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Earnings manipulation behavior in the banking industry of Bangladesh: the strategical implication of Beneish M-score model

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Abstract

Purpose – This study aims to determine the number of companies involved in earnings manipulation. Additionally, this study has empirically investigated the common manipulation items among the companies.
Design/methodology/approach – Bangladesh's listed commercial banks are selected as a sample for this study, and financial data from 2009 to 2018 were collected. The likely and nonlikely manipulator Beneish model (1999) divides the sample into two groups. Based on the M-score of the model, the banks are put into two groups. To identify the most influential variables, an independent sample *t*-test was done with the help of Statistical Package for Social Sciences (SPSS).
Findings – The findings show that banks in Bangladesh have an unstable trend in making manipulated financial reports. Results of the *t*-test reveal that overstating revenues, increasing intangible assets, lessening cost and accruals are the most appealing items for preparing a fraudulent financial report. The findings of this research work will help the investors take the right decision having the idea of manipulation in the banking sector of Bangladesh.
Originality/value – In the presence of many irregularities in the banking sector Bangladesh, very few studies have been carried out in forensic accounting and fraudulent financial reporting practices. Much research has focused on earnings management techniques. This research specifically focuses on identifying earnings manipulation in financial statements for micro-level variables like accounting accruals, intangible assets, etc. This will help policy-makers and financial statement readers to be proactive while reading financial statements and taking any investment decision.

Keywords Fraud, Earnings manipulation, Beneish M-score model, Banking industry, Bangladesh
Paper type Research paper

1. Introduction

Financial statements are the core information resource for any organization that trades publicly. Publicly traded organizations are listed under any country's Securities and

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Exchange Commission. According to agency theory, firms are directed by a management body, and the company's owner selects these groups of people. Management people are responsible for preparing the financial report of any firm, screening its operating performance and proficiency. With the help of this disclosed information, investors, creditors and other related parties decide that firm. Therefore, the steadfastness of those reports depends on their clarity and exactness. Moreover, the capital market uses the company's disclosed information to place the price for the listed security, and the users rely on them to establish their decision regarding that firm.

It should be noted that managers occasionally intentionally exploit the financial report to pressure some market competitors. The intentional manner of a manager to manipulate the financial figure is known as earnings management. Nonetheless, in 2014, 40 US public companies reported profitable conditions using creative accounting techniques while in a loss position under traditional accounting methods (Bhasin, 2016). Top management of any firm discloses falsified and misleading financial information to hide the company's actual scenario or financial position. The mindset of unprincipled management people is the main cause of increasing corporate accruals, not the business cycle (Hasan, Rahman, & Hossain, 2014; Hasan, Omar, Rahman, & Hossain, 2016). Users, especially the investors' groups, are defenseless due to this falsification of accounting data. The authentication of accounting systems and the dependence on disclosed reports for creating management and investment decisions are being questioned as the recent list of failed economic and business enterprises is not too short. A few such cases are the disintegration of Enron, WorldCom, Robert Maxwell Pension Funds and the downfall of Arthur Anderson, the "Big Five" accounting firm belonging to the "Big Five" above stated issue. Undoubtedly, these issues have proved that the financial report prepared by the administration of a firm and specialized by the external auditors could not bring the actual picture of a company. Decisions made following those reports became fraudulent and destroyed the belief of stakeholders. The management body misleads the firm's owners and the organization's users by adopting unethical steps through earning management. Transparency has become a vital issue regarding the annual reports provided by the company. The authenticity of the financial reports may endanger a company's inflated profit and expertise-related information. Doing fraud is the intentional decision of a firm's top management (CEO or CFO) to optimize their personal need and uphold the company's image towards the public. However, this is unethical.

Recent scams and financial fraud in Bangladesh's banking sector have urged further scrutinization of those financial institutions' operational details and financial solvency. Hallmark Scam, Bismillah Textile Scandal and AnnonTex fraud have highlighted the loopholes in the regulatory system of the financial institutions of Bangladesh. The process of approving loan and advances are not clear and transparent. Consequently, there has been a rise in the corporate indiscipline and accountability of the banking sector of Bangladesh. Lack of good governance, the management's bad intention and the regulators' ineffective control mechanism are hurting the Bangladeshi economy's most sensitive and vital sector. This also amplifies the opportunity to engage in fraudulent activity. Following the fraud triangle theory, this study analyzes the management body's opportunistic behavior. The fraud triangle theory consists of three components: pressure, opportunity and rationalization. The pressure of making wealth may transform a white-collar employee into a white-collar criminal, as most white-collar crimes are committed by formerly good people (Ghosh, Sen, & Riva, 2020). This tendency to engage in fraudulent activity is materialized when they get a good opportunity. Such kind of opportunity arises in the company due to poor governance, ineffective internal control mechanism and immoral attitude of the management. Fraudsters usually complete their plan by giving loans and advances based on personal connections, political affiliation and personal business interests. Finally, these persuaded investments are reported as nonperforming loans (NPLs) in the financial statements and shown to stakeholders as a loss arising from normal business operations. This can be termed as the rationalization of the fraud triangle theory. The management of One Bank Limited, a listed commercial bank, has manipulated the financial statements to overstate the profit without complying with the regulatory requirements of keeping provisions for loans (Alo, 2021). PK Halder, former Managing Director of a bank and two other financial institutions, had been found guilty of laundering 100 m taka from various financial institutions (Daily Star, 2021). These are the latest scandals that have taken in Bangladesh. The result of these unexpected events hit the firm performance. Reportedly the growing level of scams and NPLs is decreasing the banks' profitability. NPLs ratio is in increasing mood over the year for every kind of bank, and according to theory, it is affecting the profit percentage of the banks in Bangladesh negatively (Financial Express, 2020). However, the profit percentage of listed private commercial banks in Bangladesh is also growing, except in 2020 (due to the COVID-19 pandemic) (Bangladesh Bank, 2022). Moreover, NPLs and profit margins do not stand in a parallel way as they have negative assertions (Financial Express, 2020). Farmers Bank was established in 2013, and by the end of 2018, it showed NPLs of 58%. It disclosed a positive profit margin with a high amount of NPLs (Dhaka Tribune, 2019). The list of these loan scams, defaults and increasing NPLs is not short in Bangladesh, and this will create the problem of authenticity and transparency of disclosed information by this banking and other financial institutions doing business here. Ghosh *et al.* (2020) highlighted that lack of board independence is one of the major causes of the poor performance of the financial institutions in Bangladesh. As a result, the board of directors feels the pressure to manage earnings using different techniques. Few cases come to the news of general investors, and others remain behind the market scene about which general investors know nothing but put their investment in the market. Recently, procedures like statistical models, financial ratios, mathematical models and data mining have been used to find fraud in financial statements. According to forensic accounting, this detection of fraud needs a long investigation process, and the primary activity of this process should be uncovering fraud. A predictive diagnosis of manipulation is needed to accelerate the fraud investigation procedure to find the fraud in financial statements or discover the intention of fraud. Five types of patterns are mainly used for the falsification of financial statements. These include fabricated revenues, inappropriate timing schemes, understating liabilities, less disclosure and problematic asset valuation procedures (Hasan, Omar, Barnes, & Handley-Schachler, 2017). Investigating each stated variable can be a good start for finding the distortion pattern in the financial statement. On that note, Beneish's M-score model (Beneish, 1999) combines eight ratios that act as a forensic accounting tool for identifying fraud in the financial statement. This research aims to find out the fraud of listed commercial banks in Bangladesh and analyze them in an organized manner with the help of the Beneish M-score (Beneish, 1999). To motivate the study, there are some specific inquiries to construct a view of the present scenario of disclosing fraudulent information in Bangladesh. These identify the number of listed banks in Bangladesh that manipulate financial statements, find the specific pattern or criteria for fraud by the banks and find the governing or leading ratios or variables mostly used in manipulation. From the analysis, it can be said that the manipulating behavior of listed private commercial banks in Bangladesh shows an unstable trend. This means those banks are not engaging themselves with the same manipulating items to falsify their disclosed accounting information. Moreover, interest income and balance with other financial institutions, an unusual growth in intangible assets, accounting accruals and growth indicators are the main items for the sampled banks to manipulate their accounting data.

2. Literature review

2.1 Financial statement and fraud

With the help of disclosed audited financial statements of any firm or company, investors can take their investment decision. Sound corporate information is the precondition to maintain the interest of the investor. However, falsification in financial statements caused by fraud is the main concern in the present corporate world. Fraud is the intentional wrong representation of something to achieve an advantage or to deprive someone of the right. In the recent corporate world, fraud in financial statements has become common. Gupta and Gupta (2015) analyzed the concept of fraud and its consequences from an Indian perspective. They concluded that a weak regulatory system, absence of fraud reporting guidelines, inefficiency of financial institutions and ineffectiveness of board members of any firm are the main reasons for corporate fraud in India. Correspondingly, Bhasin (2015) concluded that a lower level of compliance, weak internal control system, inaccurate employment procedures, less training and excessive work pressure are the main reasons for bank fraud in India. Huang, Lin, Chiu, and Yen (2017) claimed that corporate pressure and desire for incentives are the main factors behind fraud in the financial statement. Using the Analytic Hierarchy Process (AHP) model, the authors concluded that lowly performance, external financing necessity, board members' inefficiency, financial anguish and competition provoke fraud. Kizil and Kasbasi (2018) commented that fraudulent financial information reduces the possibility of the right investment decision from the users of financial information.

2.2 Empirical evidence of Beneish M-score model: fraud detective tool

Finding fraudulent financial reporting, the accrual accounting model is mostly used methods initiated by Healy (1985) and advanced by DeAngelo (1988) and Jones (1991). Nonetheless, the Beneish M-score model (Beneish, 1999) procedures a set of dissimilar variables along with the accruals to spot manipulation. The Beneish M-score model can be used as a forensic accounting tool to detect fraud in financial statements as it gives more results than measures of fraud detection tools (Özcan, 2018; Akra & Chaya, 2020). Kamal, Salleh, and Ahmad (2016) sampled 17 listed public companies charged for fraudulent financial reporting in Malaysia. Using the Beneish model to check its authenticity for working as a forensic tool and their conclusion, they claimed that 14 out of 17 (82%) companies were accused of financial misrepresentation before any community broadcast. This model is quite effective in detecting financial irregularities before any announcement. Aghghaleh, Mohamed, and Rahmat (2016) also reported average correctness of 73.17% in detecting fraud in the Malaysian context. Repousis (2016) took 25,468 companies in Greece for 2011 and 2012 and found that 33% of the total companies were engaged in earnings manipulation as their M-score is more than the benchmark (−2.22) of the Beneish model. Several studies showed that revenues, assets (current and fixed), administrative expenses and accounting accruals are indicators of financial manipulation (Repousis, 2016; Tahmina & Naima, 2016; Mamo & Shehu, 2017; Ramírez-Orellana, Martínez-Romero, & Mariño-Garrido, 2017). Tahmina and Naima (2016) pointed out that inflating intangible assets is the key to manipulating earnings in the financial statements in Bangladesh.

Sakib (2019) exposed that textile companies in Bangladesh were engaged in earnings manipulation, and receivables, cash and accruals were the significant way to misappropriate information. Arman and Sharmin (2019) used 105 listed companies on Dhaka Stock Exchange (DSE) to expose their fraud-making percentage with the help of the M-score. Using −1.78 as a benchmark, 25.81% of companies disclosed wrong information, and −2.22 as a benchmark, 54.28% of companies had a fraud-making attitude. A logistic model proved that statistically, some variables like sales, receivables and accruals were the items for fraud in financial statements. Companies engaged in fraudulent financial reporting are expected to have lower returns in the future (Subiyono & Suardi, 2020).

Umar, Partahi and Purba (2020) used fraud diamond analysis along with the Beneish model to find the reason for fraud, and they concluded that financial stability, auditor replacement, nature and rationalization of industry affected fraud in the financial statement. Anning and Adusei (2020) found that most of Ghana's manufacturing and trading companies were involved in financial manipulation and used M-score for this conclusion. However, predicting the fraud in a financial statement by M-score will give better results than by Z-score (Akra & Chaya, 2020). Hołda (2020) showed the efficacy of eight ratios M-score over five ratio M-score for finding the manipulating firms of Warshow stock exchange. In 2021, Valaskova and Fedorko (2021) showed that the Beneish model can predict the fraudulent behavior of companies by detecting the manipulating one. Shakouri, Taherabadi, Ghanbari, and Jamshidinavid (2021) did a regression analysis and found that DSRI, GMI, AQI, SGI, DEPI and TATA of the Beneish model significantly impacted fraudulent financial reporting. Durana, Blazek, Machova, and Krasnan (2022), using the indicator of creative accounting, found that both the parameter (eight ratios and five ratios) of the Beneish model were able to find and predict the fraudulent behavior of financial reporting. Samuel (2022), using the banking sector of East Africa as a sample, proved that the Beneish model result divided the sample group into likely manipulator and nonlikely manipulation with accuracy.

The above literature concludes that the Beneish model is used to predict and detect any firms' fraudulent financial reporting behavior and is also flawless in this global environment. All the variables included in the Beneish M-score model are very much interrelated. Common variables of fraud or earnings manipulation are accruals, intangible assets, noncash expenses and divergence of cash flow and accrual earnings. Variables contained in the Beneish model are explanatory variables of earnings manipulation. However, there is lacking clear-cut conclusions that which of the variables are the indicator of fraud adopted by firms to falsify their disclosed financial information. This study tried to find the specific variable of the Beneish model, mostly used for falsification of information and instigating fraud.

3. Research methodology:

3.1 Research design

The first stage activity is finding the likely and nonlikely manipulator banks using the Beneish model. Messod Daniel Beneish created an eight-variable mathematical model to classify the happening of fraud of financial nature or propensity to involve in earnings manipulation. Eight ratios create a score named M-score that can express the misrepresentation of financial data in financial statements, and this distortion will result in earnings manipulation. Sometimes this score indicates susceptibility to earnings manipulation. When M-score is less than −2.22, the respective firm or organization will be treated as a not likely manipulator, and when it is more than −2.22, the firm will be pickled as a likely manipulator (Beneish, 1999). Through his analysis, Beneish said that this model's weighted or unweighted possibilities of earnings management are significantly connected with the presence of fraud as he could correctly identify 76% of manipulators. Moreover, only 17.5% of nonmanipulators were incorrect with the model. Beneish and Nichols (2005) again found the probability of financial distortion by using five ratios in the previously stated Beneish model.

The model is as follows:

$$M = -4.84 + (0.920 \times DSRI) + (0.528 \times GMI) + (0.404 \times AQI) + (0.892 \times SGI) + (0.115 \times DEPI) - (0.172 \times SGAI) + (4.679 \times TATA) - (0.327 \times LEVI)$$

where

DSRI	=	$\textit{Days Sales in Receivales}_t \div \textit{Days Sales in Receivales}_{t-1}$
GMI	=	$\textit{Gross Margin Index}_{t-1} \div \textit{Gross Margin Index}_t$
AQI	=	$\left(1-\frac{\textit{Current Asset}+\textit{Property Plant \& Equipment}}{\textit{Total Asset}}\right)_t \div \left(1-\frac{\textit{Current Asset}+\textit{Property Plant \& Equipment}}{\textit{Total Asset}}\right)_{t-1}$
SGI	=	$\textit{Sales}_t \div \textit{Sales}_{t-1}$
DI	=	$\left(\frac{\textit{Depreciation}}{\textit{Depreciation}+\textit{Property Plant \& Equipment}}\right)_{t-1} \div \left(\frac{\textit{Depreciation}}{\textit{Depreciation}+\textit{Property Plant \& Equipment}}\right)_t$
SGAI	=	$\left(\frac{\textit{Sales, General \& Administrative Exprese}}{\textit{Sales}}\right)_t \div \left(\frac{\textit{Sales, General \& Administrative Exprese}}{\textit{Sales}}\right)_{t-1}$
TATA	=	$\left(\frac{\textit{Total Accruals}}{\textit{Total Asset}}\right)_t$
LEVI	=	$\left(\frac{\textit{Total Liabilities}}{\textit{Total Asset}}\right)_t \div \left(\frac{\textit{Total Liabilities}}{\textit{Total Asset}}\right)_{t-1}$

This eight ratios or variables model of M-score is proficient in uncovering the accounting falsification and poor eminence of reporting. This study occupies the commonly used yardstick of a −2.22 score (Beneish, 1999) for categorizing the banks into two likely and non-likely manipulators for a year.

3.2 Population and sample selection

This study aims to determine the banks engaged in fraudulent financial reports and disclosing materially misstated information in Bangladesh. In total, 61 scheduled banks in Bangladesh function under the complete governance and administration of the Bangladesh Bank. Therefore, we must take all scheduled banks to portray the overall banking scenario. However, the analysis takes ten years (2009–2018), and many scheduled banks were established after 2008. Data were taken from 2008 for calculating the ratios for M-score; previous year information is needed. Availability of annual reports is the second concern for collecting data or information for concerned banks. Considering both the issues of time and availability of resources for collecting data, 30 listed commercial banks are selected as samples for this study, covering around 50% of the total population of banks in Bangladesh.

3.3 Data analysis technique

For this study, data were analyzed in two stages. At first, the eight ratios for calculating M-score were developed using M.S. excel. With the help of the previously mentioned model (Beneish, 1999), banks are divided into the likely manipulator group and the nonlikely manipulator group. The next stage of data analysis of this research combined the statistical test to uncover the utmost substantial ratios directed to such differentiation of banks. Statistical Package for Social Sciences (SPSS) will be used here to analyze the collected data and answer the research question; an independent *t*-test was done between the two banks to find the ratios that are statistically responsible for categorizing the banks into two groups. Moreover, this test tells the dominating ratios and concern variables used mostly for manipulating financial data.

4. Analysis and findings:

4.1 Classification of banks based on M-score

All collected data from 30 commercial listed banks over the period 2009–2018 are tested using the Beneish model to find the M-score. Compared with the benchmark value of −2.22, banks are divided into groups, and summarized results are presented in Table 1. These results also help determine the pattern of banks disclosing misleading information (if any).

Table 1 shows the number of likely and nonlikely manipulator banks in Bangladesh from 2009 to 2018. Unfortunately, the result did not provide any increasing or decreasing trend of manipulation. However, the numbers of likely manipulators are more than nonlikely manipulators. In 2009, 63.33% of banks were tested to appear to be likely manipulators, and 36.67% were not-likely manipulators. Next year, the number of likely manipulators reached 80%, and the rest are not-likely manipulators. There was again a decrease in 2011 in the number of a manipulator; it was 53.33%, and 46.67% tested as not being a manipulator. Among ten years of calculation, the number of expected manipulator banks was lower in 2012 and 36.67%. However, the number of probable manipulators increased again in 2013 with 60% of the total sample. Next year, the nonprobable manipulator was 23.33%, which increased the probable manipulator. In 2015, the number of expected manipulators decreased slightly, but in 2016, it reached its peak (83.33%). The expected manipulator number is somewhat decreasing in 2017 (70.0%) compared to 2016. However, in 2018, the increasing trend of expected manipulators was again in the picture; that year, it was 73.33%. In short, the number of the expected and nonexpected manipulators did not have any increasing or decreasing trend. Rather the rate was fluctuating in nature.

4.2 Findings of most significant ratios

This part of the findings deals with the result of an independent *t*-test to find the most significant ratios among the eight ratios stated in the Beneish model (Beneish, 1999). The banks are divided into two groups based on the M-score, and these two groups are likely manipulators and non-likely manipulators by name. An independent sample *t*-test was done with the help of statistical analysis software SPSS, and analysis was done with the two groups using data yearly. The result is portrayed in Tables 2–11.

The result will be discussed with the help of the value of *t* and the value available in the significance column of the table. When the significance column value is less than or equal to 0.05, it denotes that the variability of the variable is not identical, and the difference between the first and second groups is statistically significant. Moreover, if the value is greater than 0.05, the difference between the two groups is not significant. Table 2 recapitulates the results of the year 2009. The stated results of Table 2 denote that the groups do not differ significantly among the eight ratios GMI, AQI, SGI, DI, LEVI and TATA.

Additionally, only DSRI in 2009 portrays significant differences between the group as the *p*-value is less than 0.05. In 2010, only SGI significantly differed between the groups due to manipulation. The other seven ratios in the result table do not differ significantly as the *p*-value is greater than 0.05. Table 4 depicts the statistical test result of 2011; here, only the ratio DSRI is significant. DSRI, AQI and DI are exposed significantly in terms of differences between the groups in 2012.

Other ratios like GMI, SGI, LEVI, SGAI and TATA are not differentiated. In 2013, which results showed that SGI, DI, LEVI, SGAI and TATA have no significant difference. Moreover,

Year	Likely manipulators (M-Score > −2.22)	Nonlikely manipulators (M-Score < −2.22)
2009	19 (63.33%)	11 (36.67%)
2010	24 (80%)	6 (20%)
2011	16 (53.33%)	14 (46.67%)
2012	11 (36.67%)	19 (63.33%)
2013	18 (60%)	12 (40%)
2014	23 (76.67%)	7 (23.33%)
2015	22 (73.33%)	8 (26.67%)
2016	25 (83.33%)	5 (16.67%)
2017	21 (70%)	9 (30%)
2018	22 (73.33%)	8 (26.67%)

Table 1. Proportion of likely manipulator firms to nonlikely manipulator firms

Table 2.
Result of t-test for the year 2009

Independent sample test

		Levene's test for equality of variances		t-test for equality of means					95% confidence interval of the difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. error difference	Lower	Upper
DSRI	Equal variances assumed	9.159	0.005	−3.339	28	0.037	−0.17701	0.52154	−1.24533	0.89132
	Equal variances not assumed			−2.431	22.36	0.027	−0.17701	0.41047	−1.02746	0.67345
GMI	Equal variances assumed	0.144	0.707	−0.780	28	0.442	−0.07188	0.09210	−0.26055	0.11679
	Equal variances not assumed			−0.802	22.81	0.431	−0.07188	0.08960	−0.25732	0.11356
AQI	Equal variances assumed	2.034	0.165	−0.699	28	0.490	−0.07317	0.10465	−0.28754	0.14120
	Equal variances not assumed			−0.923	18.29	0.368	−0.07317	0.07926	−0.23949	0.09315
SGI	Equal variances assumed	2.090	0.159	−0.434	28	0.667	−0.01619	0.03725	−0.09250	0.06012
	Equal variances not assumed			−0.489	27.66	0.629	−0.01619	0.03312	−0.08406	0.05169
DI	Equal variances assumed	2.222	0.147	0.776	28	0.444	1.24883	1.60843	−2.04588	4.54354
	Equal variances not assumed			1.027	18.09	0.318	1.24883	1.21580	−1.30453	3.80219
LEVI	Equal variances assumed	1.888	0.180	1.156	28	0.258	0.01784	0.01543	−0.01378	0.04945
	Equal variances not assumed			1.459	23.05	0.158	0.01784	0.01223	−0.00746	0.04314
SGAI	Equal variances assumed	0.166	0.686	−0.769	28	0.448	−0.03180	0.04135	−0.11650	0.05291
	Equal variances not assumed			−0.760	20.27	0.456	−0.03180	0.04184	−0.11900	0.05540
TATA	Equal variances assumed	0.005	0.945	−0.958	28	0.346	−0.03137	0.03275	−0.09846	0.03573
	Equal variances not assumed			−1.06	27.24	0.297	−0.03137	0.02949	−0.09185	0.02911

Table 3.
Result of *t*-test for the year 2010

Independent sample test

		Levene's test for equality of variances		*t*-test for equality of means					95% confidence interval of the difference	
		F	Sig.	*t*	df	Sig. (2-tailed)	Mean difference	Std. error difference	Lower	Upper
DSRI	Equal variances assumed	1.024	0.320	0.473	28	0.640	22.99427	48.60872	−76.5761	122.5647
	Equal variances not assumed			0.958	23.02	0.348	22.99427	23.99040	−26.6311	72.61970
GMI	Equal variances assumed	0.430	0.517	0.686	28	0.498	0.04584	0.06679	−0.09097	0.18265
	Equal variances not assumed			0.597	6.68	0.570	0.04584	0.07680	−0.13755	0.22922
AQI	Equal variances assumed	0.852	0.364	−0.373	28	0.712	−0.09381	0.25149	−0.60896	0.42134
	Equal variances not assumed			−0.752	23.53	0.460	−0.09381	0.12479	−0.35164	0.16402
SGI	Equal variances assumed	3.621	0.067	2.655	28	0.018	0.03294	0.05032	−0.07014	0.13602
	Equal variances not assumed			2.962	16.37	0.050	0.03294	0.03424	−0.03951	0.10539
DI	Equal variances assumed	0.075	0.786	0.865	28	0.395	0.20665	0.23901	−0.28293	0.69624
	Equal variances not assumed			0.908	8.20	0.390	0.20665	0.22759	−0.31592	0.72923
LEVI	Equal variances assumed	1.033	0.318	0.483	28	0.633	0.48436	1.00326	−1.57073	2.53944
	Equal variances not assumed			0.978	23.01	0.338	0.48436	0.49509	−0.53980	1.50851
SGAI	Equal variances assumed	0.414	0.525	−0.578	28	0.568	−0.05440	0.09404	−0.24702	0.13823
	Equal variances not assumed			−0.705	10.44	0.496	−0.05440	0.07716	−0.22533	0.11653
TATA	Equal variances assumed	0.459	0.503	0.185	28	0.854	0.01566	0.08461	−0.15765	0.18898
	Equal variances not assumed			0.336	27.82	0.739	0.01566	0.04660	−0.07983	0.11

Table 4.
Result of t-test for the year 2011

Independent sample test

		Levene's test for equality of variances		t-test for equality of means						
									95% confidence interval of the difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. error difference	Lower	Upper
DSRI	Equal variances assumed	9.287	0.005	3.527	28	0.026	0.30084	0.57080	−0.86839	1.47007
	Equal variances not assumed			2.560	17.42	0.058	0.30084	0.53768	−0.83149	10.43317
GMI	Equal variances assumed	1.102	0.303	1.663	28	0.107	0.17128	0.10298	−0.03966	0.38222
	Equal variances not assumed			1.691	27.70	0.102	0.17128	0.10130	−0.03633	0.37889
AQI	Equal variances assumed	4.876	0.036	1.315	28	0.199	0.01250	0.00951	−0.00698	0.03197
	Equal variances not assumed			1.376	21.53	0.183	0.01250	0.00908	−0.00637	0.03136
SGI	Equal variances assumed	5.871	0.022	−1.942	28	0.062	−0.13182	0.06787	−0.27083	0.00720
	Equal variances not assumed			−1.852	17.12	0.081	−0.13182	0.07119	−0.28192	0.01829
DI	Equal variances assumed	8.713	0.006	0.003	28	0.997	0.00043	0.12578	−0.25722	0.25808
	Equal variances not assumed			0.003	15.87	0.997	0.00043	0.13272	−0.28110	0.28196
LEVI	Equal variances assumed	0.252	0.620	1.282	28	0.210	0.01093	0.00853	−0.00654	0.02840
	Equal variances not assumed			1.292	27.97	0.207	0.01093	0.00846	−0.00641	0.02827
SGAI	Equal variances assumed	3.047	0.092	1.007	28	0.322	0.63950	0.63475	−0.66072	1.93972
	Equal variances not assumed			1.078	15.22	0.298	0.63950	0.59297	−0.62275	1.90175
TATA	Equal variances assumed	3.595	0.068	−1.511	28	0.142	−0.09121	0.06036	−0.21486	0.03244
	Equal variances not assumed			−1.608	16.72	0.127	−0.09121	0.05672	−0.21102	0.02860

Table 5.
Result of t-test for the year 2012

Independent sample test

		Levene's test for equality of variances		t-test for equality of means						
									95% confidence interval of the difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. error difference	Lower	Upper
DSRI	Equal variances assumed	4.087	0.053	−3.75	28	0.001	−0.73574	0.19579	−1.13680	−0.33469
	Equal variances not assumed			−4.29	27.96	0.000	−0.73574	0.17124	−1.08653	−0.38496
GMI	Equal variances assumed	0.077	0.784	0.618	28	0.541	0.05659	0.09150	−0.13084	0.24402
	Equal variances not assumed			0.634	22.60	0.533	0.05659	0.08929	−0.12830	0.24148
AQI	Equal variances assumed	4.478	0.043	3.525	28	0.001	0.03036	0.00861	0.01272	0.04800
	Equal variances not assumed			2.999	13.17	0.010	0.03036	0.01012	0.00852	0.05220
SGI	Equal variances assumed	2.938	0.098	−1.68	28	0.103	−0.08311	0.04930	−0.18410	0.01788
	Equal variances not assumed			−1.88	27.46	0.070	−0.08311	0.04412	−0.17357	0.00734
DI	Equal variances assumed	7.387	0.011	−2.78	28	0.045	−0.22423	0.12550	−0.48130	0.03284
	Equal variances not assumed			−2.28	21.82	0.033	−0.22423	0.09825	−0.42808	−0.02038
LEVI	Equal variances assumed	1.972	0.171	0.943	28	0.354	0.00705	0.00748	−0.00827	0.02236
	Equal variances not assumed			0.766	11.78	0.459	0.00705	0.00920	−0.01304	0.02714
SGAI	Equal variances assumed	0.312	0.581	0.902	28	0.375	0.10855	0.12034	−0.13796	0.35505
	Equal variances not assumed			0.783	13.89	0.447	0.10855	0.13857	−0.18888	0.40597
TATA	Equal variances assumed	2.004	0.168	−1.56	28	0.128	−0.04367	0.02783	−0.10068	0.01335
	Equal variances not assumed			−1.25	11.45	0.233	−0.04367	0.03469	−0.11965	0.03231

Table 6. Result of t-test for the year 2013

Independent sample test

		Levene's test for equality of variances		t-test for equality of means					95% confidence interval of the difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. error difference	Lower	Upper
DSRI	Equal variances assumed	2.596	0.118	−3.95	28	0.000	−0.67759	0.17122	−1.02831	−0.32687
	Equal variances not assumed			−3.49	14.77	0.003	−0.67759	0.19389	−1.09141	−0.26377
GMI	Equal variances assumed	15.598	0.000	−2.91	28	0.007	−0.53949	0.18488	−0.91819	−0.16079
	Equal variances not assumed			−2.41	11.72	0.033	−0.53949	0.22385	−1.02849	−0.05049
AQI	Equal variances assumed	0.182	0.673	2.426	28	0.022	0.01690	0.00697	0.00263	0.03117
	Equal variances not assumed			2.438	24.13	0.023	0.01690	0.00693	0.00259	0.03120
SGI	Equal variances assumed	0.303	0.587	−0.968	28	0.341	−0.04140	0.04276	−0.12899	0.04620
	Equal variances not assumed			−0.950	22.20	0.352	−0.04140	0.04357	−0.13170	0.04891
DI	Equal variances assumed	4.005	0.055	−1.02	28	0.316	−0.30264	0.29628	−0.90955	0.30427
	Equal variances not assumed			−0.840	11.55	0.418	−0.30264	0.36036	−1.09116	0.48588
LEVI	Equal variances assumed	0.720	0.403	0.311	28	0.758	0.00149	0.00480	−0.00833	0.01132
	Equal variances not assumed			0.345	27.62	0.733	0.00149	0.00433	−0.00738	0.01037
SGAI	Equal variances assumed	1.732	0.199	1.031	28	0.311	0.55672	0.54005	−0.54953	1.66297
	Equal variances not assumed			1.255	18.45	0.225	0.55672	0.44363	−0.37368	1.48711
TATA	Equal variances assumed	0.558	0.461	−2.25	28	0.032	−0.05562	0.02469	−0.10620	−0.00505
	Equal variances not assumed			−2.62	23.82	.015	−0.05562	0.02121	−0.09941	−0.01183

Table 7.
Result of *t*-test for the year 2014

Independent sample test

		Levene's test for equality of variances		*t*-test for equality of means					95% confidence interval of the difference	
		F	Sig.	*t*	df	Sig. (2-tailed)	Mean difference	Std. error difference	Lower	Upper
DSRI	Equal variances assumed	0.084	0.775	−2.49	28	0.046	−1.00017	0.66891	−2.37037	0.37004
	Equal variances not assumed			−2.18	23.31	0.039	−1.00017	0.45747	−1.94580	−0.05453
GMI	Equal variances assumed	0.600	0.445	−2.44	28	0.016	−0.22753	0.15784	−0.55085	0.09579
	Equal variances not assumed			−2.23	26.51	0.034	−0.22753	0.10178	−0.43654	−0.01852
AQI	Equal variances assumed	0.241	0.627	1.249	28	0.222	0.02879	0.02306	−0.01844	0.07602
	Equal variances not assumed			1.696	19.14	0.106	0.02879	0.01698	−0.00673	0.06431
SGI	Equal variances assumed	1.641	0.211	2.141	28	0.041	0.09121	0.04261	0.00392	0.17850
	Equal variances not assumed			2.727	7.715	0.012	0.09121	0.05281	−0.03136	0.21378
DI	Equal variances assumed	1.722	0.200	0.430	28	0.671	0.14375	0.33441	−0.54126	0.82877
	Equal variances not assumed			0.754	25.76	0.458	0.14375	0.19059	−0.24817	0.53568
LEVI	Equal variances assumed	0.343	0.563	1.420	28	0.167	0.00471	0.00332	−0.00208	0.01150
	Equal variances not assumed			1.094	7.411	0.308	0.00471	0.00430	−0.00535	0.01477
SGAI	Equal variances assumed	0.875	0.358	0.459	28	0.650	0.35337	0.77053	−1.22500	1.93174
	Equal variances not assumed			0.833	22.99	0.414	0.35337	0.42435	−0.52449	1.23123
TATA	Equal variances assumed	0.566	0.458	−0.723	28	0.475	−0.02328	0.03218	−0.08919	0.04264
	Equal variances not assumed			−1.01	20.94	0.322	−0.02328	0.02293	−0.07096	0.02441

Table 8. Result of t-test for the year 2015

Independent sample test		Levene's test for equality of variances		t-test for equality of means					95% confidence interval of the difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. error difference	Lower	Upper
DSRI	Equal variances assumed	4.296	0.048	0.114	28	0.910	0.11182	0.98205	−1.89981	2.12345
	Equal variances not assumed			0.182	25.02	0.857	0.11182	0.61334	−1.15132	1.37497
GMI	Equal variances assumed	0.460	0.503	0.162	28	0.873	0.07764	0.47952	−0.90462	1.05989
	Equal variances not assumed			0.251	26.94	0.804	0.07764	0.30909	−0.55664	0.71191
AQI	Equal variances assumed	1.615	0.214	3.267	28	0.021	0.03149	0.02486	−0.01944	0.08242
	Equal variances not assumed			2.004	25.84	0.056	0.03149	0.01571	−0.00082	0.06380
SGI	Equal variances assumed	1.382	0.250	0.507	28	0.616	0.01777	0.03507	−0.05406	0.08961
	Equal variances not assumed			0.455	10.42	0.659	0.01777	0.03908	−0.06883	0.10437
DI	Equal variances assumed	0.169	0.684	1.566	28	0.129	0.09868	0.06301	−0.03039	0.22774
	Equal variances not assumed			1.927	19.94	0.068	0.09868	0.05120	−0.00815	0.20551
LEVI	Equal variances assumed	1.251	0.273	−0.533	28	0.598	−0.03238	0.06075	−0.15682	0.09207
	Equal variances not assumed			−0.890	21.35	0.383	−0.03238	0.03636	−0.10791	0.04316
SGAI	Equal variances assumed	0.217	0.645	0.381	28	0.706	0.01964	0.05149	−0.08584	0.12512
	Equal variances not assumed			0.376	12.11	0.714	0.01964	0.05230	−0.09418	0.13346
TATA	Equal variances assumed	0.274	0.605	−1.00	28	0.322	−0.03745	0.03712	−0.11347	0.03858
	Equal variances not assumed			−1.40	26.35	0.173	−0.03745	0.02674	−0.09237	0.01747

Table 9.
Result of *t*-test for the year 2016

Independent sample test

		Levene's test for equality of variances		*t*-test for equality of means					95% confidence interval of the difference	
		F	Sig.	*t*	df	Sig. (2-tailed)	Mean difference	Std. error difference	Lower	Upper
DSRI	Equal variances assumed	0.036	0.850	−3.30	28	0.003	−1.27017	0.38477	−2.05834	−0.48201
	Equal variances not assumed			−3.76	6.597	0.008	−1.27017	0.33757	−2.07839	−0.46195
GMI	Equal variances assumed	1.052	0.314	0.875	28	0.389	0.12236	0.13980	−0.16401	0.40873
	Equal variances not assumed			0.673	4.764	0.532	0.12236	0.18189	−0.35224	0.59696
AQI	Equal variances assumed	0.279	0.602	0.181	28	0.858	0.01349	0.07457	−0.13926	0.16624
	Equal variances not assumed			0.364	26.64	0.719	0.01349	0.03710	−0.06268	0.08966
SGI	Equal variances assumed	0.021	0.886	−1.34	28	0.189	−0.04278	0.03174	−0.10780	0.02224
	Equal variances not assumed			−1.36	5.798	0.222	−0.04278	0.03130	−0.12001	0.03445
DI	Equal variances assumed	0.812	0.375	0.422	28	0.676	1.34457	3.18704	−5.18379	7.87293
	Equal variances not assumed			0.957	24.02	0.348	1.34457	1.40568	−1.55646	4.24560
LEVI	Equal variances assumed	0.837	0.368	0.458	28	0.650	0.15329	0.33436	−0.53162	0.83819
	Equal variances not assumed			1.040	24.00	0.309	0.15329	0.14744	−0.15102	0.45759
SGAI	Equal variances assumed	0.776	0.386	1.004	28	0.324	0.07436	0.07404	−0.07731	0.22602
	Equal variances not assumed			1.619	13.26	0.129	0.07436	0.04593	−0.02466	0.17338
TATA	Equal variances assumed	0.128	0.723	−2.29	28	0.028	−0.06024	0.04670	−0.15590	0.03541
	Equal variances not assumed			−2.23	16.75	0.039	−0.06024	0.02693	−0.11711	−0.00337

Table 10. Result of t-test for the year 2017

Independent sample test

		Levene's test for equality of variances		t-test for equality of means						
									95% confidence interval of the difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. error difference	Lower	Upper
DSRI	Equal variances assumed	2.580	0.119	−4.15	28	0.000	−0.85517	0.20604	−1.27722	−0.43312
	Equal variances not assumed			−3.37	10.42	0.007	−0.85517	0.25364	−1.41723	−0.29311
GMI	Equal variances assumed	1.576	0.220	−0.710	28	0.483	−0.27153	0.38231	−1.05465	0.51159
	Equal variances not assumed			−1.07	22.25	0.296	−0.27153	0.25374	−0.79741	0.25436
AQI	Equal variances assumed	12.222	0.002	−1.44	28	0.159	−0.41533	0.28717	−1.00357	0.17292
	Equal variances not assumed			−0.924	8.003	0.382	−0.41533	0.44929	−1.45132	0.62067
SGI	Equal variances assumed	0.000	0.989	−0.700	28	0.490	−0.02386	0.03409	−0.09368	0.04597
	Equal variances not assumed			−0.744	17.56	0.467	−0.02386	0.03206	−0.09133	0.04362
DI	Equal variances assumed	3.615	0.068	0.545	28	0.590	0.04604	0.08447	−0.12698	0.21906
	Equal variances not assumed			0.391	8.918	0.705	0.04604	0.11786	−0.22094	0.31303
LEVI	Equal variances assumed	0.775	0.386	−0.210	28	0.835	−0.00076	0.00360	−0.00814	0.00662
	Equal variances not assumed			−0.263	25.97	0.795	−0.00076	0.00288	−0.00667	0.00516
SGAI	Equal variances assumed	6.498	0.017	0.475	28	0.639	0.02042	0.04302	−0.06770	0.10853
	Equal variances not assumed			0.617	27.45	0.542	0.02042	0.03307	−0.04739	0.08822
TATA	Equal variances assumed	0.315	0.579	−0.937	28	0.357	−0.03129	0.03341	−0.09972	0.03713
	Equal variances not assumed			−1.26	27.99	0.215	−0.03129	0.02469	−0.08187	0.01928

Table 11.
Result of *t*-test for the year 2018

Independent sample test		Levene's test for equality of variances		*t*-test for equality of means					95% confidence interval of the difference	
		F	Sig.	*t*	df	Sig. (2-tailed)	Mean difference	Std. error difference	Lower	Upper
DSRI	Equal variances assumed	1.516	0.229	−6.21	28	0.000	−0.87452	0.14063	−1.16259	−0.58645
	Equal variances not assumed			−5.24	9.580	0.000	−0.87452	0.16683	−1.24848	−0.50057
GMI	Equal variances assumed	2.316	0.139	−0.779	28	0.443	−0.12357	0.15865	−0.44855	0.20140
	Equal variances not assumed			−1.25	24.53	0.221	−0.12357	0.09845	−0.32652	0.07938
AQI	Equal variances assumed	0.290	0.595	2.767	28	0.028	0.01496	0.00847	−0.00239	0.03230
	Equal variances not assumed			2.062	17.45	0.054	0.01496	0.00725	−0.00031	0.03023
SGI	Equal variances assumed	0.756	0.392	−0.363	28	0.719	−0.01673	0.04607	−0.11111	0.07764
	Equal variances not assumed			−0.339	11.05	0.741	−0.01673	0.04940	−0.12539	0.09192
DI	Equal variances assumed	1.561	0.222	−0.173	28	0.864	−0.01474	0.08496	−0.18877	0.15930
	Equal variances not assumed			−0.279	24.63	0.782	−0.01474	0.05279	−0.12354	0.09407
LEVI	Equal variances assumed	0.114	0.738	−0.469	28	0.643	−0.00201	0.00429	−0.01080	0.00677
	Equal variances not assumed			−0.585	20.64	0.565	−0.00201	0.00344	−0.00917	0.00515
SGAI	Equal variances assumed	0.128	0.723	−0.294	28	0.771	−0.01110	0.03771	−0.08834	0.06615
	Equal variances not assumed			−0.283	11.64	0.782	−0.01110	0.03919	−0.09677	0.07458
TATA	Equal variances assumed	2.093	0.159	−0.817	28	0.421	−0.05456	0.06681	−0.19141	0.08228
	Equal variances not assumed			−1.34	22.94	0.193	−0.05456	0.04068	−0.13872	0.02960

DSRI, GMI and AQI significantly vary between the groups. Table 7 states the results of the year 2014, and it displays that DSRI, GMI and SGI significantly vary between groups. The results of 2015 tell that only AQI is significant between groups. In Table 9, the results ensure that DSRI and TATA are significant in terms of statistical tests. DSRI has a p-value of .000, indicating the significant variation between the groups in Table 10. Results of AQI and DSRI in 2018 portray significant variation, and other ratios do not differ between them. According to the statistical test, the difference between the groups of the same ratio denotes the financial manipulations using those variables.

4.3 Interpretation of findings

This research tries to determine the number of listed banks involved in manipulation. From the calculated result, the intention to falsify the financial information does not have any constant increasing or decreasing trend. The pattern of manipulation in the banks of Bangladesh is fluctuating. However, the average rate of likely manipulator banks is high around 68.88% over the ten years.

The next part of the analysis portrays the result of an independent sample t-test to figure out the governing variables for misstating information. Data are divided into two groups based on M-score over ten years yearly. However, 2009–2018 shows that DSRI, SGI, AQI, DI, GMI and TATA variables have significant results. The significance level is not the same over time. In 2009, DSRI gave a significant result, but in 2010, SGI depicted significant variation between the groups. From the ten-year data, DSRI gives eight times the significant result, AQI gives four times, SGI and GMI provide two times, and DI and TATA ensure one-time significant results. Banks use DSRI variables that mean interest income and balance with other financial institutions as their main manipulation item. Inflated revenues and disproportionate balance with others denote a higher increase in DSRI (Warshavsky, 2012). As the results of this study ensure some balances are available with others, this may be the reason for inflated revenues over time.

The second manipulating item is SGI, which measures the sales growth index. However, sales growth is good for the company and should be consistent with the operating cash flow for a certain time. The next AQI that deals with the asset quality and increase in AQI expects to weaken the quality of assets portrayed in the financial statement. The high asset index denotes an increase in intangible assets without proper justification of recognition, and sometimes, firms use the increase of cost deferral to increase this asset quality index (Warshavsky, 2012).

Depreciation is one of the easiest ways to falsify information as it is a noncash item. DI has a direct connection with the asset quality of any firm. GMI is related to the revenues and direct cost of earning those revenues. It indicates the actual growth of a company, and research says that high-growth companies engage themselves in earnings manipulation. TATA is the common form of making or providing misleading information. It is concluded that a higher amount of accruals signs accounting manipulation.

4.4 Discussion

Investigating the quality of earnings is an important element of the company's financial statement. This importance is increasing due to the fall of some big companies worldwide for manipulating their earnings. The Beneish model can find the fraudulent report-making firm through its yardstick score and the eight variables (Beneish, 1999). This research tries to identify the number of manipulators and nonmanipulation-listed banks in Bangladesh from 2009 to 2018. Data are collected for 11 years to calculate the ten-year ratio as the ratio needs previous year information. The first phase of calculation shows that the numbers of manipulator banks are high in percentage. However, the manipulations in banks do not have any constant trend but rather have an unstable increasing and decreasing trend. In addition, on average, 68.88% of listed banks are engaged in earnings manipulation in Bangladesh.

The *t*-test helped determine the most persuasive ratios or how variable banks manipulated each year in these ten years took time. In the first year (2009), most banks used inflated revenues and embezzled balances with others (receivables) as their earnings mismatch. Moreover, in these ten years, banks mostly used revenues and receivables to deflate the actual scenario of financial reports. Asset quality index is the other element of manipulation. When the index of asset quality increases, this denotes misleading asset valuation as the increase intangible asset so frequently is not a sign of a trustworthy report. Cost deferral is also related to asset quality and is an easy item for misstating financial information. Sales growth index and gross margin are both related to revenues. Sales growth is a positive sign for banks, and excessive growth also raises questions.

Moreover, when the growth rate is excessively high than the competitors, it denotes the unsound mentality of the concerned organization. Gross margin growth denotes the increase in revenue in high percentage and decreases in cost in high percentage. Understating costs can be an option for inflating the amount of revenue. Lastly, total accruals are the recognized medium to manipulate. However, banks useless this item for their manipulation, which is found in the *t*-test result. Only in one year the value of p of TATA is institute significant, indicating significant variation between the groups.

This study has several policy implications. First, as the use of accruals is one of the predominant reasons of earnings manipulation in the banking industry, the Bangladesh Bank, the Central Bank of Bangladesh and the regulator of the money market, should be stricter on loan rescheduling and recognition of poor investment as an interest income. Second, investments in intangible assets should be shown in the cost price in the financial statement, which will help to avoid the overstatement of intangible assets. Finally, the regulators should impose more regulations on credit assessment and credit follow-up to reduce the NPLs in the banking sector of Bangladesh.

5. Conclusion

This research aims to identify the likely and not-likely manipulator banks in Bangladesh. Moreover, to determine the most influential ratios or variables among the eight ratios of the Beneish model through an independent sample *t*-test using SPSS. The management body is the key personnel to decide on the organization. Their intention of using earnings management for giving misled information will emerge when they feel deprived. Optimizing management needs is one of the main reasons for making materially misstated data as management has some discretionary power to control the organization. The code of corporate governance will act as a solution here. Different corporate appliances of the corporate governance code create accountability issues in management activities (Tassadaq & Malik, 2015). Management accountability will increase when the company ensures auditors' independence and increases the number of outside directors.

Moreover, the strong ethical and moral values of people involved in preparing and disclosing financial information is essential to lessen the manipulation of financial numbers; thus, the quality of financial report will accelerate. The present study only took banks as their sample. Therefore, overall, the financial sector is not included here. The next study may incorporate the nonbank financial institutions to formalize the manipulation behavior of the financial sector of Bangladesh. No corporate governance indicator impact is not considered here, and further study may try to find the mediation or moderator effect of governance variable in making misleading information.

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Appendix

Group statistics of eight indicators of M-score model

Serial	N	Minimum	Maximum	Mean	Std. deviation
1	10	−3.04	−2.06	−2.5814	0.35423
2	10	−2.79	−1.58	−2.2510	0.43086
3	10	−3.45	6.13	−1.6261	2.83577
4	10	−2.85	1.40	−1.8905	1.26803
5	10	−3.52	−0.92	−2.2969	0.84367
6	10	−3.24	−1.14	−2.4144	0.60587
7	10	−3.41	1.29	−2.0152	1.32040
8	10	−2.99	−1.45	−2.3035	0.53440
9	10	−3.51	0.41	−2.0747	1.27746
10	10	−3.42	0.77	−2.1888	1.19835
11	10	−6.91	0.48	−4.0711	2.03871
12	10	−3.58	0.36	−2.2460	1.04476
13	10	−7.25	−1.87	−2.8582	1.57963
14	10	−4.07	−1.70	−2.8486	0.75177
15	10	−3.43	1.11	−2.1907	1.38028
16	10	−3.60	−1.31	−2.4571	0.76081
17	10	−3.29	−0.56	−2.2962	0.82311
18	10	−3.26	0.94	−1.8820	1.47741
19	10	−3.20	−1.04	−2.2985	0.67837
20	10	−3.27	1.40	−1.8892	1.43707
21	10	−3.21	−1.52	−2.4529	0.50180
22	10	−4.27	0.63	−2.5612	1.25942
23	10	−4.17	526.57	50.3891	167.31541
24	10	−5.62	1.52	−1.9102	1.91271
25	10	−3.30	−1.00	−2.3095	0.62478
26	10	−3.18	−1.59	−2.3498	0.51187
27	10	−3.42	−0.74	−2.2047	0.83566
28	10	−3.44	0.74	−1.8773	1.29217
29	10	−3.46	5.11	−1.7804	2.46611
30	10	−3.49	3.98	−1.1198	2.77909

Table A1. Descriptive statistics of M-score sample wise

Table A2.
Group statistics for the year 2009

Group statistics

Group		N	Mean	Std. deviation	Std. error mean
DSRI	Likely manipulator	19	1.4651731	1.68152547	0.38576840
	Nonlikely manipulator	11	1.6421791	0.46515207	0.14024863
GMI	Likely manipulator	19	0.9925250	0.25138864	0.05767251
	Nonlikely manipulator	11	1.0644043	0.22743011	0.06857276
AQI	Likely manipulator	19	0.9260245	0.34405400	0.07893140
	Nonlikely manipulator	11	0.9991952	0.02388158	0.00720057
SGI	Likely manipulator	19	1.1831999	0.11086330	0.02543379
	Nonlikely manipulator	11	1.1993855	0.07034427	0.02120959
DI	Likely manipulator	19	2.2187949	5.29266845	1.21422142
	Nonlikely manipulator	11	0.9699650	0.20563235	0.06200049
LEVI	Likely manipulator	19	1.0067628	0.04957634	0.01137359
	Nonlikely manipulator	11	0.9889234	0.01491680	0.00449758
SGAI	Likely manipulator	19	1.0935106	0.10745752	0.02465245
	Nonlikely manipulator	11	1.1253090	0.11211804	0.03380486
TATA	Likely manipulator	19	−0.0097554	0.09646591	0.02213080
	Nonlikely manipulator	11	0.0216118	0.06463568	0.01948839

Table A3.
Group statistics for the year 2010

Group statistics

Group		N	Mean	Std. deviation	Std. error mean
DSRI	Likely manipulator	24	24.7467	117.50180	23.98496
	Nonlikely manipulator	6	1.7524	1.25183	0.51106
GMI	Likely manipulator	24	0.8164	0.13939	0.02845
	Nonlikely manipulator	6	0.7705	0.17474	0.07134
AQI	Likely manipulator	24	0.9087	0.60773	0.12405
	Nonlikely manipulator	6	1.0025	0.03326	0.01358
SGI	Likely manipulator	24	1.2017	0.11845	0.02418
	Nonlikely manipulator	6	1.1687	0.05938	0.02424
DI	Likely manipulator	24	1.2701	0.53061	0.10831
	Nonlikely manipulator	6	1.0635	0.49031	0.20017
LEVI	Likely manipulator	24	1.4736	2.42519	0.49504
	Nonlikely manipulator	6	0.9892	0.01790	0.00731
SGAI	Likely manipulator	24	1.2009	0.21548	0.04398
	Nonlikely manipulator	6	1.2552	0.15529	0.06339
TATA	Likely manipulator	24	−0.0045	0.20308	0.04145
	Nonlikely manipulator	6	−0.0202	0.05216	0.02129

Group statistics Group		N	Mean	Std. deviation	Std. error mean
DSRI	Likely manipulator	16	1.6123	2.06779	0.51695
	Nonlikely manipulator	14	1.3114	0.55332	0.14788
GMI	Likely manipulator	16	1.3360	0.31046	0.07762
	Nonlikely manipulator	14	1.1647	0.24358	0.06510
AQI	Likely manipulator	16	0.9825	0.03268	0.00817
	Nonlikely manipulator	14	0.9700	0.01486	0.00397
SGI	Likely manipulator	16	1.3912	0.10586	0.02646
	Nonlikely manipulator	14	1.5230	0.24727	0.06608
DI	Likely manipulator	16	1.0559	0.16770	0.04192
	Nonlikely manipulator	14	1.0554	0.47115	0.12592
LEVI	Likely manipulator	16	1.0089	0.02445	0.00611
	Nonlikely manipulator	14	0.9980	0.02191	0.00585
SGAI	Likely manipulator	16	1.4760	2.36301	0.59075
	Nonlikely manipulator	14	0.8365	0.19146	0.05117
TATA	Likely manipulator	16	−0.1089	0.22055	0.05514
	Nonlikely manipulator	14	−0.0177	0.04972	0.01329

Table A4. Group statistics for the year 2011

Group statistics Group		N	Mean	Std. deviation	Std. error mean
DSRI	Likely manipulator	11	0.7365	0.34775	0.10485
	Nonlikely manipulator	19	1.4723	0.59012	0.13538
GMI	Likely manipulator	11	1.1447	0.22772	0.06866
	Nonlikely manipulator	19	1.0881	0.24884	0.05709
AQI	Likely manipulator	11	1.0094	0.03124	0.00942
	Nonlikely manipulator	19	0.9791	0.01618	0.00371
SGI	Likely manipulator	11	1.2702	0.09531	0.02874
	Nonlikely manipulator	19	1.3533	0.14592	0.03348
DI	Likely manipulator	11	0.9346	0.10422	0.03142
	Nonlikely manipulator	19	1.1589	0.40576	0.09309
LEVI	Likely manipulator	11	1.0198	0.02926	0.00882
	Nonlikely manipulator	19	1.0128	0.01140	0.00262
SGAI	Likely manipulator	11	0.9509	0.42123	0.12701
	Nonlikely manipulator	19	0.8424	0.24159	0.05543
TATA	Likely manipulator	11	−0.0573	0.11112	0.03350
	Nonlikely manipulator	19	−0.0136	0.03918	0.00899

Table A5. Group statistics for the year 2012

Table A6.
Group statistics for the year 2013

Group statistics Group		N	Mean	Std. deviation	Std. error mean
DSRI	Likely manipulator	18	0.8740	0.31314	0.07381
	Nonlikely manipulator	12	1.5516	0.62107	0.17929
GMI	Likely manipulator	18	1.1500	0.16906	0.03985
	Nonlikely manipulator	12	1.6895	0.76305	0.22027
AQI	Likely manipulator	18	1.0079	0.01887	0.00445
	Nonlikely manipulator	12	0.9910	0.01842	0.00532
SGI	Likely Manipulator	18	1.0650	0.11054	0.02605
	Nonlikely manipulator	12	1.1064	0.12096	0.03492
DI	Likely manipulator	18	0.9350	0.23971	0.05650
	Nonlikely manipulator	12	1.2376	1.23290	0.35591
LEVI	Likely manipulator	18	1.0020	0.01497	0.00353
	Nonlikely manipulator	12	1.0005	0.00869	0.00251
SGAI	Likely manipulator	18	1.5361	1.84258	0.43430
	Nonlikely manipulator	12	0.9794	0.31355	0.09051
TATA	Likely manipulator	18	−0.0636	0.08106	0.01911
	Nonlikely manipulator	12	−0.0080	0.03190	0.00921

Table A7.
Group statistics for the year 2014

Group statistics Group		N	Mean	Std. deviation	Std. error mean
DSRI	Likely manipulator	23	1.2732	1.70209	0.35491
	Nonlikely manipulator	7	2.2734	0.76369	0.28865
GMI	Likely manipulator	23	0.7462	0.40498	0.08444
	Nonlikely manipulator	7	0.9737	0.15031	0.05681
AQI	Likely Manipulator	23	1.0139	0.05796	0.01208
	Nonlikely manipulator	7	0.9851	0.03155	0.01192
SGI	Likely manipulator	23	1.0573	0.08786	0.01832
	Nonlikely manipulator	7	0.9661	0.13104	0.04953
DI	Likely manipulator	23	1.1437	0.87026	0.18146
	Nonlikely manipulator	7	1.0000	0.15415	0.05826
LEVI	Likely manipulator	23	1.0024	0.00658	0.00137
	Nonlikely manipulator	7	0.9977	0.01079	0.00408
SGAI	Likely manipulator	23	1.5180	2.01183	0.41950
	Nonlikely manipulator	7	1.1646	0.16934	0.06400
TATA	Likely manipulator	23	−0.0460	0.08135	0.01696
	Nonlikely manipulator	7	−0.0227	0.04080	0.01542

Group statistics Group		N	Mean	Std. Deviation	Std. Error mean
DSRI	Likely manipulator	22	1.9991	2.72816	0.58165
	Nonlikely manipulator	8	1.8873	0.55049	0.19463
GMI	Likely manipulator	22	1.2180	1.32545	0.28259
	Nonlikely manipulator	8	1.1404	0.35422	0.12524
AQI	Likely manipulator	22	1.0290	0.06894	0.01470
	Nonlikely manipulator	8	0.9975	0.01571	0.00555
SGI	Likely manipulator	22	1.0032	0.07945	0.01694
	Nonlikely manipulator	8	0.9854	0.09962	0.03522
DI	Likely manipulator	22	1.0050	0.16548	0.03528
	Nonlikely manipulator	8	0.9063	0.10496	0.03711
LEVI	Likely manipulator	22	0.9679	0.16982	0.03621
	Nonlikely manipulator	8	1.0003	0.00942	0.00333
SGAI	Likely manipulator	22	1.1208	0.12370	0.02637
	Nonlikely manipulator	8	1.1012	0.12773	0.04516
TATA	Likely manipulator	22	−0.0604	0.10046	0.02142
	Nonlikely manipulator	8	−0.0229	0.04526	0.01600

Table A8. Group statistics for the year 2015

Group statistics Group		N	Mean	Std. deviation	Std. error mean
DSRI	Likely manipulator	25	1.2004	0.80390	0.16078
	Nonlikely manipulator	5	2.4706	0.66371	0.29682
GMI	Likely manipulator	25	0.8564	0.26413	0.05283
	Nonlikely manipulator	5	0.7341	0.38918	0.17405
AQI	Likely manipulator	25	0.9841	0.16363	0.03273
	Nonlikely manipulator	5	0.9706	0.03907	0.01747
SGI	Likely manipulator	25	0.9913	0.06498	0.01300
	Nonlikely manipulator	5	1.0341	0.06366	0.02847
DI	Likely manipulator	25	2.3347	7.02671	1.40534
	Nonlikely manipulator	5	0.9901	0.06888	0.03080
LEVI	Likely manipulator	25	1.1559	0.73719	0.14744
	Nonlikely manipulator	5	1.0026	0.00210	0.00094
SGAI	Likely manipulator	25	1.1614	0.16047	0.03209
	Nonlikely manipulator	5	1.0870	0.07346	0.03285
TATA	Likely manipulator	25	−0.0536	0.10169	0.02034
	Nonlikely manipulator	5	0.0067	0.03946	0.01765

Table A9. Group statistics for the year 2016

Table A10.
Group statistics for the year 2017

Group statistics Group		N	Mean	Std. deviation	Std. error mean
DSRI	Likely manipulator	21	0.9127	0.41519	0.09060
	Nonlikely manipulator	9	1.7679	0.71072	0.23691
GMI	Likely manipulator	21	0.6686	1.12964	0.24651
	Nonlikely manipulator	9	0.9402	0.18051	0.06017
AQI	Likely manipulator	21	1.0156	0.02845	0.00621
	Nonlikely manipulator	9	1.4309	1.34774	0.44925
SGI	Likely manipulator	21	1.0851	0.08890	0.01940
	Nonlikely manipulator	9	1.1089	0.07658	0.02553
DI	Likely manipulator	21	0.9654	0.12487	0.02725
	Nonlikely manipulator	9	0.9194	0.34399	0.11466
LEVI	Likely manipulator	21	1.0067	0.01011	0.00221
	Nonlikely manipulator	9	1.0074	0.00554	0.00185
SGAI	Likely manipulator	21	1.0214	0.12225	0.02668
	Nonlikely manipulator	9	1.0010	0.05864	0.01955
TATA	Likely manipulator	21	−0.0584	0.09607	0.02096
	Nonlikely manipulator	9	−0.0271	0.03912	0.01304

Table A11.
Group statistics for the year 2018

Group statistics Group		N	Mean	Std. deviation	Std. error mean
DSRI	Likely manipulator	22	0.8399	0.30262	0.06452
	Nonlikely manipulator	8	1.7144	0.43517	0.15385
GMI	Likely manipulator	22	0.9609	0.44117	0.09406
	Nonlikely manipulator	8	1.0845	0.08221	0.02907
AQI	Likely manipulator	22	0.9959	0.02188	0.00466
	Nonlikely manipulator	8	0.9809	0.01571	0.00555
SGI	Likely manipulator	22	1.2534	0.10719	0.02285
	Nonlikely manipulator	8	1.2701	0.12387	0.04380
DI	Likely manipulator	22	0.9457	0.23622	0.05036
	Nonlikely manipulator	8	0.9604	0.04475	0.01582
LEVI	Likely manipulator	22	1.0029	0.01131	0.00241
	Nonlikely manipulator	8	1.0049	0.00693	0.00245
SGAI	Likely manipulator	22	0.8677	0.08944	0.01907
	Nonlikely manipulator	8	0.8788	0.09684	0.03424
TATA	Likely manipulator	22	−0.0908	0.18629	0.03972
	Nonlikely manipulator	8	−0.0362	0.02484	0.00878

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