AN EMPIRICAL INVESTIGATION OF FAILING COMPANIES AND THEIR DETERMINANTS USING THE HAZARD MODEL IN AN EMERGING CAPITAL MARKET

by

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Abstract

The purpose of this study is to highlight the predictors of financial distress during the period 1990 to 2000. Previous studies highlight the inadequacies of the MDA and the logit models and suggest that a hazard model gives a more accurate result due to its consideration of time varying covariates. By applying the hazard model, we find that leverage, profit, cash flow, liquidity, size and growth play a significant role in explaining financial distress with 83% accuracy rate. This rate did not change much when the model is applied to the hold-out sample. We also find that multicollinearity problem is not a threat in our analysis.

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1. Introduction

Malaysia has achieved a remarkable growth in the early 1990's. Companies' profit increased tremendously, and new businesses started to join in. However, the sudden currency crisis, which hit the country in 1997, forced many companies into financial distress. In other word, they were facing the threat of bankruptcy and consequently being delisted from trading. Thus, this study tries to look into the classification behind delisting of companies and to determine factors that lead to this situation. In essence, we are trying to answer the following question: what are the most important factors that drag companies into the financially distressed category? In doing so, we apply the hazard model to predict bankruptcy during the period 1990 to 2000. To our knowledge, there has not been any study that examines the determinants of bankruptcy using the hazard model in Malaysia.

Academics have actively studied bankruptcy prediction since the pioneer contribution of Beaver (1966) and Altman (1968). Techniques on predicting corporate failure such as the multiple discriminant analysis (MDA), and the logit model have rapidly being

developed and being tested in many countries (Apetiti, 1984; Izan, 1984; Micha, 1984; Takahashi, Kurokawa and Watase, 1984; Lennox, 1999; Nam and Jinn, 2000; Low, Fauzias, and Puan, 2001). However, the use of MDA and the logit model have posed several problems. Therefore the use of those models is no longer valid and the results from the model are suspicious. The contribution of this study is that it uses the hazard model in the analysis. The difference between this model and the previous model is that it takes into consideration the time factor, and it is able to avoid the sample selection bias inherent in the logit model. Shumway (2001) states that this model is more reliable, accurate and consistent than the logit and the MDA model. The use of this model is also in line with Ohlson's (1980) and Jones' (1987) arguments on the invalidity of the assumptions in MDA and Hillgeist's (2004) arguments on selection bias in the logit model. Furthermore, the use of hazard model acts as one step forward in Malaysian studies on bankruptcy.

The importance of this study is that it leads the ways to recognise failing companies in advance. This is vital because corporate failure affects everybody--from shareholders to the lenders (bankers), and the economy as a whole. This study benefits various interested parties. For example, investors can use the hazard model to examine on how well a company is doing. Financial analysts may use the results as a tool to evaluate a company as an investment prospect, while lenders may use the techniques discussed to help assess the risk of loan default.

The paper is organised as follows. Section 2 provides the literature review; Section 3 discusses the method while section 4 continues with the results and discussions; and lastly, Section 5 concludes the study.

2. Literature review

Previous bankruptcy research has identified many ratios that are important in predicting bankruptcy. Altman (1993) noted that ratios measuring profitability, liquidity, solvency and cash flow are the most significant indicators of bankruptcy. Among the most popular financial ratios used by researchers are net income to total assets (Beaver, 1966; Deakin, 1972; Libby, 1975; Ohlson, 1980; Lennox, 1999), total liabilities to total assets (Beaver, 1966; Deakin, 1972; Ohlson, 1980; Zmijewski, 1984) and size (Ohlson, 1980; Lennox, 1999; Shumway, 2001). Furthermore, Ohlson (1980) added changes in net income as a factor that represents growth. Lennox (1999) utilised cash flow ratios, specifically cash to current liabilities, debtor turnover ratio and gross cash flow ratio to explain bankruptcy in the UK. In Korea, Nam and Jinn (2000) stated that financial expenses to sales, debt coverage and receivables turnover are important to explain bankruptcy. In contrast to Nam and Jinn (2001) but consistent with Lennox (1999), Low et al. (2001) found that in Malaysia the cash flow ratios are significant in explaining bankruptcy during the period 1996-1998; while Mohamed, Li and Sanda, (2001) found that the leverage ratio and efficiency ratio (total asset turnover) are found to be significant during the period 1987 to 1997. Both studies use the logit model (Low et al. 2001) and the combination of MDA and the logit model (Mohamed et al. 2001). Using only the MDA model, Zulkarnain, M.S., Mohamad Ali, A.H., Annuar, M.N. and Zainal Abidin, M. (2001) found that total

liabilities to total assets, sales to current assets, cash to current liabilities and market value to debt are significant in explaining financial distressed in Malaysia during the period from 1980 to 1996.

When we look at the development of bankruptcy prediction model, it started with the use of univariate analysis by Beaver (1966), followed by multivariate discriminant analysis (MDA) by Altman in 1968. Beaver's (1966) univariate analysis used individual financial ratios to predict distress. Using 79 failed and non-failed firms from 1954 to 1964, he matched the sample by industry and assets size. The results from the prediction error tests suggest that cash flow to total debt, net income to total asset and total debt to total assets have the strongest ability to predict failure. These ratios differ from the MDA model proposed by Altman (1968). By utilising 33 bankrupt companies and 33 non-bankrupt companies over the period 1946 to 1964, five variables are selected on the basis that they do the best overall job in predicting bankruptcy. These are 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. Z-Score is determined and those companies with a score greater than 2.99 fall into the non-bankrupt group, while those companies having a Z-Score below 1.81 are in the bankrupt group. The area between 1.81 and 2.99 is defined as the zone of ignorance or the gray area. The MDA model was able to provide a high predictive accuracy one year prior to failure of 95% from the initial sample. For this reason, MDA model has been used extensively by researchers and is the most used model in bankruptcy research (Altman, Haldeman and Narayanan, 1977; Micha, 1984; Apetiti, 1984; Izan, 1984). However, Eisenbeis (1977),

Ohlson (1980), and Jones (1987) found that there are some inadequacies in MDA with respect to the assumptions of normality and group dispersion. The assumptions are often violated in MDA. This may bias the test of significance and estimated error rates.

Logit analysis which does not have the same assumptions as MDA was made popular by Ohlson (1980). He used 105 bankrupt companies and 2058 non-bankrupt companies from 1970 to 1976. The results show that size, financial structure (total liabilities to total assets), performance and current liquidity are important determinants of bankruptcy. In Logit analysis, average data is normally used and it is considered as a single period model. Hence, for each non-distressed and distressed company, there is only one company-year observation. The dependent variable is categorised into one of two categories that is distressed or non-distressed. There are two econometric problems with the single period logit model (Hillegeist, 2004). First, is the sample selection bias that arises from using only one, non-randomly selected observation for each bankrupt company, and second, the model fails to include time varying changes to reflect the underlying risk of bankruptcy. This will induce cross-sectional dependence in the data. Shumway (2001) demonstrated that these problems can result in biased, inefficient, and inconsistent coefficient estimates. To overcome these econometric problems, Shumway (2001) predicted bankruptcy using the hazard model and found that it is superior to the logit and the MDA models.

Several studies were also implemented in Malaysia. Zulkarnain et al. (2001) used twenty-four distressed and non-distressed companies from the period 1980-1996 matched

according to the industry, failure year, closest asset size and age since incorporation. The distressed companies are defined as those companies that resort protection under section 176 of the Companies Act 1965 for the purpose of obtaining court protection against their creditors. Using the stepwise multivariate discriminant analysis to determine the discriminating variable, they compared the results from analysis using market based variable and without market based variable. They found that total liabilities to total assets, sales to current assets, cash to current liabilities and market value to debts are important determinants of corporate failures in Malaysia. The original model with market based variable correctly classified 89.7% of the sample whereas the other model only correctly classified 87.9% of the sample. Using the same definition of failure, Low et al. (2001) analysed financial distress using the logit analysis. They utilised 26 distressed companies and 42 non-distressed companies in 1988. The hold-out sample consists of 10 companies. They found that sales to current assets, current assets to current liabilities, change in net income, cash and marketable securities to total assets are significant determinants of financial distress. However, the coefficient of the first three variables are not as expected when a significant positive coefficients prevail. Therefore they claimed that measures of liquidity and profitability may be misleading, and concluded that only the cash flow ratio serves as an indicator to detect potential failure of a company. The accuracy rate is 82.4% in the estimation sample and 90% in the hold-out sample. Mohamed et al. (2001) compared the MDA and the logit model in the analysis of bankruptcy. Their sample consists of 26 companies that have sought protection under section 176 of Companies Act 1965 and 79 non-distressed companies. Their results showed that when using MDA, debt ratio and total assets turnover are found to be

significant but when logit analysis is used, debt ratio, interest coverage and total assets turnover are found to be significant. Thus, Mohamed et al. (2001) study emphasised the importance of leverage ratio as a predictor of failure. The logit model predicts 80.7% of the firms in the estimation sample and 74.4% in the hold-out sample, whereas the MDA model predicts 81.1% of the companies in the estimation sample and 75.4% in the hold-out sample. The accuracy of Mohamed et al. (2001) prediction model is lower than Low et al. (2001) and Zulkarnain et al. (2001). Since none of these studies use the hazard model, hence this study is intended to fill this gap.

3. Research Design

The sample consists of both distressed and non-distressed listed companies in the Bursa Malaysia Berhad. The distressed status was indicated by the appointment of receivership, restraining order under section 176, winding up petition, special administrator under Bank Negara Malaysia and interim judicial management order as at December 2000. A total of thirty-six distressed companies were identified from the Bursa Malaysia daily diary.[1] For each distressed companies, a non-distressed match was identified during the period from 1990 to 2000. Companies were matched if they belong to the same industry group and have the closest asset size. A one to one procedure is consistent with the previous studies documented in Beaver (1966), Altman (1968) and Blum (1974) and is an acceptable method in failure prediction studies. Financial data for both groups were collected from the annual reports in the Bursa Malaysia and Sultanah Bahiyah library.

[1] In comparison to the three studies done in Malaysia, where Zulkarnain et al. (2001) sample consists of 24 failed companies, Low et al. (2001) sample uses 26 distressed companies and Mohamed et al. (2001) sample consists of 26 distressed companies, our sample is rather large.

Companies were excluded from the sample if they are classified under the financial and property industries. The reasons for these are that their ratios are highly volatile where their businesses rely heavily on the economy. In addition, the interpretation of the ratios is slightly different because the nature of the income and expenses for these companies is different from that of non-financial companies.

Methodology

A discrete hazard model is applied to assess how well each variable explains the actual probability of bankruptcy in our sample. It is in the form:

$$\phi_{i,t} = \frac{e^{\alpha(t)+\beta X_{i,t}}}{1+e^{\alpha(t)+\beta X_{i,t}}}$$

where $\phi_{i,t}$ is the hazard function, X represents a vector of explanatory variables used to forecast failure, $\alpha(t)$ is a time-varying covariates, and β is the coefficient vector. The discrete hazard model is well suited to analyse data that consists of binary, time series and cross-sectional observations such as bankruptcy data. The hazard model has the same likelihood function and the same asymptotic variance-covariance matrix as the logit model and therefore the estimation of the hazard model is similar to the estimation of the logit model. However, the hazard model uses time varying covariates and company-year observations and consequently it is able to eliminate the sample selection bias. It will also results in more efficient coefficient estimates since all available data will be used in the estimation.

In the discrete hazard model the dependent variable is coded as 1 if company *i* failed at time t_i, and equal zero otherwise. For example if a company has been in existence for six years and was classified under section 176 in year 6, only year 6 will have the value of 1, the other 5 years will have the value of 0 indicating that the company is a healthy company during those years. Since the hazard model uses company-year data, adjustment has to be made to the test statistics from the logit model. We divide the test statistics from the estimation by the average number of company-years per company because the correct value of *n* for test statistics in the logit program is the number of companies in the data.

The discrete hazard model uses company-year data and has several advantages (Shumway, 2001). By using all company-year observations, it is able to eliminate the sample selection bias, produces more efficient out of sample forecasts and is able to adjust for risk automatically. It is also possible to track changes in bankruptcy probability since all data in each year are included in the analysis.

The independent variables used in this study can be classified according to the different set of ratios. They are leverage ratios (interest coverage and total debt to total assets), profitability ratios (net income to total assets), cash flow ratios (cash to total assets and cash to current liabilities), size (total assets employed), and growth (change in net income and change in sales). As noted by Scott (1981), many of the variables that appeared in most empirical work do not rest on any strong underlying theory, hence the use of these ratios in our study is acceptable. These ratios are selected based on the

popularity of their usage in the literatures and the predictive success stated in previous research.

Financial leverage is related to bankruptcy to the extent to which a company relies on debt financing rather than equity. Measures of financial leverage are tools in determining the probability of a company defaulting on its debt contracts. Debt ratio which is calculated by dividing total debt to total assets provides information on a company's insolvency and its ability to secure additional financing for good investment opportunities. This is to ensure that creditors are protected. As for interest coverage which is measured by dividing earnings with interest, it emphasizes the ability of a company to generate enough income to cover interest expense. Beaver (1966), Deakin (1972), Ohlson (1980) Zmijewski (1984) and Mohamed et al. (2001) find that these ratios are significant determinants of corporate failure.

Profitability ratio is represented by return on assets, computed as net income divided by total assets. This ratio is a common measure of managerial performance and is therefore vital in the study of financial distress. It is expected that companies with large profits have lower probability of bankruptcy, hence the relationship between them is negative. Libby (1985), Ohlson (1980), Lennox (1999) and Zulkarnain et al. (2001) shows that profitability is an important determinant of bankruptcy.

In addition to the above ratios, short term solvency is also an important element to be looked into as it measures the ability of a company to meet its short term financial

obligations, thus avoiding corporate failures. Cash flow ratio, represented by cash to total assets and cash to current liabilities are used as a proxy to measure short-term solvency for distressed and non-distressed companies. Lennox (1999), Low et al. (2001) and Zulkarnain et al. (2001) find that the cash flow ratios are found to be significant in their studies. It is expected that the relationship between the cash flow ratios and the probability of bankruptcy is negative, the higher the level of cash flow, the lower is the probability of bankruptcy.

Another factor that seems to discriminate between distressed and non-distressed companies is size, which is measured by total assets employed. Big companies normally have large assets base if compared with smaller companies. Ohlson (1980) find that size is significant in discriminating between distressed and non-distressed companies. It is expected that the relationship between these two variables is negative, the larger the size of a company, the lower the probability of bankruptcy. Other ratios that could probably discriminate between healthy and distressed companies are change in net income and change in sales. The rationale behind these ratios is that healthy company's net income and sales grow rapidly as compared to the distressed companies. Hence, it is expected that the greater the growth, the healthier is the company.

4. Analysis of Results

There are seven categories of distressed companies used in this study. Table 1 shows the number of companies listed under each category. Among the sample, 13 companies fall under the restraining order of Section 176 and 12 companies are under the special

administrators of Bank Negara. This is followed by 5 companies under the winding-up petition. There are 2 companies each that are categorized under receivership and winding-up petition which are overlooked by the special administrators of Bank Negara. The least number of companies in this sample, that is one in each category, falls under the interim judicial management order and receivership.

Table 1: Categories of Distressed Companies

Category	Number of Companies (%)
Interim Judicial Management Order	1 (2.8%)
Receivership	1 (2.8%)
Receivership/Special Administrators	2 (5.6%)
Restraining Order (Section 176)	13 (36%)
Special Administrators	12 (33.3%)
Winding-up	5 (13.9%)
Winding-up, Special Administrators	2 (5.6%)

Table 2 presents the correlation matrix among the variables. It is shown that the pairwise correlations among the variables are uniformly low and insignificant except for several ratios: TD/TA and NI/TA, TD/TA and C/CL, TD/TA and CA/CL, TD/TA and CHGNI, TD/TA and LN(TA), NI/TA and CHGNI, NI/TA and CA/CL, NI/TA and LN(TA), C/TA and C/CL, C/TA and LN(TA), C/CL and CA/CL, C/CL and LN(TA), CA/CL and LN(TA). Obviously, the correlation coefficients support the existence of multicollinearity problem between NI/TA and CHGNI. It is noted that the identification of these ratios is not related to any theoretical base except for the popularity of their usage and the predictive success that came from previous research. We could simply drop these ratios, but it is likely that this remedy could probably be worse than the problem of collinearity itself.

Table 2 : Pearson Correlation Coefficients (Significance Level in Parentheses)

	INT.COV	TD/TA	NI/TA	C/TA	C/CL	CHGNI	CHGS	CA/CL	LN(TA)
INT.COV	1.00	-0.026	.019	0.008	0.035	0.007	-0.006	0.076	-0.015
		(0.549)	(0.667)	(0.851)	(0.432)	(0.886)	(0.891)	(0.084)	(0.727)
TD/TA		1.00	-0.062**	0.029	-0.104**	-	-0.014	-	-0.122**
			(0.000)	(0.504)	(0.016)	0.402***	(0.756)	0.143***	(0.005)
NI/TA			1.00	-0.006	0.058	(0.000)	0.014	(0.001)	0.089*
				(0.882)	(0.177)	0.815***	0.752	0.094**	(0.038)
C/TA				1.00	0.541***	0.000	-0.024	(0.030)	-0.144**
					(0.000)	(-0.005)	(0.593)	0.049	(0.001)
C/CL					1.00	0.908	-0.013	(0.253)	-0.099**
						(.026)	(0.772)	0.244***	(0.021)
CHGNI						0.566	0.011	(0.000)	0.037
						1.00	(0.800)	0.051	(0.415)
CHGS							1.00	(0.257)	0.034
								0.008	(0.449)
CA/CL								(0.859)	-0.105**
								1.00	(0.015)
LN(TA)									1.00

*** Correlation is significant at the 1% level (2-tailed)
** Correlation is significant at the 5% level (2-tailed)

We re-examine the independent variables to check on the seriousness of the multicollinearity problem in our data by looking at the Variance Inflation Factors (VIF). It is the ratio of a variable's actual variance to the perfect variance of zero collinearity. If we were to refer to Table 3, the results show that the R^2 is rather low for most of the variables except for NI/TA that shows a figure of 0.79. Nevertheless, when the VIF is calculated, all the variables present a figure below 10. Hence, we can conclude that the degree of multicollinearity problem is not a threat to this study.

A descriptive statistics of the variables used to estimate the hazard model is presented in Table 4. As expected, the mean for interest coverage, sales growth and liquidity are lower for the non-distressed companies. Healthy companies could cover 83.27 times of their

Table 3: Multicollinearity Test Using VIF

Variables	R^2	$VIF = 1/(1-R_j^2)$
Int. Cover against other independent variables	0.009	1.009
TD/TA against other independent variables	0.486	1.946
NI/TA against other independent variables	0.790	4.762
C/TA against other independent variables	0.284	1.397
C/CL against other independent variables	0.315	1.460
CHGNI against other independent variables	0.694	3.268
CHGS against other independent variables	0.002	1.002
CA/CL against other independent variables	0.098	1.109
LN(TA) against other independent variables	0.041	1.043

interest as compared to –0.519 times for distressed companies. It appears that distressed companies rely heavily on debt, which is approximately 278.6%; whereas the build up of debt for healthy companies is only 61.3%. If we were to look at its current ratio, for every RM1 of current liabilities, there is only a support of RM0.367 from current assets for distressed companies. This ratio is 4 times higher for healthy companies where every RM1 of current liabilities is covered with RM1.78 of current assets. Cash flow ratios for both groups are almost equivalent. During the period of study, the net income to total assets is found to be negative for the distressed and non-distressed companies with a figure of –0.055 and –0.471 respectively. This figure is slightly better for the healthy companies. Surprisingly, the change in net income for distressed companies with a figure of –0.875 is better than the growth shown by healthy companies, which is –9.547.

Table 5 shows the determinants of bankruptcy by using the hazard model. The results in Panel A suggest that bankruptcy in Malaysia could be determined by interest cover, total debt to total assets, net income to total assets, cash to total assets, cash to current liabilities, change in net income, change in sales, current assets to current liabilities and natural log of total assets. Except for interest cover, total debt to total assets, change in

net income, current assets to current liabilities and ln (total assets), which is significant at the 1% level, all other variables are significant at the 5% level.

Table 4: Descriptive Statistics of Variables Used to Estimate the Hazard Model

	Non-Distressed Companies		Distressed Companies	
Variables	Mean	Std Dev	Mean	Std Dev
Int.Cover	83.27	953.28	-0.519	2.231
TD/TA	0.613	0.907	2.786	5.079
NI/TA	-0.055	0.901	-0.471	0.756
C/TA	0.021	0.027	0.025	0.039
C/CL	0.087	0.215	0.019	0.029
CHGNI	–9.547	133.76	-0.875	3.283
CHGS	1.514	19.617	-0.159	0.508
CA/CL	1.782	2.549	0.367	0.288
LN(TA)	19.006	1.279	19.117	1.306

The significant negative coefficient for the interest cover, cash to current liabilities and current assets to current liabilities suggest that as the likelihood of bankruptcy increases, companies will face problems in settling their interest payment due to lack of cash flows and liquidity. This findings is in line with Lennox (1999). The positive coefficient on leverage ratio, 1.134, shows that financially distressed companies carry a high level of debt. This is consistent to the results reported by Sulaiman (2001). However, the coefficients on net income to total assets, cash to total assets and change in net income are not as expected. Perhaps the financial crisis in 1997-1999 might play a role in explaining this phenomenon because during this period most companies have an unstable or volatile income. The significant positive coefficient from change in net income is consistent to the results reported by Low et. al (2001).

Table 5 : The Hazard Model of Financial Distressed (Estimation Sample)

	PANEL A (Include all variables)		PANEL B (Exclude CHGNI)		PANEL C (Exclude NI/TA)	
Variable	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
Interest cover	−1.114 ***	0.0032	-0.082***	0.0184	-0.101***	0.0067
TD/TA	1.134***	0.0011	1.335***	0.0003	0.870***	0.0016
NI/TA	0.864**	0.0239	1.414***	0.0008		
C/ TA	23.997**	0.0149	13.336**	0.0414	27.251***	0.0087
C/CL	−13.791**	0.0450	-6.695*	0.0848	-15.658**	0.0359
CHGNI	0.086***	0.0063			0.105***	0.0014
CHGS	− 0.287*	0.0789	-0.178*	0.0974	-0.269***	0.0080
CA/CL	− 2.977***	0.0001	-3.087***	0.0001	-2.848***	0.0001
Ln(TA)	0.685***	0.0012	0.571***	0.0026	0.704***	0.0011
Constant	−14.542	0.000	-12.476	0.0000	-12.240	0.0000

*** significant at the 1% level
** significant at the 5% level
* significant at the 10% level

Panel D: Classification table (the cut-off value is 0.05)

		Predicted		
		Non-distress	Distress	Accuracy Rate
Observed	**Non-distress**	354	76	82.3%
	Distress	3	33	91.7%
	Overall Percentage			83.0%

Panel E: Classification table without CHGNI (the cut-off value is 0.05)

		Predicted		
		Non-distress	Distress	Accuracy Rate
Observed	**Non-distress**	348	82	80.9%
	Distress	2	34	94.4%
	Overall Percentage			82.0%

Panel F: Classification table without NI/TA (the cut-off value is 0.05)

		Predicted		
		Non-distress	Distress	Accuracy Rate
Observed	**Non-distress**	353	77	82.1%
	Distress	3	33	91.7%
	Overall Percentage			82.8%

If we were to refer back to the Pearson correlations in Table 2, there are two variables that are highly correlated, 81.5% These are CHGNI and NI/TA. Although we have examined that the VIF does not show any serious multicollinearity problem with these two variables, to ensure that our results are not affected by the problem, we have excluded each variable in our analysis. The results are reported in Panel B and Panel C of Table 5. When CHGNI and NI/TA are excluded from the analysis, all the predictors are found to be significant such as what was found in Panel A when all variables are included. Hence, the results imply that CHGNI and NI/TA do not have any significant effect on the estimation sample results although they are highly collinear. This enforces the VIF results that multicollinearity is not a threat to this study.

The classification table, Panel D, shows that the hazard model is able to correctly predict 354 non-distressed companies as non-distress and 33 distressed companies as distress. The model correctly classifies 82.3% of the non-distressed companies and correctly classifies 91.7% of the distressed companies. Overall, the model correctly classifies 83% of the sample. The overall accuracy rates reduced to 82% and 82.8% for the respective CHGNI and NI/TA when either one of these variables is taken out from the analysis. The results can be observed in Panel E and Panel F of Table 5.

To check for external validity, a new sample of distressed companies and non-distressed companies is carried out. The hold out sample consists of ten distressed and ten non-distressed companies, listed on the Bursa Malaysia during the period 1990-2000. An analysis of the results from the hold-out sample (Table 6) confirms that, except for the

change in net income, all variables play a significant role in explaining financial distress in Malaysia. The TD/TA, CA/CL and Ln(TA) are significant at the 1% level and all other variables are significant at the 5% or 10% level.

Table 6 : The Hazard Model of Financial Distressed (Hold-out Sample)

Variable	Coefficients	p-value
Interest cover	–0.126**	0.0356
TD/TA	2.350***	0.0038
NI/TA	4.949**	0.0229
C/TA	20.715*	0.0568
C/CL	1.385*	0.0965
CHGNI	0.002	0.1206
CHGS	-1.417*	0.0571
CA/CL	-4.556***	0.0066
Ln(TA)	2.031***	0.0043
Constant	–41.113	0.0000

*** significant at the 1% level

** significant at the 5% level

* significant at the 10% level

Classification table (the cut-off value is 0.05)

		Predicted		
		Non-distressed	Distressed	Accuracy Rate
Observed	**Non-distressed**	83	15	84.7%
	Distressed	0	10	100%
	Overall Percentage			86.1%

In comparison to the estimation sample, the hazard model could correctly classify 100% of distressed companies and 84.7% of the non-distressed companies in the hold-out sample. Overall the model could correctly predict 86.1 % of the sample.

Predicting financial distress using the hazard model suggests that liquidity, profitability, leverage, cash flow, size and growth are important factors that can discriminate between distressed and non-distressed companies. These results differ from previous studies in Malaysia that only use the logit model, because those studies have found that only some variables are important.

5. Conclusion

Bankruptcy studies done in Malaysia have used either the MDA or the logit analysis. However, previous studies highlight the inadequacies in both types of analysis and suggest that the hazard model gives a more accurate result than the MDA or the logit models. This provides a platform for us to investigate financial distress among Malaysian listed companies by using the hazard model.

The study employs a matched sample of thirty-six distressed and thirty-six non-distressed companies listed in Bursa Malaysia. Another ten companies are used as a hold-out sample. We find that most variables are significant predictors of financial distress for both the estimation and hold-out samples except for change in net income in the latter sample. These variables are interest cover, total debt to total assets, net income to total assets, cash to total assets, cash to current liabilities, change in sales, current assets to current liabilities and ln (total assets). The results are in line with Low et al. (2001), Mohamed et al. (2001) and Zulkarnain et al. (2001) who suggest that cash flow ratio and leverage ratio are important determinants of financial distress in Malaysia. Apart from this, our results also show that other factors such as growth, profitability, size and

liquidity play a significant role in explaining financial distress during the period 1990 to 2000.

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