THESIS CERTIFICATE

This is to certify that the report titled**Prediction of Corporate Bond Rating using Multiple Discriminant Analysis and Multinomial Logistic Regression**, submitted by **SharathGiri**, to the Indian Institute of Technology, Madras, for the award of the degree of **Master of Technology**, is a bonafide record of the work done by him under our supervision. The contents of this report, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

Keywords: Credit Rating, Multiple Discriminant Analysis, Multinomial Logistic Regression.

Quantitative models were developed to predict the rating given by CRISIL to corporate bonds in an emerging economy like India using profitability ratios, debt ratios, efficiency ratios and liquidity ratios of the firms. This study also gives qualitative information on how the rating depends on the particular financial ratios. Data from CMIE was extracted from firms which issued corporate bonds for the last 5 years. Models are constructed for financial firms and non financial firms separately. A total of 5 independent variables were used by financial firm model and 7 independent variables were used by non financial firm model to predict dependent variable (Rating). Models were built using Multiple Discriminant Analysis and Multinomial Logistic Regression. Objective is to predict the rating of the new corporate bonds about to be issued and also the check the stability of the existing bonds.

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ABBREVIATIONS

MDA	Multiple Discriminate Analysis
MLR	Multinomial Logistic Regression
ROE	Return on Equity
ROA	Return on Assets
EBITDA	Earning before Interest Tax Depreciation and Amortization
EBIT	Earning Before Interest and Tax
CRISIL	Credit Rating Information Service of India Ltd
CMIE	Centre for Monitoring Indian Economy
SPSS	Statistical Package for the Social Sciences

1. INTRODUCTION

1.1 BACKGROUND

In the era of financial liberalization, both credits as well as investment are equally important. One of the most critical problems in evaluating financial instruments is the classification of dent instruments into different risk categories, based on likelihood of the default of issuing company on the promised payment, which consists of the contracted periodic interest payments and/or the principal repayment. Commercial rating agencies classify dent instruments according to the degree of default risk. These rating agencies conduct extensive analysis of the intrinsic business characteristics of the issuing organizations such as the issuer's business lines, market growth fortheir products/services, ability to pay interest and principal, willingness to do so, and protective provisions of an issue.

Corporate instruments ratings were developed prior to World War one to provide investors independent and reliable judgment about the quality of corporate bonds. The development was spurred by the interest and effort of people like Roger Babson, Freeman Rutney and John Moody. In fact, John Moody in his analysis of railroad Investments published the first rating in 1990. Rutney was associated with the development of corporate bond ratings by Poor's publishing company in 1916.

Moody's Investor Service, Standard and Poor's Corporation (S&P), Fitch and Duff & Phelps are popular credit rating agencies today in the United States. Moody's and S&P are the most important rating agencies in terms of their variety of services and the worldwide acceptance.

Credit rating is relatively new in India; CRISIL (Credit Rating Information Service of India Ltd.) is the first rating agency, which started its operations in 1987. As of date there are four other rating agencies namely – ICRA (Investment Information and Credit Rating Agency), CARE (Credit Analysis and Research Ltd.), Fitch (India) Ltd., and Duff and Phelps (India) Ltd.which are actively involved in rating debt instruments of Indian companies from different sectors.

In the Indian scenario the advent of liberalization and financial restructuring has opened up its credit market. According to the regulations of SEBI (Securities Exchange Board of India) – the financial market regulation body in India) since 1997 a rating from at least one of the rating agencies is mandatory for the listed companies to raise either long or short term debts. Besides SEBI regulations, companies are also recognizing the multiple benefits of good risk management practices. A better credit rating of an instrument helps the organization in raising the debt at favourable (lower) interest rates. Indian firms, which are becoming internally competitive, are slowly gaining access to internal financial markets. To raise funds from these markets, it becomes imperative for the firm to have good credit rating. Thus, inrecent times gaining good credit rating has gained lot of importance both domestically as well as internationally for emerging Indian firms. Methodologies followed by the credit rating agencies are different from each other. There is no universally accepted methodology for such an important process. Along these lines, researchers in countries like USA, Japan and UK have proposed different quantitative models. But to our knowledge not much work is done in India. In this research work an attempt was made to construct a model which will predict CRISIL rating for Indian firms.

1.2 RESEARCH OBJECTIVE AND SCOPE

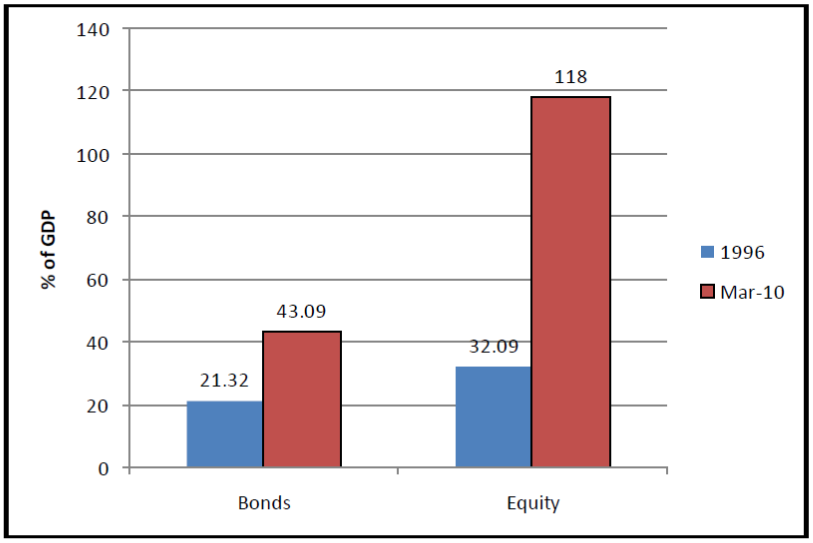
The objective of this research is to come up with models using Multiple Discriminant Analysis and Multinomial Logistic Regression which can predict the CRISIL credit rating of corporate bonds release in India. These models can be used to predict the rating before it is even released into the market. Most importantly this model can be used to check the stability of the bond rating in between then financial year. In process of constructing this model, a quantitative study can be done on all the independent variables used (i.e Financial Ratios). By this, firms will know how to manage their financial structure of the firm to reduce the default risk and achieve a better credit rating.

1.3 MOTIVATION

The Indian financial system is changing fast, marked by strong economic growth, more robust markets, and considerably greater efficiency. But to add to its world-class equity markets the country needs to improve its bond markets. While the government and corporate bond markets have grown in size, they remain illiquid. The corporate market, in addition restricts participants. To meet the needs of its firms and investors, the bond market must therefore evolve.

Since 1996, the ratio of equity market capitalization to gross domestic product (GDP) has reached to 118% from 32.1%. In contrast, the development of government and corporate bond markets has not been so fast: the bond market grew to a more modest 43.0% of GDP, from 21.3%. In March 2008, the government bond market represented 38.5% of GDP, compared to the corporate bond market, which amounted to just 4.5% of GDP.

Figure 1.1:Comparision of Equity and Bonds

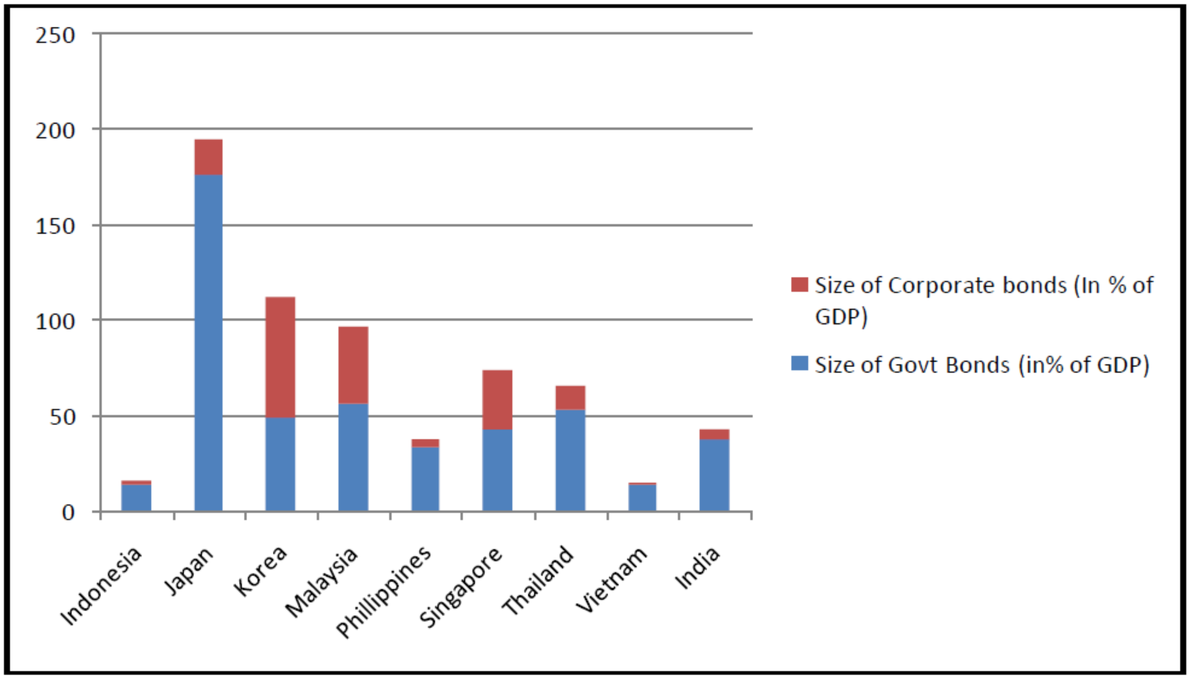


The growth seen in the bond market is contributed mostly by Government securities. Spilt between corporate and government bonds is shown in the table 1.1. This clearly projects the lag in corporate bond sector. Illiquid and undeveloped corporate is of major concern for a nation like India because of its economic growth rate. India needs to have a very strong and robust corporate bond market which can support its long term projects especially infrastructure projects. Secondly, it is very important to have a developed market so that it diversifies the risk and gives more venues for raising money for ventures.

Table 1.1: Global scenario of bond markets

Size of Bond Market in % GDP (Local Sources)							
2010	Market	Govt (in %GDP)	Corp (in %GDP)	Total (in %GDP)	Govt (in USD Billions)	Corp (in USD Billions)	Total (in USD Billions)
	Indonesia	14.4	1.7	16.1	100.16	11.57	111.73
	Japan	176.5	18.8	195.2	10149.34	1078.78	11228.12
	Korea	49.7	62.7	112.4	498	628.49	1126.49
	Malaysia	56.5	40.1	96.6	136.67	97.17	233.85
	Phillippines	33.7	4.6	38.3	63.75	8.71	72.46
	Singapore	43.4	30.7	74.1	97.29	68.67	165.96
	Thailand	53.9	12.4	66.3	176.39	40.45	216.84
	Vietnam	14.2	1.4	15.6	13.62	1.3	14.92
	India	38.55	4.5	43.05	426.6	54	480.6

Figure 1.2: Corporate Bond Vs Government Bonds



As, we have seen above that the Indian Corporate Bond market is completely underdeveloped when compared to other nations. This drove my motivation to contribute something to this market. Hence, I have taken up this topic as my research project.

1.4 METHODOLOGY

Extracted financial data using CMIE database for firms which released corporate bonds via private placements in the past five years. Now, Data refinement was done (removal of outliers) and the firms were segregated as financial or non financial firms. Used SPSS 17.0, a statistical tool for running Multiple Discriminate Analysis and Multinomial Logistic Regression.Utilized the historic data to run MDA and MLR on SPSS to develop a model for predicting CRISIL credit rating for corporate bonds in India.So, finally a MDA and MLR model was constructed for financial firms as well as non financial firms. A quantitative study on their importance in rating was made on the variables used.

1.5 ORGANIZATION OF THESIS

The report is structured as follows:

Chapter 1: This chapter gives an introduction to the history and present scenario of credit rating for corporate bonds and thus provided the motivation for carrying out such a research.

Chapter 2: Provides a glimpse of what a bond is, what its important characteristics are and the prominent literature work done till now in this field. In this chapter brief discussions are presented on previous models in the same field.

Chapter 3: In this chapter we will see what methodology is used to construct this model.How the data was extracted and processed for using it in these techniques is also discussed in this chapter.

Chapter 4:This chapter is where the results from the newly constructed model are displayed and a detailed discussion is done on each of the output. In this chapter itself we were able to judge how the model faired when compared to the previous model discussed in Chapter 2.

Chapter 5: This final Chapter is the one which provides all the conclusions about the model. Further scope of improvement in the model and its implications are also discussed in this Chapter.

2. THE BOND RATING

In the Previous chapter we have seen an overview of bond rating, the methodology we will be using in this research and the objective of this study. Now, this upcoming chapter gives a glimpse of what a bond is, why is bond rating so important, the methodology used in this research, objective of this study and literature review in the field of corporate bond rating.

2.1 WHAT IS A BOND?

2.1.1 Background to a bond

Currently an increasing number of individuals, firms and governments make use of the capital market to secure economical growth. To accomplish this economical growth many of the aforementioned groups prefer financial leverage through debt financing. In this way these groups are able to use capital assets in an earlier stage than in the situation where they have to wait for retained earnings. The capital used for debt financing originates from savings, and function as loans in contrast to savings which are put aside without exploiting it. When a firm decides to use debt financing to establish economical growth, it actually raises money for working capital or capital expenditure by selling bonds, bills, or notes to institutional investors and/or individuals.

Another way of raising capital is called equity financing. This way of raising capital is established by issuing shares of stock in a public offering to individuals and/or institutional investors. The owners of these new shares receive ownership interests in the organization who issued these shares. The scope of this report is amplified to debt financing, with in particular to corporate bonds.

Governments or firms who decide to increase their debt-to-equity ratio can issue bonds. Before describing the characteristics of a bond and mentioning the motivation of entities to issue bonds, it is helpful to define the exact meaning of a bond. Basically a bond is a loan from one entity to another entity, so there are two parties of interest when a bond is issued. The party who issues a bond is called the issuer or obligor and receives the loan from the bondholder. The bond market is known as an over-the-counter market, in contrast to the stock market which makes use of exchanges.

Bonds are divided into smaller pieces to make them more tradable. The issuer of a bond obliges itself to periodically pay an amount of interest to the bondholder and to redeem the principal, or face value, at the maturity date. For this reason bonds belong to the fixed income securities group. The following two definitions of a bond were found on the internet. The first definition is given by the financial dictionary Investopedia (2005).“A debt investment with which the investor loans money to an entity (company or government) that borrows the funds for a defined period of time at a specified interest rate.”

The second definition of a bond was found in the financial glossary of Mainstay Investments(2005) and is: A debt security issued by a company, municipality or government agency. A bond investor lends money to the issuer and, in exchange, the issuer promises to repay the loan amount on a specified maturity date. In addition, the issuer usually provides the bondholder periodic interest payments.”

2.1.2 Characteristics of a bond

Every bond has its own characteristics, although some of these characteristics are basically the same for each bond. The subsequent list comprises of the most basal characteristics of a bond:

Two entities: Each bond is a legal agreement between two entities. On the one hand the issuer and on the other hand the bondholder. Both entities are obliged to some regulations which are determined in advance.

Term-to-maturity: One of these regulations is the term-to-maturity. Before a bond is issued the termination date of the bond is prescribed. When the term-to-maturity is longer than one year the bond is considered as a long-term debt issue, all others are considered as short-terms.

Coupon: It is the periodic payment made to the owner during the life of a bond. Except for zero-coupon bonds, every bond receives interest payments. Interest on these coupon bonds is usually paid semiannually. Most often the interest rate of coupon bonds is fixed, sometimes it is floating. The level of interest is largely dependent on the extent of risk to which a bond is exposed to.

Principal: The principal of a bond is the original amount invested by the bondholder. Another term used for the principal is the face value, which is amount paid to the bondholder at maturity.

Claim on assets: Bond holders have a claim on the assets of an issuer, if situations occur in which an issuer is unable to meet his obligations. At the same time equity holders have this right; nevertheless bondholders have priority in this.

2.1.3 Different types of Bonds

Basically we can classify bonds into two categories, namely government bonds and corporate bonds. Government bonds are bonds issued by government whenever there is necessity to tighten liquid cash in the market or when there is a financial deficit. Corporate bonds are the bonds issued by the private firms. The main intension behind issuing bonds for a private firm is to raise funds for their future investments. If we go deeper, we have municipal bonds as well which are issued by state, districts or cities to finance their expenditure. We can classify them based on their characteristics mentioned in the previous section.

2.1.4 Valuation of a bond

Holding a corporate bond can be stated as equivalent to lending money with no chance of default, but at the same time giving stockholders a put option on the firm's assets. Furthermore they mentioned that owning a corporate bond is also equivalent to owning the firm's assets, but giving a call option on these assets to the firm's stockholders.

Generally speaking the value of a bond is determined by the combination of the coupon percentage and the current market interest rate. The coupon interest rate is fixed and based on the chance of default of the issuer. The market interest rate, by nature is floating. The present value of a bond can be calculated by the following equation (vanAalst et al. (1997), page 158).

$$PV = \sum_{t=1}^{T} \frac{r_c \cdot F}{(1+r_f)^t} + \frac{F}{(1+r_f)^T},$$

Where, r_c is the coupon interest rate, r_f is the current market interest rate, t is the time period between two interest payments, F is the face value and T is the term-to-maturity of the bond. This equation shows that if the market interest rate increases, the present value of a bond will automatically decrease. In such a situation the owner of the bond will probably swap his bond with another financial investment. On the other hand, if the market interest rate decreases the value of a bond will increase. Now other investors presumably want to buy these bonds.

2.2 BOND RATING

This section is devoted to the event of bond rating. Belkaoui (1983) and Tan (2000) quoted that according to Standard & Poor's, "a bond rating is an opinion of the general creditworthiness of an issuer with respect to a particular debt security or other financial obligation, based on relevant risk factors." Belkaoui (1983) recapitulated this definition and quoted that a bond rating is intended to indicate how likely it is that the issuer will be able to meet principal and interest payments on time, therefore a bond rating is intended to measure the default risk. The following subsection will discuss the importance of bond rating.

2.2.1 Importance of bond ratings

Generally, the acquired debt is used by these entities to be able to grow in an earlier stage than in the situation where they have to wait for retained earnings. Having capital in an earlier stage is frequently seen as an advantage for the issuers. Nevertheless an enormous disadvantage comes with this advantage, namely an increase in the level of risk. As discussed in the previous section, the event of lending money brings obligations with itself. For that reason it is of great importance to both the issuer and the bond holder to be informed about the capability of the issuer to keep promise to these obligations.

According to Belkaoui (1983), at least the following six arguments show the importance of bond ratings:

Bond quality: Bond rating agencies try to give a judgement on the future of a company. They tend to keep this judgment conservative and based on the future, past and present status of a organization. This judgment can be seen as an indicator of the probability of default.

Default probability: This argument is narrowly linked with the aforementioned argument. It says that bond ratings are useful because they have proved to be good predictors of bond defaults.

Bond yield to maturity: Bond ratings have proved to be inversely correlated with bond yield maturities. The definition of Yield to maturity given by Investopedia (2005) is: “The rate of return anticipated on a bond if it is held until the maturity date”. This fact can be explained in two ways. The first explanation tells that ratings actually identify the coupon rate. The second explanation is based on the fact that both bond ratings and bond yield are determined by the same underlying economic factors.

Beta: The beta of an organization, which in fact indicates the relative risk in comparison with the market, is considered as the folding ruler of risk that stock investors face. Bond ratings also measure the risk involved with an organization, and for that reason both the betas and the bond ratings of organizations are related.

Market impact: Bond rating can have a market impact, but at the same time the market can have impact on bond ratings. Evidence pointed out that the time between the realization of new market information and the interconnected bond rating change takes at least six months.

Usefulness of bond ratings: Bond ratings are useful to all parties of interest. Issuers who receive the rating of their bonds, immediately have the joint coupon rate determined by the rating company. Investors and banks receive an evaluation of the relative risk which is connected to the rated bonds.

2.3 LITERATURE SURVEY

Substantial literature can be found on bond rating prediction, most probably due to the secretiveness around the rating procedures that the rating agencies practice. What is known is the fact that these rating agencies make use of financial ratios, which are quantitative factors and qualitative factors. Most of the bond rating prediction models found in the literature utilizes only quantitative historical data. The financial information used in the literature for the construction of the bond rating models diverges greatly. This also is the case for the financial ratios derived from the financial information gathered for the bond rating prediction. The fact that these models do not utilize qualitative data most probably is the deficiency in their rating capability. The methods used in prior research can be categorized into statistical and artificial intelligence methods. Here we will study in detail about statistical methods.

In rating bonds, the agencies use financial ratios and qualitative factors, such- as their subjective judgment concerning the firm's managerial ability, the value of its intangible assets, and its ability to make interest and principal payments during the lifespan of the bond. Statistical bond rating methods, however, utilize only the quantifiable historical data of the firm or the provisions of the bond issue. Financial variables chosen are those which the researchers consider the most appropriate proxies for liquidity, debt capacity, debt coverage, size (or marketability), the variability of their earnings and such indenture provisions as subordination.In most cases, the final set of variables chosen is that which best duplicatesthe agencies' rating. The independent variable in all cases is thecoded bond ratings. Further in this chaptervarious statistical modelsare discussed in detail.

Lawrence Fisher Study (1959)

Fisher hypothesized that the risk premium on corporate bonds is a function of default and marketability risk. As risk premium can be directly correlated to bond rating, it provided with base for future studies. A multiple regression technique was used to test this proposition. Four independent variables were used: the coefficient of variation of net income, the number of years since there had been any defaults on debts, the ratio of the market value of equity securities to the par value of indebtedness, and the market value of publicly traded bonds. Professor Fisher admitted that his variables were arbitrary, but he defended them as being plausible. Professor Fisher concluded that each of his variables significantly contributed to the explanation of the difference between the yields on corporate bonds and U. S. treasury bonds with matched maturities. No attempt was made to sort industrial bonds into risk classes.

James Horrigan Model (1966)

James Horrigandescribed a study of the power of accounting data to predict corporate bond ratings using a three-step approach. The first stage in this analysis was the determination of each of the simple correlations between the coded ratings and the independent variables and of the simple inter-correlation among the independent variables. The financial ratios and other variables most highly correlated with the bond ratings were initially selected as the best variables used in regression analysis. The independent variables he finally chose were: subordination, total assets, ratio of working capital over sale, net worth over total debt, sales over net worth, and net operating profit over sale. In the second stage, he developed the "best" equation by regressing the coded bond ratings on the selected variables. The third stage aimed at making a rating scale. The mean of the estimated dependent variables in each of the rating groups was calculated and the differences between the means of adjacent rating groups were bisected, thereby forming a series of estimated intervals. Scores of the new bond were assigned to the rating group according to the interval in which they fell. Horrigan claimed his predictions were correct for 58% of the Moody's ratings during the period 1961-64

West Model (1970)

West used Fisher’s variables in James Horriganresearch procedure to predict bond rating. West argued that Fisher's suggested variables had done an excellent job of estimating risk premium and that since risk premium is highly correlated with ratings, the same variables should also perform well as predictors of ratings. The variables used in the model all in logarithmic form were: nine year earnings variability, period of solvency, debt equity ratio, and bonds outstanding. The model correctly predicted 62% of Moody's for the 1953 cross section and 60% for the 1961 cross section.

Pogue and Soldovsky (1969)

Pogue and Soldofsky employed a regression model with a dichotomous (0-1) dependent variable to predict bond rating which represents the probability of group membership in one group of the pair. Separate regressions were run for each pair of successive ratings (e.g., Aaa and Aa, Aa and A, A and Baa, and so on) with the following independent variables all expressed as a six-year mean: long-term debt as a percentage of total capitalization, after tax net income as a percentage of net total assets and its coefficient of variation, net total assets, after tax sum of net income, and interest over interest charge. At least n-1 regressions must be performed for n rating groups. A bond is assigned to the group in which its probability of occurrence is the highest. The P-S was able to predict 8 out of 10 bonds in the hold out sample taken from the period 1961-66

Pinches and Mingo (1973)

Multiple Discriminant Analysis was used for the first time by Pinches and Mingo to predict bond rating. Developing their model involved the initial screening of variables accomplished via factor analysis (35 variables were initially considered). The model incorporates the following variables: subordination (0-1), years of consecutive dividend, issue size, net income over total assets, five-year mean of net income plus interest charge over interest charge, and longterm debt over total assets. Bonds were classified on the probability of group membership. This model correctly predicted roughly 65% and 56% of the Moody's ratings for holdout samples in the periods 1967-68 and 1969

Altman and Katz (1976)

Altman and Katz applied MDA to the bond ratings of companies in the electric public utility industry. Unlike Pinches and Mingo, Altman and Katz did no a priori screening of independent variables. Starting from an initial list of 30 variables, a series of ad hoc procedures produced a set of 14 variables, many of them still highly intercorrelated, for the discriminant function. A potential defect of MDA is the inability to screen out insignificant variables through significance tests on individual coefficients. Variables which apparently contributed most to the performance of the discriminant function included the interest coverage ratio, earnings variability, interest coverage variability, return on investment, and maintenance and depreciation expense to operating revenues. Some of these variables, however, had coefficients with unexpected signs. The extensive fitting of the data with their model enabled Altman and Katz to correctly classify 80%-90% of the bonds in their estimation sample. On a complex holdout sample technique which still has some upward bias (in the selection of independent variables), the model correctly predicts about 76% of the bonds correctly.

Ang and Patel (1975)

Until this point, all studies compared their predicted results with the bond ratings given by the rating agencies. They assumed that the ratings given by these rating agencies were correct. Ang and Patel (1975) doubted this assumption, which resulted in a study with a twofold purpose. The first purpose was to compare the statistical bond rating models, proposed by Horrigan (1966), West (1970), Pogue and Soldovsky (1969) and Pinches and Mingo (1973b, 1975), on their ability to duplicate the ratings determined by Moody's. The second purpose was to compare the ability of Moody's, and all other the bond rating methods, to predict financial distress over different times periods. The study pointed out that most of the statistical models do good work at much lower costs than rating agencies, at least when the objective is to forecast short term probability of financial loss.

Kaplan and Urwitz (1979)

Kaplan and Urwitzcommented on previous models and mentioned bonds convey ordinal information and therefore regression models are less applicable because they treat the dependent variable as if it is on an interval scale. MDA models, on the other hand treat bond ratings as classifying bonds into separated categories. Kaplan and Urwitz utilized multivariate probit analysis in order to take advantage of the ordinal nature of bond rating and showed 68%

prediction accuracy for their model. However the regression model showed 71% accuracy for the same data set, implied that the regression model seemed to be more robust.

BelkaouiModel (1983)

Belkaoui preferred to use MDA for the bond rating prediction problem. Belkaoui mentioned several arguments why he chose for an MDA application. His first argument was based on the fact that multivariate probit and MDA models are better applicable than regression models to the ordinal scale which bonds convey. Another argument brought forward is that regression models are more robust than multivariate probit models. These arguments motivated Belkaoui to indicate that MDA as the most appropriate model. Belkaoui showed 62.8% prediction accuracy for the experimental example and even 65.9% for the test data set.

‘Bond Ratings Classification Models’-Vamshidhar (1999) - This was the first study undertaken for modeling CRISIL bond ratings. The methodology of attacking this problem was first streamlined through this study. In this project, Multiple Discriminant Analysis and Artificial Neural Network models were utilized for predicting CRISIL bond rating based on financial fundamentals of all the bonds rated by CRISIL for the calendar year 1996. Artificial Neural Networks were found to outperform the Multiple Discriminant Analysis models.

‘Credit Rating Model’ -Kamal Kanth (2002) In this project an unsupervised learning technique was implemented to understand the process of bond ratings provided by rating agencies like CRISIL, ICRA or CARE. Again the standard financial ratios were used as the indicators or independent variables for ratings. However the ratings by a rating agency were not used for their modeling, unlike other studies conducted on similar topic under my supervision. Instead here the objective was to discover the kind of rating a class of companies with like financial ratios should get, from the available data. Towards this end, a cluster analysis of financial ratios of manufacturing firms was conducted, and significant difference between the mean vectors of the proposed clusters were confirmed using MANOVA. Then the CRISIL and ICRA ratings of the firms falling in the same cluster were observed and a remarkable consistency was found to exist between these rating agency ratings and the formed clusters. This in a way validated and established a new relationship between ratings of rating agencies and financial ratios, apart from providing an alternative new framework and model of predicting or providing a rating.

'Using neural networks vs. multiple discriminant analysis to forecast bond rating changes' (2008) by David T. Cadden, Vincent Driscoll, Dean Mark Thompson - This paper presents the results of a study comparing the ability of neural network models and multiple discriminant analysis (MDA) models to predict bond rating changes and to exam if segmentation by investment grade improves classification. Data was collected on more than 900 bonds that had their Standard and Poor's Corporation rating changed during the period 1997 to 2002. This was matched this dataset with corresponding firms which had the same initial bond rating but which did not change. The correspondence was based on the firms being in the same industry, having the same rating at the time of the change (the time frame was one month) and the same approximate asset size (within 20%). A neural network model and a multiple discriminant analysis were used to predict both a bond change and the general direction of a movement from a particular bond rating to another bond rating. The predictive variables were financial ratios and rates of change for these ratios. In almost all cases, particularly for the larger sample studies, the neural network models were better predictors than the multiple discriminant models.

3. METHODOLOGY

In the previous chapter we have seen how a bond is defined, importance of bond rating, effects of bond rating and literature review in this field along with objective. This chapter focuses on what methodology is used to construct the model to predict corporate bond rating.

3.1 OVERVIEW

This chapter helps us to understand the basic methodology and data collection process for the prediction of corporate bond rating which is a categorical dependent variable. As seen in the above chapters, there were prediction models using Linear Regressions, Multiple Discriminant analysis, Artificial intelligence and Multinomial Logistic Regression. Going by Belkaoui arguments I opted for Multiple Discriminant Analysis. I also opted for Multinomial Logistic Regression because of its freedom in type of data. Sometimes because of the data available Multiple Discriminant Analysis's robustness can be questioned. To second the conclusions from MDA we will also do Multinomial Logistic Regression. Finally, we will be using Multiple Discriminant Analysis and Multinomial Logistic Analysis for predicting rating. Both the methods are explained in detail below.

Multiple Discriminant Analysis (MDA) is used for developing Z-score models for predicting corporate bond rating in India. MutinomialLogistic regression model is employed to directly estimate the correlation between the independent variables and the rating. (Prediction can also be made using Multinomial Logistic regression).

3.2 WHAT IS MULTIPLE DICRIMINANT ANALYSIS (MDA)?

In an attempt to choose and appropriate technique, we sometimes encounter a problem that involves a categorical dependent variable and several metric independent variables. For, example we may wish to distinguish good from bad credit risk. If we have a metric measure of risk, we will use Multiple Regression. In many cases we don't have metric measure necessary for Multiple Regression. Instead, we are only able to ascertain whether someone is in that particular group or not. This is when we use Multiple Discriminant Analysis.

Basic purpose of MDA is to estimate a relationship between a single (categorical) dependent variable and set of metric independent variables in the form given below.Rating is not a continuous variable, but a categorical variable. So, Linear Regression and Logistic Regression are not applicable here. So, Discriminant Analysis has been used here. Discriminant Analysis involves the determination of a linear equation like regression that will predict which group the case belongs to. The form of the equation or function is:

$$D = v_1X_1 + v_2X_2 + \ldots\ldots. + v_iX_i + a$$

Where D = discriminate function

v = the discriminant coefficient or weight for that variable

X = respondent's score for that variable

a = a constant

i = the number of predictor variables

This function is similar to a regression equation or function. The v's are unstandardized discriminant coefficients analogous to the b's in the regression equation. These v's maximize the distance between the means of the criterion (dependent) variable. Standardized discriminant coefficients can also be used like beta weight in regression. Good predictors tend to have large weights. What you want this function to do is maximize the distance between the categories, i.e come up with an equation that has strong discriminatory power between groups. After using an existing set of data to calculate the discriminant function and classify cases, any new cases can then be classified. The number of discriminant functions is one less the number of groups. There is only N-1 for the N group discriminant analysis.

Discriminant analysis creates an equation which will minimize the possibility of misclassifying cases into their respective groups or categories. It used Test of Equality of Group Means to check if the mean of the predictor variables is equal in the different categories of the Dependent variable. The means should different in order for the variable to be significant (<0.05) enough to help in classification in the categories.

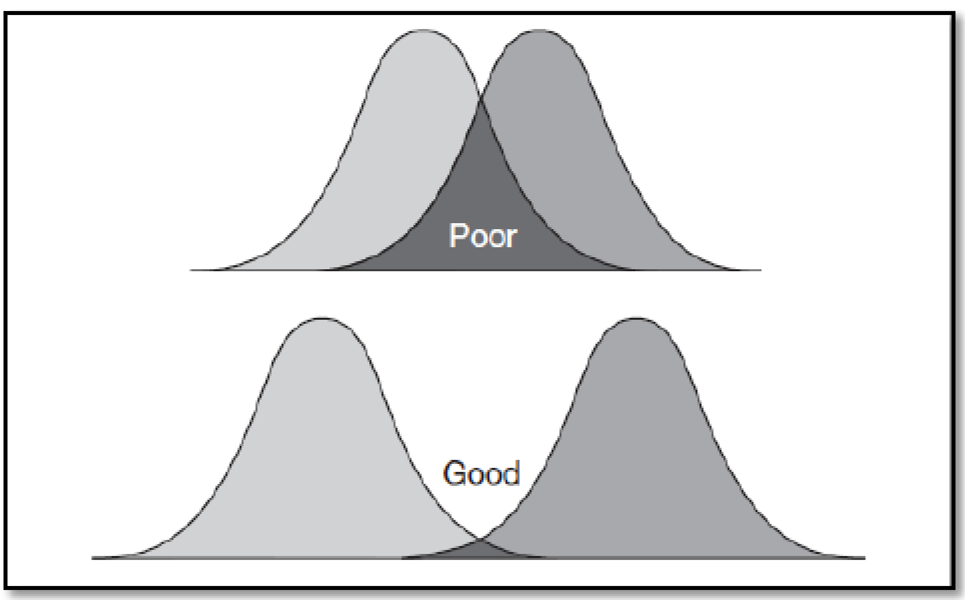


Figure 3.1: Significance of Variable

Further, Box M test checks if the covariance matrix in each category is equal. The covariance should not be equal in order to increase probability of better classification. If covariance is equal, the distribution will have high overlap as shown in Figure 3.1, giving poor results.

3.2.1 Assumptions of Multiple Discriminant Analysis:

There are few assumptions that are taken by MDA which are listed below:

- MDA assumes that there exists multivariate normality of each and every independent variable.
- The Independent variables used should not be highly correlated.
- Linearity of discriminant function so that it can take the form as given in the equation above.

3.2.2 Kruskal- Wallis test:

Additional statistical tool used in this study is the Kruskal-Wallis test. We are using this test to make sure that the independent variables used are really helping us in discriminating the cases. Using this test we can show the difference in the mean of each independent variable among dependent variable categories. The t-test is used to compare means of two samples of the same population, is this case with unequal sample size and unequal variance.

The t-test works with the assumption of normality of the sample being used in the test. But, a lot data being used these does not provide the comfort of normality. For such cases, the Kruskal-Wallis test is used. It is similar to the t-test, but works for a wider range of data.

The chi-square test statistic is given by:

$$K = (N-1)\frac{\sum_{i=1}^{g} n_i(\bar{r}_{i\cdot} - \bar{r})^2}{\sum_{i=1}^{g}\sum_{j=1}^{n_i}(r_{ij} - \bar{r})^2},$$

Where,

ni is the number of observations in group i

rij is the rank (among all observations) of observation j from group i

N is the total number of observations across all groups

$$\bar{r}_{i\cdot} = \frac{\sum_{j=1}^{n_i} r_{ij}}{n_i}$$

$$\bar{r} = \tfrac{1}{2}(N+1)$$

Notice that the denominator of the expression for K is exactly (N − 1)N(N + 1) / 12 and

$\bar{r} = \frac{N+1}{2}$ Thus,

$$\begin{aligned} K &= \frac{12}{N(N+1)}\sum_{i=1}^{g} n_i\left(\bar{r}_{i\cdot} - \frac{N+1}{2}\right)^2 \\ &= \frac{12}{N(N+1)}\sum_{i=1}^{g} n_i\bar{r}_{i\cdot}^2 - \ 3(N+1) \end{aligned}$$

Finally, the p-value is approximated by $\Pr(\chi^2_{g-1} \geq K)$. If some ni values are small (i.e., less than 5) the probability distribution of K can be quite different from this chi-square distribution. If a table of the chi-square probability distribution is available, the critical value of chi-square. The null hypothesis of equal population medians would then be rejected if $K \geq \chi^2_{\alpha:g-1}$

After doing the comparison, the significant results are discussed later.

3.3 WHAT IS MULTINOMIAL LOGISTIC REGRESSION?

Multinomial logistic regression is used when the dependent variable in question is nominal (a set of categories which cannot be ordered in any meaningful way, also known as categorical) and consists of more than two categories. Multinomial Logistic Regression is a regression model which generalizes logistic regression by allowing more than two discrete outcomes. That is, it is a model that is used to predict the probabilities of the different possible outcomes of a categorically distributed dependent variable, given a set of independent variables (which may be real-valued, binary-valued, categorical-valued, etc.).

Multinomial logistic regression is appropriate in cases where the response is not ordinal in nature as in ordered logistic. Ordered logistic regression is used in cases where the dependent variable in question consists of a set number (more than two) of categories which can be ordered in a meaningful way (for example, highest degree, social class) while multinomial logistic is used when there is no apparent order (e.g. the choice of muffins, bagels or doughnuts for breakfast)

3.3.1 Model:

Multinomial logistic regression compares multiple groups through a combination of binary logistic regressions. Multinomial logistic regression provides a set of coefficients for each of the two comparisons. The coefficients for the reference group are all zeros. The below equations can be used to compute the probability that a subject is a member of each group. A case is predicted to belong to the group associated with the highest probability.

$$\Pr(y_i = k) = \frac{\exp(X_i \cdot \beta_k)}{1 + \sum_{j=1}^{J} \exp(X_i \cdot \beta_j)}$$

And to ensure identifiability

$$\Pr(y_i = 0) = \frac{1}{1 + \sum_{j=1}^{J} \exp(X_i \cdot \beta_j)},$$

Where for the i^{th} individual, Y_i is the observed outcome and X_i is a vector of explanatory variables. The unknown parameters β_j are typically estimated by maximum a posteriori (MAP) estimation, which is an extension of maximum likelihood using regularization of the Multinomial logistic regression compares multiple groups through a combination of binary logistic regressions.

3.3.2 Assumptions for Multinomial Logistic Regression:

There are some assumptions taken by Multinomial Logistic Regression which are as mentioned below:

- The multinomial logistic model assumes that data are case specific; that is, each independent variable has a single value for each case.
- The multinomial logistic model also assumes that the dependent variable cannot be perfectly predicted from the independent variables for any case.
- Multinomial logistic regression does not make any assumptions of normality, linearity, and homogeneity of variance for the independent variables.

4. DATAPROCESSING:

In the previous chapter we have seen what methodology is used for constructing this model. A brief algorithm was also given for the techniques used along with their assumption. The following chapter provides with information on how the data is collected. It also discusses about the variables used in the model for financial as well as non financial firms along with their descriptive statistics.

4.1 DATA SAMPLE

In this study there was a particular procedure followed to extract data which is explained in this chapter along with giving an overview of the data. First of all, a list of companies issuing corporate bond via private placements was made by aggregating the information about companies releasing corporate bonds in last five years from NSE and BSE. The total number of companies was 673. The table 4.1 give us the distribution of corporate bonds issuedas private placement from 2006 to 2010.

BBB	A	AA	AAA	Total
33	122	297	221	673

2006	2007	2008	2009	2010	Total
75	77	132	168	221	673

Table 4.1: Bond issued in past 5 years

This is list was filter by considering only CRISIL rating. Now, relevant data for these companies was extracted from PROWESS and from CAPITALLINE. Companies whose data was missing were removed from the list. Considering the size number of the BBB bonds issued to that of other categories, it was clubbed with A rated bonds. Bonds below BBB were neglected because of their size. (This clearly shows the underdeveloped state of Indian Corporate Bonds sector).

For the analysis the firms were divided as financial and non financial firms. Consequently, the list was split into two by separating the financial firms from non financial firms. Now, for both MDA and Multinomial Regression methods outliers must be removed. Box plots were made for all independent variables and the serious outliers (i.e case having extreme values.) were removed one by one in a step by step fashion.For this excel stat software was used. Finally, the list shrinks down to the table below.

	Financial Firms			Non Financial Firms		
	A	AA	AAA	A	AA	AAA
No Of Issue	19	75	75	57	97	47
Total	169			201		

Table 4.2: Data Points used

The whole list of companies whose data was utilised is given in Appendix A.

4.2 FINANCIAL FIRMS:

Now, for financial firms analysis started with 39 financial ratios. As expected in MDA, highly correlated ratios were to be removed from the analysis (It was done using correlation matrix using SPSS). So, the financial ratios which will act like independent variables came down to 10 of them. Now from these only significant ratios were taken into consideration (Used Wilk’s lambda test for finding out the significant ratios which can also be supported by Kruskal-Wallis test).

4.2.1 Independent Variables used for financial firms:

Given below are the final 5 independent variables with which we will perform analysis for financial firms.

- **Return on Assets:** An indicator of how profitable a company is relative to its total assets. ROA gives an idea as to how efficient management is at using its assets to generate earnings. Calculated by dividing a company's annual earnings by its total assets.

  The formula for Return on Assets is as below:

$$= \frac{\text{Net Income}}{\text{Total Assets}}$$

- **Total Debt / Capital:**A measurement of a company's financial leverage, calculated as the company's debt divided by its total capital. Debt includes all short-term and long-term obligations. Total capital includes the company's debt and shareholders' equity, which includes common stock, preferred stock, minority interest and net debt.

  The formula can be calculated as below:

$$\text{Debt To Capital Ratio} = \frac{\text{Debt}}{\text{Shareholders' Equity} + \text{Debt}}$$

- **EBDITA / Total Income:** This ratio is a measure of financial performance of a company. Greater value means that the company is losing lot of its revenue to interest and tax payments which is not a good sign. EBITDA is essentially net income with interest, taxes, depreciation, and amortization added back to it. Total Income is nothing the residual income of a firm after adding total revenue and gains and subtracting all expenses and losses for the reporting period. This ratio is fetched directly from Prowess.

- **Solvency Ratio:**This ratio is used to measure a company's ability to meet long-term obligations. The solvency ratio measures the size of a company's after-tax income excluding non-cash depreciation expenses, as compared to the firm's total debt obligations. It provides a measurement of how likely a company will be to continue meeting its debt obligations.

$$\text{Solvency Ratio} = \frac{\text{After Tax Net Profit} + \text{Depreciation}}{\text{Long Term Liabilities} + \text{Short Term Liabilities}}$$

- **Equity Multiplier:** Like all debt management ratios, the equity multiplier is a way of examining how a company uses debt to finance its assets. Also known as the financial leverage ratio or leverage ratio.

  It's a measure of financial leverage. Calculated as:

  Equity Multiplier = Total Assets / Total Stockholders' Equity

The correlation Matrix of these ratios is as shown below:

	Return on Assets	Equity Multiplier	Total Debt / Capital	Solvecy Ratio	EBDITA / Total Income
Return on Assets	1	-0.242	0.225	-0.108	-0.46
Equity Multiplier	-0.242	1	0.216	0.059	-0.008
Total Debt / Capital	0.225	0.216	1	-0.549	-0.081
Solvency Ratio	-0.108	0.059	-0.549	1	0.069
EBDITA / Total Income	-0.46	-0.008	-0.081	0.069	1

Table 4.3: Correlation Matrix – financial Firms

Descriptive Statistics of Financial Firm's financial Ratios:

	AAA		AA		A		Total		Wilk's Lambda	Sig.
	Mean	Std. Deviat	Mean	Std. Deviat	Mean	Std. Deviat	Mean	Std. Deviation		
Return on assets	0.1209	0.047984	0.1096	0.038096	0.0952	0.030432	0.1049	0.037324	0.942	0.010
Total Debt / Capital	0.8144	0.159389	0.9276	0.071202	0.9518	0.044426	0.9241	0.088651	0.771	0.000
EBDITA / Total Income	71.129	15.0491	72.656	14.25844	77.649	12.97468	74.57	13.99813	0.964	0.057
Equity Multiplier	49.463	47.74492	151.92	144.82	361.81	410.33	227.76	306.74	0.85	0.000
Solvecy Ratio	0.0599	0.064309	0.0145	0.015726	0.0138	0.018111	0.0197	0.030833	0.764	0.000

Table 4.4: Descriptive Statistics – Financial firms

In the table 4.4 we can see a trend in the variables across the rating categories. If we observe Return on Assets we can see that the mean value is decreasing as we go to a lower grade in rating. Similarly Solvency ratio also decreases as we go to a lower grade. Whereas for Total Debt / Capital, EBITDA / Total Income and Equity Multiplier the value increases as we go to a lower grade in rating. It is also noticed that all the variables taken into account for financial firms are significant as seen from the last column of the above table. We will try and observe if the same trends are shown in our models in further chapters.

4.3 NON FINANCIAL FIRMS:

Non financial firms' analysis started with 39 financial ratios. As expected in MDA, highly correlated ratios were to be removed from the analysis (It was done using correlation matrix using SPSS). So, the financial ratios which will act like independent variables came down to 12 of them. Now from these only significant ratios were taken into consideration (Used Wilk's lambda test for finding out the significant ratios which can also be supported by Kruskal-Wallis test).

4.3.1 Variables used in model for Non Financial Firms

Given below are the final 7 independent variables with which we will perform analysis for non financial firms.

- **Return on Equity (ROE):** The amount of net income returned as a percentage of shareholders equity. Return on equity measures a corporation's profitability by revealing how much profit a company generates with the money shareholders have invested.

  ROE is expressed as a percentage and calculated as:

  Return on Equity = Net Income/Shareholder's Equity
- **Funds from Operations / Total Debt**: Funds from operations (FFO) to debt ratios are a measure of a company's ability to pay its debts using its operating income alone. Funds from operations include money the company collects during the current year from inventory it sells and services it provides to its customers.

- **Working capital / Total Assets**: The Working Capital to Debt ratio measures the ability of a company to eliminate its debt using its Working Capital. A company that has the ability to quickly pay off its debt if it needs to is looked favorably by creditors and is generally a sign of good financial health. A high or increasing Working Capital to Debt ratio is usually a positive sign, showing the company can liquidate its Working Capital to quickly pay off its debt, if it had to do so. An event like this would usually be rare; often an extreme downturn in the industry the company operates within, or drastically negative happenings within the company. Nevertheless, monitoring this ratio is very important to make sure the company has the capability to satisfy its creditors. A ratio of 1.0 or higher is desirable, as this shows the company could pay down its debt with Working Capital.

  It can be calculated as mentioned below:

$$\text{Working Capital to Debt} = \frac{\text{Total Current Assets} - \text{Total Current Liabilities}}{\text{Short-Term Debt} + \text{Long-Term Debt}}$$

- **EBITDA Interest coverage**: A ratio that is used to assess a company's financial durability by examining whether it is at least profitably enough to pay off its interest expenses. A ratio greater than 1 indicates that the company has more than enough interest coverage to pay off its interest expenses.

  It can be calculated as mentioned below:

$$\text{EBITDA to Interest Coverage Ratio} = \frac{\text{EBITDA}}{\text{Interest Payments}}$$

- **(Cash flow from operating activities-cash dividends) / (fixed assets + other assets +working capitals) :**A ratio used to compare a business's performance among other industry members. The ratio can be used internally by the company's analysts, or by potential and current investors. The ratio does not however include any future commitments regarding assets, nor does it include the cost of replacing older ones. A high cash return on assets ratio can indicate that a higher return is to be expected. This is because the higher the ratio, the more cash the company has available for reintegration into the company, whether it be in upgrades, replacements or other areas.

- **EBIDTA / Total Income:** This ratio is a measure of financial performance of a company. Greater value means that the company is losing lot of its revenue to interest and tax payments which is not a good sign. EBITDA is essentially net income with interest, taxes, depreciation, and amortization added back to it. Total Income is nothing the residual income of a firm after adding total revenue and gains and subtracting all expenses and losses for the reporting period. This ratio is fetched directly from Prowess.
- **Gross profit margin:**Funds from operations are similar to gross profit margin, except it is a cash flow measure instead of a balance sheet measure. Gross profit margin includes all the revenue the company has the right to receive, so it includes non-cash asset accounts such as accounts receivable. Funds from operations includes money the company collects this year from sales it made last year, but it does not include sales the company makes this year if the customer will pay the bill next year.

The correlation matrix among the independent variables is as shown below:

	EBITDA / Total Income	EBITDA_Interest_ coverage	X	Working Capital / Total Assets	Funds from Operations / Total Debt	ROE	Gross profit Margin
EBITDA / Total Income	1	0.01	0.037	-0.129	-0.42	-0.443	0.589
EBITDA Interest coverage	0.01	1	0.404	-0.051	0.306	-0.102	0.021
X	0.037	0.404	1	-0.18	0.235	-0.015	0.06
Working capital / Total Assets	-0.129	-0.051	-0.18	1	-0.128	0.042	-0.127
Funds from operations / Total Debt	-0.42	0.306	0.235	-0.128	1	0.32	-0.258
ROE	-0.443	-0.102	-0.015	0.042	0.32	1	-0.392
Gross Profit Margin	0.589	0.021	0.06	-0.127	-0.258	-0.392	1

Table 4.5: Correlation Matrix – Non Financial Firms

Here X is (Cash flow from operating activities-cash dividends) / (fixed assets + other assets +working capitals)

Descriptive Statistics of Financial Firm's financial Ratios:

	A		AA		AAA		Total			
	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation	Wilks' Lambda	F
J2	36.30623	28.43347	24.085	15.39274	39.5775	29.96667	31.11884	24.336	0.918	8.303
ROE	28.70703	31.74588	47.0971818	42.04553	75.23646	1.22E+02	48.4911	69.587	0.942	5.68
Funds_fror	1.756856	3.724565	2.437609	1.957882	3.244143	3.853002	2.434474	3.0612	0.97	2.895
Working_c	0.257956	0.204021	0.1702109	0.134244	0.088586	0.100658	0.175814	0.162	0.859	15.25
EBITDA_Int	5.877796	8.973876	8.1032005	9.120792	12.43244	13.73731	8.48701	10.552	0.949	4.957
E2	0.044891	0.041242	0.0669668	0.04276	0.07362	0.042792	0.062325	0.0436	0.934	6.609
Gross_prof	0.613449	0.344245	0.5000373	0.23289	0.634384	0.31391	0.563117	0.2923	0.955	4.39

Table 4.6: Descriptive Statistics- Non Financial Firms

Here,
J2 and X: (Cash flow from operating activities-cash dividends) / (fixed assets + other assets +working capitals)
E2 : EBITDA / Total income

Variable	Sig.
X	0
ROE	0.004
FFO / Total Debt	0.058
Working Capital / Total Assets	0
EBITDA Interest Coverage	0.008
EBITDA / Total Income	0.002
Gross Profit Margin	0.014

Table 4.7: Significance of variables – Non financial Firms

In the table 4.6 we can see a trend in the variables across the rating categories. If we observe ROE we can see that the mean value is decreases as we go to a lower grade in rating. Similarly FFO/Total Debt, EBITDA Interest Coverage ratio and EBITDA / Total Income also decreases as we go to a lower grade. Whereas for Working Capital / Total Assets the value increases as we go to a lower grade in rating. It is also noticed that all the variables taken into account for financial firms are significant as seen from the table 4.7.We will try and observe if the same trends are shown in our models in further chapters.

5. RESULTS:

In the previous chapter we have seen the analysis techniques and its methodology used in this study and the process of data collection and refinement. Now, in this upcoming chapter we will be implementing these techniques on the data and collected. A detail discussion and inferences made are also mentioned in this chapter. We will first look at results from Multiple Discriminant Analysis on financial firms and then Multinomial Logistic Regression on the same set of data. After this observations are done on results from Multiple Discriminant Analysis and then Multinomial Logistic Regression on non financial Firms.

Before that lets look at what we are trying to achieve from using these tools.

5.1 MULTIPLE DISCRIMINANT ANALYSIS:

This technique is used to estimate a basic relationship between a single (categorical) dependent variable and set of metric independent variables which gives a Z score for each data point. In our case the dependent variable is the rating of corporate bond (A, AA and AAA) and the independent variables are the various financial ratios mentioned above.

The objective of doing MDA is to have a model in hand which can predict the credit rating of a corporate bond if all the necessary financial ratios are provided. This also gives us an insight of which financial ratios contributes the most for the rating of the bond. Along with knowing the contribution to rating of a particular ratio it will also list down the significance of it in the process. To support to the significance of each independent variable we will perform *Kruskal - Wallis test*. Using this test we can show the difference in the mean of each independent variable among dependent variable categories. This seconds the significance of the variable in MDA. We will also analyze cross validation accuracy provided by MDA.

5.2 MULTINOMIAL LOGISTIC ANALYSIS:

Mutinomial Logistic regression model is employed to directly estimate the correlation between the independent variables and the rating and hence the prediction of the rating. This technique is used in additional to MDA as it has the advantage of data not being multivariate normal. Then again it has its own flaw. Multinomial logistic regression is appropriate in cases where the response is not ordinal in nature as in ordered logistic. Ordered logistic regression is used in cases where the dependent variable in question consists of a set number (more than two) of categories which can be ordered in a meaningful way (for example A, AA and AAA rating) while multinomial logistic is used when there is no apparent order.

Multinomial Logistic Regression gives us a more robust dependence of dependent variable on the independent variables. This analysis technique generates factors by which the independent variables control the dependent variable. This technique also gives us with an option of predicting the bond rating. We can compare the accuracy of both the models on the data in hand. But in general we take Multinomial Logistic Regression as a tool to check the coefficients but not the model as such.

As mentioned above further in the chapter we will apply MDA & Multinomial Logistic Regression on financial firms and then on non financial firms followed by discussions on the results. We use SPSS 17.0, a statistical tool to performs all the further analysis**.**

5.3 FINANCIAL FIRMS:

In this section we discuss the results of MDA and Multinomial Logistic Analysis of financial firms.

5.3.1 Multiple Discriminant Analysis:

Test Results

	Box's M	342.709
F	Approx.	10.591
	df1	30
	df2	9859.523
	Sig.	.000

Tests null hypothesis of equal population covariance matrices.

Null Hypothesis: The covariance matricesare not equal.This Box test helps us to reject the null hypothesis as the significance value is less than 0.05. That means that the covariance matrix is identical.

Table 5.1 : Tests of Equality of Group Means- Financial Firms

	Wilks' Lambda	F	df1	df2	Sig.
Return on Assets	.942	4.754	2	154	.010
Total Debt / Capital	.771	22.840	2	154	.000
EBDITA / Total Income	.964	2.914	2	154	.057
Solvency Ratio	.850	13.605	2	154	.000
Equity Multiplier	.764	23.772	2	154	.000

Null Hypothesis: Variable mean in each category is not sufficiently different.Here we are able to reject the null hypothesis as the p value is less than 0.05 for all the variables. So, in this case all the variables are significant.

Here as a supporting argument let's perform Kruskal Wallis test for these variables.

Table 5.2: Test Statistics- Financial Firms

	Return on Assets	Equity Multiplier	Total Debt / Capital	Solvency Ratio	EBDITA / Total Income
Chi-Square	11.415	16.865	26.628	18.681	10.894
df	2	2	2	2	2
Asymp. Sig.	.003	.000	.000	.000	.004

Here we can see that all the variables are significant, i.e the means of them are well distinguished.

Table 5.3: Eigenvalues- Financial Firms

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.533[a]	83.9	83.9	.590
2	.102[a]	16.1	100.0	.304

Function - This indicates the first or second canonical linear discriminant function. The number of functions is equal to the number of discriminating variables, if there are more groups than variables or 1 less than the number of levels in the group variable. In this example, rating has three levels and three discriminating variables were used, so two functions are calculated. Each function acts as projections of the data onto a dimension that best separates or discriminates between the groups.

Eigenvalues of functions: These eigenvalues are related to the canonical correlations and describe how much discriminating ability a function possesses. The magnitudes of the eigenvalues are indicative of the functions' discriminating abilities. Now, we can see that the function1 has more discriminating capability than that of function2.

% of Variance - This is the proportion of discriminating ability of the three continuous variables found in a given function. This proportion is calculated as the proportion of the function's eigenvalue to the sum of all the eigenvalues. In this analysis, the first function accounts for 84% of the discriminating ability of the discriminating variables and the second function accounts for 16%. We can verify this by noting that the sum of the eigenvalues is 0.533+0.103= 0.635. Then (0.533/0.635) = 0.84 and (0.103/0.635) = 0.16.

Table 5.4: Wilks' Lambda- Financial Firms

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1 through 2	.592	79.693	10	.000
2	.907	14.775	4	.005

Sig. - This is the p-value associated with the Chi-square statistic of a given test. The null hypothesis that a given function's canonical correlation and all smaller canonical correlations are equal to zero is evaluated with regard to this p-value. For a given alpha level, such as 0.05, if the p-value is less than alpha, the null hypothesis is rejected. If not, then we fail to reject the null hypothesis. And it is seen that both the P values are less than 0.05, i.e we reject the null hypothesis. This means data is a good fit for the model.

Table 5.5: Classification Function Coefficients – Financial Firms

	Rating		
	AAA	AA	A
Return on Assets	83.609	66.418	62.507
Total Debt / Capital	224.390	235.439	238.571
EBITDA / Total Income	.514	.513	.536
Solvency Ratio	439.008	392.154	393.385
Equity Multiplier	-.012	-.012	-.010
(Constant)	-128.657	-134.491	-139.366

Fisher's linear discriminant functions

Discussions on Financial Firms:

The coefficient of Return on Assets decreases as the grade of the rating deceases. This implies that if we keep all the variables constant and increase ROA alone then the grade of the rating will also tends to go higher. This can be supported from the fact the higher ROA projects that the company is doing well which implants trust in investor. So, this model shows us that if a firm as higher ROA it tends to get better rating.

If we observe the coefficients of Total Debt/Capital, we can conclude that model concludes that a firm with this ratio lower will tend to get better rating by the agency. This is again in line with the strong argument that investor would not want the firm to run solely on debt as it will be a problem in case of bankruptcy. So, the model concludes it is better to have lower Total Debt/ Capital ratio to get a higher grade in rating.

In case of EBITDA / Total Income as well we can see that coefficient of A category is higher when compared with that of AA and AAA which means model pushes companies with lower EBITDA / Total Income towards higher rating. This again is in line with the fact that a company is doing well if this ratio is lower.

As per definition solvency ratio provides a measurement of how likely a company will be to continue meeting its debt obligations. Higher the better. The model also concludes the same as the coefficient of AAA is higher than that of AA and A.

As mentioned above it is seen that a lower EBITDA / Total income will fetch a firm better grade in rating. Let us take an example of a firm which is graded presently as AA and wants to upgrade to AAA rating. According to the model for financial firms EBITDA / Total Income plays an important role. The firms focus should be to get EBITDA as close as to that of Total Income. Factors which play a part in this would be interest paid on Debt, Taxes and Depreciation & Amortization. Interest paid can be reduce if we are able to reduce the rate or by running the company on lesser debt percentage. In discussion of Total Debt / Capital as well we have discussed that if a company runs with lesser debt percentage, it moves towards better rating. This tells us if debt percentage is low it is better for the company. Another way is to reduce the depreciation & amortization (D&A). There are different ways company employs to write of D&A, the best method would be to show very less D&A in the initial period of assets instead of uniform distribution over its life. These things will ensure that Total Income will come as close as possible to EBITDA.

Now, it is good to have a higher solvency ratio for a firm to get better rating. For this major factor contributing will be liabilities which inturn come from debt. So, here again we will come across a situation where a firm should maintain a low percent of debt. Seconding this argument Total Debt/Capital suggest that a one unit lower debt / capital percentage will fetch them a increase of 4.416 units in probability of bond jumping from AA to AAA (From Table).

A firm should be focusing on how the assets are managed. They should ensure that all the assets are put to their best use. This is so as to ensure high return on assets. Now, one way to do it by changed their policies in writing their balance sheet. If they show lot of depreciation in their balance sheet, it will ultimately show the value of their asset to be low which will increase return on asset ratio. But this is contradicts the EBITDA / total Income reducing factors. But we still put to write higher depreciation of assets as the sensitivity of ROA is much higher than that of EBITDA/ Total Income to get better rating according to MLR results. Overall we can see that EBITDA/ Total Income, solvency ratio and Total Debt / capital move together if a firm is focusing on increasing its rating grade.

Table 5.6: Classification Results–Financial Firms

			Predicted Group Membership			
		Rating	A	AA	AAA	Total
Original	Count	A	9	10	0	19
		AA	2	54	16	72
		AAA	2	23	41	66
	%	A	47.4	52.6	.0	100.0
		AA	2.8	75.0	22.2	100.0
		AAA	3.0	34.8	62.1	100.0
Cross-validated[a]	Count	A	8	11	0	19
		AA	2	54	16	72
		AAA	2	25	39	66
	%	A	42.1	57.9	.0	100.0
		AA	2.8	75.0	22.2	100.0
		AAA	3.0	37.9	59.1	100.0

It is shown that the model to predict CRISIL credit rating for Indian corporate bonds for financial firms with 5 financial ratios as independent variables has an accuracy of **66.2 %** and with has a accuracy of **64.3%** for cross validation.

5.3.2 Multinomial Logistic Regression:

In this analysis AAA category is taken as the reference group for AA and A categories.

Case Processing Summary

		N	Marginal Percentage
Rating	A	19	12.1%
	AA	72	45.9%
	AAA	66	42.0%
Valid		157	100.0%
Missing		12	
Total		169	
Subpopulation		152[a]	

a. The dependent variable has only one value observed in 152 (100.0%) subpopulations.

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	Df	Sig.
Intercept Only	306.898			
Final	241.249	65.649	10	.000

Here the significance is 0.000 which is less than 0.05. This shows that the model is fit for this analysis technique.

Pseudo R-Square

Cox and Snell	.342
Nagelkerke	.398
McFadden	.214

Table 5.7: Parameter Estimates - Financial Firms

Rating[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
A	Intercept	8.727	5.113	2.913	1	.088			
	Returnon Assets	7.727	10.121	.583	1	.445	2269.249	5.507E-6	9.351E11
	TotalDebt / Capital	-8.372	5.303	2.493	1	.114	.000	7.079E-9	7.547
	EBDITA / Total Income	-.035	.024	2.120	1	.145	.965	.920	1.012
	SolvencyRatio	24.476	15.896	2.371	1	.124	4.262E10	.001	1.448E24
	Equity Multiplier	-.011	.005	5.105	1	.024	.989	.980	.999
AA	Intercept	6.403	4.411	2.108	1	.147			
	Return on Assets	4.757	7.027	.458	1	.498	116.389	.000	1.114E8
	TotalDebt / Capital	-4.416	4.621	.913	1	.339	.012	1.408E-6	103.634
	EBDITA / Total Income	-.028	.017	2.547	1	.110	.973	.940	1.006
	SolvencyRatio	-2.025	15.261	.018	1	.894	.132	1.351E-14	1.290E12
	Equity Multiplier	-.002	.001	4.984	1	.026	.998	.996	1.000

a. The reference category is: AAA.

A category relative to AAA category:

- **Return on Assets** - If a subject were to increase his ROA score by one point, the multinomial log-odds of preferring A to AAA would be expected to increase by 7.727 units while holding all other variables in the model constant. Then again as the significance value is higher than 0.05 , we cannot conclude this statement to be true.
- **Total Debt / Capital** - If a subject were to increase his Total Debt / Capital score by one point, the multinomial log-odds of preferring A to AAA would be expected to decrease by 8.372 units while holding all other variables in the model constant. Then again as the significance value is higher than 0.05, we cannot conclude this statement to be true.

- **EBDITA / Total Income** - If a subject were to increase his EBDITA / Total Income score by one point, the multinomial log-odds of preferring A to AAA would be expected to decrease by 0.035 units while holding all other variables in the model constant. Then again as the significance value is higher than 0.05, we cannot conclude this statement to be true.
- **Solvency Ratio -** If a subject were to increase his **Solvency Ratio** score by one point, the multinomial log-odds of preferring A to AAA would be expected to increase by 24.476 units while holding all other variables in the model constant. Then again as the significance value is higher than 0.05, we cannot conclude this statement to be true.
- Equity Multiplier - If a subject were to increase his Equity Multiplier score by one point, the multinomial log-odds of preferring A to AAA would be expected to decrease by 0.11 units while holding all other variables in the model constant. As the significance value is lower than 0.05, we can conclude this statement to be true.

AA category relative to AAA category:

- **Return on Assets** - If a subject were to increase his ROA score by one point, the multinomial log-odds of preferring AA to AAA would be expected to increase by 4.757 units while holding all other variables in the model constant. Then again as the significance value is higher than 0.05, we cannot conclude this statement to be true.
- **Total Debt / Capital** - If a subject were to increase his Total Debt / Capital score by one point, the multinomial log-odds of preferring AA to AAA would be expected to decrease by 4.416 units while holding all other variables in the model constant. Then again as the significance value is higher than 0.05, we cannot conclude this statement to be true.

- **EBDITA / Total Income** - If a subject were to increase his EBDITA / Total Income score by one point, the multinomial log-odds of preferring AA to AAA would be expected to decrease by 0.028 units while holding all other variables in the model constant. Then again as the significance value is higher than 0.05, we cannot conclude this statement to be true.
- **Solvency Ratio -** If a subject were to increase his **Solvency Ratio** score by one point, the multinomial log-odds of preferring AA to AAA would be expected to decrease by 2.025 units while holding all other variables in the model constant. Then again as the significance value is higher than 0.05, we cannot conclude this statement to be true.
- **Equity Multiplier** - If a subject were to increase his Equity Multiplier score by one point, the multinomial log-odds of preferring AA to AAA would be expected to decrease by 0.02 units while holding all other variables in the model constant. As the significance value is lower than 0.05, we can conclude this statement to be true.

Table 5.8: Classification – Financial Firms

	Predicted			
Observed	A	AA	AAA	Percent Correct
A	8	11	0	42.1%
AA	2	52	18	72.2%
AAA	2	20	44	66.7%
Overall Percentage	7.6%	52.9%	39.5%	66.2%

Here we can see an overall accuracy to predict CRISIL corporate bond rating for financial firms to be 66.2%.

5.4 NON FINANCIAL FIRMS:

In this section we discuss the results of MDA and Multinomial Logistic Analysis of non financial firms.

5.4.1 Multiple Discriminant Analysis:

Test Results

	Box's M	329.725
F	Approx.	5.534
	df1	56
	df2	57093.433
	Sig.	.000

Null Hypothesis: The covariance matrices are not equal. This Box test helps us to reject the null hypothesis as the significance value is less than 0.05. That means that the covariance matrix is identical.

Table 5.9: Tests of Equality of Group Means – Non Financial Firms

	Wilks' Lambda	F	df1	df2	Sig.
X	.918	8.303	2	186	.000
ROE	.942	5.680	2	186	.004
FFO / Total Debt	.970	2.895	2	186	.058
Working Capital / Total Assets	.859	15.250	2	186	.000
EBITDA Interest Coverage	.949	4.957	2	186	.008
EBITDA / Total Income	.934	6.609	2	186	.002
Gross Profit Margin	.955	4.390	2	186	.014

Where X is (Cash flow from operating activities-cash dividends) / (fixed assets + other assets +working capitals)

Null Hypothesis: Variable mean in each category is not sufficiently different. Here we are able to reject the null hypothesis as the p value is less than 0.05 for all the variables. So, in this case all the variables are significant.

Here as a supporting argument let's perform Kruskal Wallis test for these variables.

Table 5.10: Test Statistics - Non Financial Firms

	J2	E2	ROE	FFO/ Total Debt	Workingcapital / Total Assets	EBITDAInterestcoverage	Gross profitmargin
Chi-Square	10.290	20.397	11.762	15.907	27.706	19.507	7.895
df	2	2	2	2	2	2	2
Asymp. Sig.	.006	.000	.003	.000	.000	.000	.019

Here we can see that all the variables are significant, i.e the means of them are well distinguished.

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.323[a]	66.6	66.6	.494
2	.162[a]	33.4	100.0	.374

Function - This indicates the first or second canonical linear discriminant function. The number of functions is equal to the number of discriminating variables, if there are more groups than variables or 1 less than the number of levels in the group variable. In this example, rating has three levels and three discriminating variables were used, so two functions are calculated. Each function acts as projections of the data onto a dimension that best separates or discriminates between the groups.

Eigenvalues of functions: These eigenvalues are related to the canonical correlations and describe how much discriminating ability a function possesses. The magnitudes of the eigenvalues are indicative of the functions' discriminating abilities. Now, we can see that the function1 has more discriminating capability than that of function2.

% of Variance - This is the proportion of discriminating ability of the three continuous variables found in a given function. This proportion is calculated as the proportion of the function's eigenvalue to the sum of all the eigenvalues. In this analysis, the first function accounts for 67% of the discriminating ability of the discriminating variables and the second function accounts for 33%. We can verify this by noting that the sum of the eigenvalues is 0.323+0.162= 0.485. Then (0.323/0.485) = 0.67 and (0.162/0.485) = 0.33.

Table 5.11: Wilks' Lambda - Non Financial Firms

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1 through 2	.650	78.805	14	.000
2	.860	27.516	6	.000

Sig. - This is the p-value associated with the Chi-square statistic of a given test. The null hypothesis that a given function's canonical correlation and all smaller canonical correlations are equal to zero is evaluated with regard to this p-value. For a given alpha level, such as 0.05, if the p-value is less than alpha, the null hypothesis is rejected. If not, then we fail to reject the null hypothesis. And it is seen that both the P values are less than 0.05, i.e we reject the null hypothesis. This means data is a good fit for the model.

Table 5.12: Classification Function Coefficients- Non Financial Firms

Classification Function Coefficients

	Rating		
	A	AA	AAA
J2	.077	.051	.093
ROE	.023	.024	.037
Funds_from_operations_by_total_debt	.518	.407	.512
Working_capital_by_total_assets	16.910	12.663	10.083
EBITDA_Interest_coverage	-.009	.001	.047
E2	23.748	34.991	29.894
Gross_profit_margin	8.200	7.482	8.464
(Constant)	-8.473	-6.889	-9.693

Fisher's linear discriminant functions

Table 5.13: Classification Results – Non Financial Firms

			Predicted Group Membership			
		Rating	A	AA	AAA	Total
Original	Count	A	31	15	7	53
		AA	20	57	15	92
		AAA	5	12	27	44
	%	A	58.5	28.3	13.2	100.0
		AA	21.7	62.0	16.3	100.0
		AAA	11.4	27.3	61.4	100.0
Cross-validated[a]	Count	A	30	16	7	53
		AA	21	56	15	92
		AAA	5	16	23	44
	%	A	56.6	30.2	13.2	100.0
		AA	22.8	60.9	16.3	100.0
		AAA	11.4	36.4	52.3	100.0

It is shown that the model to predict CRISIL credit rating for Indian corporate bonds for financial firms with 5 financial ratios as independent variables has an accuracy of **66.2 %** and with has an accuracy of **64.3%** for cross validation.

Discussions on non financial Ratios:

We can see that importance of return of equity from the above table. The coefficient of ROE increases as we go to a better grade. This means keeping all the other variables constant if we increase ROE, the rating tends to a higher grade. This is in line with what is expected. If ROE is higher for the company that means it is doing well which implies the rating should be higher for its corporate bond.

We can again observe that Working capital/ total asset’s trend. If every other variable is constant and if we decrease this ratio then the rating increases. This is true again because if the company is working with a lot if working capital in turn reducing total assets (i.e the ratio increases). In such a scenario investors are sceptical about the company because if it goes bankrupt it wouldn’t have sufficient funds to repay back their liability. So investors would want to see this ratio as low as possible.

EBITDA Interest Coverage as well shows a trend which can be strongly supported by the argument that this ratio tells us if the company is able to pay its interest or not. Higher the ratio the better it is and the trend seen in the coefficients also portray the same.

5.4.2 Multinomial Logistic Regression:

In this analysis AAA category is taken as the reference group for AA and A categories.

Case Processing Summary

		N	Marginal Percentage
Rating	A	53	28.0%
	AA	92	48.7%
	AAA	44	23.3%
Valid		189	100.0%
Missing		12	
Total		201	
Subpopulation		181[a]	

a. The dependent variable has only one value observed in 181 (100.0%) subpopulations.

Table 5.14: Model Fitting Information – Non Financial Firms

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	395.512			
Final	315.515	79.997	14	.000

Here the significance is 0.000 which is less than 0.05. This shows that the model is fit for this analysis technique.

Pseudo R-Square

Cox and Snell	.345
Nagelkerke	.394
McFadden	.202

Table 5.15: Parameter Estimates – Non Financial Firms

Rating[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
A	Intercept	1.168	.944	1.532	1	.216			
	Working Capital/ Total Assets	7.183	1.959	13.449	1	.000	1316.996	28.335	61212.958
	ROE	-.016	.006	6.581	1	.010	.984	.972	.996
	FFO / Total Debt	.054	.081	.445	1	.505	1.056	.900	1.238
	EBITDA Interest coverage	-.048	.028	2.811	1	.094	.953	.902	1.008
	X	-.010	.011	.740	1	.390	.990	.969	1.013
	Gross profit margin	-.292	1.050	.077	1	.781	.747	.095	5.842
	EBITDA / Total Income	-10.740	7.001	2.353	1	.125	2.167E-5	2.379E-11	19.732
AA	Intercept	2.938	.840	12.244	1	.000			
	Working Capital/ Total Assets	3.329	1.805	3.402	1	.065	27.903	.812	958.951
	ROE	-.010	.003	9.291	1	.002	.990	.984	.997
	FFO / Total Debt	-.103	.079	1.722	1	.189	.902	.773	1.052
	EBITDA Interest coverage	-.028	.022	1.712	1	.191	.972	.932	1.014
	X	-.043	.013	10.236	1	.001	.958	.934	.984
	Gross profit margin	-.833	.979	.724	1	.395	.435	.064	2.963
	EBITDA / Total Income	3.761	4.881	.594	1	.441	42.978	.003	613109.692

a. The reference category is: AAA.

A category relative to AAA category:

- **Working Capital/ Total Assets -** If a subject were to increase his Working Capital/ Total Assets score by one point, the multinomial log-odds of preferring A to AAA would be expected to increase by 7.183 units while holding all other variables in the model constant. Then again as the significance value is less than 0.05, hence we can conclude this statement to be true.

- **ROE** - If a subject were to increase his ROE score by one point, the multinomial log-odds of preferring A to AAA would be expected to decrease by 0.016 units while holding all other variables in the model constant. Then again as the significance value is less than 0.05, we can conclude this statement to be true.
- **FFO / Total Debt** - If a subject were to increase his FFO / Total Debt score by one point, the multinomial log-odds of preferring A to AAA would be expected to increase by 0.054 units while holding all other variables in the model constant. Then again as the significance value is higher than 0.05, we cannot conclude this statement to be true.
- **EBITDA Interest coverage** - If a subject were to increase his EBITDA Interest coverage score by one point, the multinomial log-odds of preferring A to AAA would be expected to decrease by 0.048 units while holding all other variables in the model constant. Then again as the significance value is higher than 0.05, we cannot conclude this statement to be true.
- **X**- If a subject were to increase his **X** score by one point, the multinomial log-odds of preferring A to AAA would be expected to decrease by 0.01 units while holding all other variables in the model constant. Then again as the significance value is higher than 0.05, we cannot conclude this statement to be true.
- **Gross profit margin** - If a subject were to increase his Gross profit margin score by one point, the multinomial log-odds of preferring A to AAA would be expected to decrease by 0.292 units while holding all other variables in the model constant. Then again as the significance value is higher than 0.05, we cannot conclude this statement to be true.
- **EBITDA / Total Income**- If a subject were to increase his EBITDA / Total Incomescore by one point, the multinomial log-odds of preferring A to AAA would be expected to

decrease by 10.74 units while holding all other variables in the model constant. Then again as the significance value is less than 0.05, hence we can conclude this statement to be true.

AA category relative to AAA category:

- **Working Capital/ Total Assets** - If a subject were to increase his Working Capital/ Total Assets score by one point, the multinomial log-odds of preferring AA to AAA would be expected to increase by 3.329 units while holding all other variables in the model constant. Then again as the significance value is close to 0.05, hence we can conclude this statement to be true.
- **ROE** - If a subject were to increase his ROE score by one point, the multinomial log-odds of preferring AA to AAA would be expected to decrease by 0.01 units while holding all other variables in the model constant. Then again as the significance value is less than 0.05, we can conclude this statement to be true.
- **FFO / Total Debt** - If a subject were to increase his FFO / Total Debt score by one point, the multinomial log-odds of preferring AA to AAA would be expected to increase by 0.103 units while holding all other variables in the model constant. Then again as the significance value is higher than 0.05, we cannot conclude this statement to be true.
- **EBITDA Interest coverage** - If a subject were to increase his EBITDA Interest coverage score by one point, the multinomial log-odds of preferring AA to AAA would be expected to decrease by 0.028 units while holding all other variables in the model constant. Then again as the significance value is higher than 0.05, we cannot conclude this statement to be true.

- **X**- If a subject were to increase his **X** score by one point, the multinomial log-odds of preferring AA to AAA would be expected to decrease by 0.043 units while holding all other variables in the model constant. Then again as the significance value is less than 0.05, we can conclude this statement to be true.
- **Gross profit margin** - If a subject were to increase his Gross profit margin score by one point, the multinomial log-odds of preferring AA to AAA would be expected to decrease by 0.833 units while holding all other variables in the model constant. Then again as the significance value is higher than 0.05, we cannot conclude this statement to be true.
- **EBITDA / Total Income** - If a subject were to increase his EBITDA / Total IncomeAssets score by one point, the multinomial log-odds of preferring AA to AAA would be expected to increase by 3.361 units while holding all other variables in the model constant. Then again as the significance value is less than 0.05, hence we can conclude this statement to be true.

Table 5.16: Classification – Non Financial Firms

	Predicted			
Observed	A	AA	AAA	Percent Correct
A	20	28	5	37.7%
AA	9	77	6	83.7%
AAA	3	19	22	50.0%
Overall Percentage	16.9%	65.6%	17.5%	63.0%

Here we can see an overall accuracy to predict CRISIL corporate bond rating for non financial firms to be 63%.

6. CONCLUSION

6.1 SUMMARY

In this report we applied the Multiple Discriminant Analysis and Multinomial Logistic Regression for bond rating classification. The goal set was to create an accurate MDA model and MLR model which are able to predict CRISIL bond rating classes by virtue of financial quantitative data with a statistical approach. The data set that had been used for this report consisted of over 169 financial firms and 201 non financial firms of Indian market which released bonds in past five years.

Our primary objective was to create a model for accurate prediction of the corporate bond rating. In the similar field research was done previously in other countries with an accuracy of 36% to 75% using MDA and regression models. This MDA model was able to predict 66% of the bonds from financial firms correctly and 61% for non financial firms. On the other hand MLR model was able to predict 66.2% of the bonds from financial firms correctly and 63% for non financial firms. We have used five financial ratios as independent variables for financial firm models and seven for non financial firm models.

Apart from the primary objective we could also do a qualitative study on the trends in the independent variables across the rating grades and also could gauge their importance in rating of corporate bond in a growing economy like India. If we look at MDA model for financial firms we can conclude that all the five variables are significantly important in determining the category of the corporate bond rating. We can also qualitatively conclude that higher return on assets and solvency ratio are better for achieving good rating for the corporate bond. Another observation is that it is better to have a lower EBITDA / Total Income and Total Debt / Capital ratio for achieving a good rating. The above two conclusions go along with the one's observed in table4.4. But using MDA we are not able to conclude any such result about equity multiplier trend across ratings.

If we look at MLR for financial firms, we observe that to categorize between AA and AAA onlyequity multiplier and EBITDA / Total Income are significant and they both agree with the observations made in the table 5.7, i.e it is better to have a lower value of these ratios to achieve better rating. Now, also observe that to categorize between A and AAA only equity multiplier, solvency ratio, EBITDA / Total Income and Total Debt / Capital are significant and they also agree with the observations in the table 4.4, i.e it is better to have a lower value of these ratios to achieve better ratings.

Lets look at the MDA model for non financial firms. We can conclude that all the seven variables are significantly important in determining the category of the corporate bond rating. We can also qualitatively conclude that higher ROE and EBITDA Interest Coverage are better for achieving good rating for the corporate bond. Another observation is that it is better to have a lower working capital / total assets for achieving a good rating. The above two conclusions go along with the one's observed in table 4.6. But using MDA we are not able to conclude any such result about the other ratios trend across ratings.

If we look at MLR for non financial firms, we observe that to categorize between AA and AAA only Cash flow from operations/ (total assets + Working Capital), ROE and working capital / total Assets are significant and ROE and Working capital / total assets match with the observations made in the table 5.15, i.e it is better to have a lower value of Working capital / total assets and higher value of ROE to achieve better rating. Now, also observe that to categorize between A and AAA only EBITDA Interest Coverage ratio, ROE and working capital

/ total Assets are significant and ROE and Working capital / total assets match with the observations in the table 4.6, i.eit is better to have a lower value of Working capital / total assets and higher value of ROE & EBITDA Interest Coverage ratio to achieve better rating.

6.2 CONTRIBUTIONS

This is the only research to our knowledge which tried predicting the CRISIL bond rating which lays path to further research. This research gave us a pot of variables which contribute to the rating of the bonds along with their importance. Ultimately this study will help the firms to know the stability of the bonds they have released in the past. In urge to get better rating to their bonds firms can focus their financial management with the knowledge of this research. Most importantly this study can lay path to future accurate models and hence work towards a uniform rating system throughout the globe.

6.3 LIMITATION

Most of the limitations of the study are due to lack of data. This study was based on firms which released corporate bonds in past five years. Data points for bonds below BBB rating were very few when compared to that of above BBB. Due to which the study was restricted AAA, AA and A categories only. Apart from this limitation, the other limitation is due to concentration on CRISIL rating in particular. This limited our models to be applicable for CRISIL rating alone.

Finally, for multiple discriminant analysis the data is expected to be normal but in this case the data is not normal even after removal of outliers and applying log. This made our multiple discriminant analysis less robust.

6.4 SCOPE FOR FUTURE WORK

As we have seen that only theinternal firm history of financial ratios have been taken into account for building these models. Instead, we can also incorporate external factors like industry performance, future of the industry, inflation, age of the firm, whether it is a MNC or not ,etc. These kind of external factors will fetch better results. The methodologies used here are only statistical but artificial intelligence techniques have proven themselves better internationally in past, we can employ them in Indian scenario.

APPENDIX A

List of Financial Firms used:

- Andhra Pradesh State Financial Corpn.
- Bank Of Rajasthan Ltd. [Merged]
- BHARTIYA SAMRUDDHI FINANCE Ltd.
- Dhanlaxmi Bank Ltd.
- INDUSIND BANK Ltd.
- KARNATAKA BANK Ltd.
- M A S Financial Services Ltd.
- Madhya Pradesh Financial Corpn.
- Manappuram General Finance & Leasing Ltd.
- Muthoot Finance Ltd.
- P T C India Financial Services Ltd.
- TATA MOTORS FINANCE Ltd.
- Tourism Finance Corpn. Of India Ltd.
- Ujjivan Financial Services Pvt. Ltd.
- Yes Bank Ltd.
- ALLAHABAD BANK
- Andhra Bank
- Bajaj Finance Ltd.
- BANK OF MAHARASHTRA
- Central Bank of India
- Cholamandalam Investment & Finance Co. Ltd.
- CITICORP FINANCE (INDIA) Ltd.
- DENA BANK
- Deutsche Investments India Pvt. Ltd.
- DEUTSCHE POSTBANK HOME FINANCE Ltd.
- E C L Finance Ltd.
- Fullerton India Credit Co. Ltd.
- I D B I Bank Ltd.
- I D B I Homefinance Ltd. [Merged]
- I N G Vysya Bank Ltd.
- India InfolineInvst. Services Ltd.
- INDIABULLS FINANCIAL SERVICES Ltd.
- INDIAN BANK
- Indian Overseas Bank
- Infrastructure Development Finance Co. Ltd.
- Jammu & Kashmir Bank Ltd.
- L & T Finance Ltd.
- L & T Infrastructure Finance Co. Ltd.
- Magma Fincorp Ltd.
- Mahindra & Mahindra Financial Services Ltd.
- ORIENTAL BANK OF COMMERCE
- P N B Housing Finance Ltd.
- Punjab & Sind Bank
- R B S Financial Services (India) Pvt. Ltd.
- RELIGARE FINVEST Ltd.
- S B I Global Factors Ltd.

- Shriram Transport Finance Co. Ltd.
- Small Industries Devp. Bank Of India
- SUNDARAM FINANCE Ltd.
- SYNDICATE BANK
- TATA CAPITAL Ltd.
- UCO BANK
- UNION BANK OF INDIA
- VIJAYA BANK
- AXIS BANK Ltd.
- BANK OF BARODA
- BANK OF INDIA
- CANARA BANK
- CITIFINANCIAL CONSUMER FINANCE INDIA Ltd.
- CORPORATION BANK
- D S P MILL LYNCH CAPITAL Ltd.
- Export-Import Bank Of India
- G E Capital Services India
- H D F C BANK Ltd.
- I C I C I Bank Ltd.
- I C I C I Home Finance Co. Ltd.
- I C I C I Securities Primary Dealership Ltd.
- India Infrastructure Finance Co. Ltd.
- Indian Railway Finance Corpn. Ltd.
- Infrastructure Leasing & Financial Services Ltd.
- L I C Housing Finance Ltd.
- National Bank For Agriculture & Rural Development
- NATIONAL HOUSING BANK
- Power Finance Corpn. Ltd.
- PUNJAB NATIONAL BANK
- State Bank Of Bikaner & Jaipur
- STATE BANK OF INDIA
- STATE BANK OF INDORE
- State Bank Of Mysore
- STATE BANK OF PATIALA
- STATE BANK OF TRAVANCORE

List of Non Financial Firms:

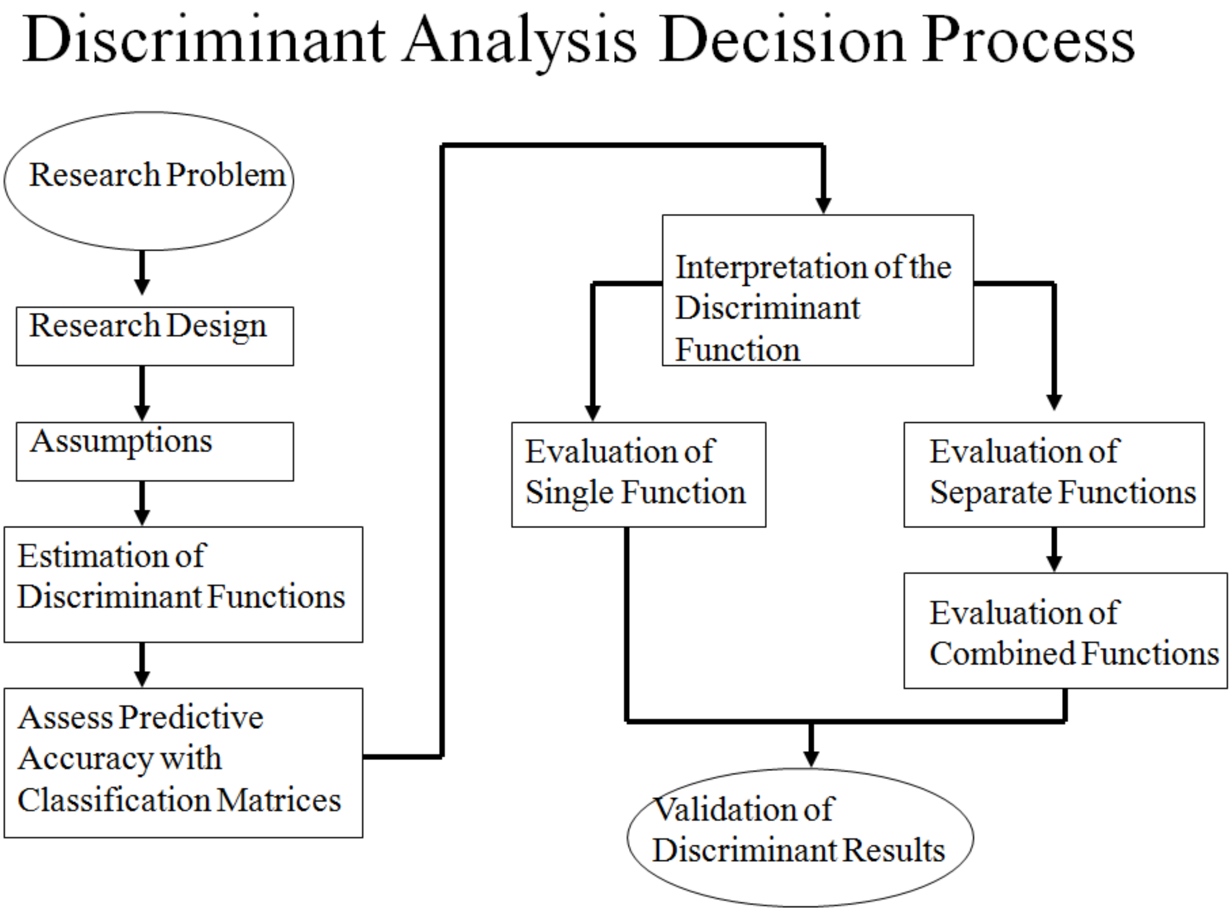
- Emaar M G F Land Ltd.
- G M R Energy Ltd.
- LAVASA CORPORATION Ltd.
- Neptune Developers Ltd.
- PARSVNATH DEVELOPERS Ltd.
- A B G Shipyard Ltd.
- Aarti Industries Ltd.
- ADVANTA INDIA Ltd.
- Alok Industries Ltd.
- BHARAT FORGE Ltd.
- Bharat Hotels Ltd.
- Bharati Shipyard Ltd.
- Bhushan Steel Ltd.
- D L F Ltd.
- D P S C Ltd.
- Delhi Transco Ltd.
- DHARAMPAL SATYAPAL Ltd.
- Dishman Pharmaceuticals & Chemicals Ltd.
- Educomp Infrastructure & School Mgmt. Ltd.
- ELDER PHARMACEUTICALS Ltd.
- Emco Ltd.
- ESSAR POWER Ltd.
- FUTURE CAPITAL HOLDINGS Ltd.
- G M R INFRASTRUCTURE Ltd.
- Gayatri Projects Ltd.
- Hotel Leelaventure Ltd.
- I V R C L Assets & Holdings Ltd.
- INDIABULLS REAL ESTATE Ltd.
- J B F Industries Ltd.
- J K Cement Ltd.
- Jaiprakash Associates Ltd.
- JaypeeInfratech Ltd.
- K M C Constructions Ltd.
- KALYANI STEELS Ltd.
- Meghmani Organics Ltd.
- Orient Paper &Inds. Ltd.
- P V R Ltd.
- Punjab State Electricity Board
- Rei Agro Ltd.
- SHREE RENUKA SUGARS Ltd.

- South West Port Ltd.
- Sterling Biotech Ltd.
- TAG Offshore Ltd.
- TATA TELESERVICES Ltd.
- Transmission Corporation of Andhra Pradesh Ltd.
- Triveni Engineering &Inds. Ltd.
- U T V Software Communications Ltd.
- Uttam Galva Steels Ltd.
- ADITYA BIRLA NUVO Ltd.
- Amtek Auto Ltd.
- Apollo Hospitals Enterprise Ltd.
- APOLLO TYRES Ltd.
- ASHOK LEYLAND Ltd.
- Ballarpur Industries Ltd.
- Bharat Aluminium Co. Ltd.
- Bilt Graphic Papers Ltd. [Merged]
- Birla Corporation Ltd.
- CADILA HEALTHCARE Ltd.
- CARBORUNDUM UNIVERSAL Ltd.
- Cox & Kings Ltd.
- Damodar Valley Corpn.
- Deepak Fertilisers & Petrochemicals Corpn. Ltd.
- E I D-Parry (India) Ltd.
- Edelweiss Capital Ltd.
- ELECTROSTEEL CASTINGS Ltd.
- ESS DEE Aluminium Ltd.
- FINOLEX CABLES Ltd.
- FINOLEX INDUSTRIES Ltd.
- GAMMON INDIA Ltd.
- Gujarat N R E Coke Ltd.
- H C L TECHNOLOGIES Ltd.
- H E G Ltd.
- Himadri Chemicals &Inds. Ltd.
- Hindustan Construction Co. Ltd.
- Hindusthan National Glass &Inds. Ltd.
- Indian Hotels Co. Ltd.
- Indian Oil Corpn. Ltd.
- J K Lakshmi Cement Ltd.
- J M C Projects (India) Ltd.
- J S W Steel Ltd.
- Jindal Steel & Power Ltd.
- Kalpataru Power Transmission Ltd.
- Kesoram Industries Ltd.

- MANAKSIA Ltd.
- MARICO Ltd.
- Mercator Lines Ltd.
- Mundra Port & Special Economic Zone Ltd.
- N I I T Ltd.
- N R B Bearings Ltd.
- NEELACHAL ISPAT NIGAM Ltd.
- C L India Ltd.
- Parekh Aluminex Ltd.
- Piramal Healthcare Ltd.
- Prism Cement Ltd.
- PunjLLoyd Ltd.
- RELIANCE INFRASTRUCTURE Ltd.
- S R F Ltd.
- Sadbhav Engineering Ltd.
- Sarda Energy & Minerals Ltd.
- Shree Cement Ltd.
- Simran Wind Project Pvt. Ltd.
- Sintex Industries Ltd.
- Talwandi Sabo Power Ltd.
- Tamil Nadu Newsprint & Papers Ltd.
- TATA AUTOCOMP SYSTEMS Ltd.
- TATA CHEMICALS Ltd.
- TATA GLOBAL BEVERAGES Ltd.
- Tata Power Co. Ltd.
- Techno Electric &Engg. Co. Ltd.
- TRENT Ltd.
- United Phosphorus Ltd.
- VEDANTA ALUMINIUM Ltd.
- Viramgam-Mahesana Project Ltd.
- Welspun Corp Ltd.
- A C C Ltd.
- Bharat Petroleum Corpn. Ltd.
- G A I L (India) Ltd.
- G M R PochanpalliExpressways Ltd.
- GREAT EASTERN SHIPPING CO. Ltd.
- Hindustan Petroleum Corpn. Ltd.
- Larsen & Toubro Ltd.
- N H P C Ltd.
- N T P C Ltd.
- Neyveli Lignite Corpn. Ltd.
- Nirmal B O T Ltd.
- North Karnataka Expressway Ltd.
- Nuclear Power Corpn. Of India Ltd.
- N G C Videsh Ltd.

- PATEL KNR INFRASTRUCTURES Ltd.
- Pidilite Industries Ltd.
- Power Grid Corpn. Of India Ltd.
- Reliance Industries Ltd.
- Reliance Utilities & Power Pvt. Ltd.
- Rural Electrification Corpn. Ltd.
- Steel Authority Of India Ltd.
- TATA COMMUNICATIONS Ltd.
- ULTRATECH CEMENT Ltd.

APPENDIX B


Discriminant Analysis Decision Process
Research Problem
Research Design
Assumptions
Estimation of Discriminant Functions
Assess Predictive Accuracy with Classification Matrices
Interpretation of the Discriminant Function
Evaluation of Single Function
Evaluation of Separate Functions
Evaluation of Combined Functions
Validation of Discriminant Results

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