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How well do Partial Least Squares and Financial Ratio Analysis Predict Corporate Failure in Malaysia

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ABSTRACT

Sustainable companies and their life span had been a recurring issue in the current millennium for developing countries. The aim of this study is to develop a failure prediction model by using partial least square (PLS) analysis with different financial ratios, and to examine which of the financial ratios can be best used to predict corporate failure in both failed and non-failed firms. A sample of 22 distressed and non-distressed companies in the same industry sector firms with 10 financial ratios for the period from 2009 until 2012 were obtained from Bursa Malaysia Listed Companies. From the ten dominant financial ratios, only profitability, liquidity, leverage and efficiency ratios had remained after modelling. This study also found that the failure prediction model using PLS showed with high predictive accuracy rates of about 90%. Amongst the financial ratios, leverage and efficiency ratios were the most significant predictor of corporate failure.

Keywords*: Financial ratios, corporate failures, failure predictions, partial least square analysis, structural equation model.*

1. INTRODUCTION

In an era of trade liberalization and globalization relatively few failure prediction studies on Malaysia firms have been published. Incidence of currency crisis in 1997 has showed that many strong and large firms collapsed. However, failure is not something unusual among Malaysian corporations nowadays due to the strong competitive business environment. Corporate failure generally classified by Bursa Malaysia (formerly the Kuala Lumpur Stock Exchange) under one of The Practice Note (PNs). These failure companies seek protection under section 176 company act 1965. Hence, it is utmost importance to understand and predict company failures. From this knowledge, it might help a company to safeguard itself from being bankrupt.

Financial statements have been used to provide information on a company's performance. Various financial ratios had proven to be an analysis tools and interpretation on profitability, leverage, liquidity and efficiency of the firms. This useful information helps the creditors and investors to know the financial health of the firms over time. Besides, it is helpful for shareholders as well as they might want to know whether the companies are suitable to invest. Hence the aim of this study is to develop a failure prediction model by using partial least square analysis (PLS) with different financial ratios and to examine which of the financial ratios can best be used to predict corporate failure in both failed and non-failed firms.

2. LITERATURE REVIEW

The development of failure and bankruptcy prediction studies are mostly done in developed countries. It first was started by [1] followed by [2], [3], [4], [5], [6] and [7]. In Malaysia, study on bankruptcy prediction was initiated in 2001 by [8] followed by [9], [10] and [11].

In 1966, [1] was the most well-known for a univariate model with the help of financial ratio analysis. Paired samples techniques of 79 failed and non-failed firms and 30 financial ratios were used for the period of 1954 to 1964. [1] had found that six financial ratios differed significantly for failed and non-failed firms. Those results differed from [2] with the use of multiple discriminant analysis (MDA). The sample involved 33 bankrupt and non-bankrupt companies for the period of 1064-1965 with 22 financial ratios. Out of the 22 ratios, only five variables were selected from Z-score and these were working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market value of equity to book value of total debt and sales to total assets [10].

However, [3] had found that there were some inadequacies in the approach using MDA due to the assumptions of normality and group dispersion. Logit analysis was then carried out by [3] to predict corporate bankruptcy. The samples compromised of 105 bankrupt and 2058 non-bankrupt firms from the period of 1970-1976. Four factors were significant viz., size, the financial structure of measure, leverage and some performance measures for current liquidity.

[8] had utilized on the stepwise multiple discriminant analysis and had found that total liabilities to total assets, sales to current assets, cash to current liabilities and market value to debts were important determinants of corporate failures in Malaysia. [9] had developed a logit model to test between Malaysian firms that did and did not seek for court protection from their creditors. Debt ratio, interest coverage and total assets turnover were found to have significant discriminating power. Besides, 80.7% of the firms were able to classify accurately from this model. However, according to [10] the accuracy rate of prediction model by [9] was lower than [8] and [12]. Thus [10] had implemented a research

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which differentiates three methods for identifying distressed companies; MDA, logistics and hazard models. Hence, the prediction accuracy of the hazard model was quite higher which was 94.9% compared to the other two model with different financial, business and operating conditions in the Malaysian context to improve the predictive abilities for a company failure in a later time frame. According to [10], MDA indicated a very reliable statistical tool with high predictive accuracy rates between 88%-94% for five years prior to actual failure by using a total of 64 companies with 7 ratios were found to be significant out of 16 financial ratios used in the study.

methods. Furthermore, the ratio of debt to total assets was a significant predictor of corporate distress regardless of the methodology used. In 2010, [11] had developed

3. RESEARCH DESIGN

3.1 Selection of Variables

It was a common practice for stakeholders to have information on the financial health of the firms as financial ratios that did provide useful information for making investment decisions [9].

Table 1 below summarized on the ratios used in this research. Ten ratios as in Table 1, were divided into four categories; profitability, leverage, liquidity and efficiency ratios. These ratios were chosen based on the popularity and simplicity. According to [11], in order to predict business failures it was not necessary to have a large set of ratios but only a dominant set that have derived from the large sets.

Table 1: The Financial Ratios Utilized

Profitability Ratios	
GPMARGIN (GPM)	Gross profit margin, defined as profit before tax divided by turnover. The higher the value of ratio the better the financial health.
NPMARGIN (NPM)	Net profit margin, defined as a net profit divided by turnover. The higher the value of ratio, the better the financial health of the company.
ROE	Return on equity, defined as profit for the period divided by shareholder's funds. Positive relationship shows better for the company.
ROA	Return on assets, defined as after tax income divided by total assets. As higher ratio value tend to be associated with stronger financial positions.
Leverage Ratios	
DBTRATIO (DBT)	Debt ratio defined as total liabilities divided by total assets. The greater the value of this ratio indicates the weaker the financial health.
LEVERAGE (LVRG)	Leverage obtained by dividing currents assets by shareholder's funds. Greater the ratio value, the weaker the financial health.
Liquidity Ratios	
CRATIO	Current Ratio, defined as current assets divided by current liabilities. The greater the ratio, the better.
ACIDTEST (ACIDTST)	Acid test ratio, obtained by dividing the difference between current assets and inventories by current liabilities. Positive relationship between the ratio and financial health.
Efficiency Ratios	
FIXOVER	Fixed asset turnover is obtained by dividing sales by net fixed assets. A positive relationship between ratios and financial health.
TOTOVER	Total asset turnover is defined as sales divided by total assets. A positive relationship between the ratios and financial health.

Source: [9]

3.2 Data Collection and Sample

Financial statements data for distress and non-distress companies were obtained from the annual reports for a period starting 2009 until 2012 from public listed companies of Bursa Malaysia. A total of 22 failed companies which had triggered any of the criteria pursuant to Practice Note 17 of the main market listing requirements of Bursa Malaysia Securities Berhad were selected. Another 22 non-failed companies were chosen based upon a paired-sample design for each failed company in the sample with the closest assets size.

3.3 Partial Least Square - Structural Equation Model (PLS-SEM)

Structural equation modeling (SEM) was first appeared in marketing studies in the early 1980's; however, its applications has become popular nowadays [13}. Besides, PLS-SEM was a casual modeling approach by maximizing the explained variance of the dependent latent constructs. In addition, this approach was suitable for prediction and theory development. Moreover, it has also been stated that PLS-SEM was quite similar to multiple regression analysis.

According to [14], there were two sets of linear equation for partial least square path model; the inner model and outer model. Inner model shows the relationship between the latent constructs while the outer model specifies the unidirectional predictive relationship between each latent constructs and associated observed indicators. Furthermore, the inner model can be written as;

$$\Xi = \Xi B + Z \qquad (1)$$

where; Ξ is the vector of latent variables, B indicates the matrix of path coefficients and Z is the inner model residuals. The inner model constitutes the causal chain system and predictor specification reduces equation 1 to:

$$E(\Xi \mid \Xi) = \Xi B \qquad (2)$$

Besides, PLS path model involves two different measurement models: Reflective and Formative. In this study, only formative measurement model is used to determine the causal relationships from the manifest variables to latent variables. The linear relationships for one block of manifest variables are given as follows;

$$\xi = X\pi + v \qquad (3)$$

where; ξ is the latent variables, X is the manifest variables, π is the loading coefficients plus a residual v. The predictor specification from equation 3 is simplified to:

$$E(\xi \mid X) = X\pi \qquad (4)$$

In PLS-SEM algorithm follows two stage approach [13].

Stage One: Iterative estimation of latent constructs scores.

Step 1: Outer approximation of latent constructs scores.
Step 2: Estimation of proxies for structural model relationships between latent constructs.
Step 3: Inner approximation of latent constructs scores.
Step 4: Estimation of proxies for coefficients in the measurement models.

Stage Two: Final estimates of coefficients are determined using the ordinary least squares method for each partial regression in the PLS-SEM model.

Figure 1 showed the conceptual models for both failed and non-failed companies. The dependent variables were Failed and Non-Failed while the profitability ratios, leverage ratios, liquidity ratios and efficiency ratios were the independent variables for this study. These independent variables were involved in the formative measurement model as the errors were pointing towards the latent constructs.

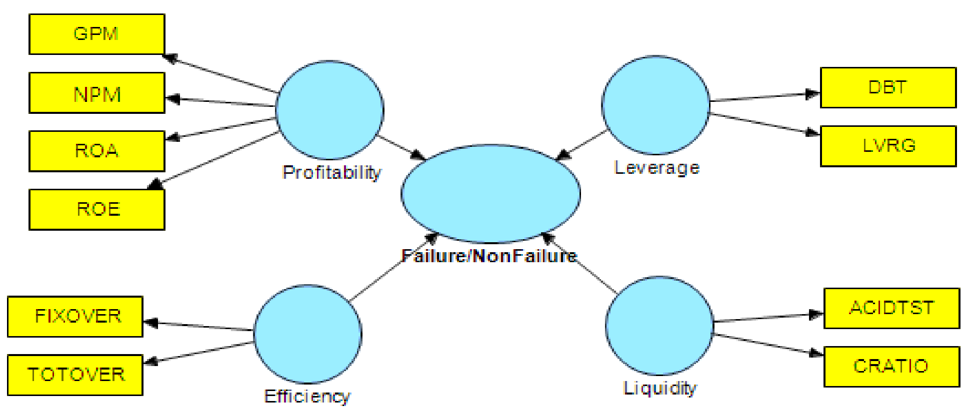

Figure 1: Conceptual Model for Failure/Non-Failure Companies

4. RESULTS

The research model for this study was tested using partial least squares (PLS). Smart PLS 2.0 M3 was used to assess the measurement and structural model for this study [15].

4.1 Failure Companies

The validity and reliability of the measurement model for this study were evaluated using the following analyses: internal consistency reliability, indicator reliability convergent reliability and discriminant validity. A measurement model is said to have satisfactory internal consistency reliability when the composite reliability (CR) of each construct exceeds the threshold value of 0.7. Table 3 showed that the CR of each construct for this failure companies ranges from 0.724 to 0.999.

Next, indicator reliability was measured by examining the item loadings. A measurement model is said to have satisfactory indicator reliability when each item's loading is at least 0.5. As shown in Table 3, each loading ranged from 0.622 to 0.999. Convergent validity is assessed by its average variance extracted (AVE) value. Convergent validity is adequate when constructs have AVE value of at least 0.5. From Table 3, it can be seen that all constructs have AVE ranging from 0.575 to 0.998.

Table 3: Failure Measurement Model

Model Construct	Measurement Item	Loadings	CR	AVE
PROFITABILITY	ROE ROA	0.929 0.943	0.934	0.876
LIQUIDITY	ACIDTST CRATIO	0.999 0.999	0.999	0.998
LEVERAGE	LVRG	1.000	1.000	1.000
EFFICIENCY	FIXOVER TOTOVER	0.919 0.935	0.924	0.859

Discriminant validity is assessed by using the Fornell and Larcker's criterion [16]. The square root of AVE exceeds the correlations between the measure and all other measures, and the indicators' loadings are higher against their respective construct compared to the other constructs. The result of discriminant validity was as shown in Table 4. Therefore, all reliability and validity tests conducted for failure measurement model were satisfactory. Overall, this model was valid and fit to be used to estimate the parameters in the structural model.

Table 4: Failure Discriminant Validity

	EFFICIENCY	FAILURE	LEVERAGE	LIQUIDITY	PROFITABILITY
EFFICIENCY	0.927				
FAILURE	0.842	1.000			
LEVERAGE	0.575	0.709	1.000		
LIQUIDITY	-0.033	-0.232	-0.193	0.998	
PROFITABILITY	0.822	0.895	0.431	-0.114	0.935

The validity of the structural model was assessed using the coefficient of determinations (R^2) and path coefficients. The R^2 value indicated the amount of variance in dependent variables that were explained by the independent variables. The larger the R^2, the higher the predictive ability. For this study, the SmartPLS algorithm was used to obtain the R^2 values, while SmartPLS bootstrapping was used to generate the statistics values. The bootstrapping generated 200 samples from 100 cases. The R^2 value for failure model was 0.997. Each path connecting two latent variables would represent a hypothesis. Based on the t-statistics output in Table 5, the significant level of each relationship was examined with a value of at least 0.1, had a positive sign direction and consisted of a path coefficient value (β) ranging from 0.146 to 0.523 [13; 17]. Assessment of path coefficients for failure model showed that all proposed hypothesis were supported except for H3.

Table 5: Failure Structural Model

	Path Coefficients (β)	T Statistics	Supported	Hypotheses
EFFICIENCY -> FAILURE	0.472	10.838	YES	H1
LEVERAGE -> FAILURE	0.192	10.226	YES	H2
LIQUIDITY -> FAILURE	-0.138	1.151	NO	H3
PROFITABILITY -> FAILURE	0.430	15.578	YES	H4

4.2 Non-Failure Companies

The composite reliability (CR) of each construct for these non-failure companies ranged from 0.903 to 1.000. For indicator reliability, each loading ranging from 0.702 to 1.000 was shown in Table 6 below. Table 6 also showed that all of the constructs had AVE ranging from 0.791 to 1.000 respectively.

Table 6: Non-Failure Measurement Model

Model Construct	Measurement Item	Loadings	CR	AVE
PROFITABILITY	ROA NPM	0.990 0.985	0.987	0.975
LIQUIDITY	ACIDTST CRATIO	0.993 0.994	0.993	0.987

LEVERAGE	DBT LVRG	0.702 0.880	0.774	0.634
EFFICIENCY	TOTOVER	1.000	1.000	1.000

Table 7: Non-Failure Discriminant Validity

	EFFICIENCY	**LEVERAGE**	**LIQUIDITY**	**FAILURE**	**PROFITABILITY**
EFFICIENCY	1.000				
LEVERAGE	0.388	0.796			
LIQUIDITY	0.379	0.395	0.993		
FAILURE	0.801	0.634	0.692	1.000	
PROFITABILITY	-0.446	-0.107	-0.016	-0.582	0.993

Discriminant validity for non-failure model was assessed by using Fornell and Larcker's criterion [16]. The result of discriminant validity was as shown in Table 7. Hence, all reliability and validity tests conducted for this non-failure measurement model were satisfactory.

The R^2 value for non-failure model was 0.992. Based on the t-statistics output in Table 8, the significant level of each relationship was examined with a value of at least 0.1, positive sign direction and consisted of a path coefficient value (β) ranging from 0.146 to 0.523 [13; 17]. Assessment of path coefficient for failure model showed that all proposed hypotheses were supported except for H4.

Table 8: Non-Failure Structural Model

	Path Coefficients (β)	**T Statistics**	**Supported**	**Hypotheses**
EFFICIENCY -> FAILURE	0.352	13.435	YES	H1
LEVERAGE -> FAILURE	0.281	6.306	YES	H2
LIQUIDITY -> FAILURE	0.441	5.717	YES	H3
PROFITABILITY -> FAILURE	-0.388	0.956	N0	H4

5. DISCUSSIONS AND CONCLUSION

The results obtained in this study showed that Partial Least Square represented an alternative statistical tool in identifying corporate failure. This was also supported by [18] which analyzed PLS-SEM as one of the statistical methods used in financial accounting research. More specifically, the PLS model constructed had good predictive abilities with accuracy rates of about 90%. The results suggested that there was a convinced relationship between financial ratios and company performance. In addition, the results suggested that for a failure model, only profitability, efficiency and leverage ratios would show significantly in predicting company's failure. However, this failure model contradicted with non-failure model. Non-failure model had found liquidity, efficiency and leverage ratios to be significant predictor. In this case, these results revealed that efficiency and leverage ratio were two important predictors to check whether a company would succeed or fail. This finding appeared to reecho with [9] who had reported that leverage played an essential role in predicting corporate failure. Besides, it was also stated that non-failed companies were able to keep profit levels within a tolerable range. In line with [2] findings, it was found out that efficiency ratios especially total assets turnover (TOTOVER) had a significant predictive ability. This ratio suggested a greater ability of the management to generate sales per each unit of its assets.

This study hence aimed to develop a failure prediction model by using partial least square (PLS) in the Malaysian context. A total of 44 companies were analyzed with 10 financial ratios. The PLS model showed an alternative statistical tool in identifying corporate failure with high accuracy rates of about 90%. Amongst the categories of financial ratios used, only leverage and efficiency had significant predictive abilities in identifying corporate failure. The results of this study, however, had a limitation of which the sample was small, owing to the small number of companies obtained. Future research was suggested especially with a large sample size, and should be tested from a different time span so that the results could be more generalized.

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