Detecting Earnings Manipulation in Nepal's Real Sector: A Beneish M-Score Analysis

Dipesh Pote Shrestha[1]

Abstract

This study investigates earnings manipulation practices among Nepalese listed companies, addressing a research gap by focusing on three underexplored industries: hospitality, hydropower, and manufacturing. Using purposive sampling, audited financial data from nine firms with at least six years of operational history (FY2018/19–FY2023/24) were analyzed. The Beneish M-Score model was computed across five periods (FY2019/2–FY2023/24), with emphasis on disaggregated index-level analysis rather than binary threshold classification. Findings show that approximately 51% of the 45 firm-year observations exceeded the manipulation threshold, with sector-specific risk profiles shaped by macroeconomic shocks, capital market events, and structural reporting incentives Key patterns include aggressive receivables recognition, depreciation adjustments, opportunistic non-core income reporting, and extended asset capitalization. Notable cases include a depreciation policy shift during NFRS adoption coinciding with a market peak and IPO lock-in expiry, and expansionary related-party credit practices during favorable market conditions followed by sharp corrections. The results suggest disaggregated index analysis proved more diagnostically informative than composite M-Score classification alone, directly challenging prior findings questioning the model's applicability in Nepal. Nonetheless, the study acknowledges key limitations, including the model's U.S. calibration, NFRS transition effects, the small purposive sample, and the absence of regulatory enforcement data precluding direct validation. Findings are therefore indicative rather than conclusive. The study recommends enhanced regulatory scrutiny, particularly around IPO approvals, lock-in expiries, market peaks, and accounting transitions, and encourages investors to interpret individual indices contextually rather than relying solely on aggregate scores. In Nepal's inefficient market, this research contributes much-needed empirical evidence on earnings manipulation patterns, offering valuable insights for policymakers, investors, and other stakeholders.

Keyword: Beneish M-Score Model, Nepal Stock Exchange (NEPSE), Earnings Manipulation, Accounting Manipulation
JEL classification: M41, M48, G14, G11

[1]ACCA, Investment Manager, Team Ventures Limited, Independent Researcher, Corresponding Email: dipesh.pote@outlook.com

INTRODUCTION

Despite theoretical frameworks emphasizing the primacy of free cash flows in firm valuation, empirical evidence reveals a persistent paradox: stock markets respond more powerfully to reported earnings. Penman and Yehuda (2004) demonstrate that earnings exert a strong multiplier effect on equity valuation, whereas free cash flows often have limited incremental explanatory power once earnings are taken into account. This divergence tends to be more pronounced in less efficient markets, where earnings figures can disproportionately influence investor sentiment and shape valuation perceptions.

Earnings play a central role in corporate performance evaluation, serving as the primary signal of financial health by linking costs, equity, capital, sales, and taxes (Valaskova & Fedorko, 2021). As a key driver of investor decision-making and capital allocation, reported profitability creates strong incentives for managers to manipulate earnings to meet market expectations and boost firm valuation. Earnings manipulation, defined as the deliberate manipulation of accounting figures within or outside permissible standards, often blurs the line between legitimate discretion and misrepresentation (Purwanti et al., 2015). The motivations are multifaceted: meeting analysts' forecasts, avoiding reported losses, optimizing managerial compensation, minimizing tax liabilities, attracting external financing, and satisfying contractual obligations. Psychological pressure arising from stakeholder expectations can further heighten such tendencies (Strakova, 2021).

Earnings manipulation manifests through two primary mechanisms. Accrual-based manipulation involves altering accounting estimates without affecting real business activities, while real earnings manipulation entails modifying actual operations, such as sales timing, production scheduling, or discretionary spending, to achieve desired reported outcomes (Gao & Gao, 2016). At its core, earnings manipulation constitutes a form of deliberate disclosure interference: an intervention in the stakeholder reporting process designed to secure disproportionate benefits to a select few at the cost of broader transparency (Valaskova & Fedorko, 2021). The concern becomes particularly acute when such practices evolve into predatory misrepresentation, deliberately skewing market sentiment and analyst opinion in ways that undermine the integrity of financial markets and the equitable dissemination of information to all stakeholders.

The consequences of earnings manipulation extend beyond firm-level distortions. Misreported earnings can mislead investors, resulting in inefficient capital allocation and inflated or mispriced securities. At the macro level, such practices may erode investor confidence, weaken market discipline, and distort government tax revenues through misrepresented taxable income. These risks are particularly acute in emerging markets, where institutional weaknesses amplify the effects of financial misreporting.

A major structural shift affecting these dynamics globally has been the adoption of International Financial Reporting Standards (IFRS), now implemented across over 160 jurisdictions, including Nepal's formal adoption of Nepal Financial Reporting Standards (NFRS) in 2012 (Foundation, 2023; Poudel et al., 2014). While IFRS enhances comparability, standardization and transparency across jurisdictions, its principle-based approach also provides the management considerable discretion, particularly in judgments, estimates and choice of accounting methods. Unlike the more prescriptive, rule-based US GAAP, this flexibility can accommodate diverse local conditions but may invite earnings-manipulation in environments with weak oversight, limited audit quality and underdeveloped investor protections.

Despite early adoption, several structural issues remains with the NFRS, these include a shortage of qualified accountants, inconsistent training programs, high compliance costs, carve outs limiting comparability, limited technological infrastructure, and weak enforcement mechanisms (Poudel et al., 2014). These challenges are compounded by structural inefficiencies in Nepal's capital market: empirical evidence suggests that the Nepal Stock Exchange (NEPSE) does not satisfy even the weak form of market efficiency (Joshi, 2024), implying that publicly available information is not fully reflected in stock prices. Consequently, manipulated earnings announcements can trigger disproportionate and potentially uninformed market reactions. Financial literacy remains critically low, with only 27.5% of adults meeting minimum competency levels (Shrestha, 2022), further heightening investor vulnerability to misleading financial information.

Governance challenges further intensify these risks. Weak regulatory enforcement, gaps in corporate governance practice, and documented instances of financial misconduct , including insider trading, delayed disclosures, and questionable accounting practices (Bhattarai, 2025; Kharel et al., 2019), highlight systemic vulnerabilities. Similar concerns raised by international institutions regarding potential loan evergreening and delayed loss recognition in Nepal's heavily regulated banking sector (Republica, 2024) raise deeper questions about the state of financial reporting in comparatively less regulated real-sector industries, where supervisory scrutiny is considerably less intensive.

Among the various diagnostic tools for detecting earnings manipulation, the Beneish M-Score (Beneish, 1999a) and Dechow F-Score (Dechow et al., 2011) are widely recognized for detecting earnings manipulation. Recent studies (Kaab Omeir et al., 2023; Yadav et al., 2023) support the superior predictive accuracy of the Beneish M-Score in identifying financial misreporting and potential bankruptcy risks. However, contradictory evidence exists as indicated by the findings of Bhavani and Tabi (2017) and Kukreja et al. (2020). In the Nepalese context, Gyawali (2021) finds limited M-Score efficacy in banking institutions, likely reflecting its design for industrial and commercial firms. Existing Nepalese research remains concentrated in the banking sector, leaving real-sector industries, particularly hydropower, hospitality, and manufacturing, underexplored despite their growing economic importance and relatively lower regulatory oversight.

This study examines the prevalence and patterns of earnings manipulation among listed real-sector firms across these three industries using the Beneish M-Score, analyzing manipulation indicators over a five-year period overlapping with NFRS adoption and comparing sectoral reporting behavior. The sample size is limited and findings are indicative rather than generalizable; moreover, the M-Score is a probabilistic tool that signals potential manipulation based on financial patterns but does not constitute evidence of misconduct. Results are therefore intended to highlight areas warranting further scrutiny rather than draw definitive conclusions about firm behavior. For investors, the study offers a quantitative basis for assessing reporting risk in an underexamined market segment; for regulators, it provides insights to inform targeted oversight; and academically, it extends the application of the Beneish M-Score to an emerging market context and establishes a foundation for future research on financial reporting practices in Nepal's real sector.

LITERATURE REVIEW

Overview of Earnings Manipulation and Associated Motivations

Earnings manipulation stems from the fundamental agency problem inherent in the separation of ownership and control. The modern corporate structures, with large number of shareholders, have widened the divide between control and ownership and led to information asymmetry that has enabled managers to pursue self-interests through financial reporting discretion (Kazemian & Sanusi, 2015), often at the expense of shareholders and other stakeholders. Furthermore, the fraud diamond framework identifies incentive, opportunity, rationalization, and capability (Wolfe & Hermanson, 2004) as the prerequisites for earnings manipulation. The fraud diamond framework indicates that beyond structural factors, individual capabilities and psychological processes significantly influence financial reporting practices within corporate environments.

Managerial compensation structures frequently amplify earnings manipulation incentives. Empirical studies demonstrate that firms linking executive remuneration to earnings performance exhibit higher levels of discretionary accruals (Beaudoin et al., 2008; Strakova, 2021). However, this relationship is not universal; Nurdiniah and Herlina (2015) found no direct correlation between compensation structures and earnings manipulation propensity, suggesting contextual factors may moderate this relationship.

Beyond direct financial incentives to managers, earnings manipulation also serves several strategic organizational objectives. These include avoiding debt covenant violations (Cheng & Chung, 2006; Nurdiniah & Herlina, 2015; Strakova, 2021), meeting critical earnings thresholds and stakeholder expectations (Cheng & Chung, 2006; Strakova, 2021) and securing favorable contractual terms with various stakeholders (Strakova, 2021). Such practices often reflect broader organizational priorities rather than solely managerial self-interest.

Equity Markets and Earning Manipulation

Capital market events consistently emerge as another significant catalysts for earnings manipulation. An entity's Initial Public Offerings (IPOs) represent such a period with heightened earnings manipulation risks as highlighted by numerous previous studies. Cheng and Chung (2006) had identified systematic earnings inflation preceding equity issuances, followed by post-issuance reversals. This underscores the predatory and opportunistic behaviors that may drive earnings manipulation, enabling certain actors to extract substantial benefits within a relatively short time frame. Similarly, Sosnowski (2021) examined 183 Warsaw Stock Exchange IPOs between 2005–2015 and identified specific earnings manipulation techniques such as discretionary accruals, production cost reductions, and discretionary expense manipulation around IPO events.

The interplay between stock market performance and earnings manipulation forms a reinforcing cycle, with manipulation under heightened pressure to manipulate financial statements due to the strong link between managerial compensation, performance evaluation, and market performance (Callao et al., 2021). Moreover, managers who benefit from inflated earnings, such as through equity sales or option exercises, are particularly incentivized to smooth or boost reported results (Beneish, 1999a), further entrenching these behaviors.

The persistence of earnings manipulation across various market environments raises critical questions about its universality. Emerging market evidence, notably from India, further underscores these concerns. Ghalke et al. (2018) found higher earnings manipulation levels among firms preparing for SME exchange listings compared to main board listings, while Nikbakht et al. (2021) observed that R&D-intensive Indian firms engage in greater pre-IPO manipulation when targeting main board listings.

The quality of monitoring mechanisms significantly moderates earnings manipulation practices. While robust underwriter and auditor reputations can mitigate manipulative behavior, manipulation pressure may sometimes trickle down to these external independent parties as well (Hamid et al., 2012; Ismail et al., 2015). Corporate governance quality and regulatory oversight consistently emerge as critical determinants of financial reporting integrity across different market contexts (Nurdiniah & Herlina, 2015; Strakova, 2021).

Analytical Tools for Detecting Earnings Manipulation

Financial statement analysis has evolved to include specialized quantitative models that can detect potential earnings manipulation. The Beneish M-Score, developed by Beneish (1999b) represents one of the most prominent detection tools, combining eight financial ratios to identify deviations from normative accounting behavior. Typically, firms exceeding the model's –2.22 threshold are flagged as potentially engaging in earnings manipulation.

Alternative detection frameworks include the F-Score (Dechow et al., 2011), which evaluates discretionary accruals and non-operating activities using factors such as changes in non-cash operational assets, receivables, and inventory. The Altman Z-Score, while primarily designed for bankruptcy prediction, incorporates financial ratios measuring liquidity, profitability, solvency, and efficiency that may indirectly signal financial strain potentially motivating manipulative behavior (Bhavani & Tabi, 2017). The Piotroski F-Score, developed by Piotroski (2000), employs a 9-point system assessing financial strength across multiple dimensions, where declining scores may signal weakening financial health and a heightened incentive for earnings manipulation.

Empirical Studies Applying the M-Score in Emerging Markets

Comparative analyses across diverse markets consistently demonstrate the Beneish M-Score's superior precision in forensic applications. Empirical evidence suggests higher accuracy and lower error rates relative to the Dechow F-Score, Z-Score, and F-Score, confirming its status as a benchmark model in early-warning detection of earnings manipulation (Kaab Omeir et al., 2023; Yadav et al., 2023). Nonetheless, the Beneish M-Score also has its inherent limitations and applicability.

Applications of the Beneish model in emerging economies yield mixed outcomes. In Bangladesh, Mollah and Sakib (2020) found the M-Score successfully identified accrual-based manipulations preceding market distress. Similarly, Adoboe-Mensah et al. (2023) established a significant link between earnings manipulation detected by the M-Score and business failures in Ghana's microfinance sector. More recently, Soufiane and Moad (2024) identified telecommunications and technology companies as high-risk sectors through M-Score analysis.

Contradictory evidence exists regarding the universal applicability of the Beneish M-Score. For instance, Bhavani and Tabi (2017) found the model failed to detect Toshiba's accounting scandal, while the Altman Z-Score proved as a superior indicator in this context. These limitations are further corroborated by Kukreja et al. (2020), who determined that the Beneish M-Score demonstrated comparatively lower predictive power in fraud detection. In Nepalese context, Gyawali (2021) found the Beneish M-Score insufficient for detecting financial fraud in listed commercial banks. However, this finding must be contextualized by recognizing the model was not designed for banking sector applications, potentially explaining its reduced effectiveness in such contexts.

Throughout the literature, The M-Score is widely regarded as a predictive rather than definitive tool for detecting earnings manipulation, primarily serving to flag potential manipulation that warrants further investigation rather than confirming misconduct. Since the model was developed using 1982–1992 U.S. Generally Accepted Accounting Principles (GAAP) based data from 74 confirmed cases (Beneish, 1999b), its sensitivity may decline under contemporary reporting frameworks such as IFRS and in different institutional contexts, potentially limiting cross-market inferences. Nevertheless, the model remains useful, particularly in emerging markets with weaker regulatory oversight, although evolving manipulation techniques may occasionally fall outside its detection parameters. Overall, the M-Score is best viewed as an early warning indicator guiding deeper financial scrutiny.

RESEARCH METHODOLOGY

Research Design, Sampling & Data Collection

This study adopts a descriptive and longitudinal research design to examine the effectiveness of the Beneish M-Score model in detecting earnings manipulation among real sector companies listed on the Nepal Stock Exchange (NEPSE). A longitudinal design is particularly suited to this purpose, as it permits the observation of financial reporting behavior across multiple consecutive periods, thereby enabling the identification of systematic and time-varying patterns that would not be discernible from a single-period cross-sectional snapshot. The study relies exclusively on secondary data drawn from audited financial statements, including balance sheets, income statements, and cash flow statements. These statements were obtained from publicly available sources, specifically the NEPSE official portal and physical and digital copies of company annual reports procured directly and official website from the respective companies.

The study period spans six consecutive fiscal years (FY 2018/19 to FY 2023/24). Because the Beneish M-Score model requires two consecutive years of financial data to construct each set of index ratios, M-Scores are computed for five periods (FY 2019/20 to FY 2023/24), with FY 2018/19 serving as the base year for initial ratio computation. The data were not processed using a statistical software package given the model's deterministic formula-based structure.

Population and Sample Selection

As of FY 2018/19, the base year of this study, 38 real sector companies were listed and actively traded on the Nepal Stock Exchange. From this population, two categories of firms were excluded to ensure data consistency and longitudinal comparability. First, ten companies newly listed during FY 2018/19 were excluded, as their financials may not reflect stable post-listing performance and could introduce volatility into ratio-based analysis. Second, two companies that underwent mergers during the study period were omitted, as such structural changes materially alter financial statement composition and impair year-on-year comparability. These exclusions resulted in a refined population of 26 firms: 17 hydropower, six manufacturing, and three hotels. A purposive sampling approach was then applied to enable cross-sectoral comparison while maintaining balanced representation. Given the limited size of the hospitality sub-sector, the sample was standardized to three firms per sector, resulting in a final sample of nine companies. Firms were selected based on continuous listing under the respective NEPSE sub-index throughout the study period, availability of six consecutive years of complete audited financial statements (FY 2018/19 to FY 2023/24), and operational continuity without major structural changes such as mergers, acquisitions, or significant shifts in business scope.

To preserve analytical objectivity, the sampled firms are presented using anonymized, sector-based identifiers (e.g., Hotel 1, Hydro-1, Manufacturer A). Given the absence of confirmed regulatory findings or enforcement actions, this ensures that model-based indicators are not misinterpreted as conclusive evidence of earnings manipulation. Accordingly, anonymity is maintained to focus the analysis on sectoral patterns and methodological insights rather than firm-specific attribution.

Beneish M-Score Model

The Beneish M-Score, developed by Beneish (1999b), is a probabilistic model designed to detect earnings manipulation using publicly available financial data. It is based on a sample of firms identified as manipulators through regulatory actions, alongside a matched group of non-manipulators. The model assumes that manipulation leaves measurable distortions in financial ratios related to revenue recognition, asset quality, expenses, and accruals. It combines eight year-on-year financial indices into a single composite score using a weighted linear formula. A key strength of the model is its practicality, allowing external analysts to assess potential manipulation without requiring access to proprietary information. The composite M-Score is calculated using the following weighted linear formula:

$$\begin{aligned} \textit{M-Score} = {} & -4.84 + 0.92 \times DSRI + 0.528 \times GMI \\ & + 0.404 \times AQI + 0.892 \times SGI + 0.155 \times DEPI \\ & - 0.172 \times SGAI + 4.679 \times TATA - 0.327 \times LVGI \end{aligned} \tag{1}$$

Where:

$$\textit{Days Sales in Receivables Index (DSRI)} = \frac{(Receivables/Sales)^{t}}{(Receivables/Sales)^{t-1}}$$

$$\textit{Gross Margin Index (GMI)} = \frac{(GP\ Margin)^{t-1}}{(GP\ Margin)^{t}}$$

$$\textit{Asset Quality Index (AQI)} = \frac{[1-(CA+PPE)/TA]^{t}}{[1-(CA+PPE)/TA]^{t-1}}$$

$$\textit{Sales Growth Index (SGI)} = \frac{(Sales)^{t}}{(Sales)^{t-1}}$$

$$\textit{Depreciation Index (DEPI)} = \frac{[Depreciation/(Depreciation+PPE)]^{t-1}}{[Depreciation/(Depreciation+PPE)]^{t}}$$

$$\textit{Selling, General and Administrative Expense Index (SGAI)} = \frac{[SGA/Sales]^{t}}{[SGA/Sales]^{t-1}}$$

$$\textit{Leverage Index (LVGI)} = \frac{[(LTD+CL)/TA]^{t}}{[(LTD+CL)/TA]^{t-1}}$$

$$\textit{Total Accruals to Total Assets (TATA)} = \frac{(\textit{Net Income} - \textit{Cash from Operations})}{TA}$$

Note: CA = Current Assets; GP = Gross Profit; PPE = Property, Plant & Equipment; TA = Total Assets; LTD = Long-Term Debt; CL = Current Liabilities; SGA = Selling, General & Administrative Expenses.

Interpretation of the M-Score and Indices

The interpretation threshold established by Beneish (1999b) is as follows: a firm with an M-Score below –2.22 is classified as unlikely to be engaged in earnings manipulation, while a firm with an M-Score exceeding –2.22 is flagged as a potential manipulator. The threshold is derived from the estimated probability distribution of the logistic regression underlying the model, and it is widely cited in the forensic accounting literature as a robust first-pass screening criterion. Values substantially above –2.22, particularly those approaching zero or entering positive territory, correspond to a materially elevated probability of manipulation.

Table 1: Interpretation of Beneish M-Score Ratios

Table 1 summarizes the interpretive benchmarks of the Beneish M-Score ratios, as proposed in the Beneish (1999b) model, outlining the theoretical link between each ratio and the likelihood of earnings manipulation.

SN	Ratios	Interpretation
1	DSRI	Measures growth in receivables relative to sales. A DSRI >1 may indicate aggressive revenue recognition.
2	GMI	A GMI >1 suggests a deterioration in gross margins, potentially prompting earnings manipulation.
3	AQI	An AQI >1 may indicate increased capitalized costs or hidden asset inflation.
4	SGI	High sales growth (SGI >1) can increase pressure to sustain results, leading to potential manipulation.
5	DEPI	DEPI >1 indicates slower depreciation, which may artificially inflate earnings, possibly due to changes in asset life estimates or methods.
6	SGAI	A rising SGAI (i.e., SGAI >1) may indicate inefficient cost control or manipulation to maintain earnings despite rising overhead costs.
7	LVGI	A rising leverage index (LVGI >1) can signal pressure to manipulate to meet debt obligations.
8	TATA	Higher (more positive) accruals indicate greater use of discretionary accounting, which could reflect earnings manipulation.

Source: Beneish (1999b)

The eight component indices collectively provide a multi-dimensional diagnostic of financial reporting quality that the composite M-Score alone cannot capture. These indices must be interpreted in conjunction with one another and within their broader operational context. In addition to the composite score and standard definition for each of the 8 ratios, Beneish (1999b) provides empirically derived benchmark values for each of the eight component indices, distinguishing the mean values observed in the manipulator sample from those in the control (non-manipulator) group. These benchmarks, reproduced in Table 2 below, are used in this study to perform component-level diagnostic analysis alongside the composite M-Score.

Table 2: Beneish Threshold Values for Ratios

Table 2 presents the comparative threshold values of the Beneish M-Score ratio indices for manipulator and control firms, based on the original classification reported by Beneish (1999b) model, serving as diagnostic benchmarks for earnings manipulation

Ratio Index	Manipulators	Non-Manipulators (Control Group)
DSRI	1.465	1.031
GMI	1.193	1.014
AQI	1.254	1.039
SGI	1.607	1.134
DEPI	1.077	1.001
SGAI	1.041	1.054
LVGI	1.111	1.037
TATA	0.031	0.018

Source: Beneish (1999b)

Analytical Approach

The analysis is conducted in two stages. First, all eight Beneish ratios and the composite M-Score are calculated for nine companies over five fiscal years (FY 2019/20–FY 2023/24) using audited financial statements, with firms grouped by sector for comparative analysis. Second, the results are contextualized through a review of annual reports, audit opinions, notes to financial statements, and relevant corporate disclosures or market events to explain unusual ratio movements. Given the model's role as a screening tool, emphasis is placed on interpreting index behavior. Firms exceeding the Beneish M-Score manipulation threshold, as outlined in Table 2, while those with notably elevated indices are separately highlighted. For hydropower companies, a contextual adjustment is applied: certain intangible assets, such as generation licenses and project development costs, are reclassified as PPE when calculating the Asset Quality Index to reflect their operational nature and ensure cross-sector comparability.

DATA ANALYSIS AND FINDINGS

This section presents a systematic analysis of nine companies across three sectors listed on NEPSE: Hospitality, Hydropower, and Manufacturing. The Beneish M-Score model and its constituent indices are applied over five fiscal periods (FY 2019/20 to FY 2023/24), with analysis conducted at both the firm and sector level. For each sector, computed M-Scores and component indices are presented in tabular form, followed by firm-specific commentary and a cross-firm sectoral assessment.

Descriptive Statistics

Table 3 presents the descriptive statistics from Panels A–D provide insights into the distributional characteristics of the Beneish M-Score indices across the hospitality, hydropower, and manufacturing sectors, as well as the full sample, drawn from nine firms over five fiscal years (FY2019/20 to FY2023/24).

Table 3: Descriptive Statistics

Index	Mean	Median	SD	Min	Max
Panel A: Hospitality Sector (n = 15)					
DSRI	1.46	0.85	1.76	0.17	7.25**
GMI	1.02	1.01	0.15	0.75	1.40**
AQI	1.52*	0.99	1.11	0.49	4.78**
SGI	1.71*	1.11	1.78	0.13	6.17**
DEPI	1.07	0.97	0.26	0.89	1.93**
SGAI	1.23*	1.02	0.88	0.25	3.68**
TATA	-0.03	-0.03	0.03	-0.07	0.04**
LVGI	1.01	1.02	0.17	0.69	1.44**
M-Score	(1.36)*	(2.06)**	1.66	-3.08	2.38**
Panel B: Hydropower Sector (n = 15)					
DSRI	1.22	1.01	0.90	0.17	3.97**
GMI	0.98	0.99	0.08	0.79	1.12
AQI	1.77*	1.02	2.08	0.07	7.95**
SGI	1.21	1.09	0.51	0.75	2.80**
DEPI	0.90	0.94	0.36	0.10	1.44**
SGAI	1.28*	0.97	1.28	0.20	5.61**
TATA	-0.01	-0.02	0.13	-0.24	0.29**
LVGI	1.00	0.89	0.36	0.60	2.07**
M-Score	(1.92)*	-2.33	2.06	-4.26	4.09**
Panel C: Manufacturing Sector (n = 15)					
DSRI	1.32	1.12	0.80	0.00	2.94**

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Table 3: Descriptive Statistics *(Cont...)*

Index	Mean	Median	SD	Min	Max
GMI	0.94	0.96	0.14	0.59	1.17
AQI	1.28*	1.06	0.81	0.44	3.30**
SGI	1.00	0.96	0.26	0.70	1.54
DEPI	2.88*	0.91	7.51	0.79	30.05**
SGAI	1.00	1.03	0.21	0.43	1.28**
TATA	-0.02	-0.04	0.14	-0.31	0.30**
LVGI	0.91	0.89	0.22	0.33	1.32**
M-Score	(1.95)*	(2.12)**	1.22	-4.18	0.18**
Panel D: Full Sample					
DSRI	1.33	1.01	1.21	0.00	7.25**
GMI	0.98	0.99	0.13	0.59	1.40**
AQI	1.52*	1.03	1.42	0.07	7.95**
SGI	1.30	1.04	1.10	0.13	6.17**
DEPI	1.62*	0.95	4.34	0.10	30.05**
SGAI	1.17*	1.01	0.90	0.20	5.61**
TATA	-0.02	-0.03	0.11	-0.31	0.30**
LVGI	0.97	0.95	0.26	0.33	2.07**
M-Score	(1.74)*	(2.17)**	1.67	-4.26	4.09**

*SD = standard deviation. Figures in parentheses denote negative values. *Indicates index values that exceed the recommended thresholds set by Beneish (1999b) in Table 2. **Indicates index values that are significantly higher than the recommended threshold.*

The hospitality sector (Panel A) records the highest mean M-Score (–1.36) and breach rate (66.7%), with mean SGI (1.71) and AQI (1.52) exceeding manipulator thresholds. High dispersion in DSRI (SD = 1.76; max = 7.25) and SGI (SD = 1.78; max = 6.17) reflects pandemic-driven volatility and uneven recovery. The hydropower sector (Panel B) shows the widest M-Score range (–4.26 to +4.09), with mean AQI (1.77) and SGAI (1.28) above benchmarks. Stable GMI (mean = 0.98; SD = 0.08) indicates predictable earnings under power purchase agreements, suggesting manipulation signals lie outside core revenues. The manufacturing sector (Panel C) has a mean M-Score of –1.95 (breach rate: 53.3%), with DEPI (2.88) distorted by an outlier (30.05); excluding it, DEPI normalizes to 0.94. Elevated DSRI (1.32) indicates accrual-based adjustments.

Furthermore, across the full sample (Panel D), the mean M-Score of -1.74 lies above the -2.22 manipulation threshold, with 23 of 45 observations (51.1%) breaching this boundary. The median of -2.17 is more conservative, reflecting extreme upper-tail distortion, while the standard deviation of 1.67 underscores substantial cross-firm and cross-temporal dispersion. At the index level, mean AQI (1.52), DEPI (1.62), and SGAI (1.17) each exceed their respective manipulator benchmarks, identifying asset quality deterioration, depreciation-based adjustments, and disproportionate overhead growth as the dominant system-wide signals. DSRI (1.33) and SGI (1.31) approach their respective thresholds, indicating receivables and revenue growth pressures are present but not uniformly elevated.

Hospitality Sector

Table 4 presents the Beneish M-Score and component indices for three listed five-star hotels operating in the Kathmandu Valley across fiscal year 2019/20 to 2023/24. All three companies have established operational histories within Nepal's hospitality segment.

Table 4: Beneish M-Score Analysis – Hospitality Sector

Particulars/Year	2023/24	2022/23	2021/22	2020/21	2019/20
HOTEL 1					
DSRI	0.91	0.56	0.17	7.25**	1.61*
GMI	1.04*	1.06*	1.09*	0.85	0.98
AQI	1.35*	0.76	2.90*	2.19*	1.83*
SGI	1.06*	1.91*	6.17**	0.13	0.56
DEPI	0.93	1.19*	1.25*	0.94	0.89
SGAI	1.08*	0.87	0.25	3.68**	1.33*
TATA	-0.01	-0.04	-0.06	-0.01	0.00
LVGI	1.02*	0.69	1.17*	1.06*	1.02*
M-Score	-2.40	(2.17)*	2.01*	2.38*	(2.07)*
HOTEL 2					
DSRI	0.85	0.70	0.44	2.82*	1.08*
GMI	1.01*	1.03*	1.13*	0.86	0.99
AQI	0.91	0.82	0.89	0.97	0.99
SGI	1.11*	1.67*	3.08**	0.36	0.66
DEPI	0.95	1.05*	1.04*	0.98	0.97

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Table 4: Beneish M-Score Analysis – Hospitality Sector *(Cont...)*

Particulars/Year	2023/24	2022/23	2021/22	2020/21	2019/20
SGAI	1.02*	0.95	0.54	1.36*	1.16*
TATA	-0.03	-0.04	-0.01	0.01	-0.07
LVGI	0.97	0.77	0.89	1.44*	0.98
M-Score	-2.69	-2.30	(1.04)*	(1.61)*	-3.08
HOTEL 3					
DSRI	1.23*	0.67	0.43	2.34**	0.81
GMI	1.10*	1.00	1.40*	0.75	0.96
AQI	1.16*	0.82	0.49	1.90*	4.78**
SGI	1.11*	1.94*	5.05**	0.16	0.61
DEPI	0.95	0.91	1.10*	1.93*	0.95
SGAI	1.00	0.84	0.37	2.71*	1.23*
TATA	-0.04	-0.02	-0.05	0.04*	-0.06
LVGI	1.03*	0.96	1.05*	0.98	1.13*
M-Score	-2.25	(2.06)*	0.47*	(1.78)*	(1.87)*
Average M-Score	-2.44	(2.17)*	0.48*	(0.34)*	-2.34

**Indicates index values that exceed the recommended thresholds set by Beneish (1999b) in Table 2. ***Indicates index values that are significantly higher than the recommended threshold. Figures in parentheses denote negative values.*

Hotel 1 exhibited potential financial statement manipulation in three of five years (FY 2019/20, 2021/22, and 2022/23), with M-Scores of -2.07, 2.01, and –2.17 respectively, all exceeding the -2.22 threshold. Pandemic-period DSRI spikes (FY 2019/20: 1.61; FY 2020/21: 7.25) indicate that receivables grew substantially faster than sales, which may reflect delayed write-offs or relaxed credit terms rather than genuine revenue generation. Persistent AQI elevation (ranging from 1.35 to 2.90 across four of five years) coincides with debt-funded renovation activity and points to potential earnings manipulation through interest capitalization and deferred depreciation of capitalized costs. The sharp SGI increase in FY 2021/22 (6.17) is consistent with post-pandemic revenue recovery but also creates conditions conducive to aggressive revenue recognition. Sustained GMI deterioration across FY 2021/22 to FY 2023/24 further suggests that margin pressure may be providing ongoing incentive for income smoothing.

Hotel 2 recorded M-Scores above the threshold in FY 2020/21 (–1.61) and FY 2021/22 (–1.04), coinciding with the pandemic recovery period. Elevated DSRI values in FY 2019/20 (1.08) and FY 2020/21 (2.82) reflect sector-wide receivables stress, while persistent GMI deterioration from FY 2021/22 through FY 2023/24 signals sustained margin erosion. The combination of rising SGI post-pandemic (FY 2021/22: 3.08; FY 2022/23: 1.67) and concurrent SGAI and GMI threshold breaches suggests that reported revenue growth may have been accompanied by earnings manipulation practices aimed at portraying a stronger recovery narrative.

Hotel 3 displayed manipulation indicators in three fiscal years (FY 2019/20: –1.87; FY 2020/21: –1.78; FY 2022/23: –2.06). Exceptionally high AQI values in FY 2019/20 (4.78) and FY 2020/21 (1.90) during renovation activity raise significant concerns regarding asset recognition practices. Sharp GMI deterioration in FY 2021/22 (1.40) and FY 2023/24 (1.10), combined with aggressive SGI growth (FY 2021/22: 5.05; FY 2022/23: 1.94), points to revenue recognition practices potentially aimed at offsetting competitive and margin pressures.

A sector-level assessment underscores systemic financial reporting vulnerabilities linked to macroeconomic shocks and sectoral dynamics. The hospitality sector recorded an overall mean M-Score of –1.36 falls above the –2.22 threshold, indicating that the sector as a whole is skewed toward the manipulation-risk zone. Pandemic-era DSRI spikes (FY 2019/20–2020/21) suggest widespread reliance on receivables-related reporting adjustments, while post-pandemic SGI surges (FY 2021/22–2022/23) reflect both genuine operational recovery and potential revenue recognition acceleration. Persistent GMI and SGAI threshold breaches (FY 2021/22–2023/24) point to ongoing margin erosion and competitive pressure, both of which elevate manipulation incentives. Asset quality concerns, particularly in Hotels 1 and 3, were amplified by renovation activities that create scope for capitalization and depreciation-related earnings manipulation. Among fifteen firm-year observations, only five (33.3%) recorded M-Scores below the –2.22 threshold, highlighting elevated and broadly distributed manipulation risk during periods of economic disruption and competitive stress.

Hydropower Sector

Table 5 presents the Beneish M-Score and component indices for three hydropower companies of varying operational scales over across fiscal year 2019/20 to 2023/24. All companies *have maintained continuous operations throughout the study period, with Hydropower 1 and Hydropower 2 simultaneously engaged in developing new generation projects.*

Table 5: Beneish M-Score Analysis – Hydropower Sector

Particulars/Year	2023/24	2022/23	2021/22	2020/21	2019/20
HYDRO-1					
DSRI	2.27**	0.79	0.89	1.05*	0.66
GMI	1.12*	0.92	0.95	0.90	1.00
AQI	0.15	1.62*	2.05**	5.16**	0.07
SGI	2.80**	0.86	1.41*	1.13*	1.82*
DEPI	1.37*	0.95	0.43	0.50	1.44*
SGAI	0.20	5.61**	0.57	0.28	0.97
TATA	-0.04	-0.18	-0.03	0.19*	-0.04
LVGI	0.89	1.09*	1.01*	0.89	0.95
M-Score	0.04*	-4.26	(1.95)*	0.32*	-2.58
HYDRO-2					
DSRI	0.17	0.44	0.97	3.97**	1.58*
GMI	0.96	1.11*	0.97	0.79	0.99
AQI	0.85	1.69*	1.09*	7.95**	0.96
SGI	0.97	1.12*	1.09*	0.75	1.04*
DEPI	1.28*	0.99	0.99	0.93	0.10
SGAI	1.76*	0.68	1.48*	1.79*	0.84
TATA	0.00	-0.24	-0.09	0.29**	0.01
LVGI	0.75	1.56*	2.07*	0.60	0.94
M-Score	-3.37	-3.80	-3.24	4.09*	(1.96)*
HYDRO-3					
DSRI	1.01*	1.14*	1.09*	1.28*	0.97
GMI	1.00*	0.97	1.00	1.00*	1.00*
AQI	1.03*	1.02*	0.92	0.98	1.02*
SGI	0.99	0.82	1.10*	0.99	1.19*
DEPI	0.80	0.80	0.94	0.84	1.20*
SGAI	1.01*	1.23*	0.88	1.05*	0.82
TATA	-0.02	-0.03	-0.01	-0.01	-0.02
LVGI	0.80	0.82	0.82	0.88	0.89

Continued on next page

Table 5: Beneish M-Score Analysis – Hydropower Sector *(Cont...)*

Particulars/Year	2023/24	2022/23	2021/22	2020/21	2019/20
M-Score	-2.51	-2.66	-2.33	-2.26	-2.33
Average M-Score	(1.95)*	-3.57	-2.51	0.72*	-2.29

**Indicates index values that exceed the recommended thresholds set by Beneish (1999b) in Table 2. **Indicates index values that are significantly higher than the recommended threshold. Figures in parentheses denote negative values.*

Hydro–1 shows a concerning pattern of threshold breaches, with M-Scores exceeding –2.22 in three of five years (FY2020/21: 0.32, FY2021/22: -1.95, FY2023/24: 0.04). DSRI spikes (FY2020/21: 1.05; FY2023/24: 2.27) coincide with substantive increases in "other income," raising concerns over revenue legitimacy. Exceptionally high AQI values (FY2020/21: 5.16; FY2021/22: 2.05; FY2022/23: 1.62) reflect large capital work-in-progress balances arising from new project development, which complicates AQI-based inference; however, the magnitude and persistence of these values warrants attention. Persistent SGI elevation (1.13–2.80) is partly attributable to the commissioning of a previously under-construction project but also creates conditions for aggressive income recognition through other income streams. Notably, TATA was positive and above the manipulator threshold in FY 2020/21 (0.19), confirming accrual-based income enhancement during that period. DEPI breaches in FY 2019/20 (1.44) and FY 2023/24 (1.37) indicate decelerated depreciation in those years, which directly inflates reported earnings.

Hydro–2 exhibits a distinct pattern of manipulation indicators concentrated in specific periods (FY2019/20: -1.96; FY2020/21: 4.09), followed by subsequent improvement. The extraordinary DSRI spike in FY 2020/21 (3.97) corresponds directly with substantial related-party advances to a sister company, raising concerns about the economic substance of those receivables. The concurrent AQI value (7.95) reflects significant increases in long-term investments in the same entity, suggesting that both receivables and asset quality distortions were connected to a single related-party arrangement. TATA reached 0.29 in FY 2020/21, well above the threshold of 0.03, confirming the accrual intensity of that year's reported income. Elevated LVGI values in FY 2021/22 (2.07) and FY 2022/23 (1.56) indicate rising leverage, which creates heightened incentives for earnings manipulation to maintain covenant compliance. The subsequent improvement in M-Scores from FY 2021/22 through FY 2023/24 suggests a degree of normalization, though volatility in other income recognition across multiple periods remains a concern.

Hydro–3 presents a remarkable contrast, with M-Scores consistently below the manipulation threshold across all five years (ranging from -2.26 to -2.66). This consistent compliance is particularly notable given that individual component indices—most commonly DSRI and SGAI—occasionally breach their respective non-manipulator thresholds, yet the composite score remains within the non-manipulation range. This pattern suggests that threshold exceedances in individual indices reflect operational and structural characteristics of the business, such as a regulated revenue environment with periodic billing lags, rather than systematic manipulation. The consistently negative and low TATA values (ranging from -0.01 to -0.03) are consistent with disciplined accrual practices and cash-generative operations. Hydro-3's performance serves as an important comparative anchor, demonstrating that it is possible for a capital-intensive hydropower firm operating within the same regulatory environment to maintain consistent reporting integrity.

The sector-level assessment reveals material heterogeneity in financial reporting integrity, with the overall sector mean M-Score of –1.92 reflecting polarization between a transparent operator (Hydro-3) and two firms with concentrated, period-specific manipulation indicators. While the sector's capital-intensive structure introduces reporting vulnerabilities, these are partly offset by a regulated operational environment, particularly in power trade and receivables manipulation. Capital work-in-progress accounting emerges as a potential avenue for earnings manipulation. The sector's regulated revenue model, reliant on state entities, shifts manipulation toward "other income" and related-party transactions rather than core revenues. This suggests that in regulated infrastructure sectors, earnings manipulation may manifests differently compared to consumer-facing industries. Moreover, the sector's dependence on debt financing creates incentives for manipulation tied to covenant compliance, although lender oversight serves as a deterrent.

Manufacturing Sector

Table 6 presents the Beneish M-Score and Index Scores for three manufacturing companies over five fiscal years (2019/20–2023/24). Manufacturers A and B operate in the alcoholic/non-alcoholic beverage industry, while Manufacturer C is associated in with the construction sector.

Table 6: Beneish M-Score Analysis – Manufacturing Sector

Particulars/Year	2023/24	2022/23	2021/22	2020/21	2019/20
Manufacturer A					
DSRI	2.28**	1.65*	0.77	1.35*	1.12*
GMI	0.98	0.96	0.92	1.13*	0.82
AQI	1.83*	0.50	0.44	0.58	1.92*
SGI	0.94	1.02*	1.48*	1.31*	0.84
DEPI	0.90	0.98	0.91	0.91	0.79
SGAI	1.11*	1.06*	0.88	0.73	0.97
TATA	-0.07	0.01	-0.08	-0.10	0.05*
LVGI	1.04*	0.97	0.86	0.89	1.05*
M-Score	(1.39)*	(2.05)*	-2.85	-2.39	(2.02)*
Manufacturer B					
DSRI	0.00	2.33**	2.03**	0.37	2.94**
GMI	0.99	0.97	1.02*	1.17*	1.02*
AQI	3.30*	0.96	1.04*	1.96*	0.66
SGI	0.70	0.73	1.10*	1.54*	0.77
DEPI	1.02*	1.00*	0.90	0.90	1.03*
SGAI	1.27*	1.12*	1.13*	1.01*	0.85
TATA	-0.31	0.30*	0.18*	-0.12	0.10*
LVGI	0.88	0.79	0.85	0.33	1.32*
M-Score	-4.18	(0.09)*	(0.58)*	-2.47	(0.65)*
Manufacturer C					
DSRI	0.80	1.03*	0.96	0.86	1.29*
GMI	0.81	0.89	0.59	0.83	0.95
AQI	1.06*	1.10*	0.52	2.23**	1.11*
SGI	0.99	0.84	0.96	1.07*	0.79
DEPI	1.04*	1.04*	30.05**	0.90	0.91
SGAI	1.01*	1.03*	1.28*	0.43	1.08*
TATA	-0.04	-0.05	-0.03	-0.01	-0.13
LVGI	0.94	0.85	1.01*	1.10*	0.72
M-Score	-2.89	-2.79	0.18*	(2.12)*	-2.91
Average M-Score	-2.82	(1.64)*	(1.15)*	-2.33	(1.86)*

Indicates index values that exceed the recommended thresholds set by Beneish (1999b) in

*Table 2. **Indicates index values that are significantly higher than the recommended threshold. Figures in parentheses denote negative values.*

Manufacturer A's Beneish M-Scores breach the –2.22 threshold in three of five years (FY 2019/20: –2.02; FY 2022/23: –2.05; FY 2023/24: –1.39), indicating a recurring pattern of manipulation risk. The DSRI has risen steadily across the study period, reaching 2.28 in FY 2023/24, coinciding with a 2.57 fold increase in unsecured receivables. This trajectory suggests an increasingly aggressive credit extension policy that may be oriented toward inflating reported sales rather than reflecting genuine commercial demand. AQI was elevated in FY 2019/20 (1.92) and again in FY 2023/24 (1.83), with the latter coinciding with a 1.72 fold increase in intangible asset balances; the nature, recognition basis, and valuation of these intangibles warrants close scrutiny. Persistent SGAI elevation in FY 2022/23 and FY 2023/24 (1.06 and 1.11 respectively) indicates that overhead expenses are growing relative to sales, while TATA was above the manipulator threshold in FY 2019/20 (0.05), confirming accrual-based income enhancement in that year. The rising LVGI in FY 2023/24 (1.04) reflects extended supplier payment terms, adding a working capital manipulation dimension to the firm's financial reporting profile.

Manufacturer B recorded M-Scores above the manipulation threshold in three of five years (FY 2019/20: –0.65; FY 2021/22: –0.58; FY 2022/23: -0.09). DSRI was exceptionally elevated in three years (FY 2019/20: 2.94; FY 2021/22: 2.03; FY 2022/23: 2.33), followed by a near-zero value in FY 2023/24, suggesting a dramatic reversal of receivables manipulation practices. Qualitative review reveals that significant related-party transactions and delayed recovery characterize the high-DSRI years, with the sharp FY 2023/24 correction consistent with the resolution or write-off of these balances. AQI was significantly elevated in FY 2020/21 (1.96) and FY 2023/24 (3.30), with the latter spike attributable to investment in securities coinciding with the recovery of previously outstanding receivables, a pattern that may indicate asset redeployment rather than independent investment. TATA exceeded the manipulator threshold in three of five years (FY 2019/20: 0.10; FY 2021/22: 0.18; FY 2022/23: 0.30), providing consistent confirmation that accrual-based reporting was a central feature of the firm's income recognition in those periods. SGAI has been persistently above the non-manipulator threshold from FY 2020/21 through FY 2023/24, reflecting ongoing overhead pressures that may be driving income smoothing behavior.

Manufacturer C exhibited potential earnings manipulation in two of five years (FY 2020/21: -2.12; FY 2021/22: 0.18). The most striking indicator is the DEPI value of 30.05 in FY 2021/22, arising from a change in depreciation method under Nepal Financial Reporting Standards (NFRS). While this change was auditor-cleared, the alignment of the accounting policy shift with a market peak (FY 2021/22) and the concurrent expiry of promoter and employee share lock-in periods following IPO listing raises the possibility of strategic earnings enhancement timed to benefit from favourable market conditions, a concern that is particularly acute because the depreciation methodology change persists across subsequent years, embedding a structural upward bias into reported earnings that would not be detectable without tracing the practice back to its initial year. AQI was elevated in FY 2020/21 (2.23), FY 2022/23 (1.10), and FY 2023/24 (1.06), attributed to large investment balances and the recognition of Right-of-Use assets under new lease accounting standards. Persistent SGAI elevation from FY 2021/22 through FY 2023/24 suggests ongoing overhead pressure despite relatively stable sales growth.

Across the three manufacturing firms, the overall sector mean M-Score of –1.95 exceeding the -2.22 threshold, indicating that on average the sector sits within the manipulation-risk zone. Seven of fifteen firm-year observations (46.7%) breach the threshold, the highest proportion across the three sectors examined. Earnings manipulation patterns are concentrated in three distinct areas: volatile receivables manipulation in Manufacturers A and B, characterized by multi-year DSRI threshold breaches and, in Manufacturer B, large TATA values; asset quality distortions through intangible assets and investment in securities in Manufacturers A and B; and depreciation-based income inflation in Manufacturer C, which is particularly concerning given the circumstances surrounding the accounting policy change and its embeds a lasting earnings manipulation mechanism into the firm's financial structure.

SUMMARY AND CONCLUSION

This study applied the Beneish M-Score to 45 firm-year observations across nine listed real-sector companies over five fiscal years (FY2019/20–FY2023/24). Approximately 51% of observations exceeded the manipulation threshold, though this figure should be interpreted cautiously given the model's U.S. calibration and Nepal's distinct institutional context including different adoption of substantially different accounting standard. In this context, the component indices, examined longitudinally and in conjunction with qualitative review of corporate disclosures, yield more reliable diagnostic insight than binary threshold classification. Abnormal index values and elevated M-Scores should accordingly be treated as investigative signals warranting further scrutiny, not as conclusive evidence of misconduct. The findings of this study are best interpreted as context-specific, firm-level analytical signals that provide a preliminary basis for further review by investors, auditors, and regulators.

Across the three sectors, risk profiles vary and are shaped by structural conditions. The hospitality sector records the highest mean M-Score (–1.36) and lowest threshold compliance (33.3%), largely reflecting the macroeconomic disruption of COVID-19. The revenue shock during FY2019/20–2020/21 resulted in elevated DSRI and AQI, linked to receivables behavior and asset capitalization during renovation periods. During recovery, SGI indicates rapid revenue rebound, while higher GMI and SGAI reflect margin pressure and rising costs. These patterns signal heightened reporting risk under stress rather than definitive evidence of manipulation.

The hydropower sector shows more heterogeneous outcomes, with a mean M-Score of –1.92. Its regulated revenue model, driven by power purchase agreements with the Nepal Electricity Authority, limits manipulation of core revenues. Detected risks are concentrated in non-core areas such as other income, CWIP accounting, related-party transactions, and depreciation. The consistent compliance of Hydro-3 highlights that strong reporting integrity is achievable within the same regulatory setting. However, large CWIP balances and project-phase transitions can create legitimate distortions in Beneish indices.

The manufacturing sector presents the strongest risk profile, with a mean M-Score of –1.95 and 46.7% threshold breaches. Three key mechanisms emerge: (i) receivables-driven income inflation (Manufacturers A and B) reflected in persistent DSRI elevation and accrual anomalies, (ii) asset quality distortions from expanding intangibles and investments affecting AQI and GMI, and (iii) depreciation-based earnings manipulation in Manufacturer C, where an NFRS-compliant policy change coincided with the FY2021/22 market peak and lock-in expiry.

The case of Manufacturer C is of particular significance from a financial reporting policy perspective. The policy change was auditor-cleared and technically compliant with applicable standards; yet its timing demonstrates that such instances need not involve misstatement to distort the informational content of financial statements. The concurrent presence of incentive and opportunity, in the sense developed by Wolfe Hermanson (2004) in the

Fraud Diamond framework, was demonstrably present, with manipulation and insiders holding both the accounting discretion and the strategic motive to influence reported earnings at a moment of maximum financial consequence. Direct evidence of rationalization remained inaccessible in the absence of regulatory proceedings.

The subsequent reversal of elevated earnings indicators in Manufacturer B further parallels the evidence documented by Cheng and Chung (2006), suggesting temporary manipulation by normalization once strategic objectives had been achieved. Furthermore, these two events can be classified into accrual and accounting based earnings manipulation and earnings manipulation through real business practices as outlined by Gao and Gao (2016). These patterns are consistent with prior empirical literature and carry analytical weight, though they remain circumstantial absent formal regulatory findings.

Notwithstanding these constraints, the study makes three contributions to the forensic accounting literature on Nepal's emerging market. It demonstrates that disaggregated, longitudinal application of the Beneish M-Score produces analytically meaningful earnings quality signals that binary classification obscures. It directly challenge the conclusions of Gyawali (2021) regarding the model's limited effectiveness in Nepal, showing that sector-specific calibration and index-level interpretation substantially enhance its diagnostic value beyond the banking sector context in which it has previously been applied and align more closely with the findings of Mollah and Sakib (2020) and Soufiane and Moad (2024), confirming that the model's limitations in emerging market contexts are methodological rather than fundamental, and are addressable through more granular application.

Recommendation

Based on the empirical findings and theoretical insights of this study, several recommendations are advanced for investors, regulators, and researchers operating within Nepal's capital market.

For investors, the Beneish M-Score should serve as an initial screening mechanism, particularly in non-banking sectors such as manufacturing, hospitality, and hydropower. However, reliance on its binary cutoff is discouraged. Greater analytical value lies in examining the individual Beneish indices to identify sector-specific vulnerabilities. Given the model's indicative rather than deterministic nature, investors should integrate its eight components with complementary financial ratios, cash flow analysis, governance indicators, and qualitative assessments to form a more comprehensive evaluation of earnings quality.

For regulators, intensified oversight is warranted in areas susceptible to manipulation, including receivables manipulation, capitalization policies, depreciation estimates, and recognition of non-core income. Monitoring should be heightened during high-risk periods such as market peaks, IPO lock-in expirations, accounting transitions, major capital expenditures, and industry downturns. The study identified sector-wide indications of potential earnings manipulation, with two cases particularly notable for the timing of accounting adjustments alongside favorable market conditions and share divestment windows. While such patterns may partly reflect economic circumstances, their sequencing justifies closer supervisory review to determine whether any stakeholders disproportionately benefited or whether material information may have been misused.

These recommendations are especially timely. With over 50 companies approaching IPO lock-in expirations in the next two years, and IPO participation becoming increasingly mainstream in Nepal amid a rising number of listing applications, performance pressures are likely to intensify. Although regulators apply eligibility criteria to screen prospective issuers, firms may still attempt to manage earnings to satisfy listing thresholds or sustain optimistic valuations. Regulatory vigilance should therefore extend beyond already listed entities to include firms in the pre-listing phase. Given that equity issuance and valuation incentives are well-established global drivers of earnings manipulation, targeted oversight during such windows is critical. Strengthening audit committee independence, enhancing external audit quality, heightened regulatory scrutiny of critical accounting estimates and reinforcing the effectiveness of independent directors and corporate governance standards remain central to mitigating agency risks in Nepal's emerging market environment.

For researchers, future studies should broaden the dataset and undertake comparative evaluations using alternative forensic frameworks such as the Dechow F-Score, Altman Z-Score, and Piotroski F-Score to assess relative detection capability. Incorporating more advanced analytical approaches, such as panel data econometrics and other quantitative techniques, would further enhance robustness and provide deeper insight into the structural determinants of earnings manipulation within Nepal's evolving capital market.

Limitations

This study acknowledges several limitations affecting the generalizability and robustness of its findings. The application of the Beneish M-Score, developed using U.S. data (1982–1992), raises concerns about its transferability to Nepal's distinct regulatory, accounting, and business context, potentially constraining diagnostic accuracy. Although disaggregating the eight indices partially mitigates this, contextual bias may persist.

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