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AN ANALYSIS OF SATYAM CASE USING BANKRUPTCY AND FRAUD DETECTION MODELS

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Abstract: *Bankruptcy, which occurs due to inability of a business, to repay its debts and obligations has caught the interest of investors and practitioners alike. Predicting bankruptcy prior to the occurrence of event has become crucial in the field of investment and lending, especially in the light of events such as the global financial crisis of 2008. Early bankruptcy prediction models used traditional statistical techniques via financial ratios. Since then there has been a constant endeavour to develop models with enhanced predictive performance. Satyam Inc. was Indian listed business which went bankrupt in 2007. In this study we apply financial models such as F score, M-score and Z-score to show how common/retail investor who cannot use sophisticated financial tool, can benefit from these simple tools and make good investment decisions. Our research adds to the discussion regarding the capability of bankruptcy prediction models. We derive our findings using the data for Satyam Inc., one of the biggest corporate scandalin India. Before the scam, Beinish M-score acted as more efficient predictor of bankruptcy and fraud than Altman Z-score and Peotroski F score. In fact, the usefulness of Z score and F score was average to poor in predicting Satyam's bankruptcy in advance. This result contradicts outcomes from several researches who had found a great ultility of Z score and F score. From the policy view, the regulator of financial market can protect the financial illiterate investor who makes investment in capital market to take informed investment decision by using the Beinish M-score for making investing decision in the stock of the company. Similarly, these models can be used by banks and financial institutions in case of existing as well as potential corporate borrowers.*

Keywords: Satyam Inc, investment decision, Peotroski F score, Beinish M-score, z-score.

JEL Classification: A1, G1.

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1. Introduction

The objectives of this study is to see if Peotroski F score, Beinish M-score and Altman z-score as investment tools can be used for making investment decision. Thus, in this study we use theSatyam case to back test bankruptcy using the F score, M-score and Z-score. By using all these three well known bankruptcy score we can see which is the most accurate and efficient formula to predict bankruptcy as well as detect fraud in financial statements.

1.1 Satyam Inc. Fraud-Anatomy of the scam

The Satyam fraud case was one of India's biggest corporate accounting scandals. It involved Ramalinga Raju, the chairman and founder of Satyam Computer Services, who admitted to manipulating the company's books and inflating its earnings over a period of several years. Satyam Computers, an Indian listed IT corporation with a multi-billion-dollar turnover felt the effects of poor corporate governance. The scam's outcome came as a great surprise to the shareholders, and it also prompted worries about better governance and accounting. The fraud revealed in 2009, when Ramalinga Raju, founder and chairman of Satyam, self-confessed to an accounting fraud of approximately Rs.7136 crores. On January 7th,2009, he submitted a letter of confession to Satyam's board of directors, revealing the extent of financial irregularities and immediately resigned. He acknowledged overstating the company's cash and bank balances, inflating revenue figures, and manipulating other financial data to create a false impression of profitability.

The revelation shocked the business world, as Satyam was considered to be one of India's most prominent and trusted companies. The scam had far-reaching consequences, including a loss of investor trust in Indian markets. Satyam's shares plummeted, and the company faced a severe financial crisis. Satyam's accounts were frozen and a new board of directors was established. Satyam was dropped from the major stock indices of India. Ramalinga Raju and a few other people involved in the fraud were arrested and charged with varied offenses, including criminal conspiracy, cheating, and forgery. Eventually, Mahindra purchased the company. In April 2015, a special court in Hyderabad convicted Raju and other key individuals, sentencing them to imprisonment and imposing financial penalties on them. Raju manipulated the company's books by creating fictitious assets, inflating revenues, and understating liabilities.

The fraud was carried out by forging bank statements, inflating cash and bank balances, fabricating invoices, and manipulating other financial data. The falsified figures comprised of inflated cash and bank balance Rs.5040 crores, non-existent accrued interest Rs.376 crores, understated liabilities Rs.1230 crore, overstated debtor position Rs.490 crores, and overstated revenues Rs.588 crores.

One of the aspects regarding this scam was the manipulation of books by the omission of certain receipts and payments, leading to an aggregate misrepresentation to the tune of Rs. 12,318 crores. Secondly, fake invoices and bills were generated utilizing software applications such as 'Ontime,' which was used to calculate an employee's hours worked. The number of employees was exaggerated by 13,000. The funds so raised were utilized to purchase hundreds of acres of property throughout Andhra Pradesh to take advantage of the state's burgeoning real estate industry.

1.2 Bankruptcy models

In order to forecast a company's likelihood of insolvency, the early finance studies resorted to analysis of financial ratios. A study made by Beaver (1966) demonstrated cash flow to debt ratio as excellent predictor of corporate failure. In times to come, financial ratios were integrated with statistical aspects and some experts some experts were able to formulate few models for bankruptcy prediction. The most popular among them are Beinish M-score, Altman Z-score and Petroski F score.

The structure of the paper is as follows: Following a literature review on bankruptcy prediction and fraud detection models as well as the financial research journey into these models, especially Altman's Z-score, Beinish M-score, and Petroski F score, financial anatomy of the scam is discussed. This is followed by research objectives and methodology, and then three financial models for predicting bankruptcy are chosen and used in the case under investigation. Subsequent results and discussion, with the implications, will highlight the principal contribution of this study.

2. Review of literature and development of hypothesis

The existence of a corporate is meant for profits. If it fails to deliver the same, its closure is evident. There has been a huge interest in research community and financial analysts, regarding determining the financial stability of a firm, and to find out in advance, if it is on the verge of failure, in the form of defaulting on its financial obligations, or to the extent of bankruptcy. Bankruptcy risk, is a consequence of the information asymmetry between lending institutions and businesses(Sengupta,1998). Predicting insolvency years before it actually occurs is of crucial importance. Early studies tried to accomplish failure prediction of firms purely using financial/accounting ratios(Beaver,1966). Then came the trend of bankruptcy predictor through accounting ratio based models, developed through interaction of financial ratios with statistical arena. These models are frequently built by sifting through a plethora of accounting ratios and estimating ratio weightings on a sample of failed and non-failing enterprises (Agarwal & Taffler, 2008). Appropriate financial parameters can serve as potential predictors of false financial statements(Spathis,2002). In 1968, Altman developed a Z-score through financial data such as working capital, EBIT, sales and assets, through a multiple discriminant analysis. Ohlson (1980) applied logistic regression analysis on selected variables, such as ratio of liabilities and income over total assets to determine default probability of potential borrower. Statistical methods, like discriminant analysis, can predict the failure of a business with a high level of accuracy up to three years in advance (Deakin, 1972). Thereafter, different theories and empirical models were developed to predict enterprise failure. Empirical work helps in determining the power and effectiveness of bankruptcy theories (Scott, 1981). Even when using statistical and AI applications, different machine learning techniques incorporate some financial variables or ratios into their model for bankruptcy prediction and detection of corporate frauds. Some financial variables/ratios for predicting financial bankruptcy, or fraudulent financial practices in models of such different empirical studies include debt ratio (Chen, 2016), current ratio (Yeh et al., 2014), net income as compared to assets (Pai et al.,2011), return on assets (Sun et al., 2011), accounts receivable turnover (Huang & Lu, 2000), inventory as compared to assets (Ravisankar et al., 2011), operating income as compared to revenues (Salehi & Fard, 2013) and others.

The widely used Altman Z-Score is a method that combines quantitative financial indicators with a limited number of variables to forecast if a company would fail financially or enter bankruptcy. The Z-score utilizes profitability, leverage, liquidity, solvency, and activity parameters to detect the same. According to Altman (1968), Z-score can accurately predict failure up to two years in advance. This model can be applied to predict bankruptcy by an organization's stakeholders as well as outsiders and the potential stakeholders (Srebro et al., 2021). Altman model was later on tested and found to be performing reasonably good by several experts. Altman's model achieved high accuracy levels in predicting the bankruptcy of Singapore retail companies (Muzani & Yuliana, 2021). Z score model was found to accurately predict business bankruptcy for textile companies in Pakistan (Hussain et al., 2014). In case of Greek companies, Altman model performed well at foreseeing failures up to five years in advance (Alexakis, 2008). Altman's model proved accurate in detecting Thomas Cook's financial distress of Thomas Cook, with a ten-year longitudinal data (Goh et al., 2022). For most countries, Z-score model serves as a good predictor of bankruptcy with an accuracy as high as 75 %, and this accuracy can be further enhanced by employing country-specific estimation that integrates additional variables (Altman et al., 2017).

Beneish M-score model, which encompasses eight different financial variables gives an idea regarding possible earnings manipulation in firms (Beneish, 1999). The M-score provides information about a business's projected returns since the businesses manipulating earnings are fast developing with deteriorating fundamentals, and resort to aggressive accounting practices (Beneish et al., 2013) Altman's model, paired with the Beneish model might have predicted Enron's bankruptcy well in advance, since the financial statements were manipulated (MacCarthy, 2017). Z-score and M-score are indications of stress and suspected financial statement falsification (Kukreja et al., 2020). Financial statement fraud is probabilistically higher to occur in business concerns with low Z scores (Spathis, 2002). Using the Beneish M-model, financial statement anomalies were substantially identified, in case of companies listed in US (Hou et al., 2023). M-score model accurately identified the firms manipulating financial statements in Poland (Hołda, 2020). Likewise, many more studies have identified M-score model to be highly accurate in identifying companies falsifying financial statements (Omar et al., 2014; Akra & Chaya, 2020; Aghghaleh et al., 2016; Narsa et al., 2023).

Piotroski's F-score is a composite accounting-based indicator of the corporation's fundamental strength and can be used to identify fundamentally weak firms (Walkshäusl, 2020). Regular F-score monitoring enables proactive risk management. F-score is a unique fundamental strength measure, which has positive correlation with stock returns (Xue, 2022). In the Indian context, the predictive power of Piotroski's F-score for default is confirmed by statistical analysis (Agrawal, 2015). The possibility of a company experiencing financial difficulties is significantly correlated with the F-Score (Rahman et al., 2021). Various research studies have effectively used F-score, or the factors therein to identify financially distressed firms (Li et al., 2020).

In the age of AI and its applicability in several aspects in the financial arena, the use of machine learning tools for predicting bankruptcy is inevitable. In the machine learning techniques, the predictions models such as Z-score have been toned further for improvement in accuracy. For example, machine learning techniques were able to achieve a substantial improvement in failure prediction when complementary financial indicators were incorporated with Altman's Z-score variables (Barboza et al., 2017). Neural network models have been used extensively for bankruptcy prediction. Neural networks can be structured in a variety of ways, and each one may perform differently when it comes to predicting bankruptcy (Milana & Ashta, 2021). Neural network models are known for their high prediction accuracy, powerful self-learning and adjusting capabilities (Odom & Sharda, 1990). For instance, Back-Propagation (BP) neural network model is a multi-layer forward network architecture based on error back-propagation (Sun & Xu, 2016). This model, when tested on Chinese listed mining companies, was found to perform with high accuracy in the field of financial early warning (Sun & Lei, 2021).

Thus, from the above literature, we develop the following hypothesis:

Hypothesis 1: Altman's Z-score has the power to predict bankruptcy of the firm.

Hypothesis 2: Beinish's M-score has the power to predict bankruptcy/ detect fraud related to the firm.

Hypothesis 3: Piotroski's F-score has the power to predict bankruptcy/detect fraud related to the firm.

3. Research methods

The high accuracy achieved by various bankruptcy prediction models makes one believe that it is possible to forecast corporate failures using financial data. It is also evident that the discussion about which failure-prediction models work best will continue in the future. This is a perspective paper, which looks at the predictive capability of models developed through financial ratios, viz. Benish M-score, Altman Z-score and Petroski F score, as regards to the biggest financial fraud and ensuring bankruptcy, viz. Satyam in an emerging economy, India.

3.1 Overview of Altman Z-score model

In 1968, Altman proposed multiple discriminant model for predicting the chances of a firm's bankruptcy, known as Z-score.

The formula for this overall index score is derived from five financial ratios as,

$Z = 1.2A + 1.4B + 3.3C + 0.6D + 1.0E$

Where:

A = Working Capital/Total Assets

B = Retained Earnings/Total Assets

C = Earnings before Interest and Taxes(EBIT)/Total Assets

D = Market Value of Equity/Book Value of Total Debt

E = Sales/Total Assets

Business enterprises with Z-scores below 1.81 have a high probability to fail (Altman, 1968), while a score below 2.675 is viewed as a grey area. Firms with scores of 3 and above are seen to be in a safe zone.

3.2 Overview of Beneish's M-score model

Beinish presented an M-score model for screening corporations regarding likelihood of earnings manipulation(Beneish,1999), with 8 variables as below:

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

where,

DSRI = Days Sales in Receivables Index

GMI = Gross Margin Index

AQI = Asset Quality Index 0.892

SGI = Sales Growth Index

DEPI = Depreciation Index

SGAI = Sales, General, and Administrative Expenses Index

TATA = Total Accruals to Total Assets

LVGI = Leverage Index

A M-Score of more than -2.22 indicates the possibility of earnings manipulation.

There also exists another version of M-score, which has lesser number of variables, viz.5, presented below:

M = -6.065+ .823 DSRI + .906 GMI + .593 AQI + .717 SGI + .107 DEPI

3.3 Overview of Piotroski's F-score model

The Piotroski F-score is a numeric value ranging from 0 to 9 that is used to assess enterprise's financial strength(Piotroski,2000), in accordance with nine criteria. Profitability, leverage, liquidity, finance source, and operational efficiency comprise these criteria. The profitability details in this criteria are based upon a positive value of net income, return on assets, operating cash flow and the comparison of operating cash flows with net income. Leverage and liquidity criteria are in terms of long-term debt and current ratio as compared to previous financial year and dilution of shares. Operating efficiency criteria is viewed in terms of gross margin and asset turnover ratio as compared to the previous accounting year. Each criterion in Piotroski F-Score is assigned a value of either 0 or 1 based on specific financial metrics and signals. The individual scores are then aggregated to calculate the overall F-Score, which can range from 0 to 9. A higher score indicates better financial strength and a higher likelihood of positive future performance. A score in the range 0-2 classifies the enterprise as a weak one, a score in the range 3-7 in the grey zone, and range of 8-9 as strong.

4. Findings and Results

Ananalysis of Satyam Inc. case: Fraudulent Financialreporting by using Z-score, M-score and F-score

Table 1. Z-Score

	2002-03	2003-04	2004-05	2005-06	2006-07	2007-08
Current asset	178.04	594.43	734.70	1,017.00	609.20	2,243.30
Current liabilities	61.55	59.30	99.67	134.20	211.20	333.10
Total assets	561.69	713.77	838.51	1,181.20	1,624.10	2,243.30
Retained earnings	87.14	172.83	279.76	497.10	721.10	1,069.80
Earnings before interest and taxes	84.32	137.04	185.17	287.00	328.20	469.80
Market value of equity	487.72	633.89	638.53	994.40	1,371.00	1,861.80
Book value of total liabilities	73.98	69.88	102.00	165.90	253.10	381.50
Sales	459.21	566.37	793.60	1,096.30	1,461.40	2,138.10
Working capital	116.49	535.13	635.03	882.80	398.00	1,910.20
X1	0.21	0.75	0.76	0.75	0.25	0.85
X2	0.16	0.24	0.33	0.42	0.44	0.48
X3	0.15	0.19	0.22	0.24	0.20	0.21
X4	6.59	9.07	6.26	5.99	5.42	4.88
X5	0.82	0.79	0.95	0.93	0.90	0.95
	Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 1.0X5					
Altman Z-score	5.73	8.11	6.81	6.81	5.73	6.26
Z-score	Zone					
< 1.81	Bankrupt/Distress					
1.81-2.99	Grey					
> 2.99	Safe					
Zones	Safe	Safe	Safe	Safe	Safe	Safe

Data source-Capitalline data base.

The Z-score for the year between 2002 to 2008 indicates that it has a safe value, as the values are in the range of 5.73 to 8.11. The Z-score indicates no bankruptcy for the Satyam case.

Table 2. F-Score

	2001-02	2002-03	2003-04	2004-05	2005-06	2006-07	2007-08
Net income	42.35	82.30	111.86	153.80	249.40	298.40	417.00
Total asset	516	561.69	713.77	838.51	1181.20	1624.10	2243.30
Operating Cash Flow		98.54	89.21	171.30	162.70	261.50	339.10
Long term debt	2.71	1.74	1.83	2.32	17.90	22.20	24.80
Current asset		178	594.425	734.7	1,017.00	609.2	2,243.30
Current Liabilities		61.55	59.30	99.67	134.20	211.20	333.10
Sales		459.21	566.37	793.60	1096.30	1461.40	2138.10
COGS		275.22	343.60	506.80	689.00	937.60	1359.20
Profitability			3.00	4.00	3.00	2.00	3.00
Return on Assets (1 point if it is positive in the current year)	0.08	0.15	0.16	0.18	0.21	0.18	0.19

Table 2 (cont.). F-Score

	2001-02	2002-03	2003-04	2004-05	2005-06	2006-07	2007-08
Operating Cash Flow (1 point if it is positive in the current year)		98.54	89.21	171.30	162.70	261.50	339.10
Change in Return of Assets (1 point if ROA is higher in the current year compared to the previous one)		0.06	0.01	0.03	0.03	-0.03	0.00
Accruals (Operating Cash Flow/Total Assets) (1 point if it is higher than ROA in the current year)		0.18	0.12	0.20	0.14	0.16	0.15
Leverage, Liquidity and Source of Funds			2.00	-	2.00	1.00	2.00
Change in Leverage (long-term) ratio (1 point if the ratio is lower this year compared to the previous one)		0.0031	0.0026	0.0028	0.0152	0.0137	0.0111
Change in Current ratio (1 point if it is higher in the current year compared to the previous one)		2.89	10.02	7.37	7.58	2.88	6.73
Change in the number of shares (new shares issued during the last year) (if no then 1 point)		yes	yes	yes	yes	yes	yes
Operating Efficiency			-	1.00	1.00	-	2.00
Change in Gross Margin (1 point if it is higher in the current year compared to the previous one)		0.40	0.39	0.36	0.37	0.358	0.364
Change in Asset Turnover ratio (1 point if it is higher in the current year compared to the previous one)		0.82	0.79	0.95	0.93	0.90	0.95
Piotroski F-Score			5.00	5.00	6.00	3.00	7.00
Good or high score = 7, 8, 9			moderate	moderate	Moderate	bad	good
Bad or low score = 0, 1, 2, 3							

The F-score of the Satyam case indicates the moderate level of risk of bankruptcy. Further, for the year between 2003 to 2008, the score varies from 3 to 7 units.

Table 3. M-Score (8 variables)

	2002-03	2003-04	2004-05	2005-06	2006-07	2007-08
Sales	459.21	566.37	793.60	1096.30	1,461.40	2,138.10
Net receivables	96.76	133.83	174.28	220.00	364.20	508.40
COGS	275.22	343.60	506.80	689.00	937.60	1,359.20
Non current asset other than PPE	314.50	50.88	22.94	57.60	851.80	144.20
Total assets	561.69	713.77	838.51	1181.20	1,624.10	2,243.30
Depreciation	35.98	24.40	25.00	31.50	33.60	41.50
PPE	69.16	68.47	80.86	106.60	163.10	236.60
SGA expense	116.89	101.63	124.30	187.60	232.20	370.20
Current liabilities	61.55	59.30	99.67	134.20	211.20	333.10
total long term debt	1.74	1.83	2.32	17.90	22.20	24.80
Income from continuing operations	82.30	111.86	153.80	249.40	298.40	417.00
CFO	98.54	89.21	171.30	162.70	261.50	339.10
Net Receivables/Sales	0.21	0.24	0.22	0.20	0.25	0.24
DSRI		1.12	0.93	0.91	1.24	0.95
(Sales-COGS)/Sales	0.40	0.39	0.36	0.37	0.36	0.36
GMI		1.02	1.09	0.97	1.04	0.98

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Table 3. M-Score (8 variables)

	2002-03	2003-04	2004-05	2005-06	2006-07	2007-08
Non-current assets other than PPE/total assets	0.56	0.07	0.03	0.05	0.52	0.06
AQI		0.13	0.38	1.78	10.76	0.12
Depreciation/(PPE+Depreciation)	0.34	0.26	0.24	0.23	0.17	0.15
DEPI		1.30	1.11	1.04	1.34	1.14
SGI		1.23	1.40	1.38	1.33	1.46
SG&A Expense/Sales	0.25	0.18	0.16	0.17	0.16	0.17
SGAI		0.70	0.87	1.09	0.93	1.09
(Current Liabilities+Total Long Term Debt)/Total Asset	0.11	0.09	0.12	0.13	0.14	0.16
LEVI		0.76	1.42	1.06	1.12	1.11
TATA (Income from Continuing Operationst - Cash Flows from Operationst) / Total Assets		0.03	-0.02	0.07	0.02	0.03
M-score = −4.84 + 0.92(DSRI) + 0.404 (AQI) + 0.115(DEPI) + 0.528(GMI) + 0.892(SGI) − 0.172(SGAI) − 0.327(LEVI) + 4.679(TATA)						
Scale					< -2.22	Not likely be a manipulator
					> -2.22	Likely to be a manipulator
M-score 8 variables		-2.19	-2.59	-1.60	2.12	-2.34
		Manipulator	Not manipulator	Manipulator	Manipulator	Not manipulator

Data source-Capitalline data base

Table 4. M-Score (5 variables)

	2002-03	2003-04	2004-05	2005-06	2006-07	2007-08
Sales	459.21	566.37	793.60	1096.30	1,461.40	2,138.10
Net receivables	96.76	133.83	174.28	220.00	364.20	508.40
COGS	275.22	343.60	506.80	689.00	937.60	1,359.20
Non current asset other than PPE	314.50	50.88	22.94	57.60	851.80	144.20
Total assets	561.69	713.77	838.51	1181.20	1,624.10	2,243.30
Depreciation	35.98	24.40	25.00	31.50	33.60	41.50
PPE	69.16	68.47	80.86	106.60	163.10	236.60
SGA expense	116.89	101.63	124.30	187.60	232.20	370.20
Current liabilities	61.55	59.30	99.67	134.20	211.20	333.10
Total long term debt	1.74	1.83	2.32	17.90	22.20	24.80
Income from continuing operations	82.30	111.86	153.80	249.40	298.40	417.00
CFO	98.54	89.21	171.30	162.70	261.50	339.10
Net Receivables/Sales	0.21	0.24	0.22	0.20	0.25	0.24
DSRI		1.12	0.93	0.91	1.24	0.95
(Sales-COGS)/Sales	0.40	0.39	0.36	0.37	0.36	0.36
GMI		1.02	1.09	0.97	1.04	0.98
Non-current assets other than PPE/total assets	0.56	0.07	0.03	0.05	0.52	0.06
AQI		0.13	0.38	1.78	10.76	0.12
Depreciation/(PPE+Depreciation)	0.34	0.26	0.24	0.23	0.17	0.15
DEPI		1.30	1.11	1.04	1.34	1.14
SGI		1.23	1.40	1.38	1.33	1.46
SG&A Expense/Sales	0.25	0.18	0.16	0.17	0.16	0.17
M-score = −6.065 + 0.823(DSRI) + 0.906(GMI) + 0.593(AQI) + 0.717(SGI) + 0.107(DEPI)						

Table 4. M-Score (5 variables)

Scale				< -2.22	Not likely be a manipulator
				> -2.22	Likely to be a manipulator
M-score 5 variable	-3.12	-2.96	-2.27	3.37	-3.14
	Not manipulator	Not manipulator	Not manipulator	Manipulator	Not manipulator

Beneish M-score of Satyam for the year 2003 to 2008 varies from -1.60 to 2.12. The manipulators zone is very well depicted for the year 2003,2005 whereas the years 2004,2006 and 2007 indicates that Satyam score is in a safe zone.

An analysis of Satyam case: Fraudulent Financial reporting

1. Beinish M-score shows that the company has manipulated its reported earnings during three fiscal years FY02-03, FY05-06 and FY06-07 which should have been seen by the auditors.

2. The Piotroski F score fails to predict anything significant in this case where the scores denote a moderate level of concerns on investment. The FY 2006-07 F-score is reaching towards weak zone and the significant improvement in the next fiscal should have been checked for its correctness.

3. Altman Z score does not flag anything adverse for the financial reporting as it is in safe zone for all the above financial years taken into consideration.

5. Conclusion

The prediction of business failure and fraud detection is valuable for investors and other users of financial statements. With this research we examined the efficacy of accounting based models such as Z-score, M-score and F-score models in fraud detection and bankruptcy prediction by applying it on Satyam Inc., one of the biggest corporate frauds in India's financial history. Our results reveal that Beneish M-score with 8 variables shows clearly that business entity has manipulated earnings in their balance sheet, whereas the Piotroski F score and Altman Z score fails to detect the fraud in the balance sheet. Even, a Beinish M-score of 5 variables is inapt to capture fraud detection. Thus, relevant stakeholders like investors and bankers can apply the M-score model with 8 variables for detecting frauds in financial statements in advance of happening of an undue event like insolvency or winding up of the firm.

Thus, we do not find any support for hypothesis 1 (Altman's Z-score). We find a partial support for hypothesis 2 (Beneish M-score, particularly with 8 variable model). Also, we do not find any support for hypothesis 3 (Piotroski F score) in our study. Thus, there exists a need to develop better financial models in the future, especially for the Indian context. Also, the models should be fine-tuned with time to better detect frauds in financial statements.

6. Implications of the study

With rising number of investors in the stock market, the indicators used in this study can provide a platform for them to stay away from companies, which are on the verge of bankruptcy. This can avoid losses of their hard-earned money. From the policy view the regulator of financial market can protect thefinancial illiterate investor who makes investment in capital market to take informed investment decision by using the Benish M- score for making investing decision in the stock of the company.

This study is also useful to banks and financial institutions to access credit-worthiness of their prospective borrowers, and to track the financial health of the corporates who have been sanctioned and disbursed credit. This study can serve as a learning case for credit officers in banks and financial institutions and help them to avoid counterparty default.

7. Limitations and further scope

This paper is limited to the analysis of a single company through the various bankruptcy models. At the same time, only financial data is used for accessing company failure and fraud detection. Further studies can be carried out on a number of companies where financial frauds have taken place in order to back-test the reliability of these models. Also, these models ought to be applied on a number of companies which are on the verge of financial distress or otherwise, in order to get early signals. Moreover, a number of companies can be explored in a single study to find out the firms on the verge of bankruptcy, or to detect fraudulent financial statements.

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