A STUDY OF WILFUL DEFAULT COMPANIES IN INDIA USING ALTMAN Z-SCORE AND OHLSON'S O-SCORE BANKRUPTCY PREDICTION MODELS[#]

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INTRODUCTION

According to the World Bank's Doing Business Index, 2018, India ranks 108 out of 189 countries on Ease of Resolving Insolvencies; it takes nearly 4.3 years to resolve the issues of insolvency in India. India's insolvency recovery rate in terms of cents on dollars comes to 26.5 as per the report (World Bank, 2019). This simply means that on every dollar invested, the secured creditors can recover slightly over one-forth of their investment through the judicial debt enforcement proceedings. Although the rate is gradually increasing and recovery has been faster than the data indicated in this report due to a strong and effective Insolvency and Bankruptcy Code (IBC) 2016. According to the same World Bank report on 'Ease of Doing Business', India jumped 23 positions to reach 77th rank in overall doing business index largely due to implementation of IBC among other reforms.

However, over the years, especially in the past decade, the weak insolvency resolution mechanism and

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significant inefficiencies in the credit appraisal system of the commercial banks resulted in a massive distress in credit market. According to another report of the World Bank, India ranks 31 among 123 countries in terms of non-performing assets (NPAs) as a percentage of total bank loans. The 2017 report indicates a 10% NPA for India's commercial banks which is far more than the average of 7.5%.

The Financial Stability Report of the Reserve Bank of India (RBI) over the recent years clearly indicates that major sectors such as infrastructure, iron and steel, mining, aviation and textiles had notably higher levels of stressed assets. Although the Indian banking system remained quite elastic, the asset quality of the public sector banks came under enormous pressure. According to the numbers that were reported by the commercial banks to the RBI, the gross NPA of public sector banks was at Rs. 56167.18 in the year 2014–2015. At the end of 2017–2018, this number increased to Rs. 73203.40 billion. The NPA of the public sector banks reached a peak of Rs. 9,62,000 crores in March 2018; Punjab National Bank (PNB) has the highest number of bad loans in their advances followed by the State Bank of India (SBI), Oriental Bank of Commerce, Canara Bank and Bank of Baroda (Financial Stability Report, RBI, 2018). Experts of the banking sector claim that the PSU banks went overboard in lending due to overoptimism and high economic growth in the early years of the third millennium. Although the NPAs of the private banks were also very high in 2007–2008 to 2010–2011, thereafter the growth in NPAs was controlled due to rational lending. The total amount of the NPA had increased from Rs. 13602.53 billion in 2013–2014 to Rs. 25984.36 in 2017–2018. HDFC Bank, Axis Bank, ICICI Bank, Kotak Mahindra Bank and Yes Bank are the banks that accumulated a massive rise in bad loans. Among them, ICICI Bank topped the list of NPA in private banks with Rs. 54,063 crores in the bad loans (Financial Stability Report, RBI, 2018).

As far as the foreign sector banks are concerned, the NPA of the foreign banks in 2010–2011 was Rs. 1949.72 billion, which grew to Rs. 3264.30 billion in 2017–2018, which is very low in comparison to other sector banks. The foreign banks accounted for lowest NPA because of their high efficiency, cautious credit lendings and the flexibility to cut their losses by selling off their assets (Financial Stability Report, RBI, 2018).

An important aspect of the rising NPA issue during the past decade has been the fact that at least half of the NPAs are caused by wilful default. The wilful defaults are those entities that have the capacity to repay, but still default in the repayment of loans, divert funds from the original purpose of borrowing, engage in selling off the assets without the knowledge or approval of the banks and methodically abuse the legal and financial sector. The RBI circular

dated 1 July 2014 clearly stated that 'Wilful Defaulter would be deemed to have occurred if the unit has defaulted in meeting its payment/repayment obligations to the lender even when it has the capacity to honour the said obligations'. Many times these defaulters have a premeditated intent not to pay off the loans despite having the capacity. As per the RBI regulations, wilful defaults cover broad areas including deliberately non-payment of dues despite having adequate assets and cash flows, misinterpretation of records and disposal of securities without the bank's knowledge.

As per the reports in media, SBI, the country's largest lender, accounted for nearly 27% of wilful defaults in 2016–2017. Nearly 1762 wilful defaulters owed over Rs. 25000 crores to SBI on 31 March 2017. This was followed by PNB with 1120 defaulters owning over 12000 crores. The total NPA in the PSU banks due to wilful defaults was nearly 92000 crores. This was an increase of 20% from 2015 to 2016 when the wilful defaults were over 76000 crores (PTI, 2018).

The volume of the NPA on this account is large and cannot be attributed only to external business environment. Therefore, it is imperative to discuss various aspects of wilful defaults and find whether there were ways and means to predict such defaults by the commercial banks while appraising their credit proposal.

Modern credit appraisal techniques use methodology that evaluates the probability of repayment using various bankruptcy prediction models, neural network and intelligent knowledge-based systems. Credit scoring is a popular technique which translates the risk factors in the form of scores. The credit scoring valuation techniques is a combination of conventional methods and advanced statistical techniques. The former includes weight of evidence, genetic algorithms, multiple linear regression, discriminant analysis, probit analysis and logistic regression. The latter comprises fuzzy algorithms, expert systems and neural networks (Abdou & Pointon, 2011; Hand & Hendly, 1997).

One of the most prominent models is the Altman's Z-score conceived by Edward Altman in 1968 (Altman, 1968). The model is a widely accepted measure for predicting bankruptcy even today. There is a plethora of research done using the model and it has been easier to compute and provides reliable results. Another contemporary model is the Ohlson's O-score, which has been recently accepted by a large number of professionals and many research studies have been conducted using this model.

The Altman's Z-score is even used by the World Bank to identify vulnerability and distress prediction for various countries by calculating the probability of default of country's banking

system. According to a report on the banking system Z-scores, published in Bankscope, TheGlobalEconomy.com in 2004, India was ranked 62 among 173 with a score of 14.98. In 2016, India's ranking slipped to 45 with a score of 18.17. The average score in 2016 was 14.38.

REVIEW OF LITERATURE

Charles Merwin in 1942 published a broad study with more than 900 companies in the United States titled 'financing small corporations' in *NBER*. He used Z-score prediction model and considered three ratios as important indicators of business failure. These ratios were the current ratio, net worth to total debt and net working capital to total assets to compare the discontinuing firms with those who were continuing and predicted the discontinuation of firms across five major sectors in the United States. He concluded that the discontinued firms show signs of weaknesses for at least 4–5 years before they actually fall (Merwin, 1942).

Later, Braddock Hickman found that the net profit to sales and the times-interest-earned ratios were the best predictors of default in his book titled 'Corporate Bond Quality and Investor Experience'. The study confirmed an inverse relationship between default rates and bond quality considering agency ratings, market ratings, earned ratios, ratio of net income to gross income and size of issue (Hickman, 1958). In 1966, Beaver came up with a single ratio known as the best performing ratio, cash flow/total debt best value. From 1968 to 1980, the period witnessed wide use of multivariate discriminant analysis. A study identified five sources (or dimensions) of variation within the 14-variable set, namely, profitability, activity, liquidity, asset balance and cash position. To represent these five dimensions, net income to total assets, current assets to sales, current assets to current liabilities, current assets to total assets and cash/total assets were selected, respectively, through use of the rotation factor matrix (Libby, 1975). Later, a version higher than the Z-score called ZETA was developed (Altman, Narayanan, & Haldeman, 1977). The details of the seven parameters are provided in the later section regarding models. However, the variables of the Zeta model are not disclosed as it is a proprietary asset.

To assess corporate failure or insolvency prediction, the most popular choice of the conditional probability–based tool is the logit model. The first ever published research within the field of corporate insolvency prediction using econometric methodology of the conditional logit analysis was propounded by Ohlson by creating the O-score (Ohlson, 1980). In further evolution, a research paper titled 'State of the art' evaluates a previous logit model

and compiles its lacunae; in addition, the concept of applied entropy with probabilities functions concluded an increase in information content as failure approaches over a 5-year period (Zavgren, 1983). The reasons for similarities in predictive abilities lie in both the logit and probit models which could be improved in terms of accuracy if they are adequately and correctly specified (Lennox, 1999).

Using a simple three-layered (1 × input, 1 × hidden, 1 × output) network with a back-propagation training algorithm, the accuracy of the network was compared with a discriminant analysis model with the use of Altman's Z-test method. 'Early warning system' with probability-based neural networks using Bayes' classification theory was then developed. (Yang, 2001). An innovative mixed logit methodology attempted to correctly classify the firms into three failure groups: non-failure, outright failure and insolvency. Where outright failure is defined as entering administration, receivership or liquidation, insolvency is defined as the failure to pay the listing fees, loan default, restructuring to meet debt payments and capital raising to finance continuing operations. The classification of the firms by their model boasted an impressive 99.16% accuracy (Jones & Hensher, 2008).

In recent years, the most popular forms of model are derived from the European call option (EC) and the down-and-out call barrier option. The shareholders of a firm are assumed to hold an EC, the exercise price being the amount required to discharge its debt liabilities. The time to maturity of the debt is therefore taken to be the option period, and the expiry date is taken as the point at which insolvency might occur. On expiry, the shareholders will be required to either discharge the debt repayment obligation if the assets of the firm exceed the liabilities or default on the debt and insolvency process if the assets of the firm are less than liabilities. The method assigns a default (failure) probability independently to each firm. The academic examples of the EC approach are found in Vassalou and Xing (2004), Heilgeist, Keating, Cram, and Kyle (2004) and Bharath and Shumway (2008).

All these techniques are well-researched and tested time to time in the West. It is found that discriminant analysis, linear regression, probit analysis and Poisson's distribution techniques resulted in 65.4%, 55.1%, 71.9% and 62.4% accuracy (Gullien & Artis, 1992). Later, the results of various studies surveyed relating to the comparison of accuracy of various credit scoring techniques from 1992 to 2005 were as follows: linear regression 67%–80% and average of 75%, logistic regression resulted in 75% average accuracy, decision tree analysis resulted in 76% average accuracy, neural net 76% and genetic programming at 82.8% (Abdou & Pointon, 2011; Crook, Edelman, & Thomas, 2007). As part of traditional

techniques, linear and logistic regression methods and advance tools like neural net and genetic programming were consistently accurate in prediction.

O-score is one of the widely used models for bankruptcy prediction; it not only considers financial performance but also the overall economic condition in the economy. It takes gross national product (GNP) as one of the variables of the model. The calculation for Ohlson's O-score is given below:

$$T = -1.32 - 0.407\log(TA_t/GNP) + 6.03TL_t/TA_t + 0.0757CL_t/CA_t - 1.72X - 2.37NI_t/TA_t - 1.83FFO/TL_t + 0.285Y - 0.521(NI_t - NI_{t-1})/|NI_t| + |NI_{t-1}|$$

where

1. TA = total assets

2. GNP = gross national product price index level

3. TL = total liabilities

4. WC = working capital

5. CL = current liabilities

6. CA = current assets

7. X = 1 if TL > TA, 0 otherwise

8. NI = net income

9. FFO = funds from operations

10. Y = 1 if a net loss is for the last 2 years, 0 otherwise

Altman Z-score

$$Z = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5$$

where

X1 = working capital/total assets (WCTA) (%)

X2 = retained earnings/total assets (RETA) (%)

X3 = earnings before interest and tax/total assets (EBITTA) (%)

X4 = market value of equity/book value of total liabilities (VETL) (%)

X5 = sales/total assets (STA) (number of times)

Z = overall index or 'Z-score'

So far, the study on bank loan defaults using Z- and O-score has been limited in India when compared with many other countries like Thailand, Vietnam and the United States. In particular, there are hardly any cases of wilful default.

OBJECTIVE

The objective of this study was to use bankruptcy models, the Altman Z-score, and Ohlson O-score models to gauge their bankruptcy prediction reliability of the wilful default companies listed after the year 2000.

RESEARCH METHODOLOGY

The study is based on the existing models with the use of historical data; it is a descriptive study based on secondary source, where the population is defined as the wilful defaulters among the listed companies after the year 2000. The rational to select the year 2000 as a cut-off year was based on the implementation of SEBI (Disclosure, Investors and Protection) Regulation, 2000. SEBI accepted the recommendations of Primary Market Advisory Committee (PMAC) with regard to the eligibility norms and pricing of IPSs among other reforms in primary market. More than 900 IPOs had arrived in the period thereafter upto 2017; out of which, 107 were declared as wilful defaulters. These 107 companies constitute the entire population of the study, and because the population is studied, no tests are required to validate.

Data Analysis

According to the Altman's Z-score, a number less than 1.81 indicates a very high chance of bankruptcy, a score between 1.81 and 2.99 implies moderate chance of bankruptcy and a score exceeding 3 indicates a very low chance of bankruptcy. A total of 75 companies scored less than 1.81 for at least 5 years, which means that the Z-score was alarming for at least 5 years consecutively. There were only seven companies in the safe zone for more than 5 years.

Table 1: Altman Results

	No. of Companies
<1.8	75
1.81–2.99	24
>3	6

Year-wise, there were 21 instances where the Ohlson's model predicted bankruptcy but not the Altman's model. A total of 77 companies were correctly predicted by the Altman's model but not by the Ohlson's model. For all the years, in all nine predictions, both the models were at par for all the years.

A total of 101 out of 107 companies were correctly predicted as plunging towards bankruptcy using the Z-score for at least 1 year of the entire period. However, six companies eluded the prediction.

Table 2: Altman's Z-Score Classification of Prediction Results

	Bankruptcy	No Bankruptcy
Total companies	101	6*

*Type Error II (not predicted but went bankrupt)

Source: *Computed from Ace Equity*

Table 3: List of Companies Not Predicted by Altman's Z-Score

1	**Amar Remedies Ltd.**
2	Ameya Laboratories Ltd.
3	Coral Hub Ltd.
4	Lumax Auto Technologies Ltd.
5	Midfield Industries Ltd.
6	Taksheel Solutions Ltd.

Source: Computed from Ace Equity

Table 4: Altman's Z-Score Year-Wise under Various Zones and Increase/Decrease in Cash Flow from Loan Funds of Number of Companies

| Year | Altman's Z-Score | | | | | Inc./Dec. Cash Flow from Loan Fund of No. of Companies | |
	Green >3	Amber 1.81–2.99	Red <1.8	Total	Amber + Red	Outflow	Inflow
2000	0	1	0	1	1	2	3
2001	1	3	15	19	18	3	6
2002	2	14	14	30	28	3	9
2003	4	10	28	42	38	9	13
2004	11	35	39	85	74	15	38
2005	12	31	53	96	84	19	31
2006	18	48	34	100	82	17	39
2007	13	55	34	102	89	11	45
2008	19	51	35	105	86	9	49
2009	4	44	56	104	100	16	51
2010	7	50	46	103	96	24	49
2011	5	24	75	104	99	19	37
2012	2	23	75	100	98	18	28
2013	0	7	86	93	93	19	22
2014	0	11	73	84	84	17	20
2015	1	3	76	80	79	18	14
2016	2	6	66	74	72	15	12
2017	2	1	53	56	54	14	7

Source: Computed from Ace Equity

The correlation between the number of companies having combined amber and red ratings and increase in loan funds is 0.76. This indicates that when the number of companies' creditworthiness was unsound, the banks were still sanctioning loans. From 2000 to 2009, the increase in the loan fund peaked at Rs. 8026.21 crores and then declined sharply. By the end of 2017, only 56 companies were left and the rest 51 ceased to exist.

The Ohlson's O-score is divided into two parts: probability more than and less than 50%. The probability less than 50% indicates that the chances of a company going bankrupt are very high and otherwise for more than 50%. The results from O-score are fairly near to the Z-score; 101 companies were predicted to go bankrupt at some point of time and only 5 companies were missed out. This shows excellent accuracy at around 95%.

Table 5: Ohlson's O-Score Classification of Prediction Results

	Bankruptcy	No Nankruptcy
Total companies	102	5*

*Type Error II (not predicted but went bankrupt)

Source: Computed from Ace Equity

Table 6: List of Companies Not Predicted by Ohlson's O-Score

1	**Jaypee Infratech Ltd.**
2	Plethico Pharmaceuticals Ltd.
3	Varun Industries Ltd.
4	Innoventive Industries Ltd.
5	Prithvi Information Solutions Ltd.

Source: Computed from Ace Equity

Interestingly, the lists of companies missed by either model are totally dissimilar. This indicates that if both the models are used, then the chances of missing out a company would decrease.

Table 7: O-Score from 2000 to 2017 and Increase/Decrease in Cash Flow from Loan Funds of Number of Companies

Ohlson's O-Score of No. of Companies				Inc./Dec. Cash Flow from Loan Funds of No. of Companies	
Year	<0.5	>0.5	Total	Outflow	Inflow
2000	6	7	13	2	3
2001	11	8	19	3	6
2002	19	11	30	3	9
2003	29	12	41	9	13
2004	69	16	85	15	38
2005	62	33	95	19	31
2006	37	61	98	17	39
2007	24	78	102	11	45
2008	18	85	103	9	49
2009	31	70	101	16	51
2010	25	76	101	24	49
2011	18	81	99	19	37
2012	22	68	90	18	28
2013	15	66	81	19	22
2014	17	61	78	17	20
2015	17	54	71	18	14
2016	14	43	57	15	12
2017	56	0	56	14	7

Source: Computed from Ace Equity

Furthermore, interesting facts have surfaced on understanding the pattern of increase and decrease in loan funds. The instances where loan funds increased indicate that there has been cash inflow through loans; additional or new loans have been provided by the banks. If loan fund increases amidst a weakening condition of the borrowers, then it would be alarming for the banks. The correlation between less than 0.5 score and increase in loan fund is 0.25. There were five companies whose bankruptcy could not be predicted using the model.

The data in Table 7 pertain to the sector-wise bifurcation of the increase in loan funds despite red and amber signals of the companies. In addition, the data in Table 8 are regarding the subsequent disbursements for 2–4 years in sequence, reinforcing the point about disbursements notwithstanding deteriorating creditworthiness which could have been discerned.

Table 8: Sector-Wise Data on Instances of *Increase in Loan Funds* and *the Number of Times a High Probability of Bankruptcy Was Predictable* According to Z-Score

Sector	High-Risk Bankruptcy Frequency of Companies														
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Agriculture				3		5									
Automobile and ancillaries			4			5									
Aviation										9					
Capital goods				6		10					10				
Chemicals							6								
Construction materials		1			4	5	6		8						
Consumer durables		1													
Crude oil	0														
Diamond and jewellery			2										12		
Electricals		1													
FMCG		1			4	5	6	7	8						
Healthcare					4	5	6		8						
Hospitality				3											
Inds. gases and fuels								7							
Infrastructure	**0**		**2**	**12**	**5**	**6**	**14**	**8**						**13**	**14**
Iron and steel								7		9					
IT	**0**	**2**		**12**		**10**			**8**	**18**		**11**			
Media and entertainment		1		3	4		6	7	8						
Mining					4										
Miscellaneous					4										
Non-ferrous metals		1		3					8						
Paper							**6**				**10**	**11**	**12**		
Plastic products				3						9					
Power							12								
Realty		1		3	4		12								
Ship building												11			
Telecom				3											
Textile		**1**		**3**	**8**	**5**	**12**	**21**	**8**	**27**		**11**	**12**		**14**
Trading		1					6			9					

Source: Computed from Ace Equity

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Most instances of the disbursement were for textiles, infrastructure and IT sectors. Interestingly, studying the pattern of disbursements even after amber and red signals for two, three and four times provided an insight into the anomaly of loan disbursements. A total of 68 companies were disbursed loans even after strong bankruptcy signals; furthermore, 50 borrowers received disbursement of loan funds consecutively three times, while with 36 companies it was consecutively four times despite strong bankruptcy signals.

Table 9: Disbursement and Risk Anomaly at Various Consecutive Instances

Total Anomaly in Disbursement and Strong Bankruptcy Signals			
No. of Times a High Probability of Bankruptcy Was Predictable According to Z-Score	Two Consecutive Years of Loan Disbursement	Three Consecutive Years of Loan Disbursement	Four Consecutive Years of Loan Disbursement
0	0	0	0
1	0	0	0
2	0	0	0
3	5	0	0
4	7	3	0
5	7	5	4
6	11	8	5
7	9	8	6
8	8	5	5
9	9	9	5
10	2	2	2
11	4	4	4
12	3	3	2
13	1	1	1
14	2	2	2
Grand total	**68**	**50**	**36**

Source: Computed from Ace Equity

This reflects if prominent bankruptcy prediction models would have been used by the bankers, then further disbursement of loan could have been controlled. Out of 107, 36 companies were consecutively provided loan for 4 years. This could also indicate gross negligence or worse some kind of collusion with the bankers in a few cases.

CONCLUSION

This study in its modest format conforms the accuracy of bankruptcy prediction models; bankruptcy can be predicted with a high degree of reliability using Altman's Z-score and Ohlson's O-score models. However, only 11 companies, 6 by Altman's and 5 by Ohlson's scores, eluded the prediction during the period. Because the sets of companies are different, it indicates that if more than one model is used by the banks, then the chances of bankruptcy prediction increase. The accuracy of the Altman's and Ohlson's models was 94% and 95%, respectively; the accuracy rate is high and attests to their reliability.

The number of listed companies continuously increased from 2000; however, after 2011, the companies started to decline. Currently, only 56 out of 107 are in existence so far. There has been a strong positive correlation of 0.76 between the increases in loan fund and high to moderate chances of bankruptcy according to the Altman's model, while with O-score it is only positive 0.26. The continual funding by the banks is an indication of warning signals apparently taken lightly in many cases.

The continuous disbursement of loans after discernible high-risk signals by the banks is not desirable. This is an indication of lapse on the part of the banks; 36, 50 and 68 companies were provided with loans for four, three and two times for consecutive years even after weakening financial condition. This may be the case of collusion with bankers under such circumstances.

This research work provides a course to consider using prediction models in a more professional manner than to limit its usage for only academic purpose. In addition, the methodology adopted by the banks for monitoring the performance of the companies by using bankruptcy prediction models warrants a close look.

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Database

- ACE Equity Database
- Annual reports of sample companies