. Table 1 shows descriptive statistics of the variables available for modeling using M-score. Evidently, such a selection process renders convenience at the cost of selection bias. This is because companies that are prone to earning manipulation may not be listed at all to avoid disclosure. Also, a number of listed companies do not have financial statements available to public despite the mandate and these companies, if included, in the study could prove to be more likely to manipulate their financial statements.

TABLE 1

Descriptive Statistics of variables available to model the likelihood of earning manipulation

Variables	Min	Max	Range	Mean	Std. Dev.
Authorized Capital (Million BDT; as on 30/06/2017)	25.0	15,000.0	14,975.0	2,497.8	2,911.8
Paid-up Capital (Million BDT; as on 30/06/2017)	14.0	14,488.0	14,474.0	1,457.7	2,165.2
Net Profit (Million BDT; as on 30/06/2017)	-227.0	9,719.2	9,946.2	461.8	1,134.1
Years since incorporation (as on 30/06/2017)	5.0	104.0	99.0	25.1	15.0
Years since listing at DSE (as on 30/06/2017)	0.0	53.0	53.0	14.3	12.5
Total No of Directors in the Board (as on 30/06/2017)	2.0	19.0	17.0	6.1	2.5
No of Independent Directors in the Board (as on 30/06/2017)	0.0	5.0	5.0	1.8	0.8
Share holding % by Director/ Sponsor (as on 30/06/2017)	0.0	80.8	80.8	41.2	18.8
Share holding % by Govt. (as on 30/06/2017)	0.0	67.6	67.6	1.7	9.6
Share holding % by Institution (as on 30/06/2017)	0.0	51.8	51.8	16.7	9.9
Share holding % by Foreign Investor (as on 30/06/2017)	0.0	42.5	42.5	2.5	7.6
Share holding % by Public (as on 30/06/2017)	4.5	94.8	90.3	38.0	18.7
Short Term Loan (Million BDT; as on 30/06/2017)	0.0	19,676	19,676	1,079	2,268
Long Term Loan (Million BDT; as on 30/06/2017)	0.0	101,732	10,1732	1,612	9,991
Revaluation Reserve & Surplus w/o OCI (Million BDT; as on 30/06/2017)	-418.0	97,087	97,505	3,325	1,1369

DATA ANALYSIS

Data from more than 100 companies selected for the study were analyzed in two steps. First of all, the Beneish M-score model was applied to assess the quality of financial reporting and then using those empirical M-scores, the companies were profiled using econometric models, such as linear regression model as well as logistic regression model.

Application of Beneish M-score Model

The maximum M-score of the 105 companies were found to be 7.1 while the minimum was -9.0. The mean score was -2.1 and the standard deviation was 1.5. Figure 1 shows distribution of the Beneish M-scores across the sample of 104 companies selected for the study while Table 2 shows the average M-score across 86 companies from 6 major sectors. If a cut-off point of -1.78 is considered we could conclude that companies in food and allied sector are more likely to be earning manipulator compared to the rest in the study. Howevr, if a cut-off point of M=-2.22 is considered, we could see that companies in engineering and IT sectors, too are more likely to fall in the category of earning manipulators.

TABLE 2

Summary of Beneish M-score and its components across major sectors

	Textile	Pharmaceuticals	Engineering	Food & Allied	Fuel & Power	IT
DSRI	1.18	1.35	1.23	1.42	1.07	0.95
GMI	0.98	0.83	0.69	1.06	0.94	1.26
AQI	1.00	0.99	0.98	1.01	1.05	1.00
SGI	1.04	1.06	1.13	1.09	1.24	1.38
DEPI	0.99	0.94	1.04	0.95	1.04	0.98
SGAI	1.10	1.14	1.01	0.97	3.00	0.83
TATA	-0.04	-0.04	0.05	0.07	-0.02	0.04
LVGI	1.09	1.01	1.05	1.12	1.01	1.15
No. of obs	28	11	21	8	10	8
Avg. M-score	-2.5	-2.4	-2.1	-1.71	-2.64	-1.91

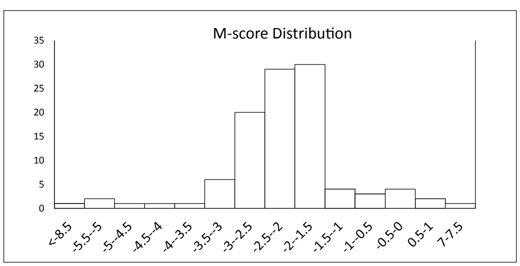

Figure 1. Distribution of Beneish M-score

Further, according to the 'gross margin index' (GMI), both IT and food & allied industries' average scores are indicative of earning manipulation. According to 'asset quality index' (AQI), any value larger than 1 may represent the tendency of avoiding expenses by capitalizing and deferring costs to preserve profitability. Food & allied sector as well as fuel & power sector should get more scrutiny in this regard. Almost all the companies in the major sectors analyzed showed that 'sales growth index' (SGI) were more than 1 and arguably, it showed good health of the industry involved. However, such a positive growth could also put pressure on managers in maintaining a company's positions, achieving earnings targets that may lead to earning manipulation in near future. Engineering and fuel & power sector involve capital machineries worth millions of taka and 'depreciation index' (DEPI) there shows alarming signs. Any DEPI value greater than 1 represents a declining depreciation rate that can increase earnings. Hence, analysts should be cautious while analyzing the financial reports in the concerned companies. A 'sales, general, and administrative expenses index' (SGAI) value more than 1 represents a disproportionate increase in sales compared to SGA and it may reveal companies' intention to manage the perception of continuing growth by manipulating sales and earnings. As the table reveals, high values of SGAI in fuel & power, textile, and pharmaceutical companies could be an indicator of earnings manipulation. Finally, companies in textile, engineering, food & allied, and IT sectors showed a 'leverage index' (LVGI) of more than 1 and this may indicate to motivation for manipulation of earnings.

Tables 3 & 4 show a relatively more general summary of the companies' M-scores as well as the eight components of the model. The companies are grouped following a cut-off point of -2.22 grouped into two categories – an M-score >-2.22 considered to be likely earning manipulator while an M-score <-2.22 considered to be less likely to fall into the group of earning manipulators.

TABLE 3

Average Beneish M-score of companies less likely to manipulate earning

Sector	*Count*	*Average M-Score*
Cement	3	-2.67
Ceramics	1	-2.68
Engineering	6	-3.05
Food & Allied	3	-2.55
Fuel & Power	5	-3.90
IT	3	-2.54
Miscellaneous	2	-2.59
Paper & Printing	1	-2.55
Pharmaceuticals	6	-2.96
Textile	18	-2.99

The two Tables 3 and 4 also reveal that distribution of companies that are less likely to be earning manipulators are negatively skewed having lower peak and less dispersion around the mean unlike the other group. Further the components values are relatively lower in the companies that are less likely to be earning manipulators.

TABLE 4

Average Beneish M-score of companies likely to manipulate earning

Sector	**Count**	**Average M-Score**
Cement	3	-2.00
Ceramics	2	-1.55
Engineering	15	-1.72
Food & Allied	5	-1.20
Fuel & Power	5	-1.39
IT	5	-1.53
Jute	1	-0.44
Miscellaneous	6	-0.26
Pharmaceuticals	5	-1.74
Textile	10	-1.63

Development of Econometric Model

Once M-scores were calculated those were regressed against variables corresponding to company's sector, size (in terms of authorized capital, paid up capital, net profit), age (in terms of age since incorporation and since listing), shareholding structure, board composition, outstanding loan – both long term and short term, and revaluation reserve etc. A multiple linear regression was developed first with probability of earning manipulation to be the dependent variable. Earning likelihood was measured using the M-score and normal probability table. Later a logistic regression model was developed to further facilitate profiling a likely earning manipulator.

TABLE 5

Multiple Linear Regression Estimation of 'the likelihood of earning manipulation'

Variable Description	Estimated Parameter	t-stat	p-value
Intercept	8.97	-1.82	0.07
% shares held by Govt (% shareholding by government)	0.59	4.02	<0.01
No of years since listing at DSE	-0.32	-1.88	0.06
Textile (1, if the sector is textile; 0 otherwise)	-5.99	-1.71	0.09
Engineering (1, if the sector is Engineering; 0 otherwise)	-5.96	-1.57	0.12
Revaluation reserve & surplus w/o OCI, in million BDT	-0.0002	-1.53	0.13
No of Independent directors in the board	-2.18	-1.29	0.20
Yr since incorporation (no of years since incorporation)	0.32	2.31	0.02
Number of Observations= 104			
Adjusted R Square = 18.2%			

Dependent variable: Probability of earning manipulation (as obtained from M-score)

Table 5 shows the estimation of multiple linear regression model with probability of earning manipulation that was calculated from Beneish M-score. The model has a poor goodness-of-fit and at α=0.10, the variables such as 'engineering', 'revaluation reserve', and 'no of independent directors in the board' were found to be statistically insignificant. The model also reveals a positive relationship between probability of earning manipulation and variables such as '% shares held by govt.' and no of years since incorporation. In the context of an emerging economy like Bangladesh, the lack of good governance could explain the positive relationship between extent of government ownership and likelihood of earning manipulation. On the other hand, 'yr since listing' and 'textile' variables are found to be negatively related to probability of earning manipulation. A company's age since incorporation may increase the chance of earning manipulation, but once it gets listed, increased pressure of corporate governance should make it less likely to manipulate financial statement. This may explain the signs of variables – age since incorporation and age since listing.

TABLE 6

Binary Logistic Regression Estimation of 'the likelihood of earning manipulation'

Variable Description	Estimated Parameter	Wald-stat	p-value
Intercept	-0.93	1.45	0.23
No of years since listing	-0.078	6.29	0.012
%shareholding by general public	0.02	2.39	0.12
Amount of short term loan outstanding in million BDT	0.00026	2.75	0.097
No of years since incorporation	0.051	3.31	0.069
Amount of long term loan outstanding in million BDT	-0.00032	0.234	0.63
Net profit in million BDT	-0.00014	0.197	0.657

Number of Observations = 104			
Cox & Snell R Square = 0.141			
Nagelkerke R Square = 0.188			
Dependent variable: 1, if earning manipulator; 0 otherwise			

Table 6 shows the estimation of binary logistic regression model with dependent variable that takes value of 1 if the company is a potential earning manipulator or, 0 otherwise. The cut-off value was taken to be -2.22. A total of 57 companies were found to fall into the category of likely earning manipulator. The resulting model reveals that variables such as % shareholding by general public, amount of long term loan and net profit in million BDT are statistically insignificant at α=0.10. The model's goodness-of-fit can be described by Cox & Snell R Square (14.1%) and Nagelkerke R Square (18.8%). Among the statistically significant variables the relationship between likelihood of earning manipulation and age since incorporation as well as age since listing seem to follow the same pattern found in multiple regression model earlier. Additionally, the positive sign of the coefficient of 'Short Term Loan' indicates that higher level of short term loan increases the chance of a company's being earning manipulator.

CONCLUSION

Beneish M-score is one of many quantitative tools to supplement the qualitative techniques to assess the quality of financial reporting. The eight component-model sought to identify companies that are likely to manipulate earning and have long been used by both corporate analysts and academic researchers worldwide. A cross sectional analysis among more than 100 companies listed in Dhaka Stock Exchange (DSE) revealed that around half of those are likely manipulators using an M-score cut-off point of -2.22. Further analysis was carried out to facilitate profiling those with respect to characteristics not readily included in Beneish M-model. The multiple linear regression model with likelihood of earning manipulation as the dependent variable pointed to a number of statistically significant variable involving age, extent of government ownership, and sector of the company. Also, the binary logistic regression model revealed few statistically significant variables such as age, short term loan, and percentage of shares owned by general public. Interestingly, both models indicated to a similar pattern of relationship between age and likelihood of earning manipulation. The relationship between likelihood of earning manipulation and age since incorporation was found to be positive, while the relationship between age since listing at DSE and likelihood of earning manipulation was found to be negative. This pattern might have suggested that once a company getting mature it tends to manipulate its earning but, once it gets listed the likelihood decreases possibly, due to increased disclosure.

Findings from such study should help the regulators remain vigilant regarding possible manipulation of financial statements of certain companies. With limited resources, the regulators such as Securities and Exchange Commission (SEC) strive to detect earning manipulation of listed companies to safeguard investors' interest. Studies similar to the current one could help regulators formulate guidelines, i.e., for internal use, to sample certain companies for in-depth analysis and focus their limited resources more prudently and with more effects. Besides, such studies could also help general investors profile suitable companies to invest and to avoid investing in companies prone to earning manipulation.

The study has been a relatively unique effort to detect possible earning manipulations using empirical method and then profiling those companies by econometric models such as linear regression and logistic regression models. The study could extend its scope by including data corresponding to multiple years. Moreover, the Beneish model needs to be calibrated using data from Bangladesh or, like nations before applying to categorize on the basis of vulnerability to earning manipulation. In order to further improve the current study, the problem of reporting bias as well selectivity bias should have been taken care of in future. Due to poor state of corporate governance, the financial data of only prominent and well established firms are available. Once the sample size increases to include the poor performing companies more lights could be shed on quality of financial reporting. In addition, inclusion of non-listed companies could enrich the sample and facilitate more in-depth analysis.

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APPENDIX

TABLE A1

Beneish M-score along with components for 105 companies listed in DSE (2016-17)

			M-Score Co-efficient							
Ticker	**Sector**	**M-Score**	**DSRI**	**GMI**	**AQI**	**SGI**	**DEPI**	**SGAI**	**TATA**	**LVGI**
SQURPHARMA	Pharmaceuticals	-4.37	1.49	0.99	1.00	1.10	1.11	1.04	-0.54	0.74
RENATA	Pharmaceuticals	-2.32	0.88	1.01	0.98	1.13	0.93	1.00	0.02	0.79
BXPHARMA	Pharmaceuticals	-2.31	1.08	1.00	1.00	1.20	1.07	0.99	-0.02	1.03
ACMELAB	Pharmaceuticals	-1.92	1.41	0.95	1.00	1.07	1.08	1.00	0.03	0.98
PHARMAID	Pharmaceuticals	-1.64	0.96	0.95	1.00	1.18	0.97	0.98	0.15	0.87
ACI	Pharmaceuticals	-1.84	1.23	0.97	1.00	1.22	1.05	1.07	0.07	1.24
ACTIVEFINE	Pharmaceuticals	-2.60	0.96	0.94	1.00	1.12	0.93	1.17	-0.02	1.11
AMBEEPHA	Pharmaceuticals	-2.97	0.96	0.99	1.00	1.03	0.34	0.98	-0.08	1.01
SALVOCHEM	Pharmaceuticals	-1.71	2.18	0.88	0.89	0.98	1.06	1.41	-0.01	1.26
IBNSINA	Pharmaceuticals	-1.59	1.57	1.00	0.99	1.15	0.86	0.99	0.05	1.00
SQURETEXT	Textile	-5.38	1.25	1.40	1.05	0.94	1.23	1.09	-0.68	1.36
ARGONDNIM	Textile	-2.42	1.04	1.02	1.00	1.01	1.00	1.00	-0.01	0.88
ENVOYTEX	Textile	-2.08	0.90	1.06	1.14	1.28	0.83	1.01	0.04	1.07
APEXSPIN	Textile	-2.82	0.93	1.01	1.00	0.95	1.13	0.99	-0.06	0.95
DELTASPIN	Textile	-2.42	1.15	0.98	0.92	1.00	1.03	0.88	-0.01	1.00
DSSL	Textile	-2.10	0.98	0.99	1.03	1.22	0.47	1.07	0.05	0.92
FAMILYTEX	Textile	-2.13	1.90	1.58	0.99	0.60	1.14	2.88	-0.01	1.25
AL_HAJTEX	Textile	-2.22	1.42	0.78	1.00	0.79	0.87	1.22	0.05	0.98
ANLIMAYARN	Textile	-2.55	0.97	1.15	1.00	0.83	1.13	1.23	0.01	0.98
ETL	Textile	-2.74	0.90	0.98	0.94	1.07	1.03	0.99	-0.04	1.02
FEKDIL	Textile	-2.07	0.99	1.22	0.99	1.04	0.91	0.91	0.05	0.86
GENNEXT	Textile	-2.61	0.93	0.77	1.08	1.09	1.06	1.30	-0.02	0.78
HFL	Textile	-2.68	0.88	0.97	1.00	0.96	0.69	1.02	0.00	1.03
HRTEX	Textile	-3.25	0.63	1.04	1.00	1.12	0.91	0.98	-0.12	0.98
HWAWELLTEX	Textile	-2.82	0.92	1.00	1.00	0.95	0.79	0.89	-0.07	0.73
RAHIMTEXT	Textile	-0.96	2.88	1.04	1.00	1.14	0.91	1.16	-0.05	1.18
MATINSPINN	Textile	-0.46	2.35	1.25	1.22	1.50	0.64	0.88	0.05	1.27
NURANI	Textile	-2.48	0.88	1.00	0.98	1.06	0.72	1.37	0.01	0.69
PTL	Textile	-4.50	0.62	1.51	0.93	1.66	1.04	0.62	-0.54	1.10
REGENTTEX	Textile	-1.61	2.08	1.14	0.95	0.53	1.62	1.27	0.07	1.41
RNSPIN	Textile	-3.95	0.62	-0.73	1.00	1.52	1.13	0.68	-0.11	1.64
SAIHAMCOT	Textile	-1.66	1.35	1.04	1.00	1.25	1.00	0.85	0.05	1.06
SAIHAMTEX	Textile	-2.54	1.10	0.79	1.00	0.93	1.01	1.16	0.01	1.08
SHASHADNIM	Textile	-2.35	0.92	1.01	0.99	1.11	1.06	1.15	0.03	1.08
SHEPHERD	Textile	-1.27	1.25	0.95	1.00	0.98	0.99	1.03	0.22	1.02
TOSRIFA	Textile	-3.45	0.72	0.88	0.71	0.85	0.99	1.20	-0.01	2.02
ZAHINSPINN	Textile	-1.92	1.38	0.83	1.09	1.09	1.24	0.76	0.03	1.08
ZAHINTEX	Textile	-2.57	1.21	0.86	1.00	0.75	1.14	1.27	0.02	1.10
CONFIDCEM	Cement	-2.56	1.12	1.25	0.87	1.00	0.97	1.41	-0.03	1.12
HEIDELBCEM	Cement	-2.24	1.08	1.30	1.00	0.92	0.94	1.14	0.03	1.01
LHBL	Cement	-2.20	1.11	1.61	1.00	1.01	0.97	1.58	0.01	1.22
MEGHNACEM	Cement	-3.21	1.61	1.02	0.97	0.94	0.93	5.72	-0.09	1.00
MICEMENT	Cement	-1.83	1.51	1.08	0.87	1.05	1.13	1.16	0.05	1.18
PREMIERCEM	Cement	-1.96	1.15	1.29	0.99	1.10	1.03	0.82	0.03	1.06
AMCL(Pran)	Food & Allied	-2.52	1.04	1.02	1.00	1.14	1.05	1.06	-0.05	0.97
APEXFFODS	Food & Allied	-1.79	1.64	0.79	1.00	0.81	1.01	1.01	0.09	1.05
FINEFOODS	Food & Allied	-1.74	0.93	1.54	1.02	1.37	1.06	0.76	0.06	1.44
GEMINISEA	Food & Allied	0.55	2.79	1.01	1.00	1.22	0.75	0.93	0.26	1.02
GHAIL	Food & Allied	-1.10	2.36	1.00	1.01	1.07	0.58	0.90	0.04	1.32
NTC	Food & Allied	-2.48	0.68	1.18	1.00	1.03	1.14	1.05	0.03	0.97

			M-Score Co-efficient							
Ticker	Sector	M-Score	DSRI	GMI	AQI	SGI	DEPI	SGAI	TATA	LVGI
OLYMPIC	Food & Allied	-1.91	0.93	1.01	0.99	1.03	1.06	1.00	0.13	1.00
RDFOOD	Food & Allied	-2.67	0.98	0.92	1.03	1.08	0.97	1.05	-0.03	1.20
FUWANGCER	Ceramics	-1.35	2.52	0.74	0.90	0.56	1.06	1.04	0.11	1.66
RAKCERAMIC	Ceramics	-2.68	0.76	1.07	1.01	1.25	0.90	0.96	-0.05	0.99
SPCERAMIC	Ceramics	-1.75	1.66	0.97	1.00	1.05	0.98	0.99	0.02	0.98
ATLASBANG	Engineering	-0.31	4.45	-0.02	1.00	0.59	1.21	1.79	0.00	1.02
AFTABAUTO	Engineering	-1.93	0.76	1.12	1.09	1.56	1.05	0.77	0.04	1.17
APOLOISPAT	Engineering	-1.93	1.12	1.16	1.01	1.08	1.01	0.98	0.07	1.10
AZIZPIPES	Engineering	-3.29	0.90	0.69	1.00	1.07	1.16	1.10	-0.13	0.99
BBS	Engineering	-1.64	1.13	1.02	1.01	1.05	1.33	0.75	0.12	0.98
BBSCABLES	Engineering	-1.89	0.85	1.01	1.00	1.36	1.06	0.88	0.07	0.93
BDAUTOCA	Engineering	-2.42	1.16	0.81	1.00	1.14	0.77	0.83	-0.03	0.92
BDLAMPS	Engineering	-2.24	1.01	0.99	1.00	0.99	0.86	1.00	0.05	0.86
DESHBONDHU	Engineering	-0.73	1.21	1.30	1.00	1.30	0.98	1.03	0.27	1.46
GOLDENSON	Engineering	-5.21	1.38	-4.30	0.99	0.76	0.96	1.28	0.01	1.20
GPHISPAT	Engineering	-2.16	1.17	0.95	0.81	1.36	1.09	0.99	-0.01	1.14
IFADAUTO	Engineering	-1.69	0.80	0.98	1.00	1.48	0.57	0.67	0.12	1.07
KDSALTD	Engineering	-2.21	1.20	1.06	1.05	0.99	1.11	0.96	0.01	1.11
NAHEEACP	Engineering	-1.93	0.87	0.97	1.00	1.31	0.97	1.04	0.08	0.88
NAVANACNG	Engineering	-2.34	1.13	1.02	0.75	1.00	1.63	1.11	0.04	1.39
NPOLYMAR	Engineering	-2.78	1.26	1.01	0.93	1.06	1.01	0.98	-0.11	1.13
OIMEX	Engineering	-2.15	1.19	1.00	1.02	1.07	0.73	1.01	0.02	0.95
OLYMPIC	Engineering	-1.91	0.93	1.01	0.98	1.03	1.14	1.00	0.13	1.00
RANFOUNDRY	Engineering	-1.80	1.29	1.01	0.98	1.12	1.00	1.08	0.06	0.87
RSRMSTEEL	Engineering	-1.45	1.00	0.72	1.00	1.39	1.07	0.89	0.17	0.97
WSMSHIPYARD	Engineering	-2.09	0.92	0.96	0.94	1.06	1.10	0.96	0.09	0.94
BARAKAPOWER	Fuel & Power	-1.78	1.21	1.18	1.00	1.18	1.11	0.80	0.04	0.99
BDWELDING	Fuel & Power	-2.04	2.07	1.16	1.00	0.46	0.47	1.36	0.01	1.22
CVOPRL	Fuel & Power	-8.98	0.00	-0.24	1.00	0.04	1.02	21.63	-0.10	1.23
DESCO	Fuel & Power	-2.67	1.07	0.82	0.97	1.07	1.10	1.05	-0.04	1.02
DOREENPWR	Fuel & Power	0.82	0.84	1.21	1.42	4.33	1.44	0.31	0.01	1.02
GBBPOWER	Fuel & Power	-2.12	1.43	1.15	1.00	1.02	0.94	1.09	-0.02	1.07
KPCL	Fuel & Power	-1.81	1.31	1.19	1.00	0.90	0.98	0.40	0.05	0.88
LINDEBD	Fuel & Power	-2.36	1.08	0.99	1.00	1.16	1.15	1.09	-0.03	0.79
POWERGRID	Fuel & Power	-2.47	0.96	0.98	1.11	1.13	1.20	1.01	-0.03	0.99
SPCL	Fuel & Power	-3.01	0.77	0.93	0.95	1.08	0.95	1.23	-0.07	0.82
AAMRANET	IT	-0.27	0.46	2.56	0.86	2.86	0.87	0.42	0.07	1.46
AAMRATECH	IT	-2.41	1.07	1.06	1.00	1.05	0.88	0.92	0.00	1.17
AGNISYSL	IT	-1.96	1.28	1.10	1.00	0.97	1.11	0.80	0.03	0.92
BDCOM	IT	-1.65	1.32	1.45	0.99	1.17	0.88	0.87	0.04	1.12
DAFODILCOM	IT	-1.94	1.31	0.81	1.01	1.05	1.06	1.05	0.08	1.14
INTECH	IT	-1.83	0.52	1.08	1.16	1.67	0.87	0.63	0.10	1.46
ISNLTD	IT	-2.45	0.81	1.05	1.00	1.10	1.11	0.90	0.01	0.95
ITC	IT	-2.76	0.81	0.99	0.98	1.16	1.02	1.07	-0.05	1.01
NFML	Miscellaneous	-1.82	1.25	0.99	1.00	1.02	0.77	0.93	0.09	1.02
MIRACLEIND	Miscellaneous	-1.70	1.73	0.94	1.00	1.02	0.49	0.87	0.04	1.07
SAVAREFR	Miscellaneous	-2.67	0.92	1.03	1.00	1.17	1.08	1.01	-0.06	1.04
USMANIAGL	Miscellaneous	7.06	11.23	1.16	0.99	0.96	1.04	1.10	0.03	1.12
SINOBANGLA	Miscellaneous	-2.52	0.95	0.98	1.00	1.11	0.98	0.96	-0.02	0.96
AMANFEED	Miscellaneous	-2.21	0.94	1.04	1.00	1.11	1.36	1.13	0.04	1.07
HAKKANIPUL	Miscellaneous	-0.88	2.26	0.88	0.94	1.25	1.02	0.74	0.07	1.20
BEXIMCO	Miscellaneous	-2.00	1.11	1.19	1.00	1.05	0.87	0.96	0.05	1.01
NORTHERN	Jute	-0.44	1.22	0.93	1.17	1.57	0.67	0.74	0.28	1.11
KBPPWBIL	Paper & Printing	-2.55	1.30	0.93	1.00	0.68	1.02	1.20	-0.01	0.87
BXSYNTH	Pharmaceuticals	-3.19	2.12	-0.52	1.00	0.44	0.96	1.90	-0.05	1.14

TABLE A2

Summary Beneish M-score components for companies less likely to be earning manipulator

	M-Score	DSRI	GMI	AQI	SGI	DEPI	SGAI	TATA	LVGI
Count	48	48	48	48	48	48	48	48	48
Mean	-2.98	1.01	0.80	0.98	1.02	1.00	1.60	-0.06	1.04
Standard Error	0.16	0.04	0.12	0.01	0.03	0.03	0.44	0.02	0.03
Median	-2.60	0.97	0.99	1.00	1.06	1.01	1.05	-0.03	1.01
Standard Deviation	1.14	0.31	0.85	0.06	0.24	0.18	3.03	0.15	0.23
Variance	1.29	0.09	0.72	0.00	0.06	0.03	9.21	0.02	0.05
Kurtosis	16.61	4.60	28.46	9.34	6.57	5.88	42.81	10.56	7.44
Skewness	-3.68	0.44	-4.99	-2.58	-1.28	-0.31	6.44	-3.24	2.10
Range	6.76	2.12	5.81	0.39	1.62	1.30	21.02	0.73	1.33
Minimum	-8.98	0.00	-4.30	0.71	0.04	0.34	0.62	-0.68	0.69
Maximum	-2.22	2.12	1.51	1.11	1.66	1.63	21.63	0.05	2.02

TABLE A3

Summary of Beneish M-score components for companies likely to be earning manipulator

	M-Score	DSRI	GMI	AQI	SGI	DEPI	SGAI	TATA	LVGI
Count	57	57	57	57	57	57	57	57	57
Mean	-1.45	1.59	1.07	1.01	1.19	0.98	0.99	0.07	1.10
Standard Error	0.17	0.19	0.04	0.01	0.07	0.03	0.05	0.01	0.02
Median	-1.81	1.23	1.01	1.00	1.08	1.01	0.98	0.05	1.07
Standard Deviation	1.32	1.46	0.31	0.09	0.54	0.22	0.35	0.07	0.17
Sample Variance	1.74	2.14	0.09	0.01	0.29	0.05	0.12	0.00	0.03
Kurtosis	31.45	34.59	11.55	8.95	21.24	1.13	14.44	2.79	1.11
Skewness	5.11	5.41	1.46	2.02	3.99	-0.18	2.82	1.53	1.09
Range	9.27	10.77	2.58	0.61	3.87	1.15	2.57	0.34	0.80
Minimum	-2.21	0.46	-0.02	0.81	0.46	0.47	0.31	-0.05	0.86
Maximum	7.06	11.23	2.56	1.42	4.33	1.62	2.88	0.28	1.66

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