A Diagnostic Analysis Of Financial Statements Using James Modified C-Score

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Abstract
Fraud within the pharmaceutical sector exists, although now fraud is emerging in new forms. Investors have begun asking increasingly severe and serious questions regarding fraud in addition to waiting until after an incident occurs and then conducting a forensic review of the situation.
The objective of this study is to determine if there is evidence that use of two financial scoring models (Piotroski F-Score and James Modified C-Score) could be used collectively to identify whether or not a publicly traded pharmaceutical company is truthfully reporting its financial results. Both of these individual models were not created for this particular type of assessment; therefore, by combining them into a single application, we will have the ability to conduct a larger assessment over all firms examined.
The C-Score analyses six binary criteria related to anomalies in accounting practices. Some of these include an increase in abnormal accruals, accounts receivable increases at a greater rate than revenue, etc. All three represent possible signs of fraudulent activity in financial reporting.
On the other hand, the Piotroski F-Score examines a firm's overall financial health through nine different measurements. The nine areas measured include net income relative to total assets, total debt (leverage), gross margin, etc. Both scores provide value through their intersection. When a firm receives a low Piotroski Score, it does not automatically mean that the firm engaged in fraudulent behavior; however, when the firm's weak financial performance correlates with anomalous accounting indicators in a high C-Score, there is sufficient reason for further investigation.

Keywords: Fraud, anomaly , investigation, c score, f score

1. Introduction

Fraud is a deliberate and intentional act of deception and/or misrepresentation intended to generate a financial advantage at the expense of other entities while simultaneously undermining public confidence in financial reporting and capital markets. In an organizational setting, fraud can be described as a deliberate manipulation of a company's financial records; a company's assets; and/or its publicly disclosed information intended to create an artificial impression of success and therefore elicit funding; avoid paying taxes; and/or increase executive compensation. When companies are managed by people who are motivated to meet specific goals and objectives (i.e., quarterly earnings) in order to meet their personal expectations and/or reward themselves with bonuses (e.g. bonuses based on the attainment of certain revenue levels), they may engage in fraudulent behavior to achieve those goals. The result of such fraudulent activities is to destroy the value of shareholders' investments and prompt regulators to take action.

Companies commit fraud for financial gain using a variety of consistent methods to exploit the accounting flexibility and internal control systems available to them. As previously mentioned, fraud committed through the improper application of accounting principles and/or rules related to revenue recognition is the most common form of accounting-related fraud. Companies commit this type of fraud when they artificially inflate reported revenues by booking sales prior to the actual date of sale through various means including but limited to the following: Channel Stuffing: Firms flood their distributors with excessive amounts of inventory which results in the distributors being unable to sell all of the products and subsequently returning the products to the firm. Bill-and-Hold Schemes: Firms claim to have shipped goods to customers prior to delivering the goods and Fictitious Customers: Firms record orders from non-existent customers.

1.1 Corporate Fraud Classification

Corporate fraud involves intentional deception for financial gain, often through financial statement manipulation, asset misuse, or corruption. The Different types of fraud are mentioned below.

1.2 Financial Statement Fraud

Revenue recognition fraud is one of the most widespread types of financial reporting fraud, and it involves a deliberate manipulation of the timing and validity of recorded revenue. Channel stuffing is an example of common mechanisms that result in artificially inflated sales figures when a company pushes excess inventory on distributors at levels far in excess of their absorption limits. Bill-and-hold arrangements enable the recognition of revenue before the transfer of goods, and the creation of sales transactions based on phantom customers and fictitious invoices enables completely fabricated commercial activities to be entered into the financial record. In addition, round-trip schemes can exacerbate this type of financial statement misrepresentation by simulating the existence of arm's length transactions between related or colluding parties by transferring funds back and forth.

Expense misstatement is usually done by misclassifying (i.e. improperly classifying) operating expenses from one time period into another time period to inflate reported profits. Misclassifying operating expenses is also an example of how a company can misclassify operating expenses. Most companies misclassify operating expenses such as marketing, or administrative costs, as an asset. Companies use these methods in conjunction with extending the life of a given asset in order to lower the amount of depreciation being recorded, reversing prior year's excess provisions when it suits management, and reducing R&D accruals that do not reflect actual economic activity.

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Expense misstatement typically occurs through the repeated misclassifications and deferments of expense items to increase reported profit. Misclassifying current period operating expenses (such as marketing and administrative) as long-term assets is one of the most commonly utilized methods for accomplishing this. These classifications are often made in conjunction with the arbitrary extensions of asset lives to reduce the amount of depreciation charged, reversing prior period excess provisions at the discretion of management, and reducing research and development accruals in a manner not consistent with the level of economic activity occurring.

2. Asset Misappropriation

While cash theft is probably the most common form of occupational fraud, the continued prevalence of this type of fraud across businesses of all sizes reflects the ease with which it can develop if there is a weakness in an organization's internal controls or if those controls are not consistently applied. While skimming may be the easiest to commit due to the fact that the theft takes place prior to the creation of any record of the transaction, thus allowing the perpetrator to intercept revenue from the point of collection, and preventing the auditor from tracing the transaction, the act of stealing cash (cash larceny) works slightly different in that the funds were recorded when they were stolen. Therefore, in theory, the discovery of the crime should be easier; however, in practice, many perpetrators create delays and/or suppress reconciliations to detect losses by exploiting weaknesses in the separation of duties.

Billing schemes are typically the most complex of the three types of crimes listed above. These schemes involve creating fictitious vendor relationships or manipulating existing billing processes to divert payments to third parties. The unique aspect of these schemes is the ability of the perpetrator to accumulate losses quietly over extended periods of time without raising suspicions.

Inventory and physical asset thefts are also likely underreported, in terms of frequency and monetary impact. This underreporting can be attributed to a lack of adequate verification procedures within organizations. Theft of inventory is often committed by removing inventory under the guise of a fictitious sale. Inventory leaves the organization as "sold" to either non-existent customers or to customers who are willing participants in the scheme. Gradual theft of inventory is also possible. Equipment, vehicles or other organizational resources can be used by employees for their own benefit over time. Since each theft event is not likely to be dramatic enough to prompt investigation, the theft goes undetected. An example of the most cynical
version of inventory/asset theft involves writing off or disposing of assets that have already been stolen.

Fraudulent payroll activity is differentiated from other forms of employee theft (asset misappropriation) by the amount of trust and access typically required to commit such frauds. Fraudulent payroll schemes generate larger losses than other types of employee theft because of the large amounts of money typically involved. A "ghost employee" scheme involves adding an entirely fake employee to an organization's payroll system so that all their wages are paid directly into accounts under the control of the perpetrator. Ghost employee schemes can continue uninterrupted for years when human resource and payroll systems do not function independently. The inflation of hours worked and/or commissions earned is a subtler version of this type of scheme. It is more prevalent because it takes advantage of the difficulty in verifying self-reported attendance/performance data. Organizations relying heavily on oversight based upon trust are especially vulnerable. Falsification of expense reimbursement claims follow the same basic principle. Employees submit claims either totally fabricated or significantly exaggerated and take advantage of business environments where the volume/pace of business activity makes independent review of each claim practically impossible.

3. Corruption

Directly, bribery and kickbacks are types of fraud that have become embedded within procurement and contracting practices; it is also clear from their prevalence how well these methods utilize an individual employee's (and thereby the organization he or she serves) informational advantage. Bribery is the simplest form of bribery where money is paid directly to an employee who has authority to select a contractor or make contract awards and thus converts what should be a source of organizational trust to a source of personal income. A related but slightly more complex version of this method of fraud is called kickbacks. In this type of fraud a vendor is awarded a contract at a higher than market price and then provides the employee who helped facilitate the contract with some percentage of the difference in cash or other form of value. Thus the organization pays for the entire agreement while the vendor and the employee split the extra money between them. Because both of these types of bribery appear to be completely legitimate on the surface – the employee does award the contract and executes all of the necessary paperwork, etc. – and because there is no overt or even subtle indication of fraud the likelihood of detection is very low.

Fraudulent conflicts of interest are frauds that differ from each other in degree rather than kind and generally involve either the intentional failure of an employee to disclose a relationship which, if disclosed, would fundamentally affect the evaluation of a transaction or the self-dealing where an employee uses their authority to direct company funds to an enterprise in which they have a personal financial interest. These types of fraud are often difficult to prosecute since the goods and/or services delivered by the vendor are almost always real and the price paid by the employee/vendor is usually reasonable, although favourable to the related party. As a result, fraudulent undisclosed related-party transactions create a compounded problem since the lack of disclosure precludes the use of an organizations internal controls to provide an independent check on related-party transactions, and as a result, the organization is left vulnerable to terms and conditions that benefit the employee and not the organization.

Bid Rigging is positioned uniquely as a form of corruption, due to its requirement for collaboration among organizations, which usually includes colluding competitors that agree upon the result of a bidding process prior to the submission of their respective tenders. Essentially, this type of bid rigging maintains the illusion of competitive bidding processes while eliminating the true essence of such processes, through the means of contract rotation (the winning bidder can rotate contract awards), suppression of legitimate bidders (to ensure no other bidder participates), or the agreement on higher than normal prices for products/services so the pre-determined "winner" will win the bid by the amount they were willing to pay above the legitimate price. In addition to the fact that the organization was deceived out of their money, the nature of bid rigging creates an additional problem for the defrauded organization in that they do not know whether something was amiss with the process itself. Therefore, they are dependent on the use of some form of forensic pricing analysis or a whistleblower disclosure, both of which many organizations lack the resources, expertise, or capability to accomplish.

4. Earnings Management (Fraudulent Borderline)

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These schemes play on discretion in GAAP/IFRS, internal control gaps, and audit loopholes. Recognition relies on ratio anomalies (e.g., accruals vs. cash flows) and models like C-Score/F-Score for red flags. Early intervention protects investors and markets from fraud.

5. Enhanced Corporate Fraud Classification with Fraud Triangle & Pentagon

Fraud is an act of deceit that is intended to generate financial gain by misrepresenting information, documents, and/or the value of a company's assets and/or those of an investor, creditor, and/or market. Companies commit fraud mainly to increase their reported profits and earnings, to receive additional compensation based on meeting earnings expectations, to enhance their stock prices, and/or to prevent default under debt covenants. The ability of companies to manipulate their reporting is due to the flexibility afforded to them when preparing their reports in accordance with Generally Accepted Accounting Principles (GAAP)/International Financial Reporting Standards (IFRS) as well as inadequate internal control systems, and/or limited audits. As such, these weaknesses create areas that can be exploited by the fraud triangle and fraud pentagon diagnostic tools. The fraud triangle was created by criminologist Donald Cressey to identify the three elements necessary for fraud to occur. They are: 1) Pressure—fraud occurs when an individual has incentives, such as earnings guidance or personal debt. An example would be the pharmaceutical executives who were under pressure from analysts and investors regarding pricing. They felt they could take advantage of capitalisation rules by deferring research and development costs. Their self-justification would be that "the cost deferral will allow us to have a more stable financial report." 2) Opportunity—this is when there is a lack of oversight and/or complexity in the structure of a company. For example, some pharmaceutical companies have a large number of foreign subsidiaries that use different accounting principles than the parent company. When the U.S. parent company issues financial statements using GAAP, the foreign subsidiaries' financial statements are issued using IFRS. The foreign subsidiaries do not provide detailed financial information regarding the transactions they engage in. Therefore, it is difficult for the auditors to verify the accuracy of the financial statement. 3) Rationalization—is when an individual believes that his/her actions are justified. An example of rationalization occurred when pharmaceutical executives believed that deferring R&D costs was acceptable because it allowed them to "smooth" their financial results for better comparability and predictability.

Donald Cressey's fraud triangle has been expanded upon by other researchers. The Fraud Pentagon model includes two new elements. One is arrogance—when a CEO feels that he/she knows what is best and therefore ignores or overrides internal controls. Another element is competence—when a CFO is able to create and/or hide fraudulent schemes. An example of the arrogant CEO in the pharmaceutical industry is a CEO who wants to sell a drug and refuses to comply with FDA regulations. He feels that he knows better than the FDA and therefore does not follow the regulations. An example of the competent CFO is when a CFO is able to create an off-balance-sheet vehicle for rebates that a distributor receives for a pharmaceutical product. The vehicle is used to shift the obligation from the manufacturer to the distributor.

The Fraudulent behavior that is most prevalent among financial statements are; Fictitious Sales (Phantom Pharma Orders), Cookie-Jar Reserves (Releasing Prior Over-Provided Reserves) and Liability Concealment (Hiding Litigation by Using Footnotes) The fraudulent behavior regarding Asset Misappropriation includes Cash Diversion through Ghost Employees or Fake Vendor Schemes. The fraudulent behavior regarding Corruption include Kickback payments to Drug Approvals. Earnings Management can cross into fraud as a result of large bath charges and/or Pro Forma metrics, and the use of technology such as AI generated invoices has greatly increased the ability for these types of fraudulent behaviors.

In addition to the above examples of fraud, these components provide an explanation of why using Quantitative Tools, such as James Modified C-Score (Identifying Red Flags of Manipulation) and Piotroski F-Score (Assessing Fundamental Strength) are necessary for the early detection of fraud in High-Risk Industries such as Pharmaceuticals.

Fraud detection and prevention is also an important function of corporate governance especially in industries where there is a lot at stake, such as the pharmaceutical industry. High risk exists for these industries because of the amount of interest and money being put into R&D; and because of the pricing pressures and complexity of their supply chains. One of the first steps in fraud prevention is to implement preventative measures based on the frameworks of the Fraud Triangle and Fraud Pentagon. Reducing the pressure to commit fraud may be achieved through offering a competitive incentive system, which includes, but is not limited to, providing balance to a company's scorecard and the elimination of an overemphasis on just the EPS. Reducing opportunities to commit fraud can be achieved by implementing strong internal control systems that include segregating duties in compliance with SOX and utilizing automation workflow. Finally, reducing the rationalization to commit fraud can be achieved through ethics training programs and establishing a "tone-at-the-top" leadership approach. The two key factors of the Pentagon – Arrogance and Competence – require independent oversight from boards of directors, whistleblower hotlines, and limits on executive override authority.

Detection is based on a multi-layered process that utilizes a combination of human observation, advanced technologies, and statistical models. While traditional audits are designed to evaluate a small number of sampled transactions, these methods have limited ability to detect sophisticated fraudulent schemes. Forensic accounting builds upon traditional audits by utilizing data analytics to identify unusual financial transaction activity such as journal entry anomalies and vendor behavior patterns. The red flag monitoring method focuses on identifying distorted ratios which may indicate fraud. An example of ratio distortion includes when the accruals of a company exceed the company's cash flows (as indicated by the C-Score signal) or when the company has declining profit margins despite the continued increase in the company's revenues (as indicated by the F-Score weakness). Additionally, there are two quantitative analytical tools, the James Modified C-Score and the Piotroski F-Score. These tools utilize objective diagnostics to identify whether a company has been manipulated. The C-Score evaluates a company for six binary flags that can be used to identify manipulation through various means including (but not limited to): net income versus Chief Financial Officer (CFO) disconnect, an increase in accounts receivable, etc. The F-Score evaluates a company for nine fundamental factors including profitability, leverage, efficiency, etc. When applied together to a pharmaceutical company, these tools can generate a risk assessment grid. For example, if the C-Score indicates that a company has a high level of manipulation and the F-Score indicates that a company has low levels of profitability, the resulting risk assessment will be a high manipulation risk signal located at the top of the weakness signal, indicating that a company has both the potential for fraud and overall weakness. This would prompt an investigation of the company's transactions and operations. The use of technology has accelerated the detection of fraud. Technology allows companies to perform an evaluation of large amounts of data using artificial intelligence (AI) to identify outliers and anomalies. Blockchain provides a secure way for companies to verify their supply chain and prevent the practice of channel stuffing. Continuous auditing through robotic process automation (RPA) provides a means for companies to test 100 percent of all transactions. Regulatory agencies provide additional support to companies in detecting and preventing fraud through the use of regulatory-based fraud prevention tools. One regulatory-based fraud prevention tool is the Benish M-Score. The Benish M-Score uses eight proxies that measure the likelihood of a company being manipulated (DSRI, GMI, etc.). Pharmaceutical companies have developed some specific strategies for reducing the risk of fraud. Some of these strategies include performing third-party due diligence on distributors, conducting rebate audits, and reviewing the capitalization of research and development costs. In order to achieve fraud prevention, companies should implement a "three" lines of protection model. The first line of defence consists of the company's operational managers who are responsible for ensuring that all employees follow the company's policies and procedures. The second line of protection is comprised of the company's risk and compliance department. and responsible for evaluating the effectiveness of the company's controls. The third line of guard is the company's internal audit department. The third line of defence is responsible for evaluating the design and operation of the company's controls. According to studies performed by the Association of Certified Fraud Examiners (ACFE), implementing a defence model reduces the occurrence of fraud by 50-70 percent.

6. Literature review

Forensic accounting has evolved into a well-established discipline integrating accounting, auditing, law, and investigative practice. Kumari Tiwari and Debnath (2017) characterize it as inherently multi-disciplinary, requiring competencies in statistics, IT, legal knowledge, and human skills, arguing that it should be developed as a separate academic discipline with dedicated professional standards. Fadilah et al. (2019), conducted an empirical study via a survey of Big Four external auditors in Indonesia to confirm whether auditing, communication, psychological, and ICT related skills have significant effects on fraud detection ability, but found that there were no independent effects from investigative or legal skills. Using professionalism theory and interviewing elite practitioners in Australia, Alshurafat (2022) identified that forensic accounting meets only a partial number of the sociological criteria for being considered a profession.

The practical implementation of forensic accounting has also been well-documented. In terms of the challenges experienced when implementing forensic accounting in a real-world setting, Abbadi et al. (2021) found that the accumulation of experience was the main barrier to be overcome; this was followed by lack of cooperation from stakeholders and availability of technology. However, the adoption of IT significantly enhanced the ability of organizations to discover fraudulent activities; although there were significant infrastructural costs and training deficits as barriers. Akinbowale et al. (2020) introduced a novel conceptual model for integrating forensic accounting methods into an organization's control system, since it is widely acknowledged that there are no operational models in the forensic accounting literature. Most recently, Naz and Khan (2025) demonstrated through structured questionnaires administered to companies in Pakistan that forensic accounting methods specifically fraud investigation, litigation support and dispute resolution all contribute positively to fraud detection and prevention.

Fraud investigations are considered the primary operational activity of forensic accounting. Lokanan (2019) identified a systematic investigation strategy for fraud investigations based upon a case study of the Polly Peck International fraud. This strategy described how fraud investigators could use both direct and indirect methods to gather evidence of concealment and conversion in order to prosecute those responsible. The theoretical foundation of fraud investigations is heavily based upon the Fraud Triangle. Abdullahi and Mansor (2018) used Structural Equation Modeling to examine the relationship between pressure, opportunity and rationalization and fraud in the public sector of Nigeria. They discovered a positive correlation between each element and fraud and recommended salary reform and enhanced internal control mechanisms as a method of structurally reducing fraud. Nortje and Bredenkamp (2020) provided a definition of the fraud investigation process by conducting a survey of seventy-five commercial forensic practitioners in South Africa and establishing a five phase model of initiation, planning, execution, reporting and reflection. Nortje and Bredenkamp (2020) also established a governance framework for the professional association that represents this field. In their study of the banking sector in India, Gangwani (2021) surveyed banking employees and discovered that the majority of bank frauds were perpetrated by insiders who collaborated with outsiders. Forensic accountants and traditional auditors have different functions in fraud investigations in the banking sector. Murthy and Gopalkrishnan (2023) investigated fraud investigations at the behavioral level using a case study of large scale banking frauds in India. Murthy and Gopalkrishnan (2023) found that "dark triad" personality characteristics were associated with the failure of corporate governance. Using phenomenological interviews with forensic professionals in Spain, Clavería Navarrete and Carrasco Gallego (2023) demonstrated that fraud investigation techniques can be used to prevent fraud before it occurs.

Data analytics has altered the way forensic accounting is practiced by allowing entire financial populations to be analyzed instead of just sampling. In their study of academic and practitioner attitudes toward big data and forensic accounting in China, Rezaee and Wang (2019), found that there was strong agreement from both groups regarding an expected increase in demand for forensic accounting professionals and big data analysts; and that big data and forensic accounting topics should be included in business curriculum.

Fay and Negangard (2017) and Weirich et al. (2017) each created accounting education cases based on IDEA and ACL Analytics software, respectively. Each case embedded fictitious fraudulent transactions into the dataset, and illustrated how fraud can be detected with analytical techniques such as identifying red flags of fraud with the assistance of software.

The application of Benford's Law has become one of the most recognized data analytics techniques used in forensic practices. Máté et al. (2017), applied this technique to Hungarian wholesale trade enterprises and found several non-conforming cases, and suggested that it could be used in conjunction with goodness-of-fit tests to further validate findings. Cluster analysis has also been recognized as a potential forensic tool. Goh et al. (2021), demonstrated the application of cluster analysis as a forensic tool using Tableau Software, and showed that complex patterns within a financial dataset can be used to identify anomalies. Additionally, Gabrielli et al. (2024), completed seventeen semi-structured interviews with forensic accountants, and concluded that big data analytics offers significant affordances for fraud detection. These were primarily attributed to the ability of visual analytics to provide insights related to the nature of fraud. Finally, Mittal et al. (2021), employed structural equation modeling to analyze relationships between awareness of forensic accounting and intentions to detect fraud among practitioners in India, and determined that big data technologies mediated the relationship. Mardjono et al. (2024), also found that big data analysis mediated the relationship between COSO-based internal control and the adoption of forensic accounting in Indonesia's audit institutions.

The use of the Beneish M-Score model to detect fraudulent accounting practices is a well-established method within the field of Forensic Accounting. In its original form, the Beneish M-Score is a quantitative model that uses eight distinct financial ratios (the days sales in receivables index, gross margin index, and total accruals to total assets) to calculate an overall score. Beneish (1999) suggests that when the overall M-Score exceeds –2.22, there may be evidence of earnings manipulation.

James' modified c-score model has built upon this work by using improved accrual quality metrics to assess the likelihood of fraud in non-manufacturing and emerging market firms. Tarjo and Herawati (2015), developed the Beneish model to assess Indonesian listed companies and identified the gross margin index, depreciation index, and total accruals as the three primary variables that are indicative of potential fraud.

Khatun et al. (2022) also assessed Bangladeshi Commercial Banks from 2009-2018, and found that while there was some instability in their ability to manipulate, they most commonly utilized revenue overstatement and reduction in accruals. Additionally, Halilbegovic et al. (2020) applied the Beneish model to 4,580 small and medium-sized enterprises (SMEs) in Bosnia and Herzegovina. They concluded that the model could be successfully applied to all industries, and that the three most successful variables included Sales Growth Index, Total Accruals to Total Assets, and Days Sales Receivable Index.

Kukreja et al. (2020) applied both the Beneish M-Score and Altman Z-Score to Comscore, Inc., and found that the type of forensic accounting model utilized had a significant effect on the success rate of detecting fraud. Specifically, they stated that the two models should be used in conjunction with one another in order to improve reliability. Lastly, Zhao et al. (2025) expanded on the traditional methods of scoring fraud models, through the application of Polytope Fraud Theory. Using a machine-learning approach and training on activist short seller data, Zhao et al. identified that the top indicators of financial statement fraud were high levels of accruals, profitability inconsistencies, and bankruptcy risks.

The Piotroski F-score is a 9 point composite index. It measures the combined effect of 9 binary signals, across 3 different aspects of company fundamentals (profitability, operating efficiency & liquidity). A higher score indicates better fundamentals and lower scores may suggest poor quality fundamentals, financial distress or possible manipulated reporting. As such, the F-score provides additional information to earnings manipulation models, as it evaluates if reported performance has been achieved via positive underlying operating cash flow(s), which are difficult to manipulate simultaneously across all 9 signals.

In Australia, Hyde (2018) evaluated the application of the F-score methodology in equity markets and demonstrated statistically significant return premiums in a market neutral, long/short portfolio format. Additionally, Hyde (2018) showed that this was most prevalent in small-cap stocks; this suggests the F-score can effectively identify companies with strong fundamentals vs. those with misleading accounting representations.

Adámiková and Corejová (2021) used both the Piotroski F-score and the Beneish M-score in an expert valuation context using Slovak listed companies. They found that the degree of creative accounting has a significant impact on the estimated value of the companies. As such, they proposed a "creative accounting coefficient" to be used to adjust forensic valuations.

Liodorova et al. (2021) developed a taxonomy of forensic accounting tools based on practitioner input and validated their taxonomy through interviews with forensic accountants and prosecutors. The taxonomy included the Piotroski F-score in addition to other forensic accounting models including the Beneish model and the Altman model. The inclusion of the Piotroski F-score confirmed that it is a useful tool in practice along with the other two models.

Sasikala (2020) used all three models to evaluate Samsung Electronics, as well as to illustrate the benefits of using all three models together. She demonstrated that when multiple models are used in conjunction, it results in a more comprehensive evaluation compared to using any one model alone.

7. Research Methodology

The JMCS is a Forensic Accounting Model that determines the Probability that Earnings have been Manipulated using Six Financial Ratio Signals. Each Ratio Signal is Designed to Target a Specific Manipulation Tactic and Aggregated into a Single Composite Risk Score. The Forensic Accounting JMCS Reverses the Logic of Investment Quality C-Scores, Where a Higher Score Indicates Greater Statistical Alignment with Patterns Historically Observed in Companies Found to Have Manipulated Their Financial Statements. The JMCS Model Is Expressed as a Linear Composite, C-Score $= \alpha + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6$, Where α Represents the Baseline Manipulation Risk Captured in the Intercept and Each β_i Represents an Empirically Derived Coefficient Reflecting the Predictive Weight of the Corresponding Financial Ratio X_i. The β_i Coefficients Were Calibrated Through Regression Analysis Using Historical Fraud and Earnings Restatement Data. The Six Constituent Ratios Test Whether Receivables Are Increasing Relative to Sales (DSRI), Whether Gross Margins Are

Deteriorating (GMI), Whether Asset Quality is Worsening Through Non-Current Asset Accumulation (AQI), Whether Accelerating Sales Growth Creates Incentives to Manipulate Earnings (SGI), Whether Depreciation is Being Slowed to Defer Expenses (DEPI), and Whether Reported Profits Are Drifting Away From Actual Cash Generation (TATA). In Practice, Forensic Auditors Use the JMCS to Escalate Companies Scoring Above the High-Risk Threshold for More In-Depth Procedures Such As Transaction Testing, Journal Entry Analysis, and Ratio Trend Investigation.

This study applies the JMCS to Dr. Reddy's Laboratories Limited (FY2015–FY2024), triangulated with the Beneish M-Score, Piotroski F-Score, Altman Z-Score, and Ohlson O-Score, to provide a multi-dimensional forensic assessment of earnings quality in an emerging-market pharmaceutical context.

2. The James Modified C-Score — Complete Formula Explained

C-Score = $\alpha + \beta_1(DSRI) + \beta_2(GMI) + \beta_3(AQI) + \beta_4(SGI) + \beta_5(DEPI) + \beta_6(TATA)$

Where each variable is scored 1 (threshold breached) or 0 (threshold not breached), then summed. Score range: 0 – 6. Benchmark: > 4 = High Risk, ≤ 4 = Low Risk.

Signal	Full Name	Formula	Threshold	What it detects
DSRI	Days Sales Receivables Index	(Rec.t / Sales t) ÷ (Rec.t-1 / Sales t-1)	> 1 → Flag	Receivables growing faster than sales — suggests premature revenue recognition or channel stuffing
GMI	Gross Margin Index	Gross Margin t-1 ÷ Gross Margin t	> 1 → Flag	Gross margin deteriorating YoY — signals cost concealment, pricing pressure, or revenue overstatement
AQI	Asset Quality Index	(1 − (CA+PPE)/TA)t ÷ (1 − (CA+PPE)/TA)t-1	> 1 → Flag	Rising share of non-current, intangible assets — indicates asset-quality inflation or expense capitalisation
SGI	Sales Growth Index	Sales t ÷ Sales t-1	> 1 → Flag	Sales growing YoY — not manipulation itself, but growth pressure creates stronger incentive to inflate earnings
DEPI	Depreciation Index	(Dep.t-1 / (Dep.t-1+PPE t-1)) ÷ (Dep.t / (Dep.t+PPE t))	> 1 → Flag	Depreciation rate slowing — consistent with extending asset lives to defer expenses and inflate profits
TATA	Total Accruals to Total Assets	(Net Income − CFO) ÷ Total Assets	> 0 → Flag	Reported earnings exceed cash from operations — the primary signal of accrual-based earnings manipulation

Fig 1.1

Data Analysis

James Modified C-Score (JMCS) — Dr. Reddy's Laboratories Ltd FY2016 (March 2016):

1. **DSRI** (Days Sales Receivables Index) = (NR_t / Sales_t) / (NR_t-1 / Sales_t-1) = (4,125.0 / 15,568.3) / (4,101.2 / 15,023.3) = **0.9706** → 0.9706 < 1 → Score = **0**
2. **GMI** (Gross Margin Index) = Prior GM / Current GM = (11,236.9/15,023.3) / (11,809.8/15,568.3) = **0.9860** → 0.9860 < 1 → Score = **0**
3. **AQI** (Asset Quality Index) = Non-current assets / Total assets (current yr) ÷ (prior yr) = **1.4737** → 1.4737 > 1 → Score = **1**
4. **SGI** (Sales Growth Index) = Sales_t / Sales_t-1 = 15,568.3 / 15,023.3 = **1.0363** → 1.0363 > 1 → Score = **1**
5. **DEPI** (Depreciation Index) = Prior depreciation ratio / Current depreciation ratio = (759.9/6,136.9) / (938.9/7,501.9) = **0.1746** → 0.1746 < 1 → Score = **0**
6. **TATA** (Total Accruals to Total Assets) = (Net Income − CFO) / Total Assets = (2,107.7 − 3,262.6) / 20,330.4 = **−0.0199** → −0.0199 < 0 → Score = **0**

C-Score = 0 + 0 + 1 + 1 + 0 + 0 = **2** (AQI and SGI fired; DSRI, GMI, DEPI, TATA did not)
→ **LOW RISK** (Score < 4).

Similarly, the James Modified C-Score was calculated for the other years in the same way.

Mar-16	Mar-17	Mar-18	Mar-19	Mar-20	Mar-21	Mar-22	Mar-23	Mar-24
2	3	3	2	4	3	5	2	3

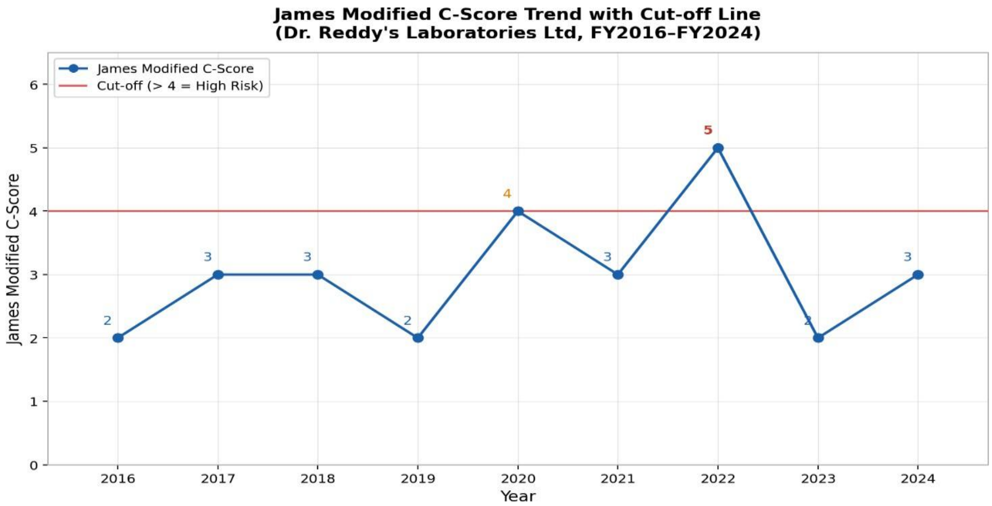

Fig 1.2

The Piotroski F-Score was introduced by Joseph D. Piotroski in his landmark 2000 paper published in the Journal of Accounting Research. Piotroski observed that while value stocks identified by high book-to-market ratios outperformed growth stocks on average, the distribution of returns within the value portfolio was highly skewed: a small number of strong performers masked a large proportion of poor-performing firms that continued to deteriorate. His research demonstrated that simple, publicly available accounting signals could be used to separate financial winners from losers within the value stock universe, generating abnormal returns of up to 23% annually when used to construct long-short portfolios. The Piotroski F-Score is a financial strength assessment tool that aggregates nine binary signals drawn from a company's financial statements into a single composite score ranging from 0 to 9. Each of the 9 indicators will be assigned a "1" for each indicator that represents an improved or strong financial position, and a "0" for all others. Of the 9 indicators, 4 reflect profitability (earnings and cash flow) , 3 represent the firm's use of leverage and its liquidity to assess the potential risk from a capital structure standpoint, and the last two relate to operational efficiency (asset usage and margin levels). Companies with a higher score (7-9) have strong financial positions, while those with a lower score (0-2) may be considered as being in a poor financial situation, and thus at increased risk of continuing their poor performance and/or experience some type of financial distress.

Formula and Signal Definitions
F-Score = F1 + F2 + F3 + F4 + F5 + F6 + F7 + F8 + F9

Pillar	#	Signal	Score = 1 if …	Data source
Profitability	**F1**	ROA > 0	Net income / total assets positive	Income statement / Balance sheet
	F2	ΔROA > 0	ROA improved year-on-year	Income statement / Balance sheet
	F3	CFO > 0	Operating cash flow is positive	Cash flow statement
	F4	CFO > ROA	Cash flow exceeds accrual earnings (Accruals)	CFS / Balance sheet
Leverage &	**F5**	ΔLeverage < 0	Long-term debt ratio decreased YoY	Balance sheet
Liquidity	**F6**	ΔLiquidity > 0	Current ratio improved YoY	Balance sheet
	F7	No dilution	No new shares issued during the year	Equity statement
Operating	**F8**	ΔGross Margin > 0	Gross margin improved YoY	Income statement
Efficiency	**F9**	ΔAsset Turnover > 0	Asset turnover ratio improved YoY	Income statement / Balance sheet

Fig 1.3

Piotroski F-Score — FY2024 Step-by-Step Calculation (Dr. Reddy's Laboratories Ltd, ₹ Crores)
FY2024 (March 2024):

1. F1 — ROA > 0 ROA = NP/TA = 5,563.2/38,863.8 = 0.1431 → 0.1431 > 0 → Score = 1
2. F2 — CFO > 0 Operating Cash Flow = ₹4,543.3 Cr → 4,543.3 > 0 → Score = 1
3. F3 — ΔROA > 0 ROA FY24=0.1431, FY23=0.1385 → ΔROA = +0.0047 → 0.0047 > 0 → Score = 1
4. F4 — CFO > Net Profit CFO=4,543.3 vs NP=5,563.2 → CFO < NP → earnings exceed cash (accruals) → Score = 0
5. F5 — ΔD/E < 0 D/E FY24=0.0585, FY23=0.0481 → ΔD/E = +0.0104 → Leverage increased → Score = 0
6. F6 — ΔCurrent Ratio > 0 CR FY24=2.5871, FY23=2.3828 → ΔCR = +0.2043 → 0.2043 > 0 → Score = 1
7. F7 — No Share Dilution Shares: 83.26→83.41 Cr → Δ = +0.15 Cr → New shares issued → Score = 0
8. F8 — ΔGross Margin > 0 GPM FY24=70.69%, FY23=68.96% → ΔGPM = +1.73% → 0.0174 > 0 → Score = 1
9. F9 — ΔAsset Turnover > 0 AT FY24=0.7208, FY23=0.7641 → ΔAT = −0.0433 → −0.0433 < 0 → Score = 0

Similarly, the Piotroski F-Score was calculated for the other years in the same way.

Mar-16	Mar-17	Mar-18	Mar-19	Mar-20	Mar-21	Mar-22	Mar-23	Mar-24
7	3	4	7	5	4	5	8	5

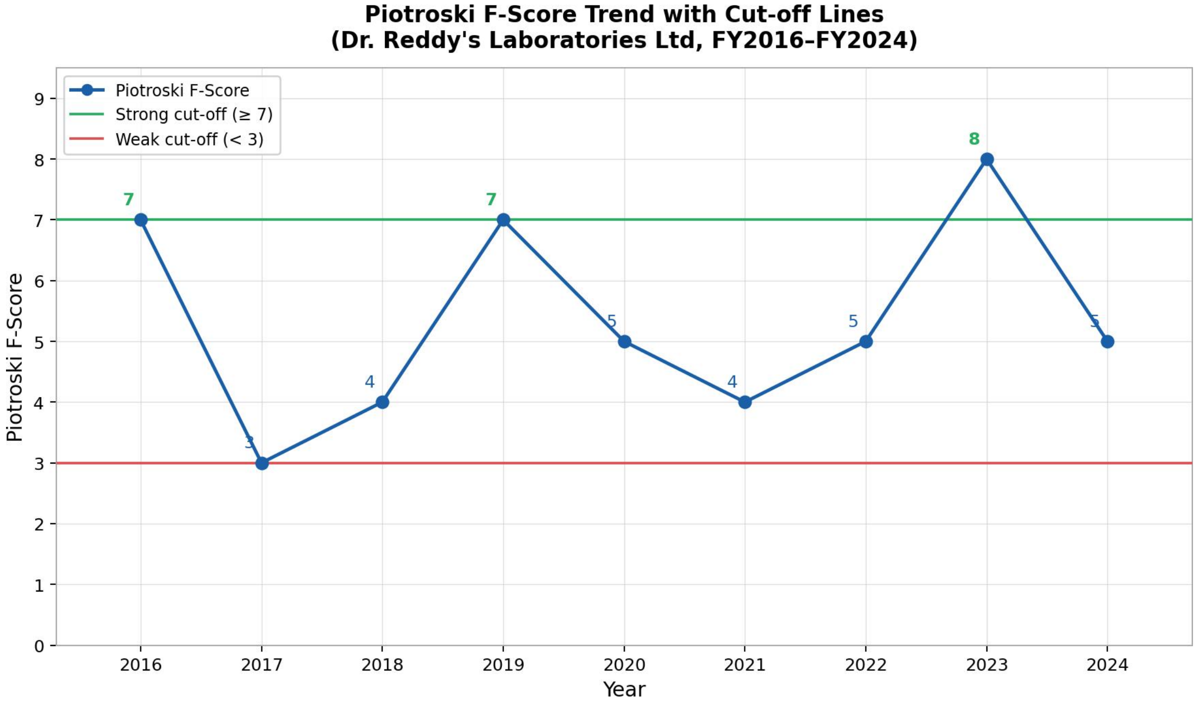

Fig 1.4

8. Data Interpretation

As show in the Fig 12 and Fig 14, the JMCS stayed in the low-risk category (2-4) for 8 out of 9 years, confirming there were no long-term manipulations. The most often triggered signals - AQI & SGI - have been based on true business factors; namely pipeline investments & real revenue growth. FY 2022 was the only time a risk level of 5 was reached - this was because of 5 signals being triggered at the same time during one year. This can be attributed to post pandemic expansion of working capital and complexity related to revenue recognition rather than a willful attempt to misrepresent income - indicated by both lack of restatement and rapid return to historical levels in subsequent years. The TATA signal was negative for 6 years consecutively (FY 2016-FY 2021) and indicated that net cash flow consistently exceed net income - the best indication of an earnings quality, while F-Score ranged from 3-8 over the course of the study and indicated a generally stable but unpredictable financial condition. FY 2023 had the highest F-Score of 8 - this was due to increased profitability, liquidity and margins concurrently - this has occurred as a result of ongoing debt reduction and revenue diversification. FY 2017 had the lowest F-Score of 3 - this was concurrent with regulatory hurdles in international export markets and lower margins. F-Scores of 5 in FY 2024 represent stability and not decline - this aligns with a period of reinvesting. F7 (share dilution) failed each year of the study period due to annual incremental issuances associated with employee stock ownership plans (ESOP) - these issuances are not representative of poor financial condition.

9. Conclusion

There is a very positive overall view of financial integrity and increasing financial strength of Dr. Reddy's Laboratories Limited through its financial statements for FY 2016 – FY 2024. Both scoring methods used here indicate that Dr. Reddy's did not demonstrate any evidence of earnings manipulation for extended periods, and that there has been an improvement in the financial health of the firm; even though the firm experienced many major challenges due to changing regulations, changes in operations, and other external factors that were present throughout the time frame studied.

Both scoring methods show that Dr. Reddy's was able to improve its financial reporting performance beginning at least in FY 2021. According to both scoring methods, the most recent year examined, FY 2023, shows a peak in the financial performance of the firm. The Piotroski F-Score indicates that the improvements seen in the profitability, liquidity, and operating efficiency of Dr. Reddy's were a result of a long-term strategic plan that included restructuring, reducing debt, and rationalizing the firm's product offerings. The decrease in the Piotroski F-score from 8 in FY 2023 to 5 in FY 2024 represents a transition into a new phase of the firm where the firm is again investing capital visible in fig 1.2.

This decline in the Piotroski F-Score does not represent a decline in the firm's fundamental financial condition. The James Modified C-Score supports the above findings. For the first eight years of the nine-year period studied, the scores remained in the low-risk area. The sole exception occurred in FY 2022 when the score was 5. The reasons cited by the authors for the high James Modified C-Score in FY 2022 include the combination of a number of large investments in pipelines, an increase in working capital and the complexity of the reported licensing revenues, not as a result of any accounting manipulations. Additionally, the consistent negative TATA signal across FY 2016 – FY 2021 further support the reliability of the reported earnings during those years as shown in fig 1.4.

In total, the findings indicate that Dr. Reddy's financial statements have provided reliable information on cash flows and do not contain the structural anomalies typically related to accounting distortions. Therefore, Dr. Reddy's appears to be a financially solid entity with strong earnings quality; thus,
representing a good candidate for further investment or credit analysis without any significant concerns regarding the potential for accounting manipulation.

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