UNIVERSITI TEKNOLOGI MARA
Cawangan Kedah
Kampus Sungai Petani

2021 iCMS
INTERNATIONAL CONFERENCE ON COMPUTING, MATHEMATICS AND STATISTICS

e-PROCEEDINGS

of The 5th International Conference on Computing, Mathematics and Statistics (iCMS2021)

4-5 August 2021

Driving Research Towards Excellence

e-Proceedings
of the 5th International Conference on Computing, Mathematics and Statistics (iCMS 2021)

Driving Research Towards Excellence

Editor-in-Chief: Norin Rahayu Shamsuddin

Editorial team:
Dr. Afida Ahamad
Dr. Norliana Mohd Najib
Dr. Nor Athirah Mohd Zin
Dr. Siti Nur Alwani Salleh
Kartini Kasim
Dr. Ida Normaya Mohd Nasir
Kamarul Ariffin Mansor

e-ISBN: 978-967-2948-12-4
DOI

Library of Congress Control Number:

Publication by
Department of Mathematical Sciences
Faculty of Computer & Mathematical Sciences
UiTM Kedah

TABLE OF CONTENT

PART 1: MATHEMATICS

PART 2: STATISTICS

PART 3: COMPUTER SCIENCE & INFORMATION TECHNOLOGY

PART 4: OTHERS

BANKRUPTCY MODEL OF UK PUBLIC SALES AND MAINTENANCE MOTOR VEHICLES FIRMS

Asmahani Nayan[1], Amirah Hazwani Abd Rahim[2], Siti Shuhada Ishak[3], Mohd Rijal Ilias[4] and Abd Razak Ahmad[5]

[1,2,5] Universiti Teknologi MARA (UiTM) Cawangan Kedah, [3,4] Universiti Teknologi MARA (UiTM) Shah Alam

([1] asmahanin@uitm.edu.my, [2] amirah017@uitm.edu.my, [3] shuhada58@gmail.com , [4] mrijal@uitm.edu.my, [5] ara@uitm.edu.my)

The classification of firms into two dichotomous groups, which are bankrupt and non-bankrupt firms, provided results which showed equality between the two groups, where on the other hand, non-bankrupt firms can be further differentiated between financially distressed firms and healthy firms, of which either can be making a comeback in terms of profits or go bankrupt. The variable that differentiates between bankrupt and non-bankrupt as well as between financially distressed and healthy firms are different. As such, this study's objective is to construct a logit bankruptcy model for all variable forms of firms that were involved in the sales and maintenance of motor vehicles. The sample for the study consists of UK based public firms that had submitted a full account to the Companies House. The data was then analysed through logit regression to predict the bankruptcy, using three different models. Based on the three models analysed, it was found that all three models recorded a significant value of below 0.05, which showed that the three models were able to predict bankruptcy. From the three models selected for analysis, the third model was found to be better compared to the other two models and was selected to be the base for the logit bankruptcy model for all types of firms in this study.

***Keywords*:** Logit Regression, Bankruptcy, Distressed Firms, public firms

1. Introduction

Most bankruptcy prediction studies classify firms into dichotomous groups of bankrupt and non-bankrupt firms. This paired-sample technique results in equal number of bankrupt and non-bankrupt firms in the samples. However, the non-bankrupt group consists of not only financially distressed firms but healthy firms that can be easily identified. As such discriminating financially distressed firms that go bankrupt from those that make a turnaround is of much information value that discriminating between bankrupt and non-bankrupt firms (Wood and Piesse, 1987). Furthermore, financial variables used to identify bankrupt firms from non-bankrupt firms are different from those variables used to discriminate financially distressed firms from the bankrupt ones (Gilbert et al., 1990). This study aims to build a logit bankruptcy model for all firms and financially distressed firms that were involved in the sales and the maintenance of motor vehicles. The firms were based in the United Kingdom. Only public firms, which submitted full account to the Companies House, were used in the analysis. This study used logit regression to predict the bankruptcy. As pointed out by Youn and Gu (2010), logit regression gives a much better bankruptcy prediction compared to Artificial Neural Networks (ANN) model.

There are many studies in the past that used financial ratios as the covariate in the bankruptcy prediction model. According to Karas and Reznakova (2012), the ratios that are significant in predicting bankruptcy are quick assets turnover, capital turnover and total assets value. A study carried by Ong et. al (2011) indicated that current asset turnover, asset turnover, days sales in receivables, cash flow to total debt and total liabilities to total assets can be used as predictors in bankruptcy model. Besides financial ratios, bankrupt firms can also be predicted by using other covariates such as non-financial information or other types of information. The inclusion of non-financial information together with other covariates in the prediction model increased the accuracy rate of the model (Wu, 2004). In addition to that finding, Abd Razak & Wan Asma' (2012) found that financial ratios will become less predictive when combined with non-financial information in bankruptcy prediction model.

All findings discussed above used a sample consisting of healthy and financially distressed firms. Our proposed study will use financially distressed firms as samples to build a logit model of bankruptcy for financially distressed firms. According to Ray (2011), a firm can be declared as financially distressed when it is unable to sustain current operations because of its current debt obligations. Poston et. al (1994) defined financially distressed as the firm met any of these criteria; two or more consecutive operating losses, a current ratio less than 1.0 as of the end of any fiscal and a negative balance in the retained earnings account as of the end of any single fiscal year. Our proposed study uses the criteria described by Poston et. al. to identify financially distressed firms.

2. Methodology

The sample used for this study is from UK public firms which are involved in the sales and maintenance of motor vehicles. The data are collected by Credit Scorer Ltd. Only the firms that submit full accounts to the UK Companies House are included in the sample. There were two samples used in this paper. The first sample included all the firms in the sales and maintenance of motor vehicles with a total of 1385 firms. For the second sample, the firms involved were the financially distressed firms. From the total of 1385 firms, only 940 firms are financially distressed firms. For both samples, the firms are then classified into bankrupt and non-bankrupt firms.

Table 1: Classification of data

	Bankrupt	Non-bankrupt	Total
Healthy and financially distressed firms	425 (30.7%)	960 (69.3%)	1385
Financially distressed firms	365 (38.8%)	575 (61.2%)	940

The classifications of bankrupt and non-bankrupt firms for both samples are shown in Table 1. As previously done by other researchers, each sample is divided into two sets; a training set containing 80 percent of the firms and another 20 percent goes into the validation set.

The dependent variable is bankrupt and non-bankrupt firms while the covariates consist of financial ratios and non-financial items. Forty-two financial ratios are used in this study, and they are categorized into five different groups which are activity, cash-flow, leverage, liquidity and profitability. For non-financial items, the variables include the firms' number of employees, the firms' account qualification status and the firms' age. The variables are applied for both samples.

In this study, three models have been developed by using logistic regression for each sample. The covariates for the first model are non-financial items which consist of 17 variables. The second model includes all financial ratios, and the third model is the combination of both non-financial items and financial ratios.

3. Results and Analysis

The analysis for the three models for both the training and validation sets are done by using logistic regression. The training set is used to identify the significant variables that will be used next when analysing the validation set. The variables are significant at 10% level and all models were checked for multicollinearity. The results are presented in Table 2 below.

Table 2: The significant variables

Model	Healthy and Financially Distressed Firms	Financially Distressed Firms
1	age in days	age in days
	firms that are more than 2 years old and less than 9 years old	firms that are more than 2 years old and less than 9 years old
	number of employees less than 10	number of employees less than 10
	late in lodging account	late in lodging account
	time since last account lodged	time since last account lodged
	Going Concern qualification (AQGC)	
2	current liabilities/debtors (Q)	current liabilities/debtors (Q)
	current assets/total assets (Q)	current assets/total assets (Q)
	net profit + depreciation/total debt (C)	net profit + depreciation/total debt (C)
	gross profit/turnover (P)	gross profit/turnover (P)
	pre-tax profit/turnover (P) trade debtors/turnover (A)	pre-tax profit/turnover (P) trade debtors/turnover (A)
	total liabilities/net profit + depreciation (C) net worth/current liabilities (V) working capital/total assets (Q) pre-tax profit/total assets (P)	total debt/total assets (V) net worth/total liabilities (V) pre-tax profit/current liabilities (P) net cash/current liabilities (Q) turnover/total fixed assets (A) working capital/turnover (A) total liabilities/earnings before tax and interest (P)
3	current liabilities/debtors (Q)	current liabilities/debtors (Q)
	current assets/total assets (Q)	current assets/total assets (Q)
	net profit + depreciation/total debt (C)	net profit + depreciation/total debt (C)
	gross profit/turnover (P)	gross profit/turnover (P)
	age in days	age in days

	late in lodging account	late in lodging account
	time since last account lodged natural logarithm of total assets number of employees less than 10 pre-tax profit/total assets (P) trade creditors/turnover (A) net worth/current liabilities (V) firms that are more than 2 years old and less than 9 years old number of employees greater or equal to 250	time since last account lodged natural logarithm of total assets number of employees less than 10 operating profit/turnover (P) total debt/total assets (V) net worth/total liabilities (V) pre-tax profit/turnover (P) trade debtors/turnover (A) pre-tax profit/current liabilities (P) net cash/current liabilities (Q) turnover/total fixed assets (A) working capital/turnover (A) total liabilities/earnings before tax and interest (P) operating cash flow/total assets (C) the firm is a subsidiary

The significant variables in model 1 for both samples are not that different since only one variable not included in the financially distressed firms which is Going Concern qualification (AQGC). This means that the Going Concern qualification can be used to predict bankruptcy for healthy and financially distressed firms while cannot be used for financially distressed firms only. Model 2 has six same financial ratios that can be used to predict bankruptcy for both samples which are current liabilities/debtors, current assets/total assets, net profit + depreciation/total debt, gross profit/turnover, pre-tax profit/turnover and trade debtors/turnover. For model 3, the same variables that can be used to predict bankruptcy for both samples are current liabilities/debtors, current assets/total assets, net profit + depreciation/total debt, gross profit/turnover, age in days, late in lodging account, time since last account lodged, natural logarithm of total assets and number of employees less than 10.

Table 3: Goodness of Fit Test

	Healthy and Financially Distressed Firms			Financially Distressed Firms		
Model	Chi-Square	df	Sig.	Chi-Square	df	Sig.
1	291.833	6	0.000	174.544	5	0.000
2	165.123	10	0.000	127.990	13	0.000
3	356.190	14	0.000	264.542	21	0.000

The model's goodness of fit can be checked by using chi-square statistics. The values for the chi-square statistics for all models are less than 0.05 (p-value < 0.05), meaning that all the models are significant.

Table 4: Model summary

	Healthy and Financially Distressed Firms		Financially Distressed Firms	
Model	Cox & Snell R Square	Nagelkerke R Square	Cox & Snell R Square	Nagelkerke R Square
1	0.231	0.325	0.207	0.281
2	0.138	0.194	0.157	0.212
3	0.274	0.385	0.297	0.403

Another useful information from the results is by looking at the values of Cox & Snell R Square and Nagelkerke R Square. These values indicate the amount of variation in dependent variables that is explained by the independent variables (Pallant, 2007).

Table 4 shows the values of Cox & Snell R Square and Nagelkerke R Square for the three models. For sample 1, the amount of variation in dependent variable that is explained by model 1 is between 23.1 percent and 32.5 percent while for model 2 the percentage is slightly lower than model 1. Model 3 is quite good compared to model 1 and 2 since the amount of variation in dependent variable that is explained by the set of independent variables is between 27.4 percent and 38.5 percent. For sample 2, comparing the three models, the variation in dependent variable is explained more by the set of independent variables in model 3. The amount of variation in dependent variable that is explained by this model is between 29.7 percent and 40.3 percent which is the best compared to the other two models.

Table 5: Classification table

	Healthy and Financially Distressed Firms		Financially Distressed Firms	
Model	Training	Validation	Training	Validation
1	77.0%	75.9%	69.8%	75.7%
2	71.7%	76.3%	69.2%	74.6%
3	78.8%	78.5%	75.6%	81%

The accuracy rates for the three models are presented in Table 5. For sample 1, model 3 is more accurate compared to the other two models with the overall accuracy of 78.5 percent. For sample 2, the results show that model 3, which contains both non-financial items and financial ratios is the best model compared to models 1 and 2. The results from the validation sample confirmed the conclusion obtained from the training sample.

4. Conclusion

From the results obtained, we can conclude that Model 3 that has both non-financial items and financial ratios is the best model for both samples. This model obtains the highest accuracy rate for both samples. Therefore, we can conclude that a model consisting of different types of input variables increases the accuracy rate of bankruptcy prediction. For the first sample (healthy and financially distressed firms), non-financial items that are significant are age in days, late in lodging account, time since last account lodged, number of employees less than 10, firms that are more than 2 years and less than 9 years old and number of employees greater than or equal to 250. For the second sample (financially distressed firms, the significant variables (non-financial items) are age in days, late in lodging account, time since last account lodged, number of employees less than 10 and the firm is a subsidiary. From these two samples the common non-financial variables are age in days, late in lodging account, time since last account lodged and number of employees less than 10.

Acknowledgment

The authors would like to express their gratitude to Universiti Teknologi MARA (UiTM) and the Malaysian Ministry of Higher Education.

References

Ahmad, A., & Abu Bakar, Wan Asma' Wan. (2012). County court judgements as a predictor of the financial failure of large firms: An empirical study in Britain. *International Journal of Management, 29*(2), 407-414.

Cheng-Ying, W. (2004). Using non-financial information to predict bankruptcy: A study of public companies in Taiwan. *International Journal of Management, 21*(2), 194-201.

Gilbert, L.R., K. Menon and K. B. Schwartz (1990). "Predicting Bankruptcy for Firms In Financial Distress", *Journal Of Business Finance And Accounting,* 17(1) Spring, 161-171.

Michal, K. & Maria, R. (2012). Financial Ratios as Bankruptcy Predictors: The Czech Republic Case. *Advances in Finance & Accounting: Proceeding of the 1st WSEAS International Conference on Finance, Accounting and Auditing (FAA 12).*

Ong, S., Voon, C. Y., & Roy W.L. Khong. (2011). Corporate failure prediction: A study of public listed companies in Malaysia. *Managerial Finance, 37*(6), 553-564. doi:http://dx.doi.org/10.1108/03074351111134745

Pallant, J. (2007). *SPSS Survival Manual: A Step by Step Guide to Data Analysis Using SPSS*. Sydney: Ligara Book Printer.

Poston K.M., Harmon W. K., & Gramlich J. D. (1994). A test of financial ratios as predictors of turnaround versus failure among financially distressed firms. *Journal of Applied Business Research, 10*(1), 41-52.

Sarbapriya Ray. (2011). Assessing Corporate Financial Distress in Automobile Industry of India: An Application of Altman's Model. *Research Journal of Finance and Accounting*, *2*(3), 155–168.

Wood, D. and J. Piesse (1987). "The Information Value Of MDA Based Financial Indicators", *Journal Of Business Finance And Accounting,* 14(1) Spring, 27-38.

Youn, H., & Gu, Z. (2010). Predict US restaurant firm failures: The artificial neural network model versus logistic regression model. *Tourism and Hospitality Research, 10*(3), 171-187. doi:http://dx.doi.org/10.1057/thr.2010.2

2021 ICMS

INTERNATIONAL CONFERENCE ON COMPUTING, MATHEMATICS AND STATISTICS

e ISBN 978-967-2948-12-4

9 7 8 9 6 7 2 9 4 8 1 2 4