A NEURAL NETWORK APPROACH TO COMPARE PREDICTIVE VALUE OF ACCOUNTING VERSUS MARKET DATA

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ABSTRACT

This research compares the use of accounting data versus market data in the prediction of bankruptcy. Comparison is made through neural networks so that prediction accuracy is model-independent. Results of this study indicate that both market and accounting data provide useful information on corporate bankruptcies. Interestingly, using market and accounting information together can achieve substantial gain in prediction accuracy.

Key word: bankruptcy, neural network, accounting information, market information

JEL classification: G33, M49

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I. INTRODUCTION

A central role of the accountants, according to the Financial Accounting Standards Board (FASB), is to provide useful information. The Board's Statement of Financial Accounting Concepts (SFAC) No. 2 recognizes relevance as a fundamental attribute of useful accounting information. To be relevant, information must carry predictive value, a quality that enhances predictions about future outcomes. In an investing environment, information provides predictive value if it helps the investor predict future economic outcomes of investment decisions.

The predictive value of accounting information is well documented in accounting literature. Ball and Brown (1968) demonstrate empirically that the sign of the abnormal returns is strongly associated with the sign of unexpected earnings. This finding is extended by Beaver, Clarke, & Wright (1979) who find a positive association between the magnitude of the unexpected component of earnings and returns. Ohlson (1991) provides a theoretical link between earnings and stock price (and returns), and shows that returns and unexpected returns are explained by current earnings divided by beginning-period price.

However, prior literature and anecdotal evidence suggest that failing firms may overstate accounting numbers. The bankruptcy of Enron and WorldCom in 2002, for instance, was preceded by substantial inflation of reported earnings and cash flows. Management's manipulation of accounting numbers may corrupt the information content of accounting-based variables.

An alternative to accounting data is market data. Assuming market efficiency, all historical accounting and non-accounting information (such as press release, well being of competitors, etc) are already incorporated in stock price and stock return. Therefore, prediction based on market information may be more accurate than that based on accounting information because of the contribution from non-accounting information. However, the finance literature provides evidence suggestive of market inefficiencies.[1] If capital markets are not sufficiently efficient, market-based variables may not dominate accounting information in prediction.

Consequently, a natural question to ask is whether accounting-based or market-based data provides more useful information in predicting corporate bankruptcies. Another interesting question is whether combining accounting and market information improves prediction accuracy. This research compares the predictive value of accounting data versus market data in the prediction of bankruptcy. This topic is relevant to the investing public. Bankruptcy prediction may help the investor avoid huge economic loss. As a user of information, the investor needs to know whether accounting or market data is more informative for investment decisions.

To ensure that the comparison between accounting and market data is based on information content rather than on the effectiveness of prediction models, this study adopts a neural networks approach. A neural network is a system of programs that approximates the operation of the human brain through a large number of networked processing units (a.k.a. neurons) operating in parallel. Typically, a neural network is trained to make prediction. During the training process, the neural network captures knowledge from large amounts of historical data by finding the set of interneuron connection strengths that minimize prediction error (DARPA, 1988; Haykin, 1994).

Multilayer perceptron (MLP), the most basic neural network topology, is used in this study. The data in a multilayer perceptron follows a single path with no recursion or memory elements. Despite its simplicity, the multilayer perceptron can be used to handle the vast majority of problems that any other neural network topologies can solve.

Neural networks have been widely adopted in financial application including corporate bond rating, credit evaluation and underwriting, bankruptcy prediction, and saving and loan failure (Jain and Nag, 1995). The neural network provides an equitable platform to compare predictive value because no specific model assumption is needed. In addition, the ability to accommodate any non-linear relationship between input parameters and outcomes is a key advantage of the neural network approach.

The rest of this paper is organized as follows. Section II reviews prior literature on bankruptcy and neural networks. Section III explains data and sample selection. Section IV presents the methodology and discusses test results. Finally, Section V summarizes findings and contributions of this study.

II. LITERATURE REVIEW

A. Bankruptcy Literature

The financial position of a firm and its propensity for bankruptcy may seriously affect the well-being of stakeholders such as shareholders, creditors, employees, and business partners. Consequently, the bankruptcy prognosis is of great interest to researchers, and has become a common research topic in multiple disciplines.

The accounting and finance literature focuses on identifying factors with predictive values. It is commonly acknowledged that several accounting-based financial ratios are useful in predicting corporate bankruptcies. Altman (1968) chose primary prognostic factors of bankruptcy from among the financial ratios. Altman used the techniques of Multivariate Discriminant Analysis to construct a prognostic rule (algorithm) to calculate the compound secondary prognostic factor Z-score based on five primary prognostic factors (financial ratios). Deakin (1972), Altman, Handelman, and Narayanan (1977), Collins (1980), Aziz, Emanuel, Lawson (1988), Boritz (1991) analyzed many financial ratios with respect to their prognostic potential and proposed various prognostic rules in the framework of Linear Discriminant Analysis and Linear Regression approaches.

The market-based approach is also adopted in research. Beaver (1968) investigated the movements of market share value as a possible prognostic factor in forecasting corporate bankruptcy. He found that the market anticipates corporate bankruptcy at least a year prior to its actual occurrence. In addition, Clark and Weinstein (1983) found that a reduction in stock returns could be observed up to three years before bankruptcy.

In addition, the management science literature contributes to bankruptcy prediction with research methodologies. In particular, Tam and Kiang (1992) feed financial ratios representing capital adequacy, asset quality, earnings, and liquidity into a neural network model, and find this methodology useful in evaluating bankruptcy risk. Tam and Kiang (1992) demonstrate that neural networks offer better predictive accuracy than discriminant analysis, logit, K nearest neighbor, and ID3 decision tree. They attribute this superiority to the neural network's ability to handle non-linear data and accommodate any kind of probability distribution. Along a similar vein, Salchenberger et al. (1992) report neural network performance superior to that of logit model in predicting thrift failure from financial ratios. Moreover, neural networks such as MLPs are known to be better at learning moderately pathological functions than are many other methods with stronger smoothness assumptions (Sarle, 2002).

Other alternatives for bankruptcy prediction, such as Methods of Linear Regression, Multivariate Linear (or Quadratic) Discriminant Analysis or Logistic Regression, suffer from a theoretical drawback. Regression models suffer from limitations when relationships between variables are ill-defined (Jain and Nag, 1995). While parametric models are based on certain strong assumptions, and are sensitive to specification errors, neural networks avoid these problems by simultaneously estimating the parameters and the model.

Regression models put severe restriction on the statistical properties of prognostic factors in the construction of prognostic algorithms. Thus, these methods, theoretically, provide optimal prognostic rules only for factors that have multivariate normal distributions for all the hypotheses considered. This becomes obvious if one agrees that the ultimate goal of processing prognostic factors (explanatory variables) must consist of calculation true posterior probability of bankruptcy. One can hardly assume that the multivariate normality is the case for prognostic factors like financial ratios. Concerns over the use of not normally distributed predictors in multivariate discriminant analysis are discussed in Ohlson (1980).

This study compares the information contents between accounting and market data. Prior research comparing bankruptcy models assumes that a single prediction methodology, such as logical regression used in Mossman et al. (1998), is equally suitable for all variable sets. This study extends prior research by relaxing such an assumption though using the neural network approach, which is flexible enough to accommodate all model and functional forms assumptions.

B. Neural Networks Literature

Neural networks have been extensively applied to accounting, finance, and other business studies in areas such as forecasting, pattern recognition, and classification (Wong et al., 1997; O'Leary, 1998;

Vellido et al. 1999). Tam and Kiang (1992) find neural networks to be a superior approach in bankruptcy predictions. Echoing Tam and Kiang (1992), other researchers in economics and finance recognize the strength of the neural network in handling non-linear relationships and accommodating various probability distributions. Azoff (1994) recommends the neural network approach as a "multivariate nonlinear nonparametric inference technique that is data driven and model free." In addition, arguing for the merits of nonlinear and nonparametric models, Hsieh (1989; 1993) remarks that "there is no reason to believe that economic systems must be intrinsically linear", and that "a misspecified parametric model can lead to inconsistent estimates and incorrect inference". Beltratti et al. (1996) provide a more fundamental explanation for the appeal of the neural network in economic modeling. They cite the unique strength of the neural network as a model of the learning behavior of the economic agent, and as a paradigm to compare theories. Kim and McLeod (1999) demonstrated superiority of neural network models in bankruptcy prediction, especially when there exist nonlinear patterns in data sets.

In addition, numerous bond rating studies (Kwon et al., 1995; Singleton and Surken, 1995; Maher and Sen, 1997) have demonstrated that neural networks are a reliable alternative to traditional statistical techniques such as discriminant analysis for business classification problem. Hill et al.(1994) and Tang and Fishwick (1993) suggest replacing conventional statistical techniques with neural networks in building financial forecasting models.

Extending the bankruptcy literature, this research compares the information contents of accounting versus market data in bankruptcy prediction. As suggested in prior neural networks literature, this study adopts a neural network approach to take advantage of its unique modeling strength, and its nonrestrictive, nonparametric, and nonlinear properties.[2]

III. RESEARCH DESIGN

A. Theoretical Basis

In comparing information contents of accounting versus market data, we need a common platform to mitigate model-effect on prediction accuracy. We adopted the neural networks approach because it is model-independent and flexible enough to accommodate relationships of various functional forms.[3] To compare the information content of accounting versus market variables, predictive validity of neural networks trained on accounting measures are compared to those trained on market measures. Prior neural network research on bankruptcy prediction typically uses accounting-based variables. For instance, in the prediction of bank failures, Tam and Kiang (1992) use 19 accounting variables.[4] Tam and Kiang's (1992) model of default probabilities is essentially based on ratios of capital adequacy, asset quality, earnings, and liquidity.

Subsequent research on the valuation of credit derivatives offers new insight on bankruptcy prediction. A key component in the valuation of credit derivatives is the estimation of default probabilities, a business condition frequently associated with bankruptcy. Jarrow (2002), representing Kamakura Corporation's valuation approach, models default risk on firm valuation and on interest rate levels. KMV, a competitor of Kamakura, proposes an alternative model that infers default rates from publicly-traded equity prices using an option-theoretic approach, assuming that equity prices capture substantially the effects of interest rates (Federal Reserve System, 1998; Spinner, 1997). Accounting variables are absent from Kamakura's and KMV's models.

Given these different approaches, the first question that this study address is whether accounting data or market data provide better prediction of bankruptcy. The second question examines whether a model that combines both accounting and market variables can offer more predictive value.

B. Data Sources and Sample Selection

Our data for this research consists of 331 pairs of bankrupt and active firms. A list of 331 firms that went bankrupt from 1991 to 2000 is first obtained from Compustat Database. For each of these 331 bankrupt firms, we choose a non-bankrupt firm in the same industry (based on four-digit SIC codes) and with closest total asset size. As a result, a list of active firms matching bankrupted firms on industry classification and total assets forms the control sample. For each firm, bankrupt or nonbankrupt, 18 accounting measures and 18 market-based measures are obtained.

The 18 accounting variables come from 6 ratios over 3 quarters. We choose 6 accounting variables that have been widely used as bankruptcy predictors in finance and accounting literature. They are ROA, coverage ratio, ratio of short to long-term debt, debt-to-equity ratio, quick ratio, and change in sales. Quarterly data is used because, according to Baldwin and Glezen (1992), models based on quarterly financial statements provides more timely bankruptcy predictions than do annual models. When the neural network is trained on accounting data, the input layer consists of 18 accounting variables that measure the credit risk of a firm.

Likewise, when the neural network is trained on market data, 18 market variables, namely 9 monthly returns and 9 monthly turnover ratios, are used in the input layer. The 18 market variables come from 2 ratios over 9 months. The finance literature considers stock return and turnover ratio as the key variables conveying equity market information. Turnover ratio is measured by trading value divided by market value of equity.

To compare bankruptcy prediction based on accounting versus market data, necessary data for every pair of bankrupt and active firm is collected over a 9-month period while the bankrupt firm is still in normal operation and bankruptcy is still uncertain. The ending point of this 9-month period is 15 months before bankruptcy declaration. For example, if a firm declared bankruptcy in the third quarter of fiscal year 2000, accounting-based data will be compiled for the third and fourth of fiscal year of 1998 and the first quarter of fiscal year 1999. Monthly market data are compiled for the 9 months corresponding to these three quarters. In essence, therefore, this design compares information contents of accounting versus market variables six to eight quarters before bankruptcy.

Using the same number of accounting versus market-based variables assures that any observed difference in performance is not driven by a difference in the number of explanatory variables. In addition, drawing input data over the same time window (over a 3 quarter or 9 month period, ending on the 15th month before bankruptcy) ensures equal timeliness of input data for the two networks. The neural network software used in this study automatically identifies the most informative input nodes from these 18 variables through a genetic algorithm.

IV. EMPIRICAL TESTS

A. Design of Empirical Tests

This study uses a three-layered (one input layer, one output layer, and one hidden layer) back propagation neural network (BPN) as a classificatory model. The Kolmogorov's theorem states that any real function can be implemented by a three-layered network. Yoon et al. (1994) and Gupta and Lam (1996) support this view. A there-layered neural network, according to Gupta and Lam (1996), can account for both linear and non-linear relationship, does not require any distribution assumptions about the data set, and is more efficient than iterative regression.

The input layer consists of 18 nodes, corresponding to 18 variables. The neural network software used in this study systematically identifies, through a Genetic Algorithm (GA), the most informative input nodes from the full set of input variables.[5] This approach reduces the number of input nodes that actually participate in the formation of the neural networks. The resulting neural networks are therefore less complex, and preserve larger degrees of freedom. The single hidden layer contains 10 nodes, roughly equal to the average number of participating input nodes. The output layer is made up of a single node representing the outcome of bankruptcy or non-bankruptcy. Table 1 describes the actual structure of neural networks used in this study.

Samples are randomly split into two subsets: a train/test subset and a validation subset. The train/test subset is used to train the model and to guide model-training decisions. An over-trained neural network may over-fit, resulting in weak performance in out-of-sample prediction. To control for over-fitting, a representative test set is reserved for monitoring predictive performance as the model is trained. This representative test set is selected in a 'Round Robin' fashion from the train/test data set. Each test set is created by randomly selecting 30% of the cases from the train/test data set. This test data set is used to assess the model's prediction performance at regular intervals. Performance heuristics based on the test set provide feedbacks for training decision. In particular, training is halted when performance starts to degrade.

Prediction accuracy based on the test data set provides only supplemental evidence on the power of neural networks. An independent validation data subset unexposed to model training is needed to validate the final model's usefulness. Usefulness of the final model is measured by how accurately it can identify bankrupt or nonbankrupt firms in the validation data set. In this study, 160 cases out of the full sample of 200 cases are used to form the train/test subset. The remaining 40 cases form the validation subset. This process is repeated 5 (200 cases/40 cases) times , yielding 5 pairs of train/test subset and validation subset, until all cases in the sample have been used in some validation subset.

Two measures of predictive validity, namely percentage accuracy (hit ratio) and the Kolmogorov-Smirnov (K-S) statistic, are adopted. The hit ratio measures how accurately the model predicts the two outcomes (bankrupt or nonbankrupt). Since the neural network model generates a value between 0 and 1, the following classification assumptions based on the output value are made:

A value of 0.8 or higher on the output node is assumed to represent non-bankruptcy.

A value of 0.2 or lower on the output node is assumed to represent bankruptcy.

A value above 0.2 and below 0.8 on the output node is considered undefined, with the prediction counted as incorrect.

The K-S statistic measures how well the model separates cases into bankrupt and nonbankrupt classes. To compute the K-S statistic, the states of bankruptcy and nonbankruptcy are assigned the values of 0 and 1 respectively. For each class, cases are sorted on the output value, and a cumulative histogram in intervals of 0.1 of the output value is computed. The cumulative histograms of the two classes are then plotted on the same graph. The K-S statistic is the maximum vertical deviation between the two histograms. Figure 1 shows how the K-S statistic is computed in this study.

B. Discussions of Results

Table 2 summarizes model performance on the 5 validation subsets. Results based on accounting data, market data, and combined data are separately tabulated. Table 3 reports the significance of differences between different variable sets.

Table 2 shows that market data on average provides better information for bankruptcy prediction than does accounting data. Consistent with current finance literature, this result suggests that equity markets incorporate public accounting information. The difference in predictive power (See Table 3), however, is insignificant. Our data supports weak or semi-strong form of stock market efficiency. We do not exclude the usefulness of accounting data in predicting bankruptcies because market data does not *significantly* outperform accounting data. The incorporation of accounting information into stock return and turnover ratio may be slow or incomplete.

A more interesting finding, however, is that using combined data (i.e. both accounting and market data) outperforms using only one set of data, either accounting or market data alone. On average, Hit ratio increases to 0.805 and K-S statistics increases to 0.64 if we use combined data. Furthermore, Table 3 shows that the predictive power of combined data significantly (p-value based on Hit-ratio < 0.1; p-value based on K-S statistics < 0.025) exceeds that of accounting data. Not surprisingly, accounting data alone provides lower predictive value than accounting and market data together.

This result suggests that accounting data and market data complement each other in revealing new information to the market. The perfect market efficiency assumes that capital markets would instantaneously and correctly reflect new information in securities prices. We, however, cannot assume this perfect case because market frictions or irrationality would hamper the market efficiency. The finance and accounting literature provides evidence of sluggish response of stock prices to some accounting information. For example, Foster, Olsen and Shevlin (1984) report that the cumulative abnormal returns of earnings surprise continue to grow for about 2 months after the earnings announcements. This observation suggests that the market adjusts to the earnings information only gradually, resulting in a sustained period of abnormal returns. In this case, the historic or public accounting information would still contain information not fully reflected in current prices. Our empirical study can be interpreted as providing supportive evidence for the significance of accounting information. Future research on bankruptcy prediction would benefit more from pooling accounting and market data together than from accounting data alone.

V. SUMMARY AND CONCLUSIONS

Assessing the financial position of a firm and its propensity for bankruptcy is of great interest to all stakeholders of the firm. This study investigates how to improve the assessment method, and what variables or combination of variables convey more useful information for bankruptcy prediction.

This research contributes to accounting, finance, and information systems research in multiple ways.

We find that using combined data (i.e. both accounting and market data) outperforms using only one set of data, either accounting or market data alone. Thus, carefully selecting explanatory variables from both accounting and market sources can improve future bankruptcy predictions.

This research adds to the market efficiency literature by comparing the information contents of market versus accounting information. Research on bankruptcy prediction traditionally depends heavily on financial ratios and accounting data. We, however, find market data provides useful additional information over accounting data in predicting corporate bankruptcies. This finding supports the view that the stock market is reasonably efficient.

This research highlights the advantages of the neural network as a platform for comparing hypotheses. Neural networks offer an equitable platform because they are model-independent and flexible enough to accommodate any functional forms. Moreover, this study adopts a neural network design that minimize over-fitting. Unlike prior neural network studies that use only two data sets (training and testing), this study uses a training data set to train the network, a testing data set to guide neural network training decisions, and a validation data set to validate the final model. The testing data set is used to detect deterioration in the neural network's prediction performance during the training phase. Over-fitting is minimized because the neural network's training is halted when performance starts to decline.

Table 1: Network Structure

This table presents the neural network structure in the I-H-O format where I = number of nodes in the input layer, H = number of hidden nodes, and O = number of nodes in the output layer.

	With Accounting Data	With Market Data	With Combined Data
Training Set 1	7-10-1	14-10-1	9-10-1
Training Set 2	9-10-1	12-10-1	8-10-1
Training Set 3	9-10-1	8-10-1	9-10-1
Training Set 4	9-10-1	13-10-1	10-10-1
Training Set 5	9-10-1	11-10-1	11-10-1

Table 2: Predictive Accuracy of Models On Validation Set

This table summarizes model performance on the 5 validation subsets. Results based on accounting data, market data, and combined data are separately tabulated.

Data Used	Accounting Data		Market Data		Combined Data	
	Hit Ratio	K-S Stat.	Hit Ratio	K-S Stat.	Hit Ratio	K-S Stat.
Train Set 1	0.725	0.5	0.9	0.775	0.875	0.75
Train Set 2	0.75	0.525	0.75	0.525	0.7	0.525
Train Set 3	0.8	0.575	0.725	0.55	0.775	0.625
Train Set 4	0.75	0.575	0.7	0.45	0.85	0.675
Train Set 5	0.675	0.4	0.675	0.475	0.825	0.625
Average	0.74	0.515	0.75	0.555	0.805	0.64

Table 3: Significance of Differences among Accounting, Market, and Combined Data

This table reports the significance of differences between different variable sets. Significance level 10% and 2.5% are denoted by * and **, respectively. The t-statistic is configured to measure by how much the superior variable set (displayed as the first set in each paring) outperforms the inferior variable set (displayed as the second set in each paring).

Paring of variable sets	t-test with Hit Ratio	t-test with K-S
Market Data vs. Accounting Data	0.23	0.61
Combined Data vs. Accounting Data	1.75*	2.56**
Combined Data vs. Market Data	1.10	1.24

Figure 1: K-S Statistic

The K-S statistic measures how well the model separates cases into bankrupt and nonbankrupt classes. To compute the K-S statistic, the states of bankruptcy and nonbankruptcy are assigned the values of 0 and 1 respectively. For each class, cases are sorted on the output value, and a cumulative histogram in intervals of 0.1 of the output value is computed. The cumulative histograms of the two classes are then plotted.

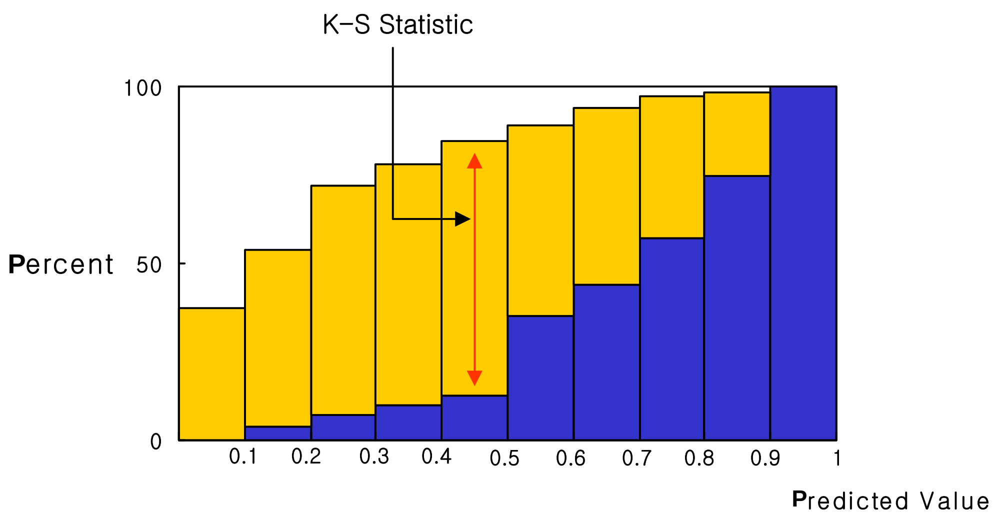
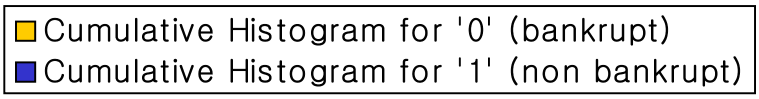


Figure 1. K-S Statistic



REFERENCES

Altman E.I. Financial Ratios, Discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance 1968 (September): 589-609.

Altman E., Handelman R., Narayanan R., Zeta analysis – A new model to identify bankruptcy risk of corporations, journal of banking and finance 1977; 1: 29 – 54.

Aziz A., Emanuel D., Lawson G. Bankruptcy prediction – An investigation of cash flow based models, journal of management studies 1988; 25: 419 - 437.

Azoff, M. Neural Network Time Series Forecasting of Financial Markets West Sussex: John Wiley & Sons, 1994.

Baldwin, J., W. Glenzen.. Bankruptcy prediction using quarterly financial statement data. Journal of Accounting, Auditing & Finance 1992; 7 (3): 269-290.

Beaver W. Market prices, financial ratios, and the prediction of failure, Journal of Accounting Research 1968: 170-192.

Beltratti, A., S. Margarita, P. Terna. Neural Networks for Economic and Financial Modeling. International Thomson Computer Press, 1996.

Board of Governors of the Federal Reserve System Division of Banking Supervision and Regulation. Supervisory guidance for credit derivatives. Federal Reserve Board Supervision and Regulation Letters 1996; SR 96-17.

Board of Governors of the Federal Reserve System Division of Banking Supervision and Regulation. Application of market risk capital requirements to credit derivatives. Federal Reserve Board Supervision and Regulation Letters 1997; SR 97-18.

Boyes, W., D. Hoffman, S. Low. An econometric analysis of the bank credit-scoring problem. Journal of Econometrics 1989; 40: 3-14.

Clark T., Weinstein M. The behavior of common stocks of bankrupt firms. Journal of Finance 1983; 38: 489 – 504.

Collins R., An Empirical comparison of bankruptcy prediction models. Financial Management 1980; Summer: 51 – 57.

DARPA. Neural Network Study. Lexington, MA: M.I.T. Lincoln Laboratory, 1988.

Das, Sanjiv. Credit risk derivatives. Journal of Derivatives 1995; Spring: 7-23.

Deakin E. A discriminant analysis of predictors of business failure. Journal of Accounting Research 1972; March: 167-179.

DeBondt, W. F., Thaler, R. Does the stock market overreact? Journal of Finance 1985; 40: 793-805.

DeBondt, W. F., Thaler, R. Further evidence on investor overreation and stock market seasonality. Journal of Finance 1987; 42: 557-581.

Duffee, G., C. Zhou. . Credit derivatives in banking: Useful tools for loan risk management? Federal Reserve Board Working Paper 1997.

Fama, E., French, K. The cross-section of expected returns. Journal of Finance 1992; 47: 427-466.

Federal Reserve System Task Force on Internal Credit Risk Models. Credit risk models at major U.S. banking institutions: Current state of the art and implications for assessments of capital adequacy 1998.

Financial Accounting Standards Board. Statement of Financial Accounting Concepts No. 2. Stamford, CT.: FASB, 1980.

Foster, G., Olsen, C., and Shevlin, T. Earnings releases, anomalies, and the behavior of securities returns. Accounting Review 1984; 59: 574-603.

Glibert, J. L. Cherniavsky. Considerations in measuring the credit risk in derivatives. Journal of Lending & Credit Risk Management 1998; 80(7):58-65.

Gupta, A., M. Lam. Estimating missing values using neural networks. Journal of the Operation Research Society 1996; 47: 229-238.

Haykin, S. Neural Networks: A Comprehensive Foundation. NY: Macmillan, 1994.

Hill, T., Marquez, L., O'Connor, M., W. Remus. Artificial neural networks for forecasting and decision making. International Journal of Forecasting 1994; 10: 5-15.

Holland, J. Genetic algorithms: Computer programs that "evolve" in ways that resemble natural selection can solve complex problems even their creators do not fully understand. Scientific America 1992; 267: 66-72.

Hsieh, D. Testing for nonlinear dependence in daily foreign exchange rates. Journal of Business 1989; 62(3): 339-368.

Hsieh, D. Implications of nonlinear dynamics for financial risk management. Journal of Financial and Quantitative Analysis 1993; 28(1): 41-64

Jarrow, R. Default parameter estimation using market prices. Financial Analysts Journal 2002; September/October.

Jarrow, R., S. Turnbull. Pricing derivatives on financial securities subject to credit risk. Journal of Finance 1995; 50(1): 53 - 85.

Kim, C., R. McLeod. Expert, linear models, and nonlinear models of expert decision making in bankruptcy prediction. Journal of Management Information Systems 1999; 16 (1): 189-206.

Kwon, Y., Han, I., K. Lee, Ordinal pairwise partitioning (OPP) approach to neural networks training in bond rating. Intelligent Systems in Accounting, Finance and Management 1997; 6: 23-40.

Lakonishok, J., Shleifer, A., Vishney, R.W. Contrarian investment, extrapolation, and risk. Journal of Finance 1995; 50: 541-578.

Maher, J., T. Sen, Predicting Bond ratings using neural networks: A comparison with logistic regression. Intelligent Systems in Accounting, Finance and Management 1997; 6: 59-72.

Mossman E., G. Bell, M. Swartz, H. Turtle. An empirical comparison of bankruptcy models. The Financial Review 1998; 33 (2): 35-53.

Neal, R. Credit derivatives: New financial instruments for controlling credit risk. Economic Review (Federal Reserve Bank of Kansas City) 1996; 81(2):15-27.

Office of the Comptroller of the Currency (OCC). Credit derivatives: Guidelines for national banks 1996.

Ohlson, J. A. Financial ratios and the probabilistic prediction of bankruptcy. Journal of Accounting Research 1980; 18 (1): 109 - 131.

O'Leary DE. Using neural networks to predict corporate failure. International Journal of Intelligent Systems in Accounting, Finance and Management 1998; 7:187–197.

Salchenberger, M. , M. Cinar, A. Lash. Neural networks: A new tool for predicting thrift failures. Decision Sciences 1992; 23(4): 899-916.

Sarle, W. The Neural Network FAQ 2002. ftp://ftp.sas.com/pub/neural/FAQ.html

Spinner, K. Building the credit derivatives infrastructure. Derivatives Strategy 1997a; Credit Derivatives Supplement, June.

Spinner, K. Pricing models for credit derivatives. Derivatives Strategy 1997b; Credit Derivatives Supplement, June.

Tam, K., M. Kiang. Managerial application of neural networks: The case of bank failure predictions. Management Science 1992; 38(7):926-947.

Tang, Z., P. Fishwick. Feedforward neural nets as models for time series forecasting. ORSA Journal on Computing 1993; 4 (4): 374-385.

Tergesen, A. Cash-Flows Hocus-Pocus. Businessweek Investor 2002; July 15.

Velido A, Lisboa PJG, Vanghan J. Neural networks in business: a survey of applications (1992–1998). Expert Systems with Applications 1999; 17: 51–70.

Wilson, T. Measuring and managing credit portfolio risk: Part I: Modeling systemic default risk. Journal of Lending & Credit Risk Management 1997; 79(11):61-72.

Wong BK, Bodnovich TA, Selvi Y. Neural network applications in business. A review and analysis of the literature (1988–95). Decision Support Systems 1997; 19: 301–320.

Yoon, Y., T. Guimaraes, G. Swales. Integrating artificial neural networks with rule-based expert systems. Decision Support Systems 1994; 11:497-507.

ENDNOTES

[1] In theoretical models, fully rational investors and noise traders interact to produce prices that diverge from intrinsic value without arbitrage opportunities being present. Empirical studies on contrarian investment strategies (DeBondt and Thaler 1985, 1987; Fama and French 1992; Lakonishok, Shleifer and Vishney 1995) appear to support these models.

[2] Nonparametric statistics do not make assumptions about the underlying distribution of the data. Thus, nonparametric statistics are useful when the data are not normally distributed.

[3] The Kolmogorov's theorem states that any real function can be implemented by a three layered network

[4] These variables are capital/assets, (agricultural production & farm loans + real estate loans secured by farm land)/net loans and leases, (commercial and industrial loans)/net loans & leases, (loans to individual)/net loans & leases, (real estate loans) /net loans & leases, (total loans 90 days or more past due)/net loans & leases, (total nonaccrual loans & leases)/net loans & leases, (provision for loan losses)/average loans, (net charge-offs)/average loans, return on average assets, (total interests paid on deposits)/total deposits, (total expense)/total assets, (net income)/total assets, (interests and fees on loans + income from lease financing rec)/net loans & leases, (total income)/total expense, (cash + US treasury & government agency obligations)/total assets, (federal funds sold + securities)/total assets, (total loans & leases)/total assets, and (total loans and leases)/total deposits.

[5] Genetic algorithms explore not only the local vicinity, but also different regions in the global domain at a frequency proportional to the regions' probabilities of hosting a good solution (Holland 1992). The optimization mechanism therefore can avoid being trapped by local minima.