An Empirical Test of Financial Ratios for Malaysian Practice Notes No. 4 (PN 4) Sector Companies

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ABSTRACT

Corporate failures are known to have high economic cost due to its impact on to investors, creditors, auditors, market analysts, loan officer, and also to the management and employees of the affected companies. Due to this reason, a fast and efficient device or model is needed to detect financially distressed companies. This study presents results on the use of financial ratios as predictors of corporate distress. Sample of financial distressed companies for this research were taken from a new classified distress companies under Practice Notes No. 4 (PN4) sector of the Kuala Lumpur Stock Exchange (KLSE). A total of 32 financial ratios which were found to be useful in previous studies were analyzed by a three step selection approach. Using multiple discriminant analysis (MDA) and logistic regression (LR), the models were able to classify 92.2%-93.9% and 93.9%-97.4% respectively of the sample correctly. The models were validated by a holdout sample that showed a predictive accuracy of 87.9%-96.5% and 89.5%-98.3% respectively for MDA and LR. This research revealed that profitability, liquidity, and financial leverage were the important determinants of a company's going concern.

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Corporate failures are known to have high economic cost due to its impact on to investors, creditors, auditors, market analysts, loan officer, and also to the management and employees of the affected companies. Due to this reason, a fast and efficient device or model is needed to detect financially distressed companies. This study presents results on the use of financial ratios as predictors of corporate distress. Sample of financial distressed companies for this research were taken from a new classified distress companies under Practice Notes No. 4 (PN4) sector of the Kuala Lumpur Stock Exchange (KLSE). A total of 32 financial ratios which were found to be useful in previous studies were analyzed by a three step selection approach. Using multiple discriminant analysis (MDA) and logistic regression (LR), the models were able to classify 92.2%-93.9% and 93.9%-97.4% respectively of the sample correctly. The models were validated by a holdout sample that showed a predictive accuracy of 87.9%-96.5% and 89.5%-98.3% respectively for MDA and LR. This research revealed that profitability, liquidity, and financial leverage were the important determinants of a company's going concern.

I. INTRODUCTION

In 1997, the Asian financial crisis that sparked from Thailand had spread rapidly throughout the region. This crisis had led many Malaysian companies to the scene of financially insolvent or distressed situation and has highlighted the need to investigate the role of corporate financial distress among Malaysian companies. The need for a reliable empirical model that is able to predict financial distressed companies promptly and accurately is crucial, in order to enable the interested parties to take either preventive or corrective action. Investors, creditors, auditors, market analysts, portfolio managers, insurers, loan officers, management and employees need a reliable prediction model to assess the financial condition of a company. The most important contribution of a financial distress prediction model is it can minimize all stakeholders' risk of losses by liquidating the investment or obtain settlement of a debt in the affected companies.

In March 2001, the Kuala Lumpur Stock Exchange (KLSE) introduced a separate classification for financial distressed companies, known as Practice Note No. 4/2001 (PN4) companies. A PN4 company must submit its plan to regularize its financial position. It has a maximum timeframe of between six to twelve months to implement its plans to regularize its financial condition. Failing to comply with the regulations, a PN4 company may be suspended and/or be de-listed.

Previous researchers in Malaysia had developed failure prediction models using sample from Section 176 Companies Act, 1965 (Ang, Sulaiman, and Sanda, 2001; Zulkanian, Mohamad, and Annuar, 2001). Section 176 list of companies are those that have been granted acourt restriction order (RO) whereby the court cannot take any legal actions againsts them for a period of time. The present study differed from previous studies in that Malaysian PN4 companies are used as sample of financially distressed companies. PN4 sector companies is a newer and broader classification of financial distressed companies on the KLSE whereby a PN4 company must regularize its financial condition within a stipulated period or would be suspended from trading which could lead to de-listing if the turnaround process is not satisfactory.

The main objective of this paper is thus to build a distress prediction model using financial ratios on to a newer and broader distressed classification sample. The study uses three different approaches in search of the significant financial ratio variables. Both the MDA and LR method are used for testing the model and a holdout sample is also used for validation. This part of the paper provides for the introduction, with the remaining part organized as follows: Section II provides the relevant literature review. Section III describes the data and methodology. Section IV presents the results and analysis, and finally Section V provides the summary and conclusion.

II. LITERATURE REVIEW

The established practice for corporate financial distress prediction is a model based on financial ratio analysis. The earliest prediction model using ratio analysis was based on univariate analysis. In univariate approach, the financial ratios between failed and non-failed groups are compared. An obvious limitation of univariate approach is the lack of integration of various ratios that reflects the financial status of a firm. To overcome this limitation, multivariate prediction models have been introduced.

Multiple Discriminant Analysis

Altman (1968) developed the first multivariate model in 1968 which is known as Z-score. A set of financial and economic ratios were investigated using multiple discriminant analysis (MDA). The model was able to provide a high predictive accuracy one year prior to failure of 95% from the initial sample. MDA had been a popular model since then mainly due to its simplicity and reported high accuracy. Among the researchers who built failure prediction model based on MDA were Sinkey (1975), Moyer (1977), Altman (1978), Ketz (1978), Norton and Smith (1979), Pettway and Sinkey (1980), Dambolena and Khoury (1980), Mensah (1983), Gentry, Newbold, and Whitford (1985), Casey and Bartczat (1985), Back, Teija, Kaisa, and Wezel, (1996), Shirata (1998), Her and Choe (1999), Ang et al. (2001), and Zulkanian et al. (2001).

Several pitfalls from Altman's (1968) work were discussed by Eisenbeis (1977). The standard discriminant analysis procedures assumed that the variables being investigated are normally distributed. However, the multivariate normality assumption had always been violated. Another assumption of linear discriminant analysis which is often violated is the group dispersion (variance-covariance) matrices being equal across all groups.

Logistic Regression Model

Another popularly used prediction model is the Logistic regression (LR) or also known as logit or logistic analysis. The advantage of this method is that it does not assume multivariate normality and equal covariance matrices (Mensah 1983). Among the early users of LR analysis in the context of financial distress was Ohlson in 1980. Due to the relaxation on the assumptions of independent variables, LR had gained its popularity since 1980s. Others who built failure prediction model based on LR were Mensah (1983), Gentry et al. (1985), Peel, Peel, and Pope (1986), Lau (1987), Peel & Peel (1988), Keasey, McGuinness, and Short (1990), Back et al. (1996), Whitaker (1999), Her & Choe (1999), Tirapat & Nittayagasetwat (1999), Charitou & Trigeorgis (2000), Kolari, Glennon, Shin, and Caputo (2000), Neophytou, Charitou, and Charalambous (2000), Back (2001), Bernhardsen (2001), and Ang et al. (2001).

Combination of Methods

In recent years, some researchers built two or more models in bankruptcy prediction with the intention to find the differences between the models in term of independent variables selection and accuracy. Casey and Bartczak (1985) had developed failure prediction models using both MDA and logistic regression. The results showed that MDA and logistic regression generated similar results.

Back et al. (1996) showed that the use of discriminant analysis, logistic regression or genetic algorithm all lead to different failure prediction models. The amount of variables included in the models also varied as different methods lead to different selection of financial ratios. Kolari et al. (2000) developed an early warning system for large banks in using both parametric and non-parametric approach. Both logistic regression (parametric) and trait recognition (non-parametric) performed well in terms of classification of results. Further, Neophytou et al. (2000) built a classification model using logistic regression and neural network. The results showed that neural network has a slightly better accuracy than logistic regression in one and three year prior to failure.

Regional and Malaysian Bankruptcy Models

Shirata (1998) studied financial ratios as predictors of Japanese corporate failure. By using linear MDA and sixty-one ratios, the result showed that the selected variables could significantly discriminate the bankrupt group independent of industry and size. Accounting data in Korea and Australia were compared to evaluate their predictive power in business failure prediction models by Her and Choe (1999). Their models were based on linear discriminant model, quadratic discriminant model, logistic regression model, and probit model. Tirapat and Nittayagasetwat (1999) used logistic regression to develop a macro and microeconomics financial distress model in Thailand. The economics variables were found to be able to differentiate the financially distressed companies from the non-distressed ones.

Ang et al. (2001) developed MDA and LR models to distinguish bankruptcy firms in Malaysia. The sample was taken from companies that were listed in KLSE and had sought court protection under Section 176 Companies Act 1965. A total of twenty-six companies were included in the study. The overall predictive power of the

MDA was 81.1% in the estimation sample, and 75.4% in the holdout sample. LR model exhibited accuracies of 80.8% and 74.5% for estimation and holdout sample respectively. Zulkanian et al. (2001) developed a failure prediction model based on MDA. Twenty-four companies which were classified under Section 176 Companies Act 1965 were included in the sample. The model correctly classified 90.2% of the original sample and 89.8% in the holdout sample.

III. DATA AND METHODOLOGY

Data

Companies' financial data were extracted from *KLSE Annual Companies Handbook* and *Company Annual Report.*

Sample

The Financial Distressed Companies

In this study, companies included in the sample must satisfy the following conditions:

1. Companies were under provision of PN4 as of 24th September 2002.
2. Not a company under Finance sector in KLSE.
3. Affected companies must have continuous data available for three years prior from the day of the first announcement to be included under the provision of PN4.

A total of eighty-eight financial distressed companies were included in this study[1]. Twenty-seven out of eighty-eight PN4 companies were also classified under Section 176 Companies' Act, 1965. In order to isolate the influence of Section 176 companies, using a subsample consisting of sixty-one companies (PN4 only) were selected and tested. Appendix B showed the PN4 companies with a note on Section 176 classification.

The Non-distressed Companies

To provide for the analysis an equal number of non-distressed companies were selected and matched with the distressed companies. Norton and Smith (1979) have highlighted the importance of the matched sample of companies be as similar as possible in all respects except for their financial ratios. For each financial distressed company, a non-distressed partner company was chosen based on these characteristics:

1. The non-distressed company must be in the same industry as its financial distressed partner.
2. Within an industry, the non-distressed company must have asset size most similar to its financial distressed partner.
3. Data must be available for three years preceding its partner's PN4 announcement.
4. Financial data for non-distressed companies were collected and matched against the distressed company's financial year.

[1] One hundred companies were listed under PN4 sector in KLSE as of 24^{th} September 2002. Ten companies formerly under Finance sector were excluded. Two companies, General Soil Engineering Holdings Berhad and Tat Sang Holdings Berhad were excluded due to incomplete data.

Empirical Models and financial ratios

The models employed in this research would be based on MDA and LR. 65% of the sample from financial distressed and non-distressed group would be used to build the estimation model, while another 35% percent would be used to validate the model.

Financial Ratios

The independents variables used in this study were as compiled by Chen and Shimerda (1981). Chen and Shimerda (1981) had incorporated thirty-four[2] financial ratios which were found to be significant variables in corporate failure prediction models by previous researchers, Beaver ([1966], Altman [1968], Deakin [1972], Edmister [1972], Blum [1974], Elam [1975], and Libby [1975]). These variables have been compiled by Chen and Shimerda (1981) to fit into the seven factor developed by Pinches, Mingo, and Caruthers (1973). The seven factors were return on investment, capital intensiveness, inventory intensiveness, financial leverage, receivables intensiveness, short-term liquidity, and cash position. Details of the ratios in each factor are illustrated in Appendix A.

Three approaches were used to determine which financial ratios should be included in the models.

First Approach – Selected Variables from t-test

In the first approach, a set of the independent variables was chosen based on significant variables from univariate t-test 1-year prior to financial distressed. This approach had been used by Norton and Smith (1979) in developing failure prediction model.

Second Approach – 7 ratios

Mensah (1983) had used the factor analytic approach to develop failure prediction model. One ratio would be selected to represent each factor in building the financial distressed prediction models. The most representative variable from the factor would be the variable with the highest loading.

Third Approach – Stepwise Technique

Stepwise technique is a widely used method in failure prediction models. In this study, probability of F to enter and removal were 0.05 and 0.1 respectively.

Validation of the Models

In this research, 35% of the sample from financial distressed and non-distressed group would be used to validate the models. The MDA models would also be validated by chance-based criterions and Press's Q statistic.

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[2] There were 34 ratios in Chen and Shimerda (1981) research. However, only 32 ratios were analyzed as the data to develop two other ratios, no credit interval and quick flow, were not available.

IV. RESULTS AND ANALYSIS

Test of Differences

Only eleven out of thirty-two independent variables were found to be significantly different between the financial distressed and non-distressed groups. The variables were NI/Equity, CA/TA, Sales/TA, WC/TA, TL/TA, CA/CL, QA/CL, CL/TA, Cash/TA, Cash/CL, and Inv/Sales. These eleven variables would be included in building financial distressed prediction models in the first approach.

Multiple Discriminant Analysis Results

Table 1 below summarized the predictive accuracies of the MDA models for three approaches.

Table 1

Predictive Accuracies for MDA Models

Prior to Financial Distress	First Approach	Second Approach	Third Approach
1-year	92.2%	92.5%	93.9%
2-year	86.1%	88.4%	89.6%
3-year	87.0%	84.1%	82.6%

Results from 1-year and 2-year prior to financial distressed showed that predictive accuracies from stepwise method (third approach) were better than the selected variables from t-test (first approach) and the variables which have the highest loading from each factor (second approach). However, the results were opposite for 3-year prior to financial distressed.

The predictive accuracies for all three approaches increased from 3-year to 1-year prior to financial distressed. These observations were consistent with the results from western studies. The distressed signals were stronger before the companies were being officially announced as distressed companies.

First Approach – Selected Variables from t-test

The loading of each variable and the discriminant function were presented in Table 2 below.

Table 2

Variable Loadings and Discriminant Function Coefficients – First Approach

1-year			2-year			3-year		
Variable	Loading	Coef.	Variable	Loading	Coef.	Variable	Loading	Coef.
NI/Equity	.56	.53	TL/TA	.82	2.50	NI/Equity	-.62	-.54
CA/CL	.54	1.38	WC/TA	-.77	1.17	CA/CL	-.49	-1.35
QA/CL	.42	-0.62	CL/TA	.74	-	TL/TA	.45	1.12
Cash/TA	.37	3.29	CA/CL	-.52	-.69	CL/TA	.41	-
WC/TA	.31	-.03	NI/Equity	-.46	-.12	WC/TA	-.39	.94
TL/TA	-.31	-.08	QA/CL	-.43	.45	QA/CL	-.37	.82
CL/TA	-.30	-	Cash/CL	-.28	.11	Cash/CL	-.29	.27
Cash/CL	.29	-0.87	Cash/TA	-.21	.34	Sales/TA	-.29	-1.05
Sales/TA	019	.37	Sales/TA	-.19	-.67	Cash/TA	-.23	-.52
Inv/Sales	-.17	-.04	CA/TA	-.11	-1.17	Inv/Sales	.16	.10

CA/TA	.12	-1.12	Inv/Sales	.11	.00	CA/TA	.14	1.07
(Constant)		-.50	(Constant)	-.45		(Constant)		.05

NI/Equity has the highest loadings in 1-year and 3-year. It showed that profitability played an important role in determining the going concern of a company. TL/TA has the highest loading in 2-year.

Second Approach – 7 Variables

The seven variables which represent each factor were showed in Table 3 below.

Table 3

Representative Variable for Each Factor

Factor	Variable
Return on Investment	NI/Equity
Capital Turnover	WC/TA
Financial Leverage	TL/TA
Short-term Liquidity	CA/CL
Cash Position	Cash/TA
Inventory Turnover	Inv/Sales
Receivables Turnover	QA/Inv

The loading of each variable and the discriminant function were presented in Table 4 below.

Table 4

Variable Loadings and Discriminant Function Coefficients – Second Approach

1-year			2-year			3-year		
Variable	Loading	Coef.	Variable	Loading	Coef.	Variable	Loading	Coef.
NI/Equity	.75	.75	TL/TA	.88	.10	NI/Equity	-.76	-.67
CA/CL	.65	.34	WC/TA	-.83	-.41	CA/CL	-.56	-.45
Cash/TA	.43	-2.12	CA/CL	-.55	-.28	TL/TA	.53	1.44
WC/TA	.36	.08	NI/Equity	-.50	-.11	WC/TA	-.46	1.11
TL/TA	-.36	.00	Cash/TA	-.22	.44	Cash/TA	-.25	.61
Inv/Sales	-.22	-.09	Inv/Sales	.12	.00	Inv/Sales	.19	.12
QA/Inv	.10	.00	QA/Inv	-.03	.01	QA/Inv	.12	.00
(Constant)		.09	(Constant)		-.72	(Constant)		-.78

The same variables were highlighted as in the first approach. This indicated that profitability was a crucial factor in deciding a company's financial status.

Third Approach – Stepwise Technique

The loading of each variable and the discriminant function were presented in Table 5 below.

Table 5

Variable Loadings and Discriminant Function Coefficients –Third Approach

1-year			2-year			3-year		
Variable	Loading	Coef.	Variable	Loading	Coef.	Variable	Loading	Coef.
NI/Equity	.56	.65	CF/NW	-.79	.04	CF/NW	.70	.16
CA/CL	.48	1.16	Sales/TA	.61	.90	NI/Equity	.61	.56
Cash/CL	.24	-1.16	TL/TA	.20	-1.49	QA/TA	.31	-2.09
CA/Sales	-.15	-.05	CF/CL	.12	.95	Sales/TA	-.19	1.06
Sales/WC	-.10	-.01	(Constant)	-	.59	CF/CL	.08	1.46
(Constant)	-	-.83				(Constant)		.31

NI/Equity has the highest loadings in 1-year, and CF/NW has the highest loadings in 2-year and 3-year. Profitability was still the main determinant of companies' financial status.

Logistic Regression Results

Table 6 below summarized the predictive accuracies of the logistic regression models.

Table 6

Predictive Accuracy for Logistic Regression Models

Prior to Financial Distress	First Approach	Second Approach	Third Approach
1-year	97.4%	93.9%	97.2%
2-year	91.3%	92.2%	92.0%
3-year	86.1%	87.8%	83.6%

First Approach – Selected Variables from t-test

Eleven variables were included in building the logistic regression model in the first approach. Table 7 below showed the significant variables in the logistic regression for first approach. Short-term liquidity, which represented by QA/CL (quick asset/current liabilities) was found to consistently appeare in the models.

Table 7

Variables in the Logistic Regression – First Approach

1-year			2-year			3-year		
Variable	Wald	Sig	Variable	Wald	Sig	Variable	Wald	Sig
TL/TA	5.07	.02	QA/CL	8.02	.00	QA/CL	4.60	.03
QA/CL	4.71	.03	CA/CL	6.97	.01	NI/EQUITY	4.28	.04
			CA/TA	5.24	.02	Sales/TA	3.98	.05
			WC/TA	5.24	.02			
			CL/TA	5.22	.02			

Second Approach – 7 Variables

The seven variables which represent each factor were showed in Table 8. These were the variables with the highest Wald values when logistic regression models were built factor by factor.

Table 8

Representative Variable for Each Factor

Factor	Variable
Return on Investment	EBIT/TA
Capital Turnover	WC/TA
Financial Leverage	TL/TA
Short-term Liquidity	CL/TA
Cash Position	Cash/CL
Inventory Turnover	Inv/Sales
Receivables Turnover	QA/Sales

Table 9 below showed the significant variables in the logistic regression for second approach. Only one variable was found to be significant for each year.

Table 9

Variables in the Logistic Regression – Second Approach

1-year			2-year			3-year		
Variable	Wald	Sig	Variable	Wald	Sig	Variable	Wald	Sig
TL/TA	3.88	.05	WC/TA	5.32	.02	QA/Sales	3.89	.05

Third Approach – Stepwise Technique

Table 10 below showed the significant variables in the logistic regression for third approach. Financial leverage of a company which represented by CF/CL (cash flow/current liabilities) was found to be consistently appeared in the models.

Table 10

Variables in the Logistic Regression – Third Approach

1-year			2-year			3-year		
Variable	Wald	Sig	Variable	Wald	Sig	Variable	Wald	Sig
CA/CL	9.11	0	CF/CL	13.28	0.00	CF/CL	6.62	0.01
CF/CL	7.34	0.01	CF/TA	5.32	0.02	RE/TA	5.13	0.02
Sales/TA	4.41	0.04	CA/TA	4.67	0.03	QA/Sales	4.25	0.04

Reduced Sample

In the reduced sample where the Section 176 companies are removed from the initial PN4 list, only sixty-one financial distressed and its matched-paired non-distressed companies were included in the analysis. Table 11 below shows the predictive accuracies for the models 1-year, 2-year, and 3-year prior to financial distress.

Table 11

Predictive Accuracies PN4 Sample and PN4 without Section 176 Sample (Stepwise Technique)

Prior to Financial Distress	MDA		Logistic Regression	
	PN4	PN4 and not 176	PN4	PN4 and not 176
1-year	93.9%	86.4%	97.2%	93.4%
2-year	89.6%	83.8%	92.0%	91.0%
3-year	82.6%	88.8%	83.6%	84.8%

Reductions in predictive accuracies were observed for 1-year and 2-year prior to financial distressed. These results showed that the exclusion of Section 176 companies had decreased the models' accuracies. This observation was expected as Section 176 companies were considered to be more financially distressed as they were all suspended or under trading restriction in KLSE.

Validation of the Results

Holdout Sample

Table 12 showed the predictive accuracies of the holdout sample for MDA and logistic regression models.

Table 12

Predictive Accuracies of Holdout Sample for MDA and LR Models

	First Approach		Second Approach		Third Approach	
	MDA	LR	MDA	LR	MDA	LR
1-year	87.9%	91.4%	96.5%	98.3%	89.7%	89.5%
2-year	90.0%	90.0%	98.2%	93.3%	90.2%	93.0%
3-year	83.6%	76.7%	82.8%	85.2%	73.8%	75.5%

Results from both MDA and LR models showed that the holdout sample produced almost the same results as the analysis sample (Table 1 and Table 4). Generally, the analysis sample showed higher predictive accuracy than the holdout sample. In second approach, however, the holdout sample presented superior accuracy than analysis sample for 1-year and 2-year prior to financial distressed.

Chance Based Criterion and Press Q

As match-paired sample design was used in this research, the maximum chance criterion and proportional chance criterion were the same, 0.5 or 50%. Hair, Anderson, Tatham, and Black (1998) had recommended that the holdout sample classification accuracy should be at least one-fourth greater than that achieved by chance. Therefore, the classification accuracy should be at least 62.5% in this research. Results from Table 14 above showed that the predictive accuracies from the holdout sample were higher than the suggested threshold, which is 62.5%. Thus, the MDA models exceeded the classification accuracy expected by chance.

The classification is considered better than chance if the calculated value is greater than the critical value. The critical value in this research is 6.64 (p=0.01, df=1). Table 13 below showed the Press's Q value for the MDA models. The values were greater than the critical value of 6.64. Thus, the classification accuracy for the analysis sample and holdout sample were significantly better than chance.

Table 13

Press's Q of Analysis and Holdout Sample from MDA Models

	First Approach		Second Approach		Third Approach	
	Analysis	Holdout	Analysis	Holdout	Analysis	Holdout
1-year	81.82	33.38	77.39	49.28	88.70	36.48
2-year	59.90	38.40	66.04	53.07	72.01	39.36
3-year	62.83	27.56	52.47	24.90	48.91	13.79

Discussion of Findings

Table 14 below presented the compilation of predictive accuracies and the most significant variables from both models.

Table 14

Summary of Predictive Accuracies and Variables

	First Approach		Second Approach		Third Approach	
	MDA	LR	MDA	LR	MDA	LR
1-year	92.2%	97.4%	92.5%	93.9%	93.9%	97.2%
Variables	NI/Equity	TL/TA	NI/Equity	TL/TA	NI/Equity	CA/CL
2-year	86.1%	91.3%	88.4%	92.2%	89.6%	92.0%
Variables	TL/TA	QA/CL	TL/TA	WC/TA	CF/NW	CF/CL
3-year	87.0%	86.1%	84.1%	87.8%	82.6%	83.6%
Variables	NI/Equity	QA/CL	NI/Equity	QA/Sales	CF/NW	CF/CL

From Table 14, both MDA and LR models showed high predictive accuracy for all three approaches. The predictive accuracies of financial distressed company 1-year prior to financial distressed were over ninety percent. Results from holdout sample and several validation tests supported the results. The findings indicate that financial ratios were able to predict corporate failure in public listed companies in Malaysia.

Table 15 below summarized the financial ratios with the most discriminating power from three approaches for 3-years prior to financial distress.

Table 15

Financial Ratios With The Most Discriminating Power

	First Approach		Second Approach		Third Approach	
	MDA	LR	MDA	LR	MDA	LR
1-year	NI/Equity	TL/TA	NI/Equity	TL/TA	NI/Equity	CA/CL
2-year	TL/TA	QA/CL	TL/TA	WC/TA	CF/NW	CF/CL
3-year	NI/Equity	QA/CL	NI/Equity	QA/Sales	CF/NW	CF/CL

For the MDA, the most important factor in the model was profitability (NI/Equity and CF/NW). This finding showed that profitability or return on investment had significant impact on a company's going concern. In LR, financial leverage (TL/TA and CF/CL) and liquidity (CA/CL and QA/CL) were the most important factors in determining the financial health of a company.

V. SUMMARY AND CONCLUSION

The primary objective of this study is to develop financial distressed prediction models for public listed companies on the KLSE. The financial distressed companies were based on companies that were classified under the new PN4 sector of the KLSE. A total of eighty-eight matched-pair of financial distressed and non-distressed companies were included in building the prediction model. Thirty-two financial ratios were analyzed on both estimation and holdout samples. Two multivariate analyses were used to develop the financial distressed prediction models namely, multivariate discriminant analysis (MDA) and logistic regression (LR).

The LR method recorded higher predictive accuracy than MDA. The average predictive accuracy 1-year prior to financial distressed for MDA was 92.9% compared to LR 96.2%. This might be due to the advantage of LR that does not assume multivariate normality and equal covariance matrices as discriminant analysis does. The predictive accuracies in this research were found to be higher than previous studies in Malaysia as by Ang et al. (2001) 81%, and Zulkanian et al. (2001) 90.2%. This could be due to use of additional new financial variables and also a larger sample size. Overall, profitability ratios (NI/Equity and CF/NW), financial leverage (TL/TA and CF/CL), and liquidity ratios (CA/CL and QA/CL) were important determinants of a company's going concern.

The financially distressed companies analyzed are mainly that which occurred following the 1997 financial crisis. These are the companies that were unable to generate profits after a decline in sales, thus were forced to service debts as the government increases interest rates. The use of financial ratios here are however static in nature and tend not to be able to identify economic events. Future research should use economic and market variables to further capture the interaction of these environmental factors, thus further providing increased robustness to the findings.

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Appendix A

Financial Ratios in Each Factor

Factor	Financial Ratios	Researcher	As in SPSS	
			Label	Name
Factor 1: Return on Investment	Net Income/Sales	El	NI/Sales	V1
	Cash Flow/Net Worth	El	CF/NW	V2
	Cash Flow/Total Assets	El	CF/TA	V3
	Net Income/Total Assets	Be, D, L	NI/TA	V4
	Net Income/Net Worth	El	NI/NW	V5
	EBIT/Sales	El	EBIT/Sales	V6
	EBIT/Total Assets	A	EBIT/TA	V7
	Net Income/Common Equity	Bl	NI/EQUITY	V8
Factor 2: Capital Turnover	Quick Assets/Total Assets	D	QA/TA	V9
	Cash Flow/Sales	El	CF/Sales	V10
	Current Assets/Total Assets	D, L	CA/TA	V11
	Net Worth/Sales	Ed	NW/Sales	V12
	Sales/Total Assets	A, El	Sales/TA	V13
	Working Capital/Total Assets	Be, A, D	WC/TA	V14
Factor 3: Financial Leverage	Total Liabilities/Total Assets	Be, D, El	TL/TA	V15
	Total Liabilities/Net Worth	Bl, El	TL/NW	V16
	Long-term Debt/Current Assets	El	LT Debt/CA	V17
	Cash Flow/Total Debt	Be, D, Bl, El	CF/TD	V18
	Cash Flow/Current Liabilities	Ed	CF/CL	V19
	Retained Earnings/Total Assets	A	RE/TA	V20
Factor 4: Short-term Liquidity	Current Assets/Current Liabilities	Be, D, El, L	CA/CL	V21
	Quick Assets/Current Liabilities	D, Ed, El	QA/CL	V22
	Current Liabilities/Net Worth	Ed	CL/NW	V23
	Current Liabilities/Total Assets	El	CL/TA	V24
Factor 5: Cash Position	Cash/Sales	D	Cash/Sales	V25
	Cash/Total Assets	D, L	Cash/TA	V26
	Cash/Current Liabilities	D, El	Cash/CL	V27
Factor 6: Inventory Turnover	Current Assets/Sales	D, L	CA/Sales	V28
	Inventory/Sales	Ed	Inv/Sales	V29
	Sales/Working Capital	D, Ed	Sales/WC	V30
Factor 7: Receivables Turnover	Quick Assets/Inventory	Bl	QA/Inv	V31
	Quick Assets/Sales	D	QA/Sales	V32

A – Altman 1968
Be – Beaver 1966
Bl – Blum 1974
D- Deakin 1972
Ed – Edmister 1972
El – Elam 1975
L – Libby 1975

Appendix B

PN4 and Matched-paired Company

No	PN4 Company (Financial Distressed)	1-year before failure	Matching Company (Non-distressed)
1	Abrar Corporation Berhad*	2000	PLB Engineering Berhad
2	Actacorp Holdings Berhad*	2000	Pintaras Jaya Berhad
3	Aktif Lifestyle Corporation Berhad	2001	Amway (Malaysia) Holdings Berhad
4	Amsteel Corporation Berhad	2000	PSC Industries Berhad
5	Angkasa Marketing Berhad	2001	OYL Industries Berhad
6	Aokam Perdana Berhad*	2000	Evermaster Group Berhad
7	Arus Murni Corporation Berhad	2000	Seni Jaya Corporation Berhad
8	Associated Kaolin Industries Berhad*	2000	Pahanco Corporation Berhad
9	Austral Amalgamated Berhad*	2000	Worldwide Holdings Berhad
10	Autoindustries Ventures Berhad	2001	Multicode Electronics Industries (M) Berhad
11	Autoway Holdings Berhad*	2000	Daibochi Plastic and Packaging Industry Berhad
12	Berjuntai Tin Dredging Berhad	2000	Kuchai Development Berhad
13	Bescorp Industries Berhad*	2000	Fajar Baru Capital Berhad
14	Bridgecon Holdings Berhad	2000	Kumpulan Jetson Berhad
15	Chase Perdana Berhad*	2000	Pembinaan YCS Berhad
16	CHG Industries Berhad	2001	Eksons Corporation Berhad
17	Construction and Supplies House Berhad	2000	CNLT (Far East) Berhad
18	CSM Corporation Berhad	2000	Mamee-Double Decker (M) Berhad
19	Cygal Berhad*	2000	Lankhost Berhad
20	Denko Industries Corporation Berhad	2000	Malaysia Packaging Industry Berhad
21	Eden Enterprise (M) Berhad	2001	Ayamas Food Corporation Berhad
22	Emico Holdings Berhad	2000	Pohmay Holdings Berhad
23	EPE Power Corporation Berhad	2001	Komarkcorp Berhad
24	Esprit Group Berhad*	2000	Pembinaan Limbongan Setia Berhad
25	Foreswood Group Berhad	2001	Subur Tiasa Holdings Berhad
26	FW Industries Berhad	2001	Leader Steel Holdings Berhad
27	Geahin Engineering Berhad	2000	Sapura Motors Berhad
28	General Lumber Fabricators & Builders Berhad	2001	KP Keningan Berhad
29	Global Carriers Berhad*	2000	Integrated Logistics Berhad
30	Hai Ming Holdings Berhad	2000	Computer Forms (M) Berhad
31	Hiap Aik Construction Berhad	2001	Gadang Holdings Berhad
32	Hotline Furniture Berhad	2000	SHH Resources Holdings Berhad
33	Jasatera Berhad	2000	Zecon Engineering Berhad
34	Jutajaya Holding Berhad	2000	HPI Resources Berhad
35	Kelanamas Industires Berhad	2000	Appollo Food Holdings Berhad
36	Kemayan Corporation Berhad*	2000	Petaling Garden Berhad
37	Kiara Emas Asia Industries Berhad*	2000	Jasa Kita Berhad
38	Kilang Papan Seribu Daya Berhad	2000	Timberwell Berhad
39	Kretam Holdings Berhad	2001	United Malacca Berhad
40	Kuala Lumpur Industris Holding Berhad*	2000	SAP Holdings Berhad
41	L&M Corporation (M) Berhad*	2000	Britac Berhad
42	Lion Corporation Berhad	2000	PSC Industries Berhad
43	Long Huat Group Berhad	2000	Woodlandor Holdings Berhad
44	Mancon Berhad*	2000	General Corporation Berhad
45	Mentiga Corporation Berhad	2000	Highlands & Lowlands Berhad
46	MGR Corporation Berhad	2000	Serisar Industries Berhad
47	MOL.COM Berhad	2000	Fiamma Holdings Berhad
48	Mycom Bhd	2000	Metroplex Berhad
49	Nauticalink Berhad	2000	Transocean Holdings Berhad

50	NCK Corporation Berhad	2000	Maruichi Malaysia Steel Tube Berhad
51	Olympia Industries Berhad	2000	Reliance Pacific Berhad
52	Pan Pacific Asia Berhad	2000	Lingui Developments Berhad
53	Pancaran Ikrab Berhad	2000	Pembinaan Limbongan Setia Berhad
54	Parit Perak Holdings Berhad	2000	Paramount Corporation Berhad
55	Penas Corporation Berhad	2000	Setegap Berhad
56	Plantation & Development (M) Berhad*	2000	Ireka Corporation Berhad
57	Promet Berhad*	2000	Ekovest Berhad
58	Rahman Hydaulic Tin Berhad	2000	Tronoh Mines Malaysia Berhad
59	Rekapacific Berhad	2000	Putera Capital Berhad
60	Repco Holdings Berhad	2000	EP Manufacturing Berhad
61	RNC Corporation Berhad*	2000	Metrod (M) Berhad
62	Saship Holdings Berhad*	2000	Amalgamated Industrial Steel Berhad
63	Sateras Resources (M) Berhad	2000	Brisdale Holdings Berhad
64	SCK Group Berhad*	2000	Pembinaan Limbongan Setia Berhad
65	Seloga Holdings Berhad	2000	Ken Holdings Berhad
66	Seng Hup Corporation Berhad	2000	FSBM Holdings Berhad
67	Sin Heng Chan (M) Berhad	2000	Lay Hong Berhad
68	Sistem Televisyen Malaysia Berhad	2000	Utusan Melayu Malaysia Berhad
69	Southern Plastics Holdings Berhad*	2000	Hil Industries Berhad
70	Sportma Corporation Berhad	2001	Prolexus Berhad
71	Sri Hartamas Berhad	2000	MK Land Holdings Berhad
72	Sriwani Holdings Berhad	2000	Diethelm Holdings (M) Berhad
73	Sunway Building Technology Berhad	2001	Kim Hin Industry Berhad
74	Tai Wah Garment Manufacturing Berhad*	2000	Hing Yiap Knitting Industries Berhad
75	Tajo Berhad	2000	Kia Lim Berhad
76	Tap Resources Berhad	2001	Bina Goodyear Berhad
77	Techno Asia Holdings Berhad	2000	Austral Enterprises Berhad
78	The North Borneo Corporation Berhad	2000	Riverview Rubber Estates Berhad
79	Timbermaster Industries Berhad*	2000	Chee Wah Corporation Berhad
80	Tongkah Holdings Berhad	2000	Grand United Holdings Berhad
81	Trans Capital Holdings Berhad*	2000	Patimas Computers Berhad
82	Transwater Corporation Berhad	2000	Chin Foh Berhad
83	UCP Resources Berhad	2000	Sarawak Concrete Industries Berhad
84	United Chemical Industries Berhad	2000	Kossan Rubber Industries Berhad
85	Wembly Industries Holdings Berhad*	2000	Malaysia Oxygen Berhad
86	Wing Tiek Holdings Berhad*	2000	Choo Bee Metal Industries Berhad
87	Woo Hing Brothers (M) Berhad	2000	Fitters Holdings Berhad
88	Zaitun Berhad	2000	Unza Holdings Berhad

* Section 176 companies