Analysing Earnings Manipulation in Pharmaceutical Company Using the Beneish M-Score and Modified C-Score: A Dual-Model Approach

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Forensic accountants, auditors and other regulatory bodies need to be able to identify fraud risk in a company's reported financial situation as well as assess the possible effects of such fraudulent activity. This is accomplished through the application of numerous statistical models that will help determine whether fraud has taken place. Different techniques have been created to do so (including both the modified C-Score as well as the Benish M-Score)

. Both scoring systems provide a quantifiable method for identifying and evaluating the level of risk related to an entity's earnings and accounting practices. In addition, these scoring systems assist fraud detection efforts, support the assessment of an entity's risk profile, and enhance corporate governance through the provision of analytical tools that can be used to prevent or intervene in fraud schemes before they occur. These models also contribute to financial transparency and accountability, protect investors from fraud, and preserve the integrity of capital markets.

Keywords: Financial statement fraud, Earnings manipulation, Forensic accounting, Risk assessment

Introduction

Fraudulence can create distrust for the organization's credibility with its customers, lead to large financial loses to organizations and their stockholders and affect public's trust in the markets where it occurs. Fraudulence is complex because of the variety of fraud techniques, fraud motivations and fraud repercussions that occur because of fraud. As a direct consequence of fraudulence, investors have lost money; organizations have paid regulatory penalties, and the general public has lost trust in organizations. Forensic accountants work on behalf of all parties who are invested in an organization.

What Constitutes Corporate Fraud

Corporate fraud refers to deliberate acts of deception, manipulation, or dishonesty committed by organizational insiders, or through collusion between insiders and third parties, typically for personal or institutional gain. Unlike errors or negligence, fraud is marked by intentionality and concealment, with acts ranging from misrepresentation of financial statements to asset theft, bribery, and more sophisticated schemes involving fraudulent investment offers or corporate espionage.

Typology of Corporate Fraud

1. Financial Statement Fraud

Financial Statement Fraud is probably the most well-known type of fraud and is basically a form of fraud where an entity has misrepresented its financial status to deceive investors, creditors or regulators. The senior executive who orchestrates this fraud generally does so for one or all of three reasons; he or she wants to attract investments, obtain a loan from a bank, or hit their quarterly/annual performance target. To accomplish these goals, senior executives will inflate revenues (which can be done in many ways), hide or conceal liabilities, create fictitious assets and/or reduce reported costs/expenses.

Methods include:

- **Manipulating revenues:** adding sales that have not taken place, showing false revenue recognition, or adding fictitious transactions.

- **Underreporting liabilities:** Omitting certain debts or obligations to present a stronger balance sheet.

- **Overstating assets:** Inflating inventory balances or capitalizing ordinary expenses to boost reported asset values.

Consequences involve not just regulatory penalties but catastrophic losses for shareholders and employees, as seen in global scandals like Enron, Satyam, or WorldCom.

2. Asset Misappropriation

Asset misappropriation denotes the theft or unauthorized use of a company's assets by employees at any level, including directors. As the most common occupational fraud, its techniques include:

- **Skimming:** Diverting cash before it is logged in the company books.

- **Payroll fraud:** Creating "ghost" employees on payroll or falsifying worked hours and overtime.

- **Falsifying reimbursement claims:** adding fake or inflated expenses.

- **Theft of inventory or tangible assets:** Direct theft or manipulation of inventory records to cover up losses.

- **Turnaround sales ("flipping"):** Purchasing company-targeted assets via shell companies at one price and reselling them, at inflated rates, to the company.

3. Bribery and Corruption

Bribery and corruption drastically harm fair business practices and decrease institutional ethics. Employees or managers exploit their authority to illegally gain profit from transactions. Examples include:

- Accepting kickbacks from vendors in return for favourable contracts.

- Diverting procurement to favoured suppliers at inflated prices.

- Using inside information or influence for   personal or third-party benefit.

Such activities distort market efficiency and undermine internal discipline.

Vendor, Invoice, and Procurement Fraud

These involve fake expenses or conspiring with external vendors:

- **Vendor fraud:** Insiders create fake supplier profiles to siphon company funds or collude with legitimate suppliers to generate fraudulent invoices.

- **Invoice fraud:** Billing the company for non-existent goods/services or overcharging for legitimate ones.

- **Procurement fraud:** Influencing tender and bidding processes for individual gain.

4. Tax Fraud

Tax fraud can be defined as an assortment of deceptions for either the intentional underreporting of taxable income or over-reporting of deductions for tax purposes. The common fraudulent schemes include

- Hiding or destroying accounting information.

- Holding two sets of accounting records (i.e., a legitimate set and a set used for the sole purpose of defrauding the government).

- Transferring profits via fictitious transactions or shell corporations.

In addition to reducing government revenue, companies that deliberately fail to comply with tax laws will also expose themselves to severe fines and legal consequences.

5. Corporate Espionage

Corporate espionage (the theft of a competitor's confidential information) has been on the rise due to the increasing level of competition and innovation in many industries. Corporate espionage occurs when a company steals its competitor's confidential and proprietary information by using technology to hack into that information, or by paying off an insider at that competitor to steal the information, or by creating a new, unrelated corporation in another state and country with the sole purpose of stealing that competitor's information. The negative effects of corporate espionage extend far beyond the financial harm caused by the theft, because companies are losing their intellectual capital.

6. Money Laundering

Companies may also be used unknowingly as vehicles for money laundering (the process of disguising criminal income so that it appears to come from legitimate sources), which is the illegal act of making a profit by converting money that was earned illegally into money that appears to have been earned legally. A sophisticated system of layers is then added to this laundered money to hide its origin, often by using multiple international locations, including banks and other financial institutions. Failure to apply adequate systems to prevent and detect money laundering can help to save penalties and charges against the companies involved.

7. Ponzi and Pyramid Schemes

Ponzi schemes engage drawing new investments with promises of very high returns, compared to exercising new investors' money to pay earlier loans, rather than generating profits from legitimate business activities. Eventually, the scheme collapses once new investments dry up, causing high losses to new and unsuspecting investors.

Drivers and Enablers of Fraud

University Scholars and Industry practitioners use conceptual models such as the Fraud Triangle to explain why fraud occurs:

• **Pressure:** Individuals face financial or personal pressure to commit fraud, often linked to unrealistic performance targets or personal debt.

• **Opportunity:** Weak internal controls, inadequate segregation of duties, or insufficient oversight create pathways for fraud.

• **Rationalization:** Perpetrators justify their behaviour, convincing themselves their acts are harmless or necessary due to perceived injustice.

Weak corporate governance, lack of ethical leadership, and faulty audit environments regularly emerge as main causes for fraudulent activities.

Detection and Prevention

The Fraudulent activities cannot be removed through compliance, Data analysis techniques or preventive culture as each element must work in synergy to prevent fraud. They need to have the following

• **Robust internal controls:** Segregation of duties, regular reconciliations, vendor due diligence, and multi-tiered approvals.

• **Vigilant monitoring:** Continuous transaction monitoring, periodic audits, and use of data analytics or AI for anomaly detection.

• **Whistleblower mechanisms:** Anonymous reporting channels, strong anti-retaliation policies, and board-level engagement.

• **Ethical culture:** Employee training, clear anti-fraud policies, and visible commitment by top management.

Literature review

The role of forensic accounting has been explored through further development in fraud detection/ prevention by recent studies. Munandar et al. (2025) performed a bibliometric analysis that identified and quantified the increased amount of current research on forensic accounting, with an emphasis placed upon the use of fraud detection models, both technologically advanced as well as legislation based. Similarly, Abbadi et al. (2021) examined whether government and audit institutions have an effective method of implementing forensic accounting measures for fraud detection, and concluded that there is a lack of institutional support for such measures.

The study of Alshurafat et al. (2021) examined both the positives and negatives of forensic accounting education and the profession, and how these could be used to create better policy to increase the adoption and efficiency of it in promoting socio-economic development. Using empirical evidence, Rehman and Hashim (2021) demonstrated that forensic

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accounting can improve sustainable corporate governance through improved transparency and reduced incidence of fraudulent financial reporting. Through a systematic review, Kaur et al. (2022), showed that forensic accounting has become widely accepted as an important method of fraud detection and improving organization's governance practices. As a complement to the above, Kukreja et al. (2020) evaluated the use of forensic accounting tools, such as the Beneish M-Score and the Altman Z-Score and found them effective in identifying corporate fraud using financial ratios.

Forensic Accounting has a high relevance for Regional Applications, and its Potential Impact can best be demonstrated by examining Regional Applications. In their study on fraud prevention in Nigerian Banking, Ewa et al., (2020) describe how the unique characteristics of Banks make them vulnerable to fraudulent acts and how they may prevent fraud by applying fraud prevention techniques that have been designed specifically to address these vulnerabilities. Tapanjeh and Tarawneh, (2020) investigated whether or not Forensic Accounting can be successfully applied within Jordan, and found that the success of Forensic Accounting depends upon Institutional and Cultural Factors.

 In this regard, Akinbowale et al. (2020), have developed new methods by combining forensic accounting and technology, and therefore planned to fight fraud with greater success than previously possible. Hamdan (2019), states that Forensic Accounting is valuable as a technique to identify financial fraud, but he suggests that there should be greater professionalism and more education/training for practitioners in the field of Forensic Accounting. Enofe et al. (2013), examined the link between the use of Forensic Accounting and fraud detection in Nigeria, they found that the use of Forensic Accounting has shown significant reduction in fraud in Nigeria. Alabdullah et al. (2013), showed the potential for Forensic Accounting to reduce the impact of corruption in Iraq, as well as the fact that it can effectively reduce corruption despite poor regulatory mechanisms.

 Forensic accounting has become increasingly important in India over the last decade. The application of forensic accounting in investigation of scams is becoming increasingly relevant and serves as a financial oversight tool with the intent to prevent frauds (Moid, 2016). Similarly, Lakshmi & Menon (2016), discuss forensic accounting as an emerging defense against corporate fraud; they emphasize the need to include forensic tools and the use of investigative skills in their work. The earlier studies on forensic accounting provided background information regarding the development of the field of forensic accounting. Dhar & Sarkar (2010) define forensic accounting as an extension of auditing and accounting that provides support to legal proceedings and identify areas where it may be used to assist in the detection of corporate fraud. Advances in forensic accounting have identified new ways to utilize data analytics, big data and machine learning in order to investigate and determine financial fraud and manipulation. Gabrielli et al. (2024), demonstrate how utilizing big data analytics enhances forensic accounting by providing greater depth of analysis and enhancing the ability to detect sophisticated fraud patterns. In addition, their study illustrates the significant impact that emerging technologies will have in forensic investigations.

. In addition to Alharasis et al. (2023) showing how big data analytics can be used to enhance fraud detection and prevention in forensic accounting systems for the government sector in Jordan by using data driven techniques to identify misstatements in financial statements, Murthy and Gopalkrishnan (2023) study behavioral and governance aspects along with data analytics from the forensic perspective to reveal weaknesses in fraud vulnerability in Indian Banking Institutions.

Dheenadhayalan et al. (2025) examine an overview of the applications of Artificial Intelligence and Machine Learning for Financial Statement Analysis, which show the use of AI/ML in detecting fraud anomalies that are presented in a financial statement. This is also supported by Bhardwaj and Choudhary (2024), who describe AI-assisted decision-making systems as tools to assist in cyber-forensic investigations and in fraud detection.

 Mardjono et al. (2024) highlight the use of internal controls and big data in forensic accounting, specifically in Indonesia, which demonstrates the data-based approach in fraud detection. Odia et al. (2021) highlighted the importance of using data analysis in forensic accounting, including prediction and anomaly pattern detection, to enhance fraud prevention & detection.

 Chu and Yong (2021), evaluated the combination of using Machine Learning in conjunction with audit methodologies to enhance fraudulent activity detection. He recommended a Hybrid model which is an integration of Expertise and Advanced Analytical Methods for detecting fraudulently manipulated activities, as well as identifying on-going unethical practices.

The study by Sharma & Panigrahi (2012), which provides a review of data mining techniques in prior studies on accounting fraud detection, provides information about some of the earliest fraud identification techniques as well as how fraud detection evolved through the use of larger data sets with fraud detection that was increasingly automatic. Bnrescu (2015), also supports the trend of the growing application of Data Analytics Frameworks to identify Suspicious Financial Activity Indicative of Fraud.

The applications of Digital Forensics in case any digital device has been used and Fraud Prevention can be seen in other domains as well. Dzomira (2014) discusses how using digital forensic tools is an important method for reducing fraud risk, especially for banks and financial institutions. Guo & Hu (2012) identified fraud patterns in online commerce and highlighted that the need to quickly identify prevent fraud through real time data analysis was a key advantage of using data analytics. Nigrini (2012) used Benford's Law as a forensic accounting tool and illustrated how it could be used to detect and audit for manipulated financial information. Big Data and Machine Learning are being applied to fraud prevention and detection by Balasupramanian et al. (2017). The authors demonstrated the increasing complexity and variety of fraud analytics and discussed the expanding field of forensic accounting analytics. Snchez-Aguayo et al. (2021) demonstrate another area where Fraud Analytics has expanded into, when they integrated psychological fraud theories such as the fraud triangle with data mining methods to create sophisticated fraud detection models. This example illustrates the growing diversity of Fraud Analytics.

Recent studies continue to support the effectiveness of Beneish M-score in detecting earnings manipulation and financial fraud across many industries. Khatun, Ghosh & Kabir (2022), in a study of the use of the Beneish M-score model in the banking sector of Bangladesh, demonstrate the model's applicability for detecting earnings manipulation, which has important strategic implications for regulatory monitoring in the banking sector of Bangladesh.

Kukreja et al. (2020) studies the combination of Beneish M-score and Altman Z-score to provide an integrated methodology for preventing & detecting corporate fraud. The results show that combining the two techniques increases the accuracy of prediction for both financial distress and fraudulently reported manipulations by corporate entities.

Sutainim, Mohammed & Amrizah (2021) conducted a study examining the application of the Beneish M-Score Model to Malaysian publicly listed firms. Their study showed the model's ability to discover potential manipulation of earnings and offered further proof as to why the model remains viable for creating strong corporate governance environments in developing countries.

Gyawali (2021) utilized the Beneish M-Score Model to examine how it can be used within the context of Nepal's banking environment in order to assess the predictive ability of the model in determining if an entity is engaging in abnormal financial practices (e.g., manipulation). Prior to Gyawali (2021), Dalnial et al. (2014) developed a model utilizing a combination of forensic tools, including the M-Score, to determine fraudulent financial reporting based on an examination of a firm's financial reports; Dalnial et al. (2014) also emphasized that, when combined with other data, financial ratios will help to show if there was an attempt to manipulate a firm's income.

Maccarthy (2017) examined whether two financial models for fraud detection can be combined into one model; specifically he examined the Altman Z-score model and the Beneish M-score model using the Enron case study as an example of this combination and demonstrated both models can be effectively utilized to determine when fraud is occurring at a company and if a

company will eventually fail.

Tarjo Herawati (2015) utilized the Beneish M-score model combined with data mining techniques to propose a new method of detecting financial fraud, providing an example of how the method can be automated in forensic accounting processes.

Research Methodology

The two score which have been used for analysis are Benish m score and James modified c score. The Beneish M-Score is a forensic accounting model developed by Messod D. Beneish to detect the likelihood that a firm has manipulated its earnings by examining specific financial statement relationships. It emerged first in a 1997 study on detecting GAAP violations, where Beneish analyzed firms with extreme financial performance and identified statistical patterns associated

with earnings manipulation, and was later refined in a 1999 Financial Analysts Journal article that expanded the model to eight variables and calibrated it using 74 firms subject to SEC enforcement actions and a large matched sample of non-manipulators. The model is based on the idea that manipulators share common economic and reporting characteristics: they often face deteriorating fundamentals such as declining gross margins, yet continue to show strong sales growth, and they rely heavily on discretionary accounting choices that increase accruals and reduce transparency. To capture these features, the M-Score combines eight indices: the Days Sales in Receivables Index (DSRI) to reflect aggressiveness in revenue recognition; the Gross Margin Index (GMI) to capture deteriorating profitability; the Asset Quality Index (AQI) to measure the growth of less reliable, intangible or deferred assets; the Sales Growth Index (SGI) to represent expansion pressure; the Depreciation Index (DEPI) to detect slowing depreciation; the SG&A Expenses Index (SGAI) and Leverage Index (LVGI) to reflect cost behavior and financing structure; and Total Accruals to Total Assets (TATA), which is the strongest single predictor, measuring the gap between earnings and operating cash flows. Each component is converted into a ratio comparing the current year to the prior year, and then weighted by coefficients estimated using probit regression, producing the full eight-variable equation:

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

In practice, the resulting score is interpreted against empirical cutoffs: values less than about −2.22 suggest the firm is unlikely to be a manipulator, scores greater than about −1.78 indicate a high likelihood of manipulation, and intermediate values represent a gray zone where further investigation is warranted. Empirical evaluations show that the Beneish M-Score can correctly flag a substantial proportion of manipulators in holdout samples, with detection rates around threequarters of known cases and an acceptable but non-trivial false positive rate, which is why researchers, auditors, and investors treat it as a powerful initial screening tool that must be complemented by qualitative analysis and additional forensic tests rather than as a stand-alone proof of fraud.

Quick Summary

Variable	Formula	Coefficient
DSRI (Days Sales Receivables)	(NR_t/Sales_t)/(NR_t-1/Sales_t-1)	0.92
GMI (Gross Margin Index)	Prior GM / Current GM	0.528
AQI (Asset Quality Index)	Index of intangible assets	0.404
SGI (Sales Growth Index)	Sales_t / Sales_t-1	0.892
DEPI (Depreciation Index)	Prior depreciation ratio / Current	0.115
SGAI (SG&A Index)	Current SG&A% / Prior SG&A%	-0.172
LVGI (Leverage Index)	Current debt ratio / Prior	-0.327
TATA (Total Accruals)	(Income - CFO) / Total Assets	4.679

Whereas the James Montier's modified C-score is a simple, rule-based forensic indicator designed to flag companies that may be engaging in earnings manipulation or "creative accounting" by scoring a set of accounting red flags derived from reported financial statements. The original C-score, developed by Montier in a short-selling and quality-investing context, assigns each company a binary score (0 or 1) on six tests, then sums them to produce a total between 0 (no evidence of manipulation) and 6 (strong suspicion the books are being cooked). Typical components include: (1) a growing divergence

between net income and operating cash flow, which points to heavy reliance on accruals rather than cash; (2) rising days sales in receivables, suggesting aggressive revenue recognition; (3) increasing days sales in inventory, which can reflect overproduction or obsolete stock not written down; (4) a worsening quality of earnings, often captured by accruals ratios; (5) falling asset turnover, indicating inefficient use of assets; and (6) expanding gross margins despite competitive or cost pressure, which can hint at accountingdriven margin improvement rather than genuine economics. A modified C-score, as implemented by some research and data providers, extends Montier's original six checks by adding further binary red flags—such as sudden changes in depreciation policy, unusual movements in other current assets or liabilities, or sharp swings in capitalized expenses—to create a broader 0–9 or similar scale while retaining the same "higher-is-worse" interpretation. In application, analysts, investors, and risk-model designers use the (modified) C-score as a first-stage quantitative filter to screen large universes of stocks for potential accounting risk: companies with consistently high scores are candidates for deeper forensic review, are often excluded from quality or low-risk portfolios, and sometimes form part of short-selling screens, whereas low-scoring firms are viewed as having cleaner, more conservative reporting.

Quick Summary

1. **Growing divergence between net income and cash flow (1 point).** A higher level of accruals is associated with a higher likelihood of profit manipulation.

2. **Increasing receivable days (1 point).** A large increase in receivable days might suggest accelerated revenue recognition to inflate profits.

3. **Increasing inventory days (1 point).** Increasing inventory days could suggest that input costs are being artificially flattered or that sales growth is slowing.

4. **Increasing other current assets (1 point).** Companies might be aware that investors often look at receivables and inventory, and might disguise problems in current assets.

5. **Declines in depreciation relative to gross fixed assets (1 point).** Firms have been known to lower depreciation charges in order to inflate profits.

6. **Total asset growth (1 point).** Some companies become serial acquirers and use acquisitions to distort profits.

Data Collection:

The Data collection was done from the Annual Report available on the website of CIPLA company which deals in pharmaceutical products including medicines and other related products. Data for year from 2016 till 2024 was collected and analysed.

Data Analysis

Benish m score Calculation for the year 2024

DSRI (Days Sales Receivables)

1. DSRI = $(NR\_t/Sales\_t)/(NR\_t\text{-}1/Sales\_t\text{-}1) = 1.04$

2. GMI (Gross Margin Index) = Prior GM / Current GM = 0.96

3. AQI (Asset Quality Index) = non-current asset/ total asset = 1.32

4. SGI (Sales Growth Index)= $Sales\_t / Sales\_t\text{-}1 = 1.13$

5. DEPI (Depreciation Index) = Prior depreciation ratio / Current = 0.12

6. SGAI (SG&A Index) = Current SG&A / Prior SG&A = 0.99

7. LVGI (Leverage Index) = Current debt ratio / Prior_t-1 = 0.01

8. TATA (Total Accruals) = (Income - CFO) / Total Assets = 0.05

M-Score = $-4.84 + 0.92 \times 1.04 + 0.528 \times 0.96 + 0.404 \times 1.32 + 0.892 \times 1.13 + 0.115 \times 0.12 -$

0.172× 0.99 + 4.679× 0.05 − 0.327× 0.01 = -1.76.

Similarly, the Benish m score was calculate for the other years in the similar way.

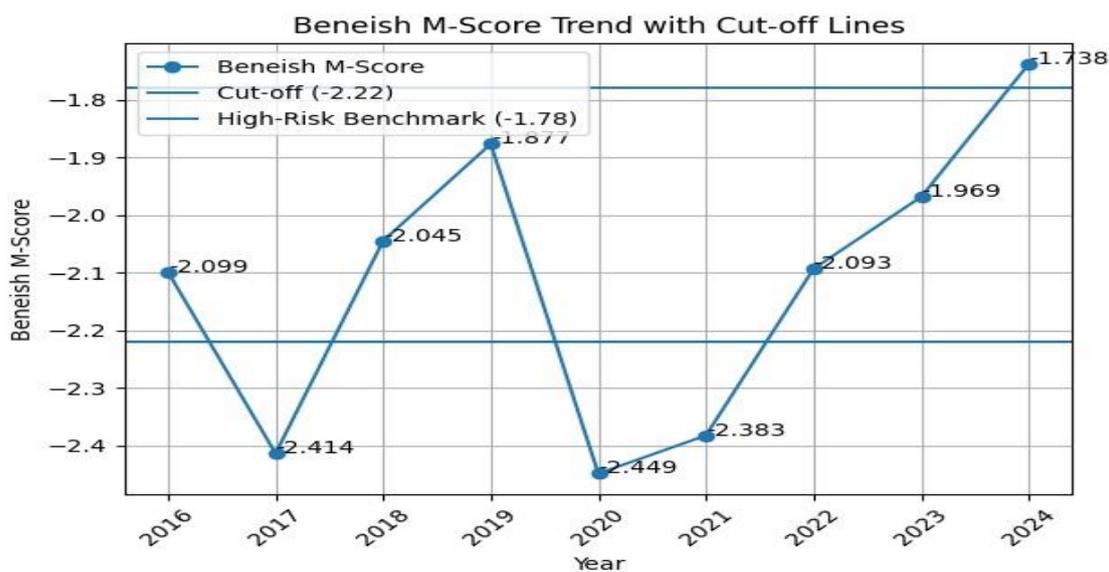| Mar-16	Mar-17	Mar-18	Mar-19	Mar-20	Mar-21	Mar-22	Mar-23	Mar-24
-2.09877	-2.41376	-2.04508	-1.87686	-2.44882	-2.38259	-2.09342	-1.96874	-1.73823

Fig 1.1

Data interpretation for Benish m score calculation

The Beneish M-Score exhibits noticeable volatility over the nine-year period. The firm remains below the −2.22 threshold in 2017, 2020, and 2021, indicating relatively lower manipulation risk in those years. However, from 2018 onward, the score frequently moves above −2.22, placing the firm in a moderate risk zone.

The most significant structural shift occurs after 2021, where the M-Score shows a consistent upward trajectory. By 2024, the score reaches −1.738, crossing even the stricter −1.78 benchmark. This movement suggests a strengthening statistical signal of potential earnings manipulation.

Overall, the trend indicates increasing risk in the recent period, warranting closer analytical scrutiny of accrual behaviour and revenue recognition practices but decision should be taken after thorough checking of financial records

Data Analysis for the James Montier's modified C-score

James Montier modified C-score was calculated for the year 2024

1. Growing divergence between net income and cash flow = 1

2. Increasing receivable days = 0

3. Increasing inventory days = 1

4. Increasing other current assets = 1

5. Declines in depreciation relative to gross fixed assets = 0

6. Total asset growth = 1

Total Score = 4

   So James Montier's modified C-score for year 2024 is 4

Similarly, the James Montier's modified C-score was calculate for the other years in the similar way.

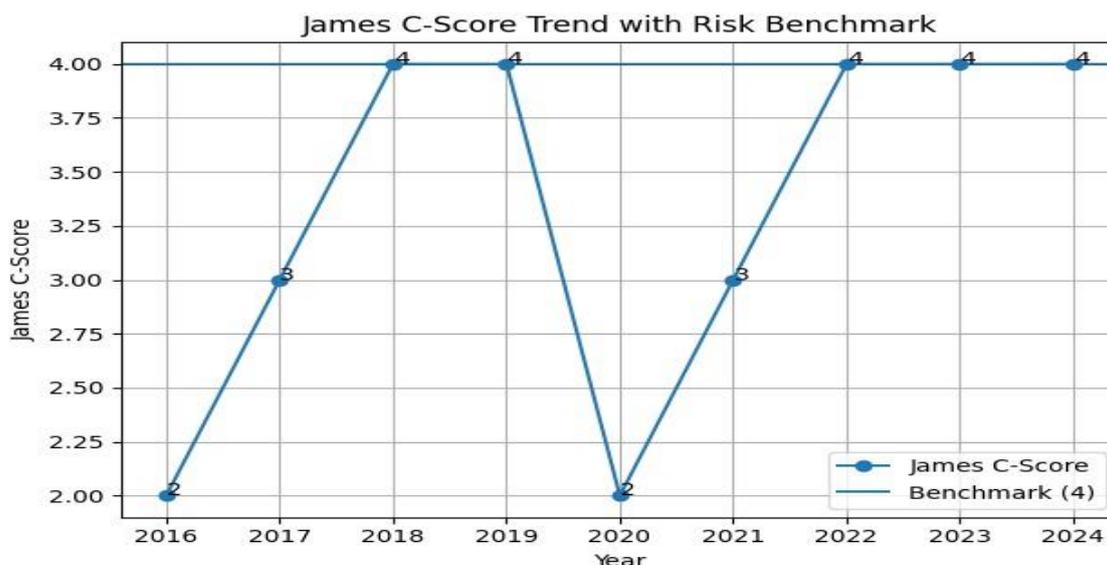| Mar-16	Mar-17	Mar-18	Mar-19	Mar-20	Mar-21	Mar-22	Mar-23	Mar-24
2	3	4	4	2	3	4	4	4

Fig 1.2

Data interpretation

The C-Score ranges from 2 to 4 over the period, suggesting low to moderate accounting aggressiveness. There is no observation above the defined high-risk threshold, which indicates the absence of a severe manipulation signal. The clustering at 4 during FY19 and again from FY22 to FY24 suggests some weakening in accounting conservatism. This pattern may reflect increased accrual reliance, receivable expansion, or working capital intensity rather than outright distortion. The temporary dip in FY20 moderates' concerns, as it interrupts what would otherwise appear as a continuous upward trajectory.

Importantly, no score crosses into a structurally high-risk zone under the defined framework. From a forensic analytics perspective, the firm remains within tolerable bounds for a large pharmaceutical entity, though the persistence at the upper end of the scale warrants monitoring of accrual quality and cash conversion efficiency.

 Conclusion

The Beneish M-Score demonstrates a gradual upward drift over the study period, with several years exceeding the −2.22 threshold and the latest observation crossing the stricter −1.78 benchmark. This pattern reflects increasing accrual intensity and a strengthening statistical signal of potential earnings manipulation. The post-2021 trajectory is particularly notable, as it indicates sustained pressure on earnings quality.

The James C-Score, by contrast, fluctuates within the 2–4 range and does not exceed the defined high-risk threshold. Although repeated scores at the upper bound suggest moderate accounting aggressiveness and possible erosion of conservatism, the absence of extreme values indicates that the firm remains within acceptable analytical limits.

Collectively, these two models symbolize potential manipulation risk rather than confirmed misstatement. They function as screening mechanisms that highlight areas requiring deeper examination. Any inference of earnings management must therefore be substantiated through detailed investigation, including transaction-level testing, accrual decomposition, revenue recognition review, and cash flow validation.

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