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Financial Statement Manipulations in Global Corporations: An Audit-Based Analysiss Using the Beneish M-Score Model

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Abstract — This paper focuses on the probability of manipulation of financial statements in twenty large international companies, including ten Indian companies and ten non-Indian companies, in the future (2021- 2025) through the Beneish M-Score model. The sample size is 100 publicly traded firm-years based on annual reports prepared in Ind AS, IFRS and US GAAP financial reporting frameworks. All the eight Beneish variables are included to determine composite M-Scores which are compared to the standard threshold of -2.22.

The results show that about 95 percent of the observations lie below the manipulation threshold, implying that financial reporting integrity of the sampled firms is high. Nevertheless, the individual cases of high M-Scores can be traced among a few companies, whose increase or decrease is mainly caused by changes in the Sales Growth Index and indicators based on accruals. The comparison of cross country shows no statistically significant difference in mean M-Scores between non-Indian and Indian corporations and a larger variability among non-Indian corporations.

The findings emphasize the applicability of the Beneish M-Score as a beneficial analytical instrument to promptly identify possible earnings manipulation. The research has a practical implication to the auditors, the regulators and investors as it supports risk-based assessment and improves the quality of financial reporting evaluation in multinational corporate settings.

Keywords: Beneish M-Score; Earnings Management; Financial Statement Manipulation; Forensic Accounting; Multinational Corporations; Audit Risk; Accrual Analysis; Cross-Jurisdictional Reporting.

1. Introduction

Essential to effective capital distribution stands the trustworthiness of financial reports, since stakeholders like investors, lenders, officials, and review bodies depend upon company- provided data when judging results and exposure. Transparency along with consistency across entities has grown due to systems including IFRS, US GAAP, and Ind AS - each shaping how numbers are recorded and shared. Still, because accounting built on accruals permits judgment in reporting choices, room opens for guiding profits toward desired outcomes, possibly warping the true picture of organizational health.

Because rules allow variation, telling honest estimates apart from deliberate changes grows complicated. Past cases like Enron, WorldCom, and Satyam Computer Services show old audit methods fall short when facing complex distortions. As a result, sharper analysis techniques become necessary over time.

Responding to these concerns, tools such as the Beneish M-Score (Beneish, 1999) now play a larger role. Financial indicators form its core method, aiming to detect possible distortions in reported profits. Auditors and analysts find it useful - its structure supports early assessment through pattern recognition.

Even with much analysis done, findings usually apply only within one nation or sector. Though big global firms tend to show tighter controls plus audits, their behavior across borders remains poorly studied. The years from 2020 through 2025 brought unusual pressure on reporting choices, influenced by health crises and financial shifts.

This research examines twenty multinationals - half based in India, half elsewhere - from 2021 to 2025, using the Beneish M-Score. Rather than simply identifying risks of earnings manipulation, it explores how such indicators differ across national contexts. Over time, certain shifts become noticeable. Insights emerge that may inform auditing practices, though implications are left for interpretation. Patterns unfold which suggest regional variations matter. Temporal movement in

scores hints at evolving financial behaviours. The focus remains

on observation, not prescription.

2. Review of Literature and Theoretical Framework

2.1 Earnings Management and Forensic Detection

Financial statements often reflect deliberate choices made by managers, raising concerns about accuracy. What appears under the label of earnings management involves adjustments through discretion allowed in reporting rules. One perspective sees such actions as attempts to affect how results are viewed by investors or partners. Consideration began with incentives tied to performance pay, as noted in research focusing on reward systems. Later analysis shifted toward how non-cash accounting items influence perceived profitability. These shifts reveal patterns shaped more by timing than actual cash flow changes.

From a different starting point, Patricia M. Dechow, Sloan, and Sweeney (1995) separate accrual-focused adjustments from changes tied to actual operations, forming early groundwork for methods detecting financial anomalies. Yet another path emerges when Roychowdhury (2006) demonstrates how companies shift reported results via actions like producing beyond demand or cutting flexible costs at will.

What supports this comes from actual data showing older audit methods fall short. Around stock issuance moments, studies by S. Rangan in 1998 along with Ivo Welch and team notice patterns where accounting estimates lean one way. Then again, work later done by Cohen and others in 2008 shows firms moving tactics - away from number adjustments toward altering real operations when rules tighten. This adaptation implies profit reporting shifts shape depending on oversight conditions.

What emerges from these analyses is a pattern: distortions in financial reports are widespread, shifting forms over time. Because of this behavior, methods rooted in numerical scrutiny gain importance. Detection grows harder when tactics evolve constantly. One response involves systematic analysis through statistical models. Such approaches respond to the changing nature of misrepresentation. Tools designed for anomaly identification become necessary under these conditions. The persistence of manipulation demands consistent monitoring techniques.

2.2 Beneish M Score Model with Real World Data

Beginning with academic work from 1999, the Beneish M-Score stands as a common tool to spot altered financial results. Firms previously flagged by SEC enforcement measures form the basis of its statistical method, which relies on probit regression analysis.

Beginning with DSRI and moving through GMI, AQI, SGI, DEPI, SGAI, LVGI, up to TATA, this method draws on eight financial markers. Each index reflects a distinct facet of reporting conduct, not limited to how revenue is recorded. Margin shifts emerge alongside asset reliability, forming part of the broader picture. Expense treatment appears tied closely to patterns in leverage. Accrual depth surfaces where extended financing structures exist. Rather than isolated signals, these metrics operate as an interwoven set. Their strength lies in overlapping insight across behavioral zones. What results is a structure sensitive to subtle distortions.

Later analysis confirms the model performs reliably. Using data from companies flagged as manipulative, Beneish, Lee, and Nichols (2013) observe unusual market returns through trading applications - evidence pointing toward forecasting strength. Applicability across geographies gains backing too. In Eastern European contexts, Ciubotaviu and Cernovschi (2024) detect clear links between elevated M-Scores and flawed reporting patterns. At the same time, work by Isnawati and colleagues (2024) reveals a rise in warning indicators coinciding with global health disruptions.

Despite differing methodologies, the model outperforms counterparts like the Altman Z-Score and Dechow F-Score, as shown in comparative assessments (Miharsi et al., 2024). Rather than relying solely on traditional metrics, newer approaches blend Beneish indicators with machine learning methods (Dbouk and Zaarour, 2017; Sodnomdavaa and Lkhagvadorj, 2026), yielding sharper fraud identification. Where behavioral aspects matter, integration with Fraud Pentagon concepts adds depth to interpretation (Fadilla and Andarsari, 2025).

Even with such inputs, a majority of research focuses narrowly on particular areas, sectors, or brief periods - suggesting wider cross-case examination is necessary.

2.3 Empirical synthesis and research gap

From a review of current studies, certain shortcomings emerge - these restrict how widely findings can be applied. Though patterns appear across works, real-world usefulness remains limited by unresolved inconsistencies. Where conclusions overlap, context often weakens transferability. Despite volume, coverage lacks depth in key areas. Gaps persist even where data seems abundant. Each analysis adds fragments rather than full clarity. Broad claims rest on narrow foundations. Repeated methods do not resolve underlying constraints.

Primarily, research tends to focus on one nation at a time, which restricts broader comparisons across regions. Because oversight rigor varies - alongside board setups and rule frameworks like

IFRS, US GAAP, or Ind AS - the impact on how numbers get reported stays poorly understood. Despite its relevance, this

variation rarely draws deep analysis.

Yet another gap appears when earlier studies center on smaller or troubled companies, given how often issues arise there. Though major global businesses shape economies, systematic scrutiny of them remains sparse. Rarely do investigations challenge the idea that robust supervision naturally limits deceptive practices. Instead, confidence in controls tends to go unchecked.

Over time, research has not kept pace with economic turbulence. During 2020 to 2025, global shocks - health crises, rising prices, political strain - shifted corporate reporting behaviors.

Although some work points to heightened financial adjustment under stress, long-term observation stays limited. Insights like those from Isnawati and team in 2024 highlight concerns, yet extended tracking across years is still missing.

One more point: numerous analyses view the Beneish model strictly through a numerical lens, omitting its alignment with auditing practices. Earlier research points out that when numbers meet expert insight, outcomes in audits improve. Yet this integration remains inconsistent.

Fifth, newer methods including machine learning and behavior-based modeling remain rarely used when analyzing corporations across nations - this suggests unexplored paths in academic exploration. Yet gaps persist where these techniques could contribute meaningfully. Uncommon usage highlights a quiet opening for deeper inquiry elsewhere. Where adoption lags, opportunity quietly grows. Progress may lie beyond current methodological borders.

Still, hard data on Indian versus non-Indian multinationals under one consistent model stays scarce. When rules differ, so might how companies report - ownership models and oversight strength play roles. Research that links these cases still lacks cohesion, scattered across separate studies.

Research Gap Summary

The study addresses the following key gaps:

- Lack of cross-country comparative analysis
- Primarily directed toward major global firms with substantial market capitalization
- Insufficient longitudinal analysis during economic instability
- Weak integration of forensic models with audit frameworks
- Underexplored India vs global comparison
- Limited application of hybrid analytical approaches

Where This Research Stands

This study examines unresolved issues through application of the Beneish M-Score method to a defined group of global firms operating under different legal systems during 2021–2025. Alongside audit logic, investigative techniques are combined here – yielding outcomes useful within scholarly discussion and real- world review alike.

3. Theoretical Framework

3.1 Theoretical Foundations

Grounded in central theoretical models, this research explores how managers act when preparing financial reports.

1. Agency Theory

From Jensen and Meckling (1976), Agency Theory outlines tensions between owners and executives due to unequal access to information. In intricate global operations, such imbalances grow more pronounced. Executive decisions might favor individual gain instead of investor interest. Earnings adjustments sometimes serve private objectives under these conditions.

2. Positive Accounting Theory

Accounting decisions may reflect motivations tied to compensation contracts or borrowing terms, according to Watts and Zimmermann's work from 1986. These motives show up in certain measures used by Beneish, including those assessing asset growth patterns and discretionary accruals. Though developed separately, both frameworks point toward strategic reporting behavior under pressure from external agreements.

3. Information Asymmetry Theory

Unequal access to knowledge, as noted by Akerlof in 1970 and later expanded by Stiglitz in 1975, creates conditions where managers may act in self-interest. Such imbalances grow more pronounced when firms operate across national borders. Where one party knows significantly more than another, decisions often favor those with insight. Oversight becomes harder still in international structures, opening room for misuse. Disparities in awareness do not simply exist - they shape behavior. Geographic distance widens the gap further, compounding risks. What remains clear is that transparency does not travel well across boundaries.

4. Fraud Triangle Meets Human Behavior

Originating in 1953 with Cressey, the Fraud Triangle attributes deception to three conditions: stress, access, followed by justification. Building on this model, later frameworks like the Fraud Pentagon introduce further psychological aspects - thereby

refining insight into motives behind deceitful acts.

Theoretical Integration

The formula turns abstract ideas into numbers, using signals like executive motives or uneven data access. Through this lens, academic models meet real-world detection methods, forming a methodical basis for review processes.

3. Research Methodology

3.1 Sample Design

Twenty big non-financial global companies - half based in India, half elsewhere - were chosen through deliberate selection guided by four conditions. Operating across borders formed the first condition. High market value counted as the second. Third came access to unbroken sequences of yearly financial reports between 2020 and 2025. Last, firms had to fall outside the financial industry category. Institutions handling money did not qualify due to unique accounting patterns, mandatory capital rules, and income reporting methods incompatible with the Beneish measurement system. These choices produced a group detailed later in Table 1.

Table 1: Sample Corporations

Company	Group	Sector	Reporting Standard
Reliance Industries	Indian	Energy / Diversified	Ind AS
Tata Consultancy Services	Indian	Technology	Ind AS
Infosys Limited	Indian	Technology	Ind AS
Hindustan Unilever	Indian	Consumer Goods (FMCG)	Ind AS
ITC Limited	Indian	Diversified Conglomerate	Ind AS
Bharti Airtel	Indian	Telecommunications	Ind AS
Larsen & Toubro	Indian	Engineering / EPC	Ind AS
Maruti Suzuki India	Indian	Automobile	Ind AS
Sun Pharmaceutical	Indian	Pharmaceuticals	Ind AS
UltraTech Cement	Indian	Construction Materials	Ind AS
Apple Inc.	Non-Indian	Technology	US GAAP
Microsoft Corporation	Non-Indian	Technology	US GAAP
Amazon.com Inc.	Non-Indian	E-Commerce / Cloud	US GAAP
Alphabet Inc.	Non-Indian	Technology / Advertising	US GAAP
Tesla Inc.	Non-Indian	Electric Vehicles	US GAAP
Johnson & Johnson	Non-Indian	Healthcare / Pharma	US GAAP
Procter & Gamble	Non-Indian	Consumer Goods	US GAAP
Toyota Motor Corp.	Non-Indian	Automobile	IFRS
Samsung Electronics	Non-Indian	Electronics / Semiconductors	IFRS
Nestlé S.A.	Non-Indian	Food & Beverage	IFRS

3.1 Data collection and standardisation

Every piece of information came strictly from verified yearly summaries, along with updates filed publicly via bourses and official regulators. Since companies apply one of three reporting systems - Ind AS, IFRS, or US GAAP - key figures in their statements were aligned carefully; take profit measures similar to EBITDA or how they spread out asset costs, adjusted so comparisons stay fair when calculating each Beneish score. Amounts listed in currencies other than the U.S. dollar shifted into dollars using rates recorded at year close, aiding consistency during group evaluations - even if all eight Beneish metrics carry no units and thus ignore currency type naturally. This dataset holds twenty businesses observed across five consecutive year-to-year transitions, totaling one hundred instances tied to financial periods running from 2021 up to 2025, where results from 2020 anchor earlier references.

3.2 The Beneish M Score Formula and Variables

The composite M-Score is calculated as:

$$\text{M-Score} = -4.84 + 0.92(\text{DSRI}) + 0.528(\text{GMI}) + 0.404(\text{AQI}) + 0.892(\text{SGI}) + 0.115(\text{DEPI}) - 0.172(\text{SGAI}) + 4.679(\text{TATA}) - 0.327(\text{LVGI})$$

M-Score begins at negative four point eight four. Following that, DSRI contributes zero point nine two times its value. GMI adds a portion: zero point five two eight multiplied by its measure. Then comes AQI, factored at zero point four zero four. SGI follows with zero point eight nine two applied. DEPI enters next, scaled by zero point one one five. A reduction occurs through SGAI, weighted minus zero point one seven two. TATA brings a notable increase of four point six seven nine. Lastly, LVGI adjusts downward by zero point three two seven

A figure above minus 2.22 marks a company-year instance as possibly involved in manipulation. Among these indicators stands the Days' Sales in Receivables Index - this one exposes aggressive reporting in sales recording. Instead of listing further, observe how the Gross Margin Index highlights stress when profits shrink unexpectedly. Shifting focus, changes toward riskier long-term holdings appear through the Asset Quality Index. Momentum enters here where rapid expansion becomes visible via the Sales Growth Index, often tied to pressure for sustained results. Watch closely when accounting methods alter silently - the Depreciation Index catches such subtle reductions in expense tracking. On another front, spending on operations growing faster than income surfaces due to the SGAI metric. When borrowing climbs, pushing financial limits tighter, the Leverage Index registers that strain. Not last, but central, is TATA, which reflects raw levels of profit adjustment using estimated entries rather than cash. Behind every value lies code written in Python, processing each case under identical rules,

avoiding human influence while supporting consistent replication.

3.2 Hypotheses

Hypothesis frameworks appear in triplicate to shape the examination. With these, interpretation gains structure through distinct lenses. Each set functions separately, yet contributes toward overall clarity.

- H_1: Selected global corporations exhibit statistically significant manipulation signals (M-Score > −2.22) during 2021–2025.
- H_2: Mean M-Scores differ significantly between Indian and non-Indian multinationals.
- H_3: M-Scores vary significantly across the study period, reflecting macroeconomic influences.

4. Data Analysis and Findings

4.1 Beneish M Score Full Panel Results

Presented in Table 2 are composite M-Scores calculated per company over five recorded financial years. Those surpassing the −2.22 level appear indicated by an asterisk. Among one hundred individual cases, exactly five - representing 5 percent - cross the defined limit for potential manipulation, resulting in a total alert frequency of 5%. Each highlighted instance occurs within the period from 2021 to 2023, aligning with economic adjustments following global health disruptions along with fluctuations tied to distribution networks.

Table 2: Beneish M-Scores by Firm and Year (2021–2025)

Company	2021	2022	2023	2024	2025	Flag?
Reliance Industries	-2.75	-2.21*	-2.54	-2.58	-2.60	2022
TCS	-2.72	-2.59	-2.69	-2.77	-2.76	None
Infosys	-2.72	-2.64	-2.68	-2.77	-2.76	None
Hindustan Unilever	-2.72	-2.64	-2.68	-2.73	-2.73	None
ITC Limited	-2.53	-2.47	-2.48	-2.52	-2.54	None
Bharti Airtel	-2.83	-2.77	-2.72	-2.73	-2.74	None
Larsen & Toubro	-2.57	-2.54	-2.48	-2.51	-2.53	None
Maruti Suzuki	-2.73	-2.55	-2.28	-2.35	-2.47	None
Sun Pharmaceutical	-2.52	-2.55	-2.46	-2.47	-2.46	None
UltraTech Cement	-2.58	-2.41	-2.53	-2.56	-2.58	None
Apple Inc.	-2.08*	-2.72	-2.71	-2.64	-2.71	2021
Microsoft	-2.49	-2.38	-2.53	-2.57	-2.63	None
Amazon	-2.75	-2.84	-2.69	-2.72	-2.79	None
Alphabet	-2.46	-2.90	-2.56	-2.63	-2.67	None
Tesla Inc.	-2.45	-2.03*	-2.11*	-2.79	-2.68	2022-23
Johnson & Johnson	-2.35	-2.53	-2.64	-2.53	-2.53	None
Procter & Gamble	-2.50	-2.47	-2.60	-2.58	-2.57	None
Toyota Motor	-2.66	-2.46	-2.56	-2.46	-2.54	None
Samsung Electronics	-2.47	-2.62	-2.79	-2.82	-2.77	None
Nestlé S.A.	-2.41	-2.45	-2.61	-2.57	-2.53	None

Company	2021	2022	2023	2024	2025	Flag?
Larsen & Toubro	-2.57	-2.54	-2.48	-2.51	-2.53	None
Maruti Suzuki	-2.73	-2.55	-2.28	-2.35	-2.47	None
Sun Pharmaceutical	-2.52	-2.55	-2.46	-2.47	-2.46	None
UltraTech Cement	-2.58	-2.41	-2.53	-2.56	-2.58	None
Apple Inc.	-2.08*	-2.72	-2.71	-2.64	-2.71	2021
Microsoft	-2.49	-2.38	-2.53	-2.57	-2.63	None
Amazon	-2.75	-2.84	-2.69	-2.72	-2.79	None
Alphabet	-2.46	-2.90	-2.56	-2.63	-2.67	None
Tesla Inc.	-2.45	-2.03*	-2.11*	-2.79	-2.68	2022-23
Johnson & Johnson	-2.35	-2.53	-2.64	-2.53	-2.53	None
Procter & Gamble	-2.50	-2.47	-2.60	-2.58	-2.57	None
Toyota Motor	-2.66	-2.46	-2.56	-2.46	-2.54	None
Samsung Electronics	-2.47	-2.62	-2.79	-2.82	-2.77	None
Nestlé S.A.	-2.41	-2.45	-2.61	-2.57	-2.53	None

Three firms raised alerts - Reliance Industries (FY2022), Apple Inc. (FY2021), and Tesla Inc. (FY2022 and FY2023) - yet differ sharply in background. Reliance, during FY2022, showed an unusually large SGI value of 1.37, tied to rapid revenue gains after the pandemic in Jio and Retail divisions, along with only slight pressure on GMI. For Apple, fiscal year 2021 brought several factors together: strong SGI at 1.33, higher AQI due to growing intangible assets, also a sudden rise in DSRI matching faster billing cycles amid robust iPhone demand. Tesla triggered warnings two years running; both periods featured elevated SGI - 1.51 then 1.19 - as well as increased TATA figures suggesting reliance on non-cash profits, plus rising AQI linked to heavy investment in physical infrastructure. Later data from each company shifted back toward typical levels, implying these were short-lived conditions instead of ongoing efforts to distort results.

4.2 Cross-Country Comparative Analysis

Comparison of central summary measures across Indian and other participants appears in Table

3. Well under −2.22 rests the average M-Score for both sets of respondents, showing no widespread tendency toward manipulation in either set. A t-statistic of 0.07 emerges when comparing averages, linked with a probability value of 0.945 - this lack of divergence proves negligible. Thus, evidence fails to uphold H_2.

Table 3: Cross-Group Descriptive Statistics and Comparative Findings

Metric	Indian MNCs	Non-Indian MNCs	Pooled	Significance
Mean M-Score (2021–2025)	-2.586	-2.588	-2.587	Not significant
Std. Deviation	0.118	0.197	0.162	—
Flagged Firm-Years (out of 50)	1 (2.0%)	4 (8.0%)	5 (5.0%)	—
Year with Most Flags	2022	2021–2023	2022	—
Primary Driver (Beneish vars.)	SGI, TATA	SGI, AQI, TATA	SGI dominant	—

Despite similar average M-Scores, spread patterns carry practical weight. Where one group shows wider scatter, the other holds tighter formation. Firms outside India show fluctuation

levels near 0.197; their Indian counterparts stay closer to 0.118. Growth-heavy segments - tech and electric vehicles - shape much of the foreign composition, introducing unevenness in financial disclosures. Stability marks the domestic players, rooted as they are in mature arenas: consumer goods, software exports, industrial design. Their Beneish indicators shift less. From this, a consequence follows: scrutiny during early phases gains importance when dealing with faster-moving enterprises abroad.

4.3 Time Patterns Meet Big Economic Forces

During the period from FY2021 to FY2023, every flagged case appeared. Despite falling just outside conventional thresholds, the statistical test result - $F(4, 95) = 2.31$, $p = 0.063$ - still aligns with expectations under economic stress. Though not fully conclusive, the pattern lends some weight to H_3. In terms of distribution, 2022 stands out with the greatest share of alerts, coinciding with a phase of recovery where fast-growing firms encountered stronger demands to deliver results. Come FY2024 and FY2025, each previously marked firm no longer shows signs of irregularity, implying the earlier deviations were shaped more by external forces than lasting internal practices.

4.4 Analysis of Key Beneish Variables

In every one of the 100 firm-year cases examined, the Sales Growth Index stands out clearly within marked instances. Ranging between 1.19 and 1.71, the index appears uniformly higher across all five highlighted years - this when compared to an overall average near 1.09. Support emerges here for what Positive Accounting Theory anticipates: entities facing strain amid expansion may lean toward bolder reporting methods. Though Total Accruals to Total Assets generally remain slightly below zero - a sign of earnings supported by cash flow - the figure shifts upward for Tesla in 2023, reaching +0.016. Given the weight assigned in the model – an estimate of 4.679 - such a shift carries notable implication. Despite differing sectors, Apple and Tesla show sensitivity to shifts in the Asset Quality Index, a pattern tied to heavy upfront spending common in tech and electric vehicle industries. On another note, Indian market indicators such as TATA and GMI display steadier behavior, which aligns with their historically muted profit swings and cautious accounting practices. While one reflects cyclical exposure, the other reveals resilience shaped by regional corporate norms.

4.5 Audit Risk Classification

Thirteen companies - TCS, Infosys, HUL, ITC, L&T, UltraTech, Nestlé, P&G, Toyota, Samsung, Microsoft, Alphabet, Johnson & Johnson - display steady M-Scores under −2.40 along with minimal annual shifts; thus, routine analysis suffices, supported by dependable internal oversight. Maruti Suzuki, Amazon, Sun Pharma, Bharti Airtel appear within a second grouping due to slight swings in SGI or AQI, though thresholds remain unbroken; scrutiny reappears at intervals, focused on how income is recorded and assets are capitalized. Apple, Reliance Industries, Tesla surface differently - one or more yearly readings exceed limits, triggering deeper examination only during outlier periods, especially where earnings, non- physical holdings, and estimated liabilities arise.

5. Findings and Discussion

Five main results emerge from the research. During 2021 to 2025, big global companies show consistent reliability in their financial reports; nearly all cases fall under the Beneish limit for possible tampering. Such patterns do not fully support claims that complex operations inherently increase fraud likelihood across these entities. Rather than chaos arising from scale, oversight structures seem to hold influence - audits by major accounting networks, along with close attention from long-term shareholders, contribute toward restraint. Stability appears more common than deviation within this group when examined over time.

It follows that signs of manipulation appear more often within fast-growing firms when broader economic conditions turn unstable. During 2021 through 2023 - marked by post-pandemic adjustments and disrupted logistics - not a single alert emerged outside these times. Such concentration supports earlier models suggesting financial strain increases management's motive to influence reported outcomes. In particular, the need to sustain appearances of upward momentum drives selective reporting choices.

Despite similarities across regions, Indian multinationals display slightly steadier M-Score trends compared to others outside India; differences in industry makeup explain this pattern more than any advantage in systems or governance. These outcomes emerge not from structural dominance but from where firms operate within the economic landscape

Among the sampled companies, a clear tilt appears toward IT services, consumer goods, and engineering - areas where income reporting tends to remain steady, with less reliance on intangibles. In contrast, firms outside India’s group often operate in fast-expanding electric vehicle and tech spaces, environments naturally linked to higher levels of earnings manipulation and quality risk.

It comes fourth that the Sales Growth Index carries greatest weight in signaling potential manipulation throughout the data set, whereas TATA gains importance only when values rise sharply. High levels of SGI together with upward shifts in TATA - seen clearly in Tesla during fiscal years 2022 through 2023 - produce clearest red flags demanding focused auditor attention.

By fiscal year 2024–25, aligning all identified companies on a shared timeline offers insight. Such timing reveals that individual Beneish indicators often track short-term business fluctuations instead of calculated, ongoing misconduct. A broader view across several years, therefore, carries more weight than judgments based on one period alone.

The results reveal that the null hypotheses were rejected in part, which means that there were some earnings manipulation signals and the financial reporting patterns varied significantly during the study period.

6. Implications for Practice

When auditors plan reviews, the Beneish M-Score serves as a quick first check, especially useful during periods of elevated SGI or when TATA shows slight or neutral values. Though helpful, its strength grows only if paired with careful judgment, non-numerical insights into company oversight, along with deeper financial analysis instead of being used alone. In multinational assignments, integrating the score systematically into risk frameworks becomes more meaningful over time. What matters emerges not from calculation but context.

Investors find value in the model's separate measure of earnings reliability, one that stands alongside standard profit and price metrics. When SGI readings rise while TATA patterns shift, such signals often emerge before deeper issues surface - especially within tech and fast- growing industries where PE multiples alone might hide weakening accounting quality.

When many warning signs appear at once during tough economic times, oversight agencies may see clearer reasons to strengthen checks on company reports. Because some organizations matter more to overall stability, closer scrutiny of their filings might become necessary under stress conditions. Should patterns repeat across different accounting rules, one method originally designed for detecting irregularities could offer consistent value beyond any single country's framework. Oversight approaches that look alike across regions might benefit from using such tools without rewriting them for local standards.

Growth itself may trigger red flags, the research shows, especially when ratios shift during rapid scaling. Because expansions alter financial patterns, clarity becomes essential in reporting. When unusual metrics appear, context helps observers understand underlying causes. Disclosing reasons behind changes in earnings components guides accurate assessment. Transparency around accounting fluctuations lessens the chance of false conclusions. Misreading data by reviewers or regulators grows less likely with added detail. Even honest progress sometimes resembles questionable behavior on paper. Providing background information supports fair evaluation over time. Unexpected results gain meaning when accompanied by explanation. Early communication about performance indicators shapes informed responses.

7. Limitations and Future Research Directions

This research faces certain limits by design. Selection of participants follows intent rather than randomness; conclusions about firms outside the largest global tier may lack reliability. Above −2.22, the Beneish M-Score raises questions - yet such a signal alone proves neither deception nor deliberate error, while silence from the metric offers no guarantee of honest disclosure. Built on data mostly from American companies decades ago, its numerical weights might not hold steady today across worldwide corporate environments.

Standardisation of financial reports under Ind AS, IFRS, and US GAAP demands interpretive alignment - this consistency sometimes brings unintended variation in reported figures. Publicly available consolidated statements form the sole basis here; absent are evaluations of corporate governance quality, insights from managerial discussions, or firsthand perspectives gathered from auditors. Though frameworks align broadly, subtle differences emerge through application rather than design. Information gaps exist by nature of reliance on published documents alone. Interpretation depends on what numbers disclose, not what lies behind them. Because only official filings are used, nuances tied to oversight practices remain outside scope. Despite structural parallels across standards, outcomes may differ due to how rules take shape in practice. Data sources limit depth, leaving contextual factors unexamined.

Further study ought to move beyond current limits by including mid-sized and smaller multinational firms - this shift could reveal if stable patterns stem solely from large-company oversight structures. A different path involves merging the Beneish method with machine-read insights from executive commentary, forming a combined warning system for irregularities. One possibility begins not with data but with time: recalibrating Beneish variables using recent worldwide datasets may correct slow shifts in predictive accuracy. Toward the end stands another consideration - linking environmental, social, and governance report consistency with standard financial metrics might show whether transparent non-monetary disclosures align with reduced risk scores.

8. Conclusion

One approach taken here involves the Beneish M-Score, tested across a diverse set of twenty major global firms during five years marked by deep economic swings. Though volatility was widespread, results show consistency - nearly all data points, specifically 95%, appear outside ranges tied to earnings tampering. Under close watch from top-tier auditors and

regulatory bodies, these enterprises seem to uphold transparent accounting practices. A small number of exceptions emerged between 2021 and 2023, where changes in revenue patterns and accumulated adjustments triggered alerts. Rather than suggesting intent, such cases likely reflect periods needing closer review, nothing more conclusive.

One outcome involves confirming how the Beneish method functions across varied economic settings today. Validation comes through testing on current multinational data under financial strain. Another aspect reveals SGI holds stronger predictive power than peers when spotting irregularities in major firms. This indicator offers auditors a practical way to rank potential risks efficiently. Findings show no significant gap between Indian and non-Indian corporate groups regarding average M-Scores. Yet variation emerges clearly when examining industry makeup instead of nationality alone. A longer view spanning multiple years proves more revealing than isolated annual checks. Tracking changes over time helps separate temporary distortions from deep-rooted issues in reports. These points together extend understanding within forensic accounting research. Patterns unfold differently when duration replaces snapshots in fraud detection models.

With financial reporting settings becoming increasingly intricate due to digital operations, international mergers, along with rising demands for non-monetary disclosures, reliance on quantitative forensic methods within routine audits and oversight processes gains weight. Though simple in design, the Beneish M-Score continues serving as a practical tool across diverse markets for such purposes.

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