Quest for Research Excellence On Computing, Mathematics and Statistics

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Faculty of Computer and Mathematical Sciences

Quest for Research Excellence on Computing, Mathematics and Statistics

Chapters in Book

The 2nd International Conference on Computing, Mathematics and Statistics (iCMS2015)

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CHAPTER 24
Logit Bankruptcy Model of Industrial Product Firms

Asmahani Nayan, Siti-Shuhada Ishak, and Abd-Razak Ahmad

Abstract. Logistic regression or logit model is one of the statistical methods that has been widely used in bankruptcy studies. Logistic regression is appropriate when the dependent variable is binary while the independent variables are either discrete or continuous. In bankruptcy studies, the dependent variable that is being used has only two categories which are failed firm and non-failed firm. Besides logistic regression there are other methods that can be used in bankruptcy studies such as Altman's z-score model and multiple discriminant analysis. These methods act differently to different data sets which also give different accuracy rate. The purpose of this study is to compare the performance of logit model and Altman's z-score model in predicting failed and non-failed firms. A total of 30 industrial product firms in Malaysia (15 failed firms and 15 non-failed firms) are used in this study. The firms were divided into training and validation sample then replicated into three groups and in each group will have 70 percent estimation sample and 30 percent validation sample. The performance of the two models were measured using accuracy rate, type I error and type II error. Results of the training and validation samples implied that logit model is slightly better than Altman's z-score model with higher value of accuracy rate and lower value of type I and type II error.

Keywords: logit model; Altman's z-score; bankruptcy; financial ratios

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1 Introduction

In literature, there are different terms used to describe business failure. The terms are default, failure, bankruptcy and insolvency. In the context of Malaysia, Zulridah Mohd Noor et.al (2012) explained that Bursa Malaysia states financial distress is often associated with the PN17 status of companies in Malaysia. In pursuant to Paragraph 8.14C(2) of the Bursa Malaysia Listing Requirements, companies that do not meet any or all of the conditions specified under the provision of Practice Note No. 17/2005 Listing Requirements are classified as PN17 and these companies are considered to have financial problems.

During the 1970s, the business failure phenomenon received some exposure and continues to receive more attention during the recession years of 1980 to 1982. The explosion of cases of defaults and large firm bankruptcies increased in the years 1989-1991 and continue an unprecedented interest in the 2001–2002 corporate debacle and distressed years [2].

According to Altman (2006 cited in Baninoe, 2010), there are several reasons failure can happen such as in poor managing cash, debt and risk, deregulation or overcapacity, severe international competition and higher interest rates in specific periods.

Mark et. al (2013) states the most commonly employed class of default prediction models also directly incorporate financial statement information, which is unlikely to be affected by pessimistic trading constraints. This accounting information being widely available and of relatively high quality, has the potential to serve as an alternative source of default risk information, partially offsetting any loss in predictive ability caused by a decrease in the informativeness of market-based variables in the presence of constraints on pessimistic trading. Accordingly, the net effect of pessimistic trading constraints on the contribution of equity market-based variables to the overall ability of market participants to accurately assess default likelihood is an empirical question. Two related empirical approaches suggested by the prior literature that capture both of these aspects of predictive accuracy to assess differences in the predictability of default. First, Beaver et al. (2005; 2012) measure the fraction of actual sample defaults (or non-defaults) with a predicted probability of default falling in the top three predicted probability of default deciles for all sample firm-years. Second, Chava and Jarrow (2004) assess model predictive accuracy based on the area under receiver operating characteristic curves.

Anandarajan et al. (2001) uses four indicators to describe firms experiencing financial distress. The first indicator, negative operating cash flows, indicates that the firms have insufficient future cash or working capital, which could affect their long-term survival. The second one is when the firms reduce or omit dividend payments, as financially healthy ones will follow a stable dividend policy. The third is when firms have problems making scheduled payments or complying with lending agreements. If debt default (including technical default) occurs it is more likely to lead to bankruptcy. Firms may, alternatively, be forced to enter into unfavourable new agreement, which might curtail the management's actions in operating the firms. The last indicator, the unsuccessful troubled debt restructuring (TDR), is a clear signal of financial distress and is the phase that precedes bankruptcy filing. A successful TDR, on the other hand, will improve current and future debt-service related cash flows.

A study in Malaysia have been carried out by Shamsher et al. (2001) which found that liquidity, profitability and cash flows of the failed firms showed a gradual deterioration, while the leverage of the companies showed a gradual increase. Zulkarnain et al. (2001) focused their study on Malaysian Industrial sector companies. By using stepwise multi-discriminant analysis, the findings show that the model accurately and significantly classified 91.1 percent and 89.3 percent of the failed and non-failed companies respectively. Mohamed et al. (2001) conducted a study by incorporating logistic regression techniques to predict corporate failures.

In Malaysia, most studies used companies of mixed industries as their sample. Examples are work done by Low et.al (2001), Mohamed et.al. (2001), Karbhari & Zulkarnain (2004), Mohmad Isa (2004), Chin (2005), Mohamad Isa et al. (2005), Rohani & Nur Adiana (2005), Tew and Enylina (2005), Nur Adiana et al. (2007), Fauzias & Chin (2001). Meanwhile, Zulkarnain et al.(2001) and Zulkarnain & Karbhari (2004) used manufacturing companies as the sample.

According to Park (2008), financial ratio figured on balance sheets and income statements reflect a firm's financial status are a typical method of assessing both firms' present and future financial performance. Beaver (1968) estimate the predictive power of financial ratios on bankruptcy that tested six groups of ratios: cash flow, debt to total asset, net income, liquid assets to total asset, liquid assets to current debt, and turnover by employed univariate analysis. The conclusion is the combination of more than one ratio will give a researcher better predictability for further study. Then, Altman (1968) use Multiple Discriminant Analysis (MDA) to set of predictor variables to determine whether dependent variables indicate either bankrupt or non-bankrupt dichotomously by introduced the Altman Z score model. According to Altman (1968), failed firm can be identified when the value of the score is more than 2.99 while non-failed firm when the value is less than 1.81.

2 Methodology

The sample consists of 30 public firms in Malaysia from the industrial product sector of which 15 are failed firms and 15 are non-failed firms. These firms are divided into three sets where in each set contains five failed firms and five non-failed firms. Then, the training sample and the validation sample are taken from the combination of these three sets. There are three groups formed and in each group there are 70 percent estimation sample and 30 percent validation sample. The dependent variable in this study is firms that are classified into failed and non-failed and the independent variables consist of 18 financial ratios that are grouped into profitability, leverage, liquidity, market value and efficiency. The information is collected for five financial years before a firm files for bankruptcy from KnowledgeCentre, Bursa Malaysia. This is a standard practice as performed by many commercial banks of the world.

The method used in this study is logistic regression since the dependent variable is in binary form (1 as failed firm, 0 as non-failed firm). Logistic analysis is available in the Statistical Package for Social Sciences 19.0 (SPSS) package. In this study, the model of Logit analysis and the definition of variables are described as follows:

$$\log \frac{P(x)}{1-P(x)} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_i X_i . \qquad (1)$$

Where,

$P(x)$ = Probability of the bankruptcy occurrence

β_0 = the intercept term

β_1-β_i = the coefficient of β with the corresponding explanatory variable X

X_1-X_i = input variation.

The results from logistic regression were then compared with Altman's z-score by looking at the overall accuracy rate, type I error and type II error. Type I error is the probability that rejecting the null hypothesis when actually the null hypothesis is true. Type II error is the probability that accepting the null hypothesis although the alternative hypothesis is true. Table 1 below shows the summary of the errors.

Table 1. Type I and type II error.

Actual	Predicted	
	The firm is failed	The firm is non-failed
The firm is failed	Good conclusion	Type I Error
The firm is non-failed	Type II Error	Good conclusion

3 Results and Discussion

The mean values of all independent variables are calculated in order to obtain the idea on how these variables behave. The mean values for failed companies is calculated by taking the values from five years data prior to bankruptcy and for non-failed companies the mean is calculated using the values of the same year as failed companies. Non-failed companies have higher mean values for most of the variables compared to failed companies except for total debt to total assets, net debt to equity, capital expenditure to sales, total debt to total equity, total debt to total capital and total debt to market capital. These six variables are leverage ratios. Failed companies are expected to have higher values for these ratios. Based on the results, failed companies are proven to have more debt compared to their assets, equity and capital. These companies also have smaller value of sales compared to their capital expenditure.

The univariate analysis in Table 2 shows that out of 18 independent variables only four variables that are not significant at five percent level. The variables are net debt to equity, price to book ratio, cash flow per share and total debt to total equity. Thus, these four variables are excluded from further analysis.

Table 2. Univariate analysis.

Independent Variables	t	Sig.
Operating Margin	2.871	0.005*
Profit Margin	2.514	0.013*
Total Debt to Total Assets	-3.496	0.001*
Net Debt to Equity	-0.652	0.516
Current Ratio	3.068	0.003*
Price to Book Ratio	0.406	0.685
Book Value per Share	4.087	0.000*
Inventory to Sales	-2.085	0.039*

Capital Expenditure to Sales	-3.233	0.002*
Cash Flow per Share	0.816	0.416
Net Fixed Asset Turnover	2.039	0.043*
Asset Turnover	3.960	0.000*
Inventory to Current Assets	4.410	0.000*
Inventory to Total Assets	3.070	0.003*
Return on Assets	4.905	0.000*
Total Debt to Total Equity	-0.913	0.363
Total Debt to Total Capital	-4.237	0.000*
Total Debt to Market Capital	-3.276	0.001*

Note: * significant at 5 percent level of significance

Table 3 shows the classification results for group 1. There are three variables that are significant in group 1 and the variables are inventory to sales, inventory to current assets and total debt to market capital. 83 percent of the companies are correctly classified into failed and non-failed companies based on estimation sample. The results from the estimation sample then used in validation sample. In validation sample, accuracy rate for logit model is much higher compared to Altman’s z-score model. The probability of accepting that the company is non-failed when the company is actually failed for both models is 0.20 and 0.26 respectively. The probability of accepting that the company is failed when in reality the company is non-failed is 0.24 for logit model and 0.40 for Altman z-score model. Logit model has the lower value of probability for both errors implying that this model is slightly better than Altman z-score model.

Table 3. Classification results for group 1.

Classification	Measurement Type	Logit Model	Altman's Z-Score
Estimation	Accuracy Rate	83%	64.35%
	Type I Error	0.20	0.17
	Type II Error	0.14	0.54
Validation	Accuracy Rate	78%	66.84%
	Type I Error	0.20	0.26
	Type II Error	0.24	0.40

The only significant variables in group 2 are total debt to total assets, inventory to total assets, return on assets and total debt to total capital. The Logit model correctly classified 72 percent for both failed and non-failed companies while Altman's z-score model only correctly classified 51.35 percent in validation sample. Type I and type II error for logit model is 0.44 and 0.12 respectively while Altman's z-score model with 0.21 and 0.76 respectively. Altman's z-score model has lower value of type I error but higher value of type II error and vice versa for logit model. By comparing the two errors, the performance of the two models do not differ much in group 2 although logit model has the highest accuracy rate.

Table 4. Classification results for group 2.

Classification	Measurement	Logit Model	Altman's Z-Score
Estimation	Accuracy Rate	74%	72.06%
	Type I Error	0.22	0.19
	Type II Error	0.30	0.37
Validation	Accuracy Rate	72%	51.35%
	Type I Error	0.44	0.21
	Type II Error	0.12	0.76

The performance of logit model is slightly better than Altman's z- score model for group 3 in validation sample with 90 percent accuracy rate. The variables that are significant are inventory to sales, inventory to current assets and total debt to market capital. These variables are the same with the results in group 1. Type I error for both models not differ much with 0.16 for logit model and 0.13 for Altman's z-score model. Logit model has lower value of type II error compared to Altman's z-score model.

Table 5. Classification results for group 3.

Classification	Measurement	Logit Model	Altman's Z-Score
Estimation	Accuracy Rate	72%	59.99%
	Type I Error	0.32	0.23
	Type II Error	0.24	0.57
Validation	Accuracy Rate	90%	76.82%
	Type I Error	0.16	0.13
	Type II Error	0.04	0.33

Table 6 shows the summary of the validation sample for all groups. The results clearly show that logit model is slightly better for all groups especially for group 1.

Table 6. Summary of validation sample results.

	Measurement	Accuracy Rate	Type I Error	Type II Error
Group 1	Logit Model	78%	0.2	0.24
	Altman's z-score	66.84%	0.26	0.4
Group 2	Logit Model	72%	0.44	0.12
	Altman's z-score	51.35%	0.21	0.76
Group 3	Logit Model	90%	0.16	0.04
	Altman's z-score	76.82%	0.13	0.33

4 Conclusion and Recommendation

Logit model has the higher accuracy rate for both estimation and validation sample for the three groups compared to Altman’s z-score model. Logit model almost has the lowest values of type I and type II error for all the groups except for group 2 and group 3 logit model has slightly higher value of type I error. These results clearly stated that logit model can predict the failed firms better than Altman’s z-score model for the industrial products firms in Malaysia.

The significant variables in the three groups are inventory to sales, inventory to current assets, inventory to total assets, total debt to market capital, total debt to total assets, total debt to total capital and return on assets. From these seven variables, the first three variables are under cash flow ratio, the next three variables are leverage ratio while the last variable comes from profitability ratio.

The results of this study only apply for public industrial product firms in Malaysia. Further research can be done using other sectors in Malaysia as the sample so that the results could be more generalize.

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