Financial Statement Fraud Detection Using Altman Z-Score and Beneish M-Score: A Comparative Case Study of Dewan Housing Finance Corporation Limited (DHFL) And Lic Housing Finance Limited in the Indian Context

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ABSTRACT

Continued financial statement fraud (FSF) is adversely impacting investor confidence and capital market stability worldwide. This research analyzes the suitability of the two most recognized models for detecting financial frauds in the form of Altman's Z-score model and Beneish's M-score model through a selective comparative case analysis of two Indian housing finance companies: the case company of Dewan Housing Finance Corporation Limited (DHFL), which is an identified case of financial manipulation being investigated by the Indian regulators since 2019, and its industry matched company of LIC Housing Finance Limited (LIC HF) that has no record of being investigated or involved in any accounting restatement. Audited standalone financial statements of the two companies have been analyzed on the basis of the four consecutive financial years from FY2015 to FY2018, i.e., the four consecutive financial years preceding the revelation of financial manipulations by DHFL. The study has estimated both the models' ratios and calculated their composite scores year wise and compared the trend of two companies. Both models have been well tested in advanced economies and, to some extent, in developing nations, but no prior study exists where these two models have been used together on a verified Indian housing finance company fraud case with direct comparisons made to its competitor firm on a year-to-year basis. It is the purpose of this research paper to fill this void, in addition to pointing out certain data quality issues in DHFL's FY2017 financial statements.

Keywords: *Financial Statement Fraud, Altman Z-Score, Beneish M-Score, Earnings Manipulation, Forensic Accounting, Housing Finance, DHFL, LIC Housing Finance, India*

CHAPTER 1: INTRODUCTION

1.1 Background of the Study

Financial statements provide the foremost means by which investors, lenders, government authorities, and other interested parties analyse the financial standing and performance of a business enterprise. The integrity of such financial statements is thus crucial for the effective functioning of the capital markets. Unfortunately, the past history of corporations reveals that there have been many cases whereby enterprises have engaged in manipulating their financial statements to misrepresent their financial position; this kind of conduct is generally referred to as financial statement fraud (FSF).

The global instances of fraud like Enron, WorldCom, and Wirecard along with domestic instances like Satyam Computer Services, IL&FS, DHFL, and Yes Bank, help understand the grave implications of FSF on investors, loss

of confidence among markets and other broader economic impacts. Out of the mentioned domestic fraud instances, DHFL case provides a valuable illustration – an Indian listed and systemic company providing housing finance services whose financial irregularities of fund diversion and loan disbursal, discovered by investigative journalism in early 2019 and subsequently studied by regulatory authorities and creditors, resulted in the insolvency of the firm. Given that the audited accounts of DHFL for the previous years prior to this discovery were already out in the public domain, the case presents a valuable real-life illustration wherein one can verify the capability of traditional quantitative fraud-detection models to detect the financial statements of the firm in advance.

One of the most popular models is the Altman Z-Score model (Altman, 1968), which was initially developed to predict corporate bankruptcy. The other model is the Beneish M-Score (Beneish, 1999), which is specifically designed to detect earnings management. Both models utilize only information present in the published accounting statements. Though both the models have been tested extensively in developed economies like the United States, and lately in some developing countries like Turkey, Indonesia and Nigeria, their joint application to particular fraud cases that occurred in India, year-by-year matched with a control firm, is still uncommon.

1.2 Statement of the Problem

While the literature from around the world is full of evidences regarding the validity of the Altman Z-score and the Beneish M-score model as fraud and distress detection methods, almost all previous studies fail to overcome the two main weaknesses. The first weakness is that most of the studies use either of these two models in isolation instead of using both the models for the same firm to check which model works better. The second limitation is that there are very few studies which apply these models in an Indian context; and out of those few, most have been done using a sample that consists of the single case study of Satyam Computer Services or other broad sectorial data sets instead of a case by case analysis of a fraud case against its peer from the same sector.

1.3 Research Objectives

- To know the efficiency of the Altman Z-Score model in determining the occurrence of financial distress and potential manipulation of financial statements at Dewan Housing Finance Corporation Limited (DHFL) for FY2015-FY2018.
- To find out the efficiency of the Beneish M-Score model in determining the probability of earnings manipulation at DHFL during the above-mentioned period.
- To compare the yearly trends of Z-Score and M-Score of DHFL with that of a matched-sector firm LIC Housing Finance Limited which does not have any record of regulatory action or restatements over the period of four years.
- To find out whether any of the above-mentioned models or their individual components could have indicated high-risk level at DHFL prior to 2019 exposure of its financial misstatements.
- To offer practical insights for the auditor, regulator, and investor community on the application of above-mentioned models as early warning signals for the Indian housing finance companies.

1.4 Research Questions

- Did the Altman Z-Score detect the existence of financial distress in DHFL for the period FY2015-FY2018? How was this compared to the results from LIC Housing Finance?

- Was the Beneish M-Score able to indicate an increased probability of earnings manipulation in DHFL for the same period? How did that measure compare with that of LIC Housing Finance?

● Between the two models used, which one gave an early or stronger indication of the problem in DHFL? Were there any divergences between the two models?

1.5 Scope and Significance of the Study

The research is purposely limited to only one matched pair of companies — DHFL and LIC Housing Finance — since due to time limitations and limited availability of confirmed Indian fraud cases with reliable, verified financial data, a bigger sample cannot be collected and studied in this research. Thus, the research results can be considered illustrative of how the models work in one case of Indian housing-finance fraud, rather than representative statistical evidence of the behavior of the models in this field. In any case, the study is going to be helpful to auditors and forensic accountants who need an example of application of these models to a particular case of Indian fraud; to regulators such as SEBI, RBI, and National Housing Bank who will consider use of these models as part of the early warning system for housing-finance companies; and to investors and researchers who need some examples of the behavior of DHFL's data prior to fraud detection.

CHAPTER 2: LITERATURE REVIEW

In this chapter, the existing empirical literature on how Altman's Z-Score model and Beneish's M-Score model have been applied in the detection of financial statement fraud is discussed based on literature from developed and developing markets in order to identify the research gap in this study.

2.1 Güler, Emgin & Uçma (2013) — Turkey

The study by Güler, Emgin and Uçma (2013) tested the usefulness of the Beneish M-Score framework for financial manipulation detection in manufacturing firms listed in Istanbul Stock Exchange (ISE 100) during 2008 (the year of global financial crisis) and 2009 (year after the global financial crisis). Applying probit analysis to manipulating and non-manipulating firms in a sample, the study found that asset quality, leverage and sales growth are statistically significant factors affecting the manipulation in 2008 but only sales growth is statistically significant in 2009. Thus, the study found that the global financial crisis has an important impact on the signal of financial manipulation.

2.2 Nindito, Avianti, Koeswayo & Tanzil (2019) — Indonesia

In their study conducted in 2019, Nindito et al. used the Beneish M-Score model to evaluate the rate of financial statement fraud using 352 firms from five different industry segments listed in the Indonesia Stock Exchange. In their findings, it was discovered that 37.5 percent of those firms showed signs of fraud in 2016, which is significantly more than the companies that have been penalized for fraud by Indonesia's Financial Services Authority. Manufacturing and Property/Real Estate were the industry segments with the highest percentage of companies showing signs of fraud, DSRI, and TATA being the red flags most commonly raised.

2.3 Parikh (2024) — India

One such study that uses both Altman Z-Score and Beneish M-Score on Indian companies is Parikh (2024). Five leading Indian pharmaceutical firms, namely Sun Pharma, Lupin, Aurobindo Pharma, Dr. Reddy's Laboratories and Cipla, were selected to be studied during the year period of 2019-2023. It was found that all five companies continuously stayed in the safe zone of Z-Score and only one company, namely Lupin, entered into the Gray zone of Z-Score in the year 2022. In the case of Beneish M-Score, it was found that there was low risk of earnings management for most of the companies. This research study proves the applicability of the use of both models together in an Indian sectoral environment but no fraud case was included in order to validate predictive ability of the model.

2.4 Bhavani & Amponsah (2017) — Japan (Toshiba Case)

This research by Bhavani and Amponsah (2017) directly compared the two methods through financial reports of Toshiba Company from 2008 to 2014 after the exposure of its accounting scandal of overstatement of its financial figures by about ¥151.8 billion. It revealed that the Beneish M-score method did not identify any form of fraud during the period, while on the other hand, the Altman Z-Score method indicated that there was something amiss with the company's financial reports. The authors found that model selection plays a significant role in fraud identification, and that there is no model that can work under all circumstances — a finding that is also independent of this study's DHFL results (Chapter 3 & Data Workbook).

2.5 Haryadi, Nurmalasari & Yanti (2026) — Indonesia

Haryadi, Nurmalasari, and Yanti (2026) carried out a comparative analysis of three fraud detection approaches: Beneish M-Score, Dechow F-Score, and Altman Z-Score using a robust classification approach involving the use of confusion matrix, ROC curves and AUC tests. Using a data set comprising 50 firms from Indonesia Stock Exchange from the years 2022 to 2024 in infrastructure, construction, property and real estate industries, it was revealed that Altman Z-Score approach had better classification ability (accuracy = 68%, F1-Score = 62.5%, AUC = 0.742) than Dechow F-Score and Beneish M-Score approaches. This study indicates that financial distress, rather than earnings manipulation scores alone, could be a stronger indicator of fraud in financing stressed sectors of the economy – a point illustrated by the case pairing for this study: DHFL being a financing stressed NBFC.

2.6 Research Gap

The above literature review shows that both the Altman Z-Score and the Beneish M-Score have been thoroughly validated in several developed markets such as the USA, Japan, as well as in some emerging markets like Turkey, and Indonesia. However, there are two reasons why the present research project is being conducted. First, most of the studies validate only one of the two indicators but not both in relation to the same firm over time (Parikh, 2024; the latter study does not include a proven fraud). Second, no previous study validates both indicators simultaneously with respect to Dewan Housing Finance Corporation Limited for the years leading up to 2019 using DHFL's originally-reported financial figures. In the Toshiba case study (Bhavani & Amponsah, 2017), it was found that the two indicators disagreed strongly – the Beneish M-Score could not identify the fraud at all while the Altman Z-Score did. Therefore, it is unclear whether the two indicators agree or disagree in relation to DHFL's figures, as there is no previous research available for this purpose.

Formally put, there exists no research in print that has attempted to use Altman's Z-Score along with the Beneish M-Score in tandem for analyzing DHFL, on an annual basis, by benchmarking it against LIC Housing Finance, with both companies' financial figures, as per their original reports for each of those years, being used for comparative analysis. The present study seeks to fill this niche but specific void, and in the process uncovers an interesting and previously unknown case of data quality issue in DHFL's reports themselves.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Research Design

The research design for this paper will be empirical and quantitative, using an ex post facto or comparative design. This is because secondary data will be used from the audited financial statements of DHFL and LIC Housing Finance, as reported in their respective annual reports. This is due to the fact that the purpose of the study is to conduct a retrospective analysis of the effectiveness of two models.

Since the sample consists of only one matched company pair (eight firm-years total: four firm-years per company for both DHFL and LIC Housing Finance), the design becomes a structured comparative case study. Inferential statistics based on a larger sample that can be applied to the current situation (binary logistic regression for many predictors, significance testing for group averages) are statistically meaningless in this sample and will not be applied. On the contrary, the design emphasizes the comparison of both models' complete set of component ratios and composite scores per firm-year, along with a comparison of DHFL development against the development of LIC Housing Finance during those four years, plus an analysis of which exact component ratios change the most for each company and why. This is a deliberate and open decision – the design gives up statistical generalizability in order to gain a deeper level of case-specific information and credibility that would not be possible with a larger but less detailed sample.

3.2 Sample Design and Data Source

Sample population and sampling approach: The research employs purposive (judgmental) sampling based on a single identified Indian fraud case in the financial services sector with a matching firm that is also in the same industry sector.

Firm under investigation: Dewan Housing Finance Corporation Limited (DHFL), a publicly listed NBFC-HFC that had financial irregularities reported since early 2019 and which subsequently became the subject of investigation by the regulators and creditors, eventually leading to its insolvency resolution process.

Control firm: LIC Housing Finance Limited, a publicly listed HFC of comparable size and similar business operations with no previous regulatory issues, restatements or fraud allegations during the sample period.

Period of sampling: FY2015-FY2018 (fiscal year ending 31 March). These are four financial years prior to the reporting of the fraud by DHFL in 2019. Thus there are four firm years per firm and a total of eight firm year samples.

Data source: The data source is the line items from the financial statements (balance sheet, statement of profit and loss and cash flow statement) from each individual company's own annual reports for each fiscal year, where each year uses its own figures that were originally reported rather than re-stated figures at any subsequent point in time.

Reasoning for small sample size: This is an intentionally small sample size because of a decision to focus on verified data for one company over a multi-company sample, which has less verified data but more companies.

3.3 Variables of the Study

Fraud/Comparison Status (categorical): DHFL (case firm) vs. LIC Housing Finance (matched control firm), tracked separately across each of the four fiscal years.

Independent Variables — Altman Z-Score:

- X1 — Working Capital / Total Assets (Liquidity)
- X2 — Retained Earnings / Total Assets (Profitability)
- X3 — EBIT / Total Assets (Operating Efficiency)
- X4 — Book Value of Equity / Total Liabilities (Solvency)

Independent Variables — Beneish M-Score:

- DSRI — Days Sales in Receivables Index

- GMI — Gross Margin Index
- AQI — Asset Quality Index
- SGI — Sales Growth Index
- DEPI — Depreciation Index
- SGAI — SG&A Expense Index
- LVGI — Leverage Index
- TATA — Total Accruals to Total Assets

3.4 Hypotheses

H1: The Altman Z-Score shows a distinguishable difference in financial distress signal between DHFL and LIC Housing Finance over FY2015–FY2018.
H2: The Beneish M-Score shows a distinguishable difference in earnings-manipulation signal between DHFL and LIC Housing Finance over the same period. H3: The Altman Z-Score and Beneish M-Score do not agree in the direction or timing of the signal they give for DHFL over this period.

3.5 Tools and Techniques of Analysis

The Altman Z''-Score (1995 version specifically developed for emerging markets, suitable because the two companies in question are NBFC-HFCs and not manufacturers) and the Beneish M-Score will be calculated for each of the eight company-years using Microsoft Excel, all figures to be directly traceable to their source annual reports and pages. With the limited number of observations, the main method is that of comparing trends and patterns: graphing and tabulating both scores and ratios of both models for DHFL versus LIC Housing Finance for each year, and finding which specific ratios differ from one another and how. Where the difference between the pairs of figures provides useful information despite the small sample (e.g., the difference in composite scores between the two companies for four matching years), it is provided as descriptive data only and is not tested for statistical significance. The case study methodology of this paper follows the spirit of Bhavani and Amponsah (2017) who did the Toshiba case, but not that of Güler et al. (2013) or Haryadi et al. (2026) with their bigger samples.

3.6 Limitations of the Study

- The sample size includes only one matched pair of firms (eight firm-years observation), which does not allow the application of any inferential statistic such as logistic regression, t-test, or ROC/AUC analysis; the results found through this study are merely examples of this case rather than generalizable statistics applicable to the housing finance industry or NBFCs in India.
- The data sources used in this research are secondary financial data that can be prone to the same accounting manipulation as we are investigating; in case the financial indicators for DHFL have been re-stated after (such as trade receivables in fiscal year 2017), in this research we use the original data and consider re-statement of financial indicator a finding rather than an error in the data sources used.

- Both models are developed and calibrated based on the data of US manufacturing sector, so applying these models to Indian NBFCs requires changing some input parameters (such as replacing cost of goods sold with finance costs and sales, general and administrative expenses with employee and administrative expenses) because neither DHFL nor LIC Housing Finance report COGS/SG&A breakdown. This set of adjustments is fully documented in the companion data worksheet and should be kept in mind when assessing the composite scores.

- This analysis is essentially a backward looking study as it determines whether or not these models would have identified DHFL's figures as such based on hindsight rather than an actual test of forecasting.
- The M-Score threshold for the Beneish model (-2.22, based on the original Beneish threshold) is one of two commonly cited thresholds (-1.78) in

literature; the reason for this choice has been clearly indicated in this section since the classification of each firm-year can easily be reconsidered using the alternative threshold.

CHAPTER 4: DATA COLLECTION, ANALYSIS AND INTERPRETATION

The data collection methodology used in this study is outlined in this chapter. Altman Z''-Score and Beneish M-Score of Dewan Housing Finance Corporation Limited (DHFL) and LIC Housing Finance Limited (LIC HF) have been evaluated based on which an interpretation has been made according to the research hypotheses stated in Chapter 3. Since the sample consists of only one matched pair, all results are discussed in the form of observations only.

4.1 Data Collection

4.1.1 Sources and procedure

All figures were drawn from the audited stand-alone financial statements in the form of balance sheet, statement of profit and loss, and cash flow statement of each respective firm for fiscal years 2015 to 2018 ended on 31 March 2015 to 31 March 2018 respectively. For each fiscal year's figures, annual report of that particular year (or comparative column of FY2016 for the base year) was considered instead of subsequent reports where restatements might have been made for the same fiscal year. This makes sure that the models are being applied to those numbers which were available to the public back then. Figures in ₹ lakh were converted to ₹ crore to make all the figures in this chapter comparable. All the inputs with their sources are recorded in the accompanying data workbook.

Four annual reports were considered for DHFL (base year FY2015 to FY2018) and four annual reports for LIC HF in the same period. Since both models make a comparison between one year and the previous year, the Beneish M-Score model is calculated based on three years per firm (FY2016, FY2017 and FY2018), whereas the Altman Z''-Score model is calculated for all four years.

4.1.2 Adapting the variables to housing finance companies

Both companies have been modeled on the basis of manufacturers and distributors. DHFL and LIC HF are both lending companies; none of them have reported costs of goods sold or SG&A. Thus, the variables have been mapped accordingly as depicted in Table 4.1. These mappings are used consistently for both companies; hence, the comparison between them is consistent even though the scores cannot be directly interpreted.

Table 4.1: Mapping of model inputs to housing finance company statements

Model input	Item used
Sales	Revenue from operations (interest and fee income)
Cost of goods sold	Finance cost (the direct cost of funds behind lending revenue)

SG&A	Employee expense plus administrative and other expense
Working capital	Current assets less current liabilities, as classified in the balance sheet
Retained earnings	Reserves and surplus
EBIT	Profit before tax (before exceptional items) plus finance cost
Market value of equity	Book value of equity (share capital plus reserves and surplus)
Operating cash flow	Cash generated from operations less tax paid, before loan disbursements and repayments
Receivables / PP&E	Trade receivables / net fixed assets
Total accruals	Net profit for the year less operating cash flow above

4.1.3 Data quality observations

- Re-stated trade receivables. The trade receivables of DHFL as at 31 March 2017 in FY2016-17 annual report is reported to be ₹379.10 crore, while the comparative column in FY2017-18 annual report is ₹3.37 crore. There is no explanation for the difference. In this study, the original figure of ₹379.10 crore will be used. The re-statement is identified as one of the results in Section 4.4.3.
- Re-stated operating cash flow. Cash from operating activities of DHFL for FY2016 is ₹1,449.00 crore in FY2015-16 report but ₹1,343.06 crore in

comparative column of FY2016-17 report. As above, the original figure is used.

- Exceptional gain. DHFL's FY2017 net profit includes an exceptional gain of ₹1,969.43 crore. EBIT and ratios based on EBIT exclude this item, while net profit (for the TATA ratio) includes this item.
- Change in accounting framework. The report for FY2019 of LIC HF is prepared using the Ind AS framework and thus does not segregate current and non-current components in the statement of financial position, which makes it difficult to prepare the working capital, receivables and several other components of the M-Score. Consequently, FY2019 is not included in the analysis.

4.2 Overview of the Sample

Table 4.2 below highlights the size and profitability of both the companies. During the financial years 2015 to 2018, the total assets of DHFL increased by almost 97 percent (from ₹54,615 crore to ₹107,572 crore), whereas its total revenue increased by 75 percent, while the respective growth figures for LIC HF were 53 percent and 40 percent. The LIC HF is the bigger firm through and through, but DHFL was growing rapidly at the same time. Fast growth is a fraud risk factor in the academic literature, even on its own.

Table 4.2: Sample overview (₹ crore, standalone)

Company	Year	Total assets	Revenue from operations	Net profit	Net operating cash flow
DHFL	FY2015	54,614.81	5,978.96	621.29	722.61
DHFL	FY2016	67,853.13	7,311.83	729.20	1,097.03
DHFL	FY2017	92,297.98	8,851.76	2,896.45	162.38
DHFL	FY2018	107,572.47	10,450.16	1,172.13	2,228.28
LIC HF	FY2015	112,545.06	10,669.35	1,386.19	2,688.73
LIC HF	FY2016	130,497.77	12,396.15	1,660.79	3,805.88
LIC HF	FY2017	150,900.57	13,986.94	1,931.05	5,125.37
LIC HF	FY2018	171,852.01	14,959.66	1,989.59	2,301.04

DHFL's profits for FY2017, on the other hand, is definitely the outlier, with the net profit rising to ₹2,896 crore, which is four times the FY2016 value, but the net operating cash flow declining to ₹162 crore. This is definitely the difference that the ratio of accruals aims to capture, except that this is due largely to one-off items.

4.3 Altman Z''-Score Analysis

The Z''-Score is computed using the formula Z'' = 3.25 + 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4, where X1 is the ratio of working capital to total assets, X2 is the ratio of retained earnings to total assets, X3 is the ratio of EBIT to total assets, and X4 is the ratio of book equity to total liabilities. A Z'' value greater than
2.6 is the "safe" zone, 1.1-2.6 is the "grey" zone, and less than 1.1 is the "distress" zone.

Table 4.3: Altman Z''-Score components and classification

Company	Year	X1	X2	X3	X4	Z''	Zone
DHFL	FY2015	-0.1606	0.0822	0.0989	0.0928	3.227	Safe
DHFL	FY2016	-0.1414	0.0678	0.0972	0.0777	3.278	Safe

DHFL	FY2017	0.0559	0.0832	0.0873	0.0948	4.574	Safe
DHFL	FY2018	-0.0850	0.0788	0.0867	0.0890	3.626	Safe
LIC HF	FY2015	-0.1668	0.0686	0.0925	0.0747	3.080	Safe
LIC HF	FY2016	-0.1792	0.0693	0.0910	0.0754	2.991	Safe
LIC HF	FY2017	-0.1824	0.0727	0.0874	0.0792	2.961	Safe
LIC HF	FY2018	-0.2413	0.0733	0.0826	0.0797	2.545	Grey

Source: author's calculations from company annual reports.

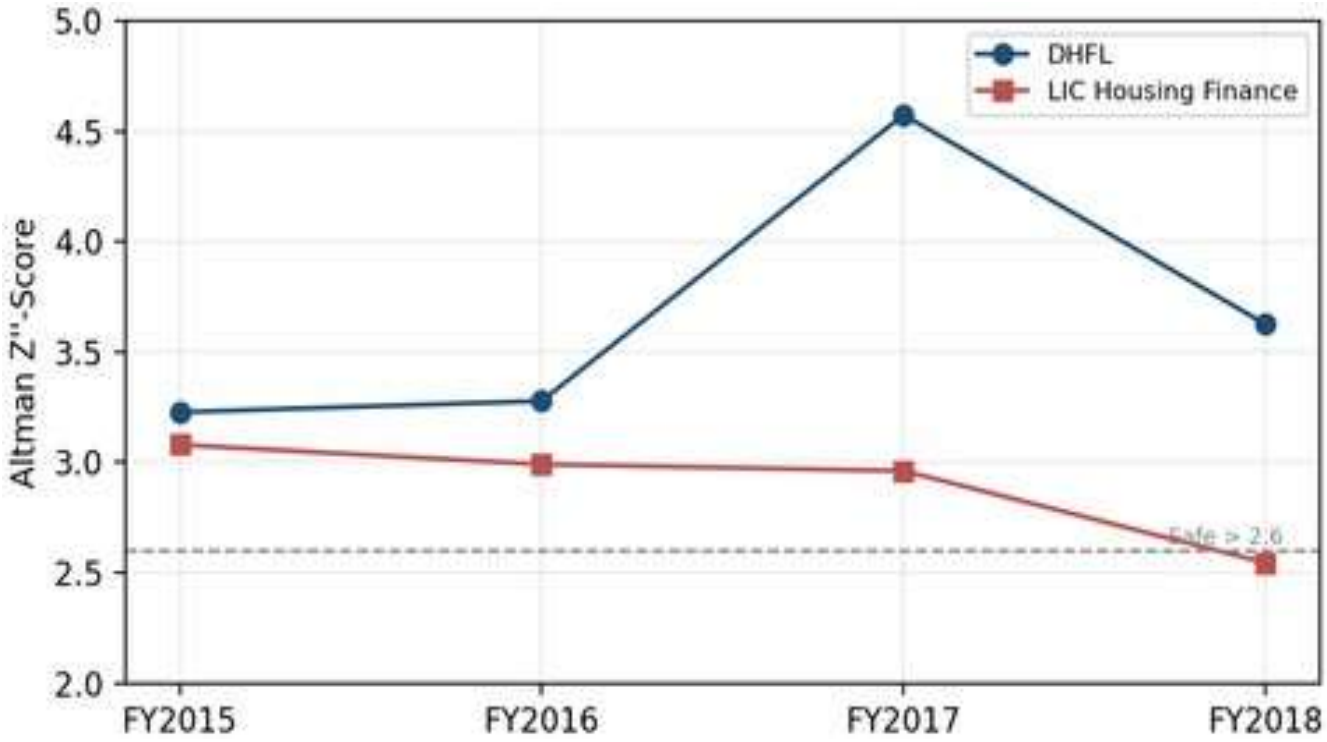


Figure 4.1: Altman Z''-Score, DHFL and LIC Housing Finance, FY2015–FY2018

Interpretation

In all the four years under study, DHFL operates within the safe zone, with the ratio scores ranging from 3.23 to 4.57. The non-fraudulent company, LIC HF, on the other hand, begins in the safe zone, with the ratio score of 3.08, but it gradually goes down every year and ends up in the grey zone with the ratio score of 2.54 in FY2018.

This is because of the component ratios. X2 (retained earnings) and X3 (EBIT) are nearly identical for both the companies, while X4 (book equity to liabilities) is slightly higher for DHFL in all years (0.078 to 0.095 versus 0.075 to 0.080). X1 is the distinguishing factor between the two firms. Both companies have negative working capital, since long-term loans are funded by short-term borrowing and current maturities. However, the value of X1 deteriorates for LIC HF consistently from -0.167 to -0.241 due to increase in current liabilities relative to current assets. X1 for DHFL is negative for three years, but is positive (0.056) in 2017, resulting in a Z''-Score of 4.57. This corresponds with the sharp rise in current investment for DHFL from around ₹173 crore in March 2016 to ₹12,587 crore in March 2017.

Two structural features of the model also matter for lenders. First, the constant of 3.25 places most financial institutions comfortably in the safe zone unless their ratios are very poor. Second, adding finance cost back into EBIT treats a lender's main operating cost as a financing cost, which flatters X3. The Z''-Score here is therefore mostly a summary of reported capitalisation, and reported capitalisation was, on the face of the accounts, heaHowever, there are two structural attributes of the model that also play an important role from the point of view of the lender. Firstly, a constant of 3.25 will put almost all financial organizations in the safe range unless their ratio is terrible. Secondly, inclusion of finance cost in the EBIT means taking into consideration as the financing cost the main operating cost of the lender, and thus flattering the X3 variable. Thus, Z''-Score in this case is nothing but the description of reported capitalization, which, from the face value of the accounts, was good for DHFL.

4.4 Beneish M-Score Analysis

The equation for the M-score is -4.84 + 0.920DSRI + 0.528GMI + 0.404AQI + 0.892SGI + 0.115DEPI - 0.172SGAI + 4.679TATA - 0.327LVGI. The original

threshold proposed by Beneish is -2.22, but scores above that level signify the probability of earnings manipulation. A more stringent threshold of -1.78 is another standard in academic literature. Findings are presented in Table 4.4 and Figure 4.2.

Table 4.4: Beneish M-Score components and classification

Co.	Year	DSRI	GMI	AQI	SGI	DEPI	SGAI	LVGI	TATA	M	Signal
DHFL	FY2016	0.856	1.020	0.964	1.223	0.837	0.958	1.011	-0.005	-2.458	Not flagged
DHFL	FY2017	1.559	1.003	0.860	1.211	1.122	0.881	0.985	0.030	-1.655	Flagged
DHFL	FY2018	0.098	0.899	1.088	1.181	0.980	1.052	1.004	-0.010	-3.225	Not flagged

LIC HF	FY2016	1.056	0.887	0.996	1.162	1.103	1.068	0.995	-0.016	-2.421	Not flagged
LIC HF	FY2017	1.136	0.928	1.001	1.128	1.073	1.163	0.995	-0.021	-2.395	Not flagged
LIC HF	FY2018	1.111	1.047	1.013	1.070	0.955	0.990	1.000	-0.002	-2.298	Not flagged

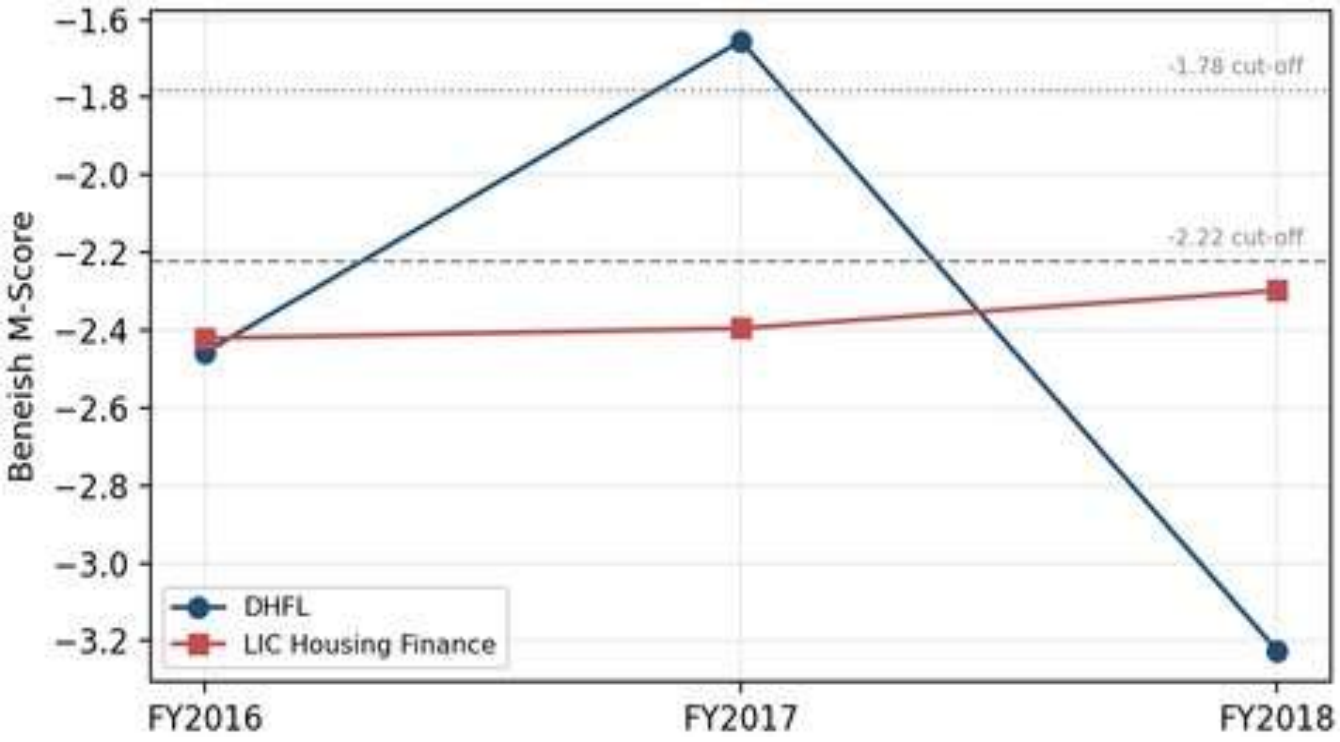


Figure 4.2: Beneish M-Score, DHFL and LIC Housing Finance, FY2016–FY2018

4.4.1 DHFL: the FY2017 signal

The M-Score of DHFL changes from -2.46 to -1.66 when we go from FY2016 to FY2017 and it crosses both the -2.22 and -1.78 thresholds. The breakdown of the change of around 0.80 gives us that the Days Sales in Receivables Index comprises almost four-fifths of it while the rest is due to Total Accruals to Total Assets. The increase of DSRI from 0.86 to 1.56 happens since the value of receivables increased from ₹201 crore to ₹379 crore while revenues increased only by 21 percent. TATA becomes positive (0.030) due to the fact that net profit of ₹2,896 crore greatly exceeded net operating cash flows of ₹162 crore.

The above alert needs careful interpretation. Accruals are overstated due to the large gain of ₹1,969 crore, and probably also due to the tax expense, while receivables are a negligible line item considering the loans held by a lender in crores of tens of thousands. This alert should not be considered as evidence of accounting manipulation but rather as an indication to examine closely the year FY2017. It is significant that the alerting year is the same year in which

receivables were restated, as well as the year when Z''-Score shows DHFL in its most favorable position.

4.4.2 DHFL: the FY2018 result

For FY2018, the M-Score drops to -3.23, which is the lowest value in the entire sample period. That's nearly a mechanical exercise – the amount of receivables goes down from ₹379 crores to ₹43.69 crores, causing DSRI to drop to 0.10. All the other ratios are mundane. The model, which resets to "low risk" because one line of accounts receivable has dropped, does not say whether earlier value or later was more reliable.

4.4.3 Sensitivity to the restatement

As seen from the FY2017-18 annual report, the March 2017 receivables are ₹3.37 crore instead of ₹379.10 crore. In such a case, using this new figure, there would be an increase in receivables to sales ratio by eleven times between FY2017 and FY2018; DSRI would also be around 11 while the M-Score of FY2018 would be around +6.8 – well within the range of concern. The above calculation is just illustrative, not a finding, since there might be some form of reclassification in the figure and these calculations are only supposed to be done on the basis of figures as published. What it proves is that the results of DHFL for FY2018 depend significantly on whether FY2017 is restated or not.

4.4.4 LIC HF

LIC HF is not identified in any year. However, its values -2.42, -2.40, and -2.30 are consistent, although rising every year, ending up 0.08 lower than the cut-off point of -2.22, indicating a very narrow margin. The reason for the FY2018 movement is an increase in the gross margin index (income growing slower than finance cost) and reduction in the operating cash flow from ₹5,125 crore to ₹2,301 crore, bringing TATA to 0. The component values are consistent with 1, as expected from a consistently growing business with no accounting adjustments.

4.5 Comparative Analysis

Table 4.5: Descriptive statistics of composite scores

Score and company	Years	Mean	Minimum	Maximum
Z''-Score, DHFL	4	3.676	3.227	4.574
Z''-Score, LIC HF	4	2.894	2.545	3.080
M-Score, DHFL	3	-2.446	-3.225	-1.655
M-Score, LIC HF	3	-2.371	-2.421	-2.298

The table shows that the Z''-score of the company DHFL is better than that of LIC HF, and the M-Score of DHFL is worse by a small amount (less suspicious). However, the important part is not the averages but rather the volatility of M-Score of DHFL compared to that of the other firm.

Table 4.6: Years flagged by each model

Rule	DHFL	LIC HF
Z'' below 2.6 (grey or distress zone)	0 of 4 years	1 of 4 years (FY2018)
M above -2.22	1 of 3 years (FY2017)	0 of 3 years
M above -1.78	1 of 3 years (FY2017)	0 of 3 years

In this comparison, the behavior of the M-Score is consistent in the direction that was anticipated since it picks out the fraud firm in one year but not the control firm in any year. The Z''-Score acts in the reverse direction since it does not pick out DHFL at all in any year but picks out the LIC HF in one year. Both models do not have a consistent result throughout the period, but their differences are at their maximum in FY2017.

4.6 Testing of Hypotheses

- Since there are eight firm-year samples for Z''-Score model and six firm-years samples for the M-score model, hypothesis testing will be done through direct outcome comparison and not statistical testing.
- H1 (Z''-Score shows a discernable difference between DHFL and LIC HF): there is a difference between the scores but not in the right direction to signify fraud detection. DHFL scores higher (more secure) than LIC HF in all four years. H1 is not supported in any practical way.

- H2 (M-score shows a discernable difference): partially supported. DHFL is flagged in FY2017 but not at all in FY2016 and FY2018. LIC HF is never flagged; therefore, there is a single-year flag from three years.
- H3 (The two models show no agreement on DHFL): supported. Z''-Score scores DHFL as safe in all four years, while M-Score flags FY2017, and the

difference is highest in FY2017.

4.7 Key Findings

- The Altman Z''-Score did not indicate stress at DHFL for any fiscal year between FY2015 and FY2018 and rated DHFL as safer than the control company during this period. When applied to data reported by a lender, this model is based mainly on reported capitalisation and therefore cannot reveal any issues in underlying asset quality.
- The Beneish M-Score model indicated DHFL during FY2017 using both commonly used cut-offs and did not indicate LIC HF in any year. This flag was due to rapid growth in receivables compared to revenues and excess

of profits over operating cash flow, and can also be explained by a non-recurring profit item.

- The two models provided conflicting signals about DHFL during FY2017, which is in line with the assertion in the literature (Bhavani and Amponsah, 2017) that there is no one model that is always reliable.
- This signal did not persist. In FY2018, the score for DHFL dropped to the lowest in the sample due to a much lower level of reported receivables, meaning a flag for one year was followed by a 'clean' year.
- There were variations in the figures reported by DHFL during various financial years: In the case of FY2017 trade receivable, the number was revised from 379.10 crore to 3.37 crore; likewise for the operating cash flow of FY2016. This itself is a quality issue concerning the data, which also impacts the outputs of our models.DHFL showed much more growth compared to its competitor firm during the relevant period (approximately 97% increase against 53%), and this trend is consistent with a high level of fraud risk.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1 Summary of the Study

Both the Altman Z''-Score and the Beneish M-Score methods were used on DHFL, which is a housing finance company, after irregularities in its financial performance were uncovered in 2019 and LIC Housing Finance, which serves as the sector control. Each was analyzed with their individual audited financial figures from financial year 2015 to 2018. The objective was to find out whether either of the models, when used on the published numbers, had already indicated that the company was a high risk candidate before the financial irregularities surfaced.

5.2 Conclusion

First, the Altman Z''-Score failed to provide any valuable early-warning signals to detect earnings management at DHFL in this case. The model put DHFL in the safety zone every year and classified it as having higher values compared to the control company, whereas the latter was moving closer to the grey zone. For a creditor, this model summarizes the reported values of the capital strength and liquidity, which looked good in the case of DHFL.

Second, the Beneish M-Score performed slightly better but still in the insufficient manner. In this case, both companies were distinguished by the test as expected – one year for DHFL and zero for LIC HF, but the signal was identified only in one out of three years and does not recur. Moreover, the M-Score is sensitive to non-recurring items and small balance sheet items like accounts receivable, which are not economically important for creditors.

Third, the two models contradict each other. In FY2017, the models gave different results. This fact proves the conclusions made in the case of Toshiba, that choosing a model determines the result.

Fourth, and possibly the most telling indicator of a problem, was the discrepancy and not a single score, namely, the balance sheet date on which there were very different receivable numbers in two years of annual reports. After all, any model screen is only as reliable as the consistency of the underlying numbers reported, and restatements need to be flagged as well as the scores.

These findings are based on a single company-pair and from a lender's perspective. This does not mean that the models don't work in general, or that this research proves that they do.

5.3 Recommendations

For auditors and forensic accountants

- Treat the M-Score not as an end but as a signal that warrants a deeper look at the relevant variables (receivables and accruals in this case), and always consider it in conjunction with the Z''-Score and the individual items behind them.
- Look for discrepancies between the current year and previous years' annual reports, especially those involving restatements of past-year values.

For regulators (SEBI, RBI, National Housing Bank)

- It is important to modify the model-based screen to fit the finance company industry (such as the proper way to measure cost of sales, accruals, and operating cash flow).
- The screens should contain some indicators which will consider the loan-book quality and funding structure, because the general purpose ratios

  discussed above have failed to do so.

For investors and analysts

- Safe-Zone Z'' Score does not serve as proof that the reporting by the company is accurate, and one year of flagged M-Score calls for more questions to be asked rather than answers. It is important to consider exceptionally fast balance sheet expansion compared to other companies, coupled with a surge of liquidity or profits.

5.4 Limitations

The limitations mentioned in Section 3.6 are applicable to these findings in totality. Firstly, the data is that of matched pairs, with three or four years per pair, and therefore statistical significance cannot be established. Secondly, the models have been modified, considering that the cost of sales and SG&A were proxies for cost of sales and SG&A for lenders. Book value rather than market value of equity is used in the Z''-Score. Lastly, the FY2017 outcome has been affected by one-time gains. The report for LIC HF for FY2019 under Ind AS is not comparable and hence, has been omitted from the analysis.

5.5 Scope for Future Research

- Generalise the model design to a wider dataset of confirmed Indian frauds cases with matched controls, allowing logistic regression and ROC analysis and determining if there is any value-added from the combination of the models.
- Include FY2019 for DHFL and LIC HF, and also include some financial sector cases such as the holding company of the IL&FS group in order to

  determine whether the observed pattern repeats itself.
- Run the models against Satyam Computer Services, where the data for the company's FY2008 accounts (the latest before the company's fraud was disclosed) has already been collected in the accompanying workbook; the preliminary estimate suggests that the M-Score is about -2.27, which is just above the -2.22 threshold, thus suggesting that the poor performance of M-Score for DHFL may not be confined to lending institutions.

- Apply market capitalization to X4 in Z-Score, and models specifically designed for financial institutions or those using the quality of loans as predictors, in order to discover what the general models overlooked.

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