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FINANCIAL DISTRESS AMONG SMEs IN MALAYSIA: AN EARLY WARNING SIGNAL

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ABSTRACT

Small and medium-sized enterprises (SMEs) play an important role in the economic development of a country. To ensure SMEs continue to survive, a failure prediction model needs to be developed so as it could serve as an effective early warning signal. By using multiple discriminant analysis (MDA) and logistic regression for 176 manufacturing companies from 2000 to 2012, controlling shareholders, number of directors, gender of managing director, earnings before interest and tax, size, and age of company are found to be significant in predicting financial distress of SMEs in Malaysia. The results show that model 3 which includes all variables provides a higher accuracy rate for both the multiple discriminant analysis and logistic regression. This indicates that a good prediction model could not focus on financial and non-financial or corporate governance variables alone. Furthermore, it is found that the accuracy rate of the logit model is higher than the MDA for all models.

Keywords: Financial distress; Governance; Logit model; Multiple discriminant analysis; Small medium-sized enterprises

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1. INTRODUCTION

One of the most significant threats for many businesses today, despite their size and the nature of their operations, is insolvency. Existing evidence shows that business failures have continue to occur at higher rates especially among small businesses (Ahmad & Seet, 2009; Cant & Wiid, 2013; Chancharat, 2011; Gray, Saunders & Goregaokar, 2012). For example, in the UK, approximately 65 percent of the small businesses remain in business after the first three years of initial start-up, but after five years less than 45 percent of the businesses have actually survived (Gray et al., 2012). In Australia, 62 percent of the small businesses failing after the third year of operations, while 74 percent fail after the fifth year of operations (Chancharat, 2011). It is also interesting to note that during the 1990s certain sectors of the Malaysian economy, such as small industrial businesses in depressed areas, experienced failure rate as high as 50 percent over a five-year period (Amran & Ahmad, 2010). Furthermore, more than 42 percent of the SMEs in the manufacturing sector that

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began operations in the year 2000 had ceased operations in 2005 (SME Corporation, 2012). More than 60 percent of Malaysian companies have ownership concentration and do not have good corporate governance practices (Amran & Ahmad, 2010). The consequences of business failure have a far-reaching impact on stakeholders either directly or indirectly. The major stakeholders in a company who are the shareholders stand to lose most of their investment. Creditors may receive partial or no repayment of their initial loans depending on whether their loans were secured or unsecured, employees will lose their jobs, the government collects less company and personal taxes, and social problems might increase. The contributions of Altman (1968), Blum (1974), Deakin (1972), and Ohlson (1980) among others have produced huge literature on company failure. Since then, a number of models have predicted corporate failure but, mostly in large public listed firms in the developed countries due to easy access to their financial data.

SMEs in Malaysia play a significant role in economic development, supporting endogenous sources of growth and establishing the infrastructure for faster economic expansion and development (Ortecho & Bergoa, 2014). Department of Statistics Malaysia (DOSM, 2013) highlighted that SMEs account for 97.3 percent of the total business formation in Malaysia (645,000 companies). Since 2004, the contribution of SMEs to GDP growth has steadily outperformed the growth of the general economy (SME Corporation, 2014). The annual growth rate of the SMEs was 6.3 percent in 2013 while the overall economic growth stood at 4.7 percent in the same year (SME Corporation, 2014). As a result of this achievement in the SMEs segment, the share of the SMEs to gross domestic product (GDP) increased from 29.4 percent in 2005 to 33.7 percent in 2013 (SME Bank, 2014), to employment 59 percent, and exports 19 percent in 2013. Therefore, understanding why SME businesses fail is vital to the stability of the Malaysian economy.

Most of the researches carried out in Malaysia on corporate failures have focused on public listed entities using many bankruptcy prediction methods. Examples include, univariate analysis, logit regression model, multiple discriminant analysis (MDA), hazard model, and probit model (see Abdullah, Ahmad, & Md. Rus, 2008; Ahmad, Md. Rus, Mohd, Taufil, Abdul Latif, & Nadakkavil, 2013; Norfian, Salamudin, & Ahmad, 2013). However, there is lack of research looking into the small and medium-sized enterprises due to difficulty in accessing their financial and other information. The study intends to examine the manufacturing sector of Malaysian SMEs in order to predict financial distress as early as two years using financial, non-financial, and corporate governance information and to examine the accuracy rate of the models using multiple discriminant analysis and logistic regression.

This paper is organized as follows. Section 1 is the introductory part of the paper. Section 2 then follows by reviewing the literature in failure prediction. In section 3, the sample and research design are elaborated. Section 4 focuses on the results, and section 5 concludes the paper.

2. LITERATURE REVIEW

For many years, researchers have explored several alternatives to predict the default probability of business failure by applying financial ratios. The research work of Edmister (1972) was among the earliest research on SME business failure that used multiple discriminant analysis (MDA) to discriminate among loss and non-loss SME borrowers. His analysis using the MDA model resulted in seven financial ratio variables. Classification accuracy rate of the model was 93 percent while the model error was 7 percent. The research revealed that classifying ratios by quartile is a particularly valuable tool because extreme values are negated and are therefore prevented from unduly affecting the function parameters (Edmister, 1972). The model of Lussier (1995) utilized qualitative data to predict financial distress among SMEs, which was considered among the first models that utilized such data. The non-financial model consists of fifteen major variables identified from twenty studies. It uses resource-based theory (RBT) to help understand better the role of resources in new ventures by focusing on the identification and acquisition of resources that are crucial for the firms' long-term success.

Lussier's (1995) model was tested and replicated by other researchers outside the US market, such as Houben, Bakker and Vergauwen (2005), Lussier and Halabi (2010), and Teng, Bhatia, and Anwar (2011) in Croatia, the Netherlands, Chile, and Singapore, respectively. Lussier and Pfeifer (2001) and Teng et al. (2011) found that staffing was a significant predictor among the non-financial factors while Lussier and Pfeifer (2001) demonstrated that education was also a significant factor among the non-financial factors. Furthermore, managerial expertise was found to be significant in explaining distress among SMEs (Teng et al., 2011). However, Keasey and Watson (1987) argued that non-financial data could only marginally predict the success and failure of SMEs; such that financial data would still need to be considered.

Lugovskaja (2009) used an MDA model to predict bankruptcy among Russian SMEs. The research sample consisted of 260 bankrupt and 260 randomly chosen healthy SMEs. The author developed two models: model one considered financial variables while model two included both financial and non-financial variables. The first MDA model found that the following six variables were significant in predicting bankruptcy: current liabilities to total assets, cash to current liabilities, ROA, cash to total assets, current assets to current liabilities, and cash plus short-term debtors to current liabilities. The second MDA model showed that both financial variables (liquidity and profitability) and non-financial variables (size and age) appeared to be significant. The classification accuracy rate for the model with financial ratios was 76.2 percent while that of the holdout sample was 68.1 percent. The model with financial ratios and non-financial variables had a higher classification accuracy rate of 77.9 percent for the estimation sample and 79 percent for the holdout sample. Abdullah, Ahmad, Md. Rus, and Zainuddin (2016a) conducted the first research that utilized financial and non-financial information to predict company failure among SMEs in Malaysia. They examined 132 privately owned SMEs in the manufacturing sector during the period 2000 to 2010. Their empirical result showed that higher gearing and lower profitability caused a higher probability of failure, and when firm age was added to the model as a non-financial variable, they found it to be significant and increased the model's classification accuracy rate.

Furthermore, a limited number of studies has analyzed the relationship between corporate governance variables and SMEs bankruptcy. For young SMEs, Dowell, Shackell, and Stuart (2011) find that small number of directors, high CEO power and board independence are likely to increase SMEs' survival chances. Abdullah, Ma'aji and Khaw (2016b) find that greater holding of controlling shareholders, few directors on board, and a male CEO are associated with the likelihood of failure among SMEs in Malaysia. With a large number of directors on board, SMEs would have access to diverse skills, experience from different members, monitor the managing director effectively on matters such as investment opportunities, and improve business efficiency among others (Eisenberg, Sundgren, & Wells, 1998). Additionally, expropriation problem by controlling shareholder is likely to be more severe to a firm's performance and might subsequently increase the likelihood of bankruptcy. Abdullah et al. (2016b) and Ciampi (2015) find that models that incorporate both financial and corporate governance variables are having a higher classification accuracy rate compared to models with only financial variables with a respective accuracy rate of 93.6 percent and 87.9 percent. Therefore, a combination of financial, non-financial variables with corporate governance variables (Model 3) should improve SMEs bankruptcy prediction accuracy rates, compared to prediction based only on financial and non-financial variables (Model 1) or corporate governance variables only (Model 2). The hypothesis is therefore:

H1. Model 3 gives a higher classification accuracy rate than Model 1 and Model 2.

3. METHODOLOGY

The database of the Companies Commission of Malaysia (CCM), an autonomous body that functions as a one-stop center for corporate information, regulation and development of conducive business environment, was used to identify the sample of both failed and healthy SMEs for a thirteen-year period from 2000 to 2012. Companies were matched based on similar business and close in asset size. We first selected the failed companies for each year. These companies were then matched with healthy companies that have almost similar business and total assets within the range of 10 percent. Matching sample is necessary because if healthy companies are to be drawn at random, there would probably be substantial differences between the two groups (Jones, 1987). The selection is done with the aim to obtain a sample company of an almost similar size (total asset) and identical composition of the sample of failed companies. Financial statements were used to extract the financial variables, and the companies' profile was used to obtain the non-financial and corporate governance variables. The study focused on companies in the manufacturing sector as SMEs accounted for 96 percent (37,863 companies) of the total establishments, and around RM191.6 billion (34.9 percent) of the total output of the sector in 2013 (SME Corporation, 2013/2014).

The list of all SMEs which operated in the manufacturing sector that wound up between 2000 and 2012 was retrieved. The record showed that there were 2,164 companies that have failed of which 1,284 companies were based on court order, 51 companies were based on creditor's request, 209 were voluntarily wound up by members and 620 companies were strike off. In order to achieve the objectives of this study, the selection of failed SMEs was based on several criteria such as these companies had (1) annual sales turnover which did not exceed RM25 million following the National SME Development Council's definition of SMEs and (2) the companies were classified under the winding up by Court Order under Part IV Cessation of Companies, Section 465 of (1) (e) or by winding up by creditors request under Section 450 of (1) of Malaysian Companies Act 1965 (Amended 2016). Subsequently, based on random sampling and availability of companies' financial data and other relevant information, the final sample for the estimation model was 172 companies based on two years prior to failures, of which 50 percent were healthy cases, and 50 percent failed cases. Twenty percent of the estimated sample was retained as a hold-out sample. Data for two years prior to failures were used in the estimation analysis, because most of the failed companies did not submit their financial reports when the winding-up period approached, which led to a small sample for the year prior to failure.

Two approaches were used to predict financial distress of SMEs, which are the multiple discriminant analysis and logit model. The multiple discriminant analysis function can be written as follows:

$$D = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \quad (1)$$

Where:

D = discriminant score
α = estimated constant
$\beta_1, \beta_2 \ldots \beta_n$ = estimated coefficients
$X_1, X_2 \ldots X_n$ = explanatory variables

Thus, each company received a single composite discriminant score that was compared with a cut-off value to determine which group the company belongs. MDA consists of three steps: (1) estimating the coefficients of variables, (2) calculating the discriminant score of each case, and (3) classifying the cases. The MDA model for this study is as follows:

$$D = \alpha + \beta_1 CONT + \beta_2 FRGN + \beta_3 NDIR + \beta_4 GENDER + \beta_5 TLA + \beta_6 SLA + \beta_7 LQT + \beta_8 STA + \beta_9 EBIT + \beta_{10} NIS + \beta_{11} LogTA + \beta_{12} LogCAP + \beta_{13} AGE \quad (2)$$

The second approach used to predict distress was the logit model. The logit model is used to predict a binary response from a binary predictor. It is used to predict the outcome of a categorical dependent variable based on one or more predictor variables (Altman et al., 2010). The prediction model used in this study is as follows:

$$Z_i = \beta' x_i + u_i \quad (3)$$

Where:

Z_i = distressed if $Z_i > 0$; non-distressed otherwise
x_i = explanatory variables
u_i = error term
Z_i ranges from –α to +α

The probability and likelihood function for distress can be defined as follows:

$$P_i = E(Y = 1/x_i) = \frac{1}{1+e^{-(\beta' x_i + u_i)}} \quad (4)$$

A logistic distribution function is represented by equation (2). If P_i represents the probability of distress as given in equation (2), then ($1-P_i$) would be the probability of non-distressed.

$$1 - P_i = \frac{1}{1+e^{Z_i}} \quad (5)$$

The company was classified as distressed if the calculated probability from the logit model was more than 0.5; otherwise, it was considered non-distressed. A logit model of the following form is estimated as follows:

$$Y_{it} = \alpha_0 + \beta_1 CONT_{it} + \beta_2 FRGN_{it} + \beta_3 NDIR_{it} + \beta_4 GENDER_{it} + \beta_5 TLA_{it} + \beta_6 SLA_{it} + \beta_7 LQT_{it} + \beta_8 STA_{it} + \beta_9 EBIT_{it} + \beta_{10} NIS_{it} + \beta_{11} LogTA_{it} + \beta_{12} LogCAP_{it} + \beta_{13} AGE_{it} + \mu_t \quad (6)$$

Table 1: Definition of Variables

Variable	Type	Definition
CONT	Governance (ownership)	Dummy variable that takes the value of 1 if the company has one shareholder holding 25 percent or more of the voting right, otherwise 0.
FRGN	Governance (ownership)	Dummy variable that takes the value of 1 if the company has foreign owners, 0 otherwise.
NDIR	Governance (board structure)	Measure of the number of directors in the board structure of the company.
GENDER	Governance (board structure)	Dummy variable that takes the value of 1 if the company's managing director is male and 0 otherwise.
TLA	Financial	Ratio of total liabilities to total assets.
SLA	Financial	Ratio of short-term liabilities to total assets.
LQT	Financial	Ratio of current assets to current liabilities.
STA	Financial	Ratio of sales to total assets.
EBIT	Financial	Ratio of earnings before interest and tax to total asset
NIS	Financial	Ratio of net income to share capital.
LogTA	Financial	Logarithm of total assets.
LogCAP	Financial	Logarithm of share capital.
AGE	Non- Financial	Years of company business operations.

Note: Foreign owner (FRGN); gender of MD (GENDER); controlling shareholder (CONT); number of directors (NDIR); age of company (AGE); logarithm of total assets (LogTA); logarithm of share capital (LogCAP); total liabilities to total assets (TLA); short-term liabilities to total assets (SLA); liquidity (LQT); sales to total assets (STA); earnings before interest and tax to total assets (EBIT); net income to share capital (NIS).

A forward stepwise procedure was applied to both the MDA and logit models that allowed the predictors to be included based on the contribution they made. A stepwise procedure is usually applied when there is a lack of theoretical basis in the selection of the predictor variables (Low, Mat Nor, & Yatim, 2001). Three models were developed: Model 1: Financial and non-financial variables only; Model 2: Governance variables only; and Model 3: Financial, non-financial, and governance variables.

Model 1 utilized financial and non-financial variables only. Abdullah et al. (2016a) model is used as a benchmark by which to compare the results obtained in model 2 and 3. Model 3 was designed to test whether the three sets of information are able to produce superior results to those obtained in either model 1 or model 2.

In most studies, the financial distress prediction models on SMEs are based on financial and non-financial variables. However, in this study, the prediction model uses three categories of variables. They are governance variables (in relation to ownership and board structure), financial variables, and non-financial variables as listed in Table 1. There is a global concern to instill corporate governance, such as board and ownership structure on SMEs, due to many failures of small businesses around the world (Headd, 2003). Additionally, studies that incorporate governance variables in their business failure prediction models of SMEs have performed relatively better and showed that the variables predict SMEs failure significantly (Abdullah et al., 2016b; Ciampi, 2015). According to Rao and Scott (1984), many of the variables appeared in most empirical work and did not rest on any strong underlying theory; as such, the use of these ratios could be accepted in the study.

4. RESULTS AND DISCUSSION

Table 2 presents the results of the mean differences of the variables used to estimate the logit and MDA models. Overall, of the thirteen independent variables, foreign owners, liquidity, and logarithm of total asset are not significantly different between distressed and non-distressed SMEs. The result indicates that 92 percent of distressed SMEs hold 25 percent or more of the voting right, whereas only 30 percent of the non-distressed SMEs hold 25 percent or more of the voting right. On average, only 29 percent and 23 percent of distressed and non-distressed SMEs have foreign ownership. It appears that 94 percent of the distressed SMEs have a male MD while only 52 percent of the non-distressed SMEs have a male MD. On average, four directors sit on the board of non-distressed SMEs. However, distressed SMEs have only two directors who sit on the board. Keasey and Watson (1987) highlight some benefits to SMEs of having a large number of directors on the board. A larger board size will increase the efficiency of the board, as directors will add value to the business and supply the necessary skills in the areas of strategy and/or management and operation oversight.

Table 2: Descriptive Statistics

	Panel Pool (2 years prior)					
Variables	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**	**t-stat**	**VIF**
	Distressed SMEs		**Non-distressed SMEs**			
FRGN	0.290	0.457	0.230	0.425	0.389	1.170
CONT	0.920	0.275	0.30	0.439	0.000***	1.449
NDIR	2.26	0.490	3.56	1.523	0.000***	1.350
GENDER	0.940	0.235	0.520	0.504	0.000***	1.463
TLA	1.6397	1.69889	1.0697	1.70744	0.000***	1.534
SLA	0.9328	0.12976	0.8677	0.18461	0.008***	1.251
LQT	1.58334	5.41478	2.1033	4.13628	0.481	1.184
STA	1.23858	1.33267	0.9462	0.70620	0.074*	1.322
EBIT	-0.26902	0.59499	0.0232	0.14107	0.000***	1.562
NIS	-0.79506	1.90868	0.0892	2.18884	0.005***	1.247
LogTA	15.49502	1.41514	15.5667	1.49847	0.747	1.640
LogCAP	14.26680	1.47773	13.7155	1.58575	0.000***	1.370
AGE	14.87	7.162	20.26	5.537	0.000**	1.277
Observations	*86*		*86*			

Note: *, **, *** significant at 10 percent, 5 percent and 1 percent, respectively. Foreign owner (FRGN); gender of MD (GENDER); controlling shareholder (CONT); number of directors (NDIR); age of company (AGE); logarithm of total assets (LogTA); logarithm of share capital (LogCAP); total liabilities to total assets (TLA); short-term liabilities to total assets (SLA); liquidity (LQT); sales to total assets (STA); earnings before interest and tax to total assets (EBIT); net income to share capital (NIS). Observation is number of SMEs in the analysis. variance-inflating factor (VIF).

Consistent with previous researches, distressed SMEs have a high level of debt and lower liquidity that result in negative basic earnings power and net income to share capital. However, both groups are considered to be relying heavily on short-term liabilities to finance their day-to-day business operations. Smaller companies often rely heavily on trade finance from suppliers when bank finance is not available to them (Altman, Sabato, & Wilson, 2010). The average age of distressed SMEs is 15 years, whereas non-distressed SMEs have been in operations for about 20 years. There are a few differences in terms of assets of distressed and non-distressed SMEs as the companies were matched based on the assets.

A Pearson correlation test was employed to investigate the relationship between the independent variables and the results are summarized in Table 3. The findings show that the correlations among the variables are relatively low, ranging from 0.007 to 0.427, and the majority of the relationships are not significant. However, FRGN against TLA, GENDER against CONT, GENDER against EBIT, CONT against NDIR, CONT against AGE, NDIR against AGE, LogTA against LogCAP, TLA against STA, TLA against EBIT, and SLA against STA are found to be significant.

Multicollinearity is not a threat to this study as indicated by the low pair-wise correlation among the variables. To further verify that multicollinearity is not a problem, variance-inflating factor (VIF) is reported in Table 2. The VIF ranges from 1.170 to 1.640, which is less than 10, indicating no issue of multicollinearity in this study.

A stepwise discriminant analysis was then executed. As presented in table 4, it appears that model 3 outperformed models 1 and 2 based on the lowest Wilks' lambda and the highest classification accuracy rate. The smaller the Wilks' lambda for an independent variable, the more likelihood that the variable adds to the discriminant function (Huberty & Olejnik, 2005). Table 4 shows that model 3 has 34.6 percent unexplained variation in the group variables while model 1 and model 2 have 63.8 and 40.7 percent, respectively. This indicates that the discriminate function in model 3 reveals a significant association between groups and all predictors, accounting for 65.4 percent of between group variability as compared to model 1 and model 2, which account for just 36.2 and 59.3 percent, respectively.

A closer analysis of the standardized canonical discriminant function coefficient in model 3, which combines financial, non-financial and governance variables, reveals three significant predictors that have the highest discriminating power, namely, CONT (0.638) NDIR (-0.524) and LogCAP (0.402) while FRGN (0.206), GENDER (0.260), EBIT (-0.233) and AGE (0.255) as having less discriminating power but statistically significant. The result on EBIT is consistent with the findings reported by Altman (1968) and Chancharat (2011), who found that EBIT could discriminate between the distressed and non-distressed SMEs. In his second MDA model that combined financial and non-financial variables, Lugovskaja (2009), found that size and age of firm appeared to have high predictive power to discriminate between distressed and non-distressed SMEs in Russia, which is consistent with this study's finding of model 1 (0.740).

Table 3: Pearson Correlation

	FRGN	GENDER	CONT	NDIR	AGE	LogTA	Log CAP	TLA	SLA	LQT	STA	EBIT	NIS
FRGN	1												
GENDER	-0.089	1											
CONT	-0.065	0.427***	1										
NDIR	0.093	-0.215***	-0.333***	1									
AGE	-0.100	-0.230***	-0.331***	0.256***	1								
LogTA	-0.062	0.150	0.106	0.174**	0.063	1							
LogCAP	0.074	0.235***	0.209***	-0.016	-0.027	0.383***	1						
TLA	0.203***	-0.038	0.065	-0.185**	0.051	-0.396***	-0.024	1					
SLA	-0.102	0.142	0.093	-0.299***	-0.094	-0.169**	0.135	0.149	1				
LQT	0.073	0.033	0.022	0.050	-0.034	-0.041	0.063	-0.215***	0.100	1			
STA	-0.179**	0.149	0.120	-0.097	-0.075	0.090	0.085	-0.094	0.171**	-0.152**	1		
EBIT	-0.051	-0.219***	-0.234***	0.161**	0.007	0.161**	-0.126	-0.268***	-0.117	0.086	-0.335***	1	
NIS	-0.040	-0.194**	-0.111	0.151**	-0.053	0.010	-0.165**	-0.127	-0.036	0.112	-0.031	0.366***	1

Note: *, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Foreign owner (FRGN), gender of MD (GENDER), controlling shareholder (CONT), number of directors (NDIR), age of company (AGE), logarithm of total assets (LogTA), logarithm of share capital (LogCAP), total liabilities to total assets (TLA), short term liabilities to total assets (SLA), liquidity (LQT), sales to total assets (STA), earnings before interest and tax to total assets (EBIT), net income to share capital (NIS).

Table 4: Stepwise MDA Analysis for Estimated Models

		Model 1		Model 2		Model 3	
Variables	Category	Standardized canonical discriminant function coefficient	Wilks' Lambda	Standardized canonical discriminant function coefficient	Wilks' Lambda	Standardized canonical discriminant function coefficient	Wilks' Lambda
FRGN	Governance			0.295	0.407 (0.389)	0.206	0.346 (0.000)***
CONT	Governance			0.739	0.547 (0.000)***	0.638	0.547 (0.000)***
NDIR	Governance			-0.539	0.461 (0.000)***	-0.524	0.461 (0.000)***
GENDER	Governance			0.377	0.428 (0.000)***	0.260	0.385 (0.000)***
TLA	Financial	-0.261	0.638 (0.000)***				
EBIT	Financial	0.484	0.653 (0.000)***			-0.233	0.355 (0.000)***
LogCAP	Financial	-0.613	0.731 (0.000)***			0.402	0.405 (0.003)***
AGE	Non-financial	0.740	0.848 (0.000)***			-0.255	0.369 (0.000)***
Constant		-8.884		-0.678		-3.122	
Wilks' Lambda		0.638 (0.000)***		0.407 (0.000)***		0.346 (0.000)***	
Observations		*138*		*138*		*138*	

***Note*:** *, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Model 1: financial and non-financial variables, model 2: governance variables, model 3: combined model 1 and 2. Foreign owner (FRGN); gender of MD (GENDER); controlling shareholder (CONT); number of directors (NDIR); age of company (AGE); logarithm of total assets (LogTA); logarithm of share capital (LogCAP); total liabilities to total assets (TLA); short-term liabilities to total assets (SLA); liquidity (LQT); sales to total assets (STA); earnings before interest and tax to total assets (EBIT); net income to share capital (NIS). Observation is number of SMEs in the analysis.

While model 3 stepwise procedure excluded total debt ratio (TLA) among the variables that have a significant influence on the group, model 1 reported that total debt ratio has high discriminating power to predict failure among SMEs. The importance of TLA is consistent with the previous work of Sirirattanaphonkun and Pattarathammas (2012), who demonstrated that total debt ratio had high predictive power to discriminate between distressed and non-distressed SMEs. The result of this study shows that if an analysis is done based on financial and non-financial variables, total debt ratio becomes significant. However, when governance variables are included, this variable is not significant in discriminating the group.

With regards to the models' accuracy rate, the cross-validated classification showed that overall model 3 has the highest predictive accuracy both in the estimated and holdout samples with 90.7 percent and 91.2 percent, respectively. Model 3 outperformed model 1 that is used as a benchmark to compare the results from the other models. The results clearly suggest that the model which incorporates financial, non-financial, and governance variables have better predictive accuracy than the model that has financial and non-financial variables only.

Table 5: Classification Accuracy Rate under MDA Model

	Estimated Sample			**Holdout Sample**		
	Distressed	**Non-distressed**	**Overall**	**Distressed**	**Non-distressed**	**Overall**
Model 1	73.3%	83.7%	78.5%	64.7%	76.5%	70.6%
Model 2	91.9%	83.7%	87.8%	94.1%	82.4%	88.2%
Model 3	95.3%	86.0%	90.7%	100%	82.4%	91.2%
Observations	*69*	*69*	*138*	*17*	*17*	*34*

Note: Model 1: financial and non-financial variables, model 2: governance variables, model 3: combined model 1 and 2. Observation is number of SMEs in the analysis.
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However, a number of shortcomings of MDA have been highlighted by Ohlson (1980) when applied to predicting failure problems. In MDA, the standardized coefficients cannot be interpreted like the slopes of a regression equation. Ohlson also notes that the requirement for the predictor variables to be normally distributed clearly is unfulfilled by the use of governance data (mostly dummy variables). One of the assumptions underlying the use of discriminant analysis is that the variables are multivariate normal in their distribution, and clearly, this condition is unfulfilled by the non-financial and governance data.

Table 6: *Stepwise logistic regression analysis for estimated models*

		Model 1		Model 2		Model 3	
Variables	Category	Coefficient	Change in -2 Log Likelihood	Coefficient	Change in -2 Log Likelihood	Coefficient	Change in -2 Log Likelihood
FRGN	Governance			1.904	7.590 (0.006)***		
CONT	Governance			3.541	49.220 (0.000)***	4.053	28.363 (0.000)***
NDIR	Governance			-1.655	37.595 (0.000)***	-1.662	23.263 (0.000)***
GENDER	Governance			2.750	18.405 (0.000)***	3.334	12.066 (0.01)***
TLA	Financial					0.138	3.656 (0.056)*
EBIT	Financial	-9.937	44.694 (0.000)***			-9.747	14.233 (0.000)***
LogCAP	Financial	0.508	14.833 (0.000)***			0.734	8.600 (0.000)***
AGE	Non-financial	-0.230	40.821 (0.000)***			-0.279	14.964 (0.000)***
Constant		-8.884		-0.473		-2.202	
Hosmer and Lemeshow test		14.270 (0.075)		6.167 (0.405)		9.450 (0.306)	
Observations		*138*		*138*		*138*	

***Note**:* *, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Model 1: financial and non-financial variables, model 2: governance variables, model 3: combined model 1 and 2. Foreign owner (FRGN); gender of MD (GENDER); controlling shareholder (CONT); number of directors (NDIR); age of company (AGE); logarithm of total assets (LogTA); logarithm of share capital (LogCAP); total liabilities to total assets (TLA); short-term liabilities to total assets (SLA); liquidity (LQT); sales to total assets (STA); earnings before interest and tax to total assets (EBIT); net income to share capital (NIS). Observation is number of SMEs in the analysis.

In view of the shortcomings of the MDA model, a stepwise logistic regression was run and presented in Table 6. The Hosmer and Lemeshow test for logistic regression is widely used to answer the question on how well the model fits the data. Overall, models 2 and 3 from the logit analysis fit the data because the observed and expected event rates in subgroups are similar which indicates that the models are consistent with the data. A p-value 0.405 and 0.306 for model 2 and model 3 respectively implies that the models fit the data. Model 1 with a p-value of 0.075 barely passes the test as it deviates from the 5 percent significance level, but it fulfills the 90 percent confidence level. Thus, the model is still considered to fit the data. Similar to MDA, model 3 appears to perform better than model 1 (benchmark) and model 2 as the model incorporates financial, non-financial and governance variables.

Seven variables are found to be significant. They are CONT, NDIR, GENDER, TLA, EBIT, LogCAP, and AGE with a respective likelihood ratio of 28.36, 23.26, 12.07, 3.66, 14.23, 8.6 and 14.96, indicating a rejection of the null hypothesis that the coefficients of the independent variables are zero. The likelihood ratio is considered more accurate in estimating the statistical significance of an independent variable as compared to the explanation of a dependent variable (Menard, 2001).

Total debt ratio is positively related to failure. The finding appears to be consistent with that of Abdullah et al. (2016a), who found debt ratio is significant to predict financially distressed SMEs in Malaysia at all periods of the study. It is also consistent with the result reported by Altman (1968), Blanco, Irimia, and Oliver (2007), and Shane (1996). Shane (1996) further illustrated that younger companies tend to take more debt as the owners have limited resources that could lead the company to have a huge amount of debt outstanding, pushing the company to a financially distressed situation if the owners are unable to settle their obligations.

Altman et al. (2010) also suggest that the high level of debt in SMEs both in terms of trade debt supplied to customers and trade credit obtained from suppliers is because small companies try to boost sales by offering credit to beat their competitors, but without the financial resources to sustain the strategy. As a result, this may lead to SMEs having financial distress, as they may be unable to settle their debt with the supplier due to late payments from large customers taking extended credit. The finding is also in line with the trade-off theory. The higher the company's debt level, the more likely the company faces default due to high-interest obligations. Furthermore, the less profitable the SME, the higher the propensity to fail as EBIT is negative. Distressed SMEs are less profitable than non-distressed SMEs, and the finding is consistent with previous work of Abdullah et al. (2016b).

Under the logit and MDA estimation, model 3 also shows that the AGE of the company is negatively related to failure and is significant in predicting failure among SMEs. The longer the company survives, the less likely that it is to fail. The finding is in line with previous studies (Abdullah et al., 2016b; Altman et al., 2010; Blanco et al., 2007; Shane, 1996). In addition, the results from the models suggest that controlling shareholders have a positive and significant impact on predicting failure among SMEs in Malaysia. This indicates that the greater the holding of controlling shareholders, the higher the likelihood of failure among SMEs. In a situation where ownership concentration exceeds a certain limit, controlling shareholders tend to use corporate resources for their own interests while other shareholders and stakeholders of the firm bear the costs (Shleifer & Vishny, 1997). The transfer of company resources by controlling shareholders comes in many forms including consuming benefits, setting excessive salaries, and making inefficient investments. This expropriation problem by controlling shareholders is likely to be more detrimental to a firm's performance and might subsequently increase the likelihood of business failure.

Furthermore, a significant negative relationship of NDIR indicates that a larger board size can decrease the probability of SMEs failure due to increased oversight and expertise. The finding is consistent with that of Keasey and Watson (1987), who tested the Argenti's (1976) model of business failure on SMEs and they found that the number of directors on the SME board is negatively related to failure.

Gender of managing director (GENDER) is also found to be significant and positively related to SME failure both in the MDA and logit models. The results show that male MDs are more likely to cause failure among SMEs than their female counterparts are. Studies show that the performance of female-led firms is better than that of the firms led by a male (Davis, Babakus, Englis, & Pett, 2010; Khan & Vieito, 2013; Peni, 2014; Singhathep & Pholphirul, 2015). Davis et al. (2010) found female-led SMEs tend to perform better than those led by men because women CEOs tend to place a greater emphasis on market orientation. This helps the female-led firms to better understand consumer preferences, the growing competition, and technological progress, which enable companies to monitor, analyze, and respond to these market changes for better performance. Additionally, Ford and Richardson (1994) believe that women are more concerned with ethical behavior than men in the workplace, because they worry more about the way the company's money is spent and normally extract less personal benefits from the company than their men counterparts (Bliss & Potter, 2002). Furthermore, women CEOs make more conservative decisions than men, and therefore, are more risk averse than men. As a result, their firm risk level will be smaller than firms managed by a male CEO (Wei, 2007), reducing the probability of a business failure.

The descriptive statistics show that foreign ownership is relatively low for both distressed and non-distressed SMEs. The result in model 3 shows that this variable could not predict failure among SMEs. However, if the model only focuses on governance variables, FRGN is found to be significant in predicting failure.

Table 7 provides a summary of the accuracy rate of the models for the estimated and holdout sample. Model 1 can correctly predict 80.2 percent, and 88.4 percent of the distressed and non-distressed SMEs in the estimated sample with an overall accuracy rate of 84.3 percent and the holdout sample has an overall accuracy rate of 85.3 percent. The result of the estimated sample is close to the accuracy rate reported by Abdullah et al. (2016a), Altman and Sabato (2007), and Behr and Guttler (2007) at 81.2 percent, 87.2 percent and 85 percent, respectively. Abdullah et al. (2016b) also report an overall holdout sample accuracy rate of 87.5 percent for two years prior to distress. Model 2 indicates that governance variables are also strong predictors of failure among SMEs. By running the governance variables only, the model can correctly predict 87.2 percent and 89.5 percent of the distressed and non-distressed SMEs, respectively, in the estimated sample with the overall accuracy rate of 88.4 percent. The holdout sample has an overall accuracy rate of 88.2 percent. Furthermore, when all categories of variables (financial, non-financial, and governance) are included in model 3, the accuracy rates of the models for both the estimated sample and the holdout sample improve significantly with an overall predictive accuracy rate of 93.6 percent and 91.2 percent. Therefore, the result illustrated in table 5 and 7 allow us to find that Model 3 gives largely higher classification accuracy levels for both estimated and holdout sample. The average overall increase in accuracy rate from model 1 to model 3 and from model 2 to model 3 for both MDA and logistic regression method is 13.3 percent and 4.6 percent respectively. H1 is therefore confirmed.

Table 7: Classification Accuracy under Logistic Regression Model

	Estimated Sample			**Holdout Sample**		
	Distressed	**Non-distressed**	**Overall**	**Distressed**	**Non-distressed**	**Overall**
Model 1	80.2%	88.4%	84.3%	88.2%	82.4%	85.3%
Model 2	87.2%	89.5%	88.4%	94.1%	82.4%	88.2%
Model 3	93.0%	94.2%	93.6%	94.1%	88.2%	91.2%
Observations	*69*	*69*	*138*	*17*	*17*	*34*

***Note*:** Model 1: financial and non-financial variables, model 2: governance variables, model 3: combined model 1 and 2. Observation is number of SMEs in the analysis.

5. CONCLUSION

The study builds on the previous work of Abdullah et al. (2016a) that utilized financial and non-financial variables in predicting failure among SMEs in the Malaysian manufacturing sector. In this study, governance variables are included to see whether it is possible to achieve a higher prediction accuracy rate of SMEs failure.

The study improves the existing models from the literature of SME distressed prediction in many ways. First, the study presents empirical findings on predicting financially distressed SMEs in the manufacturing sector for the period between 2000 and 2012. It also explores the value addition of governance variables to the prediction model, which shows that the prediction accuracy improves significantly to 93.6 percent and 90.7 percent using the logit and MDA models, respectively, against 81.2 percent of the logit model in Abdullah et al. (2016b), which utilised financial and non-financial data only. The result of the present study shows the importance of the inclusion of governance variables in failure prediction studies, particularly for SMEs.

The findings clearly confirm the results reported in past studies on large corporations where governance variables significantly improve the prediction model's accuracy rate (Lackshan & Wijekoon, 2012; Md. Rus et al., 2013). The results in MDA and logit analysis show that most of the distressed SMEs have a large number of controlling shareholders. Non-distressed SMEs have more directors on their board that may help increase oversight, monitoring, and expertise in the company's operations. However, distressed SMEs have a fewer number of directors which increases the likelihood of failure among SMEs both in the MDA and logit analysis. A male managing director is also positively related to failure. However, foreign ownership appears to be unrelated to the failure status. Young SMEs seem to be more likely to fail than established SMEs because the former lacks experience and growth development. Furthermore, debt ratio is positively related to failure among SMEs. The findings affirm that small businesses in Malaysia finance most of their business operations using bank loans as they have limited access to the capital market. The result also shows that EBIT is negatively related to failure, and distressed SMEs are less profitable than non-distressed SMEs because of an enormous amount of liabilities that trim their profit.

Despite the limited data on SMEs, the result of this study will help SMEs detect financial distress as early as two years before they fail. The findings will serve as an early warning signal for management to take proactive measures to overcome the threats. Financial institutions such as banks will benefit from this study, as it will help them to set their internal systems and procedures to manage credit risk for SMEs. The model will also be beneficial to regulatory bodies like the National SMEs Development Council. The findings will assist them in monitoring and evaluating SMEs. The result also stresses the importance of governance practices among SMEs in Malaysia.

Due to the limited number of research incorporating governance variables among SMEs in predicting financial distress, more investigations need to be carried out on SMEs in other sectors of the Malaysian economy to check the applicability of the model of this study in other sectors. Furthermore, a comparative study can be carried out among SMEs in different countries to identify country-specific variables that contribute to financial distress of SMEs.

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