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A Comparison of Neural Networks and Classical Discriminant Analysis in Anticipating Default among High-Yield Bonds

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Introduction

The last decade has seen the emergence of a variety of new tools and techniques being developed for decision support. One of the primary and emerging contributors to this area is the field of Artificial Intelligence (AI). There is no dearth of literature on the application of AI tools on decision areas like loan applications, bankruptcy of firms, and risk forecasting.

Bonds remain one of the primary source of external funding for American corporations. In the past few years there has been a lot of research on this topic, especially in the realms of bond rating, quantification of risk in bond markets and the role of bond rating agencies in the bond market. One area which has not been focused on in detail is the area of high-yield bonds or "junk bonds"

The objective of the present study is to develop and compare the performance of a neural network model relative to statistical modeling in anticipating default among high-yield bonds. We define default as a company missing either an interest or principal payment on an outstanding debt issue. One of the reasons for focusing on the high-yield bond domain is the speculative nature of such bonds. An investor in this category would find it immensely useful to have a model which can help him anticipate defaults. Such a model would help them protect their investment before the bonds go into default.

Bond Rating and High-yield Bonds

A review of bond literature in the past two decades reveals an increasing tendency by corporations of using bond issues to raise long-term funds (Block and Hirt, 1994). It is also recognized that in general bond investors place more emphasis on the "quality" of the bonds than do a common stock investor. They are not only interested in the bond ratings per se, but also keep a close eye on the bond rating procedures (Hirt and Block, 1996). In the U.S, the two primary bond-rating agencies are Moody's Investors Service and Standard & Poor's. The rating usually range from an AAA to a D category (Standard & Poor's) . Even though the ratings may differ across the two firms, the difference is small in magnitude (e.g AAA vs an A rating). The bond ratings can be broadly classified into two groups: investment-grade quality (AAA to BBB) and high-yield bonds or junk bonds (BB to D). The focus of this study is the category of high-yield bonds. It has been found that the default rates for high-yield bonds has been significantly higher than those for investment bonds (Altman, 1989; Asquith et al., 1989). Additionally, another group of

researchers (Hickman, 1958; Warner, 1977) has studied the price behavior of high-yield bonds. These studies indicate that there is a significant transfer of wealth from pre-default bondholders to post-default purchasers. The purpose of this study is to model the "defaulting" behavior of high-yield bonds using both neural network and statistical models and compare the results from the two.

The Problem Statement

The task of assigning a given high-yield bond into either the default group or the non-default group can be considered as a classification problem: given a set of input data objects, each with certain characteristics, assign each input object to one of the classes. In our study, the possibility that a high-yield bond goes into default or not form the two classes to which the input bonds can belong. The characteristics of each input (bond) object represents the financial and market information about the firm issuing the bond. The problem for our study can be stated as follows: Let N be the set of high-yield bonds, each belonging to either the default or the non-default category (D or ND), and having C_n characteristics features. Our classification problem involves finding the mapping function f, such that

$f : C_1 \ x \ C_2 \ x....C_n ---> D \ (ND)$

Literature Review

In the past few years there has been an abundance of literature in the domain of bond quality and the risks associated with bonds. However, most of these studies have concentrated on the topic of bond ratings. Srinivasan and Bolster (1990) presented a formal judgmental model of the bond rating process based on the analytic hierarchy process. They argue the advantages of the AHP-based model over informal judgmental systems. Kim et al. (1993) compare an artificial neural network system, a rule-based expert system and statistical techniques as applied to the bond rating problem. Dutta and Shekhar (1988) used neural networks to predict the ratings of corporate bonds. They concluded that neural networks perform significantly better than mathematical modeling techniques for non-conservative problem domains.

Classical Approach (Statistical Modeling)

Discriminant analysis is a statistical technique used to classify objects into distinct groups based on a set of criteria or characteristics of the objects. One of the most frequently used classification rule is Fisher's Linear Discriminant Analysis (FLDA). The rule works well in situations where the groups to be discriminated can be separated by a straight line. Objects are classified into groups on the basis of a "discriminant score", which is computed on the basis of the object's observed values on the discriminating criteria or characteristics.

Neural Networks

Neural networks are composed of highly interconnected neurons or processing elements organized in layers. In its basic form, a neural network consists of an input layer, one or more hidden layer(s) and an output layer. The hidden layer is used to develop an internal representation of the relationship between the variables. In the past, neural networks have been used to solve a multitude of business related and non-business related issues. Dutta and Shekar (1988) used neural networks to predict the ratings of corporate bonds. Their results indicated that neural net models are useful in solving generalization problems in such non-conservative domains. Some other examples of neural network application to business domain are: in processing loan-applications (Gallant, 1988), bankruptcy prediction (Wilson and Sharda, 1994), forecasting (Lee and Jhee, 1994), and fraud prevention (Rochester, 1990). Our study focuses on the domain of bond-rating and bond-quality. We use a resampling technique to study the effectiveness of neural networks versus the multivariate discriminant model in predicting the default among high-yield bonds.

Selection of Variables

Altman's [1968] original study on bankruptcy prediction noted that bankruptcy in the normal case is a gradual process of deterioration rather than an immediate shock. There is reason to believe that the same situation applies to bond defaults. i.e., defaults occur due to a gradual decay in financial conditions. Both bankruptcy and bond defaults are generally brought on by an inability to meet obligations as they come due. Therefore, financial variables that are accurate predictors of bankruptcy were initially included in this study as they may also be good predictors of bond defaults. Peavy and Edgar (1983) also point out an additional consideration in selecting variables. They argue that a selection of ratios representing the broad financial dimensions of a company is important. In our study, we included variables pertaining to financial dimensions commonly associated with businesses in general, for e.g measures of liquidity, profitability, asset utilization, and debt utilization.

Initially, we selected a list of 29 variables for our study of the default behavior among high-yield bonds. A correlation analysis was done to check the extent of relationship between the variables. Based on the correlation coefficients, 13 variables were deleted from the sample. The remaining 16 variables were used to run a step-wise discriminant analysis using Wilks' lambda. This resulted in the selection of 8 variables as significant to our study. The eight variables were PITA (pretax income/total assets), RECDAY (receivable days sales), TLTA (total liabilities/total assets), TIE (times interest earned), NSCA (net sales /current assets), NSPE (net sales/plant & equipment),TLCE (total liabilities/common equity), and INVDAY(inventories days sales).

Data Collection

Approximately 391 different companies issued high-yield bonds during the period January 1, 1984, thru December 31, 1986. A total of 629 issues raised $67.4 billion in capital during this period. For the purpose of this study, a sample group of 100 firms issuing high-yield bonds were selected from the Compact Disclosure database. The

Compact Disclosure database includes financial information on about 12,000 companies. Compact Disclosure excludes partnerships and real estate investment trusts. Additional information on defaults was obtained from several sources, including (1) the Ward-Niedermeyer Defaulted Bond Data Base, (2) the "Debt in Default" section of <u>Credit Week</u>, a weekly publication of Standard & Poors, (3) <u>Moody's Annual Bond Record,</u> and (4) <u>Distressed Securities</u> by Edward Altman. Firms for which all the information was not available were deleted from the sample.

Results

The classification results from Fischer's linear discriminant analysis using Wilk's lambda yielded an overall hit rate of 87.5% (49 out of 56 records). Using a RMS error of 0.001, the neural network model using one hidden layer (with 16 nodes and 1 bias), yielded an overall hit rate of 89.3% (50 out of 56 records). These results shows that neural network models offer great promise in the area of bond-default prediction.

Conclusion

As mentioned earlier, the last decade has seen a rapid growth of the high-yield bond market. Along with this increasing use of high-yield bonds to raise capital, there has also been a rise in the default rates. This has influenced a lot of issues like the degree of risk in bond investment, trustworthiness of the bond-ratings, and protection for investors holding securities. Even though certain areas like the link between bankruptcy and bond ratings has been extensively researched, there is a scarcity of studies relating to bond defaults. This study addresses the topic of bond defaults using two models: one using the classical multivariate discriminant analysis and the other using neural networks. Such models on bond defaults can be of immense practical value to investors of high-yield securities. Investors can use such models to preserve their investment before the bond goes into default. From a theoretical perspective, models such as the ones we developed using different tools can help researchers gain valuable insight into the nature of high-yield securities and the factors which affect their quality.

<u>References available upon request from first author</u>.