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# Evaluating Financial Stability and Fraud Detection in Selected Indian Pharmaceutical Companies Using Altman Z Score and Beneish M Score Models

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**ABSTRACT:** This study examines the financial health and the risk of financial statement fraud among five major pharmaceutical companies—Sun Pharmaceutical Industries Ltd., Lupin Limited, Aurobindo Pharma Limited, Dr. Reddy's Laboratories, and Cipla Limited—over the period from 2019 to 2023. Financial statements are crucial documents that provide insights into a company's financial performance and position. However, they can be susceptible to manipulation, leading to financial fraud. The research utilizes the Altman Z-score to assess financial stability and the Beneish M-score to detect the likelihood of financial manipulation. Findings indicate that these companies generally exhibit strong financial health, with Altman Z-scores consistently categorizing them in the "Safe" zone, suggesting a low risk of bankruptcy. Sun Pharmaceutical Industries Ltd. showed significant financial improvement throughout the period, while Lupin Limited experienced a brief dip into the "Gray" zone in 2022 before recovering. Aurobindo Pharma Limited, Dr. Reddy's Laboratories, and Cipla Limited demonstrated remarkable stability, with Cipla Limited maintaining consistently high Z-scores. The Beneish M-score analysis indicated a low risk of earnings manipulation for most companies, though Lupin Limited showed occasional high-risk years. Overall, these results suggest that these pharmaceutical companies maintain strong financial practices and transparency, promoting investor confidence and reflecting positively on the industry's financial integrity and sustainability.

**KEYWORDS**: Financial statements, Fraud detection, Financial Stability, Beneish M Score, Altman Z Score

## INTRODUCTION

Financial reports are key documents for any company. They provide a record of financial information such as performance, position, and cash flow for a specific time period. This information is important for stakeholders like investors, creditors, and managers to make informed decisions. The main goal of financial reports is to offer clarity about a company's financial status, enabling users to make good decisions. Ideally, management should be completely honest in these reports. However, there can be a temptation for management to alter the data to show a more positive financial picture. To reduce this risk and ensure accuracy, regulations and audits are in place (Syafitri, Putra, & Ermaya, 2021). Financial statement irregularities can result in the omission or distortion of information, potentially causing users to make poor decisions. When a company provides inaccurate information, the financial data cannot serve as a reliable basis for economic decision-making, rendering the analysis's conclusions invalid. (Ijudien, 2018)

Financial statement fraud (FSF) is a major issue in today's business climate. The Association of Certified Fraud Examiners (ACFE) defines ((ACFE), 2016) FSF as "a deliberate misrepresentation of a company's financial condition through intentional misstatement or the elimination of the number of disclosures in the financial statements in order to deceive users of financial statements." According to the "Occupational Fraud 2024: A Report to the Nations," a review of 1,921 incidents of occupational fraud examined between January 2022 and September 2023 yields significant lessons for improving fraud prevention, detection, and response activities. According to the research, 84% of fraudsters demonstrated at least one behavioural red flag, with the typical loss per fraud case being $1,662,000. The article emphasizes the need of comparing anti-fraud systems to peers and using heat maps for risk assessment. It emphasizes the significance of proving ROI to stakeholders and educating them using visual tools such as charts and graphs. Furthermore, it analyses important asset theft risks and typical fraud techniques across industries, highlighting the link between anti-fraud measures and lower losses. Effective occupational fraud risk mitigation requires strong anti-fraud procedures (Exminers, 2024).

In this context, the M-score and Altman Z-score are valuable tools for detecting financial statement fraud. The M-score, developed by Professor Messod Beneish, helps identify companies that are likely manipulating earnings. The Altman Z-score, created by

Edward Altman, predicts the likelihood of a company going bankrupt. Both metrics provide quantitative methods for assessing financial health and identifying potential red flags in financial statements, thereby enhancing the effectiveness of fraud detection.

## REVIEW OF LITERATURE

(Ratmono, Darsono, & Cahyonowati, 2020) investigated the effectiveness of the Beneish M-Score and F-Score models in detecting financial statement fraud within the Indonesian context. The study aimed to provide empirical evidence on additional factors that may contribute to fraud. The findings indicated that financial target variables and CEO narcissism significantly influence financial statement fraud. In contrast, factors such as financial stability, external pressure, ineffective supervision, related party transactions, auditor turnover, and CEO dominance were found to have no significant impact on financial statement fraud. Additionally, the study identified that, according to the F-Score and M-Score models, several companies were suspected or indicated to have engaged in fraudulent financial reporting, with 284 companies out of 385 observed samples showing signs of potential fraud.

( Djatnicka, Purba, & Wulandari, 2023) examined the impact of financial stability, financial targets, and external pressure on financial statement fraud among property and real estate companies listed on the Indonesia Stock Exchange from 2015 to 2017. Utilizing secondary data and a purposive sampling technique, their study found that financial stability and financial targets positively influence fraudulent financial statements, whereas external pressure does not have a positive effect on fraudulent financial statements.

(Lumadi & Rusgowanto, 2023) aimed to investigate the impact of Beneish M-Score Model, along with financial ratio analysis, on identifying indications of fraudulent financial statements within the consumer goods manufacturing sector listed on the Indonesia Stock Exchange from 2017 to 2020. Using a dummy variable, companies were categorized based on whether they restated their financial statements (scored as 1) or not (scored as 0). The study found that only financial leverage significantly influenced indications of fraudulent financial statements, while Beneish M-Score Model did not demonstrate significant effects.

(Septiani, Musyarofah, & Yuliana, 2020) evaluated the effectiveness of the Beneish M-Score in detecting fraud in financial statement presentations, using a sample of 114 financial statements from banking companies between 2016 and 2018. The findings revealed that the Beneish M-Score could detect fraud with an accuracy of 89.5%. Specifically, the DSRI, GMI, AQI, DPI, and TATA ratios within the Beneish M-Score model were significant in distinguishing between fraudulent (manipulative) and non-fraudulent (non-manipulative) companies. Among these, the DSRI ratio was the most influential. The study concluded that the Beneish M-Score model is effective in detecting financial statement fraud, with DSRI being the most dominant factor in categorizing companies based on their manipulation.

(Bhavani & Amponsah , 2017) aimed to compare the effectiveness of two information-based accounting tools, the Beneish M-Score and the Altman Z-Score, in detecting financial statement fraud in corporate entities. The study utilized data from Toshiba's corporate financial statements spanning from 2008 to 2014, with the primary objective of detecting malfeasance using these two models. The study found that the Beneish M-Score was unable to detect any fraud, whereas the Altman Z-Score provided indications that the company's financial statements were flawed. Despite the Beneish model being renowned for predicting fraudulent financial activity, it did not perform effectively in this case.

## RESEARCH METHODOLOGY:

### Objective of the Study:

The main aim of the study is to predict the financial statements fraud and performance by using Beneish M-Score Model and Altman Z-Score Model.

### Research Design:

The present study is based on ***Descriptive Research Design.***

### Sources of Data:

The study is based on the Secondary Data. Data have been collected from the various journals, articles, websites and annual reports of the selected companies.

### Sampling Method and Sample Size:

***Purposive Sampling Method*** is used in the study. Top five listed pharmaceutical companies on BSE have been selected based on market share namely Sun Pharmaceutical Industries Ltd., Cipla Ltd., Dr. Reddy's Laboratories Ltd., Lupin Ltd. and Aurobindo Pharma Ltd.

### Time Period of the Study:

The study covers the time period of five years i.e. from the year 2019 to the year 2023.

### Tools & Techniques:

Data of five years have been analysed through Beneish M-Score Model and Altman Z-Score Model.

### THERORITICAL FRAMEWORK OF BENEISH M-SCORE MODEL

The Beneish M-Score is a quantitative model that utilizes eight specific financial ratios, each with assigned weights, to determine if a company has manipulated its earnings. This model was created by Professor Messod Beneish and presented in his June 1999 paper, "The Detection of Earnings Manipulation." According to Beneish, companies may be tempted to manipulate profits when they experience rapid sales growth, declining gross margins, rising operating expenses, and increasing leverage. Companies may manipulate earnings by recognizing sales prematurely, deferring costs, increasing accruals, and reducing depreciation (Beneish, 1999). The formula of the Beneish M-Score is as under:

**Beneish 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**

The eight variables of the Beneish M-Score Model are described in the following table:

| Ratios | Formula |
|---|---|
| Days' sales in receivable index (DSRI) | (Receivables t / Sales current year t ) / (Receivables t-1 / Sales prior t-1) |
| Gross margin index (GMI) | [(Sales t-1 / Cost of goods sold t-1) / Sales t-1] / [(Sales t / Cost of goods sold t) / Sales t] |
| Asset quality index (AQI) | [1-(Current assets t + PPE t / Total assets t)] / [1-(Current assets t-1 + PPE t-1 / Total assets t-1)] |
| Sales growth index (SGI) | Sales t / sales t-1 |
| Depreciation index (DEPI) | [Depreciation t / (Depreciation t + PPE t)] / [Depreciation t-1 / (Depreciation t-1 + PPE t-1)] |
| Sales, general, and administrative expenses index (SGAI) | (Sales, general and administrative expenses t / Sales t) / (Sales, general and administrative expenses t-1 / Sales t-1) |
| Total accruals to total assets (TATA) | (Total current assets t - Total cash - Total current liabilities t - Total long term debts t - Income Tax payable t - Depreciation and amortization t ) / Total assets t |
| LVGI (Leverage Index) | [(Total long term debt t + current liabilities t) / Total assets t] / [( Total long term debt t-1 + current liabilities t-1) / Total assets t-1] |

Notes: t = Current year; t-1 = Prior year; PPE = Property, plant and equipment.

(Source: https://www.semanticscholar.org/paper/Application-Of-Beneish-M-Score-Model-In-Detecting-Aqilah-Mohammed/8ac8deb906947bf7445c5c59db7d99a59d7b5622/figure/0)

**Table 1. Beneish M Score Index Parameter**

| Variables | Index | | |
|---|---|---|---|
| | Non-Manipulator | Grey | Manipulator |
| DSRI | ≤ 1.031 | 1.031 < Index <1.465 | ≥ 1.465 |
| GMI | ≤ 1.014 | 1.014 < Index <1.193 | ≥ 1.193 |
| AQI | ≤ 1.039 | 1.039 < Index <1.254 | ≥1.254 |
| SGI | ≤ 1.134 | 1.134 < Index <1.607 | ≥1.607 |
| DEPI | ≤ 1.001 | 1.001 < Index <1.077 | ≥1.077 |
| SGAI | ≤ 1.054 | 1.054 < Index <1.041 | ≥1.041 |
| LVGI | ≤ 1.037 | 1.037 < Index <1.111 | ≥1.111 |
| TATA | ≤ 0.018 | 0.018 < Index <0.031 | ≥0.031 |

(Source: https://www.researchgate.net/figure/Beneish-M-scoreModel_tbl2_321143663)

If the calculated M-Score value exceeds -2.22, it suggests that the company is likely manipulating its financial statements. Conversely, an M-Score value below -2.22 indicates that the company is not manipulating its financial statements (Beneish, 1999).

**Altman Z-Score Model:z**

The Altman Z-score is a quantitative model known as Multiple Discriminant Analysis (MDA) that helps distinguish between companies that will survive and those that will fail, using data from published financial statements. This model is used to predict financial corporate distress (Altman, 1968).

The Altman Z-score can differentiate between companies that are financially distressed and those that are not. It analyses financial figures from financial statements, grouping them into five different variables. These ratios, or independent variables, help predict the likelihood of a firm going bankrupt within two years (Maccarthy, 2017). The model uses a following formula that assigns specific weights to these variables (X1, X2, X3, X4, and X5) to detect potential bankruptcy:

$$Z - Score = 1.2x1 + 1.4x2 + 3.3x3 + 0.4x4 + 1.0x5$$

Where,

$$x1 = \frac{Net\ Working\ Capital}{Total\ Assets}$$

$$x2 = \frac{Retained\ Earnings}{Total\ Assets}$$

$$x3 = \frac{EBIT}{Total\ Assets}$$

$$x4 = \frac{Market\ Value\ of\ Equity}{Total\ Liabilities}$$

$$x5 = \frac{Sales}{Total\ Assets}$$

The resulting Z-score is compared with the cut-off values shown in Table 1, which categorize the company into non-distress, grey, or distress zones based on the score obtained. The Altman Z-score is highly accurate in predicting corporate financial distress both in the USA and in emerging markets (Hartzell, Altman, & Peck , 1998).

**Table 2. Altman Z Score Model**

| Altman Z Score | Meaning of cut-off points |
|---|---|
| Z > 2.67 | Safe Zone |
| 1.81 < Z Score < 2.67 | Grey Zone |
| Z < 1.81 | Distress Zone |

(Source: https://www.researchgate.net/figure/Altman-Z-score-Model_tbl1_321143663)

## DATA ANALYSIS & INTERPRETATION

**Table 3. Beneish M Score of Selected Companies**

| Company | Year | DSRI | GMI | AQI | SGI | DEPI | SGAI | TATA | LVGI | M Score | Manipulation Likely |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Sun Pharma | 2023 | 1.2771 | 0.0128 | 0.8893 | 1.3142 | 0.9498 | 0.9794 | 0.0055 | 1.1716 | -2.5947 | NO |
| | 2022 | 0.5398 | 0.0054 | 0.9202 | 1.2345 | 1.1014 | 0.9498 | 0.2261 | 1.1686 | -4.3446 | NO |
| | 2021 | 0.9783 | 0.0098 | 0.9684 | 1.0558 | 1.0005 | 0.8508 | 0.0822 | 1.2166 | -3.4156 | NO |
| | 2020 | 1.0073 | 0.0101 | 1.4808 | 1.2170 | 1.5438 | 1.0743 | 0.0742 | 0.8869 | -2.8688 | NO |
| | 2019 | 0.8560 | 0.0086 | 0.8521 | 1.1150 | 0.4200 | 0.6763 | 0.2942 | 0.9656 | -4.4694 | NO |
| Lupin | 2023 | 1.0831 | 0.5361 | 2.9392 | 1.0597 | 0.9526 | 1.0493 | 0.0464 | 1.4734 | -0.6348 | YES |
| | 2022 | 0.7080 | 0.5677 | 0.9217 | 0.9467 | 1.0465 | 0.9674 | 0.1649 | 0.6241 | -3.9710 | NO |
| | 2021 | 0.9546 | 0.5915 | -1.0911 | 1.0726 | 0.9224 | 1.0727 | 0.0093 | 0.8362 | 4.5105 | YES |
| | 2020 | 0.9372 | 0.5406 | 1.3875 | 1.1807 | 0.7830 | 1.1329 | 0.1284 | 0.8258 | 2.1273 | YES |
| | 2019 | 0.9853 | 0.5119 | -2.2169 | 1.1884 | 1.0789 | 0.3980 | 0.0067 | 1.1336 | 8.4006 | YES |
| Aurbindo | 2023 | 1.0831 | 0.5361 | 2.9392 | 1.0597 | 0.9526 | 1.0493 | 0.0464 | 1.4734 | -2.1976 | YES |
| | 2022 | 0.7080 | 0.5677 | 0.9217 | 0.9467 | 1.0465 | 0.9674 | 0.1649 | 0.6241 | -3.6936 | NO |
| | 2021 | 0.9546 | 0.5915 | -1.0911 | 1.0726 | 0.9224 | 1.0727 | 0.0093 | 0.8362 | -3.5289 | NO |
| | 2020 | 0.9372 | 0.5406 | 1.3875 | 1.1807 | 0.7830 | 1.1329 | 0.1284 | 0.8258 | -3.0543 | NO |
| | 2019 | 0.9853 | 0.5119 | -2.2169 | 1.1884 | 1.0789 | 0.3980 | 0.0067 | 1.1336 | -3.8452 | NO |
| Dr Reddy | 2023 | 0.7347 | 0.1940 | 0.9141 | 1.1805 | 1.0255 | 0.9282 | 0.1291 | 1.1716 | -3.6682 | NO |
| | 2022 | 1.1246 | 0.1235 | 0.8205 | 1.0778 | 1.1266 | 1.0539 | 0.0485 | 1.1686 | -3.1080 | NO |
| | 2021 | 0.7817 | 0.1724 | 0.7844 | 1.1253 | 1.2558 | 0.9688 | 0.0640 | 1.2166 | -3.4286 | NO |
| | 2020 | 1.1177 | 0.1755 | 1.6911 | 1.1163 | 0.9431 | 0.9185 | 0.0024 | 0.8869 | -2.3907 | NO |
| | 2019 | 0.7781 | 0.1429 | 0.8798 | 1.1366 | 0.9120 | 0.9170 | 0.0980 | 0.9656 | -3.5067 | NO |
| Cipla | 2023 | 1.4244 | 0.6250 | 1.2485 | 1.0455 | 0.8639 | 1.0378 | 0.0189 | 0.7917 | -2.1891 | YES |
| | 2022 | 0.5626 | 0.6032 | 1.0370 | 1.1359 | 1.0297 | 4.6007 | 0.0072 | 0.7285 | -3.4490 | NO |
| | 2021 | 0.7623 | 0.5743 | 1.7061 | 1.1184 | 1.0724 | 0.0974 | 0.0432 | 0.6938 | -2.4710 | NO |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2020 | 1.0731 | 0.5951 | -2.2917 | 1.0471 | 1.1207 | 1.0376 | 0.0147 | 0.7264 | -3.7488 | NO |
| | 2019 | 1.2563 | 0.5908 | 0.7814 | 1.0796 | 0.9677 | 1.0191 | 0.1775 | 0.8997 | -1.6212 | **YES** |

(Source: Computed by the Researcher)

**Interpretation:**

**Sun Pharma Ltd.:**

From 2019 to 2023, Sun Pharma consistently shows no likelihood of financial manipulation based on the M-score. In 2019, Sun Pharma achieves its lowest M-score of -4.4694, denoting very low manipulation risk. The ratios show consistent performance, with the lowest DEPI and SGAI among the years, suggesting steady depreciation and sales general expenses. The DSRI of 0.8560 and AQI of 0.8521 indicate stable receivables and asset quality. In 2020, the M-score is -2.8688, suggesting no manipulation. There is a noticeable increase in AQI to 1.4808, indicating higher asset inflation, while other ratios remain stable. Throughout 2021, the M-score of -3.4156 further affirms the absence of manipulation risk. DSRI and AQI are 0.9783 and 0.9684, respectively, indicating stable receivables and slight asset quality concerns. In 2022, the M-score of -4.3446 reflects stronger stability, with particularly low GMI and TATA ratios, suggesting robust gross margins and minimal reliance on accruals. All ratios are stable, with notably low GMI and TATA, indicating consistent gross margins and non-dependence on total accruals. In 2023, with an M-score of -2.5947, the company maintains stable financial health. The DSRI of 1.2771 and AQI of 0.8893 indicate steady receivables and asset quality. GMI is low at 0.0128, suggesting stable gross margins, while SGI at 1.3142 shows moderate sales growth. DEPI and SGAI are also stable at 0.9498 and 0.9794, respectively, indicating consistent depreciation and sales general expenses. TATA is nearly neutral at -0.0055, and LVGI at 1.1716 shows slight leverage growth.

**Lupin Ltd.:**

Lupin's financial data from 2019 to 2023 reveals fluctuating risk levels for financial manipulation. The highest risk appears in 2019, with an M-score of 8.4006, largely due to extremely negative AQI of -2.2169, suggesting severe asset inflation issues, coupled with a high SGI of 1.1884. In 2020, the M-score of 2.1273 also indicates manipulation potential, with similar issues in asset quality and sales growth, as shown by an AQI of 1.3875 and SGI of 1.1807. In 2021, Lupin again shows manipulation likelihood with a high M-score of 4.5105, reflecting problematic asset quality and rapid growth concerns, as indicated by an AQI of -1.0911 and SGI of 1.0726. However, in 2022, the M-score improves significantly to -3.9710, showing no manipulation risk with more stable ratios, including a DSRI of 0.7080 and AQI of 0.9217, indicating stable receivables and asset quality. In 2023, an M-score of -0.6348 suggests a likelihood of manipulation, driven by high AQI of 2.9392 and SGAI of 1.0493, indicating potential asset quality issues and aggressive sales strategies. DSRI at 1.0831 and GMI at 0.5361 also suggest some financial anomalies.

**Aurobindo Ltd.:**

Aurobindo shows a mixed trend from 2019 to 2023 in terms of manipulation risk. In 2019, Aurobindo has a low M-score of -3.8452, showing strong financial stability and no manipulation risk, despite facing minor challenges in asset quality, as indicated by an AQI of -2.2169 and SGI of 1.1884. The 2020 M-score of -3.0543 indicates no likelihood of manipulation, supported by stable ratios. The AQI is 1.3875, and SGI is 1.1807, indicating better asset quality. In 2021, the M-score of -3.5289 also suggests no risk of manipulation, with a stable DSRI of 0.9546 and AQI of -1.0911. In 2022, the company's M-score of -3.6936 continues to show no manipulation risk, with more stable financial metrics, including a DSRI of 0.7080 and AQI of 0.9217. The 2023 M-score of -2.1976 indicates a potential for manipulation, with high AQI of 2.9392 and SGAI of 1.0493, suggesting asset quality issues and aggressive sales strategies. The DSRI of 1.0831 and GMI of 0.5361 also highlight some financial instability.

**Dr. Reddy**

Dr. Reddy demonstrates consistent financial stability from 2019 to 2023, with no significant likelihood of manipulation across these years. The 2019 M-score of -3.5067 reinforces Dr. Reddy's overall financial health, with consistently stable ratios, including DSRI of 0.7781 and AQI of 0.8798. In 2020, the M-score of -2.3907 continues to indicate no manipulation, despite slight increases in AQI reflecting minor asset quality concerns. DEPI and SGAI are stable, with a DEPI of 1.6911 and SGAI of 0.9185. In 2021, the M-score of -3.4286 also shows stability, with low GMI of 0.1724 and TATA of -0.0640, suggesting consistent gross margins and low accrual reliance. In 2022, the M-score of -3.1080 remains stable, with low GMI of 0.1235 and TATA of -0.0485, suggesting consistent gross margins and low accrual reliance. In 2023, the M-score of -3.6682 reflects no manipulation risk, supported by a DSRI of 0.7347 and AQI of 0.9141, indicating stable receivables and asset quality. The DEPI is 1.0255, and SGAI is 0.9282, showing steady depreciation and sales expenses.

**Cipla Ltd.:**

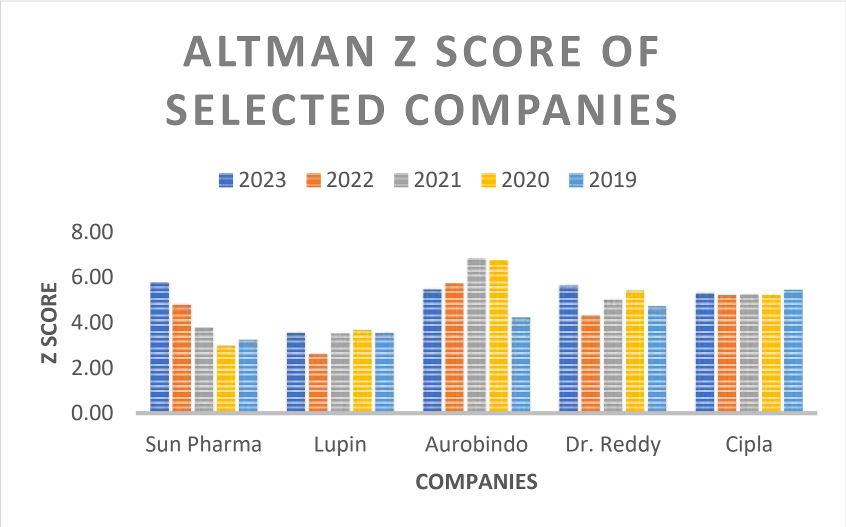
Cipla presents varied financial stability from 2019 to 2023, with occasional indications of manipulation risk. In 2019, the M-score of -1.6212 points to potential manipulation risks, driven by high DSRI of 1.2563 and SGAI of 1.0191, suggesting aggressive revenue recognition and sales strategies. The AQI of 0.7814 and SGI of 1.0796 indicate better asset quality and sales growth. In 2020, the M-score of -3.7488 reflects a solid financial position, with stable ratios indicating no manipulation, including a DSRI of 1.0731 and

AQI of -2.2917. In 2021, the M-score of -2.4710 indicates no manipulation risk, despite slightly elevated AQI of 1.7061 and DSRI of 0.7623. The DEPI and SGAI are stable, with a DEPI of 1.0724 and SGAI of 0.0974. In 2022, Cipla shows strong financial stability with an M-score of -3.4490, supported by stable ratios across the board, including DSRI of 0.5626 and AQI of 1.0370. In 2023, the M-score of -2.1891 suggests potential manipulation, driven by high DSRI of 1.4244 and AQI of 1.2485, indicating issues with receivables and asset quality. Other ratios, like DEPI of 0.8639 and SGAI of 1.0378, also hint at aggressive financial practices.

**Table 4. Altman Z-Score of Selected Companies**

| Year | Sun Pharma | Lupin | Aurobindo | Dr. Reddy | Cipla |
|---|---|---|---|---|---|
| 2023 | 5.76 | 3.54 | 5.46 | 5.63 | 5.28 |
| 2022 | 4.81 | 2.62 | 5.73 | 4.33 | 5.23 |
| 2021 | 3.78 | 3.52 | 6.83 | 5.02 | 5.24 |
| 2020 | 2.99 | 3.68 | 6.75 | 5.42 | 5.22 |
| 2019 | 3.24 | 3.56 | 4.23 | 4.72 | 5.45 |
| **AVERAGE** | **4.12a** | **3.39** | **5.80** | **5.02** | **5.28** |
| **ZONE** | **SAFE** | **SAFE** | **SAFE** | **SAFE** | **SAFE** |

(Source: Computed by the Researcher)




**Interpretation of Altman Z Score:**

The Altman Z-scores for the five pharmaceutical companies from 2019 to 2023 indicate varying degrees of financial health across different zones. Sun Pharma’s scores improved from 3.24 in 2019 to 5.76 in 2023, consistently remaining in the safe zone. This upward trend highlights Sun Pharma's significant enhancement in financial health and low risk of bankruptcy, with an average score of 4.12 reinforcing its stable financial condition.

Lupin’s Z-scores started at 3.56 in 2019, stayed strong in the safe zone with fluctuations, and experienced a dip to 2.62 in 2022, entering the Gray zone, but recovered to 3.54 in 2023, returning to the safe zone. This indicates a period of moderate risk followed by a return to stability, with an average score of 3.39 indicating overall financial stability despite temporary challenges.

Dr. Reddy’s scores fluctuated, with a peak of 5.42 in 2020 and a low of 4.33 in 2022, still within the safe zone, before recovering to 5.63 in 2023. Despite fluctuations, Dr. Reddy’s remained in the safe zone, indicating strong financial health, with an average score of 5.02 confirming its robust financial position.

Cipla consistently displayed exceptional financial stability, with scores varying slightly but consistently staying above 5.22 from 2019 to 2023, always within the safe zone, indicating a very low risk of bankruptcy. Cipla's steady performance, reflected in an average score of 5.28, underscores its financial robustness.

Aurobindo showed fluctuations from 4.23 in 2019 to a peak of 6.83 in 2021, maintaining its position in the safe zone, although it dipped slightly to 5.46 in 2023. Despite these changes, Aurobindo consistently remained within the safe zone, indicating financial stability, with an average score of 5.80 highlighting its strong financial health.

## FINDINGS & CONCLUSION

The comprehensive analysis of the financial health and integrity of five major pharmaceutical companies from 2019 to 2023, using the Altman Z-score and Beneish M-score models, provides substantial insights into their financial stability and potential for financial statement fraud.

Overall, the Altman Z-scores for all five companies consistently fell within the "Safe" zone, indicating strong financial health and a low risk of bankruptcy. Sun Pharma showed a significant improvement in its financial stability over the years, while Lupin, despite a brief dip into the "Gray" zone, managed to recover and maintain a stable financial position. Aurobindo, Dr. Reddy's, and Cipla exhibited exceptional financial stability, with Cipla particularly standing out due to its consistently high Z-scores.

The Beneish M-score analysis complemented the Z-score findings by assessing the likelihood of financial statement manipulation. The results indicated minimal risk of financial manipulation for most companies, with Lupin showing sporadic high-risk years, which raises some concerns but does not significantly undermine its overall financial stability.

In a nutshell, the pharmaceutical companies studied demonstrate robust financial health and transparency, with an overall low risk of bankruptcy and financial statement fraud. The consistent presence of these companies in the "Safe" zone of the Altman Z-score and the low likelihood of financial manipulation according to the Beneish M-score reinforce the financial robustness and credibility of this sector. These findings suggest that investors can have confidence in the financial practices and stability of these leading pharmaceutical firms, reflecting positively on the industry's overall financial integrity and sustainability.

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