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Earnings manipulation in Bangladeshi listed firms: Sectoral patterns, Covid-19 anomalies, and discriminant reliability of the Beneish M-Score

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This study examines the sectoral prevalence of earnings manipulation and evaluates the discriminant reliability of the Beneish M-Score model in Bangladeshi listed firms. Using financial statement data from 127 companies across 12 sectors over the period 2018 to 2022, the Beneish M Score is applied to identify potential manipulation, producing 635 firm-year observations. The results show that earnings manipulation is unevenly distributed across sectors, with an overall prevalence of 20%. Engineering and Miscellaneous sectors exhibit the highest susceptibility, while Pharmaceuticals and Ceramics display relatively lower manipulation levels. Volatile patterns in Travel & Leisure and Food & Allied sectors indicate sensitivity to economic shocks and industry-specific pressures. The study further identifies a methodological shift in manipulation tactics during the COVID-19 pandemic (2020–2022). While the market-wide frequency of manipulation remained statistically stable, the pandemic period introduced distinctive anomalies characterized by a significant rise in the Days' Sales in Receivables Index (DSRI) and a significant decline in Total Accruals to Total Assets (TATA), indicating a tactical pivot toward aggressive revenue recognition alongside increased use of income-deferral accrual adjustments to obscure the true impact of economic shocks. Linear Discriminant Analysis identifies TATA (Total Accruals to Total Assets), GMI (Gross Margin Index), DEPI (Depreciation Index), SGI (Sales Growth Index), and DSRI (Days' Sales in Receivables Index) as significant variables separating manipulation and non-manipulation firms, with Total Accruals to Total Assets emerging as the most influential indicator. Classification evaluation shows that the model correctly identifies 98.8% of non-manipulation firms and 71.9% of manipulation firms, with validation accuracy consistently between 91% and 93% across cross-validation and temporal holdout testing. The findings suggest that the Beneish M Score functions as a reliable screening tool in the Bangladeshi context, while sectoral differences highlight the need for targeted regulatory monitoring.

1. Introduction

Financial fraud and earnings manipulation pose serious threats to the global financial system by undermining market integrity and eroding stakeholder confidence. The issue of earnings manipulation is especially acute in frontier markets where regulatory frameworks and corporate governance systems remain underdeveloped (Del Sarto and Ozili, 2025). As Parvin (2020) indicates, the outcome of these manipulative practices is deceptive financial disclosures that ultimately hurt the interests of investors and undermine trust in financial institutions. According to the Association of Certified Fraud Examiners (2024), the world loses more than 5 trillion dollars to financial fraud every year. According to Hilal, Gadsden and Yawney (2021), financial fraud detection is becoming more challenging since fraudsters exploit weaknesses within existing regulatory controls. This problem is highly relevant to frontier economies like Bangladesh because financial institutions and corporations often operate with limited monitoring tools and evolving regulatory systems (Arman and Sharmin, 2019).

In Bangladesh, financial fraud has received attention following the Hallmark–Sonali Bank loan scam and irregularities in non-banking financial institutions such as People's Leasing and Financial Services Limited. Moreover, other incidents, including the Bismillah Group loan scam, NRB Commercial Bank irregularities, First Leasing Finance and Investment Limited, and the Janata Bank–Crescent Group loan fraud, have reinforced concerns regarding financial reporting reliability (The Daily Star, 2024). The examples cited above highlight the need to establish reliable analytical techniques for detecting manipulation in financial reporting. The Beneish M Score model is a statistical approach that uses financial ratios to estimate the likelihood of earnings manipulation (Beneish, 1999). It's been used to detect earnings manipulations in the Bangladeshi market. But most of the studies focused on a specific sector, and no comprehensive study has mapped the sectoral prevalence of earnings manipulation across Bangladeshi industries, leaving regulators without evidence-based guidance on high-risk sectors.

The objective of this research is to address this gap by examining the sectoral prevalence and characteristics of earnings manipulation among Bangladeshi listed firms. Moreover, the study tries to find out which variables drive the separation between manipulation and non-manipulation firms and the classification reliability of the Beneish M Score model in a frontier market setting. Primarily, this study attempts to answer the following question: What evidence of earnings manipulation exists across different industries in Bangladesh, and how effectively does the Beneish M Score detect and classify manipulation while identifying the variables that drive the separation between manipulation and non-manipulation firms?

This research investigates financial statement manipulation in Bangladeshi companies using the Beneish M Score model. The paper examines earnings manipulation in Bangladesh by applying the Beneish M Score model to 127 firms in 12 industries from 2018 to 2022. The study further evaluates the discriminant reliability and classification accuracy of the Beneish M Score in distinguishing manipulation and non-manipulation firms using linear discriminant analysis supported by cross-validation and confusion matrix evaluation. It also identifies the key financial ratios influencing earnings manipulation by analyzing the relative contribution of the Beneish M Score components to group separation and compares classification stability across validation procedures. Besides, it evaluates the effectiveness of the Beneish M Score model in identifying fraud in the Bangladeshi context.

The study has several implications. First, it offers a cross-sectoral analysis of earnings manipulation trends, which can be useful for understanding specific industries' weaknesses for policymakers and regulators. Second, it identifies the major financial factors associated with manipulation to help companies and auditors enhance monitoring systems. Third, the evaluation of classification performance provides evidence for adopting data-driven analytical techniques in large and complex financial reporting environments. Considering the research limitations of prior studies and the practical implications of this work, this study benefits academia, corporate governance, and policymaking to enhance the identification of financial fraud and improve transparency in frontier economies. The paper is organized as follows: Section 2 reviews the literature; Section 3 details the methodology; Section 4 presents findings on sectoral prevalence, classification accuracy, and COVID-19 anomalies; Section 5 discusses policy implications and concludes the study.

2. Literature overview

2.1 Earnings manipulation evidence in Bangladesh

The use of the Beneish M-Score model has recently been adopted in Bangladesh as a tool for analyzing earnings manipulation and financial fraud. Early firm-level evidence appears in the textile industry. Sakib (2019) examines 13 listed textile firms using data from 2012 to 2018 and reports widespread manipulation behavior. Most companies repeatedly crossed the manipulation threshold, and 7 firms remained manipulators throughout all observed years. The study links manipulation mainly to abnormal growth in receivables, weak cash backing behind reported income, and cost deferral. The rising Days Sales in Receivables Index and Asset Quality Index suggest that revenue inflation and expense capitalization were common techniques. The findings imply persistent reporting pressure in the textile sector and weak monitoring capacity.

Manufacturing sector analysis provides broader cross-industry insight. Parvin (2020) studies 105 manufacturing companies across multiple industries and finds that about 39 percent of firms are likely manipulators. However, sectoral variation is strong. Cement paper, printing, and jute sectors show extremely high manipulation rates, while ceramics, fuel, and power show relatively lower levels. The results indicate that earnings manipulation depends on industry structure and operating characteristics rather than firm presence alone. The study also notes that the Beneish model identifies likelihood rather than confirmed fraud, which limits its interpretive certainty.

Banking sector studies reveal unstable patterns rather than continuous manipulation. Khatun Ghosh and Kabir (2022) analyze 30 listed banks from 2009 to 2018 and observe large year-to-year fluctuations in manipulation probability. The share of likely manipulators ranges from about 36 percent to more than 80 percent across different years. Receivables manipulation appears most dominant as the DSRI variable becomes significant in most years, while accruals and asset quality become important only in selected periods. This suggests banks adjust their techniques over time in response to regulation and audit pressure.

Power sector evidence shows moderate but persistent manipulation. Sharif and Asfakuzzaman (2023) analyze 22 listed power companies from 2014 to 2020 and find that around 30 percent of firms engage in manipulation. Importantly, many manipulators still receive unqualified audit opinions, which signal audit detection limitations. The study further finds that accrual quality is positively related to manipulation, while firm size and audit quality reduce it, indicating that governance strength matters.

Pharmaceutical sector findings indicate repeated manipulation patterns. Mollah and Sakib (2020) studied 14 pharmaceutical firms from 2014 to 2018 and reported that most firms manipulate earnings continuously across several years. In many observed years, almost all companies cross the manipulation threshold. The authors interpret this as deteriorating financial conditions and pressure to maintain performance reporting.

A broader market-wide assessment is presented by Arman and Sharmin (2019), who examine 105 non-financial listed firms. Using the standard cutoff, they identify many suspected manipulators and later connect manipulation likelihood with firm-specific characteristics through a logistic model. Their findings reinforce that manipulation risk exists across the market rather than within isolated industries.

2.2 Significant Beneish M-score variables in detecting earnings manipulation

Several studies identify receivable-related measures and accruals as the most influential indicators. Septiani, Musyarofah, and Yuliana (2020) apply discriminant analysis and report that DSRI, GMI, AQI, DPI, and TATA significantly separate manipulators from non-manipulators, with DSRI emerging as the dominant variable. Similar evidence appears in Malaysian firms, where Aqilah, Mohammed, and Kamaluddin (2021) find SGI, TATA, and DSRI significantly different between groups. These results imply that revenue inflation and accrual-based accounting choices remain the primary mechanisms through which managers alter reported performance.

Evidence from India supports this pattern. Shah, Saraswat, and Mehta (2018) find DSRI, SGI, and TATA to be the strongest predictors of manipulation, suggesting that rapid sales growth and disproportionate receivables are key warning signals. Repousis (2016) also reports DSRI as the variable explaining the largest share of variation in manipulation likelihood. Across these studies, a common logic appears. Managers rarely change profits directly. Instead, they adjust the timing of revenue recognition and accrual accounting, and these actions are captured through receivable growth and accrual intensity.

However, other studies contradict this dominance. Tarjo and Herawati (2015) show that GMI, DEPI, SGAI, and TATA are significant, while DSRI is not statistically important. Alfian and Triani (2019) report low classification accuracy and find that several Beneish variables have no significant effect in identifying fraud. Lotfi and Chadegani (2017) similarly conclude that the model performs poorly in distinguishing fraudulent firms in some markets. These findings indicate that the predictive contribution of each ratio is context dependent and influenced by accounting practices, regulatory enforcement, and industry structure.

2.3 Classification accuracy of the Beneish M-score model

The literature assessing the accuracy of the Beneish M Score does not provide a uniform conclusion. Some studies report relatively high predictive accuracy. Septiani, Musyarofah, and Yuliana (2020) find that the model correctly detects manipulation in about 89.5% of observations when discriminant analysis is applied to banking financial statements. Tarjo and Herawati (2015) also report acceptable performance, where classification accuracy reaches about 77.1% for fraudulent firms and 80% for non-fraudulent firms. These findings suggest that the model can function as a screening device when manipulation follows recognizable accrual-based patterns.

Moderate accuracy is reported in other markets. Repousis (2016) identifies about 33% of firms as likely manipulators in a large sample and finds several variables statistically associated with manipulation behavior. Shah, Saraswat, and Mehta

(2018) detect manipulation in nearly 20% of listed companies and show meaningful financial reporting differences between groups. These results imply that the model can identify suspicious firms but does not necessarily provide precise classification.

However, several studies show weak performance. Alfian and Triani (2019) report that only 50.91% of manipulator firms and 60% of non-manipulator firms are correctly classified, indicating high misclassification risk. Evidence from emerging markets is also inconsistent. One study, summarized by Lotfi and Chadegani (2017) shows about 51% correct identification of fraud firms and 60% for non-fraud firms, while another context reports roughly 66% overall accuracy but still concludes the model is unreliable for fraud detection. These results indicate that the model may generate many false signals.

3. Methodology

3.1 Research design summary

The study is grounded in the positivist epistemology and realist ontology, which assumes that financial fraud is a definite phenomenon that can be measured with the assistance of observable information. The manipulation of earnings in the Bangladesh companies is analyzed based on financial statements and the DSE notices. The study follows a quantitative design and uses secondary data of 127 companies across 12 industries, which renders the approach systematic, data-based, and suitable to determine industry-level trends in earnings manipulation.

3.2 Data and sample construction

To analyze the prevalence of earnings manipulation across different industries, the study calculates the Beneish M-Score for 127 companies over the period 2018–2022, yielding 635 firm-year observations. While raw financial data were collected from 2017 to 2022 to enable year-over-year ratio calculations, M-Scores are computed for 2018–2022 as they require lagged values from the prior year. The following list shows the distribution of sample industries and the number of companies.

Table-1 Distribution of sample

Sector	Number of companies
Textile	28
Pharmaceuticals & Chemicals	24
Engineering	21
Fuel & Power	13
It Sector	8
Cement	7
Miscellaneous	6
Food & Allied	6
Ceramic	4
Tannery Industries	4
Travel & Leisure	3
Service & Real Estate	3
Total	127

3.3 Research model

To find out the prevalence of earnings manipulation, the study uses the Beneish M score model by Professor Messod Beneish. Beneish M score is a mathematical model that uses financial ratios to identify if a company has manipulated its earnings. The formula of the M score is given below:

M-Score = -4.84 + (0.920 × DSRI) + (0.528 × GMI) + (0.404 × AQI) + (0.892 × SGI) + (0.115 × DEPI) - (0.172 × SGAI) + (4.679 × TATA) - (0.327 × LVGI)

If the M-Score is greater than -2.22, the company is likely a candidate for an earnings manipulator. Scores below this threshold suggest no manipulation.

Here, the variables are:

DSRI: Days Sales in Receivable Index measures whether receivables and revenue are in balance. The formula for calculating this ratio:

$$\text{DSRI}= \frac{\frac{Net\ Receivables\_t}{Sales\_t}}{\frac{Net\ Receivable\_t-1}{Sales\_t-1}}$$

A DSRI > 1 indicates that receivables are growing faster than sales. This could suggest aggressive revenue recognition or difficulty in collecting payments.

GMI: Gross Margin Index measures changes in gross margin. The formula for calculating this variable is given below:

$$\text{GMI}= \frac{\frac{Gross\ Profit\_t-1}{Sales\_t-1}}{\frac{Gross\ Profit\_t}{Sales\_t}}$$

A score of above 1 indicates a decline in gross margin, potentially prompting management to manipulate earnings to mask deteriorating performance.

AQI: Asset Quality Index measures the proportion of assets with uncertain benefits. The formula for calculating this variable is given below:

$$\text{AQI}= \frac{1-\frac{(Current\ Asset_{\ t}+PPE_t)}{Total\ Assets\ \_t}}{1-\frac{(Current\ Asset_{\ t-1}+PPE_{t-1})}{Total\ Assets\_t-1}}$$

An AQI > 1 suggests an increase in intangible or less reliable assets, indicating potential capitalisation of expenses to inflate earnings.

SGI: The sales growth index reflects sales growth. The formula for calculating this variable is given below:

$$\text{SGI}= \frac{Sales\_t}{Sales\_t-1}$$

SGI > 1 reflects significant sales growth, which isn't inherently bad. However, companies experiencing rapid growth may face higher pressure to manipulate earnings to sustain momentum.

DEPI: This Depreciation Index asses the changes in depreciation rate. The formula for calculating this variable is given below:

$$\text{DEPI}= \frac{\frac{Depreciation\_t-1}{Depreciation_{\ t}-1+PPE\_t-1}}{\frac{Depreciation\_t}{Depreciation_{\ t}+PPE\_t}}$$

DEPI > 1 indicates that depreciation expense as a proportion of assets has decreased, potentially from extending asset useful lives to boost profits artificially.

SGAI: This variable analyzes the relationship between SG&A expenses and sales. The formula for calculating this variable is given below:

$$\text{SGAI}= \frac{\frac{\text{SG\&A}\ Expenses\_t}{Sales\_t}}{\frac{\text{SG\&A}\ Expenses\_t-1}{Sales\_t-1}}$$

An SGAI > 1 suggests that SG&A expenses are growing faster than sales, possibly indicating inefficiency or manipulation to mask declining profitability.

LVGI: Leverage Index examines changes in financial leverage. The formula for calculating this variable is given below:

$$\text{LVGI}= \frac{\frac{\text{Total Debt\_t}}{Total\ Asset\_t}}{\frac{\text{Total Debt\_}t-1}{Total\ Asset\_t-1}}$$

An LVGI > 1 indicates increasing financial leverage, which could put pressure on management to manipulate earnings to meet debt covenants or maintain credit-worthiness.

TATA: Total Accruals to Total Assets measures the extent to which earnings are supported by accruals. The formula for calculating this variable is given below:

$$TATA = \frac{Total\ Accruals\_t}{Total\ Assets\_t}$$

A higher TATA value indicates earnings are being supported by accruals rather than cash flows, which may signal potential manipulation.

3.4 Data analysis

3.4.1 Prevalence of earnings manipulation

In the first phase, the study analyzes the prevalence of earnings manipulation among the companies of different sectors in Bangladesh. For this purpose, the study employs the Beneish M-Score model developed by Beneish (1999). The study calculates the M-Score for all 127 companies over the period 2018–2022, yielding 635 firm-year observations. Using the established threshold of −2.22, firm-year observations scoring above this threshold are classified as potential manipulation firms, while those below are classified as non-manipulation firms. The study then presents the yearly and overall distribution of manipulation prevalence across the sample to assess the extent and trend of earnings manipulation in the Bangladeshi different sectors.

3.4.2 Impact of the Covid-19 Pandemic on earnings manipulation

To evaluate the impact of the global pandemic, a comparative analysis was conducted between the pre-COVID (2018–2019) and COVID-19 (2020–2022) periods. A Chi-square test was employed to determine if the frequency of manipulation significantly increased during the crisis. Additionally, independent samples t-tests were performed on all eight Beneish M-Score variables to identify statistically significant methodological shifts or anomalies in specific accounting drivers.

3.4.3 Discriminant Reliability of the Beneish M-Score

In the second phase, the study examines the discriminant reliability of the Beneish M-Score model — that is, the extent to which the eight constituent ratios collectively and individually retain their capacity to classify firms into manipulation and non-manipulation groups in the Bangladeshi companies' context. For this purpose, Linear Discriminant Analysis (LDA) is employed as the primary analytical method. The analysis is conducted sequentially in five stages:

Tests of Equality of Group Means: F-tests are conducted for each of the eight ratios to identify variables with statistically significant differences in group means ($p < 0.05$)

Stepwise Variable Selection: A forward stepwise procedure is applied to identify the optimal subset of variables that jointly maximizes group separation

Discriminant Model Accuracy: Eigenvalue, Wilks' Lambda, and canonical correlation are computed to assess the overall fit and discriminating power of the model

Discriminant Function Formation: Raw and standardized canonical discriminant function coefficients are derived to construct the discriminant function and rank the relative dominance of each variable

Classification Accuracy: Model performance is assessed through three validation approaches: standard five-fold cross-validation, group k-fold cross-validation by firm ID to eliminate cross-temporal data leakage, and temporal holdout testing on withheld 2022 observations

Equal prior probabilities (0.5/0.5) are applied to correct for class imbalance between the two groups. To address the violation of multivariate normality, confirmed through Shapiro-Wilk tests, robustness checks are conducted by comparing LDA against logistic regression.

and random forest classifiers. All analyses are conducted using Python and Excel.

4. Findings and analysis

4.1 Findings

The prevalence of earnings manipulation has been presented using the Beneish M score.

4.1.1 Prevalence of earning manipulation

The first objective of this research is to analyze the prevalence of earnings manipulation across different industries in Bangladesh. Table 2 offers descriptive statistics for the entire sample. The results reveal significant variability among companies, which indicates both compliance and manipulation practices. Analyzing the Beneish M-Score variables, the descriptive statistics bring intriguing insight into the dataset of 635 observations regarding potential earnings manipulation. On average, the DSRI is 1.013 and has a maximum value of 9.783, indicating that, while most firms maintain relatively stable receivables as a percentage of sales, a few firms generate substantially more revenue through receivables management. These cases point to the issue of aggressive revenue recognition by companies. GMI has a mean of 1.057. A GMI greater than 1 suggests deteriorating gross margins, potentially signaling firms that manipulate earnings to hide declining profitability. The low standard deviation (0.158) indicates most firms cluster around the mean.

Table-2 Descriptive statistics of the entire sample

Variable	Obs	Mean	Std. Dev.	Min	Max
DSRI	635	1.013	.534	.181	9.783
GMI	635	.882	1.057	.158	8.665
AQI	635	.983	.581	-11.25	5.371
SGI	635	1.101	.384	.102	5.512
SGAI	635	1.054	.469	.081	6.678
DEPI	635	1.034	.609	0	10.509
TATA	635	-.012	.096	-.961	.851
LVGI	635	1.05	.288	.177	3.509
M	635	-2.498	.788	-7.634	3.845

Source: Author's calculation

The AQI, with a mean of 0.983 and a range of -11.25 to 5.371, indicates significant fluctuation of the ratio of intangible and non-productive assets to total assets between firms. Negative AQI signifies that some of the firms might be conservatively measuring their asset quality while others seem to be inflating intangible assets, perhaps under-earning management. This has pointed to the unstable reporting practices among the sample firms.

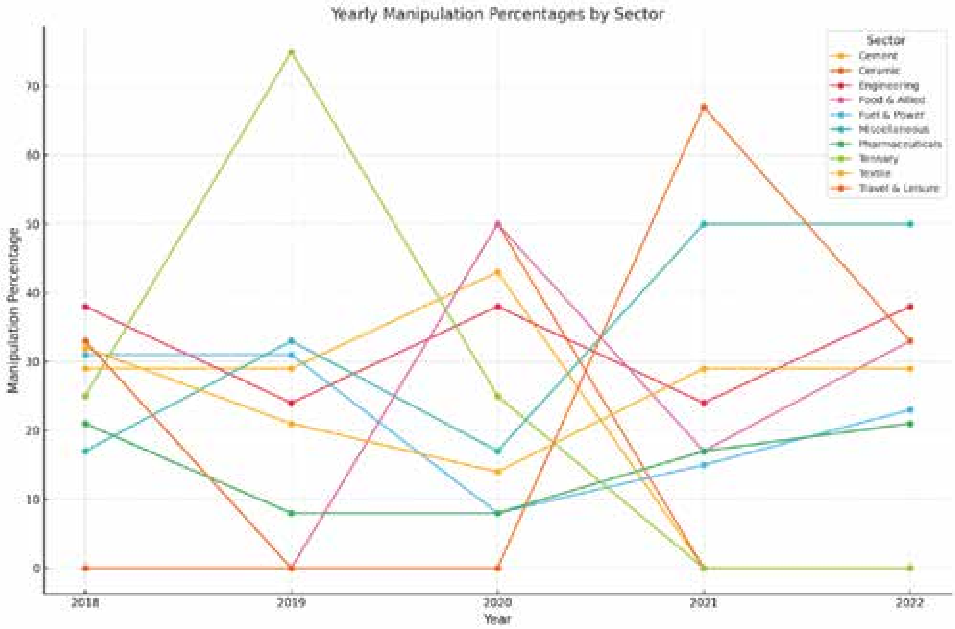
The Sales Growth Index (SGI) gives a mean figure of 1.101, indicating a moderate level of sales growth across the firms. However, the range suggests that some firms could be reporting high sales levels to meet market expectations, which is in line with manipulation tendencies. Similarly, the Depreciation Index (DEPI) with a mean of 1.034 and a maximum of 10.509 suggests that some firms may have understated depreciation expenses to improve their perceived profitability. Total Accruals to Total Assets (TATA) averaging -0.012 shows that the firms have generally taken conservative approaches to earnings through accruals. Nevertheless, the presence of outliers indicates that some firms rely on accrual-based adjustments to manage earnings. The Leverage Index (LVGI), which has a mean of 1.05 and a low standard deviation, indicates that most firms exhibit stable leverage practices, and there may be some firms that engage in manipulating the leverage practices. Overall, the dataset demonstrates that while many companies adhere to standard reporting practices, extreme values in DSRI, AQI, DEPI, and SGI indicate earnings manipulation by certain firms.

Table-3 Sector-wise analysis of manipulation

Sector	N	Mean	Std.	Min	Max
Cement	35	-2.577	0.724	-5.579	-1.434
Ceramic	20	-2.287	1.014	-3.387	1.79
Engineering	105	-2.278	1.071	-6.871	3.845
Food & Allied	30	-2.52	0.804	-5.377	-.807
Fuel & Power	65	-2.473	0.505	-4.002	-.284
IT	40	-2.77	0.783	-7.25	-2.226
Miscellaneous	30	-2.39	0.479	-3.56	-1.538
Pharmaceuticals	120	-2.524	0.665	-7.634	-.074
Service & Real Estate	15	-2.553	0.158	-2.901	-2.282
Tannery	20	-2.714	0.574	-3.507	-1.356
Textile	140	-2.567	0.843	-7.385	-.606
Travel & Leisure	15	-2.507	0.417	-3.169	-1.623

Source: Author's calculation

Table 3 presents descriptive statistics for M-Scores across various sectors. An M-Score closer to or above -2.22 implies a higher potential for manipulation. Crucially, while the mean M-Scores for all sectors fall below this threshold, sector averages inherently mask the behavior of individual manipulating firms. Evidence of manipulation is instead captured by the maximum values (outliers) within these sectors. The Cement sector displays a low average M-Score of -2.577 and a maximum of only -1.434, indicating stable financial practices with limited variability. Similarly, the Fuel & Power sector has an average M-Score of -2.473 and the lowest standard deviation of 0.505, demonstrating consistent financial reporting. The IT and Tannery sectors show minimal risk, with averages of -2.770 and -2.714. Sectors like Pharmaceuticals, Food & Allied, and Travel & Leisure also fall below the manipulation threshold on average. However, Pharmaceuticals exhibits a maximum score of -0.074, proving that individual firms within this sector still cross into manipulation territory. Conversely, sectors such as Ceramic (-2.287), Engineering (-2.278), and Miscellaneous (-2.390) hover closer to the risk threshold on average. More importantly, the Ceramic and Engineering sectors show extreme maximum M-Scores of 1.790 and 3.845, respectively. These extreme firm-level outliers confirm the presence of manipulation and signal substantial differences in company behavior, as Engineering firms face volatility due to project-based revenues. Overall, while sector averages demonstrate conservative financial behavior, maximum M-Scores clearly evidence that firms with higher operational variability carry significant risk for earnings manipulation



Source: Author's calculation

Figure-1 Yearly manipulation percentage by sector

Figure 1 illustrates year-to-year changes in sector-wise earnings manipulation percentages from 2018 to 2022. Notably, the IT and Service & Real Estate sectors are excluded due to their consistent zero manipulation rates, reflecting strong compliance and transparent financial reporting standards. Sectors like Travel & Leisure display high volatility, with manipulation peaking at 67% in 2021, likely a consequence of pandemic-induced disruptions, before dropping to 33% in 2022 and 0% in earlier years. Similarly, Food & Allied shows inconsistency, with rates fluctuating from 50% in 2020 to 17% in 2021 and rising again to 33% in 2022, suggesting vulnerability to market shocks.

Engineering stands out for its relatively stable yet elevated manipulation levels, with rates between 24% and 38% across the years. This indicates systemic challenges tied to the sector's project-based operations. In contrast, Ceramics and Pharmaceuticals demonstrate lower manipulation and less fluctuation. Ceramics only showed a spike in 2020 (50%), while Pharmaceuticals maintained rates between 8% and 21%, reflecting stronger regulatory environments. Isolated spikes in Tannery (75% in 2019) and Miscellaneous (50% in 2021 and 2022) point to sector-specific disruptions or governance weaknesses.

Overall, the average manipulation rate across all sectors is 20%, with Miscellaneous (33%) and Engineering (32%) showing the highest susceptibility. Mid-range sectors include Travel & Leisure, Food & Allied, and Textile (25–27%), while Pharmaceuticals (15%) and Ceramics (10%) remain the most compliant. These findings underscore the need for sector-specific approaches in addressing earnings manipulation, as industry characteristics significantly influence financial reporting integrity.

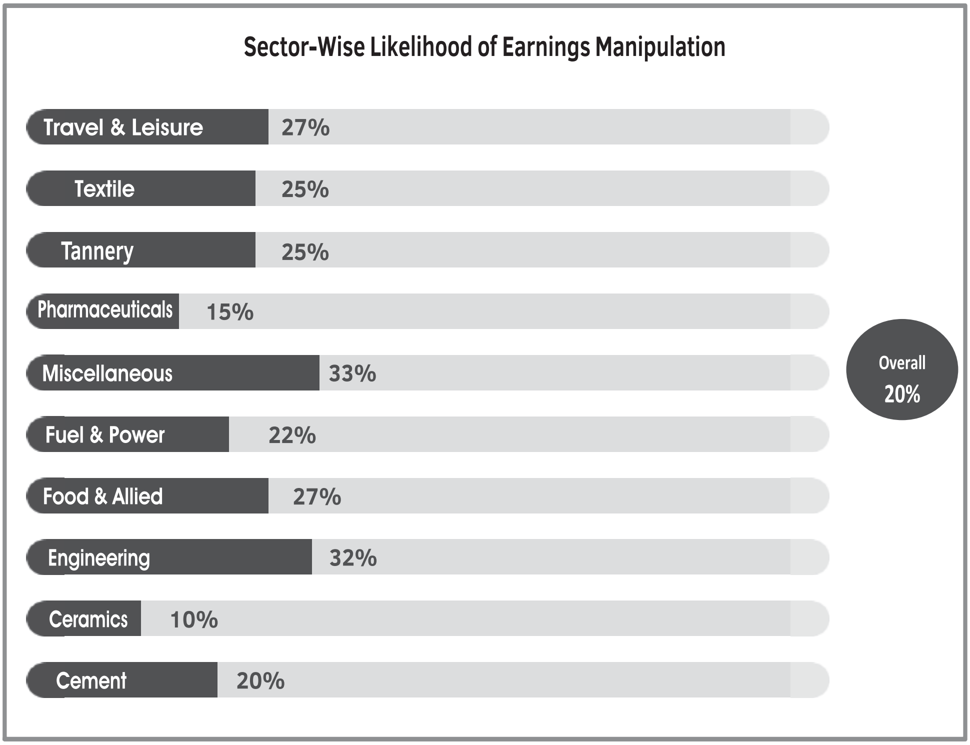


Figure-2 Overall analysis of earning manipulation

4.1.2 Impact of the Covid-19 pandemic on earnings manipulation

To situate the findings within a broader critical context, this study examines the impact of the COVID-19 pandemic by comparing financial reporting behavior across two distinct periods: Pre-COVID (2018–2019) and COVID-19 (2020–2022). The empirical evidence indicates that the overall prevalence of potential earnings manipulation increased marginally from 20.95% in the pre-pandemic period to 22.57% during the pandemic. However, a Chi-square test reveals that this change is not statistically significant (χ^2 p-value = 0.6996). This result suggests that the pandemic did not produce a systematic or market-wide escalation in fraudulent reporting. Instead, the observed variation reflects localized irregularities rather than a uniform shift in reporting practices.

To further isolate the mechanisms underlying these changes, independent sample t-tests were conducted on the eight components of the Beneish M-Score. The results show that most structural indicators, including the Gross Margin Index (GMI), Asset Quality Index (AQI), and Depreciation Index (DEPI), remained statistically stable across the two periods. This stability suggests that core operational and accounting structures were largely unaffected by the pandemic shock.

Table-4 Comprehensive t-test of Beneish variables (Pre-COVID vs. COVID Period)

Variable	Pre-COVID Mean	COVID Mean	p-value
DSRI (Receivables)	0.9517	1.0540	0.0180
TATA (Accruals)	-0.0022	-0.0187	0.0345
SGAI (Admin Exp)	1.0265	1.0721	0.2313
LVGI (Leverage)	1.0317	1.0627	0.1839
SGI (Sales Growth)	1.1156	1.0908	0.4269
GMI (Gross Margin)	1.0108	0.9610	0.6358
AQI (Asset Quality)	0.9855	0.9818	0.9381
DEPI (Depreciation)	1.0323	1.0356	0.9463

Source: Author's calculation

In contrast, the statistically significant shifts in DSRI and TATA provide clear evidence of firm-level adjustments in financial reporting during the COVID-19 period in Bangladesh. The increase in DSRI ($p = 0.0180$) indicates a greater reliance on receivables, which reflects more aggressive revenue recognition practices. This pattern suggests that firms attempted to offset declining cash inflows by accelerating or inflating credit-based sales. In periods of constrained liquidity, such behavior becomes a tactical response to sustain reported performance, even when underlying cash flows weaken.

At the same time, the significant change in TATA ($p = 0.0345$) provides evidence of a directional shift in accrual-based reporting behaviors during the pandemic. The mean TATA declined from −0.0022 in the pre-COVID period to −0.0187 during the crisis, reflecting a move toward larger negative accruals. Rather than inflating earnings, this pattern is consistent with firms employing income-deferral and loss-smoothing strategies using accrual discretion to manage the appearance of financial stress rather than to overstate performance. Under conditions of heightened uncertainty, accruals thus served not as an instrument of upward earnings inflation but as a tool to absorb and redistribute the visibility of economic shocks across reporting periods. Therefore, while the rise in DSRI captures aggressive revenue-side recognition, the decline in TATA reflects a complementary but distinct mechanism: shaping how reported income is distributed over time rather than how much is initially recognized.

These two variables, taken together, indicate a coordinated adjustment in reporting strategies. Firms did not uniformly increase manipulation across all dimensions. Instead, they concentrated on specific mechanisms that offered flexibility under crisis conditions. This targeted behavior becomes more visible at the industry level. For instance, high-risk sectors such as Travel and Leisure experienced extreme volatility, with manipulation levels rising sharply to 67% in 2021. This spike reflects the severe operational disruptions faced by such industries, where firms had stronger incentives to manage earnings in response to demand collapse and uncertainty.

In contrast, the remaining six components of the Beneish M-Score: GMI, AQI, SGI, DEPI, SGAI, and LVGI do not exhibit statistically significant changes. This stability suggests that the fundamental financial structure of firms, including profitability trends, asset composition, cost behavior, and leverage, remained largely intact during the pandemic period.

4.1.3 Discriminant Reliability of the Beneish M-Score

In the second phase of the study, firm-year observations were systematically classified into two mutually exclusive categories: potential manipulation firms (FRAUD = 1) and non-manipulation firms (FRAUD = 0). This classification was based on the threshold of the Beneish M-Score.

Table-5 Group classification based on Beneish M-Score threshold

Group	Classification Criterion	Firm-Year Observations	Percentage
Non-Manipulation (FRAUD = 0)	M-Score < −2.22	496	78.1%
Potential Manipulation (FRAUD = 1)	M-Score ≥ −2.22	139	21.9%
Total		635	100%

Source: Author's calculation

The first stage of discrimination analysis examined whether the mean values of the eight Beneish M-Score ratios differed significantly between potential manipulation and non-manipulation groups. The F-test was employed to assess group mean equality for each ratio individually, where a significant F-value ($p < 0.05$) indicates meaningful group separation by that variable.

Table-6 F-statistic result (Tests of equality of group means)

Variable	F-statistic	p-value	Significant (p < 0.05)
DSRI	8.528	0.004	Yes ***
GMI	41.034	0.000	Yes ***
AQI	3.800	0.052	Borderline
SGI	15.554	0.000	Yes ***
DEPI	17.194	0.000	Yes ***
TATA	92.639	0.000	Yes ***
SGAI	0.459	0.498	No
LVGI	0.157	0.692	No

Source: Author's calculation

*Note: *** p < 0.01. df1 = 1, df2 = 633. n = 635.*

The results indicate that five ratios — TATA ($F = 92.639$, $p < 0.001$), GMI ($F = 41.034$, $p < 0.001$), DEPI ($F = 17.194$, $p < 0.001$), SGI ($F = 15.554$, $p < 0.001$), and DSRI ($F = 8.528$, $p = 0.004$) demonstrated statistically significant differences between the two groups. TATA recorded the highest F-statistic by a substantial margin, identifying total accruals to total assets as the most individually powerful discriminator between the two groups. AQI recorded a borderline p-value of 0.052, marginally exceeding the conventional 5% threshold. In contrast, SGAI ($p = 0.498$) and LVGI ($p = 0.692$) showed no significant group differences and were identified as non-discriminating variables. These two ratios were therefore excluded from all subsequent analyses.

Stepwise Variable Selection

To identify the optimal subset of variables for constructing the discriminant function, a stepwise forward selection procedure was applied using five-fold cross-validated accuracy as the selection criterion, retaining only those variables that contributed to group separation. The results are presented in Table 6.

Table-7 Stepwise variable selection

Variable	Selected	Basis
DSRI	Yes	Significant individually and jointly
GMI	Yes	Significant individually and jointly
AQI	Yes	Borderline individually; significant jointly
SGI	Yes	Significant individually and jointly
DEPI	Yes	Significant individually and jointly
TATA	Yes	Significant individually and jointly
SGAI	No	No individual or joint discriminating power
LVGI	No	No individual or joint discriminating power

Source: Author's calculation

Six variables, DSRI, GMI, AQI, SGI, DEPI, and TATA, were retained in the final discriminant model. AQI, despite its borderline individual significance, was selected due to its meaningful joint contribution when combined with the remaining five ratios. SGAI and LVGI were excluded from all subsequent analyses. The six-variable model constitutes the basis for all subsequent tests.

Discriminant model accuracy

The overall fit of the discriminant model was evaluated using the eigenvalue, Wilks' Lambda, and canonical correlation derived from the six selected variables. The results are presented in Table 7.

Table-8 Summary of Canonical discriminant function

Metric	Value
Eigenvalue	0.4657
Wilks' Lambda	0.6823
Canonical Correlation	0.5637
Variance Explained (R^2)	31.77%

Source: Author's calculation

The discriminant model yielded an eigenvalue of 0.4657 and a canonical correlation of 0.5637. The squared canonical correlation of 0.3177 indicates that the discriminant function explains 31.77% of the total variance between the two groups. The Wilks' Lambda value of 0.6823, significantly different from unity, confirms that the discriminant function meaningfully separates the two groups and that the model possesses adequate discriminating power. These results collectively validate the statistical adequacy of the discriminant model prior to interpretation of its coefficients.

Discriminant function formation

The canonical discriminant function coefficients, both raw and standardized, are presented in Table 8. Standardized coefficients are computed by applying the discriminant function to standardized variables, enabling direct comparison of each variable's relative contribution to group separation independent of measurement scale.

Table-9 Canonical discriminant function coefficients

Variable	Raw coefficient	Standardized coefficient	Dominance rank
TATA	12.730	1.2237	1st
DSRI	2.275	1.2135	2nd
SGI	3.103	1.1893	3rd
GMI	0.742	0.9603	4th
DEPI	0.965	0.5870	5th
AQI	0.646	0.3750	6th
Constant	−9.9616	—	—

Source: Author's calculation

Discriminant Function: $D = -9.9616 + 2.275(DSRI) + 0.742(GMI) + 0.646(AQI) + 3.103(SGI) + 0.965(DEPI) + 12.730(TATA)$

The standardized coefficients reveal that TATA (1.2237) is the most dominant discriminating variable, followed closely by DSRI (1.2135) and SGI (1.1893). The dominance of TATA suggests that accrual-based earnings manipulation, characterized by income recognition without corresponding cash inflows, constitutes the primary mechanism through which financial statement manipulation occurs among Bangladeshi firms. The near-equal standardized coefficients of DSRI and SGI further indicate that revenue-side manipulation through the simultaneous inflation of trade receivables and reported sales figures represents a co-occurring manipulation pattern. GMI, DEPI, and AQI contribute less to group discrimination, with AQI recording the weakest standardized coefficient (0.375), consistent with its borderline significance in Test 1.

Classification accuracy

The classification performance of the discriminant model was evaluated using three complementary validation approaches to ensure robust and unbiased accuracy estimates. Equal prior probabilities (0.5/0.5) were applied to correct for class imbalance between non-manipulation (78.1%) and manipulation (21.9%) observations.

Table-10 Confusion matrix (balanced priors)

Classifications	Predicted non-manipulation	Predicted manipulation	% Correct
Actual non-manipulation	490	6	98.8%
Actual Manipulation	39	100	71.9%

Source: Author's calculation

The full classification matrix correctly identified 98.8% of non-manipulation firms and 71.9% of manipulation firms. The near-perfect non-manipulation classification (98.8%) demonstrates strong model specificity, while the 71.9% manipulation recall reflects typical minority-class challenges in financial datasets. Only 6 false positives occurred versus 39 false negatives, indicating reliable positive predictions but moderate sensitivity to manipulation cases.

Table-11 Multi-layer validation summary

Validation method	Accuracy	Manipulation recall	Manipulation f1	Notes
Standard 5-Fold CV	93.39%	—	—	Mild firm-level leakage
Group K-Fold CV (k=5)	91.30% (SD=0.031)	—	—	Primary estimate
Temporal Holdout (2022)	92.91%	74.3%	0.85	Trained on 2018–2021

Source: Author's calculation

Three validation methods were employed to assess model generalizability. First, standard five-fold cross-validation yielded an accuracy of 93.39%; however, this estimate carries mild upward bias as the same firm may appear in both training and test folds across years. Second, group k-fold cross-validation by firm ID, which ensures complete firm-level separation between training and test sets, yielded an accuracy of 91.30% (SD = 0.031), representing the most methodologically rigorous estimate of model performance. Third, a temporal holdout test trained the model exclusively in 2018–2021 observations (n = 508) and evaluated it on withheld 2022 firm-year data (n = 127), yielding an accuracy of 92.91% with a manipulation recall of 74.3% and an F1-score of 0.85. The convergence of all three validation estimates within a narrow 91–93% band provides strong evidence of model stability and temporal generalizability. This directly supports the study's objective of validating Beneish M-Score discriminant reliability in Bangladesh, establishing its utility as a consistent screening tool despite the circularity limitation of M-Score-derived labels.

Robustness Check

Given the violation of multivariate normality confirmed by Shapiro-Wilk tests across all six selected variables (all $p < 0.001$), robustness checks were conducted by comparing LDA against logistic regression and random forest classifiers, neither of which imposes distributional assumptions. Results are reported in Table 11.

Table-12 Robustness check — alternative model comparison

Model	CV accuracy	Std dev	Normality required
LDA (Balanced Priors)	91.30%	0.0307	Yes (violated)
Logistic Regression	90.66%	0.0334	No
Random Forest	91.61%	0.0302	No

Source: Author's calculation

The three models produced near-identical group k-fold cross-validation accuracies — 91.30% (LDA), 90.66% (Logistic Regression), and 91.61% (Random Forest), with overlapping standard deviations confirming no statistically meaningful performance differences. LDA marginally outperformed logistic regression despite violating normality, while the random forest advantage over LDA of 0.31% falls well within the margin of sampling variability. These results demonstrate that the normality violation does not substantively bias the LDA estimates, empirically justifying the retention of LDA as the primary analytical method on grounds of interpretability and validated robustness.

4.2 Discussion of Findings

The primary objective of this research is to examine the sectoral prevalence and characteristics of earnings manipulation among Bangladeshi listed firms. Sectoral Prevalence of Earnings Manipulation

The findings show that earnings manipulation in Bangladesh varies significantly across sectors and over time, with an overall average manipulation rate of 20%. This confirms prior literature that manipulation risk is not uniform but sector-dependent. While earlier studies focused on single industries, the present results provide a comparative cross-sectoral perspective.

Engineering and Miscellaneous emerge as the most susceptible sectors, with average rates of 32% and 33% respectively. The relatively stable yet elevated manipulation levels in Engineering support Parvin (2020), who argued that industry structure influences reporting behavior. Project-based revenue recognition and cost estimation flexibility likely create persistent reporting risk. In contrast, Travel & Leisure shows sharp volatility, peaking at 67% in 2021, which aligns with the idea that external economic shocks intensify manipulation incentives. This pattern reflects the instability observed by Khatun, Ghosh, and Kabir (2022) in the banking sector, where manipulation fluctuated significantly across years. Food & Allied also displays inconsistency, moving between 50%, 17%, and 33%, suggesting sensitivity to market disruption. Pharmaceuticals and Ceramics record comparatively lower average rates of 15% and 10%, indicating relatively stronger compliance. This partially contrasts with Mollah and Sakib (2020), who documented persistent pharmaceutical manipulation, suggesting that sectoral behavior may evolve over time or differ across samples. Isolated spikes in Tannery (75% in 2019) and Miscellaneous (50% in 2021 and 2022) point to episodic governance weaknesses rather than structural patterns. Overall, the findings support Arman and Sharmin (2019), who argued that manipulation risk exists across the market, but they extend the literature by showing clear sectoral differentiation. The evidence suggests that industry characteristics, economic pressure, and governance strength collectively shape earnings manipulation patterns, highlighting the need for sector-specific regulatory oversight rather than uniform monitoring.

The analysis of the COVID-19 period (2020–2022) explicitly demonstrates that global crises do not necessarily increase the volume of fraud but significantly alter its mechanisms. The statistically significant increase in DSRI and TATA suggests that firms in frontier markets like Bangladesh prioritize revenue-side manipulation and non-cash accrual adjustments as survival strategies during lockdowns. These findings corroborate the sharp volatility observed in the Travel & Leisure and Food & Allied sectors, which served as the primary epicenters for these pandemic-induced accounting anomalies. Furthermore, the stability of structural variables such as the Depreciation Index (DEPI) and Asset Quality Index (AQI) throughout the crisis indicates that the fundamental financial architecture of these firms remained resilient, while 'creative accounting' was deployed as a localized response to temporary economic disruptions.

Another objective of this research is to find out which variables drive the separation between manipulation and non-manipulation firms and the classification reliability of the Beneish M Score model. The discriminant analysis identifies five Beneish ratios as statistically significant in separating manipulation and non-manipulation firms. TATA shows the strongest discriminatory power, followed closely by DSRI, SGI, with GMI, and DEPI contributing to a lesser extent. The dominance of TATA indicates that accrual intensity is the central feature distinguishing the two groups. AQI remains marginal while SGAI and LVGI are insignificant and therefore excluded. This implies that manipulation in Bangladeshi firms is primarily associated with accrual adjustments, aggressive revenue recognition (DSRI), and sales growth pressures (SGI), rather than just margin deterioration or depreciation changes.

The classification performance confirms the discriminant validity of the model. The confusion matrix correctly classifies 98.8% of non-manipulation firms and 71.9% of manipulation firms. Validation accuracy remains stable between 91% and 93%, including fivefold validation (93.39%), grouped firm level validation (91.30%), and temporal holdout testing (92.91%). The narrow accuracy range indicates that the model generalizes well across firms and years and is not driven by sample-specific patterns.

These results closely align with prior evidence emphasizing accrual-based indicators. Septiani, Musyarofah, and Yuliana (2020) report about 89.5% detection accuracy using discriminant analysis, while Tarjo and Herawati (2015) also observe acceptable classification ability. The strong role of TATA and DSRI is also consistent with Shah, Saraswat, and Mehta (2018), who identify accrual intensity and receivable growth as key predictors. At the same time, the insignificance of leverage and administrative expense variables corresponds with findings in some international studies where not all Beneish components contribute equally.

However, the present results differ from studies reporting weak predictive performance. Alfian and Triani (2019) and the evidence summarized by Lotfi and Chadegani (2017) show classification accuracy near 51%–66%, indicating high misclassification risk in some emerging markets. Compared with those findings, the higher and stable accuracy in this study suggests that, although the Beneish M Score is context sensitive, it performs more reliably when validated using firm-level separation and temporal testing. Therefore, the evidence indicates that in the Bangladeshi listed firm environment, the model acts as a credible screening tool rather than merely a rough probabilistic signal.

5. Conclusion

This study examines the sectoral prevalence of earnings manipulation and evaluates the classification reliability of the Beneish M Score model in Bangladeshi listed firms. The results show that manipulation risk differs across industries rather than appearing uniformly in the market. Engineering and Miscellaneous sectors display consistently higher susceptibility, while Pharmaceuticals and Ceramics remain comparatively compliant. Volatile sectors such as Travel & Leisure and Food & Allied show sharp changes over time, indicating that economic pressure and industry characteristics influence reporting behavior.

The discriminant analysis identifies accrual intensity, aggressive revenue recognition, and rapid sales growth as the primary separating factors, with margin deterioration and depreciation behavior playing secondary roles. The model demonstrates stable classification performance, with validation accuracy around 91%–93%, suggesting reliable predictive ability within the sample context. Overall, the findings indicate that the Beneish M Score functions as a practical early warning tool in Bangladesh, although it should not be treated as direct proof of fraud.

Regulators should adopt sector-focused monitoring rather than uniform supervision because manipulation risk concentrates in specific industries. High-risk sectors such as Engineering and Miscellaneous require closer scrutiny and periodic financial review. Auditors should place greater emphasis on accrual-related accounts, receivables growth, and abnormal sales growth during audit procedures, as these variables most strongly signal manipulation, alongside unusual margin and depreciation changes.

Stock exchanges and supervisory authorities may incorporate the Beneish M Score as a screening mechanism to identify suspicious firms for further investigation, not as a standalone enforcement tool. Firms should strengthen internal governance and disclosure quality, particularly in revenue recognition and accrual estimation areas. Future research should extend the model with additional variables or hybrid methods to reduce misclassification and improve detection in frontier markets.

A primary limitation of this study is its foundational reliance on the Beneish M-Score, a model originally calibrated using 1999 data from US companies. The statistical insignificance of variables such as the Leverage Index (LVGI) and Sales General and Administrative Expenses Index (SGAI) in this sample indicates that the model's fixed weightings do not perfectly align with the unique accounting practices and regulatory environments of frontier markets. Bangladeshi firms likely utilize different 'creative accounting' mechanisms than those prevalent in developed economies. Another limitation of the study is that the paper does not explicitly control the macroeconomic shocks or the temporary regulatory relaxations granted during the pandemic.

Author’s contribution statement

I am the sole author of my research paper. All of the tasks of the paper have been done by me.

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