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Bankruptcy Prediction Models: Artificial Neural Networks versus Discriminant Analysis and Logit Model

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Abstract

The purpose of this paper is to develop the validation of bankruptcy prediction models for Mongolian companies by using most useful current techniques. To do this, we reviewed 510 bankruptcy prediction models that had been published in 296 academic journals from 1966 to 2015. We also focused on the methodology of the models predictability, application, and relating factors. There are more than 600 different variables in the models and 86 percent out of them are applied as financial variables. Therefore, using financial ratios is an essential method to analyze the financial reports, the prediction of financial distress and bankruptcy. Moreover, some variables, such as corporate governance, macroeconomic and industry effect reflected variables have been used to develop bankruptcy prediction models in modern studies. We selected a sample of 16 bankrupt and 426 non-bankrupt companies for the years 2010 to 2015. Based on research results, ANN model with variables of EBIT to total asset, equity to total asset, liabilities to equity and logarithm of total asset has shown more capability to predict corporate bankruptcy in Mongolia.

Keywords: bankruptcy prediction, DA model, LM model, ANN model

1. Introduction

This working paper will primarily focus on the failed companies in Mongolia; nevertheless bankruptcy is a worldwide problem. Since the financial crisis of 2008, the need for developing corporate failure prediction models has been vital than ever before in Mongolia. 41.1 percent of 126.56 thousand companies which are registered in the General Department of Taxation did not function any business operations in 2015 and 2.6 percent of them were failed. The economic growth rate is decreasing continuously from 2011 (17.5%) to 2015 (2.3%), while the number of failed firms are skyrocketing from 207 to 1,626 in the current decade. Today, all financial statement users in Mongolia use the Z-score model which is developed by Edward I, but the model can't predict well with some reasons. There is one empirical research completed for Mongolian companies which recommends M-score model developed by Batbayar *et al.*

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(2015)[1]. They used logit model and found 5 important variables out of 13 variables in Altman's Z-score and Ohlson's O-score models. The main objective of our study is to develop bankruptcy prediction models with data of Mongolian companies through using multiple discriminant analysis (MDA), logistic regression (LM) and artificial neural network (ANN), to compare the performance of the models, and to answer the following research questions:

- Which variables and techniques in the global bankruptcy models are popular?
- Which variables can be the best predictor for detecting bankruptcy of Mongolia's companies?
- Can the financial indicators be the appropriate variables to develop our model?
- Is the ANN method superior to the MDA and LM for predicting corporate bankruptcy?

The remainder of this paper is organized as follows. Section 2 provides a comparison of literature review on bankruptcy prediction models. In Section 3, we describe our data and methodology. Section 4 describes research process and present results. Section 5 summarizes and concludes the paper.

2. A comparison of literature review

The study of prediction of bankruptcy dates back to the beginning of 1930s and after that a number of academic researchers have tried to develop bankruptcy prediction models based on the different variables and statistical techniques during last 50 years. Comparing the bankruptcy prediction models is very important for the model users and researchers. The bankruptcy prediction models are differed with variables, sample sizes, industries and methods. There are a few academic studies comparing different types of the models: Bellovary *et al.* (2007)[2], Aziz and Dar (2006)[3]. We summarized and analyzed 510 bankruptcy prediction models on 296 academic journals published from 1966 to 2015. Techniques employed to develop bankruptcy prediction models originated from the univariate analysis by Beaver (1966)[4] and multiple discriminant analysis by Altman (1968)[5] in the 1960s. Furthermore, a great number of techniques for bankruptcy prediction models postulates: logit and probit models in the 1980s by Ohlson (1980)[6], Zmijewski (1984)[7], neural network models by Tam and Kiang (1992)[8], Cash Management Theory by Laitinen and Laitinen (1998)[9], rough sets model by McKee (1998)[10], discrete hazard models by Shumway (2001)[11], Bayesian network models by Sarkar and Sriram (2001)[12], genetic programming by McKee and Lensberg (2002)[13] etc. Discriminant analysis (29.8%), logit model (25.5%), and neural network (19.2%) models out of these techniques applied adorably in 380 prediction models. Moreover, hybrid techniques are used to develop bankruptcy models since 1996: genetic algorithms + multi-layer perception network by Back *et al.* (1996)[14], Multi-layer perceptron network + logistic regression by Min *et al.* (2006)[15], support vector machines + logistic regression by Hua *et al.* (2007)[16] etc. The bankruptcy prediction models often develope after the financial crisis in the world: Oil crisis 1973, Latin American debt crisis 1982, Black Monday 1987, Japanese asset price bubble and Swedish banking crisis 1990, Global financial crisis 2008-2009 etc. Some models have 2 variables in minimum: Santomero and Vinso (1977)[17]. Simultaneously, the maximum digit is accounted 47 variables: Appetiti (1984)[18]. In spite of the number of variables, the variables should be optimal predictors and non-multicollinearity.

There are more than 600 different variables in the models and 86 percent out of them are applied as financial variables. The widespread variables among the financial variables are liquidity ratios constituting 31.1 percent. A number of researchers such as Glezakos *et al.* (2010)[19], Mensah (1983)[20], and Kaaro (2004)[21] suggest that the liquidity variables are incredible essential and can be the most optimal predictors to detect bankruptcy.

Probability ratios are 24.8 percent, leverage ratios are 16.4 percent, efficiency ratios are 12.3 percent and other financial ratios are 15.5 percent in allover financial variables. Net income to total assets is used in 136 bankruptcy models such as Ohlson (1980)[6], Zmijewski (1984)[7] as an attractive variable. Besides, the variables in well-known bankruptcy prediction models such as Beaver (1966)[4], Altman (1968)[5], Zmijewski (1984)[7], Ohlson (1980)[6], Shumway (2001)[11], Springate (1978)[22] are mainly quoted in current working papers.

Apart from the financial variables, stock price changes and market value as variables based on market (Hillegeist *et al.* 2004[23], Dichev 2008[24]), size of revenue and asset volatility as other financial variables (Ohlson 1980[6]; Castanias 1983[25]; Cram *et al.* 2004[26]), branch specificity, location, and specialization of operation as non-financial variables (Derwall and Verwijmeren 2010[27]; Hensher and Jones 2004[28]), macro-economic variables such as inflation, interest rate, exchange rate and GDP growth (Nam *et al.* 2008[29]; Tsai *et al.* 2009[30]), corporate governance variables related board, management of the executive, and control (Donoher 2004[31]; Piruna and Kingkarn 2009[32]) are commonly used. We find out the top 50 financial ratios which are commonly used in the models and present it in Appendix 1.

3. Data and methodology

We sampled 1,198 failed and non-failed companies' financial statements from E-Balance system of Ministry of Finance of Mongolia. The samples are chosen randomly and our model had been developed by 426 financial statements (training samples), of which 410 non-failed and 16 failed companies from 2010 to 2015. Residual 772 financial statements (testing samples) of which 697 non-failed and 75 failed companies are used to test our models.

Dependent variable Z in our models divided into Z = 0 (if the company is failed) and Z = 1 (if the company is non-failed) and the independent variables of our models are chosen from the top 50 financial ratios. If the financial variables can't be the best predictors, we will try to develop our models with non-financial variables. The bankruptcy prediction models are developed by MDA, LM and ANN.

3.1. Multivariate Discriminant Analysis (MDA)

Discriminant analysis characterizes an individual, or a phenomenon, by a vector of variables which constitute a multivariate density function. MDA computes the discriminant coefficients and selects the appropriate weights (cut-off score) which will separate the average values of each group, while minimizing the statistical distance of each observation and its own group means (Altman 1993)[33]. When classifying companies, the financial ratios are to be put into the discriminant function making up the linear combination. The general form of the discriminant function is the following:

$$D = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n \qquad (1)$$

Where, D is the discriminant score, β_0 is constant, β_1, β_2, ... β_n are the coefficients or weights, X_1, X_2, ... X_n are the independent variables.

3.2. Logistic regression analysis (LM)

Logistic regression models also called logit model, is a special form of regression that is formulated to predict and explain a binary categorical variable rather than a metric-dependent measurement (Ong *et al.* 2011)[34]. The logistic procedure fits linear logistic regression models for binary or ordinal response data using Maximum Likelihood estimations and compares the estimated samples using Wald chi-square. The Maximum Likelihood procedure is used in an iterative manner to identify the most likely estimates for the coefficients. In the context of bankruptcy prediction, the technique weighs the financial ratios and creates a score for each company in order to be classified as bankrupt or non-bankrupt. The first practitioner of logit analysis in failure prediction was Ohlson (1980)[6]. Most of the studies conducted after 1981 used logit analysis to relax the constraints of DA (Keasey and McGuinness, 1990)[35]. The result of the function is between 0 and 1 and probability of failure in logit analysis can be written as:

$$Z = \frac{1}{1+e^{-(\beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn)}} \qquad (2)$$

Where, Z is the probability of occurrence of a bankruptcy status, $\beta 0$ is constant, $\beta 1$, $\beta 2$, ... βn are the coefficients and $X1$, $X2$, ... Xn are the independent variables.

3.3. Artificial Neural Networks (ANN)

An ANN is a computer algorism which can be 'trained' to imitate the cellular connections in the human brain (Hertz *et al.* 1991)[36]. Neural networks are used for many predictive data mining applications because of their power, flexibility, and ease of use. The most prominent ANN algorithm in the financial distress prediction domain is Multi-Layer Perceptron (MLP), which is composed of three layers; input layer contains the predictors, namely attributes, the hidden layer contains the unobservable nodes, the output layer contains the responses, and there can be several hidden layers for complex applications.

The input weights are aided by a 'genetic algorithm' optimization procedure, which simulates the model's predictive power under a large number of scenarios and allows the best weighting schemes to survive and reproduce from one generation to the next (Dorsey *et al.* 1995)[37]. ANN is more adaptive to real world situations, it can discriminate non-linear patterns, so it does not suffer from the constraints of statistical models. However, ANN has several drawbacks, it is a black box procedure, and it is hard to interpret the results owing to lack of explanatory power and lack of feature selection, it needs too much time and efforts to construct a best architecture. The mathematical representation of the model can be written as:

$$Z = f(q) = f\left(\sum_{i=1}^{n} W_i X_i + W_0\right) \qquad (3)$$

Where, Z is the output variable, W_0 is constant called bias, W_i are parameter (weight), X_i are the input variables and the output Z of the processing unit is then given by transforming the total input with a non-linear activation function f which is often used as a sigmoidal function such as the logistic and the tangent hyperbolic function.

4. Research process and results

The financial ratios used in the analysis are selected through two variable elimination stages. In the first stage, one-way ANOVA test is conducted out. The aim of this test is to define financial ratios of failed and non-failed groups that differentiate at 10% significance level. In the second stage, the remaining variables are filtered through correlation analyses. The outcome of stage 1, the ANOVA test statistics, for failed and non-failed companies is presented in Table 1. Small significance level indicates difference between group means. In our case, the selected 11 financial ratios with a significance level of less than 10% indicate that one group differs from other groups.

Table 1. ANOVA test statistics of independent variables

Variables	Bankruptcy company			Non bankruptcy company			F statistic	Significance level
	Mean	Median	Std.Dev	Mean	Median	Std.Dev		
NITA	-0.46	-0.12	0.58	0.03	0.01	0.68	8.08	0.00
WCTA	-1.55	-0.59	2.45	0.08	0.08	0.41	109.45	0.00
TLTA	2.55	1.41	2.13	0.39	0.32	0.37	243.20	0.00
RETA	-2.48	-1.63	2.82	-0.06	0.00	0.55	157.22	0.00
EBITTA	-0.46	-0.12	0.58	0.04	0.01	0.69	8.25	0.00
NIE	0.84	0.28	1.74	0.14	0.02	1.65	2.76	0.10
CLTA	1.86	1.02	2.32	0.30	0.20	0.35	121.00	0.00
ETA	-1.55	-0.41	2.13	0.61	0.69	0.37	243.20	0.00
LTDTA	0.70	0.03	1.20	0.09	0.00	0.22	57.93	0.00
LE	-15.54	-2.62	33.35	1.82	0.41	20.27	10.65	0.00
LOGTA	5.94	5.59	1.23	6.13	6.12	1.01	5.08	0.02

Source: Our own analysis

11 variables shown in the Table 1 are statistically significant by ANOVA and all values of F statistic of the variables are lower than the critical values with significance level at 0.1. Some independent variables of them, however, may be higher correlation with each other. Therefore, we tested the multicollinearity by correlation matrix.

Table 2. Correlation matrix of the independent variables

	NITA	WCTA	TLTA	RETA	EBITTA	NIE	CLTA	ETA	LTDTA	LE	LOGTA
NITA	1.00	0.19	-0.19	0.12	0.94	0.41	-0.14	0.19	-0.13	0.01	-0.01
WCTA	0.19	1.00	-0.80	0.73	0.20	-0.06	-0.92	0.80	0.09	0.02	-0.02
TLTA	-0.19	-0.80	1.00	-0.79	-0.19	0.06	0.87	-1.00	0.40	0.01	0.02
RETA	0.12	0.73	-0.79	1.00	0.13	-0.08	-0.70	0.79	-0.30	0.01	-0.01
EBITTA	0.94	0.20	-0.19	0.13	1.00	0.41	-0.14	0.19	-0.13	0.01	-0.01
NIE	0.41	-0.06	0.06	-0.08	0.41	1.00	0.08	-0.06	-0.02	-0.20	0.51
CLTA	-0.14	-0.92	0.87	-0.70	-0.14	0.08	1.00	-0.87	-0.10	0.01	0.01
ETA	0.19	0.80	-1.00	0.79	0.19	-0.06	-0.87	1.00	-0.40	-0.01	-0.02
LTDTA	-0.13	0.09	0.40	-0.30	-0.13	-0.02	-0.10	-0.40	1.00	0.01	0.01
LE	0.01	0.02	0.01	0.01	0.01	-0.20	0.01	-0.01	0.01	1.00	-0.71
LOGTA	-0.01	-0.02	0.02	-0.01	-0.01	0.51	0.01	-0.02	0.01	-0.71	1.00

Source: Our own analysis

In the next stage, 7 variables are excluded from the 11 variables due to their poor performance and multicollinearity. After that we developed our models with four variables:

EBIT to total assets (EBITTA), equity to total assets (ETA), logarithm on total assets (LOGTA) and liabilities to equity (LE). The Anova F and Welch F tests for differences between means, Med. Chi-square; Adj. Med. Chi-square; Kruskal-Wallisa and vander Waerden tests for differences between median, Bartlett; Levene and Brown-Forsythe testes for differences between variances of two groups in the four variables are statistically significant. Hence, further testes continue with 4 variables: profitability (EBITTA), liquidity (ETA), leverage (LE) and size of company (LOGTA).

4.1. Discriminant analysis result

The DA is analyzed by SPSS 21.0 software. An important step in DA analysis is a test of group means equality, which revealed that the independent variables have significant differences between non-failed and failed companies. Wilks' Lambda of the model explains that the overall model is unexplained about the variance in the grouping variables by 60.9%. The canonical correlation of 0.626 with an eigenvalue of 0.643 of the model suggested that the model explains 39.1% variation in the grouping variable of financially distress or not distress. However, chi-square of 209.55 and a significant p (p =0.000) value reported in Table 3 indicates a highly significant function in the model. Hence, it can be concluded that the model developed by us is a significant discriminant function in discriminating financially failed and non-failed company.

Table 3. Tests of equality of means and Eigenvalues

Function	1
Eigenvalue	0.643
Percentage of Variance	100.0
Cumulative Percentage	100.0
Canonical Correlation	0.626
Test of Function(s)	1
Wilks' Lambda	0.609
Chi-square	209.550
Degree of Freedom	4
Significance	0.000

Source: Our own analysis

DA model unstandardized coefficients reveal that LOGTA has negative sign meaning that increase of this variable reduces discriminate score and increased probability of being bankrupted and the other variables have positive sign, meaning that increase of these variables causes increase of discriminate score and decreases probability of being bankrupted. The discriminant model is obtained by putting the estimated weights into related places and the outcome of the model takes the form below.

$$Z = -0.916 + 0.065 * EBITTA + 1.808 * ETA - 0.009 * LOGTA + 0.016 * LE \qquad (4)$$

Great majority of researchers use the cutting score (cutoff point) with arithmetic mean of centroid 1 and centroid 2. According to this methodology, our cutting score is estimated -1.946 (C1 is -4.050 and C2 is 0.158). However, but Ramayah *et al.* (2010)[38] suggest the optimal cut off point for DA with weighted mean. Therefore, the optimal cutoff point of the discriminant function is 0.15879.

Table 4. Classification by Multiple discriminant analysis (normal and optimal cutoff point)

Z		Normal cutoff point		Optimal cutoff point		Total
		Failed	Non-failed	Failed	Non-failed	
Observed	Failed	10	6	5	11	16
	Non-failed	8	402	2	408	410
Correct Percent	Failed	62.5	37.5	31.3	68.8	100
	Non-failed	2.0	98.0	0.5	99.5	100

Source: Our own analysis

The data from the Table 4 reveal that DA model accuracy with normal and optimal cutoff points. Based on the centroids the study has analyzed the classification accuracy of the derived function. According to the results with optimal cutoff point, it can be seen that the developed model is able to classify correctly the failed companies 31.3%, non-failed companies 99.5% accurately and the overall classification accuracy is 96.95%.

4.2. Logit model result

The LM model is analyzed by Eviews 7.0 software. As the result of LM model, ETA and LE are statistically significant at 1% level. EBITTA, LOGTA are also statistically significant at 5% level. Log likelihood ratio of the model is 73.98877 and it is statistically significant at 1% level. Furthermore, McFadden R squared of the model is 54.24%. Hosmer and Lemeshow test indicates that no statistical significant difference occurs between predicted and observed values of the model. Therefore, it is reasonable to consider that the goodness of fit of the Model is quite acceptable, and expect well-performed forecast ability. The outcome of the LM takes the form below:

$$Z = \frac{1}{1+e^{-(8.506\,+\,1.209\,*\,EBITTA\,+\,3.030\,*\,ETA\,-\,0.844\,*\,LOGTA\,+\,0.024\,*\,LE)}} \qquad (5)$$

The cutoff point of the logit model is usually 0.5. It means that if the estimated probability is calculated greater than 0.5 the company will be predicted as non-failed. If not, the company will be predicted as failed. According to Soureshjani *et al.* (2013)[39], the optimal cutoff point of the LM and NN must be maximum sum of sensitivity and specifity degree of the model. Therefore, 0.9 can be the optimal cutoff point the LM model.

Table 5. Classification by logit model (normal and optimal cutoff point)

Z		Normal cutoff point (0.5)		Optimal cutoff point (0.9)		Total
		Failed	Non-failed	Failed	Non-failed	
Observed	Failed	7	9	12	4	16
	Non-failed	3	407	9	401	410
Correct Percent	Failed	43.75	56.25	75.00	25.00	100
	Non-failed	0.73	99.27	2.20	97.80	100

Source: Our own analysis

According to the results with optimal cutoff point by Soureshjani method, it can be seen that the developed model is able to classify correctly the failed companies 75.0%, non-failed companies 97.8% accurately and the overall classification accuracy is 96.95%.

4.3. Artificial neural network model result

The ANN model is analyzed by Visual Gene Developer and SPSS 21.0 software. Statistical significance for an input activation function with hyperbolic tangent is better than linear and logistic functions. The optimal architecture is four input variables, one hidden layer (node number of hidden layer is three), one output layer in accordance to our findings which is maximum AIC criteria. Input importance rates are ETA (39.35%), EBITTA (34.42%), LE (26.22%), LOGTA (0.01%). Learning rate is 0.01, analysis update interval (cycles) is 500 and initialization method of threshold is random.

Table 6. Sensitivity and specifity of ANN model with different cut off points

Cutoff Point	Specifity	Sensitivity	Average	Sum
0.01	18.8%	100.0%	96.9%	118.8
0.1	31.3%	100.0%	97.4%	131.3
0.2	68.8%	99.8%	98.6%	168.5
0.3	81.3%	99.8%	99.1%	181.0
0.4	93.8%	99.5%	99.3%	193.3
0.5	93.8%	99.5%	99.3%	193.3
0.6	93.8%	99.5%	99.3%	193.3
0.7	93.8%	99.5%	99.3%	193.3
0.8	93.8%	99.0%	98.8%	192.8
0.9	93.8%	99.0%	98.8%	192.8
0.99	93.8%	98.0%	97.9%	191.8

Source: Our own analysis

The sum of the sensitivity and specifity of ANN model with cutoff points from 0.4 to 0.7 is to be the highest overall classification accuracy. In other hands, the model classifies correctly the failed companies 93.8%, non-failed companies 99.5% correctly and the overall classification accuracy is 99.3%. Finally, we expand sample coverage in order to test the MDA, LM and ANN models accuracy with 772 financial statements, of which 697 non-bankruptcy and 75 bankruptcy companies.

Table 7. Classification of the model (testing samples)

Methods	Specifity		Sensitivity		Overall classification
	Observed	Correct %	Observed	Correct %	
Discriminant analysis	31	41.3%	678	97.3%	91.8%
Logit model	74	98.7%	393	56.4%	60.5%
Artificial neural network	61	81.3%	686	98.4%	96.8%

Source: Our own analysis

These results are presented in Table 7 and indicate that neural network reached the highest overall classification accuracy with 96.8% (classifies correctly the failed companies 81.3 percent, non-failed companies 98.4 percent correctly).

Summary

This study attempts to develop the performance of bankruptcy prediction models for Mongolian companies through using the primary models used for bankruptcy model development. We apply the top 50 financial ratios used in the 510 bankruptcy prediction models since 1966. Finally, EBIT to total asset, equity to total asset, liabilities to equity and logarithm of total asset have been selected from the variables by ANOVA test and correlation analysis. As the result of our study, using neural network analysis shows most efficient outcome compared to the MDA and LM methods. The financial variables can be the best predictors for detecting bankruptcy of Mongolian companies. The overall classification accuracy rates for 426 training samples are 99.3% (ANN), 96.95% (LM) and 96.95% (DA), while for 772 testing samples are 96.8% (ANN), 91.8% (LM) and 60.5% (DA). Thus, due to its comparative advantage ANN modeling should be in the forefront of professional attention so as to be used as successfully as possible in bankruptcy prediction in Mongolia. Due to the higher capability of financial variables, there is no necessary to apply non-financial variables in predicting the bankruptcy in Mongolia. The higher prediction capability of financial variables might depend on its own characteristic that implies non-financial variables.

References

1. Batbayar, A., Boldbaatar, M., Enkh-Amgalan, Ts. (2015). Corporate Bankruptcy Prediction Model in Mongolia, *The 13th Conference of International Federation of East Asian Management Associations in Ulaanbaatar, IFEAMA SPSCP*, 5, 136-145
2. Bellovary, J. L., Giacomino, D. E., Akers, M. D. (2007). A Review of Going Concern Prediction Studies: 1976 to Present, *Journal of Business & Economics Research*, 5, 9-28
3. Aziz, M. A., Dar, H. A. (2006). Predicting Corporate Bankruptcy: Where we stand?, *Corporate Governance International Journal of Business in Society*, 6(1), 18-33
4. Beaver, W. H. (1966). Financial Ratios as Predictors of Failure, *Journal of Accounting Research*, 4, 71-111
5. Altman, E. I. (1968). Discriminant Analysis and the Prediction of Corporate Bankruptcy, *The Journal of Finance*, 23(4), 589-609
6. Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy, *Journal of Accounting Research*, 18, 109-131
7. Zmijewski, M. E. (1984). Methodological Issues Related to the Estimation of Financial Distress Prediction Models, *Journal of Accounting Research*, 22, 59-82
8. Tam, K., Kiang, M. (1992). Managerial Applications of the Neural Networks: the Case of Bank Failure Predictions, *Management Science*, 38, 416-430
9. Laitinen, E. L., Laitinen, T. (1998). Cash Management Behavior and Failure Prediction, *Journal of Business Finance and Accounting*, 25, 893-919
10. McKee, T. E. (2000). Developing a Bankruptcy Prediction Model via Rough Set Theory, *International Journal of Accounting, Finance and Management*, 9, 159-173

11. Shumway, T. (2001). Forecasting Bankruptcy More Accurately: A Simple Hazard Model, *Journal of Business*, 74, 101–124

12. Sarkar, S., Sriram, R. S. (2001). Bayesian Models for Early Warning of Bank Failures, *Management Science*, 47, 1457-1475

13. McKee, T. E., Lensberg, T. (2002). Genetic Programming and Rough Sets: A Hybrid Approach to Bankruptcy Classification, *European Journal of Operational Research*, 138, 436-451

14. Back, B., Laitinen, T., Sere, K. (1996). Neural Networks and Genetic Algorithms for Bankruptcy Predictions, *Expert Systems with Applications*, 11, 407-413

15. Min, S., Lee, J., Han, I. (2006). Hybrid Genetic Algorithms and Support Vector Machines for Bankruptcy Prediction, *Expert Systems with Applications*, 31, 652-660

16. Hua, Z., Wang, Y., Xu, X., Zhang, B., Liang, L. (2007). Predicting Corporate Financial Distress Based on Integration of Support Vector Machine and Logistic Regression, *Expert Systems with Applications*, 33, 434-440

17. Santomero, A., Vinso, J. (1997). Estimating the Probability of Failure for Commercial Banks and the Banking System, *Journal of Banking and Finance*, 1(2), 185-205

18. Appetiti, A. (1984). Identifying Unsound Firms in Italy: An Attempt to Use Trend Variables, *Journal of Banking and Finance*, 8(2), 269-279

19. Glezakos, M., Mylonakis, J., Oikonomou, K. (2010). An Empirical Research on Early Bankruptcy Forecasting Models: Does Logit Analysis Enhance Business Failure Predictability, *European Journal of Finance and Banking Research*, 3(3), 108-122

20. Mensah, Y. M. (1983). The Differential Bankruptcy Predictive Ability of Specific Price Level Adjustments: Some Empirical Evidence, *The Accounting Review*, 58, 228-246

21. Kaaro, H. (2004). Kebangkrutan Versus Restrukturisasi: Evaluasi dan Prediksi Kelangsungan Hidup Perusahaan Pasca Krisis Keuangan 1997, *Kinerja*, 8, 1-26

22. Springate, G. L. V. (1978). Predicting the Possibility of Failure in a Canadian Firms, *Unpublished MBA Research Project, Simon Fraser University*, Canada

23. Hillegeist, S., Keating, E., Cram, D., Lundstedt, K. (2004). Assessing the Probability of Bankruptcy, *Review of Accounting Studies*, 9, 5-34

24. Dichev, I.D. (1998). Is the Risk of Bankruptcy a Systematic Risk, *The Journal of Finance*, 53(3), 1131-1147

25. Castanias, R. (1983). Bankruptcy Risk and Optimal Capital Structure, *The Journal of Finance*, 38, 1617-1635

26. Cram, D., Hillegeist, S., Keating, E. Lundstedt, K. (2004). Assessing the Probability of Bankruptcy, *Review of Accounting Studies*, 9, 5-34

27. Derwall, J., Verwijmeren, P. (2010). Employee Well-Being, Firm Leverage, and Bankruptcy Risk, *Journal of Banking and Finance*, 34, 956-964

28. Hensher, D., Jones, S. (2004). Predicting Firm Financial Distress: A Mixed Logit Model, *The Accounting Review*, 79(4), 1011-1038

29. Nam, C.W., Kim, T.S., Park, N.J., Lee, H. K. (2008). Bankruptcy Prediction Using a Discrete-Time Duration Model Incorporating Temporal and Macroeconomic Dependencies, *Journal of Forecasting*, 27, 493-506

30. Tsai, B.H., Lee, C. F., Sun, L. (2009). The Impact of Auditors' Opinions, Macroeconomic and Industry Factors on Financial Distress Prediction: An Empirical Investigation, *Review of Pacific Basin Financial Markets and Policies*, 12(3), 417-454

31. Donoher, W. J. (2004). To File or Not To File? Systemic Incentives, Corporate Control, and the Bankruptcy Decision, *Journal of Management*, 30, 239-262

32. Piruna, P., Kingkarn, S. (2009). Corporate Distress Prediction Models Using Governance and Financial Variables: Evidence from Thai Listed Firms During the East Asian Economic Crisis, *Journal of Economics and Management*, 2, 273-304

33. Altman, E. I. (1993). *Corporate financial distress: A complete guide to predicting, avoiding and dealing with bankruptcy, second edition*, John Wiley and Sons, New York

34. Ong, S., Voon, C. Y., Roy, W. L. (2011). Corporate Failure Prediction: A Study of Public Listed Companies in Malaysia, *Managerial Finance*, 37, 553-564

35. Keasey, K., McGuinness, P. (1990). The Failure of UK Industrials Firms for the Period 1976-1984, Logistic Analysis and Entropy Measures, *Journal of Business Finance and Accounting*, 17, 119-135

36. Hertz, J., Krogh, A., Palmer, R. G. (1991). *Introduction to the Theory of Neural Computation*, Addison-Wesley, New York

37. Dorsey, R. E., Mayer, W. J. (1995). Genetic Algorithms for Estimation Problems with Multiple Optima, Non-Differentiability, and Other Irregular Features, *Journal of Business and Economic Statistics*, 13, 53-66

38. Ramayah, T., Ahmad, N. H., Halim, H. A., Mohamed Zainal, S. R., Lo, M. C. (2010). Discriminant Analysis: An Illustrated Example, *African Journal of Business Management*, 4(9), 1654-1667

39. Soureshjani, M. H., Kimiagari, A. M. (2013). Calculating the Best Cut Off Point Using Logistic Regression and Neural Network on Credit Scoring Problem: A Case Study of a Commercial Bank, *African Journal of Business Management*, 7(16), 1414-1421

Appendix

№	Top 50 financial ratios	Number	Percent	Mark
1	Net income / Total assets	136	7.6%	NITA
2	Current asset / Current liabilities	126	7.1%	CACL
3	Working capital / Total assets	107	6.0%	WCTA
4	Total liabilities / Total assets	105	5.9%	TLTA
5	Retained earnings / Total assets	98	5.5%	RETA
6	EBIT / Total assets	97	5.5%	EBITTA
7	Sales / Total assets	80	4.5%	STA
8	Current assets / Total assets	71	4.0%	CATA
9	(Current assets – Inventories) / Current liabilities	69	3.9%	CICL
10	Net income / Equity	51	2.9%	NIE
11	Cash / Total assets	46	2.6%	CTA
12	Cash flow from operations / Total liabilities	45	2.5%	CFOTL
13	Market value equity / Book value of totaldebt	44	2.5%	MVED
14	Current liabilities / Total assets	34	1.9%	CLTA
15	Equity / Total assets	28	1.6%	ETA
16	Cash flow from operations / Current liabilities	26	1.5%	CFOCL
17	Cash flow from operations / Total assets	26	1.5%	CFOTA
18	Net income / Sales	25	1.4%	NIS
19	Long-term debt / Total assets	24	1.3%	LTDTA
20	EBIT / Interest	23	1.3%	EBITI
21	Operating income / Total assets	23	1.3%	OITA
22	Liabilities / Equity	23	1.3%	LE
23	Cash / Current liabilities	21	1.2%	CCL
24	Cash flow from operations / Sales	21	1.2%	CFOS
25	Current assets / Sales	21	1.2%	CAS
26	Inventor / Sales	21	1.2%	IS
27	Ln (Total assets)	19	1.1%	LOGTA
28	Change in net income	19	1.1%	CHIN
29	Book value equity / Total debt	19	1.1%	BVED
30	Cash flow (using net income) / Debt	18	1.0%	CFD
31	Ln (Total sales)	18	1.0%	LOGS
32	Working capital / Sales	17	1.0%	WCS

33	(Revenue − Cost of goods sold) / Cost of goods sold	16	0.9%	RCGS
34	Capital / Assets	16	0.9%	CA
35	Current liabilities / Current asset	16	0.9%	CLCA
36	EBIT / Current liabilities	16	0.9%	EBITCL
37	Sales / Inventory	16	0.9%	SI
38	Operating expenses / Operating income	16	0.9%	OEOI
39	Funds provided by operations / Total liabilities	16	0.9%	FULT
40	1 if total liabilities exceeds total assets, ero otherwise	16	0.9%	OENEG
41	1 if net income was negative for the last two years, zero otherwise	16	0.9%	INTWO
42	Net sales / Total assets	16	0.9%	NSTA
43	Revenue / Asset	16	0.9%	RA
44	Net income before tax / Net sales	16	0.9%	NIBTS
45	Quick assets / Sales	15	0.8%	QAS
46	Sales / Fixed asset	15	0.8%	SFA
47	Working capital / Equity	15	0.8%	WCE
48	Receivables / Sales x 360	14	0.8%	RS
49	Sales / Current asset	13	0.7%	SCA
50	Cash flow from investing activities / Total liabilities	13	0.7%	CFIATA