JOURNAL OF
GENERAL MANAGEMENT RESEARCH

Predicting Corporate Failure

An Application of Discriminate Analysis

Meena Sharma and
Vandna Saini[1]

University Business School, Panjab University, Chandigarh, Punjab

[1] SUS college of Research and Technology, Tangori, Punjab

E-mail: sharma94mk@rediffmail.com;
meenasharma@pu.ac.in;
sainivandana20@yahoo.co.in

ISSN 2348-2869 Print

Journal of General Management Research, Vol. 3, Issue 1, January 2016, pp. 1–7.

Abstract

Corporate failure is a serious problem being confronted by the corporate world. This issue has been a subject of intensive research and discussion by economists, bankers, creditors, equity shareholders, accountants, marketing and management experts. The present study aims at developing a model for prediction of corporate failure on the basis of financial ratios. The study is based on the data of selected firms from chemical industry (with equal number of failed and non failed firms). The discriminant analysis has been used to discriminate between failed and non failed firms. It is concluded that some of the financial ratios can significantly differentiate between failed and non failed firms. The finding will be useful for the banks and other financial institutions in designing a suitable credit appraisal and monitoring system for their loans. This model could guide the policy makers to prepare an early warning system to avoid bankruptcy.

Keywords: Corporate Failure, Distress Analysis, Financial Ratios, Discriminate Analysis, Credit Analysis and Appraisal

INTRODUCTION

Corporate failure is one of the serious issue being faced by the corporate world. The incidence of failure has been growing continuously. The economic consequences of corporate failure are enormous especially for public limited companies. It has become a matter of concern for all the industrial units not only for the millions of rupees locked up in number of default units but also for the fortunes of numerous stakeholders to be effected. The failure of a unit is an event that brings a lot of mental torture to entrepreneurs, managers and to their families. The society is also affected by the phenomenon of sickness as unemployment spreads widely, availability of goods and services decreases and the prices soar up. The shareholders have lost part of their hard-earned saving. The creditors have lost their cash and future prospectus of business. So the demand of having accurate credit risk analysis on loan portfolio has become greater now than in past. In the competitive environment of today, the task is not easy. Therefore banks have to constantly upgrade their credit evaluation ability and system in order to successfully manage their assets. Early prediction of borrowers is important from the point of view of both financial institutions and society as a whole, since it helps avoid or least minimize the misuse and misallocation of resources. Thus, it becomes necessary to develop a predictive model for prediction of corporate default. It is believed that model as developed will help banks and lending institutions to predict loan clearly and enable them to classify the borrowing units into potentially sick or sound category. It is also believed that result of the present study would be a great help to the lenders as a tool of credit analysis.

LITERATURE REVIEW

Numbers of research studies have been carried out to identify early warning signals of corporate financial distress. Researchers used statistical models to identify financial ratios that could classify companies into failure or non-failure groups. The statistical approach included both univariate and multivariate models.

Beaver (1966) examined the usefulness of financial ratios for predicting corporate failure. The study was based on matched sample consisting of one fifty eight firms (seventy nine sick and seventy nine non-sick). Ten year data (1954-1964), five year before and five year after the default was analysed. Data for thirty ratios indicating various aspects of performance for each of the five year prior to failure and after the failure was taken and grouped in six ratio categories. The comparison of mean value of ratio, a dichotomous classification test and analysis of likelihood ratios were also used for analysis. Study concluded that short term as well as long term cash flow to total debt ratio was the best predictor of corporate failure.

Altman (1968) examined the analytical quality of ratio analysis to solve the inconsistency problem and to evaluate a more complete financial profile of firms. The study was based on a sample size of thirty three sick and thirty three healthy firms. The author has applied multiple discriminate analyses to discriminate between failed and non-failed firms. Altman examined 22 potentially helpful financial ratios. The study concluded that working capital to total assets, earnings before interest and tax (PBIT) to total assets, market value of equity to book value of debts, sale to total assets were able to distinguish between failed and non failed firms. The variables were classified into five standard ratio categories including liquidity, profitability, leverage, solvency and activity ratio. The study concluded that working capital to total assets, earnings before interest and tax (EBIT) to total assets, market value of equity to book value of debts, sale to total assets were predictor variables. The study concluded that Z score of 2.675 was the best cut off point which maintained minimum classification. The study was able to correctly classify 95% of total sample one year before failure. But the predictive accuracy declined to 72% when data of two year prior to bankruptcy was used. When data of three, four, five year prior to failure was used, the predictive accuracy of the model reduced to 48%, 29% and 36% respectively. Altman concluded that earnings before interest and tax to total assets ratio was predictor variable in the group of discrimination.

Deakin (1972) made an attempt to develop a model for bankruptcy prediction. The analysis was based on sample containing 64 firms (32 sick and 32 healthy) over the period of 1964-1970. Each of the sick firm was compared with healthy firms on the basis of type of industry, year of the financial information provided and asset size. This analysis was based on two major empirical experiments. Firstly dichotomous classification test was applied to ascertain the percentage error of each ratio. Secondly the author applied discriminate analysis to discriminate between failed and non-failed firms. The study examined 14 financial ratios in the original model and five ratios in the revised model. The study revealed high correlation of relative predictive ability of various ratios. The study concluded that discriminate analysis can be applied to forecast company failure using ratios as prediction of failure three years in advance with a fairly high degree of accuracy.

Libby (1975) conducted a study to determine whether accounting ratios provide useful information to loan officer in the prediction of business failure. The study was based on matched sample of 60 firms (30 failed and 30 non-failed firms) drawn at random from the Deakin (1972) derivation sample. The study evaluated fourteen ratios to discriminate between failed and non-failed firms. The author applied principal component analysis with varimax rotation. The analysis identified five significant variables out of 14 variables these were (1) net income to total assets, (2) current assets to Sales, (3) current ratio, (4) current assets to total assets, (5) cash to total assets. The result showed that experience of loan officer was found to be significant variable for prediction of business failure.

Gupta (1979) made an attempt to distinguish between sick and non-sick companies on the basis of financial ratios. The author used data on a sample of 41 textile companies of which 21 were sick and 21 were non sick companies. The study was based on 24 profitability ratios and 31 balance sheet ratios. He applied simple non parametric test for measuring the relative differentiating power of various financial ratios. It was concluded that profitability ratios, earning before depreciation, interest and tax to sales and operating cash flow to sales were best ratios in predicting future bankruptcy. The result also showed that balance-sheet ratios were not as accurate as the profitability ratios. It was also observed that solvency ratios were more reliable indicators of strength than any liquidity ratios.

Kaveri (1980) made an attempt to develop a model for prediction of borrower's health. This analysis was based on sample containing 524 small unit companies. They examined 22 financial ratios and applied, f-test and t-test to develop a model. It was found that five ratios were significant in discriminating between failed and non-failed firms. It was also found that accuracy of the model was reduced as the lead time before the event increased. The results suggested that bankers can use current ratio, stock to cost of goods sold, current assets to total assets, net profit before taxes to total capital employed and net-worth to total outside liabilities to predict the corporate failure.

Gunawardana and Puagwatana (2005) developed a model for prediction of business failure in technology industry of Thailand. The study was based on a sample of 33 companies (12 failed and 21 non-failed) from year 2001. The study was based on five financial ratios. The authors conducted correlation and T-test to check the characteristics of each variable on both failed and non-failed companies. They also applied step-wise logistic regression to develop the model. It was concluded that mean of individual ratio of failed group was smaller than non-failed groups. The result also indicated that the model correctly predicted 77.8% of financial health with 95% confidence level. The result of independent T-test showed that sale to total assets was only significant variable. The study concluded that financial ratios were useful for forecasting health of companies in technology industry.

Altman, et al. (2007) made an attempt to develop a Z-score model. The study was based on a sample of 60 companies. All these companies were divided into two groups. The first group consisted of thirty sick and thirty non-sick firms and the second groups consisted of 21 failed and 39 randomly chosen healthy companies. They selected 15 financial ratios to identify the potential distress of Chinese companies. The data set covered the period from 1998 to 2006. It was concluded that z-score model was able to predict fairly accurately up to four year prior to financial distress. The result also showed that z-score model was robust with very high accuracy.

Hazak and Manasoo (2007) developed an EU-wide model that provided a warning of corporate default. The study had used four categories of ratios (leverage, liquidity, profitability, efficiency) and macroeconomic indicators to characterize the financial performance of companies. They conducted survival analysis method to obtain an insight into the effect of individual explanatory variables. The study used a sample of 0.4 million companies from the European Union for the period of 1995 to 2005. It was concluded that high leverage and low return on assets were significant variables in developing a default model. The result also suggested that micro and macro variable were statistically significant in discriminating between failed and non-failed firms.

David, et al. (2008) examined the usefulness of financial ratios for predicting corporate failure in New Zealand. The study was based on sample of 10 failed and 35 non-failed companies. They applied multivariate discriminate analysis and artificial neural network to create an insolvency predictive model. The study examined 36 financial ratios. These ratios were classified into five categories including leverage, profitability turnover liquidity and other. The result reveals that financial ratios of failed companies differ significantly from non-failed companies. The study also indicated that failed companies were less profitable and less liquid than non-failed companies. The study recommended a combination of both MDA and ANN to improve the accuracy of corporate insolvency prediction.

Lin (2009) examined the predictive performance of multiple discriminate analysis, logit, profit and artificial neural network methodology to construct financial distress prediction models. All these approaches were applied to data set of 96 failed firms and 158 non-failed firms. Each of failed firms were matched with non-failed firms on the basis of industry, year and size. The study used twenty financial ratios to construct financial distress prediction model. The author examined the data from 1998 to 2003 to construct financial distress prediction model and used the data of 2004 to 2005 to compare the performance of the discriminate model .The result showed that logit and ANN models achieve higher prediction accuracy and possess the ability of generalization. It was concluded that the model used in this study can be used to assist investors, creditors, manager's auditors and regulatory agencies in Taiwan to predict the probability of business failure.

Khan, et al. (2011) made an attempt to develop a failure prediction model for Indian companies. The study was based on a matched sample of 17 failed and 17 non-failed firms. The sample firms used in this study came from eight different industries. The dependent variable was defined as a failing or non-failing event. The independent variable was interpreted as the commonly used financial ratios. The study was based on 64 financial ratios that were chosen from the studies conducted by Beaver (1966) and Altman (1968). They conducted normality test and discriminant analysis to discriminant between failed and non-failed firm. The result showed good performance with a highly correct categorization factuality rate of more than 80%. It was found that two ratios (cash flow to sales and day's sale in receivable) were significant out of 64 financial ratios to discriminate between failed and non-failed companies.

Different studies have taken different variables for prediction of default. But most of the studies have been conducted in foreign countries for predicting the risk of default. In India, only a limited research has been done in this area. Present study is an attempt to develop an analytical predictive model for prediction of default loan.

OBJECTIVE OF THE STUDY

The objective of the present study is to examine which financial indicators (i.e. profitability, liquidity, activity and solvency) are able to predict the probability of default before the actual default occur.

RESEARCH METHODOLOGY

Sampling and Data Collection

Sample of default companies in chemical industries is taken from CIBIL database. But credit information bureau does not provide the data on year of default. This has been determined by studying three financial indicators current ratio, interest coverage ratio, and cash loss. A company incurring cash loss for two years, interest coverage ratio less than one and current ratio less than one is taken to be the year of default. On the basis of availability of data thirteen companies of this industry forms the sample. Thirteen non default companies are matched with the default companies on the basis of industry and size. For the sample of non default companies a healthy company whose size is closest to the size of default company is chosen. A healthy company is the one, whose current ratio and interest coverage ratio are more than one and incurring cash profit for two years. If the financial statements of selected healthy company are available for the preceding five years, then it is finally selected. If the financial statements are not available then again the company whose size is next close to that of failed company is considered. This procedure is followed till we get comparable healthy companies for each of corresponding non-failed companies. In this way total of twenty six companies forms the sample.

SELECTION OF VARIABLES

The financial ratios have been considered as predictors of company failure. The financial ratios have the capability to indicate the financial soundnes or distress of company. The ratio analysis is one of the most powerful tools of financial analysis. It is used as a machine to examine and interpret the financial strength of a firm. With the use of ratio analysis financial strength and weakness of an enterprise can be evaluated and conclusion drawn that whether the performance of the firm is improving or deteriorating. Therefore twenty seven financial ratios are chosen to discriminate between default and non default companies (list of ratios used in the study are given in Table 1). These ratios are categorized under the head profitability ratios, liquidity ratios, solvency ratios, activity ratios.

The ratios are selected by the following criteria:

1. The popularity of the ratio in available literature.
2. The predictive performance of financial ratios in earlier studies.
3. The relevance of ratios for present study.

Three year data prior to the year of default (for all these ratios) is taken from prowess data base.

Tools for Analysis

The data collected is analysed by applying two- group linear discriminant analysis. The predictive model has been developed for each of the three year prior to default. The purpose of discriminant function is to derive the linear combination of variables, which best discriminate between the groups. The

Table 1: List of Various Ratios Used in Differentiating between Default and Non-default Firms

Profitability Ratios	*Liquidity Ratios*	*Solvency Ratios*	*Activity Ratios*
1. Profit before interest and tax to total assets	1. Current ratio	1. Debts equity ratio	1. Sale/current assets
2. Profit before interestand tax to total sale	2. Quick ratio	2. Total liabilities/total assets	2. Sale/working capital
3. Profit after tax to sale	3. Current assets/total assets	3. Networth/total assets	3. Sale/fixed assets
4. Profit after tax to net worth	4. Quick assets/total assets	4. Interest coverage ratio	4. Sale/total assets
5. Earning per share	5. Working capital/total assets		5. Sale/net worth
6. Return on equity	6. Cash/current liabilities		6. Sale/quick assets
7. Profit after tax to total assets	7. Cash/total assets		7. Sale /inventory
8. Retained earning to total assets			8. Sale/ receivable

two group linear discriminant analysis based model take the following form:

$$D = b_0 + b_1 V_1 + b_2 V_2 + b_3 V_3 + _{...} b_K V_K$$

D – Discriminant score, b is discriminant coefficient, v is predictor or independent variable, b_0 is Constant. In this study linear discriminant analysis model has been established for each of the three years. The coefficient or weights (b) are estimated so that groups differ as much as possible on the values of the discriminant functions. This occurs when the ratio of between group sum of squares to within sum of squares for the discriminant score is maximum. Wilks λ is used to determine the overall discriminating power of the model. Wilks λ for each predictor is the ratio of the within group sum of squares to the total sum of squares. Its value varies between 0 and 1, large values of λ (near 1) indicate those groups mean do not seem to be different and small value of λ (near 0) indicate that group mean seem to the different. The discriminant coefficients of a set of variables, which do best discriminate between default and non default companies is calculated.

FINDINGS

It has been observed that the set of variable which discriminate between default and non default companies are different in different years.

The discriminant function for one year before default

D1 = 0.095 – 1.142 PBIT/SALE + 19.322 PBIT/TA + 0.057 PAT/NW – 4.209 CASH/CL

The ratio, which best discriminated between default and non default companies for one year before default are found to be profitability ratio (profit before interest and tax to sale, profit before interest and tax to total assets, profit after tax to net worth), and liquidity ratio(cash to current liabilities)

The discriminant function for two year before default

D2 = –2.85 – 0.376 Return on equity + 2.262 PAT/TA + 6.457 PAT/NW + 0.696 NW/TA

The ratio that discriminated best for the case of two year before default are profitability ratio (profit after tax to net worth, Return on equity, profit after tax to total assets) and solvency ratio (net worth to total assets).

The discriminant function for three year before default

D3 = –2.2432 – 20.856 RE/TA + 4.629 PAT/TA + 6.328 CASH/CL + 0.395 SALE/CA

The predictor variables in case of three year before default are profitability (retained earnings to total assets, profit after tax to total assets), liquidity (cash to current liabilities) and activity ratio (sale to current assets).

From the above tables, it can be concluded that a strong discriminant function is formed on the basis of twenty seven ratios considered in the study. This is evident from the fact that 87.2%, 68%, 78% of defaults can be explained by the ratios for first, second and third year before default. The Eigen value is the ratio of between groups to within group sum of squares. Larger Eigen value implies superior function. The Eigen value associated with the first year function is 3.177 The Eigen value associated with second and third year's .89, 1.59 respectively. The decrease in Eigen value is observed as one move away from year of default. Wilks λ is a multivariate measure of group difference over discriminating

Table 2: Group Centroids, Eigen Value, Wilks' λ and Canonical Correlation of Discriminant Function of Default and Non-default Companies

Year	*Eigen Values*	*Wilks' λ*	*Chi-square*	*Canonical Correlation (r)*	r^2	*Cut-off Point*	*P-Value*
1st	3.177	.24	38.60	.872	0.76	1.08	<.01
2nd	.89	.53	17.82	.68	0.46	1.56	<.01
3rd	1.59	0.39	26.40	0.78	0.61	1.61	<.01

variables. If the value of lambda is near zero, it denotes high discrimination. As the value approaches towards one discrimination goes on decreasing. The value of Wilks lambda is .24, .53, .39 for first, second year and third year before default. Which are non zero and this show high discrimination between groups. The value of Wilks λ decreased as we moved away from year of default. The significance of lambda can be tested by converting it into approximation of chi-square. The value of chi-square is 38.60, 17.82 and 26.40, for first, second and third year before default. It denotes that result is coming from a population, which has difference between the groups. It meant the function is statistically significant. Also, the value of chi-square is high at the given significance level and the value of Wilks λ is quite low which is desirable. The cutoff point or discriminatory point for classifying individual cases in the two groups is calculated. The discriminating score for each company is compared with the group centroids. If it is less than group centroids. company is classified into group one. If it is more than group centroids, it is classified in group two.

The variable, which best discriminated between default and non default companies for one year before default are found to be PBIT to sale, PBIT to total assets, profit after tax to net worth, cash to current liabilities. Among these variables PBIT to total assets contributes maximum (44 percent) in differentiating between default and non default firms and 56 percent of the variation is explained by other three variables (Table 3). The result shows that profitability and liquidity ratio are important to discriminate between defaults and non default firms for one year before default. The variables that discriminated best in case of two year before default (Table 4) are profit after tax to net worth, return on equity, profit after tax to total assets, net worth to total assets. Profitability ratio and solvency ratio are significant in two year before default. Profitability, activity ratio and liquidity ratio are also able to discriminate between default and non default companies for three year before default (Table 5). Overall result shows that profitability ratio are significant in first, second and third year with higher relative contribution.

Table 3: Relative Importance of Predictor variables for one year before the year of default

S. No.	*Variable Description*	*Standardized Coefficient*	*Relative Importance (%)*
1	Profit before interest and tax to total assets	5.043	44.0
2	Profit before interest and tax to total sale	4.083	35.6
3	Profit after tax to net worth	1.381	12.1
4	Cash to current liabilities	-.950	

Table 4: Relative Importance of Predictor Variables for Two Years before the Year of Default

S. No.	*Variable Description*	*Standardized Coefficient*	*Relative Importance (%)*
1	Profit after tax to net worth	1.113	33.5
2	Net worth to total assets	.890	26.8
3	Profit after tax to total assets	.713	21.5
4	Return on equity	602	18.1

Table 5: Relative Importance of Predictor Variables for Three Years before the Year of Default

S. No.	*Variable Description*	*Standardized Coefficient*	*Relative Importance (%)*
1	Cash to current liabilities	1.229	38.6
2	Retained earnings to total assets	-.706	22.1
3	Sale to current assets	.647	20.3
4	Profit after tax to total assets	.606	19.0

The Predictive accuracy of discriminant model is ascertained by computing the percentage of classification error over a period of three years prior to default. The misclassification rates are computed by comparing the predicted result of discriminant model with the actual status of companies. The proportion of cases correctly classified indicated the accuracy of the procedure and indirectly confirmed the degree of group separation. The accuracy of the discriminant function is 93.8 percent 81.3 percent, 78.1 percent, in predicting the corporate default in first, second and third year before the default. As one would expect the accuracy of the discriminant function decreases as we move from one year to three year before default.

CONCLUSION

The results suggested that profitability and liquidity ratio are important in discriminating between default and non default firms for one year before default. Profitability ratio show relative contribution of 91.7 percent of total contribution and liquidity ratio show only 8.3 percent contribution for one year before default. The result also shows that profitability ratio (73.1% relative contribution) and solvency ratio (26.9% relative contribution) are significant in two year before default. Profitability ratio (41.1% relative contribution), activity ratio (20.3% relative contribution) and liquidity ratio (22.1% relative contribution) are important in three year before default. Profitability ratio is important in discriminating between default and non default companies for all the three years. Liquidity ratio is also important in discriminating between defaults and non default firms for first and third year before default but their relative contribution is low as compared to profitability ratio. So it is concluded that profitability ratio is first best predictor of default and liquidity ratio is second best predictor of default.

With the help of this study one can measure the financial condition of the firm and can point out whether the condition is strong, good or poor. The conclusions can also be drawn as to whether the performance of the firm is improving or deteriorating. Thus, the model has wide application and is of immense use today. It has the ability to assist management for predicting corporate problems early enough to avoid financial difficulties. It would guide the policy makers to prepare an early warning system to avoid bankruptcy. Creditors and lenders can use the model to estimate the potential borrower's credit risk and continuously evaluate the borrower financial health in making decision for renewal or extension of loan. Investors can use the findings to help them make better selection decision of securities in their portfolio investment. Management of business are also interested in foreseeing the probability of a company's financial distress. They may change business policies to overcome the factor responsible for the imminent failure and restructure the entire working system.

REFERENCES

[1] Aggarwal, P. (2003). Corporate Sickliness and Revival in India. An Empirical study, *University Business School Punjab University Chandigarh.*

[2] Attman, E.I. (1968). 'Financial Ratio, discriminant analysis and prediction of corporate bankruptcy', *Journal of finance*, Vol. 23, No. 4, pp. 589-609.

[3] Beaver, W.H. (1966). 'Financial Ratios as predictors of failure', *Journal of Accounting Research,* Vol. 4, pp. 71-111.

[4] David, K.H., Shin, T. and Kim, C. (2008). 'Insolvency prediction Model using Multivariate Discriminant Analysis and Artificial Neural Network for The Finance Industry in Nagaland', *International Journal of Business and Management*, Vol. 3, No. 1, pp. 19-27.

[5] Deakin, E.B. (1972). 'A Discriminant Analysis of Predication of Business Failure', *Journal of Accounting Research*, Vol. 10, spring, pp. 167-169.

[6] Gunawardana, K. and Puagwatana, S. (2005). 'Logistic Regression Model for Business Failure Prediction of Technology Industry in Thailand', *International Journal of the computer and Management,* Vol. 13, No. 2, pp. 47-53.

[7] Gupta, L.C. (1979). Financial Ratios as for Warning Indicator of Corporate Sickness, *ICICI, Bombay*.

[8] Hainz, C. and Fidrmuc, J. (2010). 'Default Rates in the Loan Market for SMES: Evidence from Slovakia', *Economic System*, Vol. 34, Issue 2, pp. 133-147.

[9] Jiming, L. and Weiwei, D. (2011). 'An Empirical Study on the Corporate Financial Distress Prediction Modes: Evidence from Chinas Manufacturing Industry', *International Journal of Digital Content Technology and Its Application,* Vol. 5, No. 6.

[10] Kaveri, V.S. (1980). Financial Ratio as a Predictor of Borrowed Health: With Special Reference to Small Scale Industries in India, *Sultan Chand,* New Delhi.

[11] Khan, Bhunia and Mukhuti (2011). 'Prediction of financial distress', *Asian Journal of Business Management*, Vol. 3, No. 3, pp. 210-218.

[12] Kjatwani, H. and Arora, M. (2006). 'Constructing a Loan Default Model for Indian Bank using CIBIL Data', *IIMB Management Review*, Vol. 18, No. 2, pp. 127-135.

[13] Libby, R. (1975). 'Accounting Ratios and the Prediction of Failure: Some Behavioral Evidence', *Journal of Accounting Research*, Vol. 13, No. 1, pp. 150-161.

[14] Lin, T.H. (2009). 'A Cross Model Study of Corporate Financial Distress Prediction in Taiwan', *New Computing*, Vol. 72, Issue 16-18, pp. 3507-3576.

[15] Mishra, D.P. (1993). 'Predicting Corporate Sickness using Cash Flow Analysis', *Vikalpa,* Vol. 18, No. 3, pp. 13-19.

[16] Singh, N. and Prasain, G.P. (2010). 'Sickness Small Scale Industries: Causes and Remedies – A Case Study of Manipur', *Management Coverage*, Vol. 1, No. 1, pp. 82-89.

APPENDIX 1

		Group	Predicted Group Membership		Total
			Defaulter	Non Defaulter	
1st year 93.8% of original grouped cases correctly classified	Count	Defaulter	16	0	16
		Non defaulter	2	14	16
	%	Defaulter	100	0	100.0
		Non defaulter	12.5	87.5	100.0
2nd year 81.3% of original grouped cases correctly classified.	Count	Defaulter	12	4	13
		Non defaulter	2	14	13
	%	Defaulter	75.0	25.0	100.0
		Non defaulter	12.5	87.5	100.0
3rd year 78.1% of original grouped cases correctly classified.	Count	Defaulter	14	2	13
		Non defaulter	5	11	13
	%	Defaulter	87.5	12.5	100.0
		Non defaulter	31.5	68.7	100.0