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PREDICTING FINANCIAL DISTRESS IN MALAYSIA AND ITS EFFECT ON STOCK RETURNS

[1]Ahmad Harith Ashrofie Hanafi, [2]Rohani Md-Rus & [3]Kamarun Nisham Taufil Mohd
[1]Faculty of Business and Finance
Universiti Tunku Abdul Rahman, Malaysia
[2&3] School of Economics, Finance and Banking
Universiti Utara Malaysia, Malaysia

[1]Corresponding author: harith@utar.edu.my

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ABSTRACT

Unstable economic conditions have an adverse impact on the financial performance of firms, leading to financial distress, which is an unfavourable situation for investors as it may affect their investment returns. Thus, this study attempted to predict financial distress and to examine the effect of financial distress on stock returns by using firms listed on Bursa Malaysia from 1990 to 2020. This study used the logit model to find the probability of bankruptcy and also as a proxy for financial distress risk in the asset pricing model. From this study, financial distress risk was found to be insignificant in pricing stock returns in all tested models. This finding demonstrates that financial distress risk does not affect stock returns since this risk may be eliminated through diversification**.**

Keywords: Predicting financial distress, financial distress risk, stock returns.

JEL Classification: G12, G17, G33.

INTRODUCTION

Uncertainties in economic conditions can affect the financial performance of firms and in some cases, lead to financial distress. This situation not only affects small firms but also listed firms. Based on the records of *Bursa Malaysia*, or the stock exchange of Malaysia, the number of firms classified as Practice Note 17 (PN17) firms increased from 21 firms in 2017 to 24 firms in 2018. These numbers may seem small compared to the total number of firms in the market, but firms' bankruptcy risk level and shareholder return may be affected if this increasing trend continues. Thus, a better understanding of financial distress and its effect on returns is imperative.

Financial distress can be defined as the inability of an entity to repay its debt. It is also known as insolvency (Sathye et al., 2003). Further, financial distress risk can be defined as the probability where a firm is unable to meet its obligations. Therefore, a firm is considered financially distressed if it cannot meet its current obligations and the value of its assets is less than the value of its liabilities. This definition is in accordance with studies conducted by Altman (1968) and Ohlson (1980), which are considered to be among the earliest studies on predicting financial distress.

Since the studies by Altman (1968) and Ohlson (1980), other researchers such as Pindado et al. (2008), Bhunia and Sarkar (2011), Thai et al. (2014), and Ming and Akhtar (2014) have conducted numerous studies on predicting financial distress in many different countries. However, a model developed in one country may not be suitable to be used in another country. According to Md-Zeni and Ameer (2010), prediction models used in developed countries may not be suitable for developing countries such as Malaysia. They explained further that the models for developed countries are based on useful quality data, backed by strong research fundamentals in predicting financial distress, robust financial distress laws that help to identify financial distress clearly, and with minimal intervention by the government. These aspects support the financial distress prediction accuracy. It is therefore crucial to have a high accuracy financial distress prediction model for stakeholders such as corporations, investors, creditors, and regulators in making financial decisions and managing the market. Thus, this study intends to develop a financial distress prediction model using financial ratios based on the logit model to predict financial distress for the Malaysian market. This is to ensure that the model developed can accurately measure the financial distress risk based on the Malaysian market.

It is essential to have a highly accurate model for measuring financial distress risk, as it may affect stock returns. This is because stakeholder decisions can be affected especially investors who make investment decisions based on stock risk and return level. Due to this situation, previous studies such as by Shumway (1996), Dichev (1998), and Sabbaghi (2015) incorporated financial distress risk into stock return pricing models to determine the relationship between financial distress risk and returns. However, the results obtained were inconclusive, and in addition most of the studies were conducted in developed markets (Md-Rus, 2011; Opler & Titman, 1994; Sabbaghi, 2015; Shumway, 1996; Simlai, 2014). On the other hand, studies in emerging markets like Malaysia are relatively scarce. Thus, this study attempts to incorporate financial distress risk as one of the factors to explain stock returns in Malaysia and to understand the relationship between financial distress risk and stock returns. To the researcher's knowledge, there is a limited number of studies measuring the effects of the probability of financial distress on stock returns in Malaysia. Thus, the results of this study is expected to be significant for market players in Malaysia since it will provide a clearer picture of financial distress risk and its effect on stock returns.

LITERATURE REVIEW

Financial Distress Prediction Model

Altman (1968) and Beaver (1966) were the pioneers who contributed to the introduction of models for financial distress prediction. Beaver

(1966) used univariate analysis to predict failures among 79 firms by using financial ratios and found that the analysis could better predict failed firms in comparison to random prediction. Altman (1968), on the other hand, employed multivariate discriminant analysis (MDA) to predict financial distress. Based on the results of that study, Altman proposed the Z-score model to predict financial distress by using ratios such as profitability, liquidity, solvency, and cash flow. However, Ohlson (1980) highlighted specific problems arising from the MDA, namely that it was found to violate the assumptions of normality and group dispersion which could result in bias in the test of significance and estimated error rates.

Due to the highlighted problems, Ohlson (1980) introduced the logit model that does not have the same assumptions as the MDA. This model usually uses average data and is considered as a single period model. A total of 105 failed and 2,058 non-failed firms within the period between 1970 and 1976 were used to predict firm failure by using the logit model. The results demonstrated the suitability of the logit model for predicting firm failure. Based on the results by Ohlson (1980), many researchers have used the logit model to predict financial distress (Abdul Manab et al., 2015; Ming & Akhtar, 2014; Platt & Platt, 2008; Yap et al., 2012).

Zaki et al. (2011) shifted the research focus from non-financial firms to financial firms as the sample of their study, which included commercial and Islamic banks in the United Arab Emirates (UAE). Their study used the logit model, probit model, and log-logistic (log-log) link function. The results showed that the logit model could be used to predict financial distress among banks in the UAE.

In a study conducted by Ong et al. (2011), they used the logit model to predict corporate failure among public listed firms in Malaysia. The results obtained highlighted the importance of the ratios used in the model, whereby the model used in the study had an excellent accuracy of 91.5 percent when only five main financial ratios were used. This accuracy rate was much higher than the one recorded in a previous study by Low et al. (2001).

Nevertheless, a financial distress prediction model does not depend solely on the model used, as predictor variables also play an important role in predicting financial distress. Previous studies by Abdul Manab et al. (2015), Chiaramonte and Casu (2016), Etemadi et al. (2009), and Md-Zeni and Ameer (2010) used financial ratios to predict financial distress. Other researchers used current ratio (CR) in developing their financial distress prediction models as it directly measures the ability of a firm to meet its short-term obligations using only current assets (Abdullah, 2006; Daily & Dalton, 1994; Elloumi & Gueyié, 2001; Ganesalingam & Kumar, 2001; Youn & Gu, 2010). CR can be defined as current assets divided by current liabilities (Elloumi & Gueyié, 2001; Foster & Zurada, 2013; Parker et al., 2002; Wang & Li, 2007). Md-Zeni and Ameer (2010) used CR as one of the predictors in predicting the turnover of financially distressed firms in Malaysia. They found that liquidity, represented by the CR, was significant in predicting the turnover of distressed firms. Ugurlu and Aksoy (2006) used sales to working capital (SWC) and found a positive relationship between SWC and the probability of a firm going bankrupt. However, their results contradicted findings by Yap et al. (2012) as the SWC was found to be ineffective in predicting financial distress.

Like other ratios, the activity ratio has also been used by researchers in predicting financial distress (Abdul Manab et al., 2015; Tan & Dihardjo, 2001; Tirapat & Nittayagasetwat, 1999; Wang & Li, 2007). Parker et al. (2002) and Ong et al. (2011) included days' sales in accounts receivable (DSC) in predicting financial distress. This ratio was found to be significant since it reflected the ability of a firm to collect payments for its credit sales. Ong et al. (2011) explained that the faster the firm was able to collect payments for its credit sales, the lower the probability of the firm becoming a financially distressed one.

Earnings before interest and tax to sales (EBITS) is one of the commonly used ratios that represents profitability in the prediction of financial distress (Abdul Manab et al., 2015; Parker et al., 2002; Tan & Dihardjo, 2001; Thai et al., 2014; Ugurlu & Aksoy, 2006). Parker et al. (2002) used this ratio as a proxy for return on assets, which also represents the ability of a firm to recover from financial distress. Parker et al. (2002) claimed that EBITS should have a negative relationship with the probability of financial distress. Some researchers used the net profit margin (NPM) to represent the profitability ratio (Pindado et al., 2008; Wang & Li, 2007). Yap et al. (2012) found a negative relationship between NPM and firm financial failure. Indeed, the profitability ratios are important in predicting financial distress, as these ratios are statistically significant in distinguishing firm financial performance (Md-Zeni & Ameer, 2010).

Many ratios have been used to represent firm leverage, and one of them is debt ratio (DR). Lee and Yeh (2004) defined DR as total debt divided by total assets, and they found this ratio to be significant in predicting financial distress. Meanwhile, Ugurlu and Aksoy (2006) used long-term debt to total debt (LDTD) ratio to represent firm leverage and found it to be significantly helpful in decreasing the probability of financial distress. Abdullah and Ahmad (2005) used shareholders' funds to total liabilities (SFTD) as it represents a firm's capital structure, and they found the ratio to be significant in predicting financial distress. Thus, if a firm relies too much on liabilities, it has a high probability of getting itself into financial distress. Chen et al. (2013), Fich and Slezak (2008), and Youn and Gu (2010) considered financial cost elements such as interest coverage ratio (ICR) as one of their variables. Youn and Gu (2010) explained that this ratio contained a wide range of information related to earning, productivity, ability to pay interest, and indebtedness of a firm. They found that the ICR had a negative coefficient, indicating that a firm with a high-interest coverage ratio would have a lower probability of being in financial distress.

Financial Distress Risk and Stock Return

Previous studies showed diverse results when analysing the relationship between financial distress risk and returns. Denis and Denis (1995) found a positive relationship between financial distress risk and stock returns. Their result was supported by Shumway (1996), who suggested that the risk of default is significant to affect stock returns. Shumway (1996) explained that the average returns is strongly and positively related to distress risk and has a weak correlation to the size of a firm. The study conducted by Sabbaghi (2015) indirectly examined the relationship between systematic risk and financial distress risk by investigating the relationship between the aggregate volatility of market return and financial distress risk. Sabbaghi's study revealed a positive correlation between aggregate volatility and the momentum used to represent financial distress risk. The results indirectly showed that stock return has a positive relationship with financial distress risk.

Boubaker et al. (2018) examined whether financial distress risk affects stock return by using 12 portfolios sorted by size, book-to-market, and leverage and a portfolio of distressed firms covering an 18-year period. The main goal of this study was to identify the risk factors that best captured the default risk in the French context. The results demonstrated that the risk premium for the relative distress factor was positively significant only for the distressed firm portfolio but insignificant for the non-financial distress firm portfolio. This is because the level of financial distress risk for non-financial distress firms is too small whereby it does not give any significant effect on the stock return of non-financial distress firms.

Mselmi et al. (2019) examined financial distress, liquidity, and value-at-risk effect on stock returns for the French stock market. Financial distress was found to be consistently and positively significant to the pricing of stock returns for the financial distress portfolio in all models used in the study, which was somewhat similar to the results of Boubaker et al. (2018). Mselmi et al. (2019) also found that financial distress was significant to the pricing of stock returns only in the absence of size and book-to-market factors. This indicated that the existence of size and book-to-market factors had already captured the effects of financial distress on stock returns. Mselmi et al. (2019) further explained that the absence of size and book-to-market factors led to financial distress risk becoming significant but left the proportion of return unexplained, as the model could not explain the return well.

Chhapra et al. (2020) investigated the relationship between default risk to represent financial distress and a cross-section of stock returns based on Pakistan's stock market using monthly returns between 2001 and 2016. They found that the stock of firms that were significantly exposed to non-diversified default risk yielded higher returns. This indicated that financial distress represented by default risk was positively significant in affecting stock returns. The positively significant results obtained from these previous studies were in accordance with the risk-return trade-off theory which stated that stocks with high level risk (including financial distress risk) should generate high returns.

However, there were also studies that obtained negatively significant results such as a study by Opler and Titman (1994) which found that leveraged firms within distressed industries obtained lower stock returns, which did not portray the correct relationship between risk and stock returns. The authors explained that this result was due to the pure leverage effect therefore indicating that distress risk had a negative effect on stock returns. Instead of developing a prediction model like in the previous studies for example, Shumway (1996), Dichev (1998) used the Z-score and O-score to develop a financial distress portfolio based on the probability of financial distress generated by both models. The results demonstrated that firms with high levels of financial distress risk earned lower average returns compared to firms with low levels of financial distress risk. Thus, the author concluded that financial distress has a negative relationship with stock returns. All these negative results contradicted the risk-return trade-off theory which proposed that high risk led to high returns. This situation could be due to a firm's leverage effect (Opler & Titman, 1994). This is because high leverage effect could negatively affect a firm's income and also investor's income or dividend which would directly result in a negative effect on returns.

Lastly, there were also previous studies that obtained insignificant results such as a study by Idrees and Qayyum (2018) which investigated the relationship between financial distress risk and equity returns of financially distressed firms listed on the Pakistan Stock Exchange (PSX). They found that distress risk had a negative coefficient but proved statistically insignificant in determining stock returns. Hence, they concluded that there was no relationship between expected stock returns and bankruptcy risk. Using manufacturing companies listed on the Indonesia Stock Exchange from 2015 to 2017, Sudirgo et al. (2019) later examined the effects of financial distress, financial performance, and liquidity on stock returns. The Z-score was used to calculate the financial distress risk in the study. The results demonstrated that the financial distress variable had an insignificant effect on stock returns. These insignificant results might be due to the financial distress risk that could be reduced or eliminated through diversification since financial distress risk is a part of unsystematic risk. Thus, the study concluded that there was no significant effect of financial distress risk on stock returns.

METHODOLOGY

Data

This study focused on firms listed on the Malaysian stock market from 1990 to 2020. The estimated sample consisted of data from 1057 firms that were used to develop the prediction model. Due to the highly volatile ratios that were heavily affected by the economic conditions and the slightly different interpretation of the ratios, firms under the financial and properties industries were excluded from the sample of study (Md-Rus & Abdullah, 2005). This study focused on firms listed on the Malaysian stock market because listed firms are significant players in this market. The selected firms were later classified into two categories, namely (1) financially distressed firms and (2) non-financially distressed firms.

Thus, this study defined a financially distressed firm as a firm that fulfils one of the following conditions: (1) the firm is classified by Bursa Malaysia as a financially distressed firm under PN4, PN17 or/and amended PN 17, and (2) there is a deficit in the adjusted shareholders' equity on a consolidated basis. Firms that did not fulfil the criteria were classified as non-financially distressed firms. Unlike Ong et al. (2011), this study did not match the number of non-financially distressed firms to the number of financially distressed firms in order to avoid sample bias, as highlighted by Sori et al. (2001).

Annual reports for both groups of firms were collected from the Bloomberg terminal. Financial information was used to calculate each firm's financial ratios for each year. These ratios, consisting of liquidity, profitability, leverage, and efficiency ratios, formed the independent variables or predictors in developing the financial distress prediction model.

The stock price for each firm was used to calculate the return/excess return for each firm to identify the related risk factors. This study used firm size, value, and financial distress probability as the variables representing the risk factors for returns. Firm returns were calculated based on monthly returns starting from six months after the fiscal year-end. This was to ensure the availability of accounting data for measuring financial distress probability.

To investigate the risk factors of returns, this study first ranked all firms from the lowest to the highest financial distress risk based on the probabilities generated from the earlier part of this study to develop a set of 10 portfolios. Thus, portfolio 1 consisted of firms with the lowest financial distress risk, while portfolio 10 consisted of firms with the highest financial distress risk. The average monthly return for each portfolio was calculated. The average size, value, and financial distress probability were calculated to represent all the independent variables. Lastly, this study regressed portfolio returns with all independent variables using the Fama-MacBeth regression which is similar to the procedure used by Dichev (1998) in investigating risk factors of stock returns.

Data Analysis

According to Shumway (2001) the logistic model (logit model) is a statistical technique that is appropriate when the independent variables are metric variables and the dependent variable is a non-metric (categorical nominal) variable. The logistic analysis aims to identify the best-fitting model to explain the relationship between the predictors or explanatory variables and the dependent variable with the most parsimonious yet reasonable model based on statistics. Thus, this study adopted the logit prediction model from Ohlson (1980) and Abdullah and Ahmad (2005).

$$Z_i = \beta' x_i + u_i \tag{1}$$

Where:

$$Z_i = \begin{cases} 0 \ \cdots \ \text{non} - \text{financially distressed firms} \\ 1 \ \cdots \text{financially distressed firms} \end{cases}$$

x_i = financial ratios of companies

u_i = error term

Non-distressed companies' probability and likelihood function can be simply defined as follows:

$$P_i = \quad P_i = \frac{1}{1+e^{-z_i}} \tag{2}$$

where:

$$Z_i = \beta' x_i + u_i$$

In detail, it is written as follows:

$$P_i = \frac{1}{1+e^{-(\beta' xi + ui)}} \tag{3}$$

Equation (3) represents the cumulative logistic distribution function. Equation (1) is used to estimate the weight for each financial ratio of the selected firms. Based on equation (3), if P_i represents the probability of non-distress, then $(1 - P_i)$ represents the probability of distress. Thus,

$$1 - P_i = \frac{1}{1+e^{(\beta' xi + ui)}} \tag{4}$$

The optimal weight, β, can be estimated where the likelihood value is maximised. To obtain the probability of distress, β is substituted into the cumulative probability function (equation 4). A firm with a probability of less than 0.5 is classified as a non-distressed firm, whereas a firm with a probability of more than 0.5 is classified as a distressed firm based on the calculated probabilities from the logit model. To obtain the most appropriate predictors for the maximum likelihood estimation, this study used the stepwise procedure to exclude the insignificant independent variables and only took significant variables to be included in the model. It is crucial to identify the significant predictors based on the financial ratios that can differentiate between financially distressed and non-financially distressed firms. Thus, the stepwise procedure helps in identifying the most appropriate independent variables. This procedure excludes insignificant independent variables and only includes variables that are significant in the model. This method is similar to the method by Nam and Taehong (2000) and Md-Rus and Abdullah (2005). The financial ratios to be included in the prediction model must be statistically significant based on the *p*-values generated by the model. To confirm the significance of the independent variables, this study also tested the variables' overall significance using the likelihood ratio.

The independent variables in this model consisted of the financial ratios, namely, liquidity, activity, profitability, and leverage ratios. In this study, the liquidity ratios were represented by the current ratio (CR) and sales to working capital (SWC). Days' sales in accounts receivable (DSC) was used to represent the activity ratios. Furthermore, this study used earnings before interest and tax to sales (EBITS) and net profit margin (NPM) to represent profitability in predicting financial distress. Debt ratio (DR), long-term debt to total debt ratio (LDTD), shareholders' funds to total debt (SFTD), and interest coverage ratio (ICR) were used to represent leverage ratios. The subsequent analysis was to find the determinants of return.

Before determining the stock returns, this study first sorted all the selected stocks based on the level of financial distress, where portfolio 1 consisted of firms with the lowest financial distress probabilities whereas portfolio 10 consisted of firms with the highest financial distress probabilities to analyse the mean returns for the decile portfolios based on stock monthly returns from June 1991 to June 2020. Next, the average values of financial distress probability, monthly stock returns, firm size, and firm value were calculated for the decile portfolios. This study compared the lower financial distress decile portfolios (portfolios 1 to 5) against the higher financial distress decile portfolios (portfolios 6 to 10). The results would provide a picture on the characteristics of the stocks based on financial distress level, firm size, and firm value. Next, this study conducted further analysis to determine stock returns. This study adopted a method similar to the one used by Dichev (1998), which was based on Fama-MacBeth regression introduced by Fama and MacBeth (1973) with the inclusion of financial distress risk variables. Dichev (1998) included two major factors to represent the risk factors related to returns, namely size and value.

The model developed in this study is as follows:

$$R_{it} = \alpha + \beta_1 FD_{it} + \beta_2 Size_{it} + \beta_3 Value_{it} + \varepsilon_{it} \quad (5)$$

where R_{it} is the monthly portfolio return, α is the intercept, FD_{it} is the financial distress risk, $Size_{it}$ is the market value, $Value_{it}$ is the book-to-market value, and β_n is the coefficient for the risk factor, and ε is the error term.

This study used size and value as independent variables since both variables are the most common variables used as risk factors for returns.

This study also included financial distress risk factors as independent variable. Although there are other risk factors to determine returns such as momentum, this study only focused on these three variables since these variables are more suitable to be used in Fama-MacBeth (1973) regression and does not involve complex calculation approach.

In this study, size or market value was calculated based on the log of the product of fiscal year-end price and the number of shares outstanding. The book-to-market value was calculated as the common equity value divided by the market value of the firm. The measurements for both size and value were similar to those used in previous studies (Dichev, 1998; Zaretky & Zumwalt, 2007). As for financial distress risk, the probability of financial distress was generated using the prediction model developed in the early stage. This approach is similar to Dichev (1998) and Zaretzky and Zumwalt (2007), which used scores generated from financial distress prediction model. The simple average for all variables in each portfolio was calculated for each observation year. All variables were regressed using Fama-MacBeth (1973) regression to obtain the coefficients for the hypothesis testing of this study.

RESULTS AND ANALYSIS

The results in Table 1 shows the mean difference analysis based on the financial condition of the firms. Firms were divided into two groups: 1) distressed firms and 2) non-financial distressed firms. The mean, standard error, and mean difference values between them were calculated and analysed for each variable. The results showed that all the variables had significant mean differences between both groups. The results also showed that financial distress firms tended to have negative SWC, EBITS, NPM, and ICR. In contrast, non-financial distressed firms recorded positive values for all selected variables.

Subsequently, this study continued with a correlation analysis for all independent variables to predict financial distress. The results are shown in Table 2. The outcome clearly showed that correlations between CR and SFTD, DR and SFTD, and NPM and EBITS were quite strong, which could lead to a multicollinearity problem. Thus, this study conducted a variance inflation factor (VIF) analysis to detect the multicollinearity problem.

Table 1

Mean Different Analysis

	Distressed Firms		Non-Financial Distressed Firms			
	Mean	Std. Error.	Mean	Std. Error	Mean Diff.	p-value
CR	1.0876	0.0703	2.2101	0.0885	1.1225	0.0000***
SWC	-19.9833	21.4972	14.9699	8.4830	34.9531	0.0414**
DSC	151.2827	10.7235	103.881	2.9862	-47.4018	0.0000***
EBITS	-0.0777	0.0167	0.0839	0.0062	0.1616	0.0000***
NPM	-0.3063	0.0359	0.0418	0.0065	0.3482	0.0000***
DR	0.7275	0.0246	0.4307	0.0087	-0.2968	0.0000***
LDTD	0.2061	0.0209	0.2431	0.0083	0.0342	0.0417**
SFTD	0.7544	0.2639	1.9595	0.1058	1.2051	0.0000***
ICR	-0.3672	0.3088	0.1926	0.0714	0.5599	0.0040***

Note: CR represents current ratio, SWC represents sales to working capital, DSC represents days' sales in accounts receivable, EBITS represents earnings before interest and tax to sales, NPM represents net profit margin, DR represents debt ratio, LDTD represents long-term debt to total debt, SFTD represents shareholders' funds to total debt and ICR represents interest coverage ratio. The asterisk symbol (*) for p-value represents statistically significant at different levels: *** statistically significant at 1%, ** statistically significant at 5%, and * statistically significant at 10%.

Table 2

Correlation Analysis

	CR	SWC	DSC	EBITS	NPM	DR	LDTD	SFTD	ICR
CR	1.0000								
SWC	-0.0197	1.0000							
DSC	-0.0139	-0.0023	1.0000						
EBITS	0.1348	0.0262	-0.2681	1.0000					
NPM	0.2326	0.0247	-0.2229	0.7141	1.0000				
DR	-0.6418	-0.0003	0.1601	-0.2416	-0.4416	1.0000			
LDTD	0.0575	-0.083	-0.1964	0.2530	0.0149	0.0648	1.0000		
SFTD	0.7933	-0.0107	-0.0646	0.0075	0.1165	-0.6894	-0.0682	1.0000	
ICR	0.0388	0.0036	-0.0339	0.1347	0.1033	-0.0636	-0.0636	0.0230	1.0000

Note: CR represents current ratio, SWC represents sales to working capital, DSC represents days' sales in accounts receivable, EBITS represents earnings before interest and tax to sales, NPM represents net profit margin, DR represents debt ratio, LDTD represents long-term debt to total debt, SFTD represents shareholders' funds to total debt and ICR represents interest coverage ratio. The star symbol (*) for p-value represents statistically significant at different levels: *** statistically significant at 1%, ** statistically significant at 5%, and * statistically significant at 10%.

The results of the VIF analysis are shown in Table 3. Based on the outcome, all variables generated a VIF value of less than 10. The results indicated that none of the selected variables suffered from a severe multicollinearity problem. Thus, all variables could be used in developing a financial distress prediction model later.

Table 3

Collinearity Diagnostics Analysis

	VIF
CR	3.10
SWC	1.00
DSC	1.15
EBITS	2.38
NPM	2.66
DR	2.63
LDTD	1.22
SFTD	3.64
ICR	1.00
Mean VIF	2.09

Note: CR represents current ratio, SWC represents sales to working capital, DSC represents days' sales in accounts receivable, EBITS represents earnings before interest and tax to sales, NPM represents net profit margin, DR represents debt ratio, LDTD represents long-term debt to total debt, SFTD represents shareholders' funds to total debt and ICR represents interest coverage ratio.

This study continued with the development of a financial distress prediction model using the logit model. The results in Table 4 showed that liquidity ratios represented by the current ratio (CR) and sales to working capital (SWC) were negatively significant in predicting financial distress. These results were similar to the findings of previous studies, such as Parker et al. (2002), Juniarti (2013), and Chiaramonte and Casu (2016). The results imply that as firms' liquidity increases, the ability to meet their short-term obligations with current assets will increase, leading to a decrease in the probability of financial distress.

The activity ratios are represented by days' sales in accounts receivable (DSC) in Table 4. This variable was positively significant in predicting financial distress; similar to the results of Ong et al. (2011) and Parker et al. (2002). This is because the slower a firm collects payments for its credit sales the higher will be the probability of financial distress due to the lower revenue collections within the period, therefore impairing the ability of the firm to settle its debts.

Table 4

Financial Distress Prediction Model

	Coefficient	Std. Error	Z	P-Value
Const	-6.8162	0.7177	-9.497	0.000***
CR	-0.3278	0.1789	-1.832	0.067*
SWC	-0.0005	0.0002	-1.786	0.074*
DSC	0.0032	0.0012	2.816	0.005***
EBITS	−6.5610	1.8673	−3.514	0.000***
NPM	−3.6935	0.8706	−4.242	0.000***
DR	9.3561	0.9779	9.567	0.000***
ICR	0.0045	0.0024	1.841	0.065*
McFadden R-squared		0.6275		
Number of Observations		1057		

Note: This stepwise logit regression analysis used firm's average cross-sectional data for each variable. CR represents current ratio, SWC represents sales to working capital, DSC represents days' sales in accounts receivable, EBITS represents earnings before interest and tax to sales, NPM represents net profit margin, DR represents debt ratio, and ICR represents interest coverage ratio. The star symbol (*) for p-value represents statistically significant at different levels: *** statistically significant at 1%, ** statistically significant at 5%, and * statistically significant at 10%.

Table 4 also shows the results for profitability ratios represented by earnings before interest and tax to sales (EBITS) and net profit margin (NPM). The results showed that both profitability ratios were negatively significant in predicting financial distress. These results were in accordance with studies by Ong et al. (2011), Juniarti (2013), Polemis and Gounopoulos (2012) and Thai et al. (2014). Furthermore, these results imply that a high ability to generate profit will help a firm to reduce its financial distress risk.

Table 4 also shows the results for debt ratio (DR), which is a crucial variable for predicting financial distress. This is because the variable's coefficient recorded the highest value among all the variables and was found to be statistically significant. Previous studies by Lee and Yeh (2004), Sori et al. (2001) and Alifiah and Tahir (2018) obtained similar results. They stated that as a firm increased the proportion of its debt to finance its assets but defaulted on repaying its debt, the financial distress risk would increase. Another significant leverage ratio in predicting financial distress is interest coverage ratio (ICR), which represents the ability of a firm to meet financing cost on its debt. The results contradicted the results of previous studies by Fich and Slezak (2008) and Youn and Gu (2010). This is because high interest coverage ratio also indicates that the firm has a low debt level and at the same time ignores opportunities to grow through leverage. Thus, it is difficult for a firm to predict its future earnings, cover its future debt payment, and to increase the probability of financial distress to occur. Although increasing leverage could help the firm to grow and reduce financial distress, the firm still needs to control the level of its debt in order to avoid financial distress.

Table 5

Prediction Model Accuracy Analysis

		Main Sample Predicted		
		0	1	Accuracy Rate
Actual	0	819	43	95.01%
	1	64	131	67.17%
		Overall Accuracy		89.9%

Based on Table 5, the study found that the model could correctly predict 131 financial distress cases out of a total of 195 cases in the sample. Thus, the model recorded an accuracy of 67.18 percent in predicting financial distress. This accuracy rate is considered moderate, indicating that the model is reliable in predicting financial distress. This model could also predict 819 non-financial distress cases out of a total of 862 cases in the sample. Hence, 95.01 percent of non-financial distress cases could be predicted correctly by using the model. Thus, the overall accuracy of this model was 89.9 percent which is considered high, making it a reliable model.

After developing the financial distress prediction model, this study used the model to generate the probability of financial distress (FD). The generated FD value was used to represent financial distress risk and also as one of the variables to determine stock returns. Before determining the stock returns, this study conducted a descriptive analysis. The results of the descriptive analysis are shown in Table 6.

Table 6

Descriptive Analysis

	Mean	Std. Dev.	Min	Max
Return	0.0057	0.1909	-0.98	14.875
FD	0.1344	0.2639	0	1
Size	19.0903	1.6621	12.2234	24.8228
Value	1.7732	11.4493	-521.72	332.722

Note: FD represents financial distress risk generated from the prediction model, Return represents monthly portfolio return starting from six months after the fiscal year-end, Size represents firm's size based on market capitalisation, and Value represents firm's value based on book-to-market value.

Based on Table 6, the results showed that the firm's return was between 14.875 and -0.98 with the average return of 0.0057 or 0.57 percent. Although the range of firm return value was considered to be large, the variation was small since the standard deviation was only 0.1909. Thus, this clearly showed that only a few firms managed to generate higher than average returns. The results also showed that the average financial distress risk represented by financial distress probability was 0.1344 with the standard deviation of 0.2639. This indicated that only a few firms could be categorised as financially distressed. As for size that is based on log of market value, the data showed that firm size was within the range of 12.2234 to 24.8228 with the average size of 19.0903 and standard deviation of 1.6621. Lastly, the value presented by book-to-market value recorded the average value of 1.7732 which showed that on average most of the firms had a higher book value compared to the market value. However, the variation between the observations was considered large since the standard deviation was 11.4493 and the range of observations was between -521.72 to 332.722.

Table 7

Correlation Analysis among Independent Variables

	FD	Size	Value
FD	1.0000		
Size	-0.1577	1.0000	
Value	-0.0517	-0.1081	1.0000

Note: FD represents financial distress risk generated from the prediction model, Return represents monthly portfolio return starting from six months after the fiscal year-end, Size represents firm's size based on market capitalisation, and Value represents firm's value based on book-to-market value.

This analysis was followed by correlation analysis in order to understand the correlation between selected independent variables where the results are summarized in Table 7. Based on the results, the correlations between all variables were negative, and the values were greater than negative 0.2. The results indicated that the selected variables were weakly correlated between each other.

Next, this study continued the analysis by creating 10 decile portfolios based on firms' financial distress probabilities generated from the model developed earlier. The results in Table 8 showed that the range of average monthly returns for lower financial distress portfolios (portfolios 1 to 5) was from 0.14 to 1.42 per cent. In comparison, the range of average monthly returns for higher financial distress portfolios (portfolios 6 to 10) was from 0.33 to 0.66 percent. Thus, the lower financial distress risk portfolios tended to have higher returns compared to the higher financial distress risk portfolios. The table also shows that as financial distress risk increases, the average return decreases. This result contradicted the risk-return trade-off theory whereby high-risk state investments should obtain higher returns compared to low-risk investments. In addition, on average the lower financial distress risk portfolios consisted of more large firms and value firms compared to the higher financial distress risk portfolios.

Table 8

Average Portfolio Analysis

Portfolio	FD	Return	Size	Value
1	0.0001	0.0067	19.4563	1.8115
2	0.0007	0.0014	19.2096	2.7371
3	0.0013	0.0142	19.7713	3.3521
4	0.0030	0.0063	19.3556	1.7619
5	0.0079	0.0077	19.2523	1.6385
6	0.0201	0.0066	19.2400	1.5267
7	0.0518	0.0045	19.0783	1.9819
8	0.1307	0.0046	19.0048	1.4928
9	0.3412	0.0054	19.9124	1.3713
10	0.8059	0.0033	19.5029	0.2875
Total	0.1344	0.0057	19.0868	1.8132

Note: FD represents financial distress risk generated from the prediction model, Return represents monthly portfolio return starting from six months after the fiscal year-end, Size represents firm's size based on market capitalisation, and Value represents firm's value based on book-to-market value.

The results also showed that on average, large firms and value firms could generate higher average returns compared to small firms and growth firms. The results for low distress portfolios consisting of large size firms and generating high returns was similar to Dichev (1998) while the results for high distress portfolios consisting of growth firms and generating lower returns was similar to Griffin and Lemmon (2002). Thus, these findings could be early indicators before conducting Fama-MacBeth regression to determine the relationship between financial distress risk and stock returns.

Next, this study examined the relationship between the risk factors, including financial distress risk, and return based on Fama-MacBeth regression, and the results are shown in Table 9. First, all the selected risk factors, namely financial distress, size, and value, were combined into model 1 and the results showed size as being positively significant and value as negatively significant. In contrast, financial distress was found to have an insignificant effect on return. In model 2, this study combined the risk factors, namely size and financial distress, in affecting stock returns. The results showed size as being positively significant in affecting stock returns while financial distress was insignificant with a negative sign. These results were consistent with the results obtained in model 1.

As for model 3, value was found to be negatively significant, which was consistent with the results of model 1. However, financial distress showed a negative coefficient and an insignificant result. Thus, for this model, financial distress risk did not have a significant effect on stock returns. Model 4 consisted of only value and size. The results showed a significant value with a negative sign, indicating a significant negative effect on stock returns. Meanwhile, size was found to be positively significant in affecting stock returns. Lastly, model 5 was the model for univariate analysis, which investigated the effect of financial distress risk on stock returns. However, the result for this variable was found to be statistically insignificant to affect returns since the *p*-value for the variable's *t*-test showed values of more than 0.10.

Based on the results obtained in Table 9 using Fama-MacBeth regression analysis, all models demonstrated that a firm's value had a significant and negative coefficient in affecting stock returns. As a firm's value increases, the firm's returns will decrease (Bauer & Agarwal, 2014; Kothari & Shanken, 1997; Taneja, 2010). This result was similar to the study by Reilly and Brown (2011), who asserted that growth stocks should obtain higher returns compared to value stocks due to growth stocks' higher risk levels. Fama and French (1995) explained that a high book-to-market ratio indicated poor firm performance in earnings and profitability compared to a low book-to-market ratio stock. Thus, to obtain a high return in terms of large price appreciation and dividend from a firm's profit, investors will focus their investment on low value, or high growth stocks.

The results for all models also showed that size was positively significant in affecting returns. These results indicated that a large firm's stock earned a higher return compared to a small firm's stock (Hassan & Javed, 2011; Shoaib & Siddiqu, 2016). Mobarek and Mollah (2005) explained that the significant positive results were due to the assumptions that all investors had a homogenous expectation,

Table 9

Fama-MacBeth Regression Result

	Constant	FD	Size	Value	R-square
Model 1	-0.0084	-0.0282	0.0040	-0.0057	0.0739
	[0.0083]	[0.0268]	[0.0009]	[0.0023]	
	(-1.10)	(-1.05)	(4.54***)	(-2.46**)	
Model 2	-0.0135	-0.0270	0.0045		0.0658
	[0.0078]	[0.0269]	[0.0009]		
	(-1.72*)	(-1.00)	(4.99***)		
Model 3	0.0130	-0.0306		-0.0065	0.0551
	[0.0053]	[0.0267]		[0.0024]	
	(2.46**)	(-1.14)		(-2.76***)	
Model 4	-0.0096		0.0041	-0.0057	0.0303
	[0.0085]		[0.0009]	[0.0021]	
	(-1.13)		(4.56***)	(-2.73***)	
Model 5	0.0094	-0.0284			0.0471
	[0.0049]	[0.0267]			
	(1.93*)	(-1.06)			
Number of observations					141425

Note: FD represents financial distress risk generated from the prediction model, Size represents firm's size based on market capitalisation, and Value represents firm's value based on book-to-market value. The value inside [ ] represents standard error value, while value in ( ) represents t-statistic value. The star symbol (*) for p-value represents statistically significant at different levels: *** statistically significant at 1%, ** statistically significant at 5%, and * statistically significant at 10%.

were risk-averse and preferred investing in a large firm that was stable and with a lower risk compared to small firms. Institutional investors and foreign and local mutual funds preferred investing in a large firm that could generate high returns with higher dividend payout ratios (Gompers et al., 2010; Rashid & Abbas, 2011; Zhu, 2010).

Lastly, all models showed that financial distress risk was not significant in affecting stock returns. This result contradicted Shumway (1996), Dichev (1998), and Sabbaghi (2015) but was similar to the study by Md-Rus (2011). This result was consistent with the risk categories highlighted by Reilly and Brown (2011) who categorised financial distress as a financial risk which was a part of unsystematic risk. Thus, it could be fully diversified via portfolio diversification and would not affect return.

CONCLUSION

This study focused on predicting financial distress based on the Malaysian stock market and investigated the effects of financial distress risk on stock returns. This study began by developing financial distress prediction models using the stepwise logit regression model. This model was used to generate the probabilities of financial distress representing financial distress risk. Firms' financial distress risk, size, and value were used as independent variables to determine stock returns based on Fama-MacBeth regression.

The results of the financial distress prediction model based on the stepwise logit model showed that current ratio, sales to working capital; days' sales in accounts receivable, earnings before interest and taxes to sales, net profit margin, debt ratio, and interest coverage ratio were significant in predicting financial distress. Meanwhile, long-term debt to total debt ratio and shareholders' fund to total debt were dropped based on the results of the stepwise logit model. Subsequently, this study used the probabilities generated from the prediction model developed to represent financial distress risk together with size and value as the independent variables in determining stock returns. As for the models that included financial distress risk, size, and value, only size and value were found to be significant. Meanwhile, financial distress risk was found to be insignificant in all the models—both multivariate and univariate—in determining stock returns. The results indicated that financial distress risk does not affect stock returns, which implied that it could be eliminated through diversification.

Based on the results obtained, corporate management should carefully manage the financial aspects of liquidity, efficiency, profitability and leverage as they will impact a firm's financial distress risk level.

Meanwhile, the results also indicate that creditors should consider a firm's liquidity, efficiency, profitability and leverage aspects in making financial decisions to avoid lending capital to financially distressed firms. As for investors, the results show that investment in financial distress risk firm does not affect returns. Thus, investors should not be concerned about a firm's financial distress risk when they develop their portfolios since it can be eliminated through diversification. However, investors can still use the results from the developed prediction model as a guide to measure a firm's level of financial distress risk. The result also provides current and future researchers with an enhanced understanding in predicting financial distress and the effect of financial distress on returns in the Malaysian stock market.

In addition, this study suggests that a more comprehensive model which includes more predictors such as cash flow ratios, market ratios, corporate governance variables, and macroeconomic variables should be developed. Future studies could also try to compare as many models as possible in order to develop the best model that can be used to measure and predict financial distress risk accurately. Lastly, future studies could also incorporate the financial distress probabilities generated from the developed model into Fama and French Three-Factor Model, and Fama and French Four-Factor Model, specifically to study the emerging markets including the Malaysian market to gain a better understanding of the relationship between financial distress and stock returns.

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