ANALYSIS OF BANKRUPTCY PREDICTION MODELS AND THEIR EFFECTIVENESS: AN INDIAN PERSPECTIVE

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Abstract.Bankruptcy is a state of insolvency wherein the company or the person is not able to repay the creditors the debt amount. Bankruptcy prediction is of importance to the various stakeholders of the company as well as the society on the whole. The purpose of our research is to study the suitability of major bankruptcy prediction models by applying them to companies in the Indian Manufacturing Sector, which have been declared sick. The research shall analyze the financial statements and market data of these companies.We shall then try to determine how far back these models are able to predict that the companies would get into financial distress. The major contribution of our study will be to identify a suitable model for bankruptcy prediction in the Indian context.

Key Words: *Bankruptcy Prediction Models, Altman Z score, Merton's distance to default, Distress Levels*

LITERATURE REVIEW

Bankruptcy is a state of insolvency wherein the company or the person is not able to repay the creditors the debt amount. Bankruptcy prediction is of importance to the various stakeholders of the company as well as the society on the whole.It is necessary that we develop methods to identify firms that might run a risk of going bankrupt and more so in an environment such as the current one which is of recession. It is also imperative that the method is simple, applicable across industries and consistent in predicting bankruptcy. Also, the lead time provided by the method is critical as that can give the firm enough time to restructure and get out of the situation.

There have been many methods developed and used across the industries. Some of the more common methods are the Altman Z score andthe Merton's distance to default model. Each model has its own limitations and financial institutions are always on the look-out for finding the best method to evaluate credit worthiness.

There have been many studies in the past regarding the efficiency of the prediction models. Attempts to find out the best prediction model have been umpteen but none of have been very successful. Moreover, most of these studies have been on a global scale and concentrate more on firms that are huge multinationals. The purpose of our research is to study the suitability of major bankruptcy prediction models by applying them to companies in the Indian Manufacturing Sector that have been declared sick and by doing so find out which models are more suitable for firms in the Indian manufacturing sector.

Most studies that happened in the past lack validity and are deficient in a number of ways. A review of statistical and theoretic prediction models was presented by Scott (1981), but it was very limited in coverage and can be considered out of date in the current context. Zavgren (1983)describes only the statistical models without any mention of the theoreticmodels. The first study on prediction models applied to business outside the United States was by Altman (1984), which covered over ten countries and is an interesting study but limits itself to only one type of statistical model. Jones (1987) tries to give a comprehensive view of all the prediction models and focuses on research done in the corporate bankruptcy prediction area but it does not discuss theoretic methods ormodels Jones, (1987).

A study on limitations of the prediction models when it comes todecision usefulness was performed by Keasy and Watson (1991). But again the study was restricted to only statistical models and that too only a few of them. A successful review of various methods used to construct bankruptcy prediction models with more emphasis on recent models was done by Dimitras et al, (1996). But this study completely ignored the theoretic models, though it was one of the most comprehensive studies at that point in time. Perhaps the most comprehensive review of prediction models till date is by Morris (1998). It discusses prediction techniques and uses, from an empirical point of view. Though pretty comprehensive, it still missed out on a few prediction models and some of the models that came up later in the theoretic area have not been covered or discussed by the study. Zhang tries to understand the role of neural networks to predict bankruptcy. They also discuss the empirical applications of the networks for bankruptcy prediction but it leaves out all the other types of models which are generally used by firms (Zhang et al., (1999)). Credit risk models have been discussed in detail by a study by Crouchy (Crouchy et al., (2000)). Though it does a brilliant job of covering the credit risk models and some important bankruptcy prediction models from the theoretic area, it does not cover other types of models.

Thus, previous attempts and studies have lacked the comprehensiveness. None of them provide a single viewpoint on which prediction method is best suited for an industry or which method is superior and why. There is no comparison of different bankruptcy prediction models in any of the studies per se. Moreover, none of the above studies considered the Indian business arena let alone the Indian manufacturing sector. The purpose of our research is to study the suitability of major bankruptcy prediction models by applying them to companies in the Indian Manufacturing Sector that have been declared sick. The study maintains the hypothesis that all the prediction models are comparable and equally effective within a given industry.

The research shall analyse the financial statements of these companies over the mentioned 5 year period. By analysing certain aspects of the statements such as return on assets (net income divided by total assets), leverage (total liabilities to total assets) and cash flow to total liabilities (EBITDA divided by both short- and long-term debt), and by applying the various models to the companies under consideration, we shall try to determine how far back these models are able to predict that the companies would get into financial distress. The major contribution of our study will be to identify a suitable model for bankruptcy prediction in the Indian context.

METHOD

Altman Z-score and KMV Merton Distance to Default were the two bankruptcy prediction models which were used to check the health of companies in the Indian Manufacturing sector. While the Altman Z-score provided us with a score which could be classified into three different categories, the KMV Merton Distance to Default method provided us with a percentage which is the probability of the firm defaulting. The higher the Z-score, the better the health of the company whereas for the KMV Merton model, a smaller distance to default meant that a higher probability of the company going bankrupt.

The methodology that we followed was to apply the different prediction models across the financial data of all the firms under consideration. We picked up 9 companies from the Indian Manufacturing sector which had filed for bankruptcy in the period 2007-2012. The list of companies was picked up from the BIFR website. BIFR is Board for Industrial and Financial Reconstruction which helps companies restructure once they file for bankruptcy. These companies filed for bankruptcy under the Sick Industrial Companies Act.

For all the companies under consideration, their financial data for 5 years prior to the company's filing for bankruptcy were extracted. The financial statements were extracted from CMIE Prowess for the 5 years. Apart from the financial data, the opening and closing prices for the stock of all the companies in the Bombay Stock Exchange were collected from the Bombay Stock Exchange website. This was used to calculate the volatility of the stock over the period under consideration which is a primary requirement for the KMV Merton model. The market capitalization was calculated by taking the shareholding pattern from MoneyControl website and was multiplied by the closing price at year end which was again picked up from the Bombay Stock Exchange data. For the Altman Z-score, all the data was picked up from CMIE Prowess.

The extracted data was then put into the formula given by Edward Altman for public listed companies to arrive at the Altman Z-score. For the KMV Merton Distance to Default model, the values for market value of asset and asset volatility was generated simultaneously by running a macro on solver using excel. This gave a distance to default value which was then converted to a probability.

This provided us with a view if model was able to predict the bankruptcy or not. We analysed the frequency of correct predictions by different models which gave us a clear picture as to which model is most suited for the Indian Manufacturing Sector.

The first model to be applied was the Altman Z-score.

Altman Z-Score Model:

Z-scores are used to predict corporate defaults and control measure for the financial distress status of companies. The variables generally used are liquidity, profitability, leverage, solvency, and activity. Upon analyzing the above mentioned characteristics, the following five ratios are chosen to determine the Z-Score

The Z-score is calculated as follows,

$Z = 1.2\ X1 + 1.4\ X2 + 3.3\ X3 + 0.6\ X4 + 0.999\ X5$

X1 = working capital/total assets,

X2 = retained earnings/total assets,

X3 = earnings before interest and taxes/total assets,

X4 = market value equity/book value of total liabilities,

X5 = sales/total assets.

The Zone of discrimination of the scores are as follows,

$Z > 2.99$ -"Safe" Zones

$1.81 < Z < 2.99$ -"Grey" Zones

$Z < 1.81$ -"Distress" Zones

If a company's Z score is less than 1.81, the chances of that company going bankrupt within two years is high.

KMV-Merton distance to default model

The second model under consideration was the KMV-Merton distance to default model. The KMV-Merton default forecasting model produces a probability of default for each firm in thesample at any given point in time. The parameters required to calculate the distance to default were the market value of equity, book value of debt, equity volatility and risk-free rate. The annual market capitalization of the firm as on March 31st every year was used as the value of market capitalization. The total borrowings of the firm as provided in CMIE Prowess database was used as the value of debt. The annualized daily volatility of the firm was considered as the equity volatility. A risk-free rate of 7% was considered.

Excel solver was used to calculate the values from two non-linear equations which are given below:

$$Ve = Va * N(d1) - D * \exp(-rT) * N(d2) \qquad -- \qquad (1)$$

$$\sigma E = (Va/Ve) * N(d1) * \sigma A \qquad -- \qquad (2)$$

where d1 and d2 are given by:

$$d1: \{\ln(Va/D) + (r + \sigma\ 2A/2) * T\} / \sigma A * \sqrt{T}$$

d2 : d1 - $\sigma A * \sqrt{T}$

Once the above values were determined, the Distance to Default was calculated by the below formula:

Distance to Default = $\{\ln(Vo/D)+(\mu A - \sigma 2A/2)*T\}/\sigma A* \sqrt{T}$

Finally, the probability of default was calculated by using:

Probability of default = $1 - N(\{\ln(Vo/D)+(\mu A - \sigma 2A/2)*T\}/\sigma A* \sqrt{T})$

The optimization was run for companies and the probability of default was calculated.

RESULT AND ANALYSIS

Table 1- Z-Score Results

Company Name	Year of default	y	y-1	y-2	y-3	y-4	y-5	y-6	y-7
Agro Dutch Inds. Ltd.	2011	-0.24421	-0.52942	0.28770	-0.07464	0.86619	0.93632		
Alumeco India Extrusion	2009	2.83813	1.67767	2.60353	4.87390	8.69203			
Gujarat Themis Biosyn Ltd.	2007	0.94749	-1.08929	0.59434	1.12190	0.73999			
MarksansPharma Ltd.	2011	-1.29103	-0.87029	0.75613	0.85609	1.78100	1.45616	2.72246	2.98120
Mysore Paper Mills Ltd.	2012	NA	0.00392	0.00392	0.24719	1.59173	1.40421	1.39674	1.50634
Noble Explochem Ltd.	2010	0.29918	0.29918	-0.75577	-0.35668	-1.32026	1.22771	0.81136	0.81430
Oxford Industries Ltd.	2008	-1.12120	0.86409	0.86409	0.81059	0.26181	0.56931		
Pioneer Distilleries Ltd.	2012	-0.00878	-0.00878	-0.34881	0.56880	1.00447	1.90599	1.21858	1.17110
Shah Alloys Ltd.	2010	0.17182	0.70345	0.47758	0.58484	1.77145	1.74087	2.93279	2.81697

Y – Year of filing for bankruptcy. For e.g. **Agro Dutch Industries. Ltd.** filed for bankruptcy in 2011. Thus Y in this case is 2011.

The table provides names of the companies, followed by the year in which it filed for bankruptcy with BIFR and then the Z-score for the past years. Y denotes the year in which the company filed for bankruptcy. Thus Y for Agro Dutch is 2011 and Y-1 is 2010 and so on.

We see that as we approach the year of bankruptcy filing, the Z-score for the companies continue to fall. Of critical importance is the Z-score in the year "y-1". As mentioned earlier in the definition of the Altman Z-score model, the method helps us to figure out which companies are in distress and enables us to determine if there is a possibility that the company might file for bankruptcy in the next two.

As per the model, a company falling in the distress zone has a very high probability of filing for bankruptcy in the next two years. If we just concentrate on the Z-scores for the years "y-1" and "y-2", it is very evident that the company will file for bankruptcy by the third year. Results from the KMV Merton Distance to Default Model have been tabulated below.

Ve	Market capitalization
D	Book value of debt
Se	Equity volatility
Sa	Asset Volatility
Va	Market Value of Asset
DD	Distance to Default
P	Probability of Default

Table 2 Mysore Mills

Year	2012	2011	2010	2009	2008
Ve	61.23012	75.61622	92.14241	49.22188	87.74335
D	130.7124	194.205	124.11	152.385	135.985
Se	0.706038	0.630841	0.540335	0.618681	0.605999
Sa	0.246916	0.191698	0.240929	0.164469	0.251569
Va	182.3153	256.1172	207.7693	190.9153	214.2575
DD	1.507614	1.712833	2.308718	1.713967	1.959661
P	6.583%	4.337%	1.048%	4.327%	2.502%

Table 3 Noble Explochem

Year	2011	2010	2009	2008	2007
Ve	3.864848	8.537276	5.922255	22.07386	21.34319
D	17.525	17.445	16.905	23.765	20.375
Se	0.630841	0.540335	0.618681	0.605999	0.555991
Sa	0.126259	0.187943	0.174243	0.305082	0.295296
Va	20.15934	24.78656	21.64072	44.19362	40.32678
DD	1.600435	2.147388	1.731995	2.110344	2.401344
P	5.475%	1.588%	4.164%	1.741%	0.817%

Table 4 Shah Alloys

Year	2010	2009	2008	2007	2006
Ve	47.01916	23.3413	84.04056	167.6852	344.9721
D	648.975	503.05	424.795	371.135	243.175
Se	0.540335	0.618681	0.605999	0.555991	0.63006
Sa	0.040219	0.031281	0.110372	0.183975	0.382147
Va	651.8007	491.9667	479.2963	513.2857	571.3585
DD	1.828406	1.509922	1.672717	2.051063	2.227462
P	3.374%	6.553%	4.719%	2.013%	1.296%

Table 5 Pioneer Distilleries

Year	2012	2011	2010	2009	2008
Ve	44.04718	60.38078	47.70928	23.63398	74.12091
D	91.64	64.785	83.505	52.57	32.875
Se	0.59996	0.68858	0.611442	0.882378	0.539191
Sa	0.208149	0.350593	0.236569	0.320228	0.381582
Va	129.3019	120.5141	125.3787	71.55412	104.7697
DD	1.886246	1.794775	1.895642	1.021259	3.030148
P	2.963%	3.634%	2.900%	15.357%	0.122%

Table 6 Oxford Industries

Year	2010	2009	2008	2007	2006
Ve	7.839279	3.352049	3.916668	5.94335	7.577771
D	26.395	22.685	21.11	20.085	20.04
Se	0.86168	0.701883	0.49951	0.692821	0.604211
Sa	0.237217	0.104435	0.084123	0.176838	0.178864
Va	32.00138	24.41106	23.58937	24.56823	26.21861
DD	0.988413	1.320237	2.11013	1.446776	1.804403
P	16.148%	9.338%	1.742%	7.398%	3.558%

Table 7 Alumeco India Extrusion

Year	2010	2009	2008	2007	2006
Ve	13.69881	5.777055	21.69495	29.50513	18.4896
D	0.335	0.455	0.75	0.45	2.19
Se	0.74283	0.698122	0.876365	0.643669	0.654344
Sa	0.725098	0.647152	0.847081	0.634644	0.589275
Va	14.03381	6.232055	22.44495	29.92471	20.5315
DD	4.885144	3.828716	3.671401	6.406438	3.622137
p	0.000%	0.006%	0.012%	0.000%	0.015%

Table 8 Agro Dutch

Year	2011	2010	2009	2008	2007	2006
Ve	51.37493	122.1282	44.9946	86.42988	81.47895	104.1149
D	214.34	261.98	314.865	293.66	212.29	156.36
Se	0.641623	0.612253	0.585196	0.683867	0.533661	0.511283
Sa	0.137493	0.208762	0.080838	0.173333	0.157589	0.214007
Va	250.5833	365.7681	338.1599	358.8554	279.2275	249.8266
DD	1.576624	1.82955	1.708448	1.473898	2.104559	2.409766
P	5.74%	3.37%	4.38%	7.03%	1.77%	0.007981

Table 9 Gujarat Themis Biosyn

Year	2006	2007	2008
Ve	15.602	11.6	7.6444
D	11.745	13.835	7.765
Se	0.612126	0.50107	0.655293
Sa	0.36141	0.237869	0.340897
Va	26.53872	24.49515	14.86243
DD	2.268531	2.576978	1.939307
P	1.16%	0.50%	2.62%

Table10 Marksans Pharma

Year	2011	2010	2009	2008	2007	2006
Ve	179.4899	152.2722	682.2824	1877.656	816.7493	60.68819
D	232	242.88	217.48	188.95	182.88	181.58
Se	0.615675	0.602775	0.557017	0.655293	0.50107	0.612126
Sa	0.28279	0.246009	0.429462	0.599086	0.414529	0.166478
Va	395.32	378.2499	885.0457	2053.83	987.2651	229.5578
DD	1.990781	1.962238	3.216378	3.799999	4.02913	1.74558
P	2.33%	2.49%	0.06%	0.01%	0.00%	4.04%

FINDINGS OF THE STUDY:

Overall the Altman Z-score model is able to predict bankruptcy filing efficiently for the Indian Manufacturing sector as compared to the KMV Merton Distance to Default model.

The study shows that Altman Z-score is able to predict that a firm might get into state of distress at least two years prior to the situation occurring. KMV Merton does not have a fixed period where in it can with certainty state that a firm will get into financial distress. This is due to its dependency on the volatility of equity which is not high for Indian firms as they are traded thinly.

Companies which have Z-scores of 0.8 or less for two consecutive years have a very high probability of filing for bankruptcy in the third or fourth year. 7 out of 9 companies (77.77%) in our study had Z-scores less than 0.8 for two years and filed for bankruptcy within the next two years.

The zones of discrimination for the Z-score appear to be different for the Indian manufacturing sector as compared to original model. The zones can be defined as below:

$Z > 2.0$ - "Safe" Zones

$0.8 < Z < 2.0$ - "Grey" Zones

$Z < 0.8$ - "Distress" Zones

The value of equity volatility is expected to increase tremendously in the horizon in which a company defaults. This is primarily due to a panic in the market. However in the Indian context most of the companies which file for BIFR are thinly traded. Thus, the volatility of the stocks does not show a large shift in the event of filing.

Since the KMV model is largely dependent on market parameters for its output, it is vulnerable to type I errors. An increased volatility due to an overall panic in the market and industry as a whole could produce misleading results.

From an industrial perspective the KMV Merton is quite cumbersome to apply and hold as a benchmark measure of a company's credit worthiness. This is due to the restriction of the model in its dependency on the equity volatility. A financial institution is more likely to develop a logit model based on historical data and use it rather than apply a complex model such as the KMV. Thus, a Z-score developed on Indian data is more likely to be used by financial institutions to evaluate credit worthiness.

DISCUSSION

Implications of this study

This study is to basically understand the two bankruptcy prediction models namely KMV Merton and Altman Z-score which are used across industries to predict the health of firms and their distress levels. The study focused on the Indian Manufacturing sector alone and is probably one of the first studies to analyse the effectiveness of bankruptcy prediction models from an Indian perspective. It also has tried to provide the answer to the question of which amongst the two models is more suitable for the Indian Manufacturing sector.

The study has concluded that a logit model such as the Z-score model is more appropriate in the Indian context than the KMV Merton model. The primary reason for this conclusion stems from the limitations of the KMV model with respect to its dependency on the equity volatility. It was observed that most of the companies which filed under SICA with BIFR were very thinly traded on the stock exchange. Thus extremely less volatility of the stocks affected the ability of the KMV Merton model to predict bankruptcy.

On the other hand, logit models were more effective in terms of their simplicity and extensibility. A model could be built based on the historic financial data which is easier to interpret and use. The Altman Z-score model had a superior hit rate as compared to the KMV Merton model.

Secondly, even though the KMV model yields a probability of default as a result, the complexity of the method limits its use by institutions. Practically, a financial institution would prefer to have a ‘binary’ measure i.e whether the company is good or bad which is provided by the Altman Z-score method.

Extension of Literature

This is one of the few studies focussed on the Indian business arena, specifically the Indian Manufacturing sector. Also, there is not much literature on how the two models fare against each other when used across companies in India.

Mostly, the KMV Merton model was used to calculate the probability of default of companies which were heavily traded on the stock markets.

This study has applied the KMV model to thinly traded companies as from an Indian perspective these are companies which usually are in line for filing bankruptcy. The study has concluded that the model has a major limitation in the Indian context.

Limitations of Study

The study is applied on data as of March 31st XXXX, i.e. end of the financial year. The observation was that in a few cases of bankruptcy filing, cash been injected into the firm within months of it filing for bankruptcy. This caused the results to change abnormally specifically for the Altman Z-score model as it depends on the working capital and total assets which change with any change in the cash position of the firm.

The study is limited to only 9 companies which filed for bankruptcy and not a larger sample. Moreover the period of study is from 2007 to 2012 which was a period of lean trading in markets due to the financial crisis. Albeit it is a small factor which could have affected the outcome of the study.

How can this study be extended?

The study uses the financial data for 9 companies which had filed for bankruptcy. A study using a larger number of companies shall bring out more interesting facts regarding the bankruptcy prediction models and their use in the India Business Arena.

Moreover, the study focussed more on the manufacturing sector in India. A larger comprehensive study covering different sectors can be done to understand the real importance of the prediction models and find out if the results change from industry to industry.

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