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ASSESSMENT OF FINANCIAL STATEMENT MANIPULATION AND INSOLVENCY RISK IN A PHARMACEUTICAL COMPANY THROUGH THE COMBINED APPLICATION OF THE BENEISH MSCORE AND ALTMAN Z-SCORE

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Abstract

Forensic accountants, auditors, and regulatory bodies have been under increasing pressure to identify potential misreporting of a company's financials prior to the damage being done to investors and the capital markets. This research project applied two quantitative screening methods, the Beneish MScore and the Altman Z-Score to Zydus Lifesciences Ltd.'s (a leading Indian Pharmaceutical Company) publicly available financial statements for nine fiscal years; FY 2016 through FY 2024. The Beneish M-Score is an eight-ratio model designed to identify statistical patterns of earnings manipulation. The Altman Z-Score is a five-financial dimension model that provides a single bankruptcy-prediction score. Together the two screening models form a dual lens approach; the first lens is focused on the quality of a company's accounting records while the second lens is focused on the company's solvency risk. Each of these screening methods provides a quantifiable measurement system to evaluate and measure the degree of risk associated with a company's earnings and accounting practices. Additionally, the use of these screening methods may help to support fraud detection initiatives as well as the assessment of a company's risk profile. The use of these screening methods also supports enhanced corporate governance through the use of analytical tools that companies may utilize to prevent or intervene in fraud schemes prior to their occurrence.

Keywords: *Financial statement fraud, Earnings manipulation, Beneish M-Score, Altman Z-Score, Forensic accounting*

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1. Introduction

Fraud undermines the legitimacy of an organization, damages its reputation as a trusted business partner to its consumers, results in loss of funds for both the organizations and the shareholders, and ultimately harms public perception of the marketplaces they operate in. Fraud encompasses many different forms of fraud and frauds have various methods of occurrence. Investors have lost money due to fraudulent actions, businesses have been required to pay fines and penalties to regulatory agencies, and the general public has lost confidence in financial institutions. Forensic accountants work on behalf of each party that has an interest in the operations of an organization.

These issues are most clearly present in the pharmaceutical industry. Pharmaceutical drug development is timeconsuming; revenue recognition for pharmaceutical drugs is also complicated; and there may be a wide margin of difference between the earnings reported by a company and the actual cash generated by a company regardless of whether or not the company is acting within the law. If a pharmaceutical company has a high ratio of accruals, this could result from the company investing in legitimate research or pipelines. To distinguish between legal accounting practices and fraudulent accounting practices will require more than a single model or test. In order to detect accounting irregularities in pharmaceutical companies, this study will use the dual approach of the Beneish MScore, which identifies potential signs of earnings manipulation and the Altman ZScore, which identifies potential risk of financial distress. The subject of this study is Zydus Lifesciences Ltd., which is one of India's largest pharmaceutical companies, producing substantial amounts of revenue domestically and internationally. The data used for this study includes publicly available information from nine consecutive years (FY 2016 – FY 2024) from the company's annual reports. This study does not intend to accuse the company of any wrongdoing but rather to demonstrate how a wellstructured dual-model approach can identify possible areas of concern and alert the analyst to conduct additional analysis.

Key Elements of Corporate Fraud

Corporate fraud involves fraudulent acts committed intentionally by individuals who are part of an organization, either on their own or in conjunction with a third party. These acts are designed for personal or institutional gain. Unlike negligent behavior or accounting errors, fraud is characterized as intentional and secretive. Fraudulent acts can include financial statement misrepresentations, theft of assets, bribery, and more complex forms of fraud, including investment scams and corporate espionage.

Taxonomy of Corporate Fraud

Fraudulent Financial Reporting (FFR) is one of the most dangerous types of fraud to be studied. Fraudulent financial reporting happens when a company makes false statements about the company's financial situation to trick people into lending them money, investing in the company, or meeting government regulations. Most senior executive that commits fraudulent financial reporting do so to get investors, obtain loans, or make their performance appear better than what it really is. Some ways they accomplish this are through fictitious sales, omission of debt on a companies' balance sheet, and capitalizing operational costs as assets. The negative consequences can be extreme. They can result in severe fines from regulatory bodies and even cause a company to go bankrupt. In addition to regulatory actions, thousands of employees will lose their jobs, and millions of dollars will be lost by investors. This has happened several times throughout history. Three examples are Enron, Satyam Computers Services, and WorldCom. Asset misappropriation is the most common form of occupational fraud. Asset misappropriation consists of the theft of an asset. Some examples of

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asset misappropriation include taking cash from a company before the cash is recorded on a company's books, creating ghost employees to take advantage of the payroll system, submitting false expense reports, and stealing inventory or other tangible assets. Bribery and Corruption occur when an employee or manager uses his or her authority to receive some sort of personal benefit in exchange for using the company's resources. Examples of bribery and corruption include accepting a kickback for a purchase, bribing someone to award a contract, and selling inside information to an investor. Both bribery and corruption distort the free market and can lead to poor internal controls. Vendor, Invoice, and Procurement Fraud occur when there is either a vendor who submits false invoices for goods and services purchased by the company or when an employee and a vendor collude together to submit false invoices. Tax Fraud occurs when a taxpayer intentionally fails to report all of their income or intentionally overstates their deductions. Examples of tax fraud include maintaining two sets of accounting records, the use of shell corporations to shift profits, etc. With increasing competition in industries that rely heavily on innovation, corporate espionage has become increasingly prevalent. Corporate espionage is defined as the act of stealing another corporation's confidential information. Money Laundering is the process of using the appearance of legitimacy to hide the origin of illegally obtained funds. Companies involved in money laundering have created layers of legitimate appearing businesses across multiple jurisdictions. Ponzi Schemes and Pyramid Schemes occur when individuals invest money in a scheme where the majority of the money received is used to pay off previous investors. Ultimately, these schemes collapse when no new money is available to fund payments to prior investors.

Factors and Mechanisms Enabling Fraud

Fraud scholars and professionals use conceptual models like the Fraud Triangle to provide an explanation of how fraud occurs. The three fraud triangle conditions are: (1) Pressure, stemming from either unrealistic financial goals or extreme financial distress; (2) Opportunity, generated by a lack of internal control over an organization's assets and/or inadequate supervision; (3) Rationalization, in which the perpetrator convinces themselves that what they have done is acceptable, or at least harmless (Schuchter and Levi, 2016). Frequently appearing as factors contributing to fraud opportunities are poor corporate governance practices, absent ethical leadership, and substandard audit environment standards. Sanchez-Aguayo et al. (2021) found that combining psychology-based fraud models (e.g., the Fraud Triangle) with data mining methodologies will produce more sophisticated fraud detection models.

Detection and Prevention

Each of these fraud prevention methods can provide fraud prevention to some extent on its own. However, when used together, they are significantly more effective. In addition to a well-designed system of internal controls (segregation of duties, regular reconciliation of accounts, due diligence of vendors, etc.) that will help prevent fraud from occurring, and the use of data analytic tools for monitoring transactions, it is also necessary to have a system of auditing, which may include both external audits as well as internal audits. Auditing will provide a second level of assurance that a fraud has not occurred. A final component of a fraud prevention program is a whistleblower policy. The whistleblower policy should contain a clear procedure for employees to report suspected fraud.

Literature Review

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The role of forensic accounting has been explored through significant research development in fraud detection and prevention. Judijanto et al. (2025) performed a bibliometric analysis identifying and quantifying the growing volume of research on forensic accounting, with emphasis on fraud detection models both technologically advanced and legislation based. Munandar and Honggowati (2025) confirmed the field's expanding scope, particularly in quantitative modelling approaches through their bibliometric analysis.

Abbadi et al. (2021) examined whether government and audit institutions have effective methods for implementing forensic accounting measures for fraud detection, concluding that a lack of institutional support remains a challenge. Alshurafat, Shbail, and Mansour (2021) examined the positives and negatives of forensic accounting education and the profession, discussing how these dimensions could be used to create better policy. Rehman and Hashim (2021) demonstrated empirically that forensic accounting can improve sustainable corporate governance through improved transparency and reduced fraudulent financial reporting. Kaur, Sood, and Grima (2022), through a systematic review, confirmed that forensic accounting has become widely accepted as an important method of fraud detection.

Kukreja, Gupta, Sarea, and Kumaraswamy (2020) evaluated the combination of the Beneish M-Score and the Altman Z-Score and found that combining the two techniques increases the accuracy of prediction for both financial distress and fraudulently reported earnings manipulations. Maccarthy (2017) demonstrated the same using the Enron case study, showing that both models can identify when fraud is occurring and when a company faces failure risk.

The use of the Beneish M-Score was shown by Khatun, Ghosh, and Kabir (2022) to be applicable in Bangladeshi banking as well as useful as a regulatory device for detecting income smoothing. In terms of the model being used in Nepal's banking environment, Gyawali (2021) demonstrated that it could also be utilized for the identification of unusual financial behavior. Dalnial, Kamaluddin, Sanusi, and Khairuddin (2014) demonstrated that financial ratios in combination with additional data can be indicative if there has been an attempt at manipulating reported income. Sutainim, Mohammed, and Kamaluddin demonstrated that the Beneish M-Score is also applicable in Malaysian-listed companies. Tarjo and Herawati (2015) proposed the use of automated methods for detecting financial fraud by combining the Beneish M-Score with data-mining techniques. The Altman Z-Score model was shown to have predictive power in assessing bankruptcy risk by Raj (2016), who tested the model on Indian banks. Koshti (2019) showed that both the Altman Z-Score and Beneish M-Score were capable of being used for diagnosing both firms. Sasikala (2020) tested both models on

Samsung electronics; this illustrated how both scores are useful for providing a more comprehensive risk assessment. BarbutaMisu and Madaleno (2020) determined bankruptcy risk utilizing the Altman model in large European firms and confirmed its ongoing utility as an early warning system.

The greater area of application has been employing data analytics and artificial intelligence to advance forensic capacity. Gabrielli, Magri, Medioli, and Marchini (2024), found that using large scale data analytics improves forensic accountants ability to identify sophisticated fraud schemes. Dheenadhayalan, et al. (2025), examined AI and machine learning applications in analyzing financial statements. Alharasis, et al. (2025), demonstrated how applying large-scale data increases fraud detection in public sector accounting. Mardjono, Suhartono, and Hariyadi (2024), have identified the uses of internal controls and large-scale data in Indonesia forensic accounting. Odia, and Akpata (2021), emphasized the importance of Data Science in forensic accounting for predictive purposes and detecting anomalies.

Within India, Lakshmi, and Menon (2016) have described forensic accounting as a developing defense against corporate fraud. Murthy, and Gopalkrishnan (2023), studied behavioral/governance along with data analytics to find out vulnerabilities related to fraud within Indian banks. Sharma, and Panigrahi (2012), conducted an initial examination of data

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mining techniques in fraud detection. This established the foundation for future research into quantitative methods.

Research Methodology

The Beneish Model's (M-score) and the Altman model's (Z score) were the two different financial metrics that were used within this research study. Data for this study was collected using annual reports located on the official website of Zydus Life Sciences Limited. They develop and manufacture a wide variety of drugs along with other health care-related products. Using the information contained in the above-mentioned documents, the researchers analyzed the company's financial performance over the period FY 2016-FY 2024.

Beneish M-Score

Messod D. Beneish's M-Score is a forensic accounting model for identifying the probability of an issuer manipulating reported income by evaluating various ratios from the company's financial statements. The MScore began with Messod D. Beneish's research (Beneish, 1997), which used data to determine if companies were violating Generally Accepted Accounting Principles (GAAP). He followed up his original work with further refinement of the model to include eight new variables, and then calibrates this model in a 1999 journal article published in the Financial Analysts Journal, (Beneish, 1999), where he used a total of 74 companies under investigation by the Securities and Exchange Commission (SEC) and a control group consisting of hundreds of companies that did not manipulate their financial reports.
The M-Score uses the fact that there are certain economic and reporting similarities among all manipulation issuers: these typically have underlying business conditions deteriorate due to declining gross margins but at the same time report high increases in sales; therefore they can utilize increased amounts of discretionary accounting choices to create higher levels of accruals while reducing transparency in their financial reporting. The M-Score combines eight indices, and the full eight-variable equation is:

M-Score = −4.84 + 0.92×DSRI + 0.528×GMI + 0.404×AQI + 0.892×SGI + 0.115×DEPI − 0.172×SGAI + 4.679×TATA − 0.327×LVGI

Using the empirical cut-offs developed for this measure (scores below −2.22 are likely to be a nonmanipulative firm and scores above −1.78 are likely to be a firm with a high level of manipulation), researchers, auditors and investors can use this metric as an initial screening device. The results must then be analyzed qualitatively in conjunction with other forensic testing procedures.

Table 1.1: Beneish M-Score Variables – Quick Summary

Variable	Formula	Coeff.	Direction
DSRI (Days S Receivables)	(NR_t/Sales_t) / (NR_t−1/Sales_t−1)	0.92	↑ Risk

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GMI (Gross Mar Index)	Prior GM / Current GM	0.528	↑ Risk
AQI (Asset Quality Index)	Non-current assets / Total assets (indexed)	0.404	↑ Risk
SGI (Sales Growth Index)	Sales_t / Sales_t−1	0.892	↑ Risk
DEPI (Depreciat Index)	Prior depreciation ratio / Current	0.115	↑ Risk
SGAI (SG&A Index)	Current SG&A% / Prior SG&A%	−0.172	↑ Safe
LVGI (Leverage Index)	Current debt ratio / Prior debt ratio	−0.327	↑ Safe
TATA (Total Accruals)	(Net Income − CFO) / Total Assets	4.679	↑ Risk

Altman Z-Score

The Altman Z-score model was introduced in 1968 by Edward I. Altman as a statistical model for predicting corporate bankruptcy through a formula that applies a linear combination of five financial ratio measurements to discriminate between bankrupt and non-bankrupt companies; it utilizes a form of discriminant analysis that was based upon data from a sample of 66 U.S. manufacturing firms.

The Z-Score formula is:

$$\mathbf{Z = 1.2 \times X_1 + 1.4 \times X_2 + 3.3 \times X_3 + 0.6 \times X_4 + 1.0 \times X_5}$$

The values for the five variables are: X_1 = Working capital/total assets;

X_2 = retained earnings/total assets;

X_3 = ebit/total assets;

X_4 = market value of equity/book value of total liabilities; X_5 = sales/total assets.

A score greater than 2.99 places the firm into the "safe zone"; A score from 1.81 to 2.99 indicates that the firm is at risk, or within a "grey zone" and a score less than 1.81 suggests a high risk of potential financial distress.

Variable	Definition	Coefficient	Direction

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X_1	Working Capital / Total Assets	1.2	↓ = Risk
X_2	Retained Earnings / Total Assets	1.4	↓ = Risk
X_3	EBIT / Total Assets	3.3	↓ = Risk
X_4	Market Value of Equity / Book Value of Total Liabilities	0.6	↓ = Risk
X_5	Sales / Total Assets	1.0	↓ = Risk

Table 1.2: Altman Z-Score Variables – Quick Summary

Data Analysis Beneish M-Score Calculation for the Year 2024 (Mar-24)

The individual components for the Beneish M-Score for FY2024 are computed as follows:

DSRI = (Trade Receivables_t / Sales_t) / (Trade Receivables_t−1 / Sales_t−1) = 1.0422

1. GMI (Gross Margin Index) = Prior GM / Current GM = 0.9304
2. AQI (Asset Quality Index) = non-current assets / Total assets (indexed) = 0.9898
3. SGI (Sales Growth Index) = Sales_t / Sales_t−1 = 1.1340
4. DEPI (Depreciation Index) = Prior depreciation ratio / Current = 0.0663
5. SGAI (SG&A Index) = Current SG&A% / Prior SG&A% = 0.9834
6. LVGI (Leverage Index) = Current debt ratio / Prior = 0.0262
7. TATA (Total Accruals) = (Net Income − CFO) / Total Assets = 0.0545

M-Score = −4.84 + 0.92×1.0422 + 0.528×0.9304 + 0.404×0.9898 + 0.892×1.1340 + 0.115×0.0663 − 0.172×0.9834 + 4.679×0.0545 − 0.327×0.0262 = −1.8937

Similarly, the Beneish M-Score was calculated for all other years in the same manner

Table 1.3: Beneish M-Score Component Values – Zydus Lifesciences Ltd. (FY2016–FY2024)

Components	Mar-16	Mar-17	Mar-18	Mar-19	Mar-20	Mar-21	Mar-22	Mar-23	Mar-24
DSRI	0.9892	1.3101	1.1273	1.1188	0.8565	0.8448	1.0078	1.171	1.0422
GMI	0.9298	1.0548	0.9811	1.0209	0.9801	0.9823	1.0469	1.0044	0.9304
AQI	2.3445	1.209	0.9609	1.0867	1.0076	1.1268	1.1629	1.1522	0.9898
SGI	1.1116	0.9954	1.2489	1.1013	1.0826	1.0106	1.0598	1.1292	1.134

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DEPI	0.0871	0.0996	0.0936	0.0923	0.0573	0.0547	0.0588	0.0593	0.0663
SGAI	1.0455	0.9473	0.9184	0.9693	1.1482	0.9336	0.9498	0.9656	0.9834
TATA	0.0197	0.0199	0.0781	0.0473	-0.0453	-0.0289	0.0223	0.0196	0.0545
LVGI	0.1997	0.3249	0.283	0.3043	0.2973	0.1919	0.151	0.0452	0.0262

Table 1.4: Beneish M-Score Results – Zydus Lifesciences Ltd. (FY2016–FY2024)

Mar-16	Mar-17	Mar-18	Mar-19	Mar-20	Mar-21	Mar-22	Mar-23	Mar-24
-1.6433	-1.8660	-1.6568	-1.8845	-2.6618	-2.5396	-2.0463	-1.8419	-1.8937

Data Interpretation for Beneish M-Score

The Beneish Model's M-score exhibited some significant fluctuations across the nine-year span. In FY 2016, Zydus had an M-score of -1.6433, which crossed the -1.78 threshold and placed Zydus into the High Manipulation Risk Zone for that year. That FY 2016 M-score was primarily due to an Asset Quality Index of 2.3445, which was the largest of all the M-scores in the data set. According to the Beneish model, this represents either an overly aggressive approach to recognizing assets or capitalizing on them, related to the company's expanded use of acquisitions.

Zydus also breached the -1.78 threshold in FY 2018 with a score of -1.6568. At that time, there were large increases in the TATA of .0781 and SGI of 1.2489. The TATA in FY 2018 indicated that the net income was much greater than the cash generated from operating activities, a characteristic of the Beneish model identified as a red flag for possible accrual manipulation. Therefore, FY 2016 and FY 2018 are worthy of additional and more specific forensic analysis.

In contrast, FY 2017 saw an increase to -1.8660, returning it to the Grey Zone. The FY 2019 M-score was 1.8845 and remained in the Grey Zone. The lowest M-scores were seen in FY 2020 (-2.6618) and FY 2021 (2.5396). Both are well below the -2.22 threshold required for a firm to be classified as being outside the LowRisk Zone. There has been a very pronounced downward trend in the M-scores since FY 2020; a negative TATA of -.0453 indicates that the firm generated more cash from its operating activities than it reported as net income. This is consistent with what you would expect to see from a firm that does not manipulate its financial statements. Since FY 2021, however, the Mscore has moved back up; at -2.0463 in FY 2022, -1.8419 in FY 2023, and -1.8937 in FY 2024. The trend since FY 2021 appears to be moving the firm towards the Grey-Zone again, based on increasing TATAs and increasing DSRI values. These require ongoing evaluation of the quality of accruals used in preparing the firm's financial statements and its ability to efficiently convert those accruals to actual cash. However, neither FY 2023 nor FY 2024 have clearly breached the -1.78 threshold that requires further investigation into whether earnings management occurred.

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Altman Z-Score Calculation for the Year 2024 (Mar-24)

The Altman Z-Score for FY2024 was computed using the following financial data (all figures in INR Crore):

X_1 = Working Capital / Total Assets = 6,159.52 / 29,280.8 = 0.2103

X_2 = Retained Earnings / Total Assets = 19,728.9 / 29,280.8 = 0.6737

X_3 = EBIT / Total Assets = 4,823.1 / 29,280.8 = 0.1647

X_4 = Market Value of Equity / Book Value of Total Liabilities = 1,01,359.557 / 7,179.18 = 14.12 X_5 = Sales / Total Assets = 19,547.4 / 29,280.8 = 0.6676

Z-Score = 1.2×0.2103 + 1.4×0.6737 + 3.3×0.1647 + 0.6×14.12 + 1.0×0.6676 = 10.1179

Similarly, the Altman Z-Score was calculated for all other years in the same manner.

Table 1.5: Altman Z-Score Results – Zydus Lifesciences Ltd. (FY2016–FY2024)

Mar-16	Mar-17	Mar-18	Mar-19	Mar-20	Mar-21	Mar-22	Mar-23	Mar-24
6.0445	4.5219	3.9090	2.8722	2.3234	4.1592	3.6295	6.3159	10.1179

Data Interpretation for Altman Z-Score

Beginning with the high Altman Z-score reading for FY-2016 at 6.0445, which was significantly higher than the 2.99 (safe) threshold due to its large market value compared to its total liabilities; the Z-Score continued to show stable and positive solvency margins into FY-2017 at 4.5219. Although this reading also fell safely outside the grey area, the decrease did reflect the company's increased use of long-term borrowing to finance acquisitions.

In FY-2018, the Altman Z-Score reading decreased further to 3.9090. However, by FY-2019 the Altman ZScore had fallen to 2.8722 -- marking the first entry into the grey zone. As seen before, the trajectory of decreasing solvency margins mirrors the increasing burden on the company caused by an expanded debt-load, specifically total borrowings were rising dramatically, reducing the workingcapital-margin and diminishing the market-value-cushion between total liabilities and market capitalization. By FY-2020, the Altman Z-Score reading reached its low point of 2.3234 and while it remained safely inside the grey zone, it was just above the 1.81 distress threshold.

A clear and consistent upward trend begins in FY-2021. During this period the company successfully reduced its total debt through FY-2021 - FY-2023 and eliminated all of its long-term borrowings by FY-2023. In addition, there is an upward trend in the Altman Z-Score readings as follows: in FY-2021 (4.1592), FY-2022 (3.6295), FY-2023 (6.3159), and then surged even further in FY-2024 to 10.1179. The FY-2024 reading is especially unique since it represents a nearly complete elimination of all debt combined with a very large market capitalization compared to a much smaller liability base. None of the years examined in this study had readings less than or equal to 1.81. Therefore, the grey zone readings in FY-2019 and FY-2020 are true signal warnings of risk when considered together with the M-Score grey zone readings for each respective year.

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Table 1.6: Dual-Model Summary – Beneish M-Score and Altman Z-Score (FY2016–FY2024)

Score	Mar	Mar-17	Mar-18	Mar-19	Mar-20	Mar-21	Mar-22	Mar-23	Mar-24
M-Score	-1.6433	-1.8660	-1.6568	-1.8845	-2.6618	-2.5396	-2.0463	-1.8419	-1.8937
Z-Score	6.0445	4.5219	3.9090	2.8722	2.3234	4.1592	3.6295	6.3159	10.1179

Conclusion

Zydus Lifescience Ltd. has experienced significant variance in its Beneish M-Score results during the nineyear time frame of our analysis. With the exception of FY2017, FY2016 and FY2018 were above the more restrictive M-score value of -1.78 indicating "high" risk levels related to increased intensity of accruals and asset recognition. FY2020 and FY2021 had the lowest M-scores in the sample representing evidence of strict operating cash flow disciplines. Although the FY2021- FY2022 timeframe is in the "grey" zone, it does not meet the "high" risk criteria established at FY2024. The Altman Z-Score indicates that Zydus Lifesciences was subjected to leverage-related pressures from FY2019 through FY2020; however, they have demonstrated a long-term financial recovery since that point with no year's score being less than 1.81. The FY2024 Z-Score value of 10.119 indicates a very low level of debt (and a very favorable market multiple), establishing Zydus as having one of the strongest balance sheet positions as of the last available date. Together, the two models described are indicative of potential fraudulent earnings reporting risk and/or financial distress indicators, but do not establish actual misstatements. These models serve as filters that will provide an initial indication where additional investigation may be required. In a manner similar to Kukreja et al. (2020) we demonstrate that using both models can improve the forecasting ability for both financial distress and fraudulent earnings reporting. This integrated model can serve as a practical framework for providing early warnings to forensic accountants, auditors, regulatory bodies, and investors regarding potential earnings management activities within the pharmaceutical industry. The application of the models should complement a traditional audit, which includes an assessment based on judgmental qualitative factors.

References

1. Abbadi, H.M.A., Alrawashdeh, B., Dabaghia, M.N., & Darwazeh, R.N. (2021). The role of government and auditing offices in activating the forensic accounting to discover financial fraud. Academy of Accounting and Financial Studies Journal, 25(Special Issue 2), 1–10.
2. Alharasis, E.E., Haddad, H., Alhadab, M., Shehadeh, M., & Hasan, E.F. (2025). Integrating forensic accounting in education and practices to detect and prevent fraud

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DOI: https://doi.org/10.69980/rxx4mv92

and misstatement: case study of Jordanian public sector. Journal of Financial Reporting and Accounting, 23(1), 100–127. https://doi.org/10.1108/JFRA-04-2023-0177

3. Alshurafat, H., Shbail, M.O.A., & Mansour, E. (2021). Strengths and weaknesses of forensic accounting: an implication on the socio-economic development. Journal of Business and Socioeconomic Development. https://doi.org/10.1108/JBSED-03-2021-0026
4. Altman, E.I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance, 23(4), 589–609.
5. Bărbuţă-Mişu, N., & Madaleno, M. (2020). Assessment of bankruptcy risk of large companies: European countries evolution analysis. Journal of Risk and Financial Management, 13(3), 58. https://doi.org/10.3390/jrfm13030058
6. Beneish, M.D. (1999). The detection of earnings manipulation. Financial Analysts Journal, 55(5), 24– 36. https://doi.org/10.2469/faj.v55.n5.2296
7. Dalnial, H., Kamaluddin, A., Sanusi, Z.M., & Khairuddin, K.S. (2014). Detecting fraudulent financial reporting through financial statement analysis. Journal of Advanced Management Science, 2(1), 17– 10. 22. https://doi.org/10.12720/joams.2.1.17-22 .
11. Dheenadhayalan, K., Devapitchai, J.J., Surianarayanan, R., & Usha, S. (2025). A review of current applications of AI and machine learning methods for financial statement analysis. In Machine Learning and Modeling Techniques in Financial Data Science (pp. 211–230). IGI Global. https://doi.org/10.4018/979-8-3693-8186-1.ch008
12. Ewa, U., Adebisi, A.W., & Moses, E.J. (2020). Evaluation of forensic accounting techniques in fraud prevention/detection in the banking sector in Nigeria. International Journal of Finance and Accounting, 9(3), 56–66. https://doi.org/10.5923/j.ijfa.20200903.02
13. Gabrielli, G., Magri, C., Medioli, A., & Marchini, P.L. (2024). The power of big data affordances to reshape anti-fraud strategies. Technological Forecasting and Social Change. https://doi.org/10.1016/j.techfore.2024.123507
14. Gyawali, S. (2021). Does model reflect on reality? Exploring Beneish M Score on selected private commercial banks in Nepal. Journal of Nepalese Business Studies, 14(1), 18–28. https://doi.org/10.3126/jnbs.v14i1.41485
15. Judijanto, L., Rahman, K., Sudarmanto, E., Khikmah, S.N., & Bakri, A.A. (2025). Bibliometric analysis of forensic accounting and fraud detection research trends. West Science Accounting and Finance, 3(01), 131–138. https://doi.org/10.58812/wsaf.v3i01.1745
16. Kaur, B., Sood, K., & Grima, S. (2022). A systematic review on forensic accounting and its contribution towards fraud detection and prevention. Journal of Financial Regulation and Compliance, 31(1), 60–95.
17. Khatun, A., Ghosh, R., & Kabir, S. (2022). Earnings manipulation behavior in the banking industry of Bangladesh: the strategical implication of Beneish M-score model. Arab Gulf Journal of Scientific Research, 40(3), 302–328. https://doi.org/10.1108/AGJSR-03-2022-0001
18. Koshti, J.R. (2019). An application of Altman Z-score and Beneish M-score model on selected textiles companies.
19. Kukreja, G., Gupta, S.M., Sarea, A.M., & Kumaraswamy, S. (2020). Beneish M-score and Altman Zscore as a catalyst for corporate fraud detection. Journal of Investment Compliance, 21(4), 231–241. https://doi.org/10.1108/joic-09-2020-0022
20. Lakshmi, P., & Menon, G. (2016). Forensic accounting: A checkmate for corporate fraud. Journal of Modern Accounting and Auditing, 12(9). https://doi.org/10.17265/1548-6583/2016.09.002

Vol. 12 Issue 2s (May, 2026)
ISSN: 2208-2190 Pages- 01-12
DOI: https://doi.org/10.69980/rxx4mv92

21. Maccarthy, J. (2017). Using Altman Z-score and Beneish M-score models to detect financial fraud and corporate failure: A case study of Enron Corporation. International Journal of Finance and Accounting, 6(6), 159–166. https://doi.org/10.5923/j.ijfa.20170606.01
22. Mardjono, E.S., Suhartono, E., & Hariyadi, G.T. (2024). Does forensic accounting matter? Diagnosing fraud using the internal control system and big data on audit institutions in Indonesia. WSEAS Transactions on Business and Economics, 21, 638–655. https://doi.org/10.37394/23207.2024.21.53 24. Munandar, M.R.A., & Honggowati, S. (2025). Bibliometrics analysis of forensic accounting research.
25. Journal of Economics and Business, 8(1). https://doi.org/10.31014/aior.1992.08.01.650
26. Murthy, N., & Gopalkrishnan, S. (2023). Creating a nexus between dark triad personalities, nonperforming assets, corporate governance and frauds in the Indian banking sector. Journal of Financial Crime, 30(4), 859–876. https://doi.org/10.1108/JFC-05-2022-0097
27. Odia, J.O., & Akpata, O.T. (2021). Role of data science and data analytics in forensic accounting and fraud detection. In Handbook of Research on Engineering, Business, and Healthcare Applications of
28. Data Science and Analytics (pp. 203–227). https://doi.org/10.4018/978-1-7998-3053-5.ch011 29. Raj, U. (2016). Prediction of bankruptcy risk in Indian banks: An application of Altman's model. International Journal of Research.
30. Rehman, A., & Hashim, F. (2021). Can forensic accounting impact sustainable corporate governance? Corporate Governance (Bingley), 21(1), 212–227. https://doi.org/10.1108/CG-06-2020-0269
31. Sánchez-Aguayo, M., Urquiza-Aguiar, L., & Estrada-Jiménez, J. (2021). Fraud detection using the fraud triangle theory and data mining techniques: A literature review. Computers, 10(10), 121. https://doi.org/10.3390/computers10100121
32. Sasikala, D. (2020). Altman Z, Messod Beneish M, Piotroski F-scores of Samsung Electronics Limited. International Journal of Management Research and Social Science, 8(1), 3–6. https://doi.org/10.30726/ijmrss/v8.i1.2021.81002
33. Schuchter, A., & Levi, M. (2016). The fraud triangle revisited. Security Journal, 29(2), 107–121. https://doi.org/10.1057/sj.2013.1.
34. Sharma, A., & Panigrahi, P.K. (2012). A review of financial accounting fraud detection based on data mining techniques. International Journal of Computer Applications, 39(1), 37–47. https://doi.org/10.5120/4787-7016
35. Sutainim, N.A., Mohammed, F., & Kamaluddin, A. Application of Beneish M-Score model in detecting probable earnings manipulation in Malaysian public listed companies. https://doi.org/10.33019/ijbe.v4i3.301
36. Tapanjeh, A.M.A., & Tarawneh, A.R.A. (2020). Applicability of forensic accounting to reduce fraud and its effects on financial statement of Jordanian shareholding companies. International Journal of Financial Research, 11(2). https://doi.org/10.5430/ijfr.v11n2p436
37. Tarjo, T., & Herawati, N. (2015). Application of Beneish M-Score models and data mining to detect financial fraud. Procedia – Social and Behavioral Sciences, 211, 924–930. https://doi.org/10.1016/j.sbspro.2015.11.122