RESEARCH

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Predictive Power of Financial Risk Factors: An Empirical Analysis of Default Companies

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Executive Summary

This paper provides empirical evidence on the significance of financial risk factors in predicting default companies. Traditionally, credit decision process is built on accounting ratios derived from financial statements of the borrower. Combining various ratios through application of multivariate statistical techniques and testing their predictive power has been popular in credit risk quantification. Altman's Z-score model is the most acceptable model in this category.

In this paper, three forms of Z-score models are applied:

- The first equation is developed by surveying the internal credit rating models of the Indian banks and the ratios selected are: current ratio, debt-equity ratio, and operating margin.
- The second equation is similar to that of Altman's (1968) original equation with a slight modification: instead of debt-to-market value of equity, debt-to-book value of equity is considered. The other three ratios of the second equation are working capital to total assets, retained earnings to total assets, and earnings before interest and taxes to total assets.
- The third equation is called as Altman, Hartzell and Peck's 'Emerging Market Score Model.' Except the asset turnover ratio, all the ratios of the second equation are considered.

In all the three equations, the coefficients are estimated by using the development sample of 112 companies.

The dominant variables discriminating the default companies from non-default ones are: current ratio, debt-equity ratio, operating margin, working capital to total assets, earnings before interest and tax to total assets, net worth to debt, and asset-turnover ratio. The classification accuracy of the second and the third equations is 82 per cent while that of the first equation is only 57 per cent. It implies that the most widely used two ratios — current ratio and debt-equity ratio — are relatively poor in predicting the default companies. Similarly, the ROC accuracy ratio is the highest for Altman's equation whereas the variables considered in internal credit rating models of banks is having a relatively low accuracy ratio.

To test the ability of the model in identifying the defaulting companies correctly, an unbiased diagnostic test of the model is conducted on two separate sets of defaulted firms. The results reveal the following :

- The Altman's model is capable of predicting default in most of the sample companies.
- The hold-out sample accuracy results show that the selected variables are capable of predicting default.
- The analysis shows that the financial risk factors being considered by banks in their internal rating models are not very effective in comparison to other two models in discriminating the firms into default and non-default categories.

Banks can map the internal ratings with the Z-scores and scale this up to assign various credit ratings. By arriving at the coefficients on the basis of their own database, banks can develop Z-score calculators for various segments of borrowers.

KEY WORDS

Credit Risk

Default Prediction

Financial Risk Factors

Multiple Discriminant Analysis

Non-performing Assets

The New Basel Capital Accord (popularly known as Basel-II) is one of the main agenda before the commercial banks in India and across the world. The main focus of Basel-II is on the estimation of economic capital requirements by using the internal rating models against the current practice of deciding the capital requirements through the standardized approach where risk weights are determined by the regulators. Basel-II suggests a menu of approaches for estimation of capital requirements for three generic types of risks: credit risk, market risk, and operational risk. Of these, credit risk is more prominent and banks are required to maintain a huge proportion of capital against unexpected losses arising from credit risk. Under the New Accord (Basel Committee on Banking Supervision, 2004), banks are required to estimate credit risk either by following the Standardized approach or by adopting Internal Ratings Based (IRB) approach. While the Standardized approach links the risk weights with the external credit ratings of the credit exposure, in IRB approach, the risk weight of a credit exposure is the function of probability of default (PD) and loss given default (LGD). These two parameters are generated out of internal data of the bank and the quality of these two parameters is very important in making the bank's capital requirements more risk-sensitive.

The literature on credit risk primarily focuses on three types of approaches. In the first approach, a credit scoring model is propounded by Altman (1968) which is a sophisticated way of combining various financial (or accounting) ratios by applying multivariate statistical techniques and expressing it as a single measure of decision-making. Altman's approach is considered by several researchers in different countries and its significance in improving the quality of the credit decision process has been empirically suggested. On the other hand, Merton's (1974) approach assumes that the stockholders hold a put option over the market value of assets of a firm and if the market value of equity is below the outstanding debt amount, then that firm defaults on payment of debt. The default probability is derived out of the value of the put option. KMV[1] has slightly modified this approach and developed a proprietary model for estimating PD which is called expected default frequency (EDF). The prime risk factors under this approach are market value of assets and volatility of assets. The third approach is the mortality approach where PD is estimated on the historical data of survival rate of a loan or bond among similar rated bonds. A modified version of this approach is transformed as 'credit risk plus,' a vendor-based model. The new approaches—popularly called as 'credit value at risk models'— are capable of generating PD which is an essential input requirement for the estimation of risk capital requirements under the Basel-II environment. Although these models differ considerably from the traditional scoring approaches, their accuracy is more dependent on the underlying strength of a company which is reflected in the financial analysis. If the primary credit scoring model is sound and based on comprehensive and representative data, then the chances of accuracy of the advanced models would be more and they can, therefore, be used for the estimation of capital requirements (Altman, 2002b). Furthermore, the New Basel Accord has clearly laid down certain minimum requirements for adopting internal ratings approach, one among them being the identification of financial risk factors to be considered by a rating model and the assignment of appropriate weights to these financial risk factors. Whether it is adopting sophisticated credit risk models or improving the quality of internal rating models, financial risk factors considered by the internal rating models have greater relevance in Basel-II environment.

It is against this background that this paper attempts to test the predictive power of the financial risk factors being considered by the internal credit rating models of the Indian banks for rating the borrowers. In addition, it provides evidence on Altman's two empirically validated credit scoring models. It applies three forms of multiple discriminant analysis technique on a sample of default and non-default companies financed by the Indian commercial banks and also tests the predictive ability of models on a separate hold-out sample of default loans. However, this paper does not argue on the superiority of one set of accounting ratios over the other but emphasizes on the importance of a careful selection of accounting ratios in designing the internal rating models.

REVIEW OF RELATED LITERATURE

Traditionally, the credit decision process is built on an analysis of financial statements of the borrower. A credit scoring model rates the creditworthiness of the borrower on the strength of accounting ratios and other information. Accounting ratios measuring liquidity, profitabil-

[1] www.kmvmoodys.com

ity, and solvency are the most significant indicators of financial risk. Thus, accounting ratios discriminate between borrowers who may default and those who may not. Statistical techniques are applied to combine various ratios and to produce a single measure that discriminates between default and non-default companies. Multivariate statistical techniques have gained popularity in testing the predictive power of these accounting ratios. It is implied that failing firms exhibit ratios and financial trends that are very different from those companies that are financially sound. Altman's (1968, 1993) Z-score model is the most popular model in this category. It has endured to this day and has been applied by banks in their credit decision processes both in the developed and the emerging markets. Mester's (1997) study shows that 97 per cent of the US banks use credit scoring to approve credit card applications and 70 per cent of the banks use credit scoring in their small business lending.

Several empirical studies were conducted on the lines of Altman's Z-score, the popular ones being predicting bankruptcy of private firms (Altman, 1993), non-manufacturers' Z-score model, and the Emerging Markets Score of Altman, Hartzell and Peck (1995). In all these cases, the basic Score model was suitably modified. Altman and Narayanan (1997) present a review on international studies conducted in 22 countries in which half of them are on developing countries. The major conclusion of all these studies is that the multivariate techniques such as multiple discriminant analysis, logistic regression, and probit models built on the basis of accounting ratios are effective tools for predicting default companies. In many cases, accounting ratio-based credit scoring models have shown that they can perform quite well over many different time periods and across many different countries (Altman and Narayanan, 1997). Among them, multiple discriminant analysis is found to be a superior and a more acceptable technique. In this paper, the multiple discriminant analysis technique is applied in three different forms to test the power of financial risk factors in predicting default.

A few experiments were conducted in the Indian context as well to assess the predictive power of accounting ratios. Gupta's (1983) study on a sample of Indian companies financed by ICICI concludes that certain cash flow coverage ratios are better indicators of corporate sickness. The study has not favoured the application of either multiple discriminant analysis or any other statistical model. Bhatia (1988) and Sahoo, Mishra and Soothpathy (1996) examine the predictive power of accounting ratios on a sample of sick and non-sick companies by applying the multiple discriminant analysis technique. In both the studies, the selected accounting ratios are effective in predicting sickness with high level of accuracy. But, these studies have considered a select sample of sick companies as defined by the Sick Industries Companies Act (SICA) and not the firms under banking definition of default. The objective of SICA is neither recognition of default companies nor estimation of expected loan losses and, therefore, the coefficients obtained on the sample of sick companies may not be useful in predicting the default companies and arriving at the probability of default. Chaudhury (1999) uses the banking definition of default and applies the discriminant analysis on a sample of 270 companies financed by ICICI. This is the first study which has used the banking definition of default and Z-scores are mapped with the internal credit ratings awarded by ICICI. However, the erstwhile ICICI is more exposed to term lending and, therefore, the sample companies may not represent a commercial bank's loan portfolio.

This study is different from the earlier studies mainly in two aspects: first, the financial risk factors are selected by surveying the internal credit rating models of the Indian banks; and second, the default companies are selected by following the banking definition of default as per the default database of five largest Indian banks. The coefficients arrived at on this development sample are validated on two separate sets of hold-out samples. On the methodological side, this paper uses the Recovery Operating Characteristic (ROC) curve in addition to accuracy ratio which is a more accurate statistical technique.

PROBLEMS OF DEFAULT PREDICTION

Recognition of Default in the Indian Context

The prime factor for the absence of any strong empirical evidence on credit risk quantification in the Indian market is the lack of uniformity in the recognition of default companies. The early steps of identification of bankruptcy in India can be traced back to 1985 when, for the first time, the Government of India brought an enactment, The Sick Industries Companies (Special Provisions) Act, 1985 (SICA) and set up the Board for Industrial and Financial Reconstruction (BIFR) for the revival of sick units. According to this Act, the main criteria for identifying a sick unit are the age of the company which should not be less than five years after its incorporation and the accumulated losses of the company which should be equal to or more than its net worth. The purpose of identification of sickness is to suggest rehabilitation packages to revive the sick units. The Act had not considered non-payment of debt and interest obligations as an event of credit risk.

In 1985, the Reserve Bank of India (RBI) introduced a comprehensive system of loan categorization called the health code system. This categorization provided information regarding the health of individual advances on certain criteria and the quality of credit portfolio was expressed on a scale of eight categories. Such information was expected to be of immense use to bank management for control purposes. Subsequently, in 1989, RBI advised the commercial banks to recognize income on realization basis only up to five categories of loans out of the eight categories. With this measure, the concept of default recognition was introduced for the first time in India. Although this system was useful for loan monitoring, the absence of transparent, objective, and uniform yardsticks for measurement of problematic loans was a major weakness. As the reporting and disclosure was limited to regulatory purpose, there was no publicly available data on bad loans.

Following the recommendations of the Narasimham Committee (RBI, 1991), RBI introduced prudential norms on income recognition, asset classification, and provisioning with effect from March 1993. These regulations put in place an objective criteria for identification of default loans or non-performing assets (NPAs). A loan on which the interest or installment of principal remained due for a specific period of time[2] was recognized as NPA. Subsequently, RBI implemented the internationally accepted 90 day delinquency norm (with effect from March 31, 2004). With the change in norms, some amount of sophistication was brought in gradually for the identification of default loans. In fact, a lack of consistency in recognition of default loan has been a major problem in developing the database of such loans and has thus acted as a major limitation for conducting any serious empirical study on default loans in the Indian context.

Dissemination of Default Information

The second most important limiting factor for lack of a serious empirical study on default prediction is non-availability of information on default companies. As per the Government of India instructions, since 1994, RBI has been collecting information on borrowers who have defaulted in their dues to banks and financial institutions for an amount above Rs. 10 million and circulating it to banks and financial institutions for their confidential usage. A new entity, Credit Information Bureau (India) Limited (CIBIL), was incorporated in January 2001 with the objective of collecting credit related information regarding commercial and consumer borrowers and maintaining the credit default data. RBI has authorized CIBIL to disseminate information on the defaulters of above Rs. 10 million with effect from March 31, 2003. Therefore, the only data source available is the defaulters' list of Rs. 10 million and above on which the banks have filed legal suits for recovery of loans since March 31, 2002. This contains only the names of the default companies and not financial data. This list is used in this study.

DATA AND METHODOLOGY

This study considers the defaulters' list of five largest public sector banks: State Bank of India, Bank of India, Central Bank of India, Bank of Baroda, and Punjab National Bank as disclosed by CIBIL.[3] The total number of defaulters of these five banks as on December 31, 2002 was 2,047 out of which the private limited companies and non-banking finance companies (NBFCs) are excluded, the net figure being 1,297. A thorough scanning of the *Capital Line*[4] database reveals that financial data are available only for 56 companies for the years 2001 and 2000. The database also indicates that there are 4,507 non-defaulting companies being financed by these five largest banks. Out of these, 56 companies are selected by adopting the stratified sampling procedure, stratified on the basis of asset size and industry category (see Table 1 for asset size and Table 2 for industry category). Thus, a total of 112 companies are considered in this study. This sample is used for the development of coefficients and hence is referred to as the development sample in the study. To test the predictive power of the financial

[2] The specific period of time for the year 1993 was four quarters, for 1994 three quarters, for 1995 two quarters, and 2004 onwards one quarter.

[3] www.cibil.com

[4] *Capital Line* is a widely used corporate database. It provides accounting data of major corporate units in India.

Table 1: Asset Size of Select Default and Non-default Companies

Asset Size (Rs. in Million*)	No. of Non-default Companies	No. of Default Companies
1-100	37	37
101-200	07	04
201-300	03	04
301-400	01	04
401-500	03	00
501-600	02	03
601-700	01	00
701-800	01	00
801- Above	01	04

*10 million = 1 crore.

Table 2: Industry-wise Categorization of Sample Companies

Industry	No. of Default Companies	No. of Non-Default Companies
Aquaculture	02	01
Breweries and distilleries	03	03
Ceramics—Tiles	01	00
Chemical	10	12
Domestic appliances	01	00
Dyes and pigments	01	01
Engineering	03	02
Entertainment	01	00
Food	04	05
Mining/Minerals/Metals	01	01
Miscellaneous	05	04
Packaging	01	00
Pharmaceuticals	02	03
Plastic	02	01
Refineries	01	01
Rubber	01	00
Shipping	01	01
Steel	01	01
Sugar	01	00
Textile	14	13
Cement	00	01
Electronic-consumables	00	01
Glass and glass products	00	01
Paper	00	01
Petrochemical	00	02
Software—Medium/Small	00	01
Total	**56**	**56**

risk factors one year prior to default and two years prior to default, the financial data reported as on March 31, 2001 and March 31, 2000 respectively are considered.

To test the validity of the model, two separate independent samples are considered which are called hold-out samples. The first hold-out sample is constructed by selecting 26 default companies of all the banks from the defaulters' list of CIBIL as on December 31, 2003, and the second hold-out sample consists of 27 NPAs of the largest public sector bank as on March 31, 2003. Financial data for both the samples are obtained from *Capital Line*. It is assumed that the sample default companies were recognized as NPAs for the first time on March 31, 2002 and that the banks had initiated the legal process on December 31, 2002. Thus, the development sample consists of NPAs of March 2002 while the hold-out samples include NPAs as on March 2003.

Model Description

Multiple discriminant analysis is a statistical technique used to classify an observation into one of the several *a priori* groups dependent on certain variables of individual characteristics. It is used primarily to classify or make predictions where the dependent variable appears in a qualitative form. In this paper, the analysis is concerned with two groups consisting of default and non-default firms. The analysis is transformed into its simplest form; the discriminant function of the firm transfers the individual variables to a single discriminant score, popularly called as 'Z' value to be expressed as:

$$Z = \alpha+b_1x_1+ b_2x_2+ \ldots.b_nx_n$$

where,

Z is the latent variable formed by the discriminant function

α is a constant term

$b_1, b_2 \ldots.b_n$ are discriminant coefficients

$x_1, x_2, \ldots.x_n$ are independent variables.

The discriminant function coefficients are partial coefficients reflecting the unique contribution of each variable to the classification of the criterion variable. In this paper, Fisher's discriminant coefficients are used to assess the relative classifying importance of the independent variables—lower the discriminant score, greater the firm's default potential.

While using several financial variables, some accounting ratios have a high degree of correlation or collinearity with each other. According to Altman (2002a), who extensively worked on these models, multicollinearity or correlation is not a serious problem in discriminant analysis; it usually motivates careful selection of the predictive variables. Further, it has the advantage of potentially yielding a model with a relatively small number of measurements which convey a great deal of information. This information might indicate the differences among groups but the more important aspect of the analysis is whether the differences are significant or not.

This study uses three models which are as follows:

$$Z = \alpha_1 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 \quad (1)$$

$$Z = \alpha_2 + b_5x_5 + b_6x_6 + b_7x_7 + b_8x_8 + b_9x_9 \quad (2)$$

$$Z = \alpha_3 + b_{10}x_5 + b_{11}x_6 + b_{12}x_8 + b_{13}x_9 \quad (3)$$

where,

b_1, b_2 b_3....b_n are coefficients

x_1 is current ratio

x_2 is interest coverage ratio

x_3 is debt-equity ratio

x_4 is operating margin

x_5 is working capital to total assets

x_6 is retained earnings to total assets

x_7 is earnings before interest and taxes to total assets

x_8 is net worth to total debt

x_9 is sales to assets.

The first equation was developed by surveying the internal ratings models of the Indian banks (Jayadev, 2006). To understand the components of these models, a questionnaire was administered to various banks out of which 19 banks had responded. Furthermore, six banks had shared the documents on credit rating models. The data collected in this process show that a wide range of risk parameters is being used in assessing the financial risk of the borrowers (Table 3). Almost all the surveyed banks are considering current ratio as the prime variable for rating the borrowers. The second most prominent ratio is debt-equity ratio which explains the relationship between the total outstanding liabilities and equity. Among the profitability ratios, the net profit margin, operating profit margin, and return on capital employed are the important ratios. The exact definition of these ratios varies from bank to bank. For example, certain banks may consider term loan installments due within one year as part of the current liability for the purpose of computing current ratio whereas some other banks may not include this item in current liabilities. Most of the Asian banks (Table 4) also consider similar accounting ratios in their credit rating models.

Table 3: Financial Risk Factors Considered by Internal Credit Rating Models

Financial Risk factors	No. of Banks
Current ratio	16
Debt-equity ratio (total liability to total net worth)	16
Growth rate or trend in sales	10
Growth rate or trend in net profits	11
Net profit margin	14
Gross profit margin	10
Operating profit	08
Operating leverage	05
Interest coverage ratio	13
Debt-service coverage ratio	14
Cash flows	09
Financial leverage	06
Asset turnover ratio	09
Working capital turnover ratio	07
Return on net worth	06
Return on capital employed	13
Return on assets	05
Stock turnover ratio	12
Debtors turnover ratio	11
Asset coverage ratio	06
Bank borrowings to sales	03
Any other (trends in performance, security coverage)	02

Source: Survey conducted by the author.

The second equation is similar to that of Altman's (1968) original equation. This model has wide empirical validity till date and has been tested in different markets. The only difference is in the fourth variable where the numerator market value of equity is substituted with the book value of equity or net worth. Due to the presence

Table 4: Benchmarking of Financial Criteria Used by Asian Banks

Criteria	US Bank in Asian Market	Asian Bank 1	Asian Bank 2	Asian Bank 3	Asian Bank 4
Liquidity	Quick ratio	Current ratio		Current ratio	Current/Quick ratio
Leverage	Debt-to-equity ratio	Debt-to-equity	Debt-to-equity	Debt-to-equity	Equity-to-debt
Cash flow interest cover	EBITDA to total debt	Cash flow/Total debt Cash flow/Debt and payables Cash flow/Sales	EBITDA to interest expense	EBITDA to interest expense	Net working capital to interest EBITDA to interest expense
Profitability	Pre-tax return on average capital	ROI, Net income/Assets, Gross profit margin	ROAE, Net profit margin	ROAE, Net profit margin	ROE, Net income/ Sales
Efficiency		Assets turnover Inventory/Sales Labour, Production Sales growth rate	Inventory/Sales	Inventory/Sales Receivables/Sales	
Growth		Equity growth rate Sales growth rate			
Size	Capitalization				Sales

Source: Scott (2003).

of several asymmetries in the Indian equity market, the book value of equity is considered as more appropriate from the banker's viewpoint rather than the market value of equity. This model is popularly called as Altman's (2002a) private firm model.

The third equation is called as Altman, Hartzell and Peck's (1995) Emerging Market Score Model. The variables considered here are all the ratios of equation 2 except the asset turnover ratio. Asset turnover ratio is highly sensitive to the industry effects and the financing pattern of assets. If a firm finances its assets through lease arrangements, it tends to have higher asset turnover ratio than a similar type of firm which financed the assets out of balance sheet sources. Hence, the impact of asset turnover ratio is excluded. In all the three equations, the coefficients are estimated by using the development sample. A brief description of the selected ratios is presented in the Box.

Statistical Tests

F value gives the overall discriminating power of the model. A high value of *F*-statistic indicates the significance of selected variables. The null hypothesis is that there is no significant difference between the two groups; high *F* value rejects the hypothesis supporting the point that there is significant difference between the groups which is desirable. However, if a particular variable is insignificant, it need not be excluded as the strength of the correlations among the variables is important. It is important to emphasize that the relationships among variables are incorporated in multivariate procedures like discriminant analysis. The accuracy of the model is analysed with classification accuracy on both the development and the hold-out samples. Further, ROC curve is fitted to measure the accuracy level of selected models.

Box: Selected Financial Ratios

***Current ratio* (x_1):** A survey of internal credit rating models of Indian banks reveals that most of the banks are rating the borrower's liquidity position on the basis of current ratio. Current ratio is the relationship between current assets and current liabilities. If the borrower is contributing a minimum of 25 per cent of long-term funds (equity) for financing the current assets, the current ratio would be 1.33. A fall in the current ratio over a period indicates that the borrower has withdrawn or diverted the funds and the support for current assets financing is no longer available. The RBI study (1999) on NPAs shows that diversion of funds is the primary reason for accounts becoming NPAs. If these practices continue for a longer period, the borrower may encounter the problem of liquidity and if the bank fails to take necessary monitoring steps, this diversion of funds leads to default and the account will be recognized as NPA. Therefore, a fall in the current ratio is a symptom of liquidity problem leading to default.

***Interest coverage ratio* (x_2)**: It is the relationship between operating cash flows and interest. Operating cash flows are also defined as earnings before interest, depreciation, and tax. It indicates the number of times protection is available out of earnings for the outstanding interest amount. A fall in ratio below one leads a firm to default on interest payments.

***Debt-equity ratio* (x_3):** It is a standard form of expression of financial risk. Debt-equity ratio is the relationship between total debt and net worth of the company. Total debt is defined as sum of secured loans, unsecured loans, and current liabilities. A high ratio (more than 2) indicates that the entity is managed by debt funds and any decline in operating cash flows due to business risk factors may force the firm to delay on paying the debt service obligations. Persistence of this situation for a longer time leads to default. Almost all the credit rating models of the Indian banks assess the financial risk of borrowers by using the debt-equity ratio.

***Operating margin* (x_4):** It indicates operating margin on sales. This is the margin available to the firm after meeting all the operating expenses including depreciation. Operating margin is independent of leverage and taxes. In the first equation, profitability is measured on total assets while here profitability is linked with sales. Higher operating margin indicates availability of cash flows for repayment of debt obligations and the chances of default are less.

***Working capital to total assets* (x_5):** Working capital is the difference between current assets and current liabilities. Current assets are inventories, book debt, and other loans and advances. Current liabilities include working capital and other short-term loans. This ratio measures the net liquid assets relative to total assets. A unit experiencing consistent operating losses or cash losses will have marginal current assets in relating to total assets. This ratio is expected to have positive influence on the discriminant function.

***Retained earnings to total assets* (x_6):** This ratio indicates the degree of capitalization made through retained earnings or internal funds. Higher ratio indicates better financial health of the company. The age of the firm is implicitly considered here and younger firms are expected to have relatively lower ratio.

***Earnings before interest and taxes to total assets* (x_7)**: It measures the profitability generated on a firm's assets independent of leverage and taxes. A firm's survival depends on the earning generating power.

***Net worth to total debt* (x_8)**: An important issue in determining the credit risk is whether the net worth of a firm is sufficient to meet its total debt obligations. Therefore, the market value of equity is a more appropriate variable, but, due to several asymmetries of the Indian stock market, the book value of debt is considered here. This ratio is reciprocal of the popularly used debt-equity ratio. Excess of liabilities over assets is defined as insolvency. This ratio measures the decline in value of assets if a firm's liabilities exceed its total assets. For example, if a company's value of equity is Rs.100 and debt is Rs. 50 before insolvency, the likely decline in value of assets is 50/150, i.e., two-third. If the net worth is only Rs.25, the firm will be insolvent if assets drop by only one third in value. The probability of default increases with a drop in the value of equity. In fact, the more sophisticated models of default such as Merton's (1974) approach is built on the relationship between debt and equity.

***Sales to total assets* (x_9):** It is asset turnover ratio indicating sales generating capacity for one unit of assets. It also measures the management's ability to deal with competitive conditions. Asset turnover ratio varies among industries.

ANALYSIS OF RESULTS

Table 5 presents the mean of both defaulted and non-defaulted companies and the *F*-statistic value. The dominant variables discriminating the default companies from the non-defaulting ones (one year prior to default are) are: current ratio, debt-equity ratio, operating margin, working capital to total assets, earnings before interest and tax to total assets, net worth to debt, and asset-turnover ratio. The structure matrix values indicate the importance of that particular variable in the discriminant function. These values may be useful for assigning the weights to various ratios while architecting the internal rating models. Table 6 shows the *F*-values of the variables two years prior to default. Here, except for the asset-turnover ratio and working capital to total assets ratio, all other ratios are significant in discriminating between the default and non-default companies two years prior to default. The discriminant functions arrived on the basis of development sample are presented in Table 7.

Table 8 presents the distribution of sample companies on the basis of *Z*-values. Under the assumption of equal *a priori* probabilities of group membership, the linear model will result in a cut-off or critical score of zero. All firms scoring above zero are classified as having characteristics similar to the non-default group and those with negative scores as having characteristics similar to the default group (Altman, 2002 a). The *Z*-score gives

Table 5: Results of the Analysis One Year Prior to Default

Variables	Notation Used	Mean of Default Group	Mean of Non-default Group	*F*-Statistic	*P*-value	Structure Matrix
Equation 1						
Current ratio	x_1	1.09	1.72	3.71	0.06	0.52
Interest coverage ratio	x_2	-8.80	-2.30	0.49	0.49	0.19
Debt-equity ratio	x_3	-12.71	12.28	3.65	0.06	0.52
Operating margin	x_4	-0.93	0.07	7.58	0.01	0.74
Equation 2						
WC/TA	x_5	-0.12	0.06	5.13	0.03	0.37
RE/TA	x6	-1.28	-0.14	1.24	0.27	0.18
EBIT/TA	x_7	-0.05	0.04	6.76	0.01	0.42
E/D	x_8	0.08	1.08	6.36	0.01	0.41
S/TA	x_9	0.42	1.29	22.56	0.00	0.77
Equation 3						
WC/TA	x_5	-0.12	0.06	5.13	0.03	0.68
RE/TA	x_6	-1.28	-0.14	1.24	0.27	0.33
EBIT/TA	x_7	-0.05	0.04	6.76	0.01	0.78
E/D	x_8	0.08	1.08	6.36	0.01	0.76

Table 6: Results of the Analysis Two Years Prior to Default

Variables	Notation Used	Mean of Default Group	Mean of Non-default Group	*F*-statistic	p-value	Structure Matrix
Equation 1						
Current ratio	x_1	1.05	1.60	9.31	0.00	0.71
Interest coverage ratio	x_2	-4.95	10.15	4.61	0.03	0.50
Debt-equity ratio	x_3	-0.64	4.23	3.94	0.05	0.46
Operating margin	x_4	-8.42	0.46	2.80	0.10	0.39
Equation 2						
WC/TA	x_5	1.18	1.58	2.30	0.13	0.36
RE/TA	x_6	-0.37	-0.08	7.19	0.01	0.64
EBIT/TA	x_7	-0.10	0.07	9.88	0.00	0.75
E/D	x_8	0.10	0.75	7.55	0.01	0.66
S/TA	x_9	1.16	13.85	2.64	0.11	0.39
Equation 3						
WC/TA	x_5	1.18	1.58	2.30	0.13	0.37
RE/TA	x_6	-0.37	-0.08	7.19	0.01	0.67
EBIT/TA	x_7	-0.10	0.07	9.88	0.00	0.80
E/D	x_8	0.10	0.75	7.55	0.01	0.69

information on credit standing of a firm and a bank can rate the potential borrowers on the basis of Z-scores. A high score naturally indicates a better credit rating and a low Z-score value shows poor quality. Banks can develop the cut-off Z-score for categorizing the customers. In this paper, zero is assumed as the cut-off score and companies having Z-score less than or equal to zero are categorized as default companies. Given a cut-off Z-score, the probability of default can be estimated by using Bayes' Formula (Bessis, 2002). The posterior probabilities of a company having Z-score of zero or less than zero falling in the category of default is 71.74 per cent against *a priori* probability of 50 per cent (Table 9).

Classification Accuracy

Classification accuracy is one of the outputs examined in ascertaining whether a model will perform well in practice. This accuracy is expressed as Type I accuracy—the accuracy with which the model identified the failed firms as weak. Type II accuracy is the accuracy with which the model identified the healthy firms as such. Type I accuracy is more important than Type II accuracy because the inability to identify a failing company (Type I error) would cost the lender far more than the opportunity cost of rejecting a healthy company as a potential failure which is Type II error (Caouette, Altman and

Table 7: Discriminant Functions

	One Year Prior to Default
Equation 1	$-0.071+0.154\ x_1 + 0.004\ x_2 + 0.005\ x_3 + 0.282\ x_4$
Equation 2	$-0.939+0.111\ x_5 + 0.027\ x_6 + 3.054\ x_7 + 0.166\ x_8 + 1.030\ x_9$
Equation 3	$-0.051+0.293\ x_5 + 0.029\ x_6 + 1.943\ x_7 + 0.150\ x_8$
	Two Years Prior to Default
Equation 1	$-0.84+0.60\ x_1 + 0.01\ x_2 + 0.03\ x_3 + 0.01\ x_4$
Equation 2	$-0.20+0.01\ x_5 + 0.03\ x_6 + 1.80\ x_7 + 0.39\ x_8 + 0.01\ x_9$
Equation 3	$-0.14+0.02\ x_5 - 0.03\ x_6 + 1.94\ x_7 + 0.35\ x_8$

Table 8: *Z*-values of Sample Companies

Z-values	Equation 1		Equation 2		Equation 3	
	One Year Prior to Default (2001)	Two Years Prior to Default (2000)	One Year Prior to Default (2001)	Two Years Prior to Default (2000)	One Year Prior to Default (2001)	Two Years Prior to Default (2000)
-3.00	2	0	0	1	0	1
-2.50	1	2	0	0	0	0
-2.00	3	0	1	0	0	0
-1.50	0	1	4	3	2	3
-1.00	1	1	25	0	2	0
-0.50	7	35	20	9	8	8
0.00	32	18	12	54	54	50
0.50	55	32	19	26	30	30
1.00	7	8	9	7	10	11
1.50	3	10	8	8	3	5
2.00	0	1	5	2	2	3
2.50	1	0	2	0	0	0
3.00	0	3	3	0	0	0
More than 3	0	1	4	2	1	1
	112	112	112	112	112	112

Table 9: Default Probabilities

	Equation 1	Equation 2	Equation 3
A priori probability of default companies	50%	50%	50%
Conditional probability of default companies having z score zero or less than zero	(33/56) = 58.93%	(46/56)= 82.14%	(46/56) = 82.14%
Conditional probability of non-default companies having z score zero or less than zero	(13/56)= 23.21%	(16/56)= 28.57%	(20/56)= 35.71%
Posterior probability of a company having z score of zero or less than zero being rated as default company	71.74%	74.19%	69.70%

Narayanan, 1998). The first equation which is developed on the basis of a survey of internal rating models of the Indian banks has a relatively low level of accuracy in comparison to the other two discriminant functions (Table 10). The other two equations have a high power in predicting the default with an accuracy level of 82 per cent one year prior to default (Table 11). Again, the other two models have relatively higher accuracy than the first equation. This implies that the Indian banks will have to select the variables more carefully in designing the internal rating models. The variables considered for designing the internal rating models should be able to discriminate between the default and non-default companies effectively. As pointed out by Altman (2002b), credit scoring models are the backbone of the most advanced credit value at risk models and if the internal credit rating model is sound and is based on a comprehensive representative data, then the advanced models have a chance to be more accurate and helpful for economic capital requirements.

ROC Curve

An alternate methodology which is gaining acceptability over simple accuracy ratios is the Recovery Operating Characteristic (ROC) accuracy ratio which is computed by comparing the pairs. A firm is assigned one point if it does not default and its *Z*-score is more than zero; similarly, no points are given if the defaulted company has scored more than zero. The accuracy ratio is the relationship between all possible points and the maximum number of points which is equal to the total number of sample points (Deventer and Kenji, 2003). A model which has the highest ROC score is considered as the 'best model' among others. The ROC ratio gives certainly a better result if the firms are categorized into various credit ratings instead of two simple categories of default and non-default. The ROC accuracy ratio is the highest for Altman's equation whereas the first equation is having a relatively low accuracy ratio (Table 12). To demonstrate the ROC accuracy ratio more intuitively, the same phenomenon is depicted graphically (Figures 1 and 2). The left hand side of the graph represents the proportion of defaults that is correctly predicted as defaults by the rating model. This is called sensitivity—the percentage of positive results that are correctly classified. The horizontal axis is the percentage of the non-defaulting companies, incorrectly predicted as default companies. X-axis represents specificity or the percentage of negative results. The area under the ROC curve is the ROC accuracy ratio. A better model is where the curve bends more toward the upper left hand corner of the graph (Deventer and Kenji, 2003). A model no better than random chance has an ROC curve which is identical to the straight line running from the lower left hand corner of the graph to the upper right hand corner. The figures show that the model based on the second equation is more effective in predicting defaults than the first model.

Table 10: Classification Result: Development Sample (One Year Prior to Default)

Discriminant Function	Actual Group	Predicted Group Membership Default (%)	Non-default (%)
Equation 1	Default	57	43
	Non-default	25	75
Equation 2	Default	82	18
	Non-default	30	70
Equation 3	Default	82	18
	Non-default	36	64

Table 11: Classification Result: Development Sample (Two Years Prior to Default)

Discriminant Function	Actual Group	Predicted Group Membership Default (%)	Non-default (%)
Equation 1	Default	68	32
	Non-default	34	66
Equation 2	Default	82	18
	Non-default	37	63
Equation 3	Default	75	25
	Non-default	36	64

Diagnostic Test of the Model

To test the ability of the model in identifying the default firms correctly, a diagnostic test of the model is conducted on two separate sets of defaulted firms which are not included in the estimation of coefficients. It provides an unbiased test of the ability of the function to classify the firms on the basis of a discriminant score. The result shows that the second equation is able to predict the default in 24 out of 26 companies with a high level of accuracy (Table 13) which shows that the selected ratios are capable of predicting default. The accuracy ratios are higher even in the case of the second sample. The first equation shows higher level of accuracy in the case of the second sample. The hold-out sample accuracy results

Table 12: ROC Accuracy Ratios

Discriminant Function	One Year Prior to Default (%)	Two Years Prior to Default (%)
Equation 1	67.86	66.96
Equation 2	76.34	72.32
Equation 3	73.21	69.64

Figure 1: ROC Curve for Equation (1)

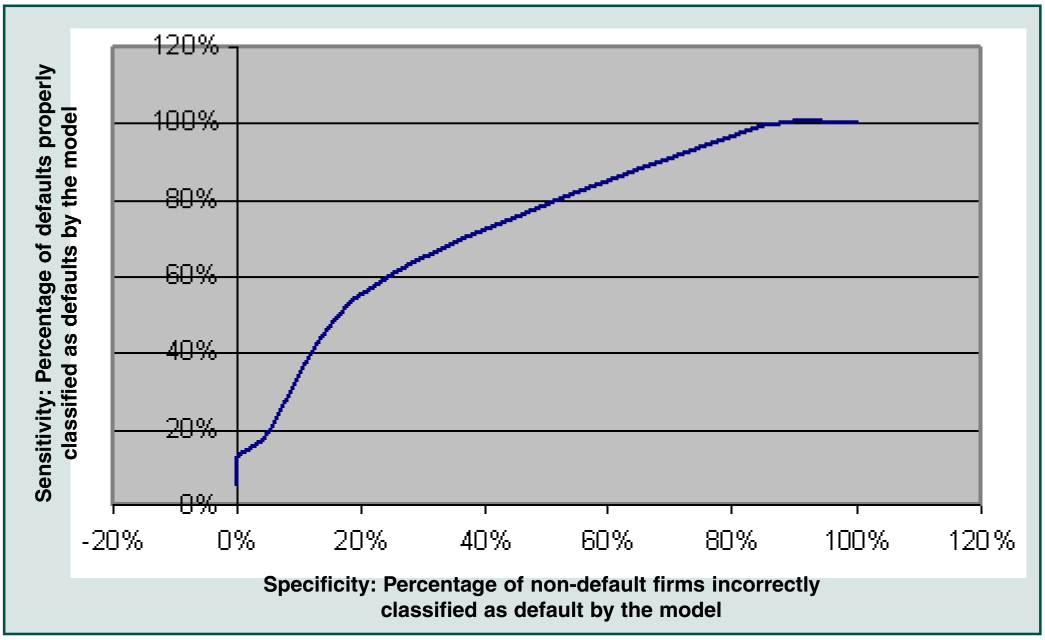

Figure 2: ROC Curve for Equation (2)

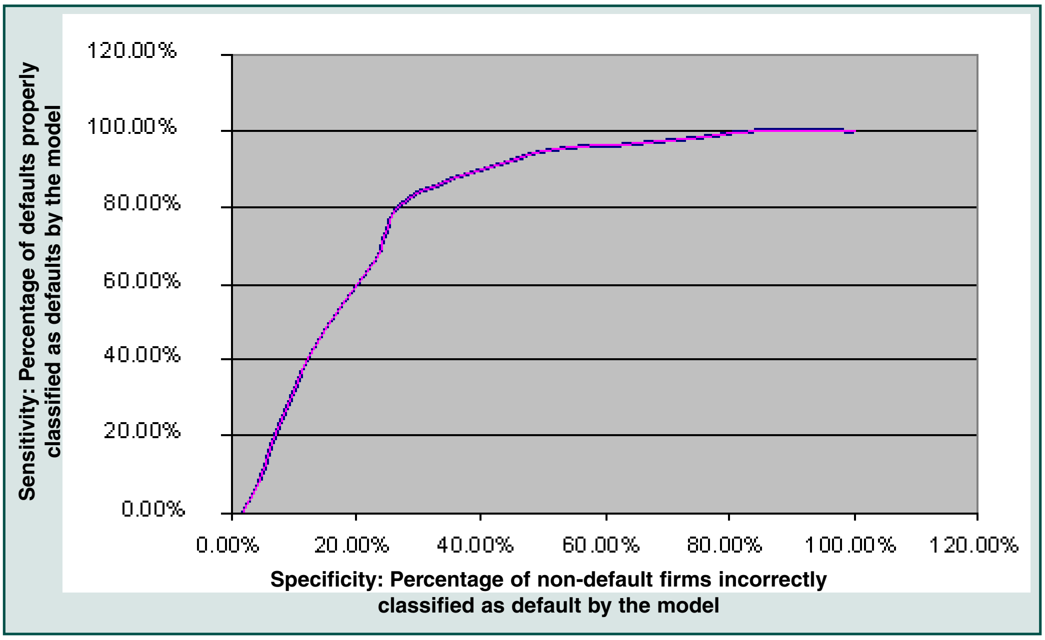

Table 13: Default Accuracy Results of Hold-out Sample

	Size of the Sample	One Year Prior to Default (No. of Firms)	Two Years Prior to Default (No. of Firms)
Sample 1			
Equation 1	26	10(38%)	3(12%)
Equation 2	26	19(73%)	24(92%)
Equation 3	26	16(62%)	14(54%)
Sample 2			
Equation 1	27	17(63%)	15(56%)
Equation 2	27	22(81%)	5(19%)
Equation 3	27	19(70%)	4(15%)

show that the selected variables are capable of predicting one year prior to default.

CONCLUSION

The analysis shows that compared to the other two models, the financial risk factors considered by the banks in their internal rating models are not very effective in distinguishing between default and non-default firms. The accuracy ratio is around 68 per cent which needs to be improved by a careful selection of risk factors.

Banks can map the internal ratings with the *Z*-scores and scale this up to assign various credit ratings. By obtaining the coefficients on the basis of their own database, banks can develop *Z*-score calculators for the various segments of borrowers like large corporate borrowers, mid-corporate segments, and SME borrowers. While rating the borrowers, the banks can assign weights to various financial ratios on the basis of discriminant coefficients. The predicted results should be compared with the actual results and the weights assigned to the various financial parameters in the internal rating models can be revised accordingly. This exercise would help the banks to put themselves on the track of Basel-II.

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