Bankruptcy Prediction for Credit Risk Using Neural Networks: A Survey and New Results

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***Abstract*—The prediction of corporate bankruptcies is an important and widely studied topic since it can have significant impact on bank lending decisions and profitability. This work presents two contributions. First we review the topic of bankruptcy prediction, with emphasis on neural-network (NN) models. Second, we develop an NN bankruptcy prediction model. Inspired by one of the traditional credit risk models developed by Merton, we propose novel indicators for the NN system. We show that the use of these indicators in addition to traditional financial ratio indicators provides a significant improvement in the (out-of-sample) prediction accuracy (from 81.46% to 85.5% for a three-year-ahead forecast).**

***Index Terms*—Asset-based model, bankruptcy prediction, corporate distress, corporate failure prediction, credit risk, default prediction, financial ratios, financial statement data, multilayer networks.**

I. Introduction

BANKRUPTCY prediction has long been an important and widely studied topic. The main impact of such research is in bank lending. Banks need to predict the possibility of default of a potential counterparty before they extend a loan. This can lead to sounder lending decisions, and therefore result in significant savings. In this study we focus only on the corporate bankruptcy prediction problem. For the consumer bankruptcy prediction problem, there is likewise an extensive amount of research, but the reader is referred to [19], [40], and [52] for a review of this topic.

To get an idea about the potential impact of the bankruptcy prediction problem, we note that the volume of outstanding debt to corporations in the United States is about $5 trillion. An improvement in default prediction accuracy of just a few percentage points can lead to savings of tens of billions of dollars. In addition to avoiding potentially troubled obligors, the research can also benefit in other ways. It can help in estimating a fair value of the interest rate of a loan (that reflects the creditworthiness of the counterparty). It can help in accurately assessing the *credit risk* of bank loan portfolios. The credit risk problem is essentially the computation of the *loss level*, which is defined as the level for which there is a probability of 1% that the loss incurred in the portfolio will exceed that level in a particular time period. Credit risk has been the subject of much research activity, especially after realizing its practical necessity after a number of high profile bank failures in Asia. As a result, the regulators are acknowledging the need and are urging the banks to utilize cutting edge technology to assess the credit risk in their portfolios. Measuring the credit risk accurately also allows banks to engineer future lending transactions, so as to achieve targeted return/risk characteristics. The other benefit of the prediction of bankruptcies is for accounting firms. If an accounting firm audits a potentially troubled firm, and misses giving a warning signal (say a "going concern" opinion), then it faces costly lawsuits.

The traditional approach for banks for credit risk assessment is to produce an internal rating, which takes into account various quantitative as well as subjective factors, such as leverage, earnings, reputation, etc., through a scoring system [48]. The problem with this approach is of course the subjective aspect of the prediction, which makes it difficult to make consistent estimates. Some banks, especially smaller ones, use the ratings issued by the standard credit rating agencies, such as Moody's and Standard & Poor's. The problem with these ratings is that they tend to be reactive rather than predictive (for the agencies to change a rating of a debt, they usually wait until they have a considerably high confidence/evidence to support their decision). There is a need, therefore, to develop fairly accurate quantitative prediction models that can serve as very early warning signals for counterparty defaults.

There are two main approaches to loan default/bankruptcy prediction. The first approach, the *structural approach*, is based on modeling the underlying dynamics of interest rates and firm characteristics and deriving the default probability based on these dynamics. The second approach is the *empirical* or the *statistical approach*. Instead of modeling the relationship of default with the characteristics of a firm, this relationship is learned from the data. The focus of this article is on the empirical approach, especially the use of NNs. In the next section we give a review on this approach. To give a flavor about the structural approach, it is also very briefly reviewed in the next section. Section III presents some results of simulations that we have performed, where we introduce novel inputs that lead to considerable improvement in prediction accuracy. Section IV is the summary and conclusion of this paper.

II. A Review of Bankruptcy Prediction Models

A. Early Empirical Approaches

The pioneers of the empirical approach are Beaver [7], Altman [2], and Ohlson [34]. Beaver was one of the first researchers to study the prediction of bankruptcy using financial statement data. However, his analysis is very simple in that it is based on studying one financial ratio at a time and on

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developing a cutoff threshold for each ratio. The approaches by Altman and Ohlson are essentially linear models that classify between healthy/bankrupt firms using financial ratios as inputs. Altman uses the classical multivariate discriminant analysis technique (MDA). It is based on applying the Bayes classification procedure, under the assumption that the two classes have Gaussian distributions with equal covariance matrices. The covariance matrix and the class means are estimated from the training set. Altman used the following financial ratios as inputs:

1) working capital/total assets;
2) retained earnings/total assets;
3) earnings before interest and taxes/total assets;
4) market capitalization/total debt;
5) sales/total assets.

These particular financial ratios have been widely used as inputs, even for NNs and other nonlinear models. They are described in more detail in the next subsection.

Ohlson introduced the logistic regression approach (LR) to the bankruptcy prediction problem. It is essentially a linear model with a sigmoid function $f(x) = 1/(1 + e^{-x})$ at the output (it is thus similar to a single-neuron network). Because the output is in between 0 and 1, the model has a nice probabilistic interpretation. Ohlson used a novel set of financial ratios as inputs. Both the MDA model and the LR model have been widely used in practice and in many academic studies. They have been standard benchmarks for the loan default prediction problem.

B. *Neural-Network (NN) Approaches*

Research studies on using NNs for bankruptcy prediction started in 1990, and are still active now. There are a number of reasons why a nonlinear approach would be superior to a linear approach. It can be argued that there are saturation effects in the relationships between the financial ratios and the prediction of default. For example, if the earnings/total assets changes say by an amount of 0.2, from -0.1 to 0.1, it would have a far larger effect (on the prediction of default) than it would if that ratio changes from say 1.0 to 1.2. One can also argue that there are multiplicative factors as well. For example, the potential for default for a firm with negative cash flow gets more amplified if it has large liabilities. The reason is that highly leveraged firms have a harder time borrowing money to finance their deficits. As will be seen from the review below, NNs have generally outperformed the other existing methods. Currently, several of the major commercial loan default prediction products are based on NNs. For example, Moody's *Public Firm Risk Model* [32] is based on NNs as the main technology. Many banks have also developed and are using proprietary NN default prediction models.

The following is a review of the NN bankruptcy prediction studies. There has been also a number of other review papers. For example, Vellido *et al.* [52] survey the use of NNs in business applications. This survey includes a section on bankruptcy prediction. Also, the survey of Wong *et al.* [56] on NNs in business applications includes some references on the bankruptcy prediction problem. Dimitras *et al.* [15] provide a survey on the classical empirical approaches. Zhang *et al.* [58] include in their paper a nice review of existing work on NN bankruptcy prediction. The majority of the NN approaches to default prediction use multilayer networks. Since this is the dominant approach, henceforth when we mention NNs we mean multilayer networks.

One of the first studies to apply NNs to the bankruptcy prediction problem was the work by Odom and Sharda [33]. Odom and Sharda used Altman's financial ratios (described above) as inputs to the NN, and applied their method, as well as MDA as a comparison, to a number of bankrupt and solvent US firms, where the data used for the bankrupt firms are from the last financial statement before declaring bankruptcy. They considered 128 firms, and performed several experiments where they varied the proportion of bankrupt/healthy firms in the training set. The NN achieved a Type I correct classification accuracy in the range of 77.8% to 81.5% (depending on the training setup), and a Type II accuracy in the range of 78.6% to 85.7%. The corresponding results for MDA were in the range of 59.3% to 70.4% for Type I acuracy, and in the range of 78.6% to 85.7% for Type II acuracy.

Let us now discuss why the particular indicators of [33] (which are the same as Altman's indicators) have been chosen. Most other studies use indicators similar in nature, and the analysis presented will somewhat apply to these studies as well. A company's total assets consists of current assets and long term assets. The total assets gives some indication of the size of the firm. Therefore it is frequently used as a normalizing factor (like in indicators 1,2,3,5 of Altman's indicators). The current assets can or will typically be turned into money fairly fast. The firm's liabilities consists of current liabilities and long term debt. The current liabilities include short term loans (less than one year due), accounts payable, taxes due, etc. The working capital is current assets minus the current liabilities. It is an indication of the ability of the firm to pay its short term obligations. If it is too negative, the company might default on some payments. The firm's total assets is financed by a) the total liabilities and b) the shareholders' equity [therefore the name "balance sheet," since the total assets have to exactly equal the sum of the two items in a) and b)]. The shareholders' equity consists of the capital raised in share offerings and the retained earnings. The retained earnings means the accumulation of the firm's earnings since the firm's inception. The shareholders' equity is also called the book value of the firm. Even though it is based on the historical costs (plus adjustments through depreciation/amortization) of the firm's assets and liabilities, rather than market values, it has been a very useful indicator in assessing the financial health of a firm. Retained earnings is a related and similarly useful indicator. The firm's earnings is also an important indicator. Highly negative earnings indicate that the firm is losing its competitiveness, and that geopardizes its survival. Another related, widely used indicator is the cash flow. It is less prone than earnings to management manipulation. In addition, it measures directly the ability of the firm to generate cash to retire debt. The rationale behind Altman's fourth indicator is the following. The firm can issue and sell new shares in the market to repay its debt. A large market capitalization (relative to the total debt) indicates a high capacity to perform that.

Finally, the firm's sales is an indication of the health of its business. However, this indicator is probably the least effective among the five Altman indicators, because sales to total assets can vary a lot from industry to industry.

Tam and Kiang [46], [47] considered the problem of bank failure prediction. They compared between several methods: MDA, LR, K-nearest neighbor (KNN), ID3 (a decision tree classification algorithm), single-layer network, and multilayer network. For the case of one-year-ahead, the multilayer network was the best, while for the case of two-year-ahead, LR was the best. When they used a leave-one-out procedure instead of a hold-out sample, the multilayer network was the clear winner (for both forecast horizons). KNN and ID3 were almost always inferior to the other methods.

Salchenberger *et al.* [41] considered the problem of predicting thrift failures. They compared NN with LR. The NN significantly outperformed the LR. For example for 18-months ahead prediction the LR achieves 83.3–85.4% accuracy (depending on some threshold), whereas the NN achieves 91.7%.

Coats and Fant [12] compared between NN and MDA. They obtained a classification accuracy in the range of 81.9% to 95.0% for the NN (depending on the horizon: from three-years ahead to less than a year-ahead), and in the range of 83.7% to 87.9% for the MDA (also depending on the horizon).

Kerling and Poddig [23] compared NN with MDA for a database of French firms for a three-year-ahead forecast. The NN achieved a prediction accuracy in the range of 85.3–87.7% compared to 85.7% for MDA. Kerling tested several cross-validation procedures and early-stopping procedures in a follow-through study [22].

Altman *et al.* [3] applied NN and MDA to a large database of 1000 Italian firms for one-year ahead prediction. The comparison yielded no decisive winner, though MDA was slightly better.

Boritz and Kennedy [9] (see also [10]) compared between a number of techniques, including different NN training procedures, LR and MDA, using the indicators chosen by Altman, and those chosen by Ohlman. The results of the comparison are inconclusive.

Fernandez and Olmeda [17] compared NN with MDA, LR, MARS and C4.5 (two well known methods that are based on the CART decision tree algorithm) on Spanish banks (no horizon is specified). The NN obtained 82.4% accuracy compared with 61.8–79.4% for the competing techniques.

Alici [1] used principal component analysis and self-organizing maps for the input selection phase, together with a skeletonization step for the NN. He achieved an accuracy in the range of 69.5% to 73.7% (dependinding on some parameter variation), compared with 65.6% for MDA and 66.0% for LR for a database of UK firms (no horizon is mentioned).

Leshno and Spector [27] used a novel NN architectures containing cross-terms and cosine terms, and achieved prediction accuracy for the two-years-ahead case in the range of 74.2–76.4% (depending on the order of the network), compared with 72% for the linear perceptron network.

Lee *et al.* [25] propose hybrid models. Specifically, they tested combinations of the models MDA, ID3, self-organizing maps, and NN. They applied their study to the problem of default prediction of Korean firms.

Back *et al.* [4] propose the use of genetic algorithms for input selection, to be used in conjunction with multilayer networks. They applied their method to data covering the periods one to three years before the bankruptcy, where it obtains significant improvement over MDA and LR.

Kiviluoto [24] use self-organizing maps on an extensive database of Finnish firms (horizon is not specified), and show that it obtains comparable results to MDA and learning vector quantization (in the range from 81% to 86%). Kaski *et al.* (this issue [60]) developed a novel self-organizing map procedure based on the Fisher metric, and applied it also to a number of Finnish firms.

Zhang *et al.* [58] compared between NN and LR, and employed a five-fold cross-validation procedure, on a sample of manufacturing firms (horizion is not specified). They used Altman's five financial ratios plus the ratio current assets/current liabilities as inputs to the NN. The NN significantly outperformed LR with accuracy of 88.2% versus 78.6%.

Piramuthu *et al.* [37] developed a technique to construct symbolic features, to be inputed to a multilayer network. They applied their technique to a collection of Belgian firms (no forecast horizon is mentioned), where they obtained an accuracy of 82.9% versus 76.1% for the nontransformed input case. They applied it also to a problem of one- and two-year ahead default prediction for US banks. They get superior results, and significantly outperform the nontransformed input case. Piramuthu [36] applies a similar input selection technique in conjunction with decision tree classifiers.

Martinelli *et al.* [29] compared between two decision tree algorithms, C4.5 and CN2, and NN on a database of Brazilian firms. C4.5 outperform the other methods.

Yang *et al.* [57] used probabilistic NNs (PNNs) [45], which essentially implement the Bayes classification rule. They tested it on firms in the oil sector. The results were mixed: PNN tied with the multilayer networks, but with a particular preprocessing step MDA was the best.

McKee and Greenstein [30] developed a method based on decision trees and applied it to a number of US firms for one year ahead forecast. Their method obtains better results than NN and MDA for Type II error, but worse results for Type I error.

Fan and Palaniswami [59] propose the use of support vector machines (SVMs) for predicting bankruptcies among Australian firms, and compared it with NN, MDA and learning vector quantization (LVQ). SVM obtained the best results (70.35%–70.90% accuracy depending on the number of inputs used), followed by NN (66.11%–68.33%), followed by LVQ (62.50%–63.33%), followed by MDA (59.79%–63.68%).

These reviewed papers are just a sample of what has been done on the topic of NN default prediction. There are many other studies (e.g., [5], [6], [11], [13], [16], [18], [21], [26], [35], [38], [39], [42], [43], [44], [49], [50], [51], [53]), but for space considerations they are not reviewed here.

C. A Brief Review of the Structural Approach

One of the earlier and commonly used methods is the asset-based approach by Merton [31] (developed further by Longstaff and Schwartz [28]). This model views a firm's equity as an option on the firm (held by the shareholders) to either repay the debt of the firm when it is due, or abandon the firm without paying the obligations. The probability of default can be derived by modeling the market value of the firm as a geometric Brownian motion. What makes that model successful is its reliance on the equity market as an indicator, since it can be argued that the market capitalization of the firm (together with the firm's liabilities) reflect the solvency of the firm. This model has been successfully developed into a successful commercial product by KMV Corporation.

Another approach, by Jarrow and Turnbull [20], models default as a point process, where the time-varying hazard function for each credit class is estimated from the credit spreads. The CreditRisk+ product, developed by Credit Suisse Financial Products, is also based on the same concept of modeling default as a Poisson process.

Wilson [54], [55] proposed a discrete-time dynamical model, whereby the default probabilities are a function of macro-economic variables. J.P. Morgan's CreditMetrics product [14] is based on modeling changes in the credit quality ratings. By modeling the "rating migrations," one can obtain an estimate for the probability of default. Several other models have been proposed. For a more detailed review of structural credit risk models refer to Crouhy *et al.* [14].

D. Challenges for the NN Prediction Models

In spite of the success of NN models, there are a number of open issues that should desirably be addressed by the research community. Even though a prediction of the default event is by itself very useful, an estimate of the *default probabilty* is very desirable. For portfolio credit risk estimation, this is essential in order to compute the loss level. (As described in the introduction section, the loss level is the level for which there is a probability of 1% that the loss incurred in the portfolio will exceed that level in a particular time period.) Also, typically banks have several prediction systems in place. They make a lending decision based on the combination of these predictions. Having a probability of default rather than a (binary) prediction of default is valuable for them. Even though there are some objective function measures that achieve that, such as cross-entropy error function [8], our experience with this objective function has not been very favorable.

The other open issue is to consider macroeconomic indicators as inputs to the NN. The prevailing economic conditions (as well as the current interest rates) can have a significant effect on the probability of bankruptcy. There are very few studies that consider these factors in conjunction with NN models. This should therefore be a recommended study.

III. The Developed Bankruptcy Prediction Model

In this work we introduce a novel set of indicators that can be used in addition to the financial ratios and lead to significant improvement in prediction accuracy. These indicators are extracted from the stock price of the firm. (We are inspired here by Merton's asset-based model, described in Section II-C, which is based on information extracted from the equity markets.) It is well known that the equity markets are very-early predictors of shortfalls (or improvements) in the performance of a firm. A problem faced by a firm will typically be reflected in the stock price well before it shows up in its balance sheet and income statement. As such, indicators obtained from the stock price can be beneficial especially in long horizon default forecast. Examples of indicators tested are: volatility, change in volatility, change in price, absolute price, price-cashflow ratio, etc. We describe the developed model below.

To test the comparative advantage of stock-price-based indicators, we have developed two systems: one system based on financial ratios alone (financial ratio system), and another based on financial ratios and price-based indicators (financial ratio and equity-based system). We will not compare here with linear models such as MDA and LR, because that is not the objective of the paper, and because there are so many previous studies that have performed such a comparison (see Section II-C). The NN is designed to predict default three-years-ahead, so it gives a fairly long-horizon forecast. Each developed system consists of two stages: the input selection stage, and the NN application stage. We have considered a pool of about 120 candidate inputs (financial statement data, ratios, stock price data, and transformations of these). Using an initial prescreening procedure based on individual indicator prediction accuracy and correlation matrix, and then a subsequent cross-validation procedure to narrow down the choice, we select the best five or six inputs from this pool of indicators. For the financial ratio system the chosen indicators were:

1) book value/total assets BV/TA;
2) cashflow/total assets CF/TA;
3) rate of change of cashflow per share ROC(CF);
4) gross operating income/total assets GOI/TA;
5) return on assets ROA.

For the financial ratio and equity-based system the chosen indicators are:

1) book value/total assets BV/TA;
2) cashflow/total assets CF/TA;
3) price/cashflow ratio P/CF;
4) rate of change of stock price ROC(P);
5) rate of change of cashflow per share ROC(CF);
6) stock price volatility VOL.

To test the system, we have collected historical data from defaulted and from solvent US firms. The defaulted firm data cover the period spanning 1 month to 36 months before the bankruptcy event. (median time-to-default is 13 months). Note that we have selected the solvent firms randomly (from among all solvent firms), so the choice covers the whole spectrum from healthy to border-line firms in order to avoid any selection bias. We have considered 716 solvent firms and 195 defaulted firms. We have performed the prediction for the defaulted firms at two or three instants before default. The number of data points then became 1160 (444 defaulted and 716 solvent). We note that the size of the data set is quite large compared to the majority of bankruptcy prediction studies. To our knowledge, only the work by Altman *et al.*[3] uses a comparable size data set (1000 firms). The in-sample set consists of 491 data points, while the

TABLE I
RESULTS FOR THE NEURAL NETWORK DEFAULT PREDICTION MODEL: FINANCIAL RATIO MODEL

Time to Default	# Correct (in Sample)	# in Sample	% Correct (in Sample)	# Correct (out of Sample)	# out of Sample	% Correct (out of Sample)
6 mnth or less	34	38	89.47	59	65	90.77
6 to 12 mnth	47	51	92.16	47	54	87.04
12 to 18 mnth	31	37	83.78	51	63	80.95
18 to 24 mnth	31	37	83.78	21	32	65.63
more than 24 mnth	14	25	56.00	24	42	57.14
Total Defaulted	157	188	83.51	202	256	78.91
Solvent	258	303	85.15	343	413	83.05
Total	415	491	84.52	545	669	81.46

TABLE II
RESULTS FOR THE NEURAL NETWORK DEFAULT PREDICTION MODEL: FINANCIAL RATIO AND EQUITY-BASED MODEL

Time to Default	# Correct (in Sample)	# in Sample	% Correct (in Sample)	# Correct (out of Sample)	# out of Sample	% Correct (out of Sample)
6 mnth or less	35	38	92.11	56	65	86.15
6 to 12 mnth	43	51	84.31	44	54	81.48
12 to 18 mnth	33	37	89.19	47	63	74.60
18 to 24 mnth	33	37	89.19	25	32	78.13
more than 24 mnth	19	25	76.00	28	42	66.67
Total Defaulted	163	188	86.70	200	256	78.13
Solvent	276	303	91.09	372	413	90.07
Total	439	491	89.41	572	669	85.50

out-of-sample set consists of 669 data points. In case of multiple prediction instants for one firm, the firm's data are either all in the in-sample set or all in the out-of-sample set in order to avoid bias. Note that we maintained a fixed ratio of number of defaulted data points/number of solvent data points for both in-sample and out-of-sample set (about 62%). The in-sample data-set is used for the design of the input selection stage and the NN design, while the out-of-sample set is reserved for the final test of the system. Using the repeated random partitioning procedure for the in-sample set into training set and validation set, and repeated training and validation for the different partitions, we determined optimal values of the different network and learning parameters and performed the input selection. Based on this tuning approach we selected a network of size 2 hidden nodes. Since training a network till death for highly noisy applications can introduce some overfitting, we have used early stopping. The best number of iterations is determined with the help of the validation set to be 100.

Tables I and II show the results for both systems, along with a break-down according to time till default. For the financial ratio system we obtained a prediction accuracy of **84.52%** for the in-sample set, and **81.46%** for the out-of-sample set. For the financial ratio and equity-based system we obtained a prediction accuracy of **89.41%** for the in-sample set, and **85.50%** for the out-of-sample set. One can see that it outperforms by a full 4 percentage points the financial ratio system, indicating the value of indicators extracted from the equity markets. Note also that its edge gets better for long horizon forecasts. It can classify significantly better data points that correspond to a large time before default (for example more than 18 months). An explanation of this observation is that financial statement data tend to be lagging, since all the figures are reported by its book value. Also, the stock market is highly predictive. It reflects qualitative factors such as business conditions and insider information that trickle through the market.

Table III shows the correlation matrix for all 8 indicators used. Of particular interest is the uniformly negative correlation of the volatility indicator (VOL) with the other indicators. This makes it a particularly useful indicator as part of the group, since it might add discriminating power not there in the other indicators.

IV. SUMMARY AND CONCLUSION

In this article we reviewed the problem of bankruptcy prediction using NNs. From the many studies existing in the literature, it can be seen that NNs are generally more superior to other techniques. Once this is established, the logical next step for the research community is to improve further the performance of NNs for this application, perhaps through better training methods, better architecture selection, or better inputs. It is this latter improvement aspect that we have addressed in the second half of

TABLE III
CORRELATION MATRIX OF THE USED INPUTS

Input	BV/TA	CF/TA	GOI/TA	ROC(CF)	ROA	P/CF	ROC(P)	VOL
BV/TA	1.000	0.386	-0.028	0.146	0.316	0.181	0.303	-0.391
CF/TA	0.386	1.000	0.186	0.442	0.697	0.320	0.420	-0.531
GOI/TA	-0.028	0.186	1.000	0.017	0.146	0.076	0.092	-0.051
ROC(CF)	0.146	0.442	0.017	1.000	0.348	0.250	0.282	-0.207
ROA	0.316	0.697	0.146	0.348	1.000	0.382	0.411	-0.483
P/CF	0.181	0.320	0.076	0.250	0.382	1.000	0.293	-0.192
ROC(P)	0.303	0.420	0.092	0.282	0.411	0.293	1.000	-0.358
VOL	-0.391	-0.531	-0.051	-0.207	-0.483	-0.192	-0.358	1.000

this paper. We have proposed novel inputs extracted from the equity markets. As can be seen from the results, the new indicators improve the prediction considerably. This is especially true for long horizon forecast. This can be explained by the tendency of the equity markets to be highly predictive, not only of the health of a firm, but also of the health of the economy, which in turn affects the creditworthiness of the firm.

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