MODELING CREDIT RISK IN INDIA: $\hat{Z}_{\text{India}}$

The Z-Score Model developed for Indian Companies

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ABSTRACT

Recognizing the success of adapting the Altman Z-Score model (1968) to different subsets of companies such as SMEs, Emerging Market companies, private companies, and companies subject to extraordinary administration, we develop a distress prediction model specifically for Indian companies. A data set of publically traded companies in India is collected and various financial ratios are analyzed. The most predictive of these ratios are selected by running multiple logistic regressions. Validation of the model is conducted by running the ratios from the model on the entire data set leaving one company each time, a method provided by Lachenbruch (1967). As per validation, the prediction power of the model has 89.09% accuracy.

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I. INTRODUCTION

Credit risk models have a wide range of applicability. From the company's perspective, the more accurate the assessment of its risk, the more accurately its risk will be priced in terms of interest rates and size of loans and advances. Bank capital requirements can also be affected by different risk models. A previous study showed that building a model specifically for the SMEs was more effective than a generic model and therefore lowered Basel II capital requirements for SMEs (Altman & Sabato 2007). From the bank's perspective, a model that is accurate and can be applied with relative ease helps to take quick yet informed decisions when dealing with a large number of clients. It helps them quantify and manage risk across different products and geographies.

Considering the success in adapting the generic models in many previous cases, we aim at developing a specific model for India so that we yield better prediction accuracy than the generic model, which for our purposes is the Z''-Score model. Our goal is to find a set of ratios that has the most predictive power of a company's credit worthiness. We therefore analyze 15 financial ratios of 55 publicly traded Indian companies and try to narrow down to a few ratios. While our output gives a probability of default, the use of the model can be seen more as identifying whether a company seems more similar to one that defaulted a year later or one that remained healthy.

The Z-Score gained popularity due to its accuracy and ease of applicability. Seeking these two goals, we furthered the model for companies in India to see if accounting for country-specific characteristics by choice of data, yields a more accurate model.

Lehmann (2003) has shown that using qualitative variables, i.e. subjective judgments of credit analysts, improves prediction quality. Our model does not account for any qualitative variables and therefore can be further improved by incorporating such input.

II. Review of Relevant Literature

II. a. *Generic Models & India-Specific Model*

One of the most well-known distress prediction models, the Altman Z-Score (1968), uses four financial statement ratios and a stock market variable. It was developed with 66 American manufacturing companies, with an equal number of defaulted and non-defaulted firms. The Z'-Score was a later adaptation of the original model to private companies (1983). Extending the model for non-US, non-manufacturers and emerging markets, the Z''-Score was introduced in 1995, by analyzing a sample of Mexican companies. The ratios of Z'' were the same as the Z', excluding the Asset Turnover ratio because of its sensitivity to industry and country.

Tables 1,2,3 outline how the score was calculated in each model.

Z =		
	+1.2	Working Capital / Total Assets
	+1.4	Retained Earnings / Total Assets
	+3.3	EBIT / Total Assets
	+0.6	Market Value Equity / Book Value of Total Debt
	+0.999	Sales / Total Assets

TABLE 1 (Source: Altman, 1968)

Z' =		
	+0.717	Working Capital / Total Assets
	+ 0.847	Retained Earnings / Total Assets
	+3.107	EBIT / Total Assets

+0.420	Book Value Equity / Total Liabilities
+0.998	Sales / Total Assets

TABLE 2 (Source: Altman, 1983)

Z'' =

+6.56	Working Capital / Total Assets
+ 3.26	Retained Earnings / Total Assets
+6.72	EBIT / Total Assets
+1.05	Book Value Equity / Total Liabilities

TABLE 3 (Source: Altman, Hartzell & Peck, 1995)

An India-specific model was developed by Bhatia (1988) for identifying 'sick' companies, referring to those companies that continue to operate despite incurring losses for 2 years, or has four successive defaults on its debt service obligations, or taxes in arrears for 1-2 years. A sample of 18 sick and 18 healthy companies in the period 1976-95 was used, and seven ratios were shortlisted. The Type I accuracy was 87.1% and Type II error was 86.6%. Validation on a hold out sample of 20 healthy and 28 sick companies was performed and the results verified the efficacy of the model. Table 4 lists the coefficients of the discriminant analysis by Bhatia.

Y =

+6.56	Current Ratio
+ 3.26	Stock of Finished Goods / Sales
+6.72	Profit After Tax / Net Worth
+1.05	Interest / Value of Output
+6.56	Cash Flow / Total Debt
+ 3.26	Working Capital Management Ratio
+6.72	Sales / Total Assets

TABLE 4 (Source: Bhatia, U. 1988)

II. b. *Choice of Regression*

The seminal works in the field of default prediction studies were those by Beaver (1967) and Altman (1968). Altman had used the Multiple Discriminant Analysis (MDA) technique for creating the Z-Score, and for long, MDA was the general tool used in default prediction studies. After many scholars pointed out two drawbacks of the method- 1) MDA assumes that the independent variables are multivariate normally distributed 2) Variance-Covariance matrices are equal across defaulted and non-defaulted firms (McLeay and Omar 2000), Ohlson (1980) for the first time used a logit regression for default prediction. While his model had a lower classification accuracy than Altman's Z and Z'', the reasons for using a logit model in default prediction were powerful.

III. MODEL DEVELOPMENT

III. a. *Data Set*

Our analysis uses financial data from 55 companies of which 21 are defaulted companies and 34 are non-defaulted. While the early models used equal number of defaulted and non-defaulted firms, in later studies, the number of defaulted companies in the set was chosen so that the prior probability input was the same as the expected average default rate (Altman & Sabato 2006). For our set, the prior probability is 38%, which is considerably higher than 5.3%, the overall default rate for CRISIL-rated firms (includes approximately 6400 Indian firms). Moreover, since we could *match* at most 34 non-defaulted companies to the 21 defaulted companies, we kept 55 companies in our set.

The companies were identified using two resources, Fitch's Update of Indian FCCB Redemption for FY2013 and cases registered with the Board for Industrial & Financial Reconstruction (BIFR India). The financial data was collected from company filings with the Bombay Stock Exchange, India. The defaults in the data set occurred between 2009 and 2012. The set contains companies from the following industries- Pharmaceuticals, Construction & Contracting, Telecom Equipment, Telecom Services, Coke Manufacturing, Computer Software, Computer Hardware, Textiles, Edible Oils and Solvents, Ceramics, Sponge Iron, Mining & Minerals, and Sugar.

The non-defaults were matched with the defaulted companies with respect to year of default, industry, and either size of sales or size of total assets in order to establish comparability. The size of sales for the companies in the set falls in the range of 15 million USD to 1.5 billion USD. All financial ratios were collected from a year prior to default, so the model developed is a 1-year default prediction model. The y variable was taken to be 0 for non-defaults and 1 for defaulted companies.

III. b. *Selection of Variables*

While there are a large number of ratios to choose from, we collected 15 financial ratios. These ratios were collected across five categories – Leverage, Liquidity, Profitability, Activity and Coverage. The different categories were selected in order to capture different measures of a company's operations as explained in Altman's paper. Within each category, some of the ratios are the ones developed by Altman for his original Z-Score model, and others are common ratios used in the general discipline of Accounting.

A list of the ratios used in the analysis is presented in Table 5.

Ratio Category	Variables Used
Leverage	1. Long Term Debt / Book Value Equity 2. Debt / EBITDA 3. Short Term Debt / Book Value Equity
Liquidity	1. Current Assets / Current Liabilities 2. Cash / Total Assets 3. Working Capital / Total Assets
Profitability	1. Gross Profit / Sales 2. EBITDA / Total Assets 3. Net Income / Total Assets 4. Retained Earnings / Total Assets
Activity	1. Sales / Total Assets 2. Accounts Receivable / Sales * 365 3. Accounts Payable / Cost of Goods Sold * 365
Coverage	1. EBITDA / Interest Expenses 2. EBIT / Interest Expenses

TABLE 5

III. c. *Logistic Regression & Results*

After running multiple combinations of different number of variables and using forward and backward stepwise logistic regression, we developed the model shown in Table 6. The signs of the coefficients are consistent with our expectations; we expect higher Short Term Debt / Equity, lower EBITDA / Total Assets and lower Reserves / Total Assets to predict a higher chance of default.

Log (pd / (1-pd)) =		
	+2.805	
	+ 0.293	Short Term Debt / Book Value Equity
	-19.869	EBITDA / Total Assets
	-5.473	Retained Earnings / Total Assets

TABLE 6

The p-values of the coefficients are lower than .035 indicating that there is strong statistical evidence of a relation between the variables and the default event. Table 7 gives the p-values.

VARIABLE	COEFFICIENT	STD ERROR OF COEFF	Z VALUE	P VALUE
Constant	2.80505	1.25367	2.24	0.025
Short Term Debt / BV Equity	0.29306	0.12726	2.30	0.021
EBITDA / Total Assets	-19.8693	9.06304	-2.19	0.028
Retained Earnings / Total Assets	-5.47297	2.57488	-2.13	0.034

TABLE 7

The *Deviance test*, an equivalent of the sum of squares of residuals in Ordinary Least Squares for logistic regression, is also statistically significant with a p-value of .98. A low p-value for the Deviance test indicates that the predicted probabilities deviate from the observed probabilities in a manner that the binomial does not predict. The *Log-Likelihood test*, an equivalent of the F test, has a p-value of 0 up to three significant digits, providing evidence that there exists a significantly strong relation between the selected variables and the default event.

With regard to misclassification rates, for a cutoff of 0.5, the *Type I Error*, cases when the model predicts a non-default when the firm defaulted is 9.52% and the *Type II Error*, cases when the model predicts a default when the firm in fact did not default, is 8.82%.

III. d. *Validation Results*

Given the size of the sample we found it appropriate to use Lachenbruch's method of leaving-one-out validation. As per validation results, we found that the model has an accuracy of 89.09%. The 10.91% error comes from 3 Type I and 3 Type II errors in the sample of 55 companies, where we used the same cutoff score of 0.5.

III. e. *Running Z'' on the Sample*

After running the ratios from the Z'' model, we get a good model that works well on the data set and gives statistically significant results. Table 8 shows the coefficients along with the p values (all < 0.05) obtained by regressing the Z'' ratios on the India sample.

VARIABLE	COEFFICIENT	STD ERROR OF COEFF	Z VALUE	P VALUE
Constant	4.79226	2.11856	2.26	0.024
Working Capital / Total Assets	5.99765	3.03577	1.98	0.048
Retained Earnings / Total Assets	-7.39158	2.81348	-2.63	0.009
EBIT / Total Assets	-30.2255	12.8587	-2.35	0.019
Book Value Equity / Total Liabilities	-16.1025	7.83849	-2.05	0.040

TABLE 8

The *Deviance* Test for this model is significant at a p-value of .97. The sign of the Working Capital / Total Assets is of concern since it is contrary to expectation (i.e. a higher WC/TA ratio should give lower probability of default); the signs of other variables are consistent. For calculating the misclassification rates, we chose a cutoff of 0.09 which gave a Type I error of 19% and a Type II error of 8.82%.

IV. Conclusion

Developing the Z-Score for Indian companies gives a statistically significant model. The validation of the model suggests 89.09% accuracy. The model can be further improved with a different set of potential variables and also by the inclusion of qualitative variables.

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