# DISTRESS RISK AND STOCK RETURNS:

# MALAYSIA EVIDENCE

AHMAD HARITH ASHROFIE BIN HANAFI



DOCTOR OF PHILOSOPHY

UNIVERSITI UTARA MALAYSIA

March 2023

# DISTRESS RISK AND STOCK RETURNS: MALAYSIA EVIDENCE

**BY**

**AHMAD HARITH ASHROFIE BIN HANAFI**



**Thesis Submitted to**
**School of Economics, Finance and Banking**
**Universiti Utara Malaysia,**
**in Fulfillment of the Requirement for the Degree of Doctor of Philosophy**

# Pusat Pengajian Ekonomi, Kewangan dan Perbankan
*(School of Economics, Finance and Banking)*

## Kolej Perniagaan
*(College of Business)*

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Tarikh: **05 April 2022**
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Nama Pelajar
(Name of Student) : **Ahmad Harith Ashrofie Hanafi**

Tajuk Tesis / Disertasi
*(Title of the Thesis / Dissertation)* : **Distress Risk and Stock Returns: Malaysia Evidence**

Program Pengajian
*(Programme of Study)* : **Doctor of Philosophy (Finance and Banking)**

Nama Penyelia/Penyelia-penyelia
*(Name of Supervisor/Supervisors)* : **Assoc. Prof. Dr. Rohani Md Rus**

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# ABSTRACT

Predicting firms' financial distress is important as accurate prediction would improve financial and investment decisions. The logit model and multiple discriminant analysis are commonly used predicting approaches among researchers, but both models encounter econometric problems that may affect the model's consistency and validity. In order to overcome the issues, researchers suggest hazard model to produce more consistent and valid prediction model. Thus, this study examines and compares the accuracy, consistency, and validity of the logit and hazard model in predicting financial distress. A model with high accuracy, consistency, and validity is used to measure distress risk, which represents one of the risk factors in estimating returns. Prior studies have employed a small sample size and short study period in predicting financial distress or estimating the relationship between distress risk and returns for the Malaysian market, where the results may not have adequately represented the entire market. To address this issue, this study utilises data from 1079 firms during the period of 1990 to 2020 to develop prediction models based on 18,314 firm-year observations. Meanwhile, in estimating return, this study uses 141,425 monthly observations. The results show that liquidity, activity, profitability, and leverage ratios are significant factors in predicting financial distress. Furthermore, the hazard model seems to generate higher accuracy and consistency relative to the logit model. In estimating returns, financial distress risk is consistently insignificant in all models while size and value show consistent significant results in all models. As the developed model could be used to complement the existing guidelines, these results are useful for policymakers such as Bursa Malaysia in improving the policies and guidelines related to Amended Practice Notes 17 (APN17). As for the creditors, the developed model is useful in making a lending decision since the model is helpful in measuring and monitoring firms' distress levels.

**Keywords:** financial distress, logit model, hazard model, distress risk, return

**ABSTRAK**

Meramal kesulitan kewangan adalah penting kerana ramalan yang tepat dapat menambah baik keputusan kewangan dan pelaburan. Model logit dan analisis diskriminan berganda adalah pendekatan ramalan yang kerap digunakan di kalangan penyelidik namun kedua-dua model menghadapi masalah ekonometrik yang mempengaruhi ketekalan dan kesahan model. Bagi mengatasi isu tersebut, penyelidik mencadangkan model *hazard* untuk menghasilkan model ramalan yang lebih tekal dan sahih. Oleh itu, kajian ini mengkaji dan membandingkan ketepatan, ketekalan, dan kesahihan model logit dan *hazard* dalam meramal kesulitan kewangan. Model dengan ketepatan, ketekalan dan kesahan yang tinggi digunakan untuk mengukur risiko kesulitan yang mewakili salah satu faktor risiko dalam menganggar pulangan saham. Kajian terdahulu menggunakan saiz sampel yang kecil dan tempoh kajian yang singkat dalam meramalkan kesulitan kewangan atau menganggarkan hubungan antara risiko kesulitan kewangan dan pulangan saham dalam pasaran Malaysia, di mana hasilnya mungkin tidak menggambarkan keseluruhan pasaran. Bagi mengatasi isu ini, kajian ini menggunakan data daripada 1079 firma dalam tempoh 1990 hingga 2020 untuk membangunkan model-model ramalan berdasarkan 18,314 pemerhatian tahun-firma. Manakala dalam menganggar pulangan saham, kajian ini menggunakan 141,425 pemerhatian bulanan. Keputusan menunjukkan nisbah kecairan, aktiviti, keuntungan dan leveraj adalah signifikan dalam meramalkan kesulitan kewangan dengan model *hazard* menjana ketepatan dan ketekalan yang lebih tinggi berbanding model logit. Dalam menganggar pulangan saham, risiko kesulitan kewangan secara konsisten adalah tidak signifikan dalam semua model manakala saiz dan nilai menunjukkan keputusan yang signifikan secara konsisten dalam semua model. Oleh kerana model yang dibangunkan boleh digunakan untuk melengkapkan garis panduan sedia ada, keputusan kajian ini bermanfaat kepada penggubal dasar seperti Bursa Malaysia dalam menambah baik dasar dan garis panduan berkaitan *Amended Practice Notes 17 (APN17)*. Bagi pemiutang, model yang dibangunkan berguna dalam membuat keputusan kewangan kerana model itu membantu dalam mengukur dan memantau tahap kesulitan firma.

**Kata kunci:** kesulitan kewangan, model *logit*, model *hazard*, risiko kesulitan, pulangan

## ACKNOWLEDGEMENTS

***<u>In the name of Allah, the Most Gracious and the Most Merciful.</u>***

Alhamdullillah and thank Allah for all the opportunities, experiences, and strength to complete this thesis. My humblest gratitude to the holy Prophet Muhammad (Peace be upon him) whose always be my ultimate hero, teacher and his way of life has been a continuous guidance for me.

First and foremost, I would like to sincerely thank both of my supervisors Prof. Madya Dr. Rohani Md-Rus and Prof. Dr. Kamarun Nisham Taufil Mohd for their guidance, understanding, positive encouragement, and a warm spirit to finish this thesis. It has been a great pleasure and honour to have them as my supervisors.

As for my family, I would like to express my highest appreciation goes to my late father Allahyarham Hanafi bin Omar and my lovely mother Jamilah binti Shamsudin as they are my guardian angels that always showered me with love and support in everything that I do. Their dua always is one of the elements that help me to complete this thesis. I would also like to give deepest gratitude to my wonderful wife Nur Zaty Iwani binti Mohamad Nizam and my parents- in-law family for their love, understanding, and continuous support in completing my thesis. Thank you to all my siblings, and in-laws as they are always by my side to make this PhD journey easy.

A special thank you to my all teachers and lecturer in Sekolah Kebangsaan Jitra, Sekolah Menengah Kebangsaan Jitra, Universiti Teknologi Mara (Perlis), and Universiti Utara Malaysia (Sintok) for all guidance and knowledge which is important for me to complete this thesis. Last but not least, thank you to all my friends for their support and believe that motivated me in completing this study.

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| ABBREVIATION | EXPLANATION |
|---|---|
| MDA | Multiple Discriminant Analysis |
| APN17 | Amended Practice Notes 17 |
| ANN | Artificial Neural Network |
| GN3 | Guide Note 3 |
| PN4 | Practice Note 4/2001 |
| SC | Securities Commission |
| CAPM | Capital Assets Pricing Model |
| APT | Arbitrage Pricing Model |
| M&M | Modigliani-Miller Theorem |
| FFTF | Fama-French Three Factor Model |
| VIF | Variance Inflation Factor |
| AIC | Akaike Information Criterion |

# CHAPTER 1

# INTRODUCTION

## 1.1 Introduction

During Asian Economic Crisis from 1997 to 1999, the number of firms facing financial difficulty increased drastically due to mounting debts, large amounts of accumulated losses, and poor cash flows. In order to overcome the effect of this crisis, the Malaysian government introduced Economic Bailout Schemes in 1998 as one of the government interventions that focused on helping firms to improve their financial position. Schemes such as Dana Harta, Dana Modal, and JawatanKuasa Pengurusan Semula Hutang were introduced to provide funds and assistance in managing the firm's debts which helped improve the firm's financial position. During this period, there were no clear guidelines to identify and categorise firms with the poor financial position as financial distress firms. Later, Bursa Malaysia introduced Practice Note 4/2001 in 2001, explaining how firms could be classified as financial distress based on specific criteria. Based on PN4 criteria, 91 firms were categorised as financially distressed firms due to the effect of the economic crisis.

From the introduction of Practice Note 4/2001 (PN4) until the latest Amended Practice Note 17 (APN17), firms have used the practice note criteria as a guideline to avoid financial distress. However, over time, many firms triggered the practice note's criteria which indicate those firms are in financial distress. According to Bursa Malaysia records, large firms such as Renong, Malaysia Airlines, and Utusan Melayu (Malaysia) Berhad were among the firms that triggered the criteria in the past. These cases indicate that financial distress situations are not only among small firms but could also affect large firms. Based on these past events and records, it is crucial for stakeholders to be able to predict financial distress among firms as it is helpful for financial and investment decision-making. Thus, an understanding of predicting financial distress is needed in order to develop a comprehensive financial distress prediction model.

Research related to the prediction of financial distress first introduced by Beaver (1966) and later popularised by Altman (1968), who introduces Z-score based on multivariate discriminant analysis. Based on these pioneering studies, many researchers start to focus on this area and use more complicated prediction models in predicting the financial distress (see for example, Ohlson (1980) who introduces logit model, Barker (1990) who uses Artificial Neural Network (ANN), Shumway (2001) who introduces hazard model and Hillegeist, Keating, Cram, and Lundstedt (2004) who use option pricing method in predicting financial distress).



Even though Multiple Discriminant Analysis (MDA) and logistic regression (logit) are popular among researchers (Abdul Manab, Yen, & Md-Rus, 2015; Bhunia & Sarkar, 2011; Ogachi, Ndege, Gaturu, Zoltan, 2020; Pham, Do, & Vo, 2018; Rafatnia, Ramakrishnan, Abdullah, Nodeh & Farajnezhad, 2020), the prediction model should be carefully developed to ensure its validity and accuracy within all possible situations, as the model's validity and accuracy will determine its reliability. This is because prediction models developed based on MDA face econometric issues that lead to problems of validity and accuracy (Abdullah, Ahmad, & Md-Rus, 2008; Ohlson, 1980; Shumway, 2001).

In order to avoid issues face by MDA, researchers such as Balasubramanian, Radhakrishna, Sridevi, and Natarajan (2019) Ugurlu and Aksoy (2006), Vo, Pham, Ho, and McAleer (2019),  and Yap, Munuswamy, and Mohamed (2012) use logit model while Shumway (2001), Foster and Zurada (2013), and Bauer and Agarwal (2014) use hazard model to predict financial distress. This is because both logit and hazard models could generate higher accuracy rates. However, in terms of consistency and validity, Shumway (2001) suggests that the hazard model is better than the logit model.

Hence, this study examines the accuracy, consistency, and validity of these two models using a more comprehensive dataset, so that a more reliable model could be adopted in identifying financial distress firms in Malaysia. It is important to have a good prediction model as its probability can be used to measure financial distress risk, where the information is useful to a firm's stakeholders such as creditors, investors, and managers.



Estimating financial distress risk is also important as it could be one of the factors that affect stock returns (Chhapra, Zehra, Kashif, & Raja Rehan, 2020; Dichev, 1998; Malik Aftab & Noreen, 2013). The capital asset pricing model (CAPM) states that the only risk factor that affects stock returns is market risk and all unsystematic risks including financial distress risk are assumed to be fully diversified. Thus, it indicates that financial distress risk should not give any significant effect on investors returns since it could be eliminated. However, previous studies find mixed results on the relationship between financial distress risk and stock returns. Researchers such as Li, Lai, Conover, Wu, and Li (2017), Mselmi, Hamza, Lahiani, and Shahbaz (2019), and Sabbaghi (2015) find that financial distress risk is significant in affecting returns which contradict CAPM.

Meanwhile, Chhapra et al. (2020), Md-Rus (2011), Simlai (2014), and Sudirgo Yuniarwati, and Bangun (2019) find that financial distress risk is insignificant in affecting the returns. Based on all these results, further research is needed to understand the relationship between financial distress risk and returns.

Thus, this study also investigates the relationship between financial distress risk and returns in Malaysia, an emerging market. This is to increase the understanding on the effect of financial distress risk on returns in emerging markets. At the same time, it would increase the number of studies related to this field in emerging markets since the number of studies is relatively less compared to the studies that are based in developed markets (Boubaker, Hamza, & Vidal-garcía, 2018; Md-Rus, 2011; Mselmi et al., 2019; Simlai, 2014). To meet this objective, this study first develops a prediction model with various independent variables based on the Malaysian market as suggested by Md-Zeni and Ameer (2010). Subsequently, the estimated probability from the distress model is used as a proxy to represent distress risk, which is used to investigate the relationship between financial distress risk and returns. Some studies in Malaysia such as Li et al. (2017) and Samad, Yusof, and Shaharudin (2009) estimate the probability of distress using coefficients from Altman Z-score or Ohlson O-score, which are developed in the US. Therefore, this approach does not reflect Malaysian's firms' financial conditions.

## 1.2 Problem Statement

During Asia Financial Crisis on 1997 to 1998, many listed firms become financially distressed due to factors such as mounting debts, large accumulated losses, and poor management in cash flows (Hussain, Nassir, Mohamad & Hasan , 2005). This led to the introduction of Practice Note 4/2001 (PN4) by Bursa Malaysia on 15 February 2001. Bursa Malaysia later amended it a few times until it became Amended Practice Note 17 (APN17) and Guide Notes 3 (GN3). As at 31st December 2020, the number of financially distressed firms increased to 25 firms from 23 firms in 31st December 2019. However, this number does not include firms that triggered the PN17 and GN3 distress criteria after 17th April 2020. This is because starting from that date until 30th June 2021, Bursa Malaysia has decided to suspend the PN17 and GN3 listing due to economic shock related to Covid-19 pandemic. According to The Edge and Securities Commision (SC) Annual Report for 2020, 13 listed firms benefited from this Bursa Malaysia's relief. Based on this situation, it clearly shows that financial distress does not only occur among small non-listed firms but also among large listed firms. Thus, the ability to predict financial distress before it occurs will be crucial for market players as it will be helpful in measuring financial distress risk before making any financial decisions.

In predicting a firm's financial distress, the Altman Z-score by Altman (1968) and O-score by Ohlson (1980) models are commonly used for calculating a firm's credit risk and predicting financial distress. Based on these models, researchers like Abdul Manab (2015), Md-Rus and Abdullah (2005), Ong, Yap, and Khong (2011), and Jaafar, Muhamat, Alwi, Karim, and Rahman (2018) develop financial distress prediction models using Malaysia data. However, previous studies only focus on specific industries or a short study period. This could be due to those studies only interested in estimating prediction models based on certain economic events or industry characteristics. Although it is good to have models that focus on industry characteristics, models based on data from all firms within the market could help avoid the selection biases that could affect the prediction model and produce more consistent and reliable results (Shumway, 2001). Thus, a more comprehensive prediction model should be developed with the focus on a larger sample that consists of firms from many industries and for a longer study period. This is to ensure that the model could be used to measure financial distress risk for all firms within the Malaysian market. This aligns with the arguments by Md-Zeni and Ameer (2010) that prediction models that are developed based on developed countries might not be suitable to be used in developing countries like Malaysia due to difference in data quality, having different financial distress laws for each country, and the existence of intervention by the government.



In developing a comprehensive financial distress prediction model, researchers need to consider two major components, which are predictors of financial distress and an analytical model to estimate financial distress. Researchers commonly use firms' financial ratios as predictors since some ratios have the ability to predict financial distress and at the same time represent firms' specific characteristics (Baimwera & Muriuki, 2014; Sudirgo et al., 2019; Wang & Wu, 2017; Waqas & Md-Rus, 2018). Financial ratios such as liquidity ratios, activity ratios, profitability ratios, and leverage ratios are the most common ratios used by previous studies. This is because all these ratios represent the firms' liquidity level, assets management efficiency, profit generation, and capital structure. However, previous studies obtain inconclusive results related to financial ratios used to predict financial ratios (Ming & Akhtar, 2014; Sudirgo et al., 2019; Wang & Wu, 2017; Yap et al., 2012). Thus, the major issue is to find ratios that do not only represent a firm's specific financial characteristics, but are also relevant to predict financial distress. This is because those ratios will affect the model's accuracy and consistency.

Instead of using large numbers of financial ratios to predict financial distress, this study refers to previous studies to find financial ratios that are relevant in predicting financial distress. Based on previous studies that use financial ratios to predict financial distress, this study identifies 12 financial ratios from four major groups of financial ratios that are commonly used and found to be significant by previous researchers to predict financial distress. The results help to identify which financial ratios are significant and relevant in predicting financial distress, which helps to increase the numbers of literature on the usage of financial ratios in predicting financial distress.



The second component that also affects the accuracy and consistency of the prediction model is the analytical method used to estimate the model. MDA and logit model are models that commonly used by many previous studies use (Abdullah & Ahmad, 2005; Ming & Akhtar, 2014; Thai, Goh, Teh, Wong, & Ong, 2014; Waqas & Md-Rus, 2018; Yap et al., 2012). However, MDA violates the normality and group dispersion's assumption. This could lead to bias in the test of significance and estimated error rates (Ohlson, 1980). In order to overcome these issues, Ohlson (1980) introduces the logit model. Subsequently, this model has been replicated in other countries such as in Malaysia (Noor, Iskandar, & Omar, 2012; Sulairnan, Jili, & Sanda, 2001), Vietnam (Vo et al., 2019), and Pakistan (Waqas & Md-Rus, 2018). However, Shumway (2001) highlights econometric problems related to the logit model. The problems are sample selection bias and failure to include time-varying element that affect financial distress risk. Therefore, the logit model's result is considered to be biased, inconsistent and inefficient.

To overcome these problems, Shumway (2001) introduces the hazard model as an alternative model in predicting financial distress. Bauer and Agarwal (2014), Foster and Zurada (2013) and Kim and Partington (2015) use hazard models to measure the probability of financial distress and obtain similar results to those of Shumway (2001). However, some researchers still continue to use the logit model in developing financial distress prediction models due to its simplicity (Balasubramanian et al., 2019; Waqas & Md-Rus, 2018). Thus, this study intends to develop and compare the accuracy and consistency of financial distress prediction models based on logit and the hazard models.



The studies on predicting financial distress are not only beneficial to creditors but also to investors since the studies help in enhancing the understanding of financial distress risk. However, does financial distress risk affect stock returns? According to the risk return trade-off theory, the riskier stock should enable investors to earn higher expected returns. Thus, investment in a financial distress firm, which has higher risk, should generate higher return. However, this contradicts the capital asset pricing model (CAPM), which states that stock returns are only affected by market beta that represents systematic risk while all unsystematic risks including financial distress risk are assumed to be fully diversified and should not affect stock return. Fama and French (2004) criticize CAPM over its oversimplified assumption that beta (β) is the only relevant risk factor to describe stock returns. This inconclusive situation opens an opportunity to investigate the relationship between financial distress risk and stock returns.

Using Arbitrage Pricing Theory (APT) by Ross (1976) and multiple factor models by Fama and French (1993), many studies incorporate a number of factors to examine their effects on stock returns. These models are more realistic compared to CAPM as they allow researchers to include other risk factors, such as financial distress risk, size, and book-to-market (or value), that affect stock returns (Dichev, 1998; Samad et al., 2009; Boubaker et al., 2018; Li et al., 2017; Idrees & Qayyum, 2018; Sudirgo et al., 2019). Previous studies such as Dichev (1998), Idrees and Qayyum (2018), Md-Rus (2011), and Sudirgo et al. (2019) find that financial distress risk does not affect returns. Meanwhile, some studies find that financial distress risk affects returns (Boubaker et al., 2018; Li et al., 2017; Mselmi et al., 2019; Sabbaghi, 2015). These mixed empirical results show that the effects of financial distress on stock returns remain inconclusive and further analysis is required, especially in a developing country such as Malaysia. Thus, this study attempts to incorporate financial distress risk as one of the factors that explains stock returns in Malaysia and to understand the relationship between financial distress risk and stock returns. Most studies are conducted in developed markets (Acheampong & Swanzy, 2015; Boubaker et al., 2018; Dichev, 1998; Griffin & Lemmon, 2002; Vassalou & Xing, 2004) while studies in emerging markets like Malaysia are scarce. To the researcher's knowledge, there is a limited number of studies that focus on the financial distress risk effect on stock returns in Malaysia (Li et al., 2017; Samad et al., 2009).

Unlike previous studies such as Gichaiya, Muchina, & Macharia (2019), Li et al. (2017), Samad et al. (2009), and Sudirgo et al. (2019), that use coefficients from Z-score or O-score to measure financial distress risk, this study does not use available coefficient from previous prediction models. Instead, this study develops prediction models based on the Malaysian market and uses the coefficients to generate probabilities representing distress risk. The approach differs from Samad et al. (2009) and Li et al. (2017), which use pre-determined coefficients based on Z-score and O-score to measure financial distress risk. This study approach helps to ensure that the measured financial distress risk is more accurate and related to the Malaysian market.

This study compares two models, logit and hazard, to find the model with higher accuracy rate and provide better consistency. Model with better accuracy and consistency is then used to estimate financial distress risk. This financial distress risk together with firm size and book-to-market are used as the risk factors to determine the return. The results would explain the effect of financial distress risk on return. Another contribution of this study is that it uses a sample size of 1079 listed firms from 1990 to 2020, which is relatively larger compared to most of the previous studies based on the Malaysian market (Li et al., 2017; Ong, Hanifa, & Isa, 2018; Samad et al., 2009). This study uses listed firms instead of unlisted ones, as listed firms would be considered significant market players that help provide the market's overall picture. Thus, this helps to increase understanding and literature on predicting financial distress and the effect of financial distress on stock return in the Malaysian and developing markets.

## 1.3 Research Questions

This study develops four main research questions based on the problem statement which are:

1. What are the determinants of financial distress using the logit and the hazard models in Malaysia?
2. Which model (hazard or logit) is more accurate and consistent in predicting financial distress in Malaysia?
3. Does financial distress risk affect stock returns in Malaysia?
4. What is the effect of financial distress risk on stock returns after including size and value in Malaysia?

## 1.4 Research Objectives

In general, there are four objectives of this study which are as follows:

1. To identify the determinants of financial distress using the logit and hazard models in Malaysia.
2. To compare the accuracy and the consistency of the logit model and hazard model in Malaysia.
3. To examine the effect of financial distress risk on stock returns in Malaysia.
4. To identify the effect of financial distress risk on stock returns after including size and value in Malaysia.

## 1.5 Scope of the study

This study focuses on determining the effect of financial distress risk on stock return. Thus, the result from this study is beneficial for investors to protect the value of their investment and generate a good return. This study has started with developing prediction models to measure the probability of financial distress that represents financial distress risk. Using yearly data from 1079 firms with the period of 1990 to 2020, this study compares the prediction models that are based on logit and hazard models according to the results' accuracy and consistency. Model with high accuracy and consistent result is used to generate an accurate probability of financial distress. This probability value examines the effect of financial distress risk on stock returns. In examining the effect of financial distress risk on returns, this study uses monthly data of 1079 firms within the period of June 1990 to December 2020 collected from Bloomberg Terminal. However, this study eliminates firm-month observations with zero percent return since it could represent firms being suspended for various reasons during that particular month. These firms' stocks are commonly not traded within the suspension period, which makes no return observations available. Eliminating these observations is crucial as it helps prevent zero-return firm-month observations from affecting the estimation result validity. This study also utilises other risk factors such as firm value and book-to-market value into the analysis model in order to clearly explain the effect of financial distress risk on stock returns.

## 1.6 Significance of the Study

This section discusses the significance of study to investors (1.6.1), managers (1.6.2), creditors (1.6.3), policymakers (1.6.4), and academicians and researchers (1.6.5).

### 1.6.1 Significance for Investors

Financial distress prediction models developed in this study are useful for investors to measure and identify firm distress risk level. This is important as investors have to consider all aspects including distress risk level before making investment decisions. Results obtained from this study are also useful to gain a better understanding of risk, especially the relationship between financial distress risk and returns. This could assist investors in developing techniques or strategies that may help to generate better returns or to protect their investment capital.

### 1.6.2 Significance for Managers

This study examines the ability of financial ratios to predict firms' financial distress. The results could help managers by identifying factors that affect firms' financial position. This is important as they have to develop strategies to improve financial performance and avoid financial distress.

### 1.6.3 Significance for Creditors

Results obtained from this study are useful for creditors such as financial institutions in determining factors that affect financial distress among firms. Since the model developed in this study is based on the Malaysian data, the model is more relevant in predicting distress in Malaysia as compared to models developed in other developing countries. Thus, this study helps financial institutions to analyse a firm's financial position before approving or rejecting any financial facilities application.

### 1.6.4 Significance for Policymakers

As for the policymakers such as Bank Negara Malaysia, Securities Commission, and Bursa Malaysia, the findings could provide meaningful information for them to amend or update current policies and guidelines related to financial distress for the Malaysian market. Financial distress prediction model from this study could also be used by policymakers to develop an indicator or a score to complement APN17 in identifying a distressed firm. This could assist policymakers in ensuring good performance of the capital market especially the equity market in Malaysia. This is essential in attracting investors to invest in this market.

### 1.6.5 Significance for Academicians and Researchers

Although there are many studies conducted using the Malaysian data, most of the studies focused only on certain industries and small sample size that limit the generalizability of the results. To overcome this problem, this study uses a relatively larger sample size (1079 firms available within the period 1990 to 2020). Thus, the results are more comprehensive and provide better evidence related to predicting financial distress and the effect of financial distress risk on returns. Furthermore, this study compares financial distress prediction models based on logit and hazard models that are useful to determine which model is more accurate and consistent. The study also could give a better picture on which financial ratios are useful in predicting financial distress. This is useful for academicians and researchers as it could provide guidelines for future study in developing more comprehensive models especially for the Malaysia market. In investigating the effect of risk factors and returns, the result is useful for academicians and researchers in understanding the effect of distress risk, size, and value on stock return.

## 1.7 Organisation of the study

Discussions on the background of the study, problem statements, objectives, and significance of this research are discussed in this chapter. Next, review of existing literature and theories that are related to this study is elaborated in Chapter 2. Chapter 3 outlines the methodologies of this study including the hypotheses development. The results of this study are reported and discussed in Chapter 4. In Chapter 5, the conclusion is drawn, the limitations are highlighted, the implications are identified, and suggestions are made for potential future study.

# CHAPTER 2

# LITERATURE REVIEW

## 2.0 Introduction

Empirical evidence related to this study is laid out in this chapter starting with the discussion on the financial distress definition, underlying theories, and empirical evidence on the relationship between financial distress risk and stock return. This is followed by literature regarding prediction models and ratios to be used in this study.

## 2.1 Definition of Financial Distress Risk

Financial distress definition in Malaysia stock market commonly based on Amended Practice Note No.17 (APN17). According to APN17, A firm will be classified as a financially distressed firm if the firm meets one or more of the following criteria: (1) Shareholders' equity of the listed firm on a consolidated basis is equal to or less than 25% of the issued and paid up capital of the listed firm and such shareholders' equity is less than the minimum issued and paid up capital as required under paragraph 8.16A(1) of the listing requirements; (2) Appointment of receivers and/or managers over the asset of the listed firm, its subsidiary, or associated firm which asset accounts for at least 50% of the total asset employed by the listed firm on a consolidated basis; (3) A winding up order of the listed firm's subsidiary or associated firm which accounts for at least 50% of the total assets employed by the listed issuer on a consolidated basis; (4) The auditors have expressed adverse or disclaimer opinion in the listed firm's latest audited accounts; (5) The auditors have expressed a modified opinion with emphasis on the listed firm's latest audited accounts and the shareholders' equity of the listed firm on a consolidated basis is equal to or less than 50% of the issued and paid up capital of the listed firm; (6) A default in any payment by the listed firm, its major subsidiary, or major associated firm, as the case may be, and the listed issuer is unable to provide a solvency declaration; (7) The listed issuer has suspended or ceased all of its business or its majority business or its entire or major operations for any reason whatsoever, and (8) The listed issuer has an insignificant business operation. This study uses the first definition of financial distress under APN17 in order to standardise the criteria. This is because the data used for this study are from 1990 to 2020 of which within this study period, the regulations and requirements set by the authority have changed a few times[1].

**2.2 Underlying Theories**



This section discusses theories related to this study which are useful in achieving this study's objectives. Section 2.2.1 focuses on discussing theories related to financial distress prediction models that help in achieving objective one and two. Meanwhile, Section 2.2.2 focuses on theories that explain the relationship between financial distress risk and stock return to achieve objective three and four.

[1] Practice Note No. 4/2001 (PN4) was introduced by Bursa Malaysia on 15 February 2001. On 3 January 2005, Bursa Malaysia revised PN4 and introduced Practice Note No. 17/2005 (PN17). Later, PN17 was further amended on 5 May 2006 to Amended Practice Note No.17 (APN17) in order to improve Bursa Malaysia's approaches in dealing with financial distress firms.

### 2.2.1 Predicting Financial Distress

Financial distress risk affects not only investors but also financial institutions that are involved in providing financial services to business customers (Sathye, Bartle, Vincent & Boffey, 2003). Thus, predicting financial distress is crucial for both investors and financial institutions. Before predicting bankruptcy, concepts like the working capital management, the trade-off theory, and pecking order theory should be understood as these concepts provide explanation on firm's financial structure which might be a factor leading the firm to bankruptcy.

#### 2.2.1.1 Working Capital Management

Working capital management is a concept that is linked to firm liquidity management. According to this concept, a firm should aim to efficiently use the firm's working capital by monitoring and maximising both elements of current assets and current liabilities (Smith,1980). In detail, this concept highlights the importance of managing working capital such as cash, inventories, account receivables, account payables, and short-term loans since all these elements could impact the firm's profitability and value. This concept also highlights the importance of time required by firms to convert their working capital elements into cash. According to this concept, controlling the timing of payment to suppliers and collection from credit buyers is very important. Firms could either delay the payment to suppliers or reduce collection time from the credit buyer, and both actions affect firms' cash. Thus, firms need to ensure the ability to maintain enough cash and meet all short-term obligations, such as operating costs and short-term debt obligations. This could help to maximize the firm's profitability.

From the risk perspective, working capital management is crucial in managing risk related to a firm's financial obligations (Prasana, 2000). This is because it would affect a firm's ability to meet short-term obligations and the firm's default risk level. According to working capital management theory, firms with poor working capital management tend to have a low ability to meet short-term obligations, leading to an increase in default risk and financial distress. This indicates that a firm's liquidity and efficiency based on working capital could be the factors that affect a firm's financial distress level. Thus, the inclusion of liquidity ratios and activity ratios in this study would be crucial in measuring and predicting financial distress.

#### 2.2.1.2 Trade-Off Theory

Leverage commonly relates to the capital structure of the firms and could be explained by the Modigliani-Miller theorem (M&M) introduced in 1958. M&M is based on the idea that under certain assumptions the firm's capital structure does not affect the firm's overall value. However, some assumptions under Modigliani-Miller for perfect capital markets such as no taxes and no bankruptcy cost environment are irrelevant in the real world. Due to this situation, Modigliani and Miller (1963) look at the effects of taxation on capital structure. They find that as firms increase debt financing, the value of the firms will increase due to the tax-deductible element of interest. However, in the real world firms do not maximize their debt level since there are costs associated with using debt (Modigliani & Miller, 1963). This in essence is the basic idea of trade-off theory.

The trade-off theory states that firms will pursue an optimal capital structure in order to balance the benefits and the costs of debt. DeAngelo and Masulis (1980) use tax benefit–bankruptcy cost trade-off models and find that firms will try to maintain an optimal capital structure by balancing the advantages and the costs of debt. Thus, this clearly shows that debts and the cost of debts are essential elements in managing a firm's capital structure. However, mismanaging these elements could increase default risk and financial distress risk. As the firm continues to increase the debt level beyond the optimal capital structure point, the cost of debt will also increase, making debt riskier in the stakeholders' eyes. This is because the probability of a firm being unable to meet debt and the cost of debt obligations will increase. Thus, the default risk will increase and might lead to a financial distress situation. Based on this idea, it clearly shows that the trade-off theory could be used to explain the link between capital structure elements and the cost of debt in predicting financial distress. Thus, this study includes a few leverage ratios that could represent debts and the cost of debts to capture the effect of debts and the cost of debts in predicting financial distress.



#### 2.2.1.3 Pecking Order Theory

According to the pecking order theory, firms firstly finance their projects or operations using retained earnings that represent the firms' internal source. Once the internal source is fully exhausted, firms would turn to external sources of finance starting from safe debt, risky debt, and finally equity. The debt will expand as the total investment becomes bigger than retained earnings, and it will shrink if the investment is less than retained earnings. However, it also creates or increases firms' financing costs that could affect the firms' financial performance. Shyam-Sunder and Myers (1999) find that by holding investment value fixed, leverage is lower for more profitable firms while holding profitability of firms fixed would increase the leverage as investment increases.

Based on the financial distress prediction view, this theory could also explain the effect of firm financing decisions on the firm level of risk. This is because the risk level for each source of funds is different, which the firm risk level will increase as firms proceed from internal fund to external funds. Using internal funds, such as a firm's retained earnings and profit, reduces the firm's risk compared to external funds (debts and equity). As the firm turns to debts to finance its business, it will increase its risk level, especially the default risk level. Thus, if the firm fails to generate enough profit, the firm's level of debt will increase due to the firm needing more funds to finance the business activities. This could lead to an increase in default and financial distress risk. Based on this idea, it clearly shows that the pecking order theory could also explain the link between the firm's profitability and financial distress. Thus, this study uses profitability ratios to capture the effect of a firm's profitability in predicting financial distress.



### 2.2.2 Relationship between Financial Distress Risk and Stock Return

Relationship between risk factors such as size, value (book-to-market), and financial distress risk and stock return commonly explain based asset pricing models.

#### 2.2.2.1 Asset Pricing Models

In understanding the relationship between distress risk and stock return, the understanding of the risk return trade-off is needed. According to this concept, risk has a positive relationship with return in which high risk investments should be compensated with high returns. Based on this premise, financial distress firms should provide high returns to investors. Thus, financial distress is expected to have a positive effect on stock return.

Sharpe (1964) has formalized the risk return trade-off and introduces Capital Asset Pricing Model (CAPM) that is based on the idea that the market portfolio of the invested fund is mean-variant efficient. This asset pricing model is developed based on the premises that (1) a stock's expected return is positively related and is a linear function of market beta, and (2) market return is represented by the cross-section of expected return. Based on these premises and model developed, it clearly shows that all unsystematic risks including financial distress risk do not affect stock return. According to Reilly and Brown (2011), unsystematic risk could be eliminated through the diversification process. This is because covariance between assets or stocks help to reduce and eliminate unsystematic risk in developing diversified portfolios. Since financial distress risk is considered as one of firm specific risks, thus, it could be diversified away and it has an insignificant effect on return of the portfolio. Therefore, based on CAPM, financial distress risk could not affect the stock return which contradicted to risk return trade-off theory.



However, the ability of beta (β) in CAPM has been under criticism and it should not be the only risk factor to describe stock return. Fama and French (2004) highlighted that the empirical problem of CAPM is caused by its oversimplified and unrealistic assumptions. This shows that uni-factor pricing models become less reliable in explaining stock return. This situation leads to the increasing popularity of the multi-factor asset pricing model as researchers look for new asset pricing models. Ross (1976) introduces the Arbitrage Pricing Theory (APT) as an alternative model to overcome the problem of CAPM. APT has fewer assumptions and is more realistic as compared to CAPM since it is able to explain stock return based on more than one factors that are affecting stock return. APT allows for an unspecified number of important factors to be included in the model. Thus, other risk factors including financial distress risk can also be included in the model and might affect the stock return. However, APT also has a few problems such as: (1) APT does not specify which risk factors are suitable for the model, and (2) APT does not specify the number of unknown risk factors. This situation leads to the creation of models with ambiguous risk factors. Thus, it is concluded that a model that specifies the number and types of risk factors is needed.

To overcome the problem of APT, Chen, Roll, and Ross (1986) use specific economic factors such as monthly growth rate in industrial production, change on expected inflation, unanticipated inflation, unanticipated change in the risk premium, and unanticipated change in the term structure together with market risk as risk factors in the APT model to determine stock return. Instead of using economic factors, Fama and French (1993) use a multi-factor model and introduce a three-factor model to explain the stock return, which is also known as the Fama-French three-factor model (FFTF). Instead of only focusing on market beta, this model also includes firm size and book-to-market ratio as risk factors to explain stock return. Both firm size and book-to-market ratio (value) are found to be very important since these variables represent risk factors that directly affect the return. Based on FFTF, the firm size represents a risk factor that indicates the level of risk based on the firm market capitalisation. Commonly, firms with large market capitalisation are categorised as large and more stable than small firms. Thus, it will affect the firm risk level, which at the same time affects stock return. Meanwhile, the book-to-market ratio identifies whether the firm categories as value or growth firms. Investors need to clearly identify the firm category based on the book-to-market ratio before making any investment decision since each category comes with different investor perspectives and risk levels. Hence, it could positively or negatively affect the stock return. Thus, based on FFTF and APT assumptions, both size and value variables are expected to affect returns. Based on this idea, researchers have extensively tested determinants of stock return models and both variables, and obtained inconclusive empirical results on the effect of both firm size and value on return. By using APT assumption and risk return trade-off concept, some researchers like Shumway (1996), Dichev (1998), Md-Rus (2011), and Sabbaghi (2015), also include financial distress risk as one of the risk factors in their multi-factor model to determine the financial distress risk effect on return in their studies. This is because the distressed firm has a high level of risk and is expected to generate high returns. This expectation is aligned with the risk return trade-off theory but contradicts the CAPM assumptions. However, researchers obtained mixed results on the relationship between financial distress and stock return. Thus, more studies are needed in this area to obtain a deep understanding of factors affecting return. Therefore, to clearly understand the effect of financial distress risk, firm size, and value (book-to-market) on return, this study uses all these variables to determine returns. The results help to provide a better picture of financial distress risk, size, and value on stock return, especially in the Malaysian market.

## 2.3 Financial Distress Prediction Models

One of these study objectives is to compare between the logit and hazard models in predicting financial distress. Therefore, this section will only focus on reviewing literature related to these two models. In addition, since MDA is the pioneering model in predicting financial distress, this study also compares MDA to logit and hazard.

Altman (1968) employs the multiple discriminant analysis (MDA) to predict financial distress by using financial ratios based on the US market. The result shows that the selected ratios are significant to predict financial distress. Altman proposes the Z-score model for predicting financial distress based on this result. This Z-score model uses ratios such as liquidity, profitability, cash flow, and solvency. Thus, failure of the firms could be predicted in advance by combining prediction models with financial ratios.

Blum (1974) also used the MDA to develop a model for predicting financial distress that utilises 12 financial ratios as variables in the model. Blum's study matches 115 failed firms with 115 non-failed firms covering the period from 1954 to 1968 based on certain criteria such as types of industry, sales level, the number of employees, and the same fiscal year. The result obtained is similar to Altman's (1968), which shows the ability of the MDA to predict financial distress.

Based on Altman (1968) and Blum (1974), researchers started to use financial ratios to predict financial distress and the MDA has been the most popular model for predicting financial distress and financial distress. However, Ohlson (1980) highlights certain problems related to the MDA such as normality's assumption violation and group dispersion, that could lead to bias results in significance test and estimated error rates. This problem has led researchers after Altman to also start using other models.

Due to the highlighted problems, Ohlson (1980) introduces the logit model to overcome the MDA's issues. This model is considered as a single period model and normally uses average data. 105 failed and 2,058 non-failed firms within the period from 1970 to 1976 are used to predict firm failure by using the logit model. The result shows that the logit model is suitable to predict firm failure. Lo (1986) compares between the MDA model and the logit model and finds that the predictability of the MDA model is better compared to the logit model. However, Lo's result could only be obtained if the data satisfied the normal distribution assumption, and logit is better than MDA if the data is not normally distributed.

Some researchers compare other models with the MDA, such as Wilson and Sharda (1994), who compare the MDA with the neural network (NN). The result shows that the neural network performs better than the MDA in terms of classification accuracy in predicting financial distressed firms. This result aligns with an earlier study by Odom and Sharda (1990). They compare the predictability level between the MDA and the neural network, and find that the neural network is better than the MDA because it is more robust than MDA. However, the study uses a smaller sample size as compared to the former study. Altman, Marco, and Varetto (1994) use Italian industrial firms that include over 1,000 healthy, in danger, and unsound firms in the industry between 1982 and 1992 to make a comparison between the logit and neural network. The result highlights some of the problems faced by the neural network such as illogical weighting of indicators and overfitting at the training stage. These problems have negatively affected the model's predictive accuracy.

Although the logit model is found to be better than the MDA and the neural network, it also has problems. Shumway (1996) and Hillegeist et al. (2004), highlight two main econometric problems related to the logit model that could affect the prediction model. The problems are: (1) sample selection bias, and (2) failure to include time-varying elements that reflect financial distress risk. Thus, the result will be biased, inefficient, and inconsistent. Shumway (2001) introduces the hazard model for predicting financial distress to overcome these issues. The study focuses on financial distressed and non-financial distressed NYSE and AmEx firms within the period of 1962 to 1992. The study finds that 75 percent of financial distressed firms are classified in the first decile (first decile represents a group of firms with the highest risk of financial distress).

Using a similar sample as in Shumway (2001), Beaver et al. (2005) finds that based on the sample analysis, 75 percent of financially distressed firms are in the first decile while out-of-sample analysis shows that 61 per cent of financially distressed firms are classified in the first decile. Thus, this study supports the earlier study by Shumway (2001). Bauer and Agarwal (2014) compare hazard model that based on Shumway (2001) with Z-score based on MDA. They find that the hazard model is superior compared to the Z-score as the hazard model has average default probabilities that are closer to observed default rates.

In Malaysia, researchs have been conducted to predict financial distress among Malaysian firms. Sulairnan et al. (2001) compare between MDA and the logit model based on model accuracy and finds that the MDA is more accurate compared to the logit model in predicting financial distress. However, the results of accuracy for both logit and MDA models are lower as compared to Low, Nor, and Yatim's (2001) study.

Md-Rus and Abdullah (2005) use the hazard model in their study after considering the weaknesses of the logit model and the MDA model. By using 1990 to 2000 as the period of study, the result shows the hazard model has high accuracy to predict financial distress. Abdullah, Ahmad, and Md-Rus (2008) compares the model accuracy between MDA, logit and hazard model and find that the overall accuracy rate for hazard model is higher compared to MDA and logit in the estimation model for both main and holdout sample although both models show accuracy level above 90 percent. Thus, this study uses a similar approach like Abdullah et al. (2008) to generate and compare prediction models that are based on logit and hazard models. Finally, this study chooses a model that could provide high accuracy and consistent results to generate financial distress probability that is used in determining its effect on stock return.



## 2.4 Determinants of Financial Distress Prediction

Previous studies use various types of ratios as predictors to predict financial distress. Thus, in this section, this study discusses ratios that are used by many previous studies based on four main groups of ratios which are liquidity ratios, activity ratios, profitability ratios and leverage ratios

### 2.4.1 Liquidity Ratios

Liquidity is an indicator that represents the ability of a firm to meet its short-term obligations (Nyamboga, Omwario, Muriuki and Gongera, 2014). Based on this definition, the firm will try to avoid a low liquidity position since this situation will lead to loss of confidence among creditors, poor creditworthiness, or might lead to the closure of the firm. Liquidity is usually measured using liquidity ratios such as current ratio and quick ratio.

Altman et al. (1977) find that the current ratio that represents liquidity is efficient in identifying failure as compared to other ratios and use this ratio to predict financial distress. Researchers like Youn and Gu (2010) use the current ratio to develop financial distress prediction models. Current ratio (CR) is equal to current assets divided by current liabilities (Elloumi & Gueyié, 2001; Foster & Zurada, 2013; Parker 2002; Wang & Li, 2007). This ratio directly shows a firm's ability in meeting its short-term obligation using current assets. A lower current ratio indicates a lower ability of the firm to liquidate its current assets to meet its short-term obligation. Parker et al. (2002) find that as the ratio increases, the likelihood of the firm to be in a financial distress position will decrease and it will have a significantly negative effect on the firm's probability of financial distress. The result obtained by Parker et al. (2002) is similar to an earlier study by Daily and Dalton (1994) and supported by later studies such as Bakhri, Listyaningsih, and Nurbaiti (2018) and Ogachi et al. (2020).

However, Abdullah and Ahmad (2005) who use logit model as one of their models in predicting financial distress find that current ratio is not significant in predicting financial distress. This result indicates that firm liquidity level does not have significant impact and does not lead to financial distress. This is similar to the studies by Elloumi and Gueyié (2001) and Foster and Zurada (2013) that also concluded that the current ratio is insignificant in predicting financial distress. In a later study by Fitri and Syamwil (2020), they include this ratio in the financial distress prediction model based on manufacturing firms in the Indonesia market. They find that the current ratio is not significant in predicting financial distress. This study explains that this could be due to no significant difference in this ratio value between all firms within the study sample. This insignificant result could be due to the fact that the current ratio only measures the ability of firms to meet short term obligations and common short-term obligations' values are relatively smaller than that of long-term obligations. Thus, firms would commonly be able to meet their short-term obligation but might fail in meeting their long-term obligations. This situation might lead to the prediction model failing to capture the effect of current ratio.

Altman (1968) suggests net working capital to total assets as one of the best indicators of financial distress since this ratio is commonly used in studies of corporate problems. This ratio is defined as the difference between current assets and current liabilities to total assets. Normally, a firm that experiences consistent operating losses will have shrinking current assets in relation to total assets. Altman suggests the use of this ratio since it is able to capture the impact of a firm's liquidity in predicting financial distress. This is supported by Abdul Manab et al. (2015) who use the logit model and find that this ratio is negatively significant to predict financial distress.

Using the logit model, Waqas and Md-Rus (2018) include  working capital to total assets  as a predictor of financial distress. The result shows that this ratio is negatively significant to predict financial distress. Vo et al. (2019) who uses the logit model in trying to predict financial distress during these two periods. They use the net working capital to total assets to represent the liquidity of the firms. They find that this ratio is consistently negatively significant in predicting financial distress for the post-global financial crisis period but not significant for the financial crisis period.

However, Rafatnia et al. (2020) use working capital to total assets which in predicting financial distress in the Iran market. The logit model results show this ratio is found to be positively significant to predict financial distress. There are previous studies such as Thai et al. (2014) who use MDA and find that net working capital to total assets is positively significant in predicting financial distress and identifying PN17 firms in the Malaysian market. Darmawan and Supriyanto (2018) also use the same ratio as Thai et al. (2014) in predicting financial distress for mining firms within Indonesia market using the MDA model. This study finds that this ratio is positively significant in predicting financial distress and this indicates that liquidity could help to predict financial distress.

There are also other liquidity ratios used by previous such as sales to working capital (SWC). Sales to working capital (SWC) is calculated by dividing sales with net working capital. Ugurlu and Aksoy (2006) find that this ratio has a significant positive relationship with financial distress probability. Although the increase in sales to working capital indicates that the firm is highly efficient in utilising current assets and current liabilities in generating sales, Ugurlu and Aksoy (2006) explain that a failed firm mostly depends on short-term loans and/or trade credit in financing its operations and generating sales. Thus, current liabilities of such firms will be high, which will lead them to experience a decreasein the firm's ability in meeting short-term debt and due to shrinking current assets value. This result is not supported by Yap et al. (2012) who find that this ratio is insignificant to predict financial distress.

All these previous studies show that the current ratio, working capital to total assets, and sales to working capital ability to predict financial distress remain inconclusive. This could be because the models used to predict financial distress failed to capture the current ratio's effect. According to this study's collected literature, most previous studies commonly used the logit model and MDA. In certain conditions, both models failed to capture the effect of the current ratio in predicting financial distress. Both models also produce mixed results for working capital to total assets and sales to working capital showing the model's inability to produce consistent results. In order to overcome both issues, this study uses the hazard model to analyse these ratios as this model is expected to produce more consistent results. It is very important to correctly capture the effect of the current ratio, working capital on total assets, and sales to working capital since both ratios commonly represent liquidity ratios.

**Table 2.1**
*Summary of Literature for Liquidity Ratios.*

| Researchers | Study Sample | Variable | Methodology | Result |
|---|---|---|---|---|
| Youn and Gu (2010) | Korea market from 2000-2005 | Current Ratio | Logit | Negative significant |
| Parker et al. (2002) | United State market from 1988 to 1996 | Current Ratio | Cox Proportional Hazards | Negative significant |
| Daily and Dalton (1994) | United State market from 1972 to 1982 | Current Ratio | Logit | Negative significant |
| Bakhri et al. (2018) | Indonesia market from 2014 to 2016 | Current Ratio | Logit | Negative significant |
| Ogachi et al. (2020) | Kenya market | Current Ratio | Logit | Negative significant |
| Abdullah and Ahmad (2005) | Malaysia market year 2000 | Current Ratio | Logit | Insignificant |
| Elloumi and Gueyié (2001) | Canada market from 1994 to 1998 | Current Ratio | Logit | Insignificant |
| Foster and Zurada (2013) | United State market from 2003 to 2007 | Current Ratio | | Insignificant |
| Fitri and Syamwil (2020) | Indonesia market from 2014 to 2018 | Current Ratio | Logit | Insignificant |
| Altman (1968) | United State market from 1946 to 1965 | Net Working Capital to Total Assets | MDA | Negative significant |

**Table 2.1**
*Summary of Literature for Liquidity Ratios.(cont.)*

| Researchers | Study Sample | Variable | Methodology | Result |
|---|---|---|---|---|
| Abdul Manab et al. (2015) | Malaysia market from 2006 to 2012 | Net Working Capital to Total Assets | Logit | Negative significant |
| Waqas and Md-Rus (2018) | Pakistan Market from 2007 to 2016 | Net Working Capital to Total Assets | Logit | Negative significant |
| Vo, Pham, Ho, and McAleer (2019) | Vietnam market from 2007 to 2017 | Net Working Capital to Total Assets | Logit | Negative significant |
| Rafatnia et al. (2020) | Iran market from 2000 to 2016 | Net Working Capital to Total Assets | Logit | Positive significant |
| Thai et al. (2014) | Malaysia market from 2009 to 2013 | Net Working Capital to Total Assets | MDA | Positive significant |
| Darmawan and Supriyanto (2018) | Indonesia market from 2011 to 2014 | Net Working Capital to Total Assets | MDA | Positive significant |
| Ugurlu and Aksoy (2006) | Turkey market from 1996 to 2002 | Sales to Working Capital | Logit | Positive significant |

**Table 2.1**
*Summary of Literature for Liquidity Ratios.(cont.)*

| Researchers | Study Sample | Variable | Methodology | Result |
|---|---|---|---|---|
| Yap et al. (2012) | Malaysia market from 1996 to 2005 | Sales to Working Capital | Logit | Insignificant |

### 2.4.2 Activity Ratios

Activity ratios are part of the financial ratios that could be used to indicate a firm's financial performance. Like other ratios, the activity ratios are widely used by researchers to predict financial distress (Tirapat & Nittayagasetwat, 1999; Tan & Dihardjo, 2001; Wang & Li, 2007; Abdul Manab et al., 2015). Activity ratios or efficiency ratios could be used to evaluate the firm's productivity in utilizing all firm's assets. Productivity of the firm can be viewed from many aspects such as the ability to generate sales and in managing assets.

Altman (1968) uses sales to total assets or total assets turnover as one of the predictors in his model. This ratio indicates the ability of the firm in using its assets to generate sales and the capacity of the firm's management in managing under competitive conditions. Using the multiple discriminant analysis model (MDA), Altman (1968) find that this ratio is positively significant in predicting firm failure, and it is the second largest contributor to the overall discriminating ability of the prediction model. Ong et al. (2011) include asset turnover as one of the activity ratios to predict financial distress using logit. They find that the asset turnover is negatively significant to predict firm failure in the Malaysian market. Thus, as this ratio increases, the probability of failure will decrease due to the ability of the firm in producing the product and generating the sale. Fitri and Syamwil (2020) use total asset turnover as one of the predictors in predicting financial distress. Their result shows that this ratio is negatively significant in predicting financial distress and this result aligns with Ong et al. (2011), Thai et al. (2014) and Alifiah and Tahir (2018). The study explains that a firm's financial distress risk could be reduced if a firm is able to manage and generate sales from the asset.

Ogachi et al. (2020) also include asset turnover that represents activity ratios in their prediction model. This study uses the logit model to develop a financial distress prediction model based on the Kenya market. The result shows that this ratio is positively significant to predict financial distress. Thus, activity ratios consider the crucial variables in predicting financial distress in the Kenya market. However, there are also studies such as study by Mbanwie and Edmond's (2009) that use the Mann-Whitney U (MWU) and find total sales to total assets ratio is insignificant in predicting corporate financial distress. Youn and Gu (2010) use logit model to predict financial distress in the Korean market and find sales to total assets insignificant in predicting financial distress. The result aligns with the previous study by Mbanwie and Edmond's (2009).

Some previous studies use unpopular ratios such as days' sales in receivables to predict financial distress. Ong et al. (2011) also include days' sales in receivables in predicting financial distress. The result shows that the days' sales in receivables is positively significant in predicting firm failure based on the Malaysian market. There are also previous researchers who also use other activity ratios such as Dambolena and Khoury (1980) who include activity ratios in their analysis together with other ratios. They use sales to net worth, sales to net worth of capital, sales to inventory, and cost of sales to inventory to represent activity ratios in predicting financial distress. They find that all selected ratios are insignificant for predicting financial distress. Meanwhile, Vuran (2009), also uses sales to accounts receivable, cost of goods sold to inventories, sales to current assets, sales to fixed assets, sales to tangible fixed assets, and sales to total equity to represent activity ratios as part of the variables to predict financial distress.

He concludes that the activity ratios are insignificant to predict financial distress and differentiating between financially distressed firms and healthy firms.

Although this study's literature shows a few previous studies that use activity ratios to predict financial distress, the number of studies that use activity ratios as one of the predictors is relatively smaller than other ratios. Activity ratios remain unpopular among researchers in this field, maybe due to activity ratios not being directly related to a firm's ability to meet financial obligations. However, this study believes activity ratios are also important in predicting financial distress. This is because ratios such as total asset turnover and days' sales in receivables could provide information on how a firm generates and manages its sales, which could affect the firm's cash and working capital management. Thus, it could indirectly impact the firm's ability to meet financial obligations and distress levels. Based on this argument, this study includes both ratios to represent activity ratios in predicting financial distress to ensure the developed models are based on a firm's financial aspects and aligned with the working capital management concept. This is very important to ensure the models are comprehensive and could represent the current market situation.

**Table 2.2**
*Summary of Literature for Activity Ratios.*

| Researchers | Study Sample | Variable | Methodology | Result |
|---|---|---|---|---|
| Ong et al. (2011) | Malaysia market from 2001 to 2007 | Total Assets Turnover | Logit | Negative significant |
| Fitri and Syamwil (2020) | Indonesia market from 2014 to 2018 | Total Assets Turnover | Logit | Negative significant |
| Alifiah and Tahir (2018) | Malaysia market from 2001 to 2015 | Total Assets Turnover | Logit | Negative significant |
| Thai et al. (2014) | Malaysia market from 2009 to 2013 | Total Assets Turnover | Logit | Negative significant |
| Ogachi, et al. (2020) | Kenya market | Total Assets Turnover | Logit | Positive significant |
| Mbanwie and Edmond's (2009) | Sweden market from 1996 to 2003 | Total Assets Turnover | Mann-Whitney U (MWU) | Insignificant |
| Youn and Gu (2010) | Korea market from 2000-2005 | Total Assets Turnover | Logit | Insignificant |
| Ong et al. (2011) | Malaysia market from 2001 to 2007 | Days' Sales in Receivables | Logit | Positive significant |
| Dambolena and Khoury (1980) | United State market from 1969 to 1975 | Net Worth, Sales to Net Worth of Capital, Sales to Inventory, and Cost of Sales to Inventory | MDA | All insignificant |
| Vuran (2009) | Turkey market from 1997 to 2007 | Sales To Accounts Receivable, Cost of Goods Sold to Inventories, Sales to Current Assets, Sales to Fixed Assets, Sales to Tangible Fixed Assets, And Sales to Total Equity | Logit | All insignificant |

### 2.4.3 Profitability Ratios

Profitability ratio represents the ability of the firm to generate profit (Nyamboga et al., 2014). The firm's profitability ratios indicate the ability of the firm to generate profit after meeting all of its financial obligations or debts. Thus, sufficient profit must be earned through the firm's operations to attract potential investors or creditors and obtain extra funds from existing investors and creditors. This is because the firm needs funds either from investors or creditors to survive and grow. However, if the firm failed to obtain funds due to poor profitability level, it might lead to financial distress. Similarly, if the firms cannot pay its current obligations because of poor profitability level, it could also lead to financial distress.

Earnings before interest and tax to sales (EBITS) is one of the profitability ratios that are popular among researchers such as Parker et al. (2002) and Ugurlu and Aksoy (2006). Parker et al. (2002) use earnings before interest and tax to sales (EBITS) as a proxy for return sales that represents the firm's ability to overcome financial distress. Results show that this ratio has a negative relationship with financial distress. Meanwhile, Ugurlu and Aksoy (2006) use logit model and they find that firms with a high EBITS have a high probability to be in a financially distressed situation because EBITS is found to be significant and has a higher positive relationship with financial distress as compared to firms with lower EBITS. Later study by Herlina and Murhadi (2020) that uses the Indonesian market  also obtained similar results like Ugurlu and Aksoy (2006).

However, Osho and Idowu (2018) who also include EBITS into their logit model to predict financial distress for the Nigerian market find that this variable is insignificant. This result is similar to many past studies such as Azwar (2017) and Lakshan and Wijekoon (2013). Using the Indonesia market as a study area to predict financial distress, Nur and Panggabean (2020) include EBITS into MDA and logit model. However, this study finds that EBITS is insignificant in predicting financial distress for all models that they developed. This could be due to the fact that this variable only shows the firm's ability to generate operating income and does not directly show the firm's ability in meeting interest obligation or debt obligation. Thus, the model failed to capture this ratio's effect in predicting financial distress.

Another ratio that is also popular among researchers in this area is RETA or retained earnings to total assets (Anjum, 2012; Pindado et al., 2008; Thai et al., 2014; Ugurlu & Aksoy, 2006; Yap et al., 2012). Thai et al. (2014) use RETA as one of the ratios to represent profitability in MDA to predict financial distress in Malaysia market. They explain that retained earnings are the proportion of profit that firms keep as a reserve after paying dividends to all shareholders. It also indicates the availability of the firm's internal source of capital before taking any external source of capital. If this ratio is too low, then it shows that the firm might need to take and use debt to finance its business, which leads to an increase in the probability of default. Darmawan and Supriyanto (2018) use retained earnings to total assets to represent the firm's profitability ratios to predict financial distress based on MDA. The result shows that profitability ratios have significant negative ability in predicting financial distress which align with Thai et al. (2014).

Abdul Manab et al. (2015), Waqas and Md-Rus (2018) and Nur and Panggabean (2020) use logit model and find retained earnings to total assets is negatively significant to predict financial distress. Using the hazard model to predict financial distress, Foster and Zurada (2013) also include RETA as one of the variables and find that RETA is negatively significant to predict financial distress.

However, Vo et al. (2019) who also use logit model and find a mixed result for profitability ratios represented by retained earnings to total assets (RETA) in their study. Their results show retained earnings to total assets is insignificant in predicting financial distress during the global financial crisis but during the post-global financial crisis this variable is significant to predict financial distress. They conclude the that ability of RETA to predict financial distress is different depending on the market situation.



Some researchers use ratios such as net profit margin (NPM) as a proxy for profitability (Pindado et al., 2008; Wang & Li, 2007). NPM is defined as net income divided by sales (Yap et al., 2012) and this ratio indicates the ability of the firm to generate net profit from its sales. Thus, this ratio basically focuses on the ability of the firm to generate net profit after meeting all of its obligations or debt.

Bakhri et al. (2018) use logit model in Indonesian market in predicting financial distress and include net profit margin as one of the predictors. The result shows that net profit margin is negatively significant in predicting financial distress. There are many studies that use logit models and also include net profit margin such as Alifiah & Tahir (2018), and Balasubramanian et al. (2019) and find that net profit margin consistently shows negative significant results to predict financial distress. However, these results are not consistent with those of Yap et al. (2012) who also include net profit margin in predicting financial distress for the Malaysia market. Yap et al. (2012) find that net profit margin is not significant in predicting financial distress. Herlina and Murhadi (2020) and Nur and Panggabean (2020) also find similar results as Yap et al. (2012).

Altman (1977) and Polemis and Gounopoulos (2012) use earnings before interest and taxes divided by total assets (EBITTA) as a proxy for profitability. Altman (1977) finds that the ratio is extremely beneficial in evaluating the firms' financial performance and the ability of the firm in meeting its financial obligation. Thai et al. (2014) also include this ratio into their MDA model to predict financial distress and result shows that this ratio significantly reduces the firm's financial distress risk level. This result is supported by a later study conducted by Abdul Manab et al. (2015). The study also includes this ratio in their logit model to predict financial distress. Their results show that earnings before interest and taxes divided by total assets is negatively significant in predicting financial distress based on the Malaysia market.

Using MDA, Darmawan and Supriyanto (2018) find earnings before interest and taxes to total assets is negatively significant in predicting financial distress in Indonesia. Vo et al. (2019), using logit model in Vietnam, find that this ratio is negatively influence financial distress level for both periods of during and post global financial crisis while it is not significant before the financial crisis. Thus, the predictability of profitability ratios could vary depending on the economic situation.

By using the Pakistani market, Waqas and Md-Rus (2018) find that EBITTA is negatively significant based on the logit model. Thus, any increase in EBITTA will the reduce probability of financial distress. Rafatnia et al.  also find negative significant results in Iranian market. However, Yap et al. (2012), Foster and Zurada (2013), and Nur and Panggabean (2020) using logit, hazard and MDA respectively and find that EBITTA cannot be used to predict financial distress.

Based on all these previous studies, profitability ratios are popular among researchers in predicting financial distress. Earnings before interest and tax to sales, retained earnings to total assets, net profit margin, and earnings before interest and taxes to total assets are profitability ratios commonly used by previous studies to predict financial distress. All these ratios are good representatives of profitability ratios since these ratios show a firm's ability to generate profit and manage retained earnings. However, the previous studies show that these variables' ability to predict financial distress remains inconclusive. This could be due to the factors such as differences in study location, models used to analyse data, and study periods. In order to avoid these issues, this study uses hazard and logit models to predict financial distress using a more extensive study period. This study also includes earnings before interest and tax to sales, retained earnings to total assets, net profit margin, and earnings before interest and taxes to total assets as variables to predict financial distress. This is to ensure both models capture the effect of profitability ratios in predicting financial distress. The result later hopefully could provide concrete answers on the ability of these selected profitability ratios to predict financial distress.

**Table 2.3**
*Summary of Literature for Profitability Ratios.*

| Researchers | Study Sample | Variable | Methodology | Result |
|---|---|---|---|---|
| Parker et al. (2002) | United State market from 1988 to 1996 | Earnings before interest and tax to sales | Cox Proportional Hazards Regression | Negative significant |
| Ugurlu and Aksoy (2006) | Turkey market from 1996 to 2002 | Earnings before interest and tax to sales | Logit | Positive significant |
| Osho and Idowu (2018) | Nigeria market from 2012 to 2017 | Earnings before interest and tax to sales | Logit | Insignificant |
| Azwar (2017) | Indonesia market from 2012 to 2013 | Earnings before interest and tax to sales | Logit | Insignificant |
| Lakshan and Wijekoon (2013) | Sri Lanka market from 2002 to 2008 | Earnings before interest and tax to sales | Logit | Insignificant |
| Nur and Panggabean (2020) | Indonesia market from 2015 to 2018 | Earnings before interest and tax to sales | Logit | Insignificant |
| Thai et al. (2014) | Indonesia market from 2015 to 2018 | Retained earnings to total assets (RETA) | MDA | Negative relationship |
| Darmawan and Supriyanto (2018) | Indonesia market from 2011 to 2014 | Retained earnings to total assets (RETA) | MDA | Negative relationship |

**Table 2.3**
*Summary of Literature for Profitability Ratios. (cont.)*

| Researchers | Study Sample | Variable | Methodology | Result |
|---|---|---|---|---|
| Waqas and Md-Rus (2018) | Pakistan Market from 2007 to 2016 | Retained earnings to total assets (RETA) | Logit | Negative significant |
| Nur and Panggabean (2020) | Indonesia market from 2015 to 2018 | Retained earnings to total assets (RETA) | Logit | Negative significant |
| Abdul Manab et al. (2015) | Malaysia market from 2006 to 2012 | Retained earnings to total assets (RETA) | Logit | Negative significant |
| Foster and Zurada (2013) | United State market from 2003 to 2007 | Retained earnings to total assets (RETA) | Hazard | Negative significant |
| Bakhri et al. (2018) | Indonesia market from 2014 to 2016 | Net profit margin | Logit | Negative significant |
| Alifiah & Tahir (2018) | Malaysia market from 2001 to 2015 | Net profit margin | Logit | Negative significant |
| Balasubramanian et al. (2019) | India market from 2014 to 2016 | Net profit margin | Logit | Negative significant |

**Table 2.3**
*Summary of Literature for Profitability Ratios. (cont.)*

| Researchers | Study Sample | Variable | Methodology | Result |
|---|---|---|---|---|
| Yap et al. (2012) | Malaysia market from 1996 to 2005 | Net profit margin | Logit | Insignificant |
| Herlina and Murhadi (2020) | Indonesia market from 2014 to 2018 | Net profit margin | Logit | Insignificant |
| Nur and Panggabean (2020) | Indonesia market from 2015 to 2018 | Net profit margin | MDA and Logit | Insignificant |
| Thai et al. (2014) | Malaysia market from 2009 to 2013 | Earnings before interest and taxes divided by total assets | MDA | Negative relationship |
| Abdul Manab et al. (2015) | Malaysia market from 2006 to 2012 | Earnings before interest and taxes divided by total assets | Logit | Negative significant |
| Darmawan and Supriyanto (2018) | Indonesia market from 2011 to 2014 | Earnings before interest and taxes divided by total assets | MDA | Negative relationship |

**Table 2.3**
*Summary of Literature for Profitability Ratios. (cont.)*

| Researchers | Study Sample | Variable | Methodology | Result |
|---|---|---|---|---|
| Vo et al. (2019) | Vietnam market from 2007 to 2017 | Earnings before interest and taxes divided by total assets | Logit | Negative significant |
| Waqas and Md-Rus (2018) | Pakistan Market from 2007 to 2016 | Earnings before interest and taxes divided by total assets | Logit | Negative significant |
| Rafatnia et al. (2020) | Iran market from 2000 to 2016 | Earnings before interest and taxes divided by total assets | Logit | Negative significant |
| Yap et al. (2012) | Malaysia market from 1996 to 2005 | Earnings before interest and taxes divided by total assets | Logit | Insignificant |
| Foster and Zurada (2013) | United State market from 2003 to 2007 | Earnings before interest and taxes divided by total assets | Hazard | Insignificant |
| Nur and Panggabean (2020) | Indonesia market from 2015 to 2018 | Earnings before interest and taxes divided by total assets | MDA and Logit | Insignificant |

### 2.4.4 Leverage Ratios

Leverage is one of the important elements in determining a firms' financial position. Long-term debt position of a firm is important as it will affect the capital structure of the firm (Nyamboga et al., 2014). This is because a higher level of leverage relative to equity will lead the firm to become riskier. A firm relies more on debt compared to equity needs in fulfilling a huge obligation of paying interest as well as the principal amount borrowed. Nyamboga et al. (2014) explain that this situation would also affect the profitability of the firm because of an increase in the cost of interest. As this cost keeps on increasing, the firm's operating profit will suffer which will lead to losses and finally will affect shareholders' earnings. If this situation is not managed properly by the firm, it will lead to insolvency. Hence, it shows the importance of leverage ratios, which are directly related to the debt position of the firm, especially long-term debt. Researchers like Anjum (2012), Elloumi and Gueyié (2001), Noor et al. (2012), Nyamboga et al. (2014), and Ugurlu and Aksoy (2006) use leverage ratios in predicting financial distress.

There are many ratios under leverage ratios and one of them is debt ratio. Lee and Yeh (2004) define debt ratio as total debt divided by total assets. This ratio shows the proportion of debt that is used to finance the firm's assets. Lee and Yeh (2004) shows that as the degree of financial risk increases, the probability of financial distress will also increase as indicated by the debt ratio. This aligns with earlier study by Ohlson (1980) that also finds that this ratio is positively significant in predicting financial distress.

In predicting financial distress in Sri Lanka, Lakshan and Wijekoon (2013) use debt ratio in their logit model to represent leverage elements. The result shows as the debt ratio increases, firm probability to be in financial distress will also increase. Using the Malaysia market, Ong et al. (2011) show that the debt ratio is positively significant to predict financial distress in Malaysia. They explain that a firm's level of financial distress risk increases as a firm's leverage increases. Similar results are obtained by and Yap et al. (2012) and Abdullah et al. (2019). Waqas and Md-Rus (2018) who use the Pakistani market, find debt ratio is significantly positive to predict financial distress. Thus, it clearly shows that leverage affects financial distress.

Abdullah and Ahmad (2005) use shareholders' funds to total liabilities (SFTD) to represent capital structure. Using the logit model, they find that this ratio directly influences financial distress in Malaysia. Similarly, Darmwan and Supriyanto (2018) obtain similar results in Indonesia, which indicates SFTD is important to predict financial distress.



Abdul Manab et al. (2015) show SFTD does not influence financial distress, which does not support the findings of Abdullah and Ahmad (2005). Vo et al. (2019) examine the financial distress prediction models in Vietnam based on economic conditions. They find that this ratio is only negatively significant for the post-global financial crisis. The results indicate that the ability of SFTD to predict financial distress depends on economic conditions.

Fich and Slezak (2008), Youn and Gu (2010) and Chen et al. (2013) incorporate financial cost factors such as interest coverage ratio (ICR), which is measured by dividing operating income with interest expenses, to predict financial distress. Youn and Gu (2010) explain that this ratio shows the ability of the firm in meeting its interest repayment obligation, which is essential for measuring the solvency of the firm. Using the logit model, Youn and Gu (2010) find this ratio shows negative significant results in predicting financial distress. This shows that if a firm has a high-interest coverage ratio, the probability of financial distress will be lower. They explain that ICR contains information such as a firm's earnings, level of productivity, interest payment ability, and firm's indebtedness. Waqas and Md-Rus (2018) obtain similar results and highlight that this ratio is essential in developing prediction models since it relates to a firm's ability in managing debts. However, Parker et al. (2002) find that this variable is not significant in predicting financial distress by using hazard model. This finding is supported by Abdullah and Ahmad (2005) who find that ICR cannot predict financial distress.



Ugurlu and Aksoy (2006) use long-term debt to total debt ratio. They find that this ratio influences financial distress negatively. They explain that low equity levels together with heavy reliance on short-term liabilities in financially distressed firms indicate severe liquidity problems which increase the risk of financial distress. According to all these previous studies, two elements in leverage ratios could predict financial distress: capital structure and the ability to meet financing costs. Both elements are essential as these elements could affect the ability of the prediction model to predict financial distress. Thus, the inclusion of ratios such as debt ratio, shareholders' funds to total liabilities, long-term debt to total debt ratio, and interest coverage ratio could help capture both elements' effect in predicting financial distress. Although previous studies were conducted in various locations and using various analysis models, the results obtained for ratios that represent both elements of leverage ratios are pretty similar and commonly found to be significant. These results also aligned the trade-off theory that firms should try to balance the optimal capital structure and bankruptcy cost. Thus, this study includes debt ratio, shareholders' funds to total liabilities, and long-term debt to total debt ratio as variables to capital structure elements of the leverage ratios. This study also uses the interest coverage ratio to capture the effect of the ability to meet financing costs to predict financial distress. The use of all these ratios ensures the models develop comprehensively and include all essential elements in predicting financial distress.

**Table 2.4**
*Summary of Literature for Leverage Ratios.*

| Researchers | Study Sample | Variable | Methodology | Result |
|---|---|---|---|---|
| Lee and Yeh (2004) | Taiwan market from 1996 to 1999 | Debt ratio | Logit | Positively significant |
| Sori et al. (2001) | Malaysia market from 1980 to 1996 | Debt ratio | MDA | Positively significant |
| Lakshan and Wijekoon (2013) | Sri Lanka market from 2002 to 2008 | Debt ratio | Logit | Positively significant |
| Ong et al. (2011) | Malaysia market from 2001 to 2007 | Debt ratio | Logit | Positively significant |
| Yap et al. (2012) | Malaysia market from 1996 to 2005 | Debt ratio | Logit | Positively significant |
| Abdullah et al. (2019) | Malaysia market (non-listed) from 2000 to 2010 | Debt ratio | Logit | Positively significant |
| Waqas and Md-Rus (2018) | Pakistan Market from 2007 to 2016 | Debt ratio | Logit | Positively significant |
| Abdullah and Ahmad (2005) | Malaysia market from 2000 | Shareholders’ fund to total liabilities | Mda | Insignificant |
| | | | Logit | Positively significant |
| Darmwan and Supriyanto (2018) | Indonesia market from 2011 to 2014 | Shareholders’ fund to total liabilities | Logit | Positively significant |

**Table 2.4**
*Summary of Literature for Leverage Ratios. (cont.)*

| Researchers | Study Sample | Variable | Methodology | Result |
|---|---|---|---|---|
| Abdul Manab et al. (2015) | Malaysia market from 2006 to 2012 | Shareholders' fund to total liabilities | Logit | Insignificant |
| Vo et al. (2019) | Vietnam market from 2007 to 2017 | Shareholders' fund to total liabilities | Logit | Negative significant only on post-global financial crisis |
| Youn and Gu (2010) | Korea market from 2000-2005 | Interest coverage ratio | Logit | Negative significant only on post-global financial crisis |
| Waqas and Md-Rus (2018) | Pakistan Market from 2007 to 2016 | Interest coverage ratio | Logit | Negative significant only on post-global financial crisis |
| Parker et al (2002) | United State market from 1988 to 1996 | Interest coverage ratio | Hazard model | Insignificant |
| Abdullah and Ahmad (2005) | Malaysia market from 2000 | Interest coverage ratio | Logit | Insignificant |
| Ugurlu and Aksoy (2006) | Turkey market from 1996 to 2002 | Long-term debt to total debt | Logit | Negative significant only on post-global financial crisis |

## 2.5 Determinants of Stock Return

### 2.5.1 Financial Distress Risk

Researchers like Dichev (1998), Md-Rus (2011), and Shumway (1996) define financial distress risk as probability of financial distress based on the financial distress prediction model. In early study by Shumway (1996), it is found that average return is strongly and positively related to distress risk even during the period that it is weakly correlated to size or another firm's characteristic. Thus, it shows that high financial distress risk increases the average stock return. Shumway's study is unique because instead of using the Z-score and the O-score, this study uses the hazard model to generate the probability of distress before estimating its relationship with the return.

Using a similar approach as Shumway (1996), Md-Rus (2011) uses UK firms to study the relationship between financial distress and stock return. This study uses the hazard model in developing a prediction model and uses it to generate financial distress. The study finds that financial distress risk is not significant to affect the excess return. The similar result is also obtained by Mselmi, et al. (2019) who examine financial distress as part of systematic risk in the stock returns for the French stock market. This study finds that financial distress is consistently insignificant to priced stock return for financial distress portfolios in most of the models developed.

The similar result obtained by Boubaker et al. (2018) who examine whether financial distress risk is a systematic risk using twelve portfolios sorted by size, book-to-market, and leverage and a portfolio of distressed firms covering 18 years. The main goal of this study is to identify the risk factors that best capture the default risk in the French context. The result shows that the risk premium for the relative distress factor based on probability of distress is positively significant only for the distressed firm portfolio. In the current study by Chhapra et al. (2020) that investigates the relationship between financial distress risks based on O-score and stock returns for the Pakistan stock market using monthly returns from 2001 to 2016. The result shows that stocks of firms significantly exposed to undiversified financial distress risk yield higher returns. All these significant positive results are aligned with the risk-return trade-off theory that states risky investments should be compensated with high returns. Although these studies use various approaches to measure financial distress risk, the results indicate that distress risk could be a risk factor that could increase return. The main reason for the phenomenon is that distressed firm commonly tries to improve their financial position and avoid being delisted from the stock market. Thus, as this firm's financial position improves, the demand for the stock also improves, which leads to an increase in stock price and return.



There are also studies that use pre-determined prediction models such as Altman Z-score and Ohlson O-score to represent distress risk in estimating return. Dichev (1998) uses both Z-score and O-score to measure financial distress risk. The result shows that high financial distress risk firms significantly earn lower average returns as compared to low financial distress risk firms. Similarly Malik et al. (2013) also use Z-score to represent financial distress risk in investigating its effect on stock return in emerging markets. The result shows as financial distress risk increases, it significantly reduces stock return. Although these studies also use similar approaches in measuring financial distress, like those that show significant positive results, the results obtained are unique since the results show distress risk negatively significant to effect return. These contradicted to risk return trade-off theory that explains the correlation between risk and return should be positive. One of the possible reasons is that investors are more attracted to low distress risk firms and avoid investing in distressed firms with a higher risk level. This situation leads to a drop in distressed firms' stock prices, makes the stocks less attractive to investors, and decreases returns.

However, there are also studies that find distress risk is insignificant to affect return such as study by Samad et al. (2009), Husein and Mahfud (2015), and Idrees and Qayyyum (2018) Sudirgo et al. (2019). Samad et al. (2009), Husein and Mahfud (2015), and Sudirgo et al. (2019) uses Z-score to measure distress risk and use it to determine stock return. The results show distress risk is insignificant to effect returns. Meanwhile, Idrees and Qayyyum (2018) use O-score to represent financial distress risk in investigating the relationship of financial distress risk and the equity returns of financially distressed firms listed on the Pakistan Stock Exchange (PSX). These previous studies' results indicate that distress risk does not affect stock returns. Investors ignoring the distress risk due to difficulty in estimating the risk could have led to the estimation model failing to capture the effect of distress on return.

The study by Li et al. (2017) focus on markets such as Australia, Hong Kong, Indonesia, Korea, Malaysia, Singapore, Thailand within the period of 1995 to 2009 also used Z-score to measure distress risk in determining stock returns. The study finds that financial distress serves as additional factors in determining the return in these Asian-Pacific markets since it gives various impacts on stock returns in different markets. They explain that the financial distress, like the momentum factor, is a separate and significant factor that may affect asset pricing in these seven Asian-Pacific markets. There are also studies that use different definitions for financial distress risk such as

Simlai (2014) who tries to use momentum in representing the financial distress effect on return. However, they find that the momentum portfolio is not suitable to represent distress risk although it might be useful to explain the time-variation in the average returns for low-distressed portfolios. This study also suggests that future researchers should focus on finding evidence on the relationship between systematic risk and financial distress risk in explaining the negative distress risk premium.

Based on all these previous studies, previous studies obtained inconclusive results explaining the relationship between distress risk and returns. Previous studies also show that using pre-determined prediction models such as O-score and Z-score in measuring financial distress risk leads to inconsistent results on the relationship between distress risk and return. In order to overcome this issue, this study develops its prediction models and uses them to measure distress risk. This study avoids using the pre-determined prediction model to ensure the reliability of the measured financial distress probability. Thus, the return estimation model could provide a clear picture of the relationship between distress risk and return.

**Table 2.5**
*Summary of Literature for Financial Distress Risk.*

| Researchers | Study Sample | Variable | Methodology | Result |
|---|---|---|---|---|
| Shumway (1996) | United State market from July 1963 to December 1993 | Probability of financial distress | Panel data regression | Positive significant |
| Boubaker et al. (2018) | France Market from 1995 to 2012 | Probability of financial distress | Fama and French Factor model | Positive significant |
| Md-Rus (2011) | United Kingdom market from 1988 to 1997 | Probability of financial distress | Fama and French Factor model | Insignificant |
| Mselmi et al. (2019) | France Market from 1998 to 2012 | Probability of financial distress | Fama and French Factor model | Insignificant |
| Dichev (1998) | United State market from 1981 to December 1995 | Z-score and O-score | Fama MacBeth Regression | Negative significant |
| Malik, Aftab, and Noreen (2013) | Pakistan Market from 2006 to 2011 | Z-score | Correlation matrix | Negative significant |
| Conover 2017 | Australia, Hong Kong, Indonesia, Korea, Malaysia, Singapore, and Thailand market from 1995 to 2009 | O-score | Fama and French Factor model | Significant |
| Chhapra et al. (2020) | Pakistan Market from 2001 to 2016 | O-score | Fama and French Factor model | Positive significant |
| Samad (2009) | Malaysia market | Z-score | Fama and French Factor model | Insignificant |

**Table 2.5**
*Summary of Literature for Financial Distress Risk. (Cont.)*

| Researchers | Study Sample | Variable | Methodology | Result |
|---|---|---|---|---|
| Husien and Mahfud (2015) | Indonesia market from 2009 to 2013 | Z-score | Regression | Insignificant |
| Idrees and Qayyum (2018) | Pakistan Market from 2010 to 2016 | O-score | Fama and French Factor model | Insignificant |
| Sudirgo et al. (2019) | Indonesia market from 2015 to 2017 | Z-score | Panel data regression | Insignificant |
| Simlai (2014) | United State market from 1972 to December 2008 | Momentum | Fama and French Factor model | Momentum not suitable to represent financial distress risk |

### 2.5.2 Firms' Size

In an early study by Banz (1981), firms' size effect towards stock return is the first discovered. He finds that firms with small market capitalisation give high returns while firms with big market capitalisation only generate low returns. Using Fama-MacBeth regression, Dichev (1998) and Avramov and Chordia (2006) incorporate logarithm of the individual firm market capitalisation measure in billions of dollars to represent size as one of the risk factors to affect stock return. Both studies find that size is negatively significant in affecting return. There are also studies in emerging markets such as Husein and Mahfud (2015) that use the Indonesia market as a study area in determining the relationship between size and returns. Their results show size is negatively significant to affect stock returns. Aziz and Ansari (2016) and Ferdaous and Barua (2020) in later studies also obtain similar results. The possible explanation for these results is that small market capitalization stocks are more volatile than large market capitalization stocks. Thus, this could lead to high return potential for small firm stocks. However, there is another approach to examining the effect of size on returns which might lead to different results.



Instead of directly use market capitalization to represent size factor, Fama and French (1993) introduce small-minus-big (SMB) in three-factor model (FF model) as a proxy for size to mimic the risk that is related to return on the size. They find that size gives a significant effect towards stock returns. Similarly Connor and Sehgal (2001) use the Indian stock market to test the three-factor model . They find that size has a positive significant effect on stock return in the Indian market. Thus, as a whole, this study supported the findings by Fama and French (1993). Using the same approach as Fama and French (1993), Simlai (2009) finds that size is positively significant in capturing variations in stock return over time. He also finds that persistence in volatility is significant in improving the impact of size and book-to-market sorted portfolio in explaining time series variation. Taneja (2010) later obtains a similar result to Simlai (2009), which shows that size is one of the factors that helps to improve the performance of CAPM.

Following the steps of Taneja (2010), Hassan and Javed (2011) use the Pakistan stock market to examine the relationship between size, value, and the stock market by using three-factor model. The researchers used 250 stocks that are listed on the Karachi Stock Exchange from June 2000 to June 2007. The result shows that size has a significantly positive effect on portfolio return. Sehgal and Balakrishnan (2013) revisit the study by Connor and Seghal (2003) but use 1996 to 2010 as the study period. The result confirms Connor and Seghal's (2003) finding that size factor has a significant effect on returns. Lindaas and Simlai (2016) report that size has a positive significant effect on average return and conditional volatility of benchmark stock portfolios. His result is supported by Das and Barai (2016) as they also find that size is positively significant to influence the expected return. Ong et al. (2018) use the Malaysian market to examine the effect of size based on SMB on return. The result shows size gives a positive significant effect on stock return in Malaysia. This result aligns with previous study by Teh and Lau (2017) and Gunathilaka et al. (2017), and supported by later studies by Abu Bakar and Rosbi (2019) and Hoque, Wah, and Shah Zaidi (2020).

However, Aziz and Ansari (2014) later argue against Taneja's (2010) result since its only represents a specific sample, which is too short and too small since he only uses the 2004 to 2009 period as his study period and only includes 187 stocks as the sample of the study. This is because Aziz and Ansari (2014) find return on large stock is lower than small stock and this result is statistically and economically significant. Similarly, Boubaker et al. (2018) results show that size is negatively significant in determining returns and could be concluded as one of the systematic risks in the stock market. This result is similar to the later study by Mselmi et al. (2019) that confirms the finding by Boubaker et al. (2018).

Based on all these studies' results, both SMB and market capitalization could represent the size factor since they significantly affect the return. Although these variables could have either positive or negative significant results, they clearly show the importance of the size factor to effect return. Previous studies also used various types of analysis methods, such as Fama-MacBeth regression and Fama-French factors models, which could be one of the reasons behind the inconclusive results on the effect of size factor on the return. Based on previous studies, this study includes the size factor as one of the risk factors in examining the determinants of stock return using Fama-MacBeth regression. Instead of using SMB, this study uses market capitalization to represent the firm size. This is because SMB is more suitable for examining the effect of size-based investment strategies on return. Meanwhile, this study only focuses on the effect of size on return and ignores the effect of investment strategies. Thus, the use of market capitalization is more appropriate for this study.

**Table 2.6**
*Summary of Literature for Firm's Size.*

| Researchers | Study Sample | Variable | Methodology | Result |
|---|---|---|---|---|
| Dichev (1998) | United State market from 1981 to December 1995 | Market capitalisation | Fama-MacBeth Regression | Negative significant |
| Avramov and Chordia (2006) | United State market from 1964 to 2001 | Market capitalisation | Fama-MacBeth Regression | Negative significant |
| Husien and Mahfud (2015) | Indonesia market from 2009 to 2013 | Market capitalisation | Regression | Negative significant |
| Aziz and Ansari (2016) | India market from 2000 to 2014 | Market capitalisation | Fama-MacBeth Regression | Negative significant |
| Ferdaous and Barua (2020) | Bangladesh market from 2009 to 2019 | Market capitalisation | Fama-MacBeth Regression | Negative significant |
| Connor and Sehgal (2001) | India market from 1989 to 1999 | Small-minus-big (SMB) | Fama and French Factor model | Positive significant |
| Simlai (2009) | United State market from 1926 to 2007 | Small-minus-big (SMB) | Fama and French Factor model | Positive significant |
| Taneja (2010) | India market from 2004 to 2009 | Small-minus-big (SMB) | Fama and French Factor model | Positive significant |
| Hassan and Javed (2011) | Pakistan market 2000 to 2007 | Small-minus-big (SMB) | Fama and French Factor model | Positive significant |
| Sehgal and Balakrishnan (2013) | India market from 1996 to 2010 | Small-minus-big (SMB) | Fama and French Factor model | Positive significant |
| Aziz and Ansari (2014) | India market from 2002 to 2012 | Small-minus-big (SMB) | Fama and French Factor model | Negative significant |

**Table 2.6**
*Summary of Literature for Firm's Size. (Cont.)*

| Researchers | Study Sample | Variable | Methodology | Result |
|---|---|---|---|---|
| Lindaas and Simlai (2016) | United State market from 1963 to 2011 | Small-minus-big (SMB) | Fama and French Factor model | Positive significant |
| Das and Barai (2016) | India market from 1998 to 2013 | Small-minus-big (SMB) | Fama and French Factor model | Positive significant |
| Boubaker et al. (2018) | France Market from 1995 to 2012 | Small-minus-big (SMB) | Fama and French Factor model | Negative significant |
| Mselmi et al. (2019) | France Market from 1998 to 2012 | Small-minus-big (SMB) | Fama and French Factor model | Negative significant |
| Ong et al. (2018) | Malaysia market from 2005 to 2015 | Small-minus-big (SMB) | Fama and French Factor model | Positive significant |
| Abu Bakar and Rosbi (2019) | Malaysia market from 2016 to 2018 | Small-minus-big (SMB) | Fama and French Factor model | Positive significant |
| Gunathilaka et al. (2017) | Malaysia market from 2000 to 2013 | Small-minus-big (SMB) | Fama and French Factor model | Positive significant |
| Hoque et al. (2020) | Malaysia market from 2010 to 2018 | Small-minus-big (SMB) | Fama-MacBeth Regression | Positive significant |
| Teh and Lau (2017) | Malaysia market from 2001 to 2015 | Small-minus-big (SMB) | Fama-MacBeth Regression | Positive significant |

### 2.5.3 Firms' Value

Another risk factor that is commonly used to determine stock returns is book-to-market ratio. Previous studies such as Boubaker et al. (2018), Dichev (1998), Ferdaous and Barua (2020), Kothari and Shanken (1997) use this ratio in various ways to capture the effect of value on stock returns. Early study by Kothari and Shanken (1997) directly uses book-to-market ratio as a representative of the value factor to predict the market return in Dow Jones Industrial Average Index (DJIA). Using Ordinary Least Square (OLS), they find that book-to-market ratio positively significant to affect expected returns. Similarly, Bryant and Eleswarapu (1997) use New Zealand market data and find that book-to-market ratio has a significantly positive effect on stock market return. Lau, Lee, and McInish (2002) compare the effect of risk factors on return in the Malaysia and Singapore market. The result shows book-to-market ratio is positively significant in affecting return.



Avramov and Chordia (2006) include book-to-market ratio as one of the independent variables in Fama-MacBeth regression. Results show that this variable has a consistent positive significant effect on stock return and the effect can be captured by the various asset pricing models tested. Studies like Cordeiro da Cunha Araújo and André Veras Machado (2018), Novak and Petr-Petr's (2010), and  Yuliarto Nugroho (2020) also obtain similar results which book-to-market ratio that represents value is positively significant to affect return. Aziz and Ansari (2014) find high value stocks generate higher return compared to growth stocks, which are economically and statistically significant in affecting returns.

Husein and Mahfud (2015) use book-to-market ratio to represent value in determining stock return in the Indonesian market. However, the result shows this variable is negatively significant to affect returns. Thus, they conclude that firms with high book-to-market are expected to generate lower returns compared to firms with low book-to-market ratios. Meanwhile, Idrees and Qayyyum (2018) use unbalanced panel data from the Pakistan Stock Exchange (PSX) to examine the relationship between risk factors including book-to-market with stock returns. However, the result shows that book-to-market equity is insignificant to determine the stock returns of distress firms. They suggest that it could be due to the inefficiency of the Pakistan stock market. All these results show that the book-to-market ratio could represent the value factor in explaining the determinants of stock returns. However, previous studies obtained mixed results on the book-to-market effect on return. It could be due to the inability of the ratios to capture the effect of value on return consistently. Due to this issue, some researchers extend the book-to-market ratio to generate a high- minus low-value portfolio (HML) variable to represent the value effect in determining the stock return. HML is expected to produce a more consistent result in capturing the effect value on return.

Instead of directly using book-to-market ratio, Fama and French (1993) use book-to-market ratio (BE/ME) in forming high- minus low-value portfolio (HML) that is used as a proxy for portfolio mimicking risk that affects return related to BE/ME. The results show on average that BE/ME has a negatively significant effect on average stock return and conclude that the three-factor model can capture each factor's effect on average return better than CAPM. Using the Indian market, Connor and Sehgal (2001) also use the three-factor model and find HML has a positive significant effect on market return and reject the null hypothesis of joint significance for CAPM. Therefore, as a whole, this study results are similar to Fama and French (1993).

Aleati, Gottardo, and Murgia (2000) use the Italian market to determine the relationship between risk factors like SMB and HML with average stock returns. The results show HML has a positive significant effect on average stock returns and can be captured by cross-section average returns. Using both unconditional model and conditional model, Das and Barai (2016) find that HML has a positive significant effect on expected return and the effect of this factor is the strongest among all of the factors used in the model. This indicates that investors choose the stock to be invested based on the value of the stock. This study further explains that book-to-market ratio is consistently similar to factors meant for both models. This is similar to Lindaas and Simlai (2016) who also find that HML with positive sign has economically and statistically significant effect on return.



Taneja (2010) examines the effect of size and value towards the performance of CAPM and finds HML is negatively significant, which contradicts Fama and French (1993), Brayant and Eleswarapu (1997), and Davis et al. (2000). Later study by Boubaker et al. (2018) in the French stock market find that HML is negatively significant to affect the stock returns. This is similar to finding by Taneja (2010). However, Chhapra et al. (2020) in later study aims to verify a role played by financial distress in the pricing of Pakistani distressed and non-distressed portfolios within the period of January 2001-December 2016. The result shows book-to-market insignificant to price stock in Pakistan stock market, which confirms the suggestion by Idrees and Qayyyum (2018).

There are also studies that use the Malaysia market but the results are inconclusive (Abu Bakar & Rosbi, 2019; Mohmmad Enamul Hoque et al., 2020; Teh & Lau, 2017). Abu Bakar and Rosbi (2019) and Gunathilaka et al. (2017) also define value as HML in the factor model and find that value is positively significant to effect returns. However, this contradicts the studies by Hoque et al. (2020) and Teh and Lau (2017) that find HML that represents value in determining returns in the Malaysia market is negatively significant to effect returns. Similar to the book-to-market ratio, the works of literature also show mixed results on the effect of HML on return. There are two significant findings on the relationship between value and return, which are negative or positive significance to effect return. The negative relationship between value and return could be due to the high growth potential among growth firms compared to value firms. This leads to a high-risk situation that should generate higher returns. Meanwhile, results showing a significant positive relationship between value and return could be due to growth firms having a higher risk than value firms. Thus, investors, especially corporate investors, are more attracted to invest in value stocks, which increases the demand and price of value stocks and leads to higher returns than growth stocks.

According to previous studies and researcher observations, the mixed results for book-to-market and HML are due to study locations, the definition of value, and the analysis approach. Thus, this study includes value as one of the risk factors to determine the return. This study uses the book-to-market ratio to represent the value factor instead of HML because this ratio is more appropriate to capture the effect of value on return. HML is only suitable for a study focusing on the effect of value-based investment strategies on return. The result of this study hopefully could provide a clearer picture of the effect of value on return.

**Table 2.7**
*Summary of Literature for Firm's Value.*

| Researchers | Study Sample | Variable | Methodology | Result |
|---|---|---|---|---|
| Kothari and Shanken (1997) | United State market from 1926 to 1991 | Book-to-market ratio | OLS | Positive significant |
| Bryant and Eleswarapu (1997) | New Zealand market from 1971 to 1993 | Book-to-market ratio | OLS | Positive significant |
| Lau et al. (2002) | Malaysia and Singapore from 1988 to 1996 | Book-to-market ratio | OLS | Positive significant |
| Avramov and Chordia (2006) | United State market from 1964 to 2001 | Book-to-market ratio | Fama-MacBeth Regression | Positive significant |
| Aziz and Ansari (2014) | India market from 2000 to 2014 | Book-to-market ratio | Fama-MacBeth Regression | Positive significant |
| Husien and Mahfud (2015) | Indonesia market from 2009 to 2013 | Book-to-market ratio | Regression | Negative significant |
| Idrees and Qayyum (2018) | Pakistan Market from 2010 to 2016 | Book-to-market ratio | Fama and French Factor model | Insignificant |
| Connor and Sehgal (2001) | India market from 1989 to 1999 | High-minus-low (HML) | Fama and French Factor model | Positive significant |
| Aleati et al. (2000) | Italy market from 1981 to 1993 | High-minus-low (HML) | Fama and French Factor model | Positive significant |
| Das and Barai (2016) | India market from 1998 to 2013 | High-minus-low (HML) | Fama and French Factor model | Positive significant |
| Lindass and Simlai (2016) | United State market from 1963 to 2011 | High-minus-low (HML) | Fama and French Factor model | Positive significant |

**Table 2.7**
*Summary of Literature for Firm's Value. (Cont.)*

| Researchers | Study Sample | Variable | Methodology | Result |
|---|---|---|---|---|
| Taneja (2010) | India market from 2004 to 2009 | High-minus-low (HML) | Fama and French Factor model | Negative significant |
| Chhapra et al. (2020) | Pakistan Market from 2001 to 2016 | High-minus-low (HML) | Fama and French Factor model | Insignificant |
| Abu Bakar and Rosbi (2019) | Malaysia market from 2016 to 2018 | High-minus-low (HML) | Fama and French Factor model | Positive significant |
| Gunathilaka et al. (2019) | Malaysia market from 2000 to 2013 | High-minus-low (HML) | Fama and French Factor model | Positive significant |
| Hoque et al. (2020) | Malaysia market from 2010 to 2018 | High-minus-low (HML) | Fama-MacBeth Regression | Negative significant |
| Teh and Lau (2017) | Malaysia market from 2001 to 2015 | High-minus-low (HML) | Fama-MacBeth Regression | Negative significant |

### 2.6 Summary

This chapter focuses on reviewing previous studies that highlights the relevant underlying theories, prediction of financial distress, and factors affecting excess return. Discussion on the underlying theories for this study focuses on the pecking order theory, and trade-off theory that are important in supporting the development of the prediction model for this study. The assets pricing model is used to explain the relationship between risk factors and return. This chapter also discusses the predictive model in terms of the variables used to predict financial distress. The last part of this chapter discusses the risk factors that affect return including financial distress risk, which directly shed some light on determining whether financial distress risk is a systematic risk. Next, the research framework and the methodology for this study will be developed and discussed in the next chapter.

# CHAPTER 3

# METHODOLOGY

## 3.0 Introduction

This chapter focuses on explaining the method used to achieve all of the objectives set in this study. The discussion within this chapter is divided into five major sections. This chapter starts with the first section which explains the theoretical framework including an explanation of all the related variables used in this study. This is continued by the following section which discusses the process of sample selection and data collection, followed by a section on the method used. This is then followed by an explanation of the hypothesis testing, and the final section summarises the chapter.



## 3.1 Theoretical Framework

Two theoretical frameworks are used to fulfill the research objectives. The first framework focuses on the factors affecting the probability of financial distress that is used to achieve objectives 1 and 2. The framework shows in Figure 3.1. Based on this framework, the independent variables are liquidity, activity, profitability, and leverage ratios. Meanwhile the dependent variable is the financial distress probability. The probability of financial distress generated from this model is used as one of the independent variables in determining returns.

### 3.1.1 Predicting Financial Distress

Based on the idea of trying to predict financial distress, Beaver (1966) is the first study that uses firms' specific financial characteristics to predict financial distress. According to this early study, financial ratios are helpful predictors in developing the prediction model. Financial ratios are more proper to portray firms' financial condition and could provide some outlook on firms' future conditions. Since financial distress represents firms' poor financial condition, financial ratios are crucial in predicting it and measuring the probability of financial distress. Based on this concept, researchers like Altman (1968) and Ohlson (1980) developed Z-score and O-score, respectively, that are useful to measure financial distress probability. The concept of predicting financial distress continues by later researchers using various types of financial ratios (Shumway, 2001; Abdullah & Ahmad, 2005; Foster & Zurada, 2013; Waqas & Md-Rus, 2018). Although there are many previous studies in this area, no specific theory directly explains the relationship between financial ratios and financial distress. However, a few concepts and theories, such as working capital management, pecking order theory, and trade-off theory of capital structure, explain the relationship between a firm's specific financial characteristics and their indirect impact on financial distress.

According to the working capital management concept, it is crucial for a firm to correctly manage the working capital since it directly affects the firm's level of profitability and risks (Smith, 1980). Working capital management focuses on maintaining optimal working capital components such as cash, account receivables, inventories, and account payables. Afzar and Nazir (2009) further explain that working capital management is a trade-off between profitability and risk based on the firm's current assets and current liabilities. Thus, it indirectly shows that poor financial performance that leads to financial distress could be due to poor working capital management. Since working capital represents a firm's liquidity, this also shows that a firm's liquidity could lead to poor financial performance and distress. This explains why many previous studies, such as Youn and Gu (2010), Foster and Zurada (2013), Alifiah and Tahir (2018), and Fitri and Syamwil (2020), include liquidity and activity ratios as predictors in predicting financial distress.

The firm's current assets and current liabilities represent working capital liquidity elements. Both elements provide information on how firms manage current assets and short-term obligations. Researchers like Mbanwie and Edmond (2009), Elloumi and Gueyie (2001), Abdul Manap et al. (2015), and Darmawan and Supriyanto (2018) use liquidity ratios as predictors in predicting financial distress. By using liquidity ratios in predicting financial distress, it provides evidence of the effect of a firm's liquidity management on financial distress risk. The liquidity ratios also show the ability of firms to meet short-term obligations, which also affect the firm's distress risk level. Based on the working capital management concept and evidence from previous studies, liquidity ratios are essential in predicting financial distress. Thus, this study includes liquidity and activity ratios such as current ratio, working capital to total assets, sales to working capital, sale to total assets, and day's sales in account receivables as predictors. This study expects that firms with a low ability to meet short-term obligations might have poor financial performance, leading to an increased risk of financial distress.

Another theory that links to the study on predicting financial distress is the pecking order theory. According to this theory, firms finance their business using internal and external sources of funds (Myers & Majluf, 1984). In detail, this theory assumes that firms prioritise using internal sources of funds such as retained earnings and profit. However, once firms' internal funds are fully exhausted, firms would shift to external sources of funds, starting with debts. Next, firms would raise funds using equity once debts are no longer enough to finance the business activities. However, firms less prefer the use of external funds since it could provide a negative signal about firms' financial position. If firms increase funds using debt, it could increase the risk level, especially default risk. Meanwhile, if a firm increases funds by issuing new equity, it could lead to a decreasing proportion of ownership in the firm, which is not a favorable situation for investors.

According to this theory, high profitability firms commonly have significant internal funds. They tend to have lower leverage or debt financing since firms finance their business activity and investment using only internal funds (Shyam-Sunder & Myers, 1999). From the risk perspective, internal funds are less risky than external funds like loans and bonds that create financial obligations. Thus, firms that increase their debt would increase their obligations and lead to an increase in default risk if they fail to meet the obligations, which could also lead to an increase in financial distress risk. Based on this idea, researchers like Yap et al. (2012), Thai et al. (2014), and Nur and Panggabean (2020) include profitability ratios to represent firm profitability in predicting financial distress. Thus, the inclusion of profitability ratios such as operating profit margin, retained earnings to total assets, net profit margin, and earnings before interest and taxes to total assets in this study are crucial as the ratios align with pecking order theory and evidence from previous studies.

The trade-off theory of capital structure is another theory that links firms' specific characteristics with financial distress. According to this theory, firms should manage their capital structure to balance the benefits and costs of debts. In detail, this theory states that firms' leverage level is based on balancing the tax-saving benefits of debts against the cost of bankruptcy. The theory further explains that as firms increase their debts beyond a certain point (optimal capital structure point), it could increase the cost of financing. As this cost increases, it could lead to an increase in default risk and financial distress risk. Thus, managing capital structure is crucial for firms to reduce risk and maintain their financial position. Based on this concept, Abdullah and Ahmad (2005), Youn and Gu (2010), Lakshan and Wijekoon (2013), and Vo et al. (2019) used leverage ratios based on a firm's capital structure information as predictors in predicting financial distress. Thus, the inclusion of leverage ratios in financial distress prediction models could provide evidence of how a firm's capital structure affects a firm's financial position and financial distress risk level. Based on previous study results and the concept of the trade-off theory of capital structure, this study also includes debt ratio, long-term debt to total debt ratio, shareholders fund to total debt, and interest coverage ratio in predicting distress. These ratios help ensure that this study's prediction models are relevant and reliable in predicting financial distress based on the Malaysian market. Based on all theories and evidence, this study develops an operational framework to be used in this study, as shown in Figure 3.1

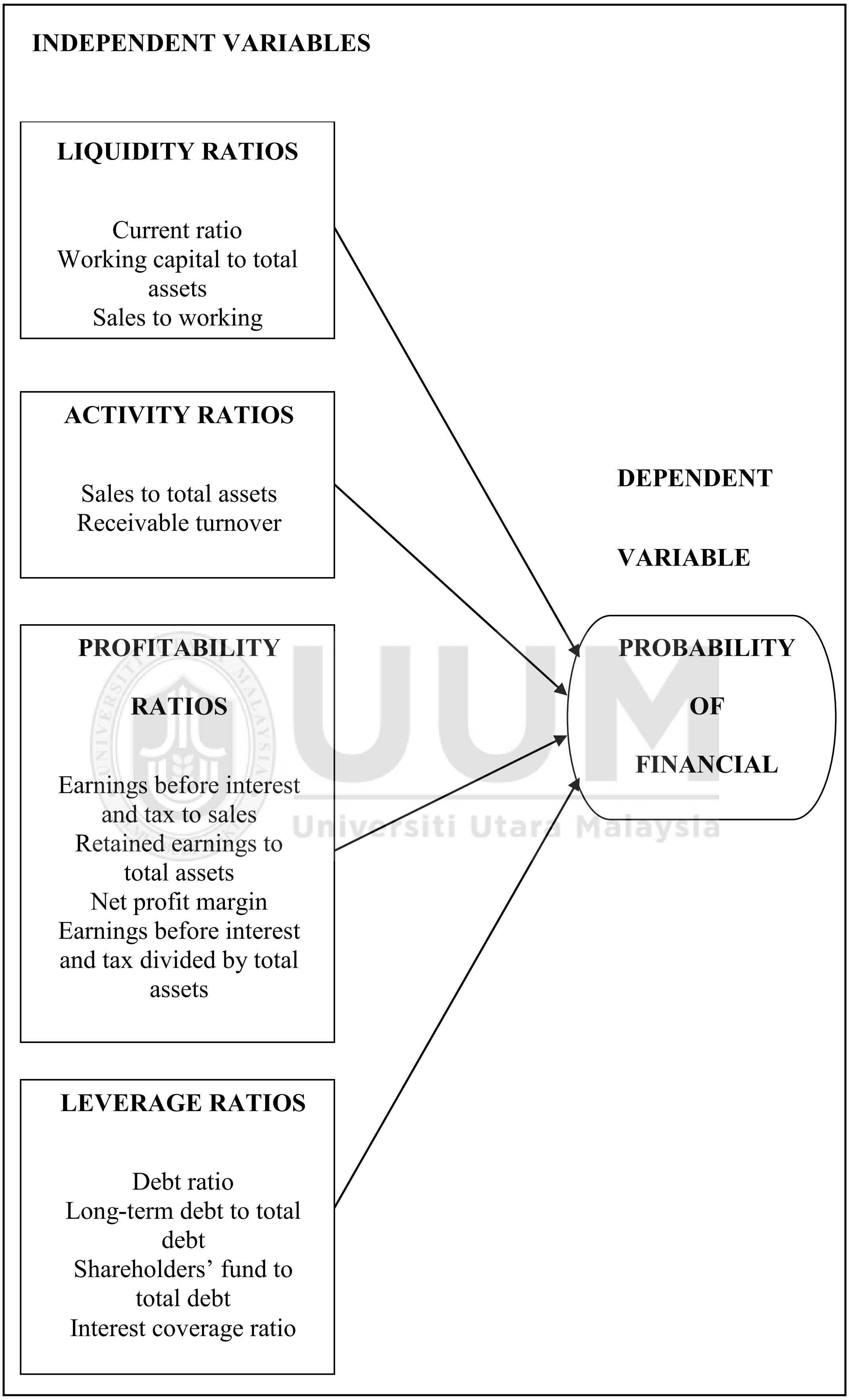


Figure 3.1:
*Financial Distress Prediction Framework*

### 3.1.2 Determinants of Return

The second framework is to study the factors affecting returns. This framework is to achieve objectives 3 and 4. The relationship between risk factors is commonly explained based on Arbitrage Pricing Theory (APT), introduced by Ross (1976). This theory is to overcome criticism of CAPM, which assumes that only market risk is the only factor affecting stock return. According to APT, more than one factor affects stock returns, making APT more realistic. Thus, risk factors based on unsystematic risks, such as financial and business risks, could be used to estimate stock returns. Although APT did not specify factors suitable to explain return, it helped lay the foundation for later studies to include various risk factors to affect the return.

This concept also led Fama and French (1993) to introduce a three-factor model to explain stock return and suggest market beta, firm market size, and book-to-market ratio as risk factors to estimate returns based on excess return. Market beta represents a market risk that commonly affects all firms and measures based on market return volatility. Meanwhile, market size measured by a firm's market capitalization and book-to-market ratio based on a firm's equity book value represents the firm's specific risk factors which show the effect of a firm's size and ability to grow on returns. Previous studies commonly include both size and book-to-market risk factors in estimating the effect of firm risk factors on returns (Husien & Mahfud, 2015; Idress & Qayyum, 2018; Ferdaous & Barua, 2020). Both risk factors commonly show significant results with mixed directions to effect returns, indicating both factors are essential.

Based on the APT assumption and three-factor model, previous studies also include financial distress risk as one of the risk factors that might affect stock returns (Dichev, 1998; Husien & Mahfud, 2015; Chhapra et al., 2020). Researchers include this risk factor because financial distress risk is the element that affects a firm's financial position and could affect the stock return. Previous studies use financial distress risk based on the probability of financial distress generated from the financial distress prediction model. Based on the risk return trade-off concept, a financially distressed firm that commonly has a high risk is expected to generate higher returns compared to a non-distressed firm. Following APT, Fama and French (1993) and previous studies, this study uses distress risk represented by financial distress probability, size represented by market value, and value represented by a book-to-market ratio as risk factors to estimate stock returns. This study develops an operational framework based on this idea, as shown in Figure 3.2. Following previous studies by Dichev (1998), Chhapra et al. (2020), and Idrees and Qayyum (2018), this study uses distress risk, size, and value to determine the return. This study examines the effect of all these factors on returns in Malaysia based on univariate and multivariate analysis.

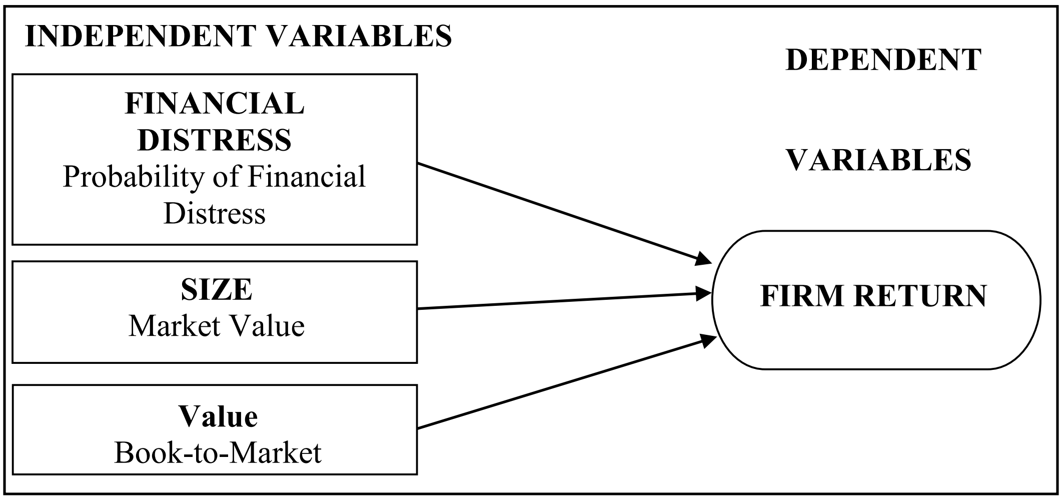


Figure 3.2:
*Determinants of Return Framework*

### 3.2 Sample Selection and Data Collection

This study's sample consists of firms listed in Bursa Malaysia[2] from 1990 to 2020. However, firms within the financial industry are excluded since these firms use different accounting systems as compared to firms from other industries, and the financial industry is a highly regulated industry that is constantly being monitored by government and financial regulators. Hence, the interpretation of the ratios are different (Md-Rus & Abdullah, 2005). This study focuses on listed Malaysian firms (excluding financial firms) as these firms represent the major players within the Malaysian market and are used as an indicator of the country's economic performance. The selected firms are classified either into distressed firms or non-distressed firms.

To categorise firms into either of these groups, this study refers to financial distress definitions given by Bursa Malaysia as stated in Amended Practice Note No.17 (APN17). This definition is commonly used by previous studies like Sori et al. (2001), Abdullah (2006), and Abdul et al. (2015). However, to standardise the criteria for the whole period of study, this study only defines a financial distress firm as a firm that has negative shareholders equity. This is because from the year 1990 to 2020, the regulations and requirements have changed a few times. This definition is similar to previous studies such as Lee and Yeh (2004), Ugurlu and Aksoy (2006), Anjum (2012), and Ashraf et al. (2019). Based on this criterion, distressed firms are firms with negative shareholders' equity. Negative shareholders' equity is due to the firm's liabilities exceeding the value of the assets since the firm has to increase debts to cover accumulated losses. This situation would increase the firm's default risk because it might have problems generating enough earnings to cover its debts in the future. As

[2] Bursa Malaysia was previously known as the Kuala Lumpur Stock Exchange (KLSE).

this happens, it might lead to financial distress. Thus, negative shareholders' equity could be a red flag that the firm might be financially distressed.

Meanwhile, non-distressed firms are firms with positive shareholders equity. However, this study does not match the non-distressed firms with distressed firms based on firm characteristics such as type of industry or asset size. Thus, shareholders' equity value is the only criterion determining the firm's category. This study also does not match the number of non-distressed firms with distressed firms since this study does not use the one-to-one match approach like Lakshan and Wijekoon (2013) and Lin (2009). The main reason is that this study not only uses the prediction model to rank the firms but also to estimate the probability of financial distress for further analysis. According to Sori et al. (2001), matching the number of non-distressed firms with distressed firms could create bias in the estimated prediction model. Sori et al. (2001) further explain that bias created from the one-to-one match is not vital if the model is only used to rank firms. However, this bias is significant for further analysis, such as estimating return, identifying an investment portfolio selection, or creating a portfolio. Since this study has created portfolios based on distress probability from the prediction model, the one-to-one match between distressed and non-distressed firms is inappropriate (Sori et al., 2001).

Financial information and share price information related to all selected firms are collected from Bloomberg Terminal. The financial data collected for predicting financial distress is divided into two subsets which are the main sample and holdout sample using random sampling approach. Main sample consists of data from randomly selected 912 firms that exist within the year of 1990 to 2020. This main sample consists of 739 non-financial distress firms and 173 financial distress firms. The main sample data set is then used in estimating the main financial distress prediction model. Meanwhile, data from 167 firms that are not a part of the main sample and within the year of 1990 to 2020 use as a holdout sample. This holdout sample consists of 132 non-financial distress firms and 35 financial distress firms. This is a similar approach used by previous studies such as Abdullah and Ahmad (2005), Etemadi et al. (2009), Yap et al. (2012) and Abdullah et al. (2019),. The reason this study uses this approach is to ensure firms in both samples are operating in the same economic environment.

Financial information is used to calculate the financial ratios for each of the firms. These ratios include liquidity ratios, profitability ratios, leverage ratios, and efficiency ratios. These ratios are used as independent variables or predictors in developing the financial distress prediction model. The entire information is in the form of panel data from the year 1990 to 2020. This study develops prediction models based on 18,314 firm-year observations. Since this study uses the hazard model for one of the analyses in predicting financial distress, the usage of panel data that records all cross-sectional data and time-series data is required. The application of the hazard model helps to eliminate sample selection bias, which means the result has more efficient coefficient estimates as it uses all data (Abdullah et al., 2008; Kim & Partington, 2015; Md-Rus, 2011; Shumway, 2001).

Next, this study proceeds with collecting data to determine stock returns. This study uses monthly data such as share price, number of stocks, and book value of the stock for all 1079 selected firms from June 1990 to December 2020 which equal to 141,425 monthly observations. The share price is used to calculate return for each firm in identifying the related risk factors. This study uses size, value, and financial distress probability as variables to represent risk factors for returns. Firms' returns are calculated based on monthly returns starting from six months after the fiscal year-end of year *t*. This is to ensure that accounting data are available to measure financial distress probability.

The monthly return for each firm within the portfolios represents the dependent variable. Size, value, and financial distress probability are calculated to represent all independent variables for each firm. Following Dichev (1998), Aziz and Ansari (2016), and Ferdaous and Barua (2020), returns are regressed with all independent variables by using Fama and Macbeth's (1973) regression.



## 3.3 Method

In this subsection, this study discusses all the methods used to analyse the collected data. All the methods are useful to achieve this study's objectives.

### 3.3.1 Descriptive Analysis

Descriptive analysis is used to analyse and summarise the basic characteristics of the data in a more meaningful way. It allows the researcher to present the data in a way that it is easy to be understood and interpreted. Descriptive analysis includes; (1) the measure of central tendency and (2) the measure of dispersion.

The measure of central tendency is very useful in describing the central position of a frequency distribution. It includes the mean and the median. The mean represents the average value for all data. Meanwhile, the measure of dispersion helps to explain how the values are spread around the central tendency. This analysis includes standard deviation as well as the minimum and the maximum value within the data.

### 3.3.2 Correlation Analysis

Correlation analysis is used to measure the correlation strength between two individual variables. Correlation coefficient measures the strength of this relationship. The values of the correlation coefficient will be between -1 and +1. If the result shows that the correlation coefficient value is near to +1, it indicates that the variables are positively correlated whereas if the correlation coefficient is close to -1, it indicates that the variables are negatively correlated. However, if the correlation coefficient is equal to 0, it indicates that the variables have no linear correlation.



Next, this study furthers the analysis to check for multicollinearity problems among variables using the Variance Inflation Factor (VIF) analysis. The VIF is a tool that helps to identify the degree of multicollinearity among variables. Since there is no specific benchmark for VIF, this study compares the VIF value generated for each variable with the VIF benchmark of 10. Although Hair, Hult, Ringle, and Sarstedt (2014) and Hair, Hult, Ringle, and Sarstedt (2017) recommend the VIF benchmark of 4 and 3, respectively, it does not confirm that multicollinearity problems do not exist (Becker, Ringle, Sarstedt, & Völckner, 2015; Mason & Perreault, 1991). Hair et al. (2009) state that the researcher should determine the acceptable level of multicollinearity that allow for a substantial level of multicollinearity. Thus, this study uses a VIF benchmark of

10, which is the most popular benchmark among previous studies in this area (Lin, 2009; Sayari & Mugan, 2017; Abdullah et al., 2019). This benchmark also aligns with Kennedy (1998) and Gujarati (2009) suggestions. The main reason is that financial ratios commonly use as predictors to predict financial distress. However, some financial ratios use the same nominator or denominator, leading to a moderate correlation among the predictors. Thus, following previous studies, this study still allows for moderate correlation (VIF more than 5 but less than 10) among variables as it expects not to affect the results (Larose & Larose, 2015). This study eliminates variables with a VIF value of more than ten and is less relevant to the theories.

### 3.3.3 Financial Distress Prediction Models

One of the aims of this study is to identify the determinants of financial distress using the logit and the hazard models. Based on the framework described in the earlier section, financial distress is the function of financial ratios such as liquidity ratios, activity ratios, profitability ratios, and leverage ratios, which could be written as follows:

$$\textit{Financial distress} = f(\textit{Financial ratios}) \tag{1}$$

For empirical analysis, the financial distress model would be:

$$\textit{Financial distress} = \beta_0 + \beta_n \textit{ Financial ratios} + u \tag{2}$$

Thus, equation (2) could be simplified as equation (3), of which the model is as follows:

$$Z_i = \beta_0 + \beta_n' x_i + u_i \tag{3}$$

where:

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

$X_i$ = firm $i$ financial ratios

$u_i$ = error term of firm $i$

In predicting financial distress, this study uses logistic regression (logit model) and the hazard model. Based on Ohlson (1980) and Shumway (2001), the logistic model is an appropriate statistical approach for model with metric variables for independent variables and non-metric (categorical nominal) variable for dependent variable. Logit model is also useful for explaining and predicting a binary categorical variable between two groups as compared to the metric-dependent measurement. The logistic analysis helps identify the best model in explaining the relationship between independent variables and dependent variables based on statistics Thus, the previous studies by Waqas and Md-Rus (2018), and Vo et al. (2019) used logit model for predicting financial distress.

To obtain the probability of financial distress, researcher adopts the Ohlson (1980) logit model. The probability is estimated as follows:

$$P_i = \frac{1}{1+e^{-(\beta_0+\beta_n{}'x_i+u_i)}} \tag{4}$$

In a simplified way, it is written as follows:

$$P_i = \frac{1}{1+e^{-z_i}} = \frac{e^{z_i}}{1+e^{z_i}} \tag{5}$$

where:

$Z_i = \beta_0 + \beta_n' x_i + u_i$

It means that equation (3) becomes a part of equation (4) and is used to estimate the weight for each financial ratio of the selected firms based on equation (4) that represents the cumulative logistic distribution functions. The value $P_i$ generated from equation (5) represents the probability of distressed firms.

The second method used is the hazard model. This model is based on the multiperiod logit model with hazard function (Shumway, 2001). The multiperiod logit model could be defined as:

$$P_{it} = Z_{it} = \beta_0 + \beta_n' x_{it} + u_{it} \tag{6}$$



where:

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

$x$ = firm's financial ratios

$it$ = time that each firm faces financial distress

$u$ = error term

Simply, it is written as follows:

$$P_{it} = \frac{1}{1+e^{-z_{it}}} = \frac{e^{z_{it}}}{1+e^{z_{it}}} \tag{7}$$

The hazard model or discrete-time hazard model is based on the hazard function ($\Phi_{i,t}$) and survivor function ($S_{it}$) (Shumway, 2001). The hazard function is expressed in the following equation:

$$\Phi_{it} = \frac{e^{a\,(t) + \,\beta_n X_{it}\, + \,u_{it}}}{1 + \,e^{a\,(t) + \,\beta_n X_{it}\, + \,u_{it}}} \tag{8}$$

where $X$ represents a vector of the predictor variables used to predict distress, $a(t)$ is a time-varying covariate, β is the coefficient for the predictor variables, and $\Phi_{i,t}$ is the hazard function.

Equation (8) could be rewritten as:

$$\Phi_{it} = \frac{e^{z_{it}}}{1 + e^{z_{it}}} \tag{9}$$

Thus, it is clear that equation (9) that represents the discrete-time hazard model and equation (7) that represents the multiperiod logit model are equivalent. This model assesses the ability of each independent variable to explain the actual distress probability. Although both hazard and logit models seem similar in terms of likelihood function and asymptotic variance-covariance matrix, the hazard model uses firm-year observation and considers time-varying covariates. This helps to produce more efficient coefficient estimates and eliminate sample selection bias ( Shumway, 2001; Md-Rus, 2011).

Based on the hazard model, 1 will be recorded for firm *i* if they failed in year *t* while 0 otherwise. Thus, if firm *i* failed in year 9, only year 9 will be coded as 1 while the previous eight years will be recorded as 0, to represent the firms is in good condition within those 8 years period. Due to the hazard model uses firm-year data, an adjustment has to be made to the t-statistic from the logit model. The estimated model's t-statistic is divided by the average number of firm-year per firm. This is because the logit model's t-statistic is based on *n* (number of firm observations). Both models (logit and hazard) use financial ratios as independent variables, which are liquidity, activity, profitability, and leverage ratios.

Most of the previous studies used financial ratios to capture the effect of ratios on financial distress (Altman, 1968; Bhunia & Sarkar, 2011; Polemis & Gounopoulos, 2012; Sori et al., 2001). Researchers commonly use liquidity ratios as predictors since they relate to the company's ability to meet its short-term obligation (Md-Zeni & Ameer, 2010).



Referring to previous studies such as Abdul et al. (2015) and Md Zeni and Ameer (2010), this study uses the current ratio, working capital to total assets, and sales to working capital to represent a firm's liquidity element in predicting financial distress. All these ratios use the firm's working capital components, such as current assets and current liability. These ratios show a firm's ability to meet short-term obligations, which could predict financial distress.

This study also includes activity ratios, which help show a firm's efficiency. However, a previous study by Ong, Yap, and Khong (2011) found that not all activity ratios can capture and predict bankruptcy or financial distress. This situation is similar to other researchers, including Abdul et al. (2015), Tan and Dihardjo (2001), Tirapat and Nittayagasetwat (1999), and Wang and Li (2007), who found that the selection of ratios to represent activity ratios in the prediction model is critical for capturing their effect in predicting financial distress. Thus, this study includes sales to total assets and receivable turnover as predictors to present activity ratios. Both ratios are among a few activity ratios found significant by previous studies such as Ong et al. (2011), Alifiah and Tahir (2018), and Fitri and Syamwil (2020). Both variables represent the ability to generate sales from firms' assets and the ability of the firm to collect their account receivable. These ratios would show how a firm's ability to manage assets could predict financial distress.



Profitability ratios are also helpful in predicting financial distress. This group of ratios shows the ability and performance of the firm in generating profit. Abdullah (2006), Chen et al. (2013), Polemis and Gounopoulos (2012), and Wang and Li (2007) found that profitability ratios are significant in predicting financial distress, which indicates that a firm's profitability ratios are essential predictors in the prediction models. Thus, this study includes profitability ratios such as operating profit margin, retained earnings to total assets, net profit margin, and earnings before interest and taxes to total assets in the financial distress prediction models. The inclusion of these ratios would show the effect of a firm's ability to generate and manage profits in predicting financial distress.

Besides liquidity, activity, and profitability ratios as financial distress factors, another proper financial factor for predicting bankruptcy is the leverage ratios. According to Sathye et al. (2003), leverage ratios are considered the crucial factor that shows a firm's ability to manage its debt and equity, and failure to manage leverage factors of the firm might lead to a financial distress situation. Anjum (2012), Elloumi and Gueyié (2001), Noor, Iskandar, and Omar (2012), Nyamboga, Omwario, Muriuki, and Gongera, (2014), and Ugurlu and Aksoy (2006) used leverage ratios in predicting financial distress. The main reason is that leverage ratios are directly related to the company's debt position, especially its long-term debt. Some researchers such as Chen et al. (2013), Fich and Slezak (2008), and Youn and Gu (2010) included the financial cost element in the prediction model and financial expenses ratios since these ratios contain a wide range of information related to the ability of a company to pay interest and its debts. Based on these previous studies, leverage is a combination of the proportion of debt and the cost of debt. However, the main question is which ratios can truly capture the effect of leverage in predicting financial distress. Thus, this study includes debt ratio, long-term debt to total debt ratio, shareholders fund to total asset, and interest coverage ratio as predictors of financial distress. These ratios expect to capture the effect of a firm's capital structure management in predicting financial distress. The measurement of all selected ratios are in Table 3.1

**Table 3.1**
*Financial Ratios used in Financial Distress Prediction Models*

| Group | Measurement / ratio | Formula | Symbol |
| --- | --- | --- | --- |
| Dependent Variable | Binary 1 and 0 | 1 equal to financial distress firms<br>0 equal to non-financial distress firms | FD |
| Independent Variables | | | |
| Liquidity ratios | Current ratio | $\frac{\text{Current asset}}{\text{Current liabilities}}$ | CR |
| | Working capital to total assets | $\frac{\text{Current asset} - \text{Current liabilities}}{\text{Total assets}}$ | WCTOTA |
| | Sales to working capital | $\frac{\text{Sales}}{\text{Current asset} - \text{Current liabilities}}$ | SWC |
| Activity ratios | Sale to total assets | $\frac{\text{Sales}}{\text{Total assets}}$ | TATO |
| | Receivable turnover | $\frac{\text{Accounts receivable}}{(\text{sales / 365 days})}$ | DSC |
| Profitability ratios | Operating profit margin | $\frac{\text{Earnings before interest and tax}}{\text{Sales}}$ | OPM |
| | Retained earnings to total assets | $\frac{\text{Retained Earnings}}{\text{Total assets}}$ | RETA |

**Table 3.1**
*Financial Ratios used in Financial Distress Prediction Models* (*Cont.*)

| Group | Measurement / ratio | Formula | Symbol |
|---|---|---|---|
| | Net profit margin | $\frac{\text{Net profit}}{\text{Sales}}$ | NPM |
| | Earnings before interest and taxes to total assets | $\frac{\text{Earnings before interest and tax}}{\text{Total assets}}$ | EBITTA |
| Leverage ratios | Debt ratio | $\frac{\text{Total ebts}}{\text{Total assets}}$ | DR |
| | Long-term debt to total debt ratio | $\frac{\text{Long} - \text{term debts}}{\text{Total debts}}$ | LDTD |
| | Shareholders fund to total debt | $\frac{\text{Shareholder's fund}}{\text{Total debts}}$ | SFTD |
| | Interest coverage ratio | $\frac{\text{Earnings before interest and tax}}{\text{Interest expenses}}$ | ICR |

### 3.3.4 Classification Accuracy of the Prediction Model

Next, researcher tests each developed models' accuracy using McFadden's pseudo-R squared, likelihood ratio, confusion matrix and Akaike information criterion (AIC),. These analyses are helpful to compare the validity and accuracy between both models. First, this study uses McFadden's pseudo-R squared to test the goodness of fit for each model in which it will help the ability of the predictors to explain any variation in the models. Pseudo-R statistic useful in assessing the strength of the logit model. Thus, the higher value of McFadden's pseudo-R squared indicates the model is well fitted, and the predictors could highly explain any variation in the model.

This study tests the accuracy of the model by using the confusion matrix. This analysis tests the model's accuracy according to correctly predicted cases' percentage for the developed model. In order to generate the accuracy percentage, the results for predicted cases based on the developed model are compared to the actual observations in the sample. This is the similar approach to previous studies by Ong et al. (2011), Darmawan and Supriyanto (2018), and Waqas and Md-Rus (2018). This study continues with conducting the likelihood ratio test by comparing the constrained and unconstrained models for both logit and hazard models. This study uses chi-square based on degrees of freedom that equal to the number of constraints to test the level of significance for the deviances of constrained and unconstrained models. The result later would show whether the model is well fitted or not. Finally, this study also conducts the Akaike information criterion (AIC) that uses in-sample fit in estimating the model's likelihood in predicting future values. The value generated from the test could be used in the comparison between the models. The model with the lowest AIC value is considered as a good model compared to other models.

### 3.3.5 Model Robustness Analysis

In examining the financial distress prediction models' robustness, this study divides the data into two groups which are the main sample and holdout sample. The approach is similar to the technique used by Abdullah and Ahmad (2005) and Waqas and Md-Rus (2018) that divided the data into two subsets. Thus, the data collected is divided into two subsets which are the main sample and holdout sample.

The main sample consists of data for 912 firms that exist from the year 1990 to 2020. The main sample data set is used in estimating the prediction model to predict financial distress. Meanwhile, the holdout sample consists of 167 firms' data that are not part of the main sample and are within the period of the year 1990 to 2020. The result of predicting using holdout sample serves to validate the result obtained by a prediction model that uses main sample data. The accuracy of the estimated prediction model is then compared to the accuracy of the estimated model in predicting cases within the holdout sample. This is to examine the model's robustness and consistency. The model with similar accuracy between main sample estimated model and holdout sample estimated model is considered to be consistent and reliable.

### 3.3.6 Portfolio Mean Analysis

The researcher then furthers the analysis to examine the effect of financial distress on stock returns. This analysis starts by analysing the mean returns for decile portfolios that are sorted based on certain criteria. First, this study assigns each stock into ten decile portfolios based on the probability of financial distress. This study generates financial distress probability based on the best prediction model in the previous part of this study. The stocks are then sorted based on the level of financial distress with portfolio 1 consisting of firms that have the lowest financial distress probability, while portfolio 10 consisting of stocks with the highest financial distress probability.

Next, the average financial distress probability, average monthly stock returns, average firm size and average firm book-to-market are calculated for each decile portfolio. The average value for low financial distress decile portfolios is then compared with the average value for high financial distress decile portfolios. All these steps to analyse mean portfolios are repeated for decile portfolios based on size and value. The outcomes from these analyses help to give a picture of the characteristics of the stocks based on financial distress level, firm size, and the firm value.

### 3.3.7 Determinants of Return

The next analysis is to find the determinants of returns. This study adopts a similar method to Dichev (1998), Chhapra et al. (2020), and Idrees and Qayyum (2018) based on Fama-MacBeth regression introduced by Fama and McBeth (1973). Originally, Fama and McBeth (1973) introduced Fama-MacBeth regression that used the Fama-MacBeth two-pass estimation technique in estimating the relationship between risk factors and stock returns to create the asset pricing model. Since one of this study's objectives is to estimate the effect of risk factors on return in Malaysia, which focuses on the model coefficient or beta, the Fama-MacBeth approach is more appropriate than the Fama-French approach three-factors model (FFTF). FFTF model is more focused on explaining the intercept or alpha value and generating coefficients that explain the factor-return based on investment strategies (such as small minus big or high minus low). Meanwhile, the Fama-MacBeth approach generates gamma-coefficients ($\gamma$) that useful to explain changes in return based on changes in risk factors which are more appropriate and align with this study's objectives.



According to Fama-MacBeth regression, firstly the stock returns are regressed on each risk factor variable to generate each factor's beta (factor loading) for each month. The analysis continues with the second stage whereby asset returns are regressed cross-sectionally on beta generated in the first stage of the analysis. This process helps to diminish the problem related to heteroscedasticity and autocorrelation problems. According to Fama and MacBeth (1973) this approach only uses coefficients from the first step of cross-sectional coefficient estimates, but not the standard error. Thus, any heteroscedasticity or residual-dependent problem from the first step does not alter the unbiasedness of the coefficient from the second step. Both steps are also solely corrected for cross-sectional correlation. However, this approach does not solve the time-series autocorrelation problem that arises from the standard error. This problem is not a concern for stock trading with short holding periods such as daily, weekly, or monthly (Fama & French, 1988). Although this problem is not a primary concern, this study uses the Fama-MacBeth regression with NeweyWest adjustment to correct the time-series autocorrelation problem (Gow, Ormazabal & Taylor, 2010). This action ensures the results are valid even in the presence of cross-sectional correlation and time-series autocorrelation. Following Dichev (1998), Idrees and Qayyum (2018), and Chhapra et al. (2020) that include two major factors such size and value that represent risk factors, this study also includes financial distress (Distress) as part of risk variables. This study's model for the first stage of the analysis is as follows:

$$R_{it} = \alpha + \beta_{1t}\,Distress_{it} + \beta_{2t}\,Size_{it} + \beta_{3t}\,Value_{it} + \beta_{4t}\,DNegValue_{it} + \varepsilon_{it} \qquad (10)$$



where $R_{it}$ is the portfolio's monthly return that based on the difference between the current month's price and the previous month's price divided by the previous month's price. The $\alpha$ is the intercept, $Distress_{it}$ is financial distress risk, $Size_{it}$ represents market value, $Value_{it}$ is book-to-market value, and $\beta_t$ is the coefficient for the risk factor during time t. $\varepsilon_{it}$ represents the error terms. Since firms with negative book-to-market value also includes into the sample, this study includes DNegValue to investigate in detail the effect of negative book-to-market on return. DNegValue represents dummy variable of negative value that based on negative book-to-market value. This dummy variable recorded use 1 to rerpesent firm with negative book-to-market value while 0 represent firm with positive book-to-market value. The significant level for this variable's coefficient tested based on one-tailed T-test.

Next, this study continues the analysis with the second stage of Fama-MacBeth two-pass estimation technique. This study's model for second stage of the analysis is as follows:

$$R_t = \alpha + \gamma_{Distress}\,\beta_{1t} + \gamma_{Size}\,\beta_{2t} + \gamma_{Value}\,\beta_{3t} + \gamma_{DNegValue}\,\beta_{4t} + \varepsilon_t \quad (11)$$

where $\beta_1$ represent beta or factor loading for financial distress, $\beta_2$ represent beta or factor loading for size, $\beta_3$ represent beta or factor loading for value, $\beta_4$ represent beta or factor loading for dummy negative book-to-market value, and Meanwhile $\gamma_{Distress}$, $\gamma_{Size}$, $\gamma_{Valu,}$ and $\gamma_{DNegValue}$, represent the risk premiums on the estimated betas and $\varepsilon_{it}$ represents the error terms.

Based on equation (10) and (11), the study starts the analysis by developing pricing models that are based on univariate analysis of which the selected three risk factors that are distress, size, and value are regressed with stock returns individually. This analysis helps to provide individual significance of each risk factor. Next, this study continues the analysis by using multivariate analysis and combines the selected risk factors. First, this study combined size and financial distress (distress) into one model.

The model of this combination for the first stage of the Fama-MacBeth regression is as follows:

$$R_{it} = \alpha + \beta_{1t}\,Distress_{it} + \beta_{2t}\,Size_{it} + \varepsilon_{it} \quad (12)$$

This study continues with the second stage of Fama-MacBeth regression for equation (12) based on equation (13).

$$R_t = \alpha + \gamma_{Distress}\,\beta_1 + \gamma_{Size}\,\beta_2 + \varepsilon_t \qquad (13)$$

Next, this study combines the value and financial distress into one model. The first stage of the Fama-MacBeth regression for this as follow:

$$R_{it} = \alpha + \beta_{1t}\,Distress_{it} + \beta_{2t}\,Value_{it} + \beta_{3t}\,DNegValue_{it} + \varepsilon_{it} \qquad (14)$$

Using equation (14), this study proceeds with second stage of Fama-MacBeth regression for that combination using the following equation;

$$R_t = \alpha + \gamma_{Distress}\,\beta_{1t} + \gamma_{Value}\,\beta_{2t} + \gamma_{DNegValue}\,\beta_{3t} + \varepsilon_t \qquad (15)$$

This study continues the analysis by combining size, value, DNegValue, and ValuexDNegValue into one model. The model of this combination for the first stage of the Fama-MacBeth regression as follow:

$$R_{it} = \alpha + \beta_{1t}\,Size_{it} + \beta_{2t}\,Value_{it} + \beta_{3t}\,DNegValue_{it} + \varepsilon_{it} \qquad (16)$$

Based on equation (16), this study continues with second stage of Fama-MacBeth regression for that combination using follow equation;

$$R_t = \alpha + \gamma_{Size}\,\beta_{1t} + \gamma_{Value}\,\beta_{2t} + \gamma_{DNegValue}\,\beta_{3t} + \varepsilon_t \qquad (17)$$

Lastly, this study combines all selected risk factors into the model. The first stage of the Fama-MacBeth regression is based on following equation:

$$R_{it} = \alpha + \beta_{1t}\,Distress_{it} + \beta_{2t}\,Size_{it} + \beta_{3t}\,Value_{it} + \beta_{4t}\,DNegValue_{it} + \varepsilon_{it} \qquad (18)$$

Next, this study continues the analysis with the second stage of Fama-MacBeth two-pass estimation technique. The equation is as follows:

$$R_{t} = \alpha + \gamma_{Distress}\,\beta_{1t} + \gamma_{Size}\,\beta_{2t} + \gamma_{Value}\,\beta_{3t} + \gamma_{DNegValue}\,\beta_{4t} + \varepsilon_{t} \qquad (19)$$

For all models, Distress represents financial distress risk is measured by the probability of financial distress generated from the financial distress prediction model developed at the earlier stage. Size or market value is calculated based on the log of fiscal-year-end price times the number of shares outstanding. The book-to-market value that represents value is calculated based on common equity divided by the market value of the firm. DNegValue represents dummy variable of negative value that based on negative book-to-market value.

The measurements of both size and value are similar to the previous studies by Aziz and Ansari (2016), Dichev (1998), and Idrees and Qayyum (2018). All variables are regressed every month using Fama-MacBeth (1973) regression based on monthly cross sections. This is to generate each month's coefficients for all variables. The estimated coefficient of the second stage Fama-MacBeth regression model based on those monthly coefficients is calculated to represent the model's coefficient that is useful for hypothesis testing of this study.

### 3.4 Hypothesis Testing

Based on the model developed, this study has tested a few hypotheses related to both stages of the analysis. Thus, this part is divided into two parts, namely (1) financial distress prediction models and (2) determinants of returns.

#### 3.4.1 Hypotheses for Financial Distress Prediction Models

The hypotheses for all independent variables in predicting financial distress are tested to determine whether the independent variables are significant predictors or not. There are four major hypotheses based on four major categories of financial ratios which are liquidity, efficiency, profitability, and leverage ratios are tested.

Firms commonly avoid poor liquidity positions since the situation might lead to the closure of the firm (Abdul Manab et al., 2015; Bakhri et al., 2018; Pham et al., 2018). Low liquidity affects the firms' ability in meeting its short-term obligation, which might lead to financial distress. The previous study by Abdul Manab et al. (2015) and Pham et al. (2018) use liquidity ratios to represent a firm's liquidity to predict financial distress, and the results show liquidity ratios are important for prediciting financial distress in the Malaysian market. Thus, this study uses current ratio, working capital to total assets, and sales to working capital to represent the liquidity ratios as these ratios have been commonly found to be significant by researchers. Generally, the hypothesis for this ratio is as follows:

$H_1$: Liquidity ratios are significant predictors of financial distress

The efficiency of the firm could also help in determining financial distress probability since it indicates firm ability to generate sales and manage assets. A firm with poor efficiency level is expected to have a higher financial distress probability due to its poor ability in generating sales by using its assets (Alifiah & Tahir, 2018; Fitri & Syamwil, 2020; Thai et al., 2014). This situation will directly affect the firm's ability to generate enough earnings to cover its financial cost. Researchers like Youn and Gu (2010) highlight activity ratios or efficiency ratios as useful tools in evaluating the efficiency of the firm. These ratios are also used by many previous studies to predict financial distress (Mbanwie & Edmond, 2009; Ong et al., 2011; Alifiah & Tahir, 2018; Fitri & Syamwil, 2020; Ogachi et al., 2020).

Although researchers like Thai et al. (2014) and Alifiah and Tahir (2018) find efficiency ratios as significant for predicting financial distress, some researchers like Dambolena and Khoury (1980) and Mbanwie and Edmond (2009) obtain contradictory results. Thus, this study tests the hypothesis related to efficiency ratios to clearly understand the effect of these ratios in predicting financial distress based on Malaysia's data. Sales to total assets and days' sales in receivables are used to represent efficiency ratios in this study. Thus, this study develops the following hypothesis:

$H_2$: Efficiency ratios are significant predictors of financial distress

A firm's profitability represent a firm's ability in generating profit after meeting its financial obligations (Nyamboga et al., 2014). Thus, a firm with negative profit might have a higher probability to be distressed as compared to a firm with positive profit. This is because the firm with negative profit is unable to generate enough earnings to cover its debt obligation, which might lead to financial distress. Abdul Manab et al. (2015), Alifiah and Tahir (2018), Vo et al. (2019), and Waqas and Md-Rus (2018) highlight the importance of profitability ratios in predicting financial distress. Thus, to test the hypothesis developed, this study uses earnings before interest and tax to sales, retained earnings to total assets, net profit margin, and earnings before interest and taxes divided by total assets. Thus, the hypothesis for this ratio is as follows:

$H_3$: Profitability ratios are significant predictors of financial distress

Leverage is an important element in determining the financial position of a firm because it affects the firm's capital structure and the level of financial cost that the firm has to bear (Darmawan & Supriyanto, 2018; Waqas & Md-Rus, 2018). If a firm has a higher level of leverage relative to equity, it indicates that the firm relies more on debt as compared to equity. This will increase the probability of financial distress since the firm needs to fulfil the obligation of paying higher interest and the principal amount borrowed. Previous studies by Lakshan and Wijekoon (2013), Sori et al. (2001), and Ugurlu and Aksoy (2006), and Vo et al. (2019) highlight the important of leverage ratios to predict financial distress since these ratios show significant results to predict financial distress. This study uses debt ratio, long-term debt to total debt, shareholders' fund to total debt, and interest coverage ratio to represent leverage ratios. In order to test this ratio, this study develops the following hypothesis:

$H_4$: Leverage ratios are significant predictors of financial distress

In predicting financial distress, the analytical model also plays an important role in generating precise, accurate, and consistent prediction models. This is because an accurate and consistent prediction model is useful in producing probability of financial distress that is reliable and could represent financial distress risk for firms. Previous studies such as Abdullah et al. (2008), Lin (2009), and Noor et al. (2012) compare results generated using a few analytical models in terms of the accuracy and consistency to find a model that is reliable. Thus, this study compares the results obtained from the logit model and hazard model in order to find the most reliable model in predicting financial distress. This is aligned with the objective of this study to compare logit model and hazard model consistency and the accuracy rate in predicting financial distress. According to the previous study, the hazard model has a higher accuracy rate and more consistent compared to the logit model. Based on these previous studies finding, this study expects that hazard model to be better than logit model in predicting financial distress. Thus, this study uses the outcome from the comparison between logit and hazard model to test the following hypothesis:



$H_5$: hazard model better prediction model compared to logit

### 3.4.2 Hypotheses for Determinants of Return

According to CAPM, market risk is considered as the only factor that affects returns while other risk factors are assumed to be fully diversified. Based on this assumption, financial distress risk should not have a significant effect on returns. However, this is contradictory to APT, which assumes that there are many risk factors that affect returns and financial distress might be one of it and market risk is not the only risk factor. Based on the studies by Md-Rus (2011), Idrees and Qayyum (2018), Mselmi et al. (2019), and Sudirgo et al. (2019), the results show that financial distress risk is not affecting the returns. This is contradictory to the studies by Dichev, (1998), Shumway (1996), Boubaker et al. (2018), and Chhapra et al. (2020), which show that stock returns have a relationship with financial distress risk.

Due to these inconclusive results, this study uses financial distress risk based on probability of distress to identify the relationship between financial distress risk and return. To achieve this study's objective in measuring the effect of financial distress risk on stock equity return, a hypothesis has been developed to test the effect:

$H_6$: Financial distress risk has a significant effect on return

Referring to the APT's assumption, various risk factors might affect returns, and Fama and French (1993) include size and book-to-market to represent the factors that affect returns. This is because investors commonly invest based on size and value of the firms and expect to receive higher returns from small firms (Banz, 1981) or high-value firms Stattman (1980) due to the level of risk for both types of firms. However, previous studies show different results related to the significant of both variables or direction of the relationship (Avramov & Chordia, 2006; Dichev, 1998; Ferdaous & Barua, 2020; Husein & Mahfud, 2015; Idrees & Qayyum, 2018; Lau et al., 2002). These show that both variables are important and hence, should be included in this study's return determination model. Thus, a hypothesis has been developed to test the effect:

$H_7$: Firm's size (Size) has a significant effect on return.

$H_8$: Firm's value (Value) has a significant effect on return.

**3.5 Summary**

In conclusion, this chapter discusses in detail the research sample used, the process of developing the model for predicting financial distress, the process of determining the factors affecting excess return, and the hypotheses for this study. The empirical results generated from all these analyses are discussed in Chapter 4.

# CHAPTER 4

# ANALYSIS AND DISCUSSION

## 4.0 Introduction

This chapter presents the statistical results generated from the hazard model and logit model analysis in predicting the financial distress and regression analysis based on the Fama-MacBeth approach to estimate the relationship between risk factors such as financial distress risk, value and size and stock returns. This chapter is divided into ten sections. Section 4.1 presents the descriptive statistical analysis for data used to predict financial distress. Section 4.2 describes the results for correlation analysis and variance inflation factor (VIF) analysis for each variable related to predicting financial distress. Section 4.3 discusses the regression analysis results based on the hazard model and logit model to predict financial distress. Section 4.4 compares the accuracy between these two models. Section 4.5 concludes which prediction model is used to generate probability of financial distress. Section 4.6 focuses on the statistical results from descriptive analysis, correlation analysis and VIF analysis to ensure the validity of the data in determining stock returns. Section 4.7 presents the comparison of portfolios based on financial distress risk, size and value. Section 4.8 presents the result from univariate while Section 4.9 discusses the results for multivariate Fama-MacBeth regression that will explain the effect of risk factors of financial distress risk, value and size on stock returns. Section 4.10 presents the result for additional analysis for portfolio-based regression that is based on the economic period. Section 4.11 summarises the hypothesis testing. The last section provides the overall summary of this chapter.

## 4.1 Descriptive Analysis

### 4.1.1 Descriptive Analysis for Hazard Model Data

Table 4.1 shows the distressed and non-distressed firms' mean and standard deviation based on all selected financial ratios for prediction model based on the hazard model. Based on Table 4.1, distressed firms are found to have poor liquidity performance compared to those of non-distressed firms. This is because distressed firms' mean values for CR, WCTA, and SWC are lower compared to non-distressed firms. WCTA and SWC for distressed firms also show negative value compared to those non-distressed firms. Since total assets and sales cannot be negative, this shows that the value of working capital is negative. This is reflected in the value of CR, or current assets over current liabilities of less than one. The mean difference results show that non-distressed firms have better liquidity ratios compared to those of distressed firms with the differences in CR and WCTA are significantly different between the two groups. Thus, all these clearly show that distressed firms tend to have poor liquidity management compared to non-distressed firms. It indicates that on average, distressed firms face problems in meeting their short-term financial obligation.

Next, the table also shows the mean and standard deviation of TATO and DSC for distressed firms and non-distressed firms. The distressed firms' mean and standard deviation value for TATO are higher than non-distressed firms. This indicates that distressed firms show better performance in terms of asset management compared to non-distressed firms. This could be due to the size of assets held by distressed firms that might be relatively small compared to non-distressed firms. However, TATO for distressed firms is found to be more volatile compared to non-distressed firms.

As for DSC, non-distressed firms show lower value compared to distressed firms for both mean and standard deviation. This shows that on average, non-distressed firms have better management on their account receivables compared to financial distressed firms. The mean differences between distressed firms and non-distressed firms for both ratios are significantly different values. Thus, in terms of managing their assets, there is a significant difference between both groups of firms. It clearly shows that distressed firms are better compared to non-distressed firms in generating sales from their assets, but they require longer time in collecting account receivables.

Table 4.1 also illustrates the results for mean value and standard deviation for profitability ratios. OPM, RETA, NPM, and EBITTA mean value for distressed firms are negative. Meanwhile for non-distressed firms, all those ratios show positive value. The result also shows distressed firms recorded higher standard deviation value than non-distressed firms. This indicates that all these ratios for distressed firms fluctuate within a larger range compared to non-distressed firms which are more stable and fluctuate within a smaller range. All profitability ratios show positive significant differences indicating that non-distressed firms performed better compared to distressed firms in generating profit. This clearly shows that financially distressed firms could have problems in terms of generating high revenues and utilising assets to generate positive operating profit and net income. Distressed firms also might have problems in terms of generating positive retained earnings using their assets. Thus, the result suggests that distressed firms might have problems generating positive profit compared to non-distressed firms. Table 4.1 also shows distressed firms' DR value is significantly higher than non-distressed firms. Thus, compared to non-distressed firms, financial distress firms depend too much on debt in financing their assets which could lead to financial distress situation. The table also shows that distressed firms have lower LDTD compared to non-distressed firms. This indicates that the long-term debt proportion to total debt for distressed firms is lower than non-distressed firms, which shows that distressed firms use more short-term debt compared to long-term debt.

Next, the value of SFTD for distressed firms shows negative value while non-distressed firms recorded positive value. This clearly shows that distressed firms also use debt to cover the firm's negative shareholders' capital. Meanwhile, non-distressed firms depend less on debt but use shareholders' capital to finance their assets and operation. Finally, distressed firms also show negative value for ICR while non-distressed firms show significant positive ICR value. This indicates on average that distressed firms might have problems in meeting their financing cost while non-distressed firms should not have any problem to meet their financing cost. Based on the results of mean difference for all ratios in leverage ratios, LDTD, SFTD, and ICR show positive significant difference while DR recorded negative significant difference. This clearly signifies that non-distressed firms have better performance in managing total debt, equity, and financial cost compared to distressed firms. Based on this table, it clearly shows distressed firms have poor financial positions while non-distressed firms show better financial performance.

**Table 4.1**
*Mean and Standard Deviation of Distressed and Non-Financially Distressed Firms for Hazard Model*

| | | Distressed Firms | | Non-Financially Distressed Firms | | | |
|---|---|---|---|---|---|---|---|
| Ratios | Variable | Mean | Std. Dev. | Mean | Std. Dev. | Mean Diff. | p-value |
| Liquidity | CR | 0.3732 | 0.3321 | 3.3179 | 16.7024 | 2.9446 | 0.010** |
| | WCTA | -7.7154 | 80.7077 | 0.2062 | 0.2403 | 7.9217 | 0.000*** |
| | SWC | -3.4777 | 28.7116 | 4.1830 | 114.6016 | 7.6607 | 0.194 |
| Activity | TATO | 2.2260 | 18.9271 | 0.74425 | 0.5324 | -1.4817 | 0.000*** |
| | DSC | 106.2386 | 118.9858 | 95.6330 | 88.35486 | -10.6056 | 0.065* |
| Profitability | OPM | -0.8890 | 0.7542 | 0.0535 | 0.2714 | 0.9425 | 0.000*** |
| | RETA | -81.3734 | 792.9471 | 0.0839 | 0.4253 | 81.4573 | 0.000*** |
| | NPM | -1.6510 | 1.1714 | 0.0064 | 0.4873 | 1.6574 | 0.000*** |
| | EBITTA | -14.2363 | 178.3718 | 0.0508 | 0.1345 | 14.2871 | 0.000*** |
| Leverage | DR | 8.8216 | 80.9690 | 0.4065 | 0.2121 | -8.4151 | 0.000*** |
| | LDTD | 0.0930 | 0.1549 | 0.2077 | 0.2015 | 0.1147 | 0.000*** |
| | SFTD | -0.3038 | 0.2602 | 3.5428 | 14.6414 | 3.8466 | 0.000*** |
| | ICR | -11.4514 | 26.8098 | 101.7398 | 551.5335 | 113.1912 | 0.004*** |

**NOTE**: CR represents current ratio, WCTA represent working capital to total assets, SWC represents sales to working capital, TATO represents total assets turnover, DSC represents day's sales in account receivable, OPM represents earnings before interest and tax to sales, NPM represents net profit margin, EBITTA represents earnings before interest and tax to total assets, RETA represents retained earnings total assets, DR represents debt ratio, LDTD represents long term debt to total debt, SFTD represents shareholders fund to total debt, and ICR represents interest coverage ratio. The asterisk (*) on p-value represents statistically significant at certain level; *** statistically significant at 1% level, ** statistically significant at 5% level, and * statistically significant at 10% level

### 4.1.2 Descriptive Analysis for Logit Model Data

All the financial ratios' mean value and standard deviation for distressed firms and non-distressed firms for prediction model based on the logit model are shown in Table 4.2. The results from this table are generated based on the average value of financial ratios for each firm cross-sectionally. Based on the table, the mean liquidity ratios such as CR, WCTA, and SWC for distressed firms show value lower compared to non-distressed firms. The results are similar to those based on the hazard model shown in Table 4.1. This indicates that distressed firms have lower ability in meeting their short-term obligation, generating sales from their working capital and financing their assets with working capital compared to non-distressed firms. However, only WCTA recorded significant mean difference value while CR and SWC show insignificant mean difference. Thus, this indicates that both distressed firms and non-distressed firms only differ in terms of how the firms generate working capital based on total assets.



As for activity ratios, distressed firms record higher TATO than non-distressed firms, which shows that distressed firms managed their total assets better. However, they also recorded higher DSC, which shows a longer time period to collect their receivable. The mean differences with both ratios are significant. This is similar to the result based on the hazard model in Table 4.1.

**Table 4.2**
*Mean and Standard Deviation of Distressed and Non-Financially Distressed Firms for the Logit Model*

| | | Distressed Firms | | Non-Financial Distressed Firms | | | |
|---|---|---|---|---|---|---|---|
| Ratios | Variable | Mean | Std. Dev. | Mean | Std. Dev. | Mean Diff. | p-value |
| Liquidity | CR | 2.2142 | 6.3606 | 4.0843 | 21.4562 | 1.8702 | 0.131 |
| | WCTA | -0.0724 | 0.2176 | 0.2290 | 0.1872 | 0.3014 | 0.000*** |
| | SWC | 1.7842 | 27.7702 | 4.3805 | 24.8501 | 2.5962 | 0.1162 |
| Activity | TATO | 1.0665 | 4.7721 | 0.7649 | 0.4394 | -0.3016 | 0.0456* |
| | DSC | 130.8701 | 76.0998 | 94.9383 | 59.7366 | -35.9317 | 0.000*** |
| Profitability | OPM | -0.1293 | 0.2056 | 0.0584 | 0.1482 | 0.1876 | 0.000*** |
| | RETA | -0.7850 | 0.9582 | 0.0953 | 0.3294 | 0.8803 | 0.000*** |
| | NPM | -0.3451 | 0.3268 | 0.0160 | 0.1814 | 0.3611 | 0.000*** |
| | EBITTA | -0.0678 | 0.1405 | 0.0561 | 0.0646 | 0.1239 | 0.000*** |
| Leverage | DR | 1.2690 | 4.8186 | 0.3947 | 0.1649 | -0.8743 | 0.000*** |
| | LDTD | 0.1871 | 0.1685 | 0.2104 | 0.1408 | 0.0233 | 0.031** |
| | SFTD | 1.8726 | 7.0921 | 3.6454 | 6.1561 | 1.7728 | 0.001*** |
| | ICR | 20.5858 | 84.1708 | 153.9183 | 464.9612 | 133.3325 | 0.000*** |

**NOTE**: CR represents current ratio, WCTA represents working capital to total assets, SWC represents sales to working capital, TATO represents total assets turnover, DSC represents day's sales in account receivable, OPM represents earnings before interest and tax to sales, NPM represents net profit margin, EBITTA represents earnings before interest and tax to total assets, RETA represents retained earnings total assets, DR represents debt ratio, LDTD represents long term debt to total debt, SFTD represents shareholders fund to total debt, and ICR represents interest coverage ratio. The asterisk (*) on p-value represents statistically significant at certain level; *** statistically significant at 1% level, ** statistically significant at 5% level, and * statistically significant at 10% level.

Profitability ratios for distressed firms are negative for OPM, RETA, NPM, and EBITTA, while non-distressed firms show positive value. The mean differences for all ratios are significant at one-percent level which the results are similar to Table 4.1.

As for leverage ratios, the results are also similar hazard model's results. DR, SFTD, and ICR are better for non-distressed firms as compared to those of distressed firms. The differences in these ratios are significant at one-percent level. LDTD's are results also similar to the results for the hazard model.

It can be concluded that based on average financial ratios for each firm, distressed firms have poor performance in managing their liquidity, receivables, and debt. The distressed firms also show poor ability in generating profit from their sales and assets.



## 4.2 Correlation Analysis

This section focuses on correlation analysis and variance inflation factor (VIF) analysis for both hazard model and logit model. The result describes the direction and strength of correlation between each independent variable. Meanwhile, VIF analysis is conducted to test the existence of multicollinearity problems between each variable to avoid problems in later analysis.

### 4.2.1 Correlation and VIF Analysis for Hazard Model Data

This study analyses the correlation between all independent variables and Table 4.3 shows the result of this analysis. According to the table, the correlation between most independent variables is found to be less than 0.7 which is considered as moderate or weak correlation. This might also show that these variables do not suffer from multicollinearity problems.

However, there are also certain variables with high correlation between them such as correlations between CR and SFTD, TATO and EBITTA, TATO and DR, OPM and NPM, and EBITTA and DR. All these variables show correlation values within the range of 0.78 to 0.94 among them. The outcome for TATO and EBITTA, TATO and DR, and EBITTA and DR might be due to the same denominator of these variables, which is total assets. These situations might lead to multicollinearity between the variables. Thus, this study extends the analysis by conducting diagnostic checking for all the variables using VIF analysis.

**Table 4.3**
*Correlation Analysis for Hazard Model Data*

| | CR | WCTA | SWC | TATO | DSC | OPM | RETA | NPM | EBITTA | DR | LDTD | SFTD | ICR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CR | 1 | | | | | | | | | | | | |
| WCTA | 0.4523 | 1 | | | | | | | | | | | |
| SWC | -0.0046 | 0.0079 | 1 | | | | | | | | | | |
| TATO | -0.0264 | -0.0076 | -0.0387 | 1 | | | | | | | | | |
| DSC | 0.0483 | 0.0753 | -0.0035 | -0.0705 | 1 | | | | | | | | |
| OPM | -0.0171 | 0.2853 | 0.0050 | 0.0257 | -0.2071 | 1 | | | | | | | |
| RETA | 0.0907 | 0.4222 | 0.0108 | -0.0024 | -0.0994 | 0.4025 | 1 | | | | | | |
| NPM | 0.0595 | 0.3418 | 0.0042 | 0.0330 | -0.2036 | 0.8071[4] | 0.4278 | 1 | | | | | |
| EBITTA | 0.0121 | 0.1430 | -0.0350 | 0.8893[2] | -0.0484 | 0.2511 | 0.2463 | 0.2013 | 1 | | | | |
| DR | -0.1147 | -0.2283 | -0.0401 | 0.9451[3] | 0.0086 | -0.0605 | -0.1324 | -0.0783 | 0.8224[5] | 1 | | | |
| LDTD | 0.0275 | -0.0754 | -0.0071 | -0.0770 | -0.0530 | 0.1362 | 0.0449 | 0.0576 | 0.0084 | 0.0295 | 1 | | |
| SFTD | 0.7852[1] | 0.2876 | -0.0071 | -0.0307 | 0.0078 | -0.0425 | 0.0741 | 0.0447 | 0.0032 | -0.1184 | -0.0901 | 1 | |
| ICR | 0.1402 | 0.1658 | -0.0017 | 0.0046 | -0.0352 | 0.1250 | 0.0894 | 0.1010 | 0.0453 | -0.0447 | -0.0570 | 0.1378 | 1 |

NOTE: CR represents current ratio, WCTA represents working capital to total assets, SWC represents sales to working capital, TATO represents total assets turnover, DSC represents day's sales in account receivable, OPM represents earnings before interest and tax to sales, NPM represents net profit margin, EBITTA represents earnings before interest and tax to total assets, RETA represents retained earnings total assets, DR represents debt ratio, LDTD represents long term debt to total debt, SFTD represents shareholders fund to total debt, and ICR represents interest coverage ratio. The superscript figure represents a pair of variables with strong correlation.

**Table 4.4**
*Variance Inflation Factor (VIF Analysis)*

| Variable | VIF |
|---|---|
| CR | 3.35 |
| WCTA | 2.98 |
| SWC | 1.00 |
| TATO | 27.23[1] |
| DSC | 1.30 |
| OPM | 3.52 |
| RETA | 1.85 |
| NPM | 3.18 |
| EBITTA | 9.34 |
| DR | 27.23[2] |
| LDTD | 1.31 |
| SFTD | 2.91 |
| ICR | 1.05 |
| Mean VIF | 6.64 |

NOTE: CR represents current ratio, WCTA represents working capital to total assets, SWC represents sales to working capital, TATO represents total assets turnover, DSC represents day's sales in account receivable, OPM represents earnings before interest and tax to sales, NPM represents net profit margin, EBITTA represents earnings before interest and tax to total assets, RETA represents retained earnings total assets, DR represents debt ratio, LDTD represents long term debt to total debt, SFTD represents shareholders fund to total debt, and ICR represents interest coverage ratio. The superscript figure represents a variable with VIF value above 10.

According to Table 4.4, variables such as CR, WCTA, SWC, DSC, OPM, RETA, NPM, EBITTA, LDTD, SFTD, and ICR record the VIF value lower than 10. According to Gujarati and Porter (2009) and Hair et al. (2010), the VIF value should be lower than 10 indicating that the data does not suffer from any serious multicollinearity problem. Although high correlation between CR and SFTD is recorded in correlation analysis earlier, VIF analysis shows that these variables do not suffer from any serious multicollinearity problem.

However, variables such as TATO and DR show VIF of more than 10 therefore indicating that these variables suffer from serious multicollinearity problems. In order to overcome this issue, this study eliminates one of the variables suffering from the multicollinearity problem (Gujarati & Porter, 2009). Based on previous studies such as Ohlson (1980), Parker et al. (2002), and Lee and Yeh (2004), debt ratio is the most important variable since it is directly related to firm's capital structure that helps to predict financial distress, making it one of the crucial variables to predict financial distress. Thus, this study eliminates TATO in order to avoid serious multicollinearity problems. This is because TATO indicates how firms manage their assets to generate sales but not how firms use financial obligation in their capital structure.

**Table 4.5**
*Variance Inflation Factor (VIF Analysis)*

| Variable | VIF |
|---|---|
| CR | 3.32 |
| WCTA | 2.22 |
| SWC | 1.00 |
| DSC | 1.09 |
| OPM | 3.47 |
| RETA | 1.85 |
| NPM | 3.15 |
| EBITTA | 8.45 |
| DR | 8.14 |
| LDTD | 1.11 |
| SFTD | 2.88 |
| ICR | 1.05 |
| Mean VIF | 3.14 |

**NOTE**: CR represents current ratio, WCTA represents working capital to total assets, SWC represents sales to working capital, DSC represents day's sales in account receivable, OPM represents earnings before interest and tax to sales, NPM represents net profit margin, EBITTA represents earnings before interest and tax to total assets, RETA represents retained earnings total assets, DR represents debt ratio, LDTD represents long term debt to total debt, SFTD represents shareholders fund to total debt, and ICR represents interest coverage ratio.

After eliminating TATO, the VIF analysis is again conducted in order to confirm that there is no issue related multicolliearity problem. Based on Table 4.5 shows that after eliminating TATO, all variables record VIF lower than 10, thus signifying that no serious multicollinearity issue among all variables. This study hence only uses CR, WCTA, SWC, DSC, OPM, RETA, NPM, EBITTA, DR, LDTD, SFTD, and ICR as independent variables to predict financial distress.

### 4.2.2 Correlation and VIF Analysis for Logit Model Data

Table 4.6 illustrates the result for correlation analysis for the logit model. Based on Table 4.7, most of the correlations are lower than 0.7. This indicates that many variables are considered to have moderate or weak correlation between the variables. However, there are still a few variables that recorded correlations higher than 0.7 such as correlations between CR and SFTD, OPM and NPM, OPM and EBITTA, RETA and EBITTA, and EBITTA and NPM. The correlations for these pairs of variables are within the range of 0.70 to 0.87 showing strong correlation between them. These could lead to serious multicollinearity problems among the variables.

Further analysis to detect the existence of multicollinearity using VIF analysis is performed. Table 4.7. shows results for the VIF analysis. The results show that VIF for all variables that are less than 10. Therefore, all variables for the logit model did not suffer from any serious multicollinearity problem. The variables such as CR and SFTD, OPM and NPM, OPM and EBITTA, RETA and EBITTA, and EBITTA and NPM did have strong correlation, but these variables did not suffer from any correlation analysis.

Although the results show all variables could be used in developing financial distress prediction models, researcher dropped TATO as one of the variables in developing financial distress prediction models. Due to the multicollinearity problem in the hazard model, this study excludes TATO for both logit and hazard models. This is to ensure that the models developed using both hazard and logit are comparable

**Table 4.6**
*Correlation Analysis for Logit Model Data*

| | CR | WCTA | SWC | TATO | DSC | OPM | RETA | NPM | EBITTA | DR | LDTD | SFTD | ICR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CR | 1.0000 | | | | | | | | | | | | |
| WCTA | 0.4581 | 1 | | | | | | | | | | | |
| SWC | -0.0427 | 0.0117 | 1 | | | | | | | | | | |
| TATO | -0.0500 | -0.0119 | -0.1111 | 1 | | | | | | | | | |
| DSC | 0.1504 | 0.0779 | -0.0187 | -0.0777 | 1 | | | | | | | | |
| OPM | -0.1479 | 0.2680 | 0.0446 | 0.0389 | -0.4457 | 1 | | | | | | | |
| RETA | -0.0284 | 0.4516 | 0.0366 | 0.0290 | -0.2550 | 0.5987 | 1 | | | | | | |
| NPM | -0.0859 | 0.3565 | 0.0476 | 0.0598 | -0.4264 | 0.8685[2] | 0.6396 | 1 | | | | | |
| EBITTA | -0.0561 | 0.4106 | 0.0368 | 0.1110 | -0.3278 | 0.7499[3] | 0.7483[4] | 0.7073[5] | 1 | | | | |
| DR | -0.0558 | -0.2025 | -0.0377 | 0.3442 | -0.0126 | -0.0528 | -0.2531 | -0.0722 | -0.2026 | 1 | | | |
| LDTD | 0.0049 | -0.2210 | 0.023 | -0.1220 | -0.1183 | 0.1828 | 0.0563 | 0.0282 | 0.0694 | -0.0352 | 1 | | |
| SFTD | 0.7020[1] | 0.2553 | -0.0416 | -0.0512 | 0.0837 | -0.1618 | -0.1926 | -0.1240 | -0.1071 | -0.0413 | -0.0310 | 1 | |
| ICR | 0.1790 | 0.3091 | -0.0168 | 0.0044 | -0.0962 | 0.1927 | 0.1277 | 0.1754 | 0.2174 | -0.0234 | -0.1331 | 0.1400 | 1 |

**NOTE**: CR represents current ratio, WCTA represents working capital to total assets, SWC represents sales to working capital, TATO represents total assets turnover, DSC represents day's sales in account receivable, OPM represents earnings before interest and tax to sales, NPM represents net profit margin, EBITTA represents earnings before interest and tax to total assets, RETA represents retained earnings total assets, DR represents debt ratio, LDTD represent long term debt to total debt, SFTD represents shareholders fund to total debt, and ICR represents interest coverage ratio. The superscript figure represents a pair of variables with strong correlation.

**Table 4.7**
*Variance Inflation Factor (VIF Analysis)*

| Variable | VIF |
|---|---|
| CR | 2.63 |
| WCTA | 2.27 |
| SWC | 1.02 |
| TATO | 1.24 |
| DSC | 1.38 |
| OPM | 5.84 |
| RETA | 2.89 |
| NPM | 4.99 |
| EBITTA | 3.69 |
| DR | 1.31 |
| LDTD | 1.31 |
| SFTD | 2.16 |
| ICR | 1.18 |
| MEAN VIF | 2.45 |

**NOTE**: CR represents current ratio, WCTA represents working capital to total assets, SWC represents sales to working capital, TATO represents total assets turnover, DSC represents day's sales in account receivable, OPM represents earnings before interest and tax to sales, NPM represents net profit margin, EBITTA represents earnings before interest and tax to total assets, RETA represents retained earnings total assets, DR represents debt ratio, LDTD represents long term debt to total debt, SFTD represents shareholders fund to total debt, and ICR represents interest coverage ratio.



## 4.3 Predicting Financial Distress

This section presents the results based on hazard and logit models. Both models are probabilistic models and used by Kim and Partington (2015), Waqas and Md-Rus (2018), Vo et al. (2019), and Balasubramanian et al. (2019).

### 4.3.1 Predicting Financial Distress

Using yearly data of 1079 firms from the year of 1990 to 2020, this study applies hazard and logit models to develop financial distress prediction models. Table 4.8 summarizes the findings from both models to estimate financial distress in Malaysia.

**Table 4.8**
*Financial Distress Prediction Model Regression*

| Model | Hazard Model | | | Logit Model | | |
|---|---|---|---|---|---|---|
| | β | $\chi^2$ | p-value | β | $\chi^2$ | p-value |
| Constant | -21.5011 | 0.1714 | 0.679 | -8.1367 | 52.8234 | 0.000*** |
| CR | 0.1462 | 0.0008 | 0.977 | 0.0263 | 0.1789 | 0.672 |
| WCTA | -1.9405 | 3.5482 | 0.060* | -3.3494 | 3.6214 | 0.057* |
| SWC | -0.0019 | 3.5311 | 0.060* | 0.0010 | 0.0562 | 0.813 |
| DSC | 0.0016 | 3.2850 | 0.069* | 0.0040 | 1.8578 | 0.173 |
| OPM | 0.4592 | 1.7509 | 0.1858 | 4.4018 | 2.7756 | 0.096* |
| RETA | -0.4347 | 8.9188 | 0.003*** | -1.1443 | 8.5615 | 0.003*** |
| NPM | -0.1385 | 3.7090 | 0.054* | -2.9734 | 2.6929 | 0.101 |
| EBITTA | -1.9638 | 0.1333 | 0.715 | -22.7872 | 22.3634 | 0.000*** |
| DR | 19.2598 | 13.1045 | 0.000*** | 10.3669 | 47.8726 | 0.000*** |
| LDTD | -0.3222 | 0.0116 | 0.914 | -1.5453 | 1.2432 | 0.265 |
| SFTD | -4.0442 | 8.0894 | 0.004*** | 0.0103 | 0.0638 | 0.801 |
| ICR | -0.0082 | 0.0632 | 0.801 | -0.0105 | 0.3096 | 0.578 |

**NOTE**: The $\chi^2$ test represents $\chi^2$ distribution with one degree of freedom test used to test predictive significance of each individual predictor variable. As for the hazard model, this study adjusted the $\chi^2$ value by dividing the $\chi^2$ value with the average number of firm-year per year (14.3). CR represents current ratio, WCTA represents working capital to total assets, SWC represents sales to working capital, TATO represents total assets turnover, DSC represents day's sales in account receivable, OPM represents earnings before interest and tax to sales, NPM represents net profit margin, EBITTA represents earnings before interest and tax to total assets, RETA represents retained earnings total assets, DR represents debt ratio, LDTD represents long term debt to total debt, SFTD represents shareholders fund to total debt, and ICR represents interest coverage ratio. The asterisk (*) on p-value represents statistically significant at certain level; *** statistically significant at 1% level, ** statistically significant at 5% level, and * statistically significant at 10% level



#### 4.3.1.1 Liquidity Ratios and Financial Distress

Based on Table 4.8, hazard model's results show that liquidity ratios are significant to predict financial distress since two out of three selected ratios show significant results. The results for working capital to total assets (WCTA) and sales to working capital (SWC) show negatively significant to predict financial distress. As for WCTA, the variable shows negative significant results in both hazard and logit models. The negative coefficient of WCTA indicates a firm that experiences consistent operating losses leading to lower current assets in relation to total assets and it also affects the ability of the firm to meet its short-term liability which could lead to financial distress position. Thus, the result is aligned with Abdul Manab et al. (2015), Waqas and Md-Rus (2018), and Vo et al. (2019).

As for sales to working capital, the hazard model shows negative result in predicting financial distress which is contradictory Ugurlu and Aksoy (2006) and Yap et al. (2012). Ugurlu and Aksoy (2006) find that SWC has a positive significant effect on financial distress. This negative significant result is because a firm that is highly efficient in utilising current assets and current liabilities in generating sales should be able to generate revenue that is enough to cover a firm's short-term obligations which help to lower the financial distress risk.

However, sales to working capital for the logit model is found to be insignificant to predict financial distress. The result is similar to findings by Yap et al. (2012). The insignificant logit model's results for sales to working capital contradict hazard model's results. The different result between both models could be due to data quality as logit is using cross-sectional data that is based on average firm-year data for each variable while hazard model uses panel data that is based on firm-year data. Thus, logit model eliminates the time effect which leads to different results compared to the hazard model.

The results for current ratio show that current ratio is insignificant to predict financial distress for hazard and logit model. This is aligned with findings by Abdullah and Ahmad (2005) and Fitri and Syamwil (2020). These insignificant results indicate the current ratio is not important in predicting financial distress. One of the possible reasons is that the current ratio does not clearly show the ability of a firm in meeting its short-term obligations. This is because elements such as account receivable and inventories that are also included in calculating current ratio could have different effects in predicting financial distress. Thus, this situation could lead to both models failing to capture the effect of current ratio to predict financial distress.

Both models' results clearly show that liquidity elements based on working capital help predict financial distress. Thus, the results indirectly show that liquidity could also affect a firm's financial position and risk, which aligns with working capital management's concept that working capital management could impact the firm's profitability and risk. The results show firm with a large proportion of working capital to assets (based on hazard and logit models) that manage to maximise it in generating sales could reduce the firm's risk, especially financial distress risk. The results also indirectly explain the link between the working capital management concept and financial distress, which is valuable in understanding the effect of liquidity in predicting financial distress.



#### 4.3.1.2 Activity Ratios and Financial Distress

Based on Table 4.8, both models use day’s sales in account receivable (DSC) which represents activity ratios. The results show day’s sales in account receivable for the hazard model is positively influence financial distress. The results are similar to findings by Ong et al (2011) which also used Malaysian market data. The ratio represents the number of days needed by the firm to collect revenue from their credit sales. Positive significant result indicates as numbers of day’s sales in account receivable increases, the higher the probability of financial distress. Thus, firms that manage to collect their credit sale within a short period could reduce the financial distress risk because firms can use it to settle debts. This helps to lower the probability of a firm falling into financial distress (Ong et al., 2011). The result also aligned with the working capital management concept. The results show that as firms improve account receivable management, it helps to reduce financial distress risk. Thus, the working capital elements are also vital in reducing a firm's risk, especially financial distress risk.

However, the result logit model shows day's sales in account receivable are insignificant in predicting financial distress. This illustrates that activity ratios do not give a significant effect on firms' financial distress risk. The results are contradictory to results from hazard models. These different results could be due to data quality between logit and hazard model. This is because the logit model eliminates the time effect while the hazard model considers time variation elements. These situations lead to different results generated by both models.

#### 4.3.1.3 Profitability Ratios and Financial Distress

Results for profitability ratios are shown in Table 4.8. The results for the hazard model show that only retained earnings to total assets (RETA) and net profit margin (NPM) are negatively significant. Meanwhile, there are two insignificant variables which are operating profit margin (OPM) and earnings before interest and tax to total assets (EBITTA). However, in logit model that show all ratios that represent profitability are significant except for net profit margin.

The negative significant result for retained earnings to total assets in both models illustrates the probability of financial distress will reduce as retained earnings to total assets increase. The results are similar to Foster and Zurada (2013), Waqas and Md-

Rus (2018), and Darmawan and Supriyanto (2018). This is because as this ratio increases, firms will have more internal funds to finance their future investment and thus, reduce the probability of financial distress. Thai et al. (2014) explained that without retained earnings, a firm might need to use more external financing such as debt to finance the business which could increase a firm's financial distress risk. This clearly illustrates the importance of retained earnings to total assets in predicting financial distress which is aligned to the study by Waqas and Md-Rus (2018) whereby the study shows that retained earnings to total assets is one of the most crucial predictors of financial distress.

Net profit margin (NPM) also shows negative significant result based on the hazard model. The result indicates that as a firm is able to generate net profit from its sales, the probability of financial distress is reduced. This result is similar to those of Bakhri et al. (2018) and Alifiah and Tahir (2018). The situation might be due to the firm's ability to meet all debt obligations that helps in reducing financial distress. However, net profit margin shows insignificant result which contradict the hazard model result. This clearly shows the logit model that ignores the elements of firm-years observations failed to distinguish the effect of net profit margin to predict distress.

The results also show that for the hazard model, OPM and EBITTA are insignificant. The results are similar to Yap et al. (2012), Azwar (2017), , Osho and Idowu (2018) and Nur and Panggabean (2020) . These results could be due to the firms commonly able to generate operating income from their assets and sales but some firms still failed to meet their debt obligations. Although firms that generate high enough operating profit could help them to meet financing cost, it is not a guarantee that firms could also meet their debts payment that is relatively higher than financial cost. This situation might be the reason why the hazard model failed to distinguish the effect of these ratios.

As for the logit model, Table 4.8 shows OPM is positively significant in predicting financial distress. Thus, as firms generate high earnings before interest and tax from their sales, the firm's financial distress probability will increase. This is similar to Ugurlu and Aksoy (2006) but contrary to Parker et al. (2002). One explanation is that as firms make higher operating profits, they are willing to increase their debts as they expect that they could pay off their debts, as predicted by the trade-off theory (DeAngelo & Masuli,1980). However, as time passed the expectation failed to materialize, which could be due to economic shocks in the market, leading the firms into financial distress.

According to logit model, EBITTA is negatively significant in predicting distress according to the logit model. This significant result is similar to the findings by Parker et al. (2002), Darmawan and Supriyanto (2018), Pham et al. (2018), and Waqas and Md-Rus, 2018). The result indicates that firms that are able to generate high earnings before interest and tax have lower probability of financial distress. This is because firms have no problem to meet debt obligations from their operating income. Although the results for both models are different, profitability ratios remain important to predict financial distress. This is because profitability ratios show significant results in both models.

In general, the results for profitability ratios indicated that a firm with a high ability to generate profit and have a large amount of retained earnings has a lower financial distress risk. The results are consistent with the pecking order theory that firms with substantial internal capital commonly rely less on external funds such as debts which helps reduce the firm's default risk level. If the firm relies less on debt, the firm will have less financial commitment, such as interest payments and loan payments. Thus, a firm with a high ability to generate profit commonly has enough ability to the financial commitment, which directly reduces default risk and indirectly reduces the financial distress risk level.

#### 4.3.1.4 Leverage Ratios and Financial Distress

Finally, debt ratio (DR) has the highest chi-squared value among all variables, which shows that it is the most important variable in predicting financial distress for both models according to Table4.8. Debt ratio has a positive coefficient which indicate a firm with high level of debt will have high probability to face financial distress and this is aligned with the theoretical argument. Previous studies by Lee and Yeh (2004), Yap et al. (2012), Waqas and Md-Rus (2018), and Abdullah et al. (2019) explain that debt will increase the degree of financial risk. Thus, if firms over-financed their assets using debts and fail to manage their debts, it could lead to financial distress. Shareholder's fund to total debt (SFTD) is negatively significant for the hazard model but insignificant for the logit model. The result from the logit model contradicts Darmawan and Supriyanto (2018) but is similar to Vo et al. (2019). The result from the hazard model indicates that as a firm relies more on shareholders' equity to finance its business and increase its equity proportion compared to total debt, the firm could reduce financial distress. This contradicting result between logit and hazard model is due to the difference in data type since logit uses cross-sectional data while hazard uses panel data which lead to different results obtained for each model.

In both prediction models, long-term debt to total debt (LDTD) is insignificant to predict disrtess which indicates that both models failed to capture the influence of long-term debt to predict financial distress. These results contradict those of Ugurlu and Aksoy (2006). This situation might be due to not all firms having long term debt especially firms that are fully funded by shareholder capital and some of the firms have a really small long-term debt. So, the long-term debt's proportion does not provide a significant effect to predict financial distress.

Table 4.8 shows that interest coverage ratio (ICR) is insignificant for both hazard and logit models. The results are similar to Parker et al. (2002) but contradict to Waqas and Md-Rus (2018). This situation might be due to firms being commonly able to meet their financial and interest cost using their operating profit or internal source of funds but having problems in paying the principal amount of the debt. Thus, the effect of interest cost in predicting firm financial distress becomes insignificant.



In conclusion, the results show that a firm's ability to manage capital structure elements such as debts and equities is crucial in predicting financial distress. According to the results, if a firm depends too much on debt to finance, the bankruptcy cost will be high, which could lead to financial distress. These results aligned with the trade-off theory that believes a firm should pursue achieving optimal capital structure in order to obtain tax benefits and reduce bankruptcy costs. Thus, the firm should not only rely on debts but should be balanced with other sources of funds such as equity to reduce the bankruptcy cost and obtain tax benefits which indirectly helps reduce the firm's financial distress risk.

## 4.4 Classification Accuracy of the Prediction Model

In order to test the model fitness, this study starts by using McFadden R-squared and adjusted McFadden R-squared. Result Table 4.9 shows that McFadden R-squared and adjusted McFadden R-squared value are 0.9122 and 0.8859 for the hazard model which is considered to be high and the model fits well with the data.

**Table 4.9**
*Classification Accuracy for Hazard Model*

| Observed | Predicted | | |
|---|---|---|---|
| | Non-Financial Distressed | Financial Distressed | Percentage Correct |
| Non-Financial Distressed | 14176 | 1134 | 92.59 |
| Financial Distressed | 45 | 128 | 73.99 |
| Overall Accuracy Percentage | | | 92.38 |
| McFadden R-squared | 0.9122 | | |
| Adjusted McFadden R-squared | 0.8859 | | |
| Likelihood Ratio test | 79.55*** | | |
| Akaike Criterion (AIC) | 112.45 | | |

In Table 4.9, hazard model shows 92.38 percent overall accuracy percentage based on estimated sample used. The Hazard model manage to correctly predict non-distressed cases at 92.59 percent and correctly predict financial distressed firms at 73.99 percent. The accuracy is considered high and greater compared to Md-Rus (2011) and Wang and Wu (2017). Next, this study tests the level of significance for the deviances of constrained and unconstrained models based on the likelihood ratio test. The results show the chi-squared value of likelihood ratio test is significant at one percent level which indicates that the hazard model's independent variables could well explain the dependent variable.

**Table 4.10**
*Classification Accuracy for Logit Model*

| Observed | Predicted | | |
|---|---|---|---|
| | Non-Financial Distressed | Financial Distressed | Percentage Correct |
| Non-Financial Distressed | 721 | 18 | 97.56 |
| Financial Distressed | 41 | 132 | 76.30 |
| Overall Accuracy Percentage | | | 93.53 |
| McFadden R-squared | 0.6704 | | |
| Adjusted McFadden R-squared | 0.6293 | | |
| Likelihood Ratio test | 424.06**** | | |
| Akaike Criterion (AIC) | 234.43 | | |

Table 4.10 shows the fitness of the logit model. Based on this table, results show that the McFadden R-squared and adjusted McFadden R-squared for the logit model are 0.6704 and 0.6293 respectively. This indicates that although the model developed is well fitted with the data, they are still lower to those of hazard model. In terms of accuracy, the logit model has shown the ability to accurately predict non-distressed cases at 97.56 percent accuracy level. The logit model also shows the ability to accurately predict financial distress at 76.30 percent accuracy level which is considered as high. Finally, the overall accuracy of the model is 93.53 percent in predicting all cases within the used sample, which is slightly higher than the hazard model. In the likelihood ratio test, the result shows a chi-squared value of 424.06 and significant at one percent level.

This study compares the accuracy for both models using Akaike information criterion (AIC). Based on AIC value, the hazard model is lower than the logit model. Thus, the hazard model is better than the logit model in estimating the model's likelihood to predict future values based on in-sample fit.

In conclusion, the results show both models are well fitted and have a high level of accuracy based on the McFadden R-squared, adjusted McFadden R-square, confusion matrix and likelihood ratio test. However, when comparing Akaike information criterion (AIC) for both models, the result shows that hazard in model is better at estimating the in-sample fit based on model's likelihood to predict future values compared to logit model.

Further, to analyse the consistency of the result obtained, this study uses a holdout sample. This study analyses data for 167 randomly chosen firms from the year of 1990 to 2020 with 2831 observations for hazard model and 167 observations for logit model. Table 4.11 shows results for hazard model's classification of accuracy based on holdout sample.



**Table 4.11**
*Classification Accuracy Based on Holdout Sample (Hazard Model)*

| Observed | Predicted | | |
|---|---|---|---|
| | Non-Financial Distressed | Financial Distressed | Percentage Correct |
| Non-Financial Distressed | 2611 | 185 | 93.38 |
| Financial Distressed | 9 | 26 | 74.28 |
| Overall Accuracy Percentage | | | 93.14 |

Table 4.11 shows the hazard model is able to accurately predict 74.28 percent of financial distressed cases and 93.38 percent of non-distressed cases, which are almost similar to the accuracy rates shown in the estimation sample of the hazard model in Table 4.9. Thus, it indicates that the hazard model generates consistent results for both samples.

**Table 4.12**
*Classification Accuracy Based on Holdout Sample (Logit Model)*

| Observed | Predicted | | |
|---|---|---|---|
| | Non-Financial Distressed | Financial Distressed | Percentage Correct |
| Non-Financial Distressed | 125 | 7 | 94.69 |
| Financial Distressed | 10 | 25 | 71.42 |
| Overall Accuracy Percentage | | | 89.82 |

Next, Table 4.12 shows the logit model's accuracy classification result based holdout sample. The results show the holdout model accurately predicted 71.42 percent of financial distressed cases and 94.69 percent of non-distressed cases, which are lower than the values in Table 4.10. Therefore, it could be concluded that the hazard model is better for predicting financial distress compared to the logit model as it is able to generate more consistent results when comparing the accuracy between the main sample and the holdout sample.



## 4.5 Selecting Model to Estimate Probability of Financial Distress

Since the intention of this study is to investigate the effect of financial distress risk on stock returns, the probability of financial distress is needed as it will be used as a proxy for distress risk. Hence, this study has to choose the better prediction model between hazard and logit models.

According to the results obtained from the previous sections, the hazard model shows that the seven out of 12 ratios are significant to predict financial distress with all selected groups of ratios being presented by at least one ratio. Meanwhile, only five out of 12 ratios are found are significant for the logit model with all ratios that represent activity ratios are found to be insignificant. In terms of model accuracy, both models show high accuracy with the logit model's accuracy rate being a bit higher than the hazard model. However, in-sample fitness based on the model's likelihood to predict future values show the hazard model is better compared to the logit model. Hazard model also shows better consistency in its accuracy compared to logit model since hazard model has more consistent result between main sample and holdout sample compared to logit model.

In conclusion, the hazard model is chosen as the better model in predicting financial distress for this study compared to logit model. This is because the hazard model generates high accuracy model, more consistent results and better model fitness which is crucial for prediction models. Another reason for choosing the hazard model as the best model for this study is due to the econometric problem faced by the logit model as highlighted by Md-Rus (2011), and Shumway (2001). Shumway (2001) highlighted a few problems of using the logit model in predicting financial distress since it has bias in sample selection and the model does not consider time-varying element in reflecting the financial distress risk. These problems could lead to biased, inefficient, and inconsistent results. Shumway (2001) introduces the hazard model to overcome the problem. Thus, this study chooses the hazard model to predict financial distress and generate financial distress's probability to represent financial distress risk in determining stock returns.

### 4.6 Distress and Asset Pricing Model

Section 4.6 onwards focuses on the risk factors' effect on stock returns. The risk factors of interest are distress risk, size, and value. The section starts by looking at descriptive of and correlations between risk factors affecting stock returns.

#### 4.6.1 Descriptive Analysis

Table 4.13 displays results from descriptive analysis for this study's selected variables. The results consist of mean, standard deviation, minimum value, and maximum value for all variables. Based on Table 4.13, the result shows the average return for stocks listed in the Malaysian market during the sample period is 0.005. The maximum value for return is 0.618 while the minimum value is -0.372 with the return standard deviation of 0.147. The average expected probability for financial distress risk is 0.016 with the standard deviation of 0.119.



**Table 4.13**
*Descriptive Analysis for Asset Pricing Model*

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Return | 0.005 | 0.147 | -0.372 | 0.618 |
| Distress | 0.016 | 0.119 | 0 | 1 |
| Size | 18.955 | 1.610 | 15.955 | 23.967 |
| Value | 1.314 | 1.178 | -0.383 | 6.742 |

**NOTE**: Distress represents financial distress risk generated from prediction model, Size represents firm size based on market capitalisation, and Value represents firm book-to-market value

Next, the table shows the mean value of 18.955 for size based on the natural logarithm of market value. Table 4.13 also shows standard deviation of size is 1.610. Meanwhile, the firm's size is within the range of 15.955 and 23.967. Lastly, the table also shows that the average value that is represented by book-to-market value of firms is 1.314 with the standard deviation of 1.178. This shows the wide range of value for firms used within the study sample. The wide range of values could be clearly seen based on the minimum and maximum value of the data which are -0.383 and 6.742 respectively.

### 4.6.2 Correlation and VIF Analysis

Next, this study continues with correlation analysis to examine the correlation among the variables. The results are summarised in Table 4.14.

**Table 4.14**
*Correlation Matrix for Asset Pricing Model*

| | Distress | Size | Value |
|---|---|---|---|
| Distress | 1 | | |
| Size | -0.1256 | 1 | |
| Value | -0.1093 | -0.3496 | 1 |

**NOTE:** Distress represents financial distress risk generated from prediction model, Size represents firm size based on market capitalisation, and Value represents firm value based on book-to-market value.



Based on Table 4.14, financial distress shows negative correlation with firm value and size. This is because the correlation value between financial distress with size and value are -0.1256 and -0.1093 respectively. The correlation between value and size is-0.3496 which indicates that these two variables have negative weak correlation. Based on 0.9 as the benchmark suggested by Gujarati and Porter (2009) for very strong correlation, it clearly shows that all variables have weak and moderate correlation between each other which could avoid serious multicollinearity problems. However, to confirm that this study is free from multicollinearity problems, variance inflation factors (VIF) are estimated and the results are shown in Table 4.15.

**Table 4.15**

*Variance Inflation Factor Analysis for Asset Pricing Model*

| Variable | VIF |
|---|---|
| Distress | 1.04 |
| Size | 1.18 |
| Value | 1.17 |
| Mean VIF | 1.13 |

**NOTE:** Distress represents financial distress risk generated from prediction model, Size represents firm size based on market capitalisation, and Value represents firm value based on book-to-market value.

Based on the result in Table 4.15, the VIF values for all variables are within the range of 1.04 to 1.18 with the average of 1.13. Based on Hair et al.(2010), all variables should have VIF value below 10 in order to avoid any serious multicollinearity problem. Thus, based on the results in correlation analysis and VIF analysis, all variables for this study do not suffer from any serious multicollinearity problem.



### 4.7 Portfolio Based Mean Analysis

This study proceeds by analysing the returns for portfolios that are developed based on financial distress probability, firm size, and firm value. As for financial distress-based portfolios, all firms are sorted into 10 portfolios based on financial distress probabilities with portfolio 1 consisting of firms with the lowest financial distress risk and portfolio 10 containing stocks with the highest financial distress. Based on these portfolios, this study compares the mean values of return, size, and value. The results for this analysis show in Table 4.16.

**Table 4.16**
*Financial Distress-Based Portfolio Mean Analysis*

| Portfolio | Observations | Distress | Return | Size | Value |
|---|---|---|---|---|---|
| 1 | 14290 | $1.34e^{-20}$ | 0.0067 | 18.9040 | 1.1533 |
| 2 | 14140 | $1.24e^{-15}$ | 0.0065 | 18.9167 | 1.1765 |
| 3 | 14156 | $8.26e^{-13}$ | 0.0072 | 19.0383 | 1.2874 |
| 4 | 14142 | $5.14e^{-11}$ | 0.0057 | 18.9823 | 1.3725 |
| 5 | 14072 | $1.09e^{-9}$ | 0.0063 | 19.0801 | 1.3669 |
| 6 | 14207 | $1.41e^{-8}$ | 0.0071 | 19.1412 | 1.3919 |
| 7 | 14160 | $1.42e^{-7}$ | 0.0034 | 19.0014 | 1.5065 |
| 8 | 14153 | $1.85e^{-6}$ | 0.0037 | 18.993 | 1.4713 |
| 9 | 14506 | 0.000042 | 0.0035 | 19.0240 | 1.3987 |
| 10 | 13599 | 0.1643 | 0.00002 | 18.4615 | 1.0132 |
| Total | | 0.0163 | 0.0051 | 18.9548 | 1.3140 |

**NOTE:** Distress represents financial distress risk generated from prediction model, Size represents firm size based on market capitalisation, and Value represents firm value based on book-to-market value.

The results show that the lowest financial distress portfolios, which are portfolios 1, 2, and 3, have average returns relatively higher than highest financial distress portfolios that are represented by portfolios 8, 9, and 10. The total average firms' size for lowest financial distress portfolios are relatively larger than highest financial distress portfolios. As for value, the table shows that portfolio with lowest level of financial distress (portfolio 1) have average value of firm that is relatively higher than highest financial distress portfolios (10). The highest financial distress portfolios also show lowest firms' value with portfolio 10 shows the lowest average firms' value among all portfolios. Based on all these results, it clearly shows that the high financial distress risk firms tend to have lower return, relatively small size and lower or negative firms' value compared to low financial distress risk firms.

Next, this study sorts the sample into ten size-based portfolios with portfolio 1 consisting of the smallest size firms and portfolio 10 containing the largest firm. Based on these portfolios, this study compares the average (means) of return, distress risk, and value. Table 4.17 shows the result of this analysis.

**Table 4.17**
*Size-Based Portfolio Mean Analysis*

| Portfolio | Observations | Size | Return | Distress | Value |
|---|---|---|---|---|---|
| 1 | 14291 | 16.7617 | -0.0234 | 0.0750 | 1.8694 |
| 2 | 14136 | 17.4249 | -0.0022 | 0.0202 | 1.8025 |
| 3 | 14159 | 17.8367 | 0.0043 | 0.0154 | 1.6345 |
| 4 | 14132 | 18.1804 | 0.0054 | 0.0134 | 1.5230 |
| 5 | 14068 | 18.5174 | 0.0083 | 0.0108 | 1.4200 |
| 6 | 14215 | 18.8745 | 0.0087 | 0.0104 | 1.2455 |
| 7 | 14149 | 19.2977 | 0.0125 | 0.0060 | 1.1503 |
| 8 | 14140 | 19.8407 | 0.0132 | 0.0049 | 1.0336 |
| 9 | 14155 | 20.5966 | 0.0114 | 0.0049 | 0.8731 |
| 10 | 13980 | 22.2636 | 0.0128 | 0.0012 | 0.5772 |
| Total | | 18.9548 | 0.0051 | 0.0163 | 1.3140 |

**NOTE:** Distress represents financial distress risk generated from prediction model, Size represents firm size based on market capitalisation, and Value represents firm book-to-market value.

Table 4.17 shows returns for the smallest size-based portfolio are negative while the largest size-based portfolio shows the second highest return. The result also shows that the return increases as portfolio size increases which demonstrates a direct relationship between size and return. In terms of financial distress risk, the result shows that the three largest size-based portfolios (portfolios 8, 9, and 10) have lower financial distress risk compared to the smallest size-based portfolios that have higher financial distress risk. Lastly, the table shows that the smallest size-based portfolio (portfolio 1) has the highest value.

Next, this study extends the analysis by examining the return, financial distress risk, and size for portfolios based on firm value with all firms sorted into 10 portfolio-based values. Portfolio 1 consists of the lowest value while portfolio 10 contains the highest value. The results are presented in Table 4.18.

**Table 4.18**
*Value-Based Portfolio Mean Analysis*

| Portfolio | Observations | Value | Return | Distress | Size |
|---|---|---|---|---|---|
| 1 | 14984 | 0.1124 | 0.0236 | 0.1013 | 19.8656 |
| 2 | 14351 | 0.3878 | 0.0217 | 0.0108 | 19.9242 |
| 3 | 13724 | 0.5704 | 0.0184 | 0.0073 | 19.5094 |
| 4 | 13745 | 0.7416 | 0.0091 | 0.0065 | 19.1848 |
| 5 | 13982 | 0.9203 | 0.0067 | 0.0061 | 18.9975 |
| 6 | 14213 | 1.1256 | 0.0045 | 0.0049 | 18.8245 |
| 7 | 14150 | 1.3759 | -0.0003 | 0.0055 | 18.6237 |
| 8 | 14140 | 1.7100 | -0.0051 | 0.0055 | 18.4139 |
| 9 | 14235 | 2.2741 | -0.0092 | 0.0074 | 18.2427 |
| 10 | 13901 | 3.9543 | -0.0191 | 0.0068 | 17.9458 |
| Total | | 1.3140 | 0.0051 | 0.0163 | 18.9548 |

**NOTE:** Distress represents financial distress risk generated from prediction model, Size represents firm size based on market capitalisation, and Value represents firm on book-to-market value.

Based on Table 4.18, it shows that portfolio 1, 2, and 3 have the lowest average value while portfolio 8, 9, and 10 show the highest average value. However, the result for average portfolios returns show portfolios 1, 2, and 3 with low value have relatively higher return compared to highest value portfolios. Portfolio 10 has lower returns compared to those of portfolio 1. In terms of financial distress risk, the portfolio with the lowest value shows very high average financial distress risk compared to those of the highest value portfolios. The result clearly shows that as value increases, the financial distress risk decreases which indicates a reverse relationship between both risk factors. However, Table 4.18 also shows that the portfolio with the highest value (portfolio 10) has relatively lower size compared to all portfolios except portfolio 1.

## 4.8 Univariate Analysis

Next, to understand the relationship of financial distress towards returns, this study uses Fama-MacBeth regression that was introduced by Fama and MacBeth (1973) that also includes the financial distress variable. This study develops a few models that are based on the Fama-MacBeth regression procedure. This study starts by testing the individual effect of financial distress, value, and size on returns and finally, all these independent variables are regressed together within one model.

**Table 4.19**
*Effect of Financial Distress on Return*

| | Fama-MacBeth | | | |
|---|---|---|---|---|
| Variables | Coefficient ($\beta_i$) | Standard Error | t-value | p-value |
| Constant | 0.0076 | 0.0021 | 3.58 | 0.000*** |
| Distress | 0.5065 | 0.5751 | 0.88 | 0.379 |
| $R^2$ | 0.008 | | | |

**Note:** Constant represents constant variable and Distress represents financial distress risk generated from the hazard prediction model. The asterisk (*) on p-value represents statistically significant at certain level; *** statistically significant at 1% level, ** statistically significant at 5% level, and * statistically significant at 10% level.

Results on financial distress risk effect returns show in Table 4.19. The results show the variable's coefficient is 0.5065 with the p-value of 0.379 which indicates financial distress does not influence return. Although the result seems to align with the capital assets pricing model's (CAPM) assumption that only market risk affects stock return, other variables might affect return, as argued by Roll (1977). According to Roll (1977), the CAPM assumption is applicable only if the exact composition of the actual market portfolio is known and used in the tests. This argument implies that the assumption of CAPM is irrelevant unless the sample consists of all individual assets. Thus, it could lead to other risk factors such as size and book-to-market being significant in affecting returns. Another possible explanation is that CAPM has oversimplified and unrealistic assumptions, which are against the real-world situation where stock return could be affected by many risk factors (Fama & French, 2004).

**Table 4.20**
*Effect of Size on Return*

| | Fama-MacBeth | | | |
|---|---|---|---|---|
| Variables | Coefficient ($\beta_i$) | Standard Error | t-value | p-value |
| Constant | -0.0955 | 0.0103 | -9.28 | 0.000*** |
| Size | 0.0054 | 0.0005 | 11.24 | 0.000*** |
| $R^2$ | 0.096 | | | |

**Note:** Constant represents constant variable, and Size represents firm size based on market capitalisation. The asterisk (*) on p-value represent statistically significant at certain level; *** statistically significant at 1% level, ** statistically significant at 5% level, and * statistically significant at 10% level.

Another variable that is also used to test individual effects on return is size. Table 4.20 shows the results based on the Fama-MacBeth regression model. The coefficient for size is 0.0054 which clearly indicates that size has a positive effect on returns. It supports findings in Table 4.17 where if size increases, the return also increases. Based on the p-value, the result shows the value that is smaller than 0.01, which shows that size is statistically significant in affecting stock returns at 1% significance level. This is aligned with Lindaas and Simlai (2016), Das and Barai (2016), and Ong et al (2018).



The results in Table 4.21 represent results on the effect of value on stock return. The results show that value, which is represented by book value to market value, has a coefficient of -0.0105 which indicates that value has a negative effect on stock returns. Thus, high value firms should have lower return compared to low value firms. This variable has a p-value of 0.000 which indicates that the variable is significant to affect return at 1% significant level and consistent with previous studies (Taneja, 2010; Husein and Mahfud, 2015;). This is also in line Table 4.18's results. This is because high value firms have lower growth opportunities thus leading to lower return.

**Table 4.21**
*Effect of Firm's Value on Return*

| Variables | Fama-MacBeth Coefficient ($\beta_i$) | Standard Error | t-value | p-value |
|---|---|---|---|---|
| Constant | 0.0207 | 0.0020 | 10.22 | 0.000*** |
| Value | -0.0105 | 0.0005 | -19.27 | 0.000*** |
| DNegValue | -0.0190 | 0.0056 | -3.41 | 0.001*** |
| $R^2$ | 0.1553 | | | |

**Note**: Constant represents constant variable and Value represents firm value based on book-to-market value. DNegValue represents dummy variable of negative value that based on negative book-to-market value. The asterisk (*) on p-value represent statistically significant at certain level; *** statistically significant at 1% level, ** statistically significant at 5% level, and * statistically significant at 10% level.

The results also show DNegValue is significant with negative sign in affecting returns. The negatively significant DNegValue indicates that negative value stocks generate lower return compared to positive value stocks. This result show that investors try to avoid investing in firms with negative values as they are very risky and could be delisted from the market.

## 4.9 Multivariate Analysis

### 4.9.1 Multivariate Regression Results

This study extends the analysis by using multivariate analysis that combines the selected independent variables into different models to examine the risk factors effect on stock returns. Table 4.22 shows the results.

**Table 4.22**
*Multivariate Fama-MacBeth Regression Analysis*

| Model | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Constant | -0.0937<br>[0.0105]<br>(-8.88***) | 0.0211<br>[0.0020]<br>(10.38***) | -0.0354<br>[0.0105]<br>(-3.36***) | -0.0329<br>[0.0108]<br>(-3.04***) |
| Distress | 0.8061<br>[0.5800]<br>(1.39) | 0.3047<br>[0.5758]<br>(0.53) | | 0.4594<br>[0.5815]<br>(0.79) |
| Size | 0.0053<br>[0.0005]<br>(10.79***) | | 0.0029<br>[0.0005]<br>(5.85***) | 0.0028<br>[0.0005]<br>(5.47***) |
| Value | | -0.0104<br>[0.0005]<br>(-19.39***) | -0.0094<br>[0.0005]<br>(-17.57***) | -0.0095<br>[0.0005]<br>(-17.69***) |
| DNegValue | | -0.0120<br>[0.0059]<br>(-2.02**) | -0.0168<br>[0.0056]<br>(-2.99***) | -0.0113<br>[0.0060]<br>(-1.90*) |
| $R^2$ | 0.1790 | 0.2330 | 0.2257 | 0.3049 |

**Note:** Constant represents constant variable, Distress represents financial distress risk generated from prediction model, Size represents firm size based on market capitalisation, and Value represents firm value based on book-to-market value. DNegValue represents a dummy variable of negative value that is based on negative book-to-market value. The value inside [ ] represents standard error value, while value in ( ) represents t-statistic value. The asterisk (*) on p-value represents statistically significant at certain level; *** statistically significant at 1% level, ** statistically significant at 5% level, and * statistically significant at 10% level.

As for model 1 in Table 4.22, this study uses only distress risk and size as the risk factors in the model. The result shows size is significant with a positive sign which is consistent with the result in model 3. However, distress risk shows insignificant result. Thus, distress risk for this model does not affect returns.

In model 2, distress risk and value are used as the risk factors. The results show value is negatively significant to affect stock returns where the results are similar to those of model 3. Meanwhile, the financial distress shows negatively insignificant result, which is similar to the results of model 1. As for the result of the dummy variable, the variable is significant in explaining returns.

Based on Table 4.22, model 3 only consists of size and value as the risk factors.  The results for model 3 show that size is positively significant in explaining returns. The results also show that value is negatively significant. The results for model 3 also show that the dummy variable for negative book-to-market value has negative coefficient significant to effect return. This indicate stocks with negative value generate lower returns compared to those of positive value.

Next, all selected risk factors are combined into model 4. The results show that size, value, and dummy variable for value are significant in explaining returns which are similar to previous models. Thus, it can be concluded that size and value-based factors are crucial to determine stock returns in the Malaysian market. Distress risk also shows consistent results with previous models which show that it is not significant in explaining returns.

### 4.9.2 Discussion of Results

Table 4.22 illustrates that risk of financial distress is insignificant to affect returns in all models tested. The result contradicts to Malik et al. (2013), Boubaker et al. (2018), and Chhapra et al. (2020) but similar to study by Md-Rus (2011), Idrees and Qayyum (2018), and Sudirgo et al. (2019). This is aligned with risk categories highlighted by Reilly and Brown (2011) who categorised financial distress is a part of unsystematic risk. Thus, it could be fully diversified via portfolio diversification and will not have any effects on return.

Another possible explanation on the insignificance of distress risk on returns is related to investors' inability to accurately measure distress risk. This is because investors have to accurately identify variables that affect distress risk and it is not an easy process. Thus, most investors make investment decisions without considering the distress risk. The insignificant result could also be due to the investors' investment preferences toward risk (Das & Barai, 2016). These preferences are difficult to be measured by asset pricing models. Due to these reasons, it might lead to the asset pricing models failure to capture the effect of financial distress on stock returns. This resulted in the insignificance of financial distress in explaining stock returns.

Arguments by Fama and French (1992) could also be the reason for this insignificant result as they argued that the size and value could be used as a proxy to represent financial distress risk. This is in line with the results for univariate analysis and model 1, 2, and 4 in this study. The results in univariate analysis distress are found to be close significant at 10 percent. However, when this study includes size and value variables into the pricing model, the results (model 1,2, and 4) show distress risk become insignificant to affect return. Thus, it clearly shows distress risk subsume inside size and value factors in pricing the return.

The results in Table 4.22 show that size has a significant effect on return based on developed models. The coefficient for size is consistent as it shows positive coefficient in all models. These results are similar to findings by Das and Barai (2016) and Ong et al. (2018). This indicates that a large firm's stock earns higher return compared to a small firm's stock. The positive significant results are due to risk aversion of investors that lead them to invest in large firms or blue-chip stocks that are commonly more stable and have lower risk compared to small firms. This is supported by Abbas and Badshah (2015) who explained that institutional investors, foreign, and local mutual funds prefer to invest in large firms that could generate high return through higher dividend payout ratio. Thus, this explains why stocks for firms with large market capitalisation generate higher return compared to small market capitalisation firms.



Table 4.22 shows that value is negative explain stock returns. Thus, it illustrates that as value increases, returns decrease. This result is similar to Taneja (2010) and Husein and Mahfud (2015). This might be due to high book-to-market firms (value firms) commonly having less growth opportunities compared to low value book-to-market firms (growth firms) Thus, investors will be attracted to low value stocks that are expected to generate high return in terms of dividend from the firm's profit and large price appreciation. This clearly shows that value firms perform poorly in generating return compared to growth firms. This is aligned with expectations by Reilly and Brown (2011) who suggested growth stocks should generate higher returns compared to value stock.

The results also show the dummy variable (DNegValue) is negatively significant almost all models of this study. These significant results indicate that stocks with negative value generate lower return compared to positive value stocks. This could be due to investors avoiding investing in firms with negative value since these firms are in financial trouble. Thus, potential investors avoid investing in this firm while current investors will sell their investment to avoid holding high risk investments. This situation leads to reduction in stock price and lower or negative return.

In terms of theory, the results clearly show that a few variables could affect stock returns. According to the results, financial distress is insignificant in affecting returns. The results contradict to risk return trade-off concept since the distress risk level does not contribute to higher returns. The main reason is distress risk being a part of the unsystematic risk that can be diversified and does not impact return. Meanwhile, risk factors such as size and value significantly affect returns, which align with the arbitrage pricing theory (APT) and the Fama-French three-factors model (FFTF). The results show that a firm's specific factors, such as firm size and value, are essential in explaining stock returns. This is because both size and value (book-to-market) provide risk information that is essential for determining returns and for investors to make investment decisions. Thus, this indirectly indicates that the model to explain return should include multiple risk factors based on more realistic assumptions which align with APT and FFTF assumptions.

The results for all models to estimate returns (univariate and multivariate analysis) also show low $R^2$ values, which are between 0.008 to 0.3049. The results indicate only 0.8% to 30.49% percent of changes in returns explained by this study's estimation models. The results are similar to previous studies that only focus on the effect of a firm's specific risk factors on returns, such as Jais and Gunathilaka (1983) and Yuliarto and Nugroho (2020). Although the $R^2$ for this study's estimation models is low, the results show the explanatory power of the selected variables in explaining return changes. In order to improve the $R^2$, the model should add more risk factors since the $R^2$ improves as more relevant variables add to the model, and $R^2$ for multivariate models is relatively higher compared to univariate models with Model 4, which have three variables that have the highest $R^2$.

## 4.10 Effect of Risk Factors on Return Based on Economic Periods

Next, this study conducts an analysis to understand the effect of selected risk factors on returns based on two different economic periods which are the non-crisis period and the crisis period. Crisis period basically refers to three crisis periods which are Asian Financial Crisis (from July 1997 to December 1999), Global Financial Crisis (from January 2007 to December 2008), and Covid-19 Pandemic (from March 2020 to December 2020, the end of this study period). Meanwhile, the non-crisis period represents the period outside the crisis period. This analysis aims to examine the main analysis's robustness. Table 4.23 summarises the result. Models 1 and 2 report the results for the non-crisis period while models 3 and 4 summarise the results for the crisis period.

The results show that financial distress risk is insignificant in all univariate models (model 1 and model 3) and in multivariate models (model 2 and 4). These results clearly show that the financial distress factor does not have any effect on returns either during both crisis or non-crisis periods. These are consistent with the main result of this study which indicate that distress risk is not priced into stock returns.

**Table 4.23**
*Multivariate Fama-MacBeth Regression Analysis Based on Economic Period*

| | Non-Crisis Period | | Crisis Period | |
|---|---|---|---|---|
| Model | 1 | 2 | 3 | 4 |
| Constant | 0.0094 | -0.0157 | -0.0017 | -0.1132 |
| | [0.0019] | [0.0098] | [0.0008] | [0.0396] |
| | (5.01***) | (-1.60) | (-2.12**) | (-2.86***) |
| Distress | 0.5511 | 0.5480 | 0.2980 | 0.0447 |
| | [0.6901] | [0.6977] | [0.5005] | [0.5065] |
| | (0.80) | (0.43) | (0.60) | (0.09) |
| Size | | 0.0019 | | 0.0066 |
| | | [0.0005] | | [0.0017] |
| | | (4.10***) | | (3.78***) |
| Value | | -0.0092 | | -0.0106 |
| | | [0.0006] | | [0.0014] |
| | | (-15.85***) | | (-7.85***) |
| DNegValue | | -0.0141 | | -0.0167 |
| | | [0.0064] | | [0.0332] |
| | | (-2.21**) | | (-1.99*) |
| $R^2$ | 0.0093 | 0.2981 | 0.0042 | 0.3325 |

**Note:** Constant represents constant variable, Distress represents financial distress risk generated from prediction model, Size represents firm size based on market capitalisation, and Value represents firm value based on book-to-market value. The value inside [ ] represents standard error value, while value in ( ) represents t-statistic value. The asterisk (*) on p-value represents statistically significant at certain level; *** statistically significant at 1% level, ** statistically significant at 5% level, and * statistically significant at 10% level.

Table 4.23 also shows that in model 2 and 4, size is positively significant in affecting returns in both periods. It clearly shows that investment in large firms could provide better returns in all periods compared to investment in small firms. It could be due to large firms commonly more stable and lower risk which attract risk averse investors. The results are also consistent with the main analyses' results of this study.

The results also show that value is negatively significant in models 2 and 4, which represent non-crisis period and crisis period respectively. Results for both models are consistent with those of the main analyses of this study. This is because firms with high value are expected to have lower growth opportunities which lead to lower returns in both non-crisis and crisis periods. Finally, the dummy variable (DNegValue) is significant in explaining returns in both periods. These are consistent with results in the main analyses of this study. The results indicate that investors avoid investing or holding investment with negative book-to-market ratio in both periods.

### 4.11 Summary of Hypotheses Rejection and Acceptance

This section summarises the research objectives and the corresponding hypotheses to test the objectives of this study. Research objectives 1 and 2 test the hypotheses associated with distress prediction models while research objectives 3 and 4 examine the risk factors relationship with stock return. The hypothesis testing results are shown in Table 4.24.

**Table 4.24**
*Summary of Research Objectives and Hypotheses*

| Research objectives | Hypotheses | Findings |
|---|---|---|
| One: To identify the determinants of financial distress under the logit and hazard models in Malaysia. | H1: Liquidity ratios are significant predictors of financial distress | Hazard: WCTA and SWC are significant while CR is not significant |
| | | Logit Model: Accept hypothesis for WCTA. CR and SWC reject the |
| | H2: Efficiency ratios are significant predictors of financial distress | Hazard: DSC is significant. |
| | | Logit: DSC is insignificant |
| | H3: Profitability ratios are significant predictors of financial distress | Hazard: RETA and NPM are significant while OPM and EBITTA are not significant |
| | | Logit: OPM, RETA, and EBITTA are significant while NPM is not significant |
| | H4: Leverage ratios are significant predictors of financial distress | Hazard: DR and SFTD are significant while LDTD and ICR are not significant |
| | | Logit: Only DR is significant while SFTD, LDTD and ICR are not significant. |

**Table 4.24**
*Summary of Research Objectives and Hypotheses (Cont.)*

| Research objectives | Hypotheses | Findings |
| --- | --- | --- |
| Two: To compare the consistency and the accuracy rate of the logit model and hazard model in Malaysia. | H5: Hazard model is a better prediction model compared to logit's | Hazard model is a better model since it produces high accuracy rate and more consistent results compared to logit model. |
| Three: To examine the effect of financial distress risk on stock returns in Malaysia | H6: Financial distress risk has a significant effect on return | Distress risk is not significant in explaining returns in both univariate and multivariate analyses. |
| Four: To identify the effect of financial distress risk on stock returns after including size and value effect in Malaysia. | H7: Firm's size (Size) has a significant effect on return. | Size is positively significant in explaining returns. |
| | H8: Firm's value (Value) has a significant effect on return. | Value is negatively significant in explaining returns. |

### 4.12 Chapter Summary

This chapter discusses the findings of predicting financial distress using hazard and logit models and factors affecting returns (distress, size, and value) using the Fama-MacBeth approach. Based on descriptive statistics of hazard model and logit model, most of the selected financial ratios have significant mean differences between both categories of firms. Next, this study continues with correlation analysis and variance inflation factor (VIF) analysis. The findings show that certain variables suffer from serious multicollinearity problems for the hazard model. However, data for the logit model does not suffer from any serious multicollinearity problem. This study eliminates TATO to tackle this issue.

The regression results show the hazard model has seven variables that are significant to predict financial distress with all groups of ratios being presented by at least one ratio. Meanwhile, the logit model only has five significant variables to predict financial distress. As for the logit model, the activity ratios are found to be insignificant. The difference in the results between both models are due to different data quality used in the analyses.

Next, this study examines the accuracy and the consistency of both hazard and logit prediction models. Both models generate high accuracy results in the main sample. However, for the holdout sample, the hazard model produces higher accuracy results compared to the logit model. Hazard also produces more consistent results compared to logit model. Furthermore, the logit model suffers statistical problems. Therefore, this study chooses the hazard model in estimating financial distress probability and uses the probability to estimate the financial distress risk effect on returns.

Next, distress risk, size, and value are used in determining stock returns. The process is repeated where the descriptive analysis, correlation analysis and VIF analysis are carried out to ensure the validity of the data. The results show all variables are free from multicollinearity problems since the VIF values for each selected variable are within the tolerance level. Further, this study compares means of ten different portfolios based on either financial distress risk, size, or value. The results show portfolios with lower distress risk, larger size, and lower value generate higher average returns compared to portfolios with high distress risk, smaller size, and higher value.

This study continues the analyses by using univariate and multivariate Fama-MacBeth regression to examine the relationship between risk factors (financial distress risk, size and value) and returns. The results show financial distress risk is insignificant in affecting stock returns. Meanwhile size is positively and value is negatively significant in explaining returns. The result remains the same even after this study controls for different economic periods where distress risk remains insignificant while size and value are significant.

# CHAPTER 5

# CONCLUSION AND RECOMMENDATIONS

## 5.0 Introduction

This chapter concludes the study on predicting financial distress and factors affecting returns. The motivation of the study is discussed in Section 5.1. Meanwhile, Section 5.2 summarises the results of financial distress prediction models and determinants of stock returns. Section 5.3 elaborates the implications of this study. Next, limitations and recommendations for future research are highlighted in Section 5.4. Finally, the summary of this chapter is in Section 5.5.

## 5.1 Motivation of the Study

This study is carried out because of the following motivations. The first motivation is the lack of an exhaustive sample that covers a long period of time. This study uses all 1,079 firms in the Main Market that cover a period of 31 years, from 1990 to 2020. Thus, this study uses 18,314 firm-year observations. By using a larger sample, this study intends to provide more robust analysis and could shed more light on the inconclusive results of predicting financial distress. Although there are many studies on predicting financial distress in Malaysia, these studies use small sample sizes as they focus on only certain industries or a short research period. Thus, the results might not be suitable to represent financial distress for the overall Malaysia market. This indicates research on the determinants of financial distress that uses a large sample size is needed.

This is to ensure that the model could better represent financial distress prediction for the Malaysia market.

The same motivation also applies in examining the relationship between selected risk factors (distress risk, size, and value) based on large sample size. This is because most previous studies in Malaysia only focus on certain industries or within a short study period. In order to avoid this issue, researcher uses monthly data for all public listed firms in Malaysia (excluding financial firms) from 1990 to 2020, which is equivalent to 141,425 observations. Thus, it makes this study unique since the sample is larger, covers almost all industries, and has a longer study period compared to previous studies in Malaysia. The results produced could represent the whole Malaysia market and would help to give a clear picture on the effect of risk factors such as distress risk, size, and value on returns.

The second motivation of this study is the lack of previous studies that use the hazard model to predict financial distress in Malaysiam market. Most of the studies in Malaysia use MDA or logit model in predicting financial distress. However, these models suffer from econometric problems that could affect model accuracy and consistency such as violated the normality and group dispersion's assumption, bias in sample selection and failure to include time-varying elements in reflecting financial distress risk. Furthermore, the logit model uses the average value of firm-year observations to estimate financial distress which might not reflect the real situation of the firms.

In order to overcome this issue, Shumway (2001) introduces a hazard model that considers time varying elements. Thus, the prediction model based on the hazard model is expected to be more consistent compared to the logit model. Based on this expectation, this study compares the prediction models' accuracy and consistency for both hazard and logit models. Although Abdullah et al. (2008) use Malaysia data to compare the prediction models of logit and hazard, a more comprehensive study is still needed to compare the quality of results generated by both models. It is important to know the prediction model quality since it determines the prediction model's reliability. This is because an accurate, consistent, and reliable model would be crucial in measuring financial distress risk.

The third motivation is the lack of studies that examine the effect of distress risk and returns in Malaysia. Many previous studies in Malaysia, such as Lau et al. (2002), Ong et al. (2011), and Li et al. (2017), examined the relationship between distress risk, size, value and other risk factors with stock returns. However, these studies use the coefficients estimated by Altman's Z-score, which is developed in 1968, or Ohlson's O-score, which is developed in 1980, to measure distress risk. Since both Z-score and O-score are developed using US data, it is not suitable to be used in Malaysia due to differences in market characteristics and data quality (Md-Zeni & Ameer, 2010). Based on this argument, this study starts with developing a prediction model for financial distress and uses it to generate the probability that represents distress risk. This is to ensure the distress risk generated is based on the Malaysia environment and could represent the distress risk factor in estimating return for the Malaysia market.

## 5.2 Summary of the Results

The findings of this study could be divided into two main parts whereby the first part focuses on predicting financial distress and the second part focuses on explaining the determinants of stock returns based on the Malaysian stock market.

In predicting financial distress, seven of 12 variables are significant for hazard while for logit there are five significant variables The results show working capital to total assets (WCTA) and sales to working capital (SWC) that represent liquidity ratios are found to be negatively significant in predicting financial distress based on hazard model. This indicates that as firms' liquidity increases, the financial distress risk will decrease. Meanwhile, results in the logit model show only working capital to total assets (WCTA) ratio is significant in predicting financial distress.

The results also show that day's sale in account receivable (DSC) that represents activity ratio, is found to be positively significant in predicting financial distress based on the hazard model. This demonstrates that the faster is the collection of receivables, the lower is the probability of having financial distress. However, DSC is not significant for the logit model. The difference in results for both models is caused by different data treatment, where logit used average data while hazard allows for time varying covariates. Results for liquidity and activities ratios indicate that working capital elements such as current assets and current liabilities components could help reduce financial distress risk, which aligns with the working capital management concept.

The findings of this study also show that only retained earnings to total assets (RETA) is negatively significant in predicting financial distress in both models. Meanwhile, net profit margin (NPM) is negatively significant only in the hazard model. However, operating profit margin (OPM) and earnings before interest and tax to total assets (EBITTA) that also represent profitability ratios are significant in predicting financial distress only in the logit model. Despite the difference in the number of variables that are significant to predict financial distress, both results show that ability to generate profit could be a factor in predicting financial distress. Thus, this aligns with the pecking order theory, which states that firms with a high ability to generate profit commonly have significant internal funds that help reduce the firm's reliability on external funds (debts) and reduce financial distress risk.

Finally, the results show that debt ratio (DR) is positively significant in predicting financial distress for both models. Meanwhile, shareholders' fund to total debt (SFTD) is negatively significant for the hazard model but is insignificant in the logit model. However, long term debt to total debt (LDTD) and interest coverage ratio (ICR) are insignificant in both models. The results clearly show that managing leverage is one of the key factors in avoiding financial distress. Thus, the results align with the trade-off theory that states firms should pursue achieving optimal capital structure by managing debts and shareholders' equity to balance the benefit and cost of debts which also helps to reduce financial distress risk.

Next, this study compares the accuracy between hazard and logit models. The findings show hazard model accuracy is lower than accuracy for logit model. However, this is not the indicator that the logit model is better than the hazard model. This study also analyses the robustness of the results for both models using the holdout sample. The findings show that the accuracy of the holdout sample for hazard models is similar and consistent with estimated models while the logit model shows inconsistent accuracy between main sample and holdout sample. Finally, this study chose the hazard model as the better model as it has better consistency compared to the logit model which is similar to the conclusion reached by Shumway (2001).

This study uses probability generated from the hazard model to represent financial distress risk in determining stock returns. Based on portfolio-based mean analysis, the results show portfolios with high financial distress risk generate average lower returns compared to low financial distress risk. Meanwhile, value portfolios also generate average lower returns compared to growth portfolios. As for size, large-sized portfolios yield higher average returns compared to small-sized portfolios.

This study conducts further analysis using Fama-MacBeth regression to determine the relationship between value, size, and financial distress with returns. Based on univariate Fama-MacBeth regression, the findings show that financial distress might explain stock returns. The univariate Fama-MacBeth regression for size shows a positive significant relationship with stock returns. Meanwhile, value shows negative significant effect on stock returns based on Fama-MacBeth regression.

This study progresses further with the analysis using multivariate Fama-MacBeth regression to understand in detail the effect of value, size, and financial distress risk on stock returns. This study has made a few combinations of the selected risk factors to be included into asset pricing models. The results for financial distress risk show a consistent pattern as it remains insignificant in explaining stock returns in all tested multivariate models. The insignificant results could be due to low awareness on the financial distress risk and low ability to accurately measure the financial distress risk among investors, which lead to investment decisions that ignore financial distress risk. Thus, the effect of distress risk cannot be captured by the assets pricing models.

Size has a positive significant effect on stock returns in all models. This indicates that large firms earn better returns compared to small firms. The positive significant results show that investors are risk averse where they choose to invest in large firms or blue-chip stocks which are more stable, have lower risk and generate high return. The findings also show consistent results for value in all models since value is negatively significant in affecting stock returns. This is because low book-to-market value firms have better growth opportunities compared to high book-to-market value firms which lead to higher returns. However, the results also show firms with negative book-to-market value tend to have lower performance compared to positive book-to-market value firms.



The findings suggest that financial distress risk does not affect returns which indicates that it could be diversified and eliminated through portfolio diversification. Although the results contradict to risk return trade-off theory and arbitrage pricing theory, they align with the capital asset pricing model and modern portfolio theory, which states that financial distress is unsystematic risk. Furthermore, it could be concluded that size and value are the risk factors affecting Malaysia's stock returns. Results for size and value align with arbitrage pricing theory, which states that more than one factor affects return. However, the signs of the coefficients for size and value do not align with previous studies (Aziz & Ansari, 2014; Ferdaous & Barua, 2020; Lindaas & Simlai, 2016; Mselmi et al., 2019).

## 5.3 Implications of Findings

The findings of this study have implications to investors, managers, creditors, policymakers, and academicians and researchers. The implications are discussed in the following subsections.

### 5.3.1 Implication for Investors

The first implication to investors is that the financial distress prediction model based on hazard could be used to measure the firms' probability of financial distress. Although financial distress is not significant in affecting returns, the probability of financial distress measured helps investors to avoid firms that have the potential to be delisted or bankrupt. This will help investors to protect their investment from losing value such as in the case of bankruptcy. The second implication is that this study also explains the risk factors that affect stock returns. According to the results, investors should consider risk factors such as firms' size and book-to-market value before making any investment decision. The results suggest that investors should focus their investment on large market capitalisation firms with low book-to-market value since these characteristics help to generate higher returns.

### 5.3.2 Implication for Managers

Based on the result, managers could use the hazard model to predict and measure the firm's financial distress risk level. This is important as it helps managers to make adjustments on related financial aspects if the financial distress risk level is too high. The managers should focus more on improving the firm's liquidity, asset efficiency, and profitability. The firm's manager also needs to improve the firm's leverage position by reducing the reliability of debts to finance the business. All these factors are crucial in sustaining the future of their business and reducing the firm's level of risk.

The findings also alert the managers to improve and maintain their firms' financial position as this could improve their market position in terms of market capitalisation and the book value of equity. The actions help to attract more investors to invest in the firms' stocks and lead to an increase in stock price that could provide better returns.

### 5.3.3 Implication for Creditors

The financial distress prediction models provide guidelines for creditors in assessing firms' financial situation and it could be used by creditors to monitor borrowers distress risk level. Creditors could use the model developed in this study as one of the indicators in measuring the firm's distress level. The distress model based on this study is:

$$P_{it} = \frac{1}{1+e^{-z_{it}}}$$



With

Z = -21.5011 + 0.1462CR - 1.9405WCTA - 0.0019SWC + 0.0016DSC + 0.4592OPM - 0.4347RETA - 0.1385EBITTA + 19.2598DR - 0.3222LDTD - 4.0442SFTD - 0.0082ICR

This model is more applicable compared to Altman's Z-score or Ohlson's O-score since it is developed based on Malaysia data where the probability of distress generated reflects local conditions. The model also aligns with the concept of working capital management, trade-off, and pecking order theories. The results show that the hazard model could generate consistent results with high accuracy than the logit model. Thus, creditors could use the probability generated from this study's model to predict financial distress and make financing decisions. The model is more reliable in measuring financial distress risk for Malaysian firms since the model uses Malaysian market data, aligns with financial concepts and theories, and produces a consistent outcome that is important to predict financial distress accurately.

### 5.3.4 Implication for Policymakers

The findings could provide helpful information for policymakers and market regulators such as Bursa Malaysia. Bursa Malaysia could use the findings of this study to improve its method in identifying distress firms in Malaysia. Instead of relying solely on APN17, Bursa Malaysia should also look at the financial ratios of listed firms, especially in terms of leverage, profitability, efficiency, and liquidity.



Furthermore, Bursa Malaysia could adopt the model used in this study to generate distress probability as this probability reflects the distress level of every firm listed in Bursa Malaysia. This score could serve as a complement to APN17 guidelines in identifying distressed firms. This indicator also will be useful for market participants such as investors in making investment decisions and managers to monitor their firm's distress level.

### 5.3.5 Implication for Academicians and Researchers

As for academicians and researchers, the findings of this study highlight the importance of estimation methods (logit versus hazard) in predicting financial distress. The results show the superiority of the hazard model compared to the logit model in generating consistent results which are important for researchers in developing a more reliable financial distress prediction model. Therefore, future research should adopt the hazard model as one of the estimation methods in financial distress studies. The findings also highlight the importance of ratios in predicting financial distress. According to the results, ratios such as liquidity, efficiency, profitability, and leverage are ratios that future researchers should consider in predicting financial distress. The main reason is that these ratios were significant in predicting financial distress.

Although this study finds that financial distress risk does not affect returns in Malaysia, the effects of size and value are not as predicted by previous researchers (Husein & Mahfud, 2015; Lindaas & Simlai, 2016; Ong et al., 2018; Taneja, 2010). So, researchers should investigate these results further.

In conclusion, these study results are helpful for investors, managers, creditors, policymakers, academicians, and researchers since the results explain the ability of the hazard model and financial ratios to predict financial distress. The results also align with the working capital management, trade-off, and pecking order theories. The result is relevant to the real world and could be explained based on theories and concepts. As for estimating the return, the results remain aligned with the APT and FFTF, especially for size and value risk factors.

### 5.4 Limitations and Recommendations

This section focuses on highlighting limitations faced by the researcher in conducting this study and recommendations for future study.

#### 5.4.1 Limitations of Study

There are a few limitations in estimating prediction models and asset pricing models in this study. The first limitation is related to complete data availability. This study uses two types of data which are the annual data for financial ratios to estimate the prediction models and monthly data for firms' share price, size, and value in estimating the asset pricing model. Although this study is able to collect data for 1079 firms, some firms are excluded since information about those firms are not available either in Bloomberg Terminal or in Datastream.

Another limitation faced by this study is the difference in accounting practices by firms in the financial sector which leads to the models being developed by focusing only on non-financial firms. Furthermore, this study only focuses on specific financial factors in predicting financial distress to the exclusion of governance factors as collecting these factors would be time consuming. In addition, governance factors need to be collected from annual reports and prior to 2000, these reports are not readily available.

#### 5.4.2 Recommendations for Future Research

Based on the findings of this study, there are a few recommendations that will help future researchers to further examine the areas of financial distress prediction and asset pricing model. In order to enhance future research, inclusion of unlisted firms will help in obtaining more comprehensive models to represent the Malaysian market.

Furthermore, future study may also include corporate governance and macroeconomic variables into the model since all these factors might affect financial distress for both financial distress prediction model and asset pricing models.

Since this study only focuses on hazard model, logit model and Fama-MacBeth regression, future study could also compare various types of analysis techniques such as artificial neural network and dynamic logit model technique in predicting financial distress and using Fama-French four-factor or five-factor model to estimate stock returns. Thus, this will create a more comprehensive model to explain financial distress and stock returns in the Malaysian market. Finally, future study should also make comparisons between countries in order to understand the distinct characteristics of different countries.

## 5.5 Chapter Summary

This chapter started with the motivations of this study. Next, the summary of results and findings obtained from financial distress prediction models and asset pricing models are presented. This chapter further explained the implications of this study towards investors, managers, creditors, policymakers, and future researchers. This chapter later highlighted the limitations of this study and recommendations for future studies.

## References


Abbas, M., & Badshah, I. (2015). Preferences of Institutional Investors at Karachi Stock Exchange. *Int'l Conference on Business, Marketing & Information System Management (BMISM'15)*, 1–4.

Abdul Manab, N., Yen, N., & Md-Rus, R. (2015). The Determinants of Credit Risk in Malaysia. *Procedia - Social and Behavioral Sciences*, *172*, 301–308. https://doi.org/10.1016/j.sbspro.2015.01.368

Abdullah, N. A., & Ahmad, A. H. H. (2005). Detecting Financial Distress. *International Journal of Management Studies*, *12*(1), 77–95.

Abdullah, N. A. H., Ahmad, A. H. H., & Md-Rus, R. (2008). Predicting corporate failure of Malaysia's listed companies: Comparing multiple discriminant analysis, logistic regression and the hazard model. *International Research Journal of Finance and Economics*, *15*, 201–217.

Abdullah, N. A. H., Ahmad, A. H., Zainudin, N., & Md-Rus, R. (2019). Predicting Financially Distressed Small- and Medium-sized Enterprises in Malaysia. *Global Business Review*, *20*(3), 627–639. https://doi.org/10.1177/0972150919837053

Abdullah, S. N. (2006). Board structure and ownership in Malaysia: the case of distressed listed companies. *Corporate Governance*, *6*(5), 582–594. https://doi.org/10.1108/14720700610706072

Abu Bakar, N., & Rosbi, S. (2019). Evaluation of Long Term Performance for Initial Public Offerings (IPO) in Malaysia: A Fama-French Method. *International Journal of Scientific Research and Management*, *7*(01). https://doi.org/10.18535/ijsrm/v7i1.em04

Acheampong, P., & Swanzy, S. K. (2015). An Empirical Investigation into the Applicability of Fama-French Three Factor Model in Explaining Portfolio

Returns: Evidence from Non-Financial Firms on the Ghana Stock Exchange, p75. *International Journal of Financial Research*, *7*(1), p75.

Aleati, A., Gottardo, P., & Murgia, M. (2000). The pricing of Italian equity returns. *Economic Notes*, *29*(2), 153–177.

Alifiah, M., & Tahir, M. (2018). Predicting financial distress companies in the manufacturing and non-manufacturing sectors in Malaysia using macroeconomic variables. *Management Science Letters*, *8*(6), 593–604.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *XXIII*(4), 589–609.

Altman, E. I., Haldeman, R. G., & Narayanan, P. (1977). ZETATM analysis A new model to identify bankruptcy risk of corporations. *Journal of Banking & Finance*, *1*(1), 29–54. https://doi.org/10.1016/0378-4266(77)90017-6

Altman, E. I., Marco, G., & Varetto, F. (1994). Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience). *Journal of Banking & Finance, 18*(3), 505–529.

Anjum, S. (2012). Business bankruptcy prediction models : A significant study of the Altman ' s Z-score model. *Asian Journal of Management Research*, *3*(1), 212–219.

Ashraf, S., Félix, E. G. S., & Serrasqueiro, Z. (2019). Do Traditional Financial Distress Prediction Models Predict the Early Warning Signs of Financial Distress? *Journal of Risk and Financial Management*, *12*(2), 55. https://doi.org/10.3390/jrfm12020055

Avramov, D., & Chordia, T. (2006). Asset pricing models and financial market anomalies. *Review of Financial Studies*, *19*(3), 1001–1040.

Aziz, T, & Ansari, V. A. (2014). *Size and value premiums in the Indian stock market*.

Aziz, Tariq, & Ansari, V. A. (2016). Idiosyncratic Risk and Stock Returns: a Quantile Regression Approach. *5th Economics & Finance Conference*, *March*, 2–11. https://doi.org/10.20472/efc.2016.005.002

Azwar, I. (2017). Application of Binary Logit Regression on Financial Distress Prediction of Jakarta Islamic Index. *Journal of BPPK*, *8*(1), 1–23.

Baimwera, B., & Muriuki, A. M. (2014). ANALYSIS OF CORPORATE FINANCIAL DISTRESS DETERMINANTS : A SURVEY OF NON-FINANCIAL FIRMS LISTED IN THE NSE. *International Journal of Current Business and Social Sciences*, *1*(2), 58–80.

Bakhri, S., Listyaningsih, E., & Nurbaiti. (2018). Pengaruh Likuiditas Dan Profitabilitas Terhadap Financial Distress Pada Perusahaan Transportasi. *Jurnal Riset Akuntansi Dan Manajemen*, *7*(1), 40–47.

Balasubramanian, S. A., Radhakrishna, G. S., Sridevi, P., & Natarajan, T. (2019). Modeling corporate financial distress using financial and non-financial variables. *International Journal of Law and Management*, *61*(3/4), 457–484. https://doi.org/10.1108/IJLMA-04-2018-0078

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*(1), 3–18.

Barker, D. (1990). Analysing Financial Health: Integrating Neural Networks and Expert Systems. *PC Al*, *4*(3), 24–27.

Bauer, J., & Agarwal, V. (2014). Are hazard models superior to traditional bankruptcy prediction approaches? A comprehensive test. *Journal of Banking & Finance*, *40*(C), 432–442.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research.*, 71–111.

Beaver, W. H., McNichols, M. F., & Rhie, J. W. (2005). Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy. *Review of Accounting Studies*, *10*(1), 93–122.

Becker, J. M., Ringle, C. M., Sarstedt, M., & Völckner, F. (2015). How collinearity affects mixture regression results. *Marketing Letters*, *26*(4), 643-659.

Bhunia, A., & Sarkar, R. (2011). A study of financial distress based on MDA. *Journal of Management Research*, *3*(2), 1.

Blum, M. (1974). Failing Company Discriminant Analysis. *Journal of Accounting Research*, *12*(1), 1–25.

Boubaker, S., Hamza, T., & Vidal-garcía, J. (2018). Financial distress and equity returns : A leverage-augmented three-factor model. *Research in International Business and Finance*, *46*, 1–15. https://doi.org/10.1016/j.ribaf.2016.09.003

Bryant, P. S., & Eleswarapu, V. R. (1997). Cross- sectional determinants of New Zealand share market returns. *Accounting & Finance*, *37*(2), 181–205.

Carhart, M. M. (1997). On Persistence in Mutual Fund Perfromance. *The Journal of Finance*, *52*(1), 57–82.

Chen, N.-F., Roll, R., & Ross, S. A. (1986). Economic Forces and the Stock Market. In *The Journal of Business* (Vol. 59, Issue 3, pp. 383–403).

Chen, Y., Zhang, L., & Zhang, L. (2013). Financial Distress Prediction for Chinese Listed Manufacturing Companies. *Procedia Computer Science*, *17*, 678–686. https://doi.org/10.1016/j.procs.2013.05.088

Chhapra, I. U., Zehra, I., Kashif, M., & Rehan, R. (2020). Is Bankruptcy Risk a Systematic Risk ? Evidence from Pakistan Stock Exchange. *Etikonomi*, *19*(1), 51–62.

Connor, G., & Sehgal, S. (2001). Test of the Fama and French model in India. *Financial Markets Group Discussion Paper*, No.329.

Connor, G., & Sehgal, S. (2003). Tests of the Fama-French model in India. *Decision*, *30*(2), 1–20.

Cordeiro da Cunha Araújo, R., & André Veras Machado, M. (2018). Book-to-Market Ratio, return on equity and Brazilian Stock Returns. *RAUSP Management Journal*, *53*(3), 324–344. https://doi.org/10.1108/RAUSP-04-2018-001

Daily, C. M., & Dalton, D. R. (1994). Bankruptcy and Corporate Governance: the Impact of Board Composition and Structure. *Academy of Management Journal*, *37*(6), 1603–1617. https://doi.org/10.2307/256801

Dambolena, I. G., & Khoury, S. J. (1980). Ratio Stability and Corporate Failure. *Journal of Finance*, *35*(4), 1017–1026.

Darmawan, A., & Supriyanto, J. (2018). The Effect of Financial Ratio on Financial Distress in Predicting Bankruptcy. *Journal of Applied Managerial Accounting*, *2*(1), 110–120.

Das, S., & Barai, P. (2016). Size, value and momentum in stock returns: evidence from India. *Macroeconomics and Finance in Emerging Market Economies*, *9*(3), 284–302. https://doi.org/10.1080/17520843.2016.1148754

DeAngelo, H., & Masulis, R. W. (1980). Optimal capital structure under corporate and personal taxation. *Journal of Financial Economics*, *8*(1), 3–29.

Dichev, I. D. (1998). Is the Risk of Bankruptcy a Systematic Risk? *Journal of Finance*, *53*(3), 1131–1147. https://doi.org/10.1111/0022-1082.00046

Elloumi, F., & Gueyié, J.-P. (2001). Financial distress and corporate governance: an empirical analysis. *Corporate Governance*, *1*(1), 15–23. https://doi.org/10.1108/14720700110389548

Etemadi, H., Anvary Rostamy, A. A., & Dehkordi, H. F. (2009). A genetic programming model for bankruptcy prediction: Empirical evidence from Iran. *Expert Systems with Applications*, *36*(2 PART 2), 3199–3207. https://doi.org/10.1016/j.eswa.2008.01.012

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56.

Fama, E. F., & French, K. R. (2004). The Capital Asset Pricing Model : Theory and Evidence. *Journal of Economic Perspectives*, *18*(3), 25–46.

Fama, E. F., & MacBeth, J. D. (1973). Risk , Return , and Equilibrium : Empirical Tests. *The Journal of Political Economy*, *81*(3), 607–636.

Fama, E. F.; French, K. R. (1988). "Permanent and temporary components of stock prices". *Journal of Political Economy*. 96 (2): 246–273.

Ferdaous, J., & Barua, S. (2020). Firm-specific factors and stock returns: Evidence from selected private commercial banks listed on the dhaka stock exchange. *Asian Economic and Financial Review*, *10*(11), 1259–1268. https://doi.org/10.18488/journal.aefr.2020.1011.1259.1268

Fich, E. M., & Slezak, S. L. (2008). Can corporate governance save distressed firms from bankruptcy? An empirical analysis. *Review of Quantitative Finance and Accounting*, *30*(2), 225–251. https://doi.org/10.1007/s11156-007-0048-5

Fitri, R. A., & Syamwil, S. (2020). Pengaruh Likuiditas, Aktivitas, Profitabilitas dan Leverage Terhadap Financial Distress (Studi Kasus pada Perusahaan Manufaktur yang Terdaftar di Bursa Efek Indonesia Periode 2014-2018). *Jurnal Ecogen*, *3*(1), 134. https://doi.org/10.24036/jmpe.v3i1.8532

Foster, B. P., & Zurada, J. (2013). Loan defaults and hazard models for bankruptcy prediction. *Managerial Auditing Journal*, *28*(6), 516–541.

Ganesalingam, S., & Kumar, K. (2001). Detection of Financial Distress via Multivariate Statistical Analysis. *Managerial Finance*, *27*(4), 45–55.

Gichaiya, M.W., Muchina, S. and Macharia, S. (2019). Corporate Risk, Firm Size and Financial Distress: Evidence from Non-Financial Firms Listed In Kenya. *IOSR Journal of Economics and Finance*, *Volume 10,*(Issue 4 Ser. III), PP 75-86. https://doi.org/10.9790/5933-1004037586

Gompers, P., Ishii, J., & Metrick, A. (2010). Extreme Governance: An Analysis of Dual-Class Firms in the United States. *Review of Financial Studies*, *23*(3), 1051–1088.

Gow, I. D., Ormazabal, G., & Taylor, D. J. (2010). Correcting for Cross-Sectional and Time-Series Dependence in Accounting Research. *The Accounting Review*, 85(2), 483–512.

Griffin, J. M., & Lemmon, M. L. (2002). Book–to–market equity, distress risk, and stock returns. *The Journal of Finance*, *LVII*(5), 2317–2336. https://doi.org/10.1111/1540-6261.00497

Gujarati, D. N., & Porter, D. C. (2009). *Basic Econometrics* ((A. E. Hil). Douglas Reiner.

Gunathilaka, C., Jais, M., Balia, S. S., Abidin, A. Z., & Manaf, K. B. A. (2017). Reversed size, book-to-market and momentum effects: A review of Malaysian equity returns behavior. *Advanced Science Letters*, *23*(1), 15–19. https://doi.org/10.1166/asl.2017.7285

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate Data Analysis* (7th ed.). Prentice Hall.

Hair Jr, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European business review*.

Hair Jr, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2017). *Advanced issues in partial least squares structural equation modeling*. saGe publications.

Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2017), *A Primer on Partial Least SquaresStructural Equation Modeling (PLS-SEM)*, Sage, Thousand Oaks, CA

Hassan, A., & Javed, M. T. (2011). Size and value premium in Pakistani equity market. *African Journal of Business Management*, *5*(16), 6747.

Herlina, M. T., & Murhadi, W. R. (2020). Financial Distress Prediction On Agricultural Sector Companies In Indonesia Stock Exchange. *International Journal of Research Science and Management*, *7*(1), 155–159.

Hillegeist, S. A., Keating, E. K., Cram, D. P., & Lundstedt, K. G. (2004). Assessing the Probability of Bankruptcy. *Review of Accounting Studies*, *9*(1), 5–34.

Hoque, M.E, Low, S. ., & Zaidi, M. A. S. (2020). The Effects of Oil and Gas Risk Factors on Malaysian Oil and Gas Stock Returns: Do They Vary? *Energies*, *13*(15), 3901.

Hoque, Mohmmad Enamul, Wah, L. S., & Shah Zaidi, M. A. (2020). Do oil and gas risk factors matter in the Malaysian oil and gas industry? A FAMA-MACBETH two stage panel regression approach. *Energies*, *13*(5). https://doi.org/10.3390/en13051154

Husein, F., & Mahfud, M. K. (2015). Analisis Pengaruh Distress Risk, Firm Size, Book To Market Ratio, Return On Assets, dan Debt Equity Ratio terhadap Return Saham. *Diponegoro Journal of Management*, *4*(3), 1–15.

Hussain, M. I., Nassir, A. M., Mohamad, S., & Hasan, T. (2005). Prediction of Corporate Financial Distress of Pn4 Companies in Malaysia: a Logistic Model Approach. *Journal of Restructuring Finance*, *02*(02), 143–155. https://doi.org/10.1142/s0219869x05000440

Idrees, S., & Qayyum, A. (2018). The Impact of Financial Distress Risk on Equity Returns : A Case Study of Non-Financial Firms of Pakistan Stock Exchange. *Munich Personal RePEc Archive*, *85346*, 1–22.

Jaafar, M. N., Muhamat, A. A., Alwi, S. F. S., Karim, N. A., & Rahman, S. binti A. (2018). Determinants of Financial Distress among the Companies Practise Note 17 Listed in Bursa Malaysia. *International Journal of Academic Research in Business and Social Sciences*, *8*(11), 800–811. https://doi.org/10.6007/IJARBSS/v8-i11/4956

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Lossers: Implications for Stock Market Efficiency. *Journal of Finance*, *48*(1), 65–91.

Kennedy, P. (2008). *A guide to econometrics*. John Wiley & Sons.

Kim, M. H., & Partington, G. (2015a). Dynamic Forecasts of Financial Distress of Australian Firms. *Australian Journal of Management*, *40(1)*(November 2013), 135–160. https://doi.org/10.1177/0312896213514237

Kim, M. H., & Partington, G. (2015b). Dynamic forecasts of financial distress of Australian firms. *Australian Journal of Management*, *40*(1), 135–160. https://doi.org/10.1177/0312896213514237

Kothari, S. P., & Shanken, J. (1997). Book-to-market, dividend yield, and expected market returns: A time-series analysis. *Journal of Financial Economics*, *44*(2), 169–203.

Lakshan, A. M. I., & Wijekoon, W. M. H. N. (2013). The Use of Financial Ratios in Predicting Corporate Failure in Sri Lanka. *GSTF Journal on Business Review(GBR)*, *2*(4), 37–43. https://doi.org/10.5176/2010-4804

Larose, D. T., and Larose, C. D. (2015). *Data Mining and Predictive Analytics* (2nd ed.), Hoboken, NJ: Wiley

Lau, S. T., Lee, C. T., & McInish, T. H. (2002). Stock returns and beta, firms size, E/P, CF/P, book-to-market, and sales growth: Evidence from Singapore and Malaysia. *Journal of Multinational Financial Management*, *12*(3), 207–222. https://doi.org/10.1016/S1042-444X(01)00051-2

Lee, T., & Yeh, Y. (2004). Corporate Governance and Financial Distress : evidence from Taiwan. *Corporate Governance*, *12*(3), 378–388.

Li, H.-C., Lai, S., Conover, J. A., Wu, F., & Li, B. (2017). Stock Returns and Financial Distress Risk: Evidence from the Asian-Pacific Markets. In *Research in Finance* (Vol. 33, pp. 123–158). https://doi.org/10.1108/S0196-382120170000033007

Lin, T.-H. (2009). A cross model study of corporate financial distress prediction in Taiwan: Multiple discriminant analysis, logit, probit and neural networks models. *Neurocomputing*, *72*(16–18), 3507–3516. https://doi.org/10.1016/j.neucom.2009.02.018

Lindaas, K. F., & Simlai, P. (2016). *Size, Value, and Momentum Risk in the Cross-Section of Average Returns and Volatility*.

Lo, A. W. (1986). Logit versus discriminant analysis: A specification test and application to corporate bankruptcies. *Journal of Econometrics*, *31*(2), 151–178.

Low, S. W., Nor, F. M., & Yatim, P. (2001). Predicting corporate financial distress using the logit model: The case of Malaysia. *Asian Academy of Management Journal*, *6*(1), 49–61.

Malik, U. S., Aftab, M., & Noreen, U. (2013). Distress Risk and Stock Returns in An Emerging Market. *Research Journal of Finance and Accounting*, *4*(17), 81–86.

Mason, C. H., & Perreault Jr, W. D. (1991). Collinearity, power, and interpretation of multiple regression analysis. *Journal of marketing research*, *28*(3), 268-280.

Mbanwie, G., & Edmond, N. N. (2009). Financial Ratios as bankruptcy Indicators: The case of Financially Distressed Firms in Sweden. *Msc Thesis, University of Gothenburg*.

Md-Rus, R. (2011a). An Empirical Investigation on the Relationship between Risk of Bankruptcy and Stock Return. *International Journal of Management Studies*, *18*(1), 117–134.

Md-Rus, R. (2011b). AN EMPIRICAL INVESTIGATION ON THE RELATIONSHIP BETWEEN RISK OF BANKRUPTCY AND STOCK RETURN. *International Journal of Management Studies*, *104*(1), 214–229. https://doi.org/10.1016/j.ijpe.2004.12.024

Md-Rus, R., & Abdullah, N. A. H. (2005). An Empirical Investigation of Failing Companies in an Emerging Capital Market. *In 16th Asian Finance Association Conference, Malaysia.*

Md-Zeni, S., & Ameer, R. (2010). Turnaround prediction of distressed companies: evidence from Malaysia. *Journal of Financial Reporting and Accounting*, *8*(2), 143–159.

Ming, X., & Akhtar, H. (2014). Impact of Corporate Governance on Financial Distress: An Evidence from Shanghai Stock Market An Analysis Based on a Panel Data and Logit Model. *Interdisciplinary Journal of Contemporary Research In Business*, *6*(6), 1–11.

Mior Ahmed Shahimi, W. R., Hanafi, A. H. A., & Mohamad Yusof, N. A. (2021). THE IMPACT OF COVID-19 ON THE FINANCIAL PERFORMANCE OF PN17 AND GN3 STATUS FIRMS: DOES IT ADD SALT INTO THE WOUND? *Advanced International Journal of Banking, Accounting and Finance*, *3*(7), 47–58.

Modigliani, F., & Miller, M. H. (1963). Corporate Income Taxes and the Cost of Capital : A Correction. *The American Economic Review*, *53*(3), 433–443.

Mselmi, N., Hamza, T., Lahiani, A., & Shahbaz, M. (2019). Journal of International Money and Finance Pricing corporate financial distress : Empirical evidence from the French stock market. *Journal of International Money and Finance*, *96*, 13–27.

Noor, Z., Iskandar, T. and, & Omar, N. (2012). Malaysian Companies Distress Prediction: DEA and Multinomial Logit Model. *PROSIDING PERKEM VII*, *2*, 1536–1551.

Novak, J., & Petr-Petr's, D. (2010). Capm beta, size, book-to-market, and momentum in realized stock returns. *Finance a Uver - Czech Journal of Economics and Finance*, *60*(5), 447–460.

Nur, T., & Panggabean, R. R. (2020). Accuracy of Financial Distress Model Prediction: The Implementation of Artificial Neural Network, Logistic Regression, and Discriminant Analysis. *Proceedings of the 1st Borobudur International Symposium on Humanities, Economics and Social Sciences (BIS-HESS 2019)*, *436*, 402–406. https://doi.org/10.2991/assehr.k.200529.084

Nyamboga, T. O., Omwario, B. N., Muriuki, A. M., & Gongera, G. (2014). Determinants of Corporate Financial Distress : Case of Non- Financial Firms Listed in the Nairobi Securities Exchange. *Research Journal of Finance and Accounting*, *5*(12), 193–207.

O'brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality & quantity*, *41*(5), 673-690.

Odom, M. D., & Sharda, R. (1990). A neural network model for bankruptcy prediction. *Neural Networks, 1990., 1990 IJCNN International Joint Conference*, 163–168.

Ogachi, D., Ndege, R., Gaturu, P., & Zoltan, Z. (2020). Corporate Bankruptcy Prediction Model, a Special Focus on Listed Companies in Kenya. *Journal of Risk and Financial Management*, *13*(3), 47. https://doi.org/10.3390/jrfm13030047

Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, *18*(1), 109–131.

Ong, P. B., Hanifa, M. H., & Isa, M. M. (2018). Do firm size and value affect shareholder returns in Malaysia? *Capital Markets Review*, *26*(2), 53–69.

Ong, S.-W., Yap, V. C., & Khong, R. W. L. (2011). Corporate failure prediction: a study of public listed companies in Malaysia. *Managerial Finance*, *37*(6), 553–564. https://doi.org/10.1108/03074351111134745

Osho, A. E., & Idowu, A. S. (2018). Relevance of Accounting Theory in Forecasting Techniques and Default Prediction in an Organization in Nigeria. *European Journal of Business and Management*, *10*(29), 116–129.

Parker, S., Peters, G. F., & Turetsky, H. F. (2002). Corporate governance and corporate failure: a survival analysis. *Corporate Governance: The International Journal of Business in Society*, *2*(2), 4–12. https://doi.org/10.1108/14720700210430298

Pham, V. N. B., Do, T. T., & Vo, D. H. (2018). Financial distress and bankruptcy prediction: An appropriate model for listed firms in Vietnam. *Economic Systems*, *42*(4), 616–624. https://doi.org/10.1016/j.ecosys.2018.05.002

Pindado, J., Rodrigues, L., & de la Torre, C. (2008). Estimating financial distress likelihood. *Journal of Business Research*, *61*(9), 995–1003.

Polemis, D., & Gounopoulos, D. (2012). Prediction of Distress and Identification of Potential M&As Targets in UK. *Managerial Finance*, *38*(11), 1085–1104. https://doi.org/10.1108/03074351211266801

Rafatnia, A. A., Ramakrishnan, S., Abdullah, D. F. B., Nodeh, F. M., & Farajnezhad, M. (2020). Financial distress prediction across firms. *Journal of Environmental Treatment Techniques*, *8*(2), 646–651.

Reilly, F. K., & Brown, K. C. (2011). *Investment analysis and portfolio management*. Cengage Learning.

Roll, R. (1977). A critique of the asset pricing theory's tests Part I: On past and potential testability of the theory. *Journal of Financial Economics*, *4*(2), 129–176. https://doi.org/10.1016/0304-405X(77)90009-5

Ross, S. A. (1976). The Arbitrage Theory of Capital Asset Pricing. *Journal of Economics Theory*, *13*, 341–360.

Sabbaghi, O. (2015). Volatility, Distress Risk, and The Cross-Section of Portfolio Peturns. *Review of Accounting and Finance*, *14*(2), 149–171.

Samad, F., Yosof, M. A. M., & Shaharudin, R. S. (2009). Financial distress risk and stock returns: Evidence from the Malaysian Stock Market. *Journal of International Finance and Economics, 9(2), 19-38.*, *9*(2), 19–38.

Sathye, M., Bartle, J., Vincent, M., & Boffey, R. (2003). *Credit Analysis and Lending Management* (illustrate). Wiley.

Sehgal, S., & Balakrishnan, A. (2013). Robustness of fama-french three factor model: further evidence for indian stock market. *Vision*, *17*(2), 119–127.

Sharpe, W. F. (1964). Capital asset prices: A theroy of market equilibrium under conditions of risk. *The Journal of Finance*, *19*(3), 425–442. https://doi.org/10.2307/2329297

Shumway, T. (1996). *Size, overreaction, and book-to-market effects as default premia* (pp. 1–25).

Shumway, T. (2001). Forecasting Bankruptcy Mode Accurately: A Simple Hazard Model. *The Journal of Business*, *74*(1), 101–124.

Shyam-Sunder, L., & Myers, S. C. (1999). Testing static tradeoff against pecking order models of capital structure. *Journal of Financial Economics*, *51*(2), 219–244.

Simlai, P. (2009). Stock returns, size, and book-to-market equity. *Studies in Economics and Finance*, *26*(2), 198–212.

Simlai, P. (2014). Firm characteristics, distress risk and average stock returns. *Accounting Research Journal*, *27*(2), 101–123.

Sori, Z. M., Hamid, M. A. A., Nassir, A. M., & Mohamad, Z. A. (2001). Forecasting corporate failure in Malaysian industrial sector firms. In *Asian Academy of Management Journal* (Vol. 6, Issue 1, pp. 15–30).

Stattman, D. (1980). Book Values and Stock Returns. *The Chicago MBA: A Journal of Selected Papers*, *4*, 25–45.

Sudirgo, T., Yuniarwati, & Bangun, N. (2019). PENGARUH FINANCIAL DISTRESS, FINANCIAL PERFOMANCE DAN LIKUIDITAS TERHADAP STOCK RETURN. *Business Management Journal*, *15*(2), 77–92.

Sulairnan, M., Jili, A., & Sanda, A. U. (2001). Predicting corporate failure in Malaysia: An application of the Logit Model to financial ratio analysis. *Asian Academy of Management Journal*, *6*(1), 99–118.

Tan, C. N. W., & Dihardjo, H. (2001). A Study on Using Artificial Neural Networks to Develop an Early Warning Predictor for Credit Union Fi. *Managerial Finance*, *27*(4), 56–77.

Taneja, Y. P. (2010). Revisiting fama french three-factor model in indian stock market. *Vision: The Journal of Business Perspective*, *14*(4), 267-274.

Teh, K.-S., & Lau, W.-Y. (2017). The Dual-Beta Model: Evidence from the Malaysian Stock Market. *Indonesian Capital Market Review*, *9*(1). https://doi.org/10.21002/icmr.v9i1.6367

Thai, S. B., Goh, H. H., Teh, B. H., Wong, J. C., & Ong, T. S. (2014). A Revisited of Altman Z- Score Model for Companies Listed in Bursa Malaysia. *International Journal of Business and Social Science*, *5*(12), 197–207.

Tirapat, S., & Nittayagasetwat, A. (1999). An investigation of Thai listed firms' financial distress using macro and micro variables. *Multinational Finance Journal*, *3*(2), 103–125.

Ugurlu, M., & Aksoy, H. (2006). Prediction of corporate financial distress in an emerging market: the case of Turkey. *Cross Cultural Management: An International Journal*, *13*(4), 277–295.

Vassalou, M., & Xing, Y. (2004). Default risk in equity returns. *The Journal of Finance*, *59*(2), 831–868.

Vo, D. H., Pham, B. N. V., Ho, C. M., & McAleer, M. (2019). Corporate Financial Distress of Industry Level Listings in Vietnam. *Journal of Risk and Financial Management*, *12*(4), 155. https://doi.org/10.3390/jrfm12040155

Vuran, B. (2009). Prediction of business failure: a comparison of discriminant and logistic regression analyses. *Istanbul University Journal of the School of Business Administration*, *38*(1), 47–65.

Wang, L., & Wu, C. (2017). Business failure prediction based on two-stage selective ensemble with manifold learning algorithm and kernel-based fuzzy self-organizing map. *Knowledge-Based Systems*, *121*, 99–110.

Wang, Z., & Li, H. (2007). Financial distress prediction of Chinese listed companies: a rough set methodology. *Chinese Management Studies*, *1*(2), 93–110. https://doi.org/10.1108/17506140710758008

Waqas, H., & Md-Rus, R. (2018). Predicting financial distress: Importance of accounting and firm-specific market variables for Pakistan's listed firms. *Cogent Economics and Finance*, *6*(1), 1–16.

Wilson, R. L., & Sharda, R. (1994). Bankruptcy prediction using neural networks. *Decision Support Systems*, *11*, 545–557.

Yap, B. C. F., Munuswamy, S., & Mohamed, Z. (2012). Evaluating Company Failure in Malaysia Using Financial Ratios and Logistic Regression. *Asian Journal of Finance & Accounting*, *4*(1), 330–344. https://doi.org/10.5296/ajfa.v4i1.1752

Youn, H., & Gu, Z. (2010). Predicting Korean lodging firm failures: An artificial neural network model along with a logistic regression model. *International Journal of Hospitality Management*, *29*(1), 120–127.

Yuliarto Nugroho, B. (2020). The Effect of Book to Market Ratio, Profitability, and Investment on Stock Return. *International Journal of Economics and Management Studies*, *7*(6), 102–107.

Zhu, T. (2010). Do Domestic and Foreign Institutional Investors Have Similar Portfolio Preferences? *2010 International Conference on Management and Service Science*, 1–4.