Analysing Financial Distress in Malaysian Islamic Banks: Exploring Integrative Predictive Methods

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ANALYSING FINANCIAL DISTRESS IN MALAYSIAN ISLAMIC BANKS: EXPLORING INTEGRATIVE PREDICTIVE METHODS

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Abstract

Against the background of global financial crisis, some argue in favour of the 'resilience' of Islamic finance, while others suggest that Islamic financial institutions are not more prone to distress and crisis than their conventional counterparts. However, there have been a number of cases of Islamic finance and banking distress in recent years, including instances in Malaysia. These cases, hence, motivated this study in terms of emphasising the importance of employing financial distress prediction models for analysing Islamic banks.

This study aims at empirically exploring, examining and analysing the financial distress of the Malaysian Islamic banks. In doing so, the effectiveness of the existing early warning statistical insolvency prediction models that have been used in previous studies, and a particular model adapted by Islamic banks in Malaysia were critically evaluated. This study, hence, employed a number of models to predict the financial distress faced by Islamic banks in Malaysia. In addition, an attempt was made at the modification of the existing early warning insolvency prediction models in evaluating and analysing the financial distress of Malaysian Islamic banks. This research is constructed within four empirical chapters by employing three prediction models in assessing the financial distress of Islamic banks.

The first empirical chapter analyses the secondary data collected from a sample of Islamic banks, based on selected ratios developed in the literature, whereby a comprehensive description of these selected financial ratios in terms of descriptive statistical analysis for the selected Islamic banks in Malaysia is provided.

The second empirical chapter investigates the performance of the 'emerging market *Z*-score', introduced by Altman in predicting the performance of Islamic banks and conventional banks in Malaysia. The study aimed to introduce the *EM Z*-score as a valuable analytical tool in monitoring the deterioration of the performance of banks as well as looking at the impact of the global financial crisis on the performance of Islamic and conventional banks. This chapter examines thirteen Islamic banks and ten conventional banks during the period of 2005-2010. The results show that the *EM Z*-score for all banks is well above the cut-off point of 2.6, although for Islamic banks the *EM Z*-score showed a declining trend whilst for conventional banks it showed an increasing trend. This empirical evidence is important for the banks since it provides a warning signal to the banks' management as well as the related parties involved in the planning, controlling and decision making process.

The third empirical chapter presents the newly constructed integrated predictive model designed to evaluate and analyse the financial distress of Islamic banks in Malaysia, which can be used as an alternative model for regulators in monitoring the performance of Islamic banks that are experiencing any serious financial problems. This paper develops a preliminary model for the prediction of the performance level of Islamic financial institutions for the period of December 2005 to September 2010 by using quarterly data for ten selected Islamic banks in Malaysia. For this, factor analysis and three parametric models (discriminant analysis, logit analysis and probit analysis) are used. The results depict that the first few quarters before the benchmark quarter are the most important period for making a correct prediction and crucial decisions on the survival of Islamic banks. Thus, the results demonstrate the predictive ability of the integrated model to differentiate between the healthy and non-healthy Islamic banks, therefore reducing the expected cost of bank failure.

The fourth empirical chapter conducts further exploration in predicting the financial distress position of Islamic banks by introducing new variables such as the funding structure, deposit composition, and macroeconomic variables. Using the same sample and data set for Islamic banks as in the previous chapter, this study shows the relationship between the banks' funding profiles and other alternative variables, and the Islamic banks' performance in Malaysia. For this, the logit model is used. Based on the results of all models, this study recommended two final models, which showed an excellent fit for predicting the Islamic banks' performance. The results indicate that none of the macroeconomic variables included were significant, thus suggesting that the performance of Islamic banks in Malaysia was not affected by the economic conditions throughout the study period. This can perhaps be attributed to efficient regulation and supervision by the relevant authorities in the country.

DECLARATION

I hereby declare that no portion of the work that appears in this study has been used in support of an application of another degree in qualification to this or any other University or institution of learning.

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LIST OF ABBREVIATIONS

AAOIFI	Accounting and Auditing Organization for Islamic Financial Institution
AIES	Artificial Intelligent Expert System
ALM	Assets and Liabilities Management
ANOVA	Analysis of Variance
ARCIFI	Arbitration and Reconcilation Centre for Islamic Financial Institutions
ATD	Assets to Deposits
BAFIA	Banking and Financial Institutions Act
BASEL	Basel Committee on Banking Supervision
BFR	Base Financing Rate
BIMB	Bank Islam Malaysia Berhad
BNM	Bank Negara Malaysia
BPNN	Back Propagation Neural network
CAMELS	Capital Adequacy, Asset Quality, Management, Earnings, Liquidity, and Sensitivity to Market Risk
CB	Central Bank
CDF	Cumulative Distribution Function
CDRC	Corporate Debt Restructuring Committee
CFA	Confirmatory Factor Analysis
CIBAFI	Council of Islamic Banks and Financial Institutions
DD	Demand Deposit
DFA	Discriminant Function Analysis
DIB	Dubai Islamic Bank
EFA	Exploratory Factor Analysis
FA	Factor Analysis
FSB	Financial Sector Blueprint
FSMP	Financial Sector Masterplan
FTD	Financing to Deposit
GDP	Gross Domestic Product
HLIB	Hong Leong Islamic Bank
HSBC	Hong Kong and Shanghai Banking Corporation
IAH	Investment Account Holder
IBA	Islamic Banking Act
IBF	Islamic Banking and Finance
IBIs	Islamic Banking Institutions
IBS	Islamic Banking scheme
ICM	Islamic Capital Market
IDB	Islamic Development Bank
IEWS	Integrated Early Warning Systems
IFSB	Islamic Financial Service Board
IIFM	International Islamic Financial Market
IIRA	International Islamic Rating Agency
IMF	International Monetary Fund
IMM	Interbank Money Market
IRR	Investment Risk Reserve
KFH	Kuwait Finance House
KLCE	Kuala Lumpur Commodity Exchange
KLOFFE	Kuala Lumpur Options and Financial Futures Exchange

KLSE	Kuala Lumpur Stock Exchange
KMO	Keiser-Meier-Olkin
LDA	Linear Discriminant Analysis
LMC	Liquidity Management Centre
LOFSA	Labuan Offshore Financial Services Authority
LOLR	Lender of Last Resort
MANOVA	Multivariate Analysis of Variance
MARC	Malaysian Rating Corporation Berhad
MDA	Multivariate Discriminant Analysis
MDEX	Malaysia Derivative Exchange
MDIC	Malaysia Deposit Insurance Corporation
MD	Mudarabah Deposit
ME	Macro Economic Variables
MIBB	Maybank Islamic Bank Berhad
MIFC	Malaysia International Islamic Financial Centre
NMD	Non Mudarabah Deposit
NORMSDIST	Normal Distribution
NORMSINV	Normal Inverse
NPF	Non Performing Financing
PCA	Principal Component Analysis
PER	Profit Equalization Reserve
PFA	Principal Factor Analysis
PIBB	Public Islamic Bank Berhad
PLS	Profit and Loss Sharing
QDA	Quadratic Discriminant Analysis
RAM	Rating Agency of Malaysia
RAROC	Risk-adjusted Return on Capital
ROA	Return on Asset
ROE	Return on Equity
RTA	Reserve to Total Assets
RWCR	Risk Weighted Capital Ratio
SAC	*Shari'ah* Advisory Board
SCM	Securities Commission of Malaysia
SPSS	Statistical Package for the Social Sciences
TCE	Tangible to Common Equity

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Jaizah Othman
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Chapter 1
INTRODUCTION

1.1 INTRODUCTION

As long as there have been banks, containing the risk of failure has induced academics and practitioners to find methods for predicting the failure of banks. At the same time, Bank regulators have aimed at developing policies, strategies and instruments to prevent failure from occurring, and investors and depositors want to protect themselves from losing their money. According to earlier studies in this area, many early warning models have been proven to have some predictive power in detecting distress, which provides the rationale for this study in researching similar models for Islamic banks.

The early detection of insolvent institutions is of vital importance, especially if the failure of those institutions would pose a serious systemic risk to the financial system and the economy as a whole. In the Malaysian banking industry, the Central Bank of Malaysia (BNM) and the relevant authorities utilise on-site and off-site examination methods in order to determine which institutions are insolvent, and thus should be either closed or provided with financial assistance in order to rescue them. Off-site examinations are typically based on statistical and other mathematical methods, and constitute complementary tools to the on-site visits made by supervisors to institutions considered at risk. An effective off-site examination tool must aim at identifying problem banks sufficiently prior to the time when a marked deterioration of their financial health would occur, which would force supervisors to undertake the necessary corrective actions needed to remedy the financial turmoil. Therefore, it is desirable to develop a model which would identify future failures with a high degree of accuracy and would not unnecessarily flag healthy banks as being at risk of closure.

Accurate statistical models that serve as early warning tools, and which can be used as an alternative to, or complementary to, the costly on-site visits made by supervisors to institutions considered at risk, have been well documented in the banking literature.

Early warning models mostly refer to models that can identify and predict the realisation of some event with a high probability well in advance. These models have been successfully applied to study the failures of banking and other financial institutions in other countries. Most of the literature that deals with the bankruptcy prediction of financial and non-financial institutions is vast, and there are a myriad of papers that specifically refer to banking industry failures, especially concerning conventional banks and mostly in western countries. This study discusses a few important papers that are closely related to the research questions of this study, and these present models that can be viewed as early warning models for Islamic banks in Malaysia.

This study presents an attempt to analyse the underlying reasons behind the distressed financial conditions of the selected Malaysian Islamic banks and the effects of these on their performance. The objective is to develop an early warning model for Islamic banks in Malaysia based on the financial data of the selected Malaysian Islamic banks. It is perhaps among the first academic and systematic attempts to conduct such a study for Islamic banking in Malaysia, which aims to draw out lessons for all the stakeholders in the case of Islamic banking in general and in Malaysia in particular.

1.2 PROBLEM STATEMENT

Previous research on the study of Islamic banking mainly revolves around the conceptual issues underlying the interest free banking system. Given the uniqueness of the nature of the Islamic banking system as well as the dynamic changes in the world financial markets, which pose numerous risks to the Islamic banks, there is a need to identify empirically, a suitable early warning tool to predict insolvency in Islamic banking in general for the industry and in particular for the Malaysian Islamic banking, as this is still lacking.

Considering the devastating impact of the current financial crisis globally, the impact on Islamic finance has been rather limited: there have been few defaults in Islamic finance. This is not because these institutions are 'religiously constructed banks' and hence protected, but rather is due to Islamic banks being in the infancy stage of development as compared to conventional banks. In addition, the business cycle of the countries where Islamic finance has some presence has not been affected deeply by the global financial crisis.

Over the years, however, there have been a few episodes of Islamic banking distress that are worthy of consideration, and these have prompted the conduct of this study. Among such defaults and failures the following can be mentioned: the cancellation of Al-Taqwa's bank license by the authorities in the Bahamas in 2001 due to new laws designed to crack down on money laundering (AML) or to combat the financing of terrorism (CFT); the closing of Al-Baraka International Bank - operating in the UK - due to regulatory reasons; the crash in the Souk Al-Manakh Stock Market (1986-87) that caused all the banks in Kuwait (including the Kuwait Finance House) to become insolvent due to the large amount of debts arising from the crash.

Most of the above cases are mainly related to political and economic instability. However, there are a few other cases that are related to the financial condition of Islamic banks, among others these include:

(i) The liquidation of the International Islamic Bank of Denmark in 1986 due to excessive financing exposure to a single client;

(ii) The closure of Islamic Investment Companies of Egypt (IICE) in 1988 due to weak corporate governance, irresponsible management, and improper regulatory frameworks as well as engagement in *Shari'ah* non-compliant activities (Zuhaida, 1990);

(iii) The closure of Islamic Bank of South Africa (IBSA) in November 1997 due to a debt of between R50-R70 million. Lack of supervision from the regulatory authority, bad management, weak risk management and numerous loans to insiders were considered to be important factors leading to the closure of IBSA (Okeahalam, 1998: 37-38).

(iv) Bank Islam Malaysia Berhad (BIMB) had incurred losses of RM457 million in the year ending June 30, 2005, that were associated to a RM774 million provision against bad loans and investment, which were mostly incurred by the bank's Labuan branch;

(v) The collapse of Ihlas Finance House (IFH) in Turkey in 2001 signified the most serious case of Islamic bank failure. Among the factors that contributed to the collapse of Ihlas Finance House were poor corporate governance leading to a crisis that affected other Islamic financial institutions, difficulty in managing liquidity due to the absence of a *Shari'ah*-compliant money market, and lack of decisive early warning action against failing banks on the regulator's part.

A more recent crisis, known as the 'Dubai Debt Crisis' in late 2009, left the world economies shaken when Dubai World requested a restructuring of USD$26 billion in debts. The main concern in this case was the delay in the repayment of a USD$4 billion Islamic bond or *sukuk*, well known as 'Nakheel *Sukuk*', which matured on December 14, 2009.

This was followed by another case of failure, this time of the Gulf Finance House (GFH), which started at around the same period. GFH is a *Shari'ah* compliant wholesale investment bank that was established in 1999 in Bahrain. In 2009, due to its concentration on real estate development, it incurred a net loss of nearly $728 million. Among the other reasons related to this loss the following can also be mentioned: operating during a period of unprecedented real estate collapse; absence of a diversification amplified market and liquidity risk; an unsustainable business model; flawed modification and implementation of *murabaha*; and escalating fixed operational costs (Khnifer *et al*., 2010). Thus, GFH registered the biggest loss ever for an Islamic financial institution in 2010 and is currently in the process of restructuring.

Finally, the most recent case is the filing of Chapter 11 by Arcapita Bank BSC, which is formerly known as the First Islamic Investment Bank. A manager of Islamic compliant investments filed for bankruptcy in the U.S. after failing to reach an agreement with the creditors. Arcapita failed to reach an agreement with their creditors on a $1.1 billion syndicated *Shari'ah* compliant loan falling due on 28th March 2012. The recent global financial crisis held back the Arcapita Group's ability to attain liquidity from the capital markets thus resulting in a reduction in their asset values.

As these examples demonstrate, financial distress is something that has been experienced in Islamic banking as well. This study, hence, aims to gauge the financial distress prediction modelling for Islamic banks, which should be considered as an important contribution in filling the observed gap in the literature.

1.3 RESEARCH AIM, OBJECTIVES AND RESEARCH QUESTIONS

This study aims at exploring, empirically examining and analysing the financial distress of the Malaysian Islamic banks. In doing so, the effectiveness of the existing early warning statistical insolvency prediction models used in the previous studies and the models adapted by Islamic Banking Institutions (IBIs) in Malaysia are critically evaluated.

The specific research objectives developed for the fulfilment of the identified aim of the study are as follows:

(i) to explore the statistical insolvency prediction models used in the previous studies for predicting the financial distress of banks;

(ii) to examine the features of the existing statistical insolvency prediction models with the objective of identifying their suitability for IBIs in Malaysia;

(iii) to empirically examine and measure the financial distress of Malaysian Islamic banks with the available models;

(iv) to modify the existing models by adding new variables that are relevant to IBIs in Malaysia with the objective of enhancing their predictive power.

Based on the aim and objectives, the following research questions were formulated:

(i) What kind of statistical insolvency prediction models are used by previous studies in predicting the financial distress of banks?;

(ii) Which of the existing statistical insolvency prediction models available in the literature is more appropriate to predict financial distress for Islamic banks in Malaysia?;

(iii) What types of variables that are relevant to Islamic banks can be added to the existing statistical insolvency prediction models in an attempt to improve their predictive efficiency?;

(iv) How efficient are the models used in predicting financial distress?;

(v) How robust Malaysian Islamic banks have been in terms of financial distress?

Within these aims, objectives and the research questions, this study is constructed as an empirical study which benefits from statistical and econometrics methods and models, which are explained in detail in Chapter 4.

1.4 RESEARCH METHODS

The research questions identified in this study are answered using a mixture of statistical and econometrics models previously used in other research studies. As discussed in Chapter 4, the data was assembled from secondary sources related to the Islamic banks in Malaysia. Due to having secondary statistical data in the form of financial data, the data analysis for this research is quantitative in nature and involves statistical and econometric methods.

Secondary data involves quarterly financial reports/statements - *i.e.* balance sheets and income statements for the selected Islamic banks in Malaysia that represent more than 50% of the market share of total assets. The quarterly reports of the Islamic banks can be extracted from the websites of the respective Islamic banks.

This research involves an extensive statistical and econometrics configurations of the existing insolvency prediction models that have employed statistical models - such as Multivariate Discriminant Analysis (MDA), Logit and Probit Analysis, Factor Analysis - with the data gathered from the quarterly reports of the selected Islamic Banks. The data are regressed against the selected insolvency prediction models before being selected as a suitable prediction model for Islamic banks.

It should be noted that the research attempts to evaluate the existing commonly used insolvency statistical models to predict the insolvency (the dependent variable) of Malaysian Islamic banks. The classical prediction techniques or statistical models may include univariate and multivariate analyses using multiple discriminant, linear probability, logit, or probit models to predict insolvency using the financial data/information.

1.5 SIGNIFICANCE OF THE RESEARCH

This research is of significance to the Islamic banks in Malaysia, as it extends the insolvency measurement techniques that currently exist in the field. In addition, it provides direct empirical evidence on a subject which have not been studied extensively before, which should be considered as the knowledge oriented contribution of this study, as it fills an important gap.

As a practical contribution, the proposed insolvency prediction model in this study will act as an early warning tool to predict the financial distress faced by the Islamic banking institutions in Malaysia.

It should be noted that an effective prediction tool to forecast financial distress is crucial to assist Malaysia to achieve its goals, based on the recommendations outlined in the Financial Sector Blueprint 2011-2020, as well as to promote Malaysia as an International Islamic Financial Centre (MIFC) that aims at strengthening economic and financial inter-linkages.

This study has been of significance to over sixteen Malaysian Islamic banks and five international Islamic banks in Malaysia, since they are expected to benefit from the outcome of this research in their attempts to lead a robust and stable industry. Besides Islamic banks, the other beneficiaries of this research are as follows: Bank Negara Malaysia (the central bank); Islamic Financial Institutions Services Board (IFSB); academics and system vendors.

It should be noted that the following outputs are expected from this research

(i) A systematic documentation of the amended statistical insolvency prediction model to be used to predict the financial distress of Islamic banks by the regulator and users;

(ii) Identification of the key variables of financial distress faced by Islamic banking institutions;

(iii) Identification of statistical insolvency prediction models used by the regulator and Islamic banking institutions.

Such contributions will help to overcome the observed gap in the literature as only a very limited numbers of studies are available in relation to Islamic banks vis-à-vis financial distress prediction models.

Based on the findings in the empirical chapter (Chapter 5) as well as the discussion in the literature review chapter, the researcher found that there are some gaps in past research especially in the case of the Islamic banking industry in Malaysia. Amongst those gaps that require further attention are:

(i) Since most of the bankruptcy studies are from developed economies and the case from the emerging countries or economies is still under studied or lacking, this study aims to fill the gap by studying and examining the insolvency prediction for Islamic banks.

(ii) Bankruptcy research specifically in Islamic banking in Malaysia is still lacking, thus this study aims to fill this gap by selecting a sample of banks and there is no distinction made between the public-listed and non-public listed Islamic banks.

1.6 OVERVIEW OF THE RESEARCH

This research consists of four important empirical chapters: The first empirical chapter is more concerned with descriptive analyses, while the rest of the empirical chapters focus on adapting and developing new models for predicting the financial distress of Islamic banks in Malaysia. The overview of the research is as follows:

The first chapter provides an introduction to the intended study. It is focused on the background of the research, the research problem statement, the aims of the research and objectives, some research questions which are related to the research objectives and the significance of the research.

Chapter Two explores the existing insolvency/bankruptcy prediction models including a survey of the empirical studies through a critical literature review.

Chapter Three concentrates on the Islamic Banking and Finance (IBF) industry in Malaysia, focusing more on insolvency issues as well as the regulation involved in the issue. The regulation of insolvency issues analyses the relevant rules and laws governed by the Central Bank of Malaysia.

Chapter Four highlights the methodology of the research as well as the modelling by discussing issues with regards to data collection and the research design/framework. This chapter also reviews the prediction modelling research. It provides an overview of prediction models and how they have been used with more stress on the methodology and findings.

Chapter Five is the first of four empirical chapters, which analyses the secondary data collected about the selected Islamic banks based on the selected ratios.

Chapter Six provides the second empirical chapter by adapting the existing models and developing the new early warning system for Islamic banks. It presents the newly constructed integrated model using the publicly available data of Islamic banks in Malaysia, which can be used as an alternative model for regulators in monitoring the performance of Islamic banks that are experiencing any serious financial problems.

Chapter Seven is the third part of the empirical study. In this chapter, the process of selecting the explanatory variables that have the necessary discriminating power continues, but the empirical strategy is more concentrated on the funding structure, composition of deposits, macroeconomics variables, and other alternative bank-specific variables.

Chapter Eight is the final part of the empirical chapters that analyses whether the Altman Emerging Market (EM) *Z*-score models can predict bankruptcy and at the same time measure the financial performance of Islamic and conventional banks in Malaysia. This chapter examines thirteen Islamic banks and ten conventional banks during the period 2005-2010. This should be considered as a significant study, since the study also looks at the impact of the global financial crisis on the performance of Islamic and conventional banks. Furthermore, the results can be compared to previous models that have been used in the last two empirical chapters.

Chapter Nine concludes the research with discussions and by providing concluding remarks.

Chapter 2

FINANCIAL DISTRESS: A LITERATURE SURVEY ON CONCEPTS, MODELS AND EMPIRICAL STUDIES

2.1 INTRODUCTION

Bank failures threaten the economic system as a whole. Therefore, it is crucial to predict bank financial failures in order to prevent or minimise the negative effects on the economic system. This chapter will therefore discuss the classification of corporate bankruptcy prediction models, the problems concerning these prediction models, and the existing corporate bankruptcy prediction models which relate to financial institutions. In other words, the chapter will describe the methods that have been used so far and how far they were successful. Some of the existing models will be utilised in the empirical chapters as comparison.

Amongst the earliest definitions of failure is that contained in the work of Beaver (1968). Beaver defined failure as the inability of a firm to pay its financial obligations as they mature. Blum (1974), in his case, stressed that a firm that falls into any one of the categories defined by him is considered a failure. These categories are: the inability to pay debts as they fall due, entrance into a bankruptcy proceeding, and an explicit agreement with the creditors to reduce debts.

According to Altman (1993), failure, insolvency, default and bankruptcy are four different terms and they all mean that a business is in distress. Bankruptcy may be the worst case scenario for certain companies, but in the case of the business' stakeholders, default also can cause problems for them. Some studies therefore do not try to predict bankruptcy, but failure instead.

Ideally, failure, insolvency, default and bankruptcy can be defined in different ways (Altman, 1993). Failure in economic terms means that a business has a rate or return on invested capital that is significantly and continuously lower than that of similar investments, which means that the company cannot meet its obligation to the shareholders. In other words it simply means that the company cannot give enough return on its shares. Insolvency, on the other hand, can be divided into two categories: technical insolvency and insolvency in a bankrupt sense. Technical insolvency is more about the short term obligations and can be temporary. Otherwise, insolvency in a bankrupt sense is worse than technical insolvency because it means that something is continually problematic with the business, which normally happens when the total liabilities are bigger than the total assets (Mous, 2005). Default happens when a company cannot meet its obligation to the creditors. For example, a company is not paying its periodical interest or settling debts when they are due. When this happens it is a serious sign that the company is in trouble, though it may not lead to bankruptcy. Finally, bankruptcy occurs when a company files for bankruptcy. These definitions give a clear distinction between each category and make it easier for a researcher to make a distinction between failed and non-failed companies.

There are some arguments amongst researchers with regard to the definition of corporate failure or financial distress.

Cybinski (2001) explains that "failed" and "non-failed" firms do not lie in separate boxes, but rather lie on a continuum of "failed" and "non-failed". In reality there is not a cut-off point between 'failed' and 'non-failed' firms, but rather an overlap or grey area between the two. It is in this grey area that the prediction of financial distress is so difficult.

Balcaen and Ooghe (2006) mentioned that "corporate failure is not a well defined dichotomy". It appears from most research that the criterion for failure is chosen arbitrarily and could either mean judicial bankruptcy or financial distress. Foster (1986) indicates that filing for bankruptcy is a legal event which is heavily influenced by the actions of bankers and or other creditors. He further defines financial distress to mean that the firms face serious liquidity problems that cannot be resolved without a rescaling of the entity's operations or restructuring.

Kuruppu *et al.* (2003) gave a list of alternative definitions of corporate failure such as: a large loss disproportionate to assets; share exchange delisting; companies in the process of liquidation; an arrangement with creditors; negative share returns, and receipt of a going concern qualification. On the other hand, Steyn-Bruwer and Hamman (2006) defined financial distress as the situation when a company cannot continue to exist in its current form. Whitaker (1999) defined financial distress as either insufficient net operating cash flow to repay maturing debts and loss of corporate market value, or the occurrence of at least three out of the following four types of events; negative retained earnings in the last three years; net loss in the last three years.

According to Arena (2008), a bank or financial institution will be considered failed when the following situation occurs; either the central bank or government agency recapitalised the financial institution or when the financial institution required a liquidity injection from the monetary authority; when the operation of the financial institution is temporarily suspended; or when the government closed the financial institution. In his analysis, a bank is considered failed when it fits into any of the above criteria during the crisis period.

Some researchers even suggested studying financial distress instead of failure due to the narrow definition of failure (Keasey and Watson, 1991; Hill *et al.*, 1996; Kahya and Theodossiou, 1996; and Platt and Platt, 2002). Platt and Platt (2002) have defined a financially distressed firm as one which reports either several years of negative net operating income, suspension of dividend payments, or major restructuring or layoffs. On the other hand, McLeay and Omar (2000) defined a financially distressed firm as one that is making losses and selling shares to private investors, involved with either capital restructuring or reorganization, and encounters a couple of years of negative shareholders' funds or accumulated losses.

Keasey and Watson (1991) concluded that there may be a need to develop specific models for different types of financial distress due to the incomplete and arbitrary nature of the criterion of financial distress.

Besides bankruptcy and financial distress, there are several other economic definitions of failure that have been used in previous research on corporate failure such as cash insolvency and loan default (Balcaen and Ooghe, 2006). According to Laitinen (1994), cash insolvency simply means that the firm is unable to pay its financial obligations when the payments become due. Ward and Foster (1997) are of the opinion that loan default is a better way of defining failure because the loan default definition is more consistent with the economic reality. According to Hayden (2003) some default events are described in the new framework of Basel II, and can be defined as the credit loss which is associated with any delay in payment of more than 90 days or with a distressed restructuring involving the forgiveness or postponement of principal amounts or interest by financial institutions. However, this definition is not suitable when analysing business failure due to the purely credit-oriented failure definition (Balcaen and Ooghe, 2006).

Taffler and Agarwal (2007) defined failure according to respective events such as capital reconstructions, shutting down or removal of large parts of the firm, government support, and loan covenant renegotiations for solvency reasons with bankers. Hayden (2003) found that three different models developed for three definitions of failure (bankruptcy, delay in payment and loan restructuring) have very similar structures regarding the selected variables. Balcaen and Ooghe (2006) highlight that the definition of failure is a big factor in the selection of variables if the selection of the discriminating variables to be included in a failure prediction model is done empirically.

Generally, a company is defined as bankrupt when their net worth becomes negative. However, from the banking system perspective, most of the bank problems are resolved even before the net worth becomes negative. Therefore, in recent research, a bank is defined as bankrupt if it experiences the following events due to illiquidity or insolvency, such as liquidation, takeover or merger, and if the capital adequacy ratio falls below 8 percent.

2.2 CLASSIFICATION OF CORPORATE BANKRUPTCY PREDICTION MODELS

2.2.1 Statistical Models

Statistical models, according to Aziz and Dar (2004), can be divided into five main type of analysis: these are univariate analysis, multivariate analysis, linear probability, logit model and probit models. Multivariate analysis has been frequently used in many studies by using multiple discriminant analysis.

In the banking sector, the development of statistical models to predict a bank's performance has gained ground since the early 1990s (Sahajwala and Van den Bergh, 2000). According to Sahajwala and Van den Bergh (2000), in the banking system, the main focus of the statistical models is directed mainly towards the detection of risks that are likely to lead to adverse future conditions. Statistical models attempt to identify high-risks banks reasonably in advance of distress or failure. In some cases, more advanced quantitative techniques are used to determine causal economic relationships between explanatory variables and outcomes such as bank fragility, distress, failure or survival.

2.2.1.1 Univariate analysis

Univariate analysis is a traditional method of interpreting financial statements using the firms' financial ratios. These ratios serve as explanatory variables or bankruptcy predictors, which are likely to exhibit significant differences across the failing and non-failing firms. In a failure prediction model, the emphasis is placed on individual signals of failure. In other words, it means that the variables are observed and examined one after the other (Aziz and Dar, 2004). In classifying a firm as fail or non-fail, each ratio is analysed separately and measured according to the optimal cut-off point. In general, a firm is classified as fail if a firm's ratio value is below the cut-off point and vice versa (Balcaen and Ooghe, 2006).

Financial accounting information has long been widely used in explaining the possibility of corporate financial failures. Amongst the most cited examples are the work done by Beaver (1966), Altman (1968) and Ohlson (1980). Beaver was the pioneer in constructing a corporate failure prediction model using financial ratios applying the univariate model, which is called the "univariate discriminant analysis model".

2.1.1.2 Multiple Discriminant Analysis (MDA)

Discriminant analysis is a type of multivariate technique that allows for differentiating between two or more groups of objects with respect to several variables simultaneously. MDA is used to classify an observation (the firm here) into one of several a priori groupings (the bankrupt and non-bankrupt) dependent upon the observation's individual characteristics (Aziz and Dar, 2004).

Altman (1968) first differentiated the statistical multivariate analysis techniques into the failure prediction model and the model developed called the '*Z*-score model'.

According to Altman (1968), multiple discriminant analysis is "a statistical technique used to classify an observation into one of several a priori groups depending upon the observation's individual characteristics... [it] attempts to derive linear [or quadratic] combination of these characteristics which 'best' discriminates between the groups" (Altman, 1968: 592).

In other words, MDA is concerned with the classification of distinct sets of observations and tries to find the combination of variables that predicts the group to which an observation belongs. The combination of predictor variables is called a linear discriminant function and can be shown as follows:

$$D = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots\dots + \beta_n X_n;$$

where:

D is a discriminant score

β_0 is an estimated constant

β_n are the estimated coefficients, and

X_n are the variables

An observation is then classified into the appropriate group based on the discriminant function score. The discriminant coefficients are obtained by following the specialized discriminant model estimation procedure. This model is an integration of several variables into one single discriminant score. At a certain cut-off point, the firm can be classified into the failed or non failed group. If the discriminant score (*Z*-score) is less than the cut-off point, the firm is classified as a failing firm. Otherwise, if the score is more than or equal to the cut-off point, the firm is classified as a non-failing firm.

The classification of accuracy of the MDA model is measured on the basis of the type I and Type II error rates. Researchers applying MDA, as a matter of fact, will try to minimise the error rates as much as possible. This is due to the fact that the cost of the misclassification of a failing firm (type I error) is often much larger than the costs of misclassifying a non-failing firm (Type II error). A Type I error means classifying the failing firm as non-failing firm, and a Type II error means classifying the non-failing firm as a failing firm (Balcaen and Ooghe, 2006).

The best example for the multiple discriminant models is a model developed by Altman, called the Altman *Z*-score model. It is a linear combination of ratios as follows: working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, market capitalization/total debts, and sales/total assets (Altman, 1968). According to Altman (1968), it is possible that apparently insignificant variables on a univariate analysis will provide significant information in a multivariate context.

2.1.1.3 Logit Model

Logit analysis has also been used to investigate the relationship between binary or ordinal response probability and explanatory variables. Ideally, this method fits with a linear regression model for binary or ordinal response data by using the maximum likelihood method. In other words, logit models are employed to find the explanatory factors behind a certain event. The dependent variable is constructed as a binary variable. This variable will take the value of 1 if the company has failed and the value of 0 if the company has not failed within the defined period.

Using this model, each of the independent variables will be weighted and assigned a score in the form of a failure probability for each company in a sample. In other words, the probability of distress is obtained by substituting into the cumulative probability function. A company is classified as distressed if the calculated probability from the logit model is more than 0.5, otherwise it would be non-distressed.

Amongst the first users of logit analysis in the context of financial distress was Ohlson (1980). This model of bankruptcy prediction has also been very useful for various parties such as investors, auditors and analysts. However, owing to some restrictions, this model is not the complete solution to risk measurement. Hence, it is only one of the tools that have been used in evaluating the effectiveness of management and the risk associated with an investment opportunity.

2.1.1.4 Probit Model

Ideally, one could substitute the normal cumulative distribution function in place of the logistic into [*D*] and get the resulting probit model to be estimated by the Maximum Likelihood method. The rest of the interpretation remains the same as in the case of logit (Aziz and Dar, 2004).

Amongst the users of this model is Zmijewski (Zmijewski, 1984) who developed the Zmejewski model by applying probit analysis. Only three financial measures are used in this model; return on assets, financial leverage and liquidity. Two steps are applied in this model. First, the constant and each parameter of the model must be multiplied by 1.8138 and then multiplied by the financial measure. After multiplying the financial measure by the adjusted parameter, the products are aggregated to a quantity referred to as an Adjusted Score. The Adjusted Score is then translated into a measure of probability by the following formula:

Probability Bankruptcy = 1/1+(*exp* (-Adjusted Score))

Adjusted Score Probability:

1 / 1 + (1 + *exp* - (-0.000085)) = .50

>= .5 is classified as Bankrupt

< .5 classified as Not Bankrupt

The score of the above formula can be translated into a probability that will lie between 0 and 1 and be interpretable in terms of likelihood. The use of the 50 percent cut-off suggests that when failure is more likely than not, it can be deduced that the company is distressed. In other words, if probability lies at or above 50 percent, it signified a distressed condition (Wallace, 2004).

2.1.1.5 Other Statistical Methods

Among the other statistical technique employed in previous studies is survival analysis and this technique has been applied in the accounting research in the area of financial distress. Several different terms have been used to refer to survival analysis, such as reliability analysis, failure time analysis, event history analysis, duration analysis or transition analysis (Chancharat, 2008). These different terms do not imply any real difference in techniques, although different disciplines may emphasise slightly different approaches. Survival analysis is a class of statistical methods for studying the occurrence and timing of events (Allison, 1995).

The hazard function $h(t)$ is an important function in survival analysis, because it models the hazard rate, which is the basic concept of survival analysis (Chancharat, 2008). The hazard function models the probability of failure in the next period given that the firm was active at the time *t*. Given that *T* is a random variable that defines the event time for some particular observation, then the hazard function is modelled as follows:

$$h(t) = \lim_{\Delta t \to 0} \Delta r \; [\frac{p(t < T + \Delta t \mid T \geq t)}{\Delta t}]$$

There are three different techniques in survival analysis for constructing survival analysis models: non-parametric, semi-parametric and parametric technique. Two main methods that are using non parametric models are the Kaplan-meier method and the Life-Table method. Meanwhile, the key issue in parametric models is to specify a probability distribution for the time of even and referred to as accelerated failure. Finally, semi-parametric models do not require specification of the probability distribution of hazard function over time and the most widely used semi-parametric regression model for survival is the Cox proportional hazards model proposed by Cox (Chancharat, 2008). The Cox proportional hazards model ia a popular statistical model used in financial distress research (LeClere, 2000).

Cumulative sums (CUSUM) procedures are among the most powerful tools for detecting a shift from a good quality distribution to a bad quality distribution. They are a set of sequential procedures based on likelihood ratios for detecting a shift in a process. A CUSUM model determines the starting point of the shift and provides a signal of the company's deteriorating state as early as possible after the shift occurs.

In principal, the overall performance at a given point in time is assessed by the cumulative time-series performance score of a company. The CUSUM score is set to zero indicating no change in the company's financial condition as long as the company's annual time-series performance scores are positive and greater than the specified sensitivity parameter. An opposite movement in the scores indicates the company's changed condition (Aziz and Dar, 2004).

Another method is the Partial Adjustment Process. The best example for explaining this model's application in bankruptcy prediction is by using the cash management behaviour of the firms. Cash Management refers to the management of cash from the time it starts its movement into the company until it departs the company in terms of payments (Laitinen and Laitinen, 1998). According to Laitinen and Laitinen (1998), any failure in terms of cash management can be described as an imbalance between cash inflows and outflows. This could lead to failure that is normally classified as the inability of the company to pays its financial obligations as they fall due.

Discriminant analysis is one of the most utilised statistical techniques for the prediction of the performance of business firms. Although this method has been amongst the oldest of the techniques for the prediction of failures or a firm's performance, beside univariate analysis, it is more preferable due to the fact that this technique takes into consideration the possible interrelationships amongst the independent variables, which explain the variations in the groupings of the dependent variable. This technique can include other variables beside financial factors that may affect the performance of the dependent variable (Altman, 1981; Sinkey, 1975).

2.2.2 Artificially Intelligent Expert System (AIES) Models

The development of programs that could emulate human cognitive skills, like problem solving, began in the 1950s. This is always referred to in past studies as Artificial Intelligence (AI), due to this intelligence being contained in machines and not in human brains. Humans use their intelligence to solve problems by applying reasoning based on the knowledge possessed in their brains. AI, however, should benefit from similar knowledge in the application of its reasoning to the problem posed. Expert systems (ES) were developed to serve this purpose for AI (Aziz and Dar, 2004). Among the techniques that fall under this category are: Neural networks, the Recursively partitioned decision tree (inductive learning model), the Case-based reasoning model, Genetic Algorithms, and Rough sets models. Based on previous studies, the most frequently used Artificial Intelligence technique was Neural Networks. Amongst those researchers employing this method are Odom and Sharda, 1990; Tam and Kiang, 1992; Udo, 1993; Altman *et al*., 1994; Wilson and Sharda, 1994; Atiya, 2001; Swicegood and Clark, 2001; and Steyn-Bruwer and Hamman, 2006.

2.2.2.1 Neural Networks

The current development and abundance of high speed computers in recent years has made the neural network model an attractive topic for research. This method is being used in areas of prediction and classification, areas where regression models and other related statistical techniques have been traditionally used. In fact, this method has also been used in banking and finance. Neural network models have been developed from the field of artificial intelligence and brain modelling (Demyanyk and Hassan, 2009). Neural networks carry out the classification in the way a brain would do by responding to the signals of the financial health of a firm. The neurons in neural networks are called 'processing elements' or 'nodes'. These nodes are interrelated with each other. These nodes are then converted into a single output signal and then later this signal is acknowledged as the classifying decision if it satisfies the researcher. In other words, the method considers an interrelated group of artificial neurons and processes information associated with them using the so-called connectionist approach (Demyanyk and Hassan, 2009). If the result turns out to be otherwise, it is transmitted again as an input signal to many other nodes until it satisfies the researcher.

According to Aziz and Dar (2004), in predicting corporate bankruptcy, the Neural Network will take information on explanatory variables at input nodes via the input layer. The hidden layer nodes, connected to the input nodes through weighted interconnections, collect and process this information to suggest the probability of a firm failing or succeeding.

2.2.2.2 Recursively partitioned decision trees (Inductive learning Model)

Inductive learning is a form of supervised learning in which learning from examples occurs by a process of generalization; this has been used by many human experts. A decision tree divides a training data set into sub-classes and then replaces each of the subset with a decision tree. The final decision tree for the initial training set is the result of this process (Aziz and Dar, 2004). In Bankruptcy classification, the decision tree is created by recursively partitioning the training sample until the final nodes of the tree contain firms of only one type: bankrupt or healthy. Any additional firm is then categorised according to where the final node falls in the tree. This will be the identification of the firm's group membership as well as the associated probability.

Friedman (1977) was amongst the first to introduce the recursive partitioning decision rule for nonparametric classification. As suggested by other researchers, 'the basic idea of recursive partitioning is to fit a tree to the training sample by successively splitting it into increasingly homogeneous subsets until the leaf nodes contain only cases from a single class or some other reasonable stopping criterion applies' (Pompe and Feelders, 1997: 270).

2.2.2.3 Case-based reasoning (CBR) Model

The Case-Based Reasoning method is another problem solving method that operates like human experts. This method solves new classification problems by referring to the previously solved case within the same field of knowledge. Normally, there are four stages involves in a Case-Based Reasoning process of knowledge attainment: (1) identification, acceptance and representation of a new problem, (2) retrieval of old similar cases from the case library, (3) adapting the cases repossessed in step 2 in a way that they fit into the new situation and provide a suitable solution to it, and finally, (4) evaluation of the suggested solution and finally storing the evaluated solution in the case library for future use (Aziz and Dar, 2004).

Case-Based Reasoning has also been applied in bankruptcy prediction by developing a case library of previously solved prediction problems. The next step will be to identify, accept, and represent any new prediction problem before adapting a similar case from the library to match it with the new problem and give the prediction result. The other methods under the Artificial Intelligence category are Genetic Algorithms (GA) and Rough sets models. The basic ideas behind this model are genetic inheritance and also the Darwinian Theory of natural evolution, also known as the survival of the fittest. Based on these two concepts, GA work as a stochastic search technique (Aziz and Dar, 2004).

2.2.3 Theoretic models

According to Aziz and Dar (2004), the theoretic models were developed as another approach to looking at the distress conditions present in the firms. Finding symptoms of failure is the main focus of statistical and Artificial Intelligence Expert System models, but Theoretic Models focus more on the causes of failure by looking at the factors that force firms to go bankrupt. In fact, the prediction models developed under this approach are based on some theoretic arguments.

There are four techniques within the Theoretic models: Balance Sheet Decomposition Measure/Entropy theory, Gambler's Ruin Theory, Cash Management Theory, and Credit Risk Theory (Aziz and Dar, 2004).

One way of identifying a firm's financial distress condition is by looking at any changes in the firm's balance sheet. In order to be sustainable in the existing structure, the firm needs to maintain a state of equilibrium. Lets say there are some significant changes occurring in the firm's balance sheet composition of assets and liabilities; here it is most likely that the firm will be unable to survive, in other words, the firm is in financial distress. This theory is called Balance Sheet Decomposition. Gambler's Ruin Theory is another technique that is applied within theoretic models. The idea behind this technique relates to the gamblers' game that plays with the probabilities of either gain or loss, and the game will continue until the gambler loses all his money. This theory is applied to a firm's failure prediction. Then, there is a possibility that the firm's cash flow will always be negative, which, generally, will lead the firm to declare bankruptcy. According to this theory, the firm will remain solvent as long as their net worth is greater than zero (Aziz and Dar, 2004).

Another technique within Theoretic Modelling is Cash Management Theory. Cash management, especially short-term cash management, is one of the major concerns among firms. Any persistent shortage or imbalance between cash inflows and cash outflows means a failure in the cash management function and would also result in the financial distress of the firm. The fourth technique within Theoretic Modelling is Credit Risk Theories. This technique is closely related to Basel I and Basel II accords, which have been applied by most of the financial institutions. Under Basel II framework three pillars were proposed: the minimum capital requirement is set equal to 8%, the supervisory review of an institution's internal assessment process and capital adequacy, and the effective use of public disclosure to strengthen market discipline (Aziz and Dar, 2004).

2.2.4 Overview

The research done by Aziz and Dar (2004) concludes that amongst the others, the predictive accuracies of different corporate bankruptcy prediction models are generally comparable. They also found that the performance of Artificially Intelligent Expert System (AIES) is better than the statistical and theoretical models. Multiple Discriminant Analysis usage in past research has been shown to be the most popular method used in predicting corporate bankruptcy followed by the logit models.

Statistical models have been largely used in past research into corporate bankruptcy prediction. In fact, MDA and logit analysis are among the most frequently used models in predicting corporate bankruptcy.

2.3 EXISTING BANKRUPTCY PREDICTION MODELS

In past years, analysts relied principally on financial statements to evaluate the risks associated with investment. For example, simple ratio analysis was performed to consider if the company was sufficiently liquid and to see how well it managed its assets and debt. In fact, the base theory developed recently on bank failure prediction is built on the use of financial ratios in the bankruptcy prediction models of Altman (1993). Most of the prediction models that are based on ratios analysis have a predictive ability in giving a signal to management about the dwindling of the financial condition of the firm.

Many different techniques have been applied to bankruptcy financial prediction since the introduction of the first statistical and mathematical models for bankruptcy financial prediction were published in 1960s (Gepp and Kumar, 2008). In the more recent development of bankruptcy prediction models, logit analysis has been compared to more advanced analytical tools, neural networks, and support vector machines. Research has found that the methods perform likewise.

This section reviews the prediction modelling research. It provides an overview of prediction models and how they have been used in the previous studies. The studies included in this review are chosen to be representative of the rich body of literature that exists. They represent some of the best and most widely cited research articles that relate to the development and application of prediction models for banks. (Swicegood, 1998)

2.3.1 Traditional Prediction Models: Univariate, MDA, Logit and Probit

2.3.1.1 Univariate

Beaver (1966) was the pioneer in developing a corporate failure prediction model using financial ratios. In fact, cash flow analysis was the central to Beaver's work. He was the first researcher that applied the univariate discriminant analysis model on a number of financial ratios in order to predict the failure of the company. In other words, he was the first to use the statistical techniques to predict corporate failure. In the process of selecting the best financial ratios to classify failing or non-failing companies, he applied the dichotomous classification test.

Using univariate analysis, Beaver (1966) tested 14 ratios and found that the cash flow to total debt ratio was the best classifier of corporate bankruptcy. Beaver's (1966) theory of ratio analysis was a cash flow model which served as a framework for explaining the results of the tests on the ratios. Beaver used univariate methodology searching for variables with the greatest predictive ability and tested 30 separate accounting variables. His sample consisted of 79 failed firms. He found his data in the Moody's Industrial Manual for the period 1954-1964 (Beaver, 1966).

2.3.1.2 Multiple Discriminant Analysis

Research methodology has evolved from univariate methods (Beaver, 1966) to multivariate techniques (Altman, 1968). As mentioned, cash flow analysis was central to Beaver's work, but it was not included in Altman's (1968) theory of ratio analysis. Altman's work based on five ratios: working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, the market value of equity/total liabilities, and sales/total assets. Beaver's (1966) work was limited to looking at only one ratio at a time, but Altman (1968) has changed this by using a multiple discriminant analysis (MDA).

Altman (1968) was the first to apply discriminant analysis, a multivariate analysis technique, to failure classification problems. Altman (1968) experimented with multivariate models based on Beaver's univariate analysis, which included 22 significant variables. Altman reduced the constructs to 5 accounting ratios. His sample had 95% accuracy and consisted of 33 manufacturing companies that filed for bankruptcy for the period 1946-1965. Altman's *Z*-model was the result of this multiple discriminant analysis and has been used in many of the later research projects. In other words, early models of bankruptcy prediction were influenced by Beaver's (1966) cash flow theory and Altman's discriminant analysis methodology.

In the early 1970s, researchers, including Deakin (1972) found that the cash flow to total debt ratio was the best single predictor of failed and non-failed firms for the 5 years before bankruptcy. Deakin (1972) first replicated the Beaver (1966) study, using the same ratios that Beaver used. Next, Deakin searched for the linear combination of the fourteen ratios by Beaver which best predicted potential failure in each of the five years prior to failure. The results showed that multiple discriminant analysis may be better applied to short-run financial distress prediction.

Altman, Haldeman, and Narayanan (1977) modified Altman's 1968 study with updated data. The ZETA model is a discriminant analysis model that used seven variables. Altman *et al.* (1977) developed the ZETA score which was basically the second generation of the originally developed *Z*-score model. Altman, assisted by Haldeman and Narayanan, developed this model in which some of these 7 ratios were different from the original 5 ratios. Thus, the change in the number and type of ratio denotes that variable selection is important in order to achieve the best result. As in Altman's previous study, Altman *et al*. (1977) used the paired sample technique for non-failed manufacturing and retail bankrupt firms. The non-bankrupt group also included manufacturing and retail companies. The 1977 ZETA model sample selected firms that failed between 1969 and 1975. This Zeta model confirmed the accuracy of Altman's original (1968) discriminant model. The one year prior to failure classification accuracy of bankrupt firms is quite similar for both models (Altman, 2002). According to Altman *et al*. (1977), the ZETA model is deemed as the more accurate and relevant failure prediction model.

Another work related to multivariate discriminant analysis is the research done by Edminster (1972). Edminster (1972) used the ratio of funds flow/current liabilities. Another researcher, Blum (1974), used 115 failed firms and 115 non-failed firms as a sample from 1954 to1968. Blum (1974) used discriminant analysis and 12 variables to build the financial distress prediction model. The results showed that the correct classification rates are above 70% (Blum, 1974). Altman and Narayanan's (1997) study innovated research applicable to banking decisions. It linked the cost of classification errors to the lending decision. The study used the commercial bank loan process. The lending decision has consequences. If the granted loan defaults, it can be considered a Type I error. If the defaulted loan that could have been paid is not granted, it is analogous to a Type II error.

Although Altman, Deakin, and Blum each used linear discriminant analysis to develop their models, Deakin and Blum developed models for each of the five years before failure, whereas Altman used data for the first year before failure to fit his model and used the same linear function to predict failure/non-failure in each of the five years before failure. This methodological difference may, in part, account for the relatively poor reported performance of Altman's variable set (as compared to Deakin's and Blum's) in the third, fourth, and fifth years before failure.

Over the years, there has been an enormous volume of studies based on Altman's *Z*-score model. Until the 1980s, the technique of MDA dominated the literature on corporate failure models. After the 1980s, its use has decreased (Dimitras *et al.*, 1996), but the MDA method is frequently used as a 'baseline' method for comparative studies (Altman and Narayanan, 1997). In other words, MDA seems to be the generally accepted standard method.

2.3.1.3 Logit

There is also a significant body of early bankruptcy prediction research based on logit. Like MDA, logit is used to classify failed and non-failed groups. Logit is an extension of multiple regression in which the dependent variable is not a continuous variable. With the logit model, it is possible to obtain a measure of goodness-of fit analogous to the linear regression. Like multiple discriminant analysis, logit can be applied stepwise.

Ohlson (1980) is the first to apply the logit analysis to the problem of bankruptcy prediction. By using 105 bankrupt and 2, 058 non-bankrupt firms he is also the first to apply a representative sample. He states that predictive power appears to be less than reported in previous studies. Further, logit analysis actually provides a probability (in terms of a percentage) of bankruptcy, the probability calculated might be considered a measure of the effectiveness of management. Ohlson (1980) pioneered multiple logistic regression analysis, Logit, and applied it to bankruptcy prediction. He built upon the major bankruptcies studies, including several significant variables categories: the size of the company, financial structure, performance, and current liquidity. He also added to the variables economic indicators like Log total assets/gross national product; and price level index. Four of his nine ratios used total assets as the denominator. Other ratios were compared to working capital, current liabilities, funds provided by operations, and net income total assets.

Another piece of research was conducted by Zavgren (1985). Her logistic analysis paired samples of industrial firms matched according to industry and asset size and consisted of 45 failed and 45 non-failed firms. Data was collected from the New York stock exchange. Zavgren replaced the current ratio by the acid test ratio, because the inclusion of inventories in the current ratios reduces its meaning as a measure of liquidity. Data was collected from the New York stock exchange.

Gentry, Newbold and Whitford (1985) in their study use the probit-logit model as an alternative to discriminant analysis to classify failed and non-failed companies. The model used a cash-based fund flow model. Gentry *et al*. (1985) found that the addition of the traditional financial ratios to the cash-based fund flow components improved the predictive ability for bankruptcy classifications. The sample of their study consisted of 33 failed firms and was matched with 33 non-failed firms. Of these 33 companies, 21 were industrial and 12 were a mixture of other industries. Gentry *et al*. (1985) also found that dividends are significant in distinguishing between failed and non-failed companies. A measure of cash flow as a percentage of assets, the ratio of total net flow to total assets, was also statistically significant in distinguishing between failed and non-failed companies. In fact, receivables and investment components become reliable measures one year prior to bankruptcy but do not provide consistent signals of failure in the two or three years before failure.

During the 1980s and 1990s, the trend has been to use logit analysis in favour of multiple discriminant analysis. In fact, logit analysis has been compared to a more advanced analytical tool, neural networks. Research has found that the approaches perform similarly and should be used in combination (Altman *et al*., 1994). There are a few pieces of research that were conducted based on the logit model in the 2000s. Among them are Barniv *et al*. (2002), and Cybinski (2003).

2.3.2 Others :Artificial Intelligence Neural Networks

Over the past few decades there has been much research directed at the development of better prediction methods. This research has produced a new methodology for forecasting, now known as artificial neural networks. Within the past few decades neural networks have found an increasing number of useful applications in predictors of banks and corporate failure/performance.

According to Gepp and Kumar (2008), there was a major shift in corporate bankruptcy methodology in 1990s from the traditional statistical methods to the more advance technique called the Artificial Intelligence Expert System. And this shift has continued to the present. There are many studies that apply Artificial Neural Networks (ANNs) to bankruptcy financial prediction and compare the performance of ANNs with a discriminant analysis and logit analysis model, such as work done by Odom and Sharda (1990), and Fletcher and Goss (1993).

Odom and Sharda (1990) were the first to apply Neural Networks to the prediction of company failure. They compare the predictive ability of neural networks and multivariate discriminant analysis models in bankruptcy risk prediction. They found that neural networks appear to be more vigorous than the discriminant analysis method (Odom and Sharda, 1990). Another study conducted by Fletcher and Goss (1993) used a small sample size, 18 bankrupt and 18 non-bankrupt firms, and compared the neural network model with logistic regression. They found that ANNs yield much better model fitting and prediction results than logistic regression even though the training effort for building ANNs is much higher.

In another study conducted by Salchenberger *et al*. (1992), they developed a neural network model that processes input data consisting of the financial health of thrift institutions. The main purpose of Salchenberger *et al*.'s (1992) study was to test the back propagation neural networks over logistic regression. In the earlier stage, 29 variables were selected and later a stepwise regression was performed in order to reduce the number of variables to the final five test variables. Salchenberger *et al.* (1992) concluded that the neural network model performs better than the logistic regression model.

There were many research projects conducted in the 1990s applying the Neural Networks model and a few of them did comparisons between Neural Networks and other models. Amongst those researchers are: Wilson and Sharda, 1994; Boritz and Kennedy, 1995; Leshno and Spector, 1996; and Zhang *et al.*, 1999. The application of the Neural Networks models has also been useful during the 2000s. Amongst the researchers that are worthy of mention are: Atiya, 2001; Mohamed *et al.*, 2001; and Lee *et al.*, 2005.

2.3.3 Bank Failure Prediction Models

The prediction of failure for financial firms, especially banks, has been the extensively researched area since late 1960s. The past forty years have seen increasingly rapid development in the field of failure prediction models. There are various statistical and neural networks methods that have been used in bankruptcy prediction problems for banks and firms. Amongst the statistical methods that have been applied are included: multivariate discriminant analysis, linear discriminant analysis, quadratic discriminant analysis, multiple regressions, logistic regression, probit and factor analysis. As for Neural networks, amongst the methods used include: multi-layer perception, radial basis function network, probabilistic neural network, auto-associative neural network, self-organizing neural network, learning vector quantisation and a few other artificial intelligence techniques (Ravi Kumar and Ravi, 2007).

A considerable amount of literature has been published on bankruptcy prediction for banks. Several bank failures prediction models have been developed since the 1970s, with most of these models having been constructed using statistical techniques, such as multivariate discriminant analysis (Meyer and Pifer, 1970; Sinkey, 1975; Sinkey, 1977; Looney *et al.*, 1989), logit regression (Martin, 1977; Whalen and Thomson, 1988; Thomson, 1991), and factor analysis (West, 1985). Later works on bank bankruptcy prediction also involved other methods and neural networks is one of them (Tam and Kiang, 1990; Tam, 1991; Swicegood and Clark, 2001). In fact, according to Zhao *et al*. (2009), some of these models have also been applied in the regulatory practices in banking agencies. Next a brief review is presented of the applications of bankruptcy prediction models, statistical and intelligent techniques in banks.

2.3.3.1 During 1970s

Most of the bank failure models developed by the pioneers of bankruptcy research are based on financial ratios. Martin (1977), Altman *et al*. (1981) and Espahbodi (1991) are among the researchers that used accounting data as the explanatory variable. Likewise, the other models, such as duration and cox proportional research models use accounting ratios as independent variables (De los Rios, 2006).

Meyer and Pifer (1970) are the first researchers who used the multivariate statistical method to predict bank failures (Boyacioglu *et al*., 2009). The sample of their study consisted of 39 commercial banks that closed between 1948 and 1965. During this period, out of 55 insured banks closed, only 39 were selected for the study. These banks had to satisfy two main criteria to be included in the study: complete data for six years prior to bankruptcy and a comparable solvent bank was required for each closed bank. Based on this study they found that the model correctly classified about 80% of the sample for one and two years prior to failure. However, the financial variables are unable to discriminate between failed and non-failed banks if the lead time is three years or more.

Sinkey (1975) also applied multivariate discriminant analysis to the issue of predicting problem banks. The main purpose of his work is to identify and describe the characteristics which distinguish between problem and non-problem banks. In other words, this application of multivariate discriminant analysis attempts a classification of a bank's status rather than a prediction of a bank's status. The sample consisted of 110 problem banks that were identified during 1972 and early 1973, matched with non-problem banks during the same period. The financial ratios derived from the balance sheet and income statement of the respective samples are employed in this study. Sinkey (1975) focused on ratios used by most corporations related to the firm's financial condition: liquidity, efficiency, and capital adequacy. The empirical findings indicate that measures such as asset composition, loan characteristics, capital adequacy, sources and uses of revenue, efficiency, and profitability are good discriminators between problem and non-problem banks.

Santomero and Vinso (1977) in their study attempt to develop a more simplified model which classifies risky banks. The sample of the study consists of 214 banks that provided consistent weekly reports during 1965 to early 1974. They developed a theoretical risk index that estimates the probability of failure based on the stochastic process generating variations in the capital account of the banks. The discriminant analysis results indicate that only two variables, the bank's capital to asset ratio and the coefficient of variation of capital account changes, may be used to distinguish between risky banks and non-risky banks.

Al-Osaimy and Bamakhramah's (2004) work was among the pioneers in developing the prediction of Islamic banks performance. This will be a cornerstone for further development of prediction models for Islamic banks. They utilised the discriminant analysis with the profitability rate as dependent variable and the financial ratios as explanatory variables. The discriminant score extracted from the above discriminant function is used to differentiate between the high and low performance group of banks. This process formed an early warning system for the prediction of a bank's future performance.

Some early bank failure prediction research projects used a combination of statistical methods. The choice of a combined methodology continued in contemporary research. Several combinations are found: MDA combined with arctangent regression or logit; regression and market model or asset pricing and; logit and factor analysis or recursive partitioning (De los Rios, 2006).

Martin (1977) was the first to utilise logit as a methodology for prediction modelling**.** Martin (1977) compares the predictive ability of logit, linear discriminant, and quadratic discriminant models. Martin (1977) develops the model for the six-year period between 1970 and 1976. His sample includes all 5,700 banks in the Federal Reserve System, of which there were 58 bank failures for the period studied. These banks were identified as failed through an examination of publicly available sources, such as the merger decisions of Federal bank supervisory agencies, from newspaper articles as well as from the examination of the banks' balance sheets whose net worth shows a declining trend. Martin (1977) in his study also uses financial ratios as independent variables. A set of 25 financial ratios is chosen relating to asset risk, liquidity, capital adequacy, and earnings. This concluded that different indicators on capital adequacy, liquidity, and earnings were the most significant determinants of failure over his sample period. Other studies around the same time, using both logit and discriminant analysis confirmed these results. Sinkey (1978), supported these results, finding that poor asset quality and low capital ratios were the two characteristics that consistently related to banking problems in the 1970s.

Four variables are included in Martin's most effective models: net income over total assets; capital over risk assets; gross charge-offs over net operating income; and commercial loans over total loans. Martin (1977) also compared logit and discriminant analysis methods and concluded that in terms of prediction accuracy, supported by Altman (2002), both models are virtually the same. But, if a dichotomous classification of banks into 'sound' or 'unsound' is the goal, then the linear discriminant analysis model may be preferable. On the other hand, if the probability of failure estimates are needed for some other usage then the logit method is preferable (Swicegood, 1998).

After the introduction of a logit model for banking failure by Martin (1977), a few other researchers have applied the same methodology in their works (Ohlson, 1980; West, 1985; Espahbodi, 1991; Thomson, 1992; Tam and Kiang, 1992). Logit models are employed to find the explanatory factors behind a certain event taking place, in this case a bank failure.

2.3.3.2 During 1980s

West (1985) extends the logit modelling process by using factor analysis to measure the condition of individual institutions and to assign a probability of either problem or non-problem bank. The model used financial ratios and information from the bank examinations. West (1985) took the data for this study from Call and Income reports, and examination reports for commercial banks from the Eighth, Tenth, and Eleventh Federal District for the period 1980-1982. Out of 2,900 banks in the seven states, this study includes only 1,900 banks as a sample. Some of the factors that appear from the factor analysis are closely related to CAMEL components: capital adequacy; asset quality; management; earnings; and liquidity. In fact, some of these variables have been used in previous studies on early warning systems to predict failed and non-failed banks (West, 1985). The factor scores produced by the model are used in the logit estimation to test their ability to differentiate problem banks from non-problem banks. Based on CAMEL ratings, those banks with ratings of 1 or 2 are considered as sound, and banks with ratings of 3, 4, or 5 are considered to be problem banks. The empirical results show that the combination of factor analysis and logit estimation is a promising method for use as an early warning system for banks.

Bovenzi *et al*. (1983) continue the modelling literature on bankruptcy prediction by using probit analysis to predict bank performance. Bovenzi *et al*. (1983) took the data from Call Reports, Examiner ratings, and bank examination information for failed and non-failed banks for the period 1977-1983. Predictions of bank failures are made one and two years prior to the event. The results of the study show that as the number of failures increases, the accuracy of prediction declines and vice versa. Bovenzi *et al*. (1983) also reported that prediction accuracy improves if the information from the past examinations is incorporated into the models. The three models developed by Bovenzi *et al*. (1983) are then compared to a prediction scheme based on CAMEL ratings and they found that the models using financial ratios perform better in predicting the bank failures as compared to the model based on CAMEL ratings.

Zavgren's models were based on what is known as logit analysis. Zavgren (1985) developed a model that can consider the predictive capabilities five years in advance of distress. These capabilities will permit the users to assess whether the sample of companies are failing over time. According to Zavgren, the probability score will lie between 1 and 0. With a 50 percent cut-off value suggested by Zavgren, if the probability lies at or above 50 percent the distressed case is indicated or vice versa.

Whalen and Thomson's (1988) study used financial data to group banks into problem and non-problem categories by predicting the examination rating using the publicly available data. They used Call Report data in predicting the weakening condition of banks as measured by changes in CAMEL ratings. They also explore the use of factor analysis as a way to statistically imitate the procedure used by examiners to assign CAMEL ratings. Logit regression analysis has been employed to construct several different versions of a model that could be used to predict changes in CAMEL ratings or in other words, the financial condition of the sample banks. The result of Whalen and Thomson's (1988) study are in concurrence with those empirical works that have been done before on early warning failure prediction models. Particularly, their findings show that simple models created using a limited number of financial ratios derived from publicly available information do a rather good job in classifying commercial banks into different risk classes.

2.3.3.3 During 1990s

Espahbodi (1991) tests and compares the prediction ability of both logit and discriminant analysis models in distinguishing among failed and non-failed banks. The original sample consisted of 48 banks that failed in 1983 and another 48 matching non-failed banks. But, the final sample consisted of fewer banks due to a lack of data. These failed banks are paired with non-failed banks of the same time period, geographic location, and the size of the banks. Unfortunately, due to unsuccessful attempts to obtain data on the selected banks, the final sample for the models for two years before failure (1981) had to be reduced to 37 failed and 33 non-failed banks, and for the one year before failure (1982) had to be reduced to 38 failed and 35 non-failed banks. Regardless of the year or the method of analysis, four variables were found to be important in distinguishing failed banks from non-failed banks: total loan revenues over total operating income; interest income on state and local government obligations over total operating income; interest paid on deposits over total operating income; and total time and saving deposits over total demand deposits. For the logit model, the overall prediction accuracy of failed banks one and two years prior to their 1983 failures is 87.67 percent and 77.71 percent respectively. And for discriminant analysis, the overall prediction accuracy is 86.3 percent and 84.28 percent. The model for one year before failure was then applied to the 1984 failure sample. The result of this exercise shows that the logit model provides a more accurate prediction of a bank's failure than discriminant models.

While most bank failure studies are designed to model the economic insolvency of a bank, Thomson (1992), using option theory, develops a logit model which concentrates on modelling the regulator's decision to close a bank. Focusing on Call Report data from banks closed during 1984-1989, Thompson attempts to predict closure decisions one, two, and three years in advance. Another work by Thomson

(1991) models bank failures of all sizes based on Call Report data using a logit regression analysis. The probability that a bank will fail is a function of capital adequacy, asset quality, management quality, earnings performance, and the relative liquidity of the portfolio. These are CAMELS-motivated proxy variables. Thomson finds that the majority of these factors are significantly related to the probability of failure as much as four years before a bank fails.

In another major study during the 1990s, Tam and Kiang (1992) conducted research to compare the ability of a number of different types of statistical models to predict bank failures. Using bank bankruptcy data, they compared neural network models to statistical methods such as linear discriminant analysis, logistic regression, k nearest neighbour and the machine learning method of the decision tree. The data sample consisted of Texas banks that failed for the period 1985-1987. As a control measure, a failed bank was matched with a non-failed bank in terms of: assets size; number of branches; age of the bank; and charter status. In each period, 118 banks (59 failed and 59 non-failed banks) were selected as the training sample and each bank was described by 19 financial ratios that have used in previous studies. The empirical results of Tam and Kiang (1992) show that neural networks offer better predictive accuracy than discriminant analysis, logit, K nearest neighbour, and decision tree methods. Tam and Kiang concluded that neural networks are generally more accurate for evaluating bank status.

Another study on logit analysis was done by Salchenberger *et al.* (1992). Salchenberger *et al*. (1992), in their study, used back-propagation neural network and logit models to predict the probability of failure for savings and loan associations. Initially they selected 29 variables and then performed a step-wise regression to reduce the number of variables into the final five variables. Data for this study consisted of 100 thrifts that failed during the period 1986-1987, and are matched with non-failed thrifts of similar size and location for the same period. They conducted an experiment to test the possible performance difference of back propagation neural networks over logistic regression. They concluded that neural networks models perform better than logistic regression models.

Henage (1995) developed a large sample prediction model. His sample consisted of 425 failed banks paired with non-failed banks. He used Federal Deposit Insurance

Corporation (FDIC) annual reports to identify failed banks. He also used the Ferguson database. The financial statements were used for the period 1966-1993. Henage (1995) constructed prediction models and replicated the typical research methodology used in prior studies. One of Henage's inputs to the field of research is the utilisation of a large sample size as compared to the previous studies. According to Henage (1995) few prior studies have ever incorporated more than 100 failed firms into their models, and no prior studies used in excess of 165 failed banks. Henage's logit model has selected the strongest predictors from the list of 23 variables as the predictors and variables. The final set of the model consisted of five variables on the basis of financial analysis techniques. The data-driven models were created by the stepwise approach. Finally, he restricted the predictive model to the five constructs and measures. Six logit models were created, one for each of the years 1988-1993, to make an in-sample classification. Henage's (1995) study has demonstrated significant improvements in the field of research.

Clarence Tan (1996), on the other hand, has conducted a study to predict credit union failure in Australia by using a neural networks model. In his study, he compares the predictive accuracy of the neural network model and probit models in predicting financial failure. The data consisted of 1449 institutions with 20 credit unions classified as failed for the period 1989-1991. Thirteen financial ratios measuring stability, profitability, and liquidity were used in this study. Quarterly data from 1989 to 1990 has been utilized by Tan (1996) for training, and for validation purposes quarterly data in 1991 was used. Tan (1996) concluded that both probit and neural network models provide a comparable overall predictive accuracy. During the same period, Gonzalez-Hermosillo *et al.* (1996) verify that besides bank-specific variables, macroeconomic variables also seem to be important in predicting the timing of failure. Thus, they concluded that macroeconomic indicators should be utilised in the analysis of Norwegian banks.

Bell (1997) conducted a comparative study. In his study, Bell examines the ability of neural networks and logit models to predict bank failures over a 12-month horizon. The data used in the study consisted of failed banks during 1985 and 1986, matched with the non-failed banks from the same period. Bell applies a range of possible cut-off points for each of the different models, and concluded that neural networks and logit models performed equally well in the prediction of bank failures (Bell, 1998). During the same period, another comparative study was also conducted by Ethridge and Sriram (1997). The study compared three models; neural networks, logit and discriminant analysis. This was to check the ability of those models in predicting bank failures in advance. The data consisted of 991 non-failed banks and 148 failed banks during 1986 to 1989. Two different models of neural networks were applied in this study: categorical learning nets and probabilistic nets. Ethridge and Sriram (1997) concluded, in overall prediction rates, logit and discriminant analysis are similar to the two neural networks applied in this study. However, when taking into consideration the relative error costs and as the estimation time period moves away from the eventual failure date, both neural network models outperformed the logit and discriminant analysis models.

Swicegood (1998) in his PhD Thesis conducted a comparative study between neural networks, discriminant analysis and professional judgment, in predicting poor bank profitability. The information from 1991 and 1992 was used to predict the banks' performance in 1993. Swicegood (1998) concluded, for both the regional and community bank samples, that the predictive ability of neural networks outperformed the discriminant analysis model. Comparing the prediction between community and regional banks, both discriminant analysis and the neural network model display a better prediction for regional bank samples. Taking into consideration the relative costs of misclassification in both models, Swicegood concluded that neural networks provide greater accuracy as compared to discriminant analysis. Another test on a sample of 100 regional banks was conducted. Swicegood (1998) tested the predictive ability of the three models; neural network, discriminant analysis and, professional human judgement, and came to the conclusion that neural networks show better prediction ability than regulators (professional human judgement). In fact, both models, neural networks and regulators, outperformed the discriminant analysis accuracy.

2.3.3.4 During 2000s

In the 2000s, several studies have highlighted the importance of developing early warning systems to identify troubled banks, such as Kolari *et al*. (2002), Tung *et al*. (2004), Canbas *et al.* (2005), and Lanine and Vander Vennet (2006).

Kolari *et al*. (2002) used both parametric logit analysis and the non-parametric trait approach to develop computer-based early warning systems (EWSs) to identify large bank failures in the US. They concluded that computer-based EWSs can provide beneficial information about the future viability of large banks (Kolari *et al*., 2002). Tung *et al.* (2004) proposed a new neuro-fuzzy system, viz., the generic self-organizing fuzzy neural network based on the compositional rule of inference to predict bankruptcy in banks. They concluded that the MLFF-BP outperformed this neuro-fuzzy system.

Another recent study by Jagtiani *et al.* (2003) developed an early warning system model that converged on discovering banks that will have inadequate capital in the following years. Their models predict banks with an early stage of capital distress, especially those banks with a primary capital to asset ratio below 5.5 percent of the minimum capital adequacy standard relevant during the period of study. This will enable the supervisors to identify banks at risk and make a timely intervention whenever necessary. They tested their models using financial and economic data for sample banks. Among the models used are the simple logit model, stepwise logit, and trait recognition analysis.

Canbas *et al.* (2005) combined discriminant analysis, logistic regression, probit and principal component analysis in their proposed integrated early warning systems (IEWS) model. They proposed a methodological framework for constructing the IEWS that can be used as s decision tool in the bank examination and supervision process for detection of those banks experiencing serious problems. Data consisted of 40 privately owned Turkish commercial banks, 21 failed and 19 non-failed banks during the period of 1997 to 2003, and their financial ratios. Principal component analysis, also known as the multivariate statistical technique, was used in this study to explore the basic financial characteristics of the banks. On the other hand, these characteristics were used to construct IEWS for discriminant, logit and probit models. The study concluded that, if IEWS was effectively employed in bank supervision, it can be possible to avoid bank restructuring costs at a significant rate in the long run.

Alam *et al.* (2000), in their study, used fuzzy clustering and two self-organizing neural networks to identify potentially failing banks. The results showed that both the fuzzy clustering and self-organizing neural networks are promising tools in the identification of potentially failing banks. Swicegood and Clark (2001) compared the performance of Discriminant Analysis, Back Propagation Neural Network (BPNN) and human judgment in predicting bank failures. They concluded that BPNN outperformed Discriminant Analysis and human judgment in identifying the underperforming banks.

While most of the studies are concentrated in the US, there are a few other studies that were conducted in other regions such as Japan, Indonesia, Turkey, Norway, Britain, Austria and Russia. Montgomery *et al.* (2005), in their study, investigated bank failures in Indonesia and Japan by using logit analysis.

In the Russian banking sector, there were a few studies conducted to analyse the bank failure determinants during the Russian banking crisis in 1998. Among the major studies were those conducted by Kutznetsov (2003), Golovan *et al.* (2003), Lanine and Vennet (2006), and Konstandina (2006).

In Kutznetsov's study, the researcher employed a logit model for the analysis of bank failure determinants during the Russian banking crisis in 1998. The study concluded that medium-sized banks with a large investment in government bonds were more likely to survive during a crisis. But, any differences in the liquidity and profitability of banks seemed to have no impact on the probability of failure. But, contrary to Kutznetsov's findings, Golovan *et al.* (2003) discovered that the probability of failure was negatively related to liquidity, investment in government bonds as well as capital adequacy. It should be noted that his finding was in line with the recent study conducted by Lanine and Vennet (2006). Lanine and Vennet (2006) found that liquidity, asset quality and capital adequacy play an important role in bank failure prediction.

Lanine and Vennet (2006) employed a parametric logit model and non-parametric trait recognition analysis to predict failures among Russian commercial banks. In other words, they attempted to build a bank failure prediction model, based on logit and trait recognition methodologies. They tested the predictive power of the two models and found that the trait recognition approach outperforms logit in both the original and the holdout samples. As for the variables, they found liquidity plays an important role in bank failure prediction as well as asset quality and capital adequacy.

In Britain, Logan (2003) applied a logit model to study the different characteristics of banks that failed as compared to those banks that continued to exist in the early 1990s.The study found that among the best indicators for short-term failure prediction were: leverage, profit, loan growth, liquidity, and net interest income. As for long-term prediction, rapid loan growth in the previous boom was found to be a significant indicator of failure.

In Austria, with the same timeframe and samples, Hayden and Bauer (2004) and Halling and Hayden (2006), both investigated the factors behind problems encountered in around 150 Austrian banks during the period from 1995 to 2002. Hayden and Bauer (2004), in their study, defined default as a situation where a bank is facing a serious problem and there is little chance of survival unless the government or other agencies intervene. This definition of default is followed by Halling and Hayden (2006) in their later research. In their study, Halling and Hayden (2006) recommended a multi-period logit that includes an indicator measuring market share as bank size relative to total bank size in the home region, and the ratio of net interest income to the number of employees as an indicator of management quality. They concluded that the size relative to the rival banks may be a sign of the quality of management.

Another study conducted in another region was carried out in the Norwegian banking sector. A recent study by Andersen (2008) applied a logit approach in predicting the failure of Norwegian banks. Risk index has been used by the Norges banks since 1989 in order to identify potential problem banks as well as to obtain a general picture of the health of the Norwegian banking industry. In this study, a logit model is estimated based on observations from the period of 2000 to 2005. The study found that the new proposed index gives strong and early signals well in advance of the crisis end in all of the eleven banks. The new risk index consist of six main indicators: the capital adequacy ratio, ratio of residential mortgages to gross lending, an expected loss measure, a concentration risk measure, return on assets, and a Norges Bank's liquidity indicator.

In 2009, Bakar and Tahir conducted a study using a multiple linear regression technique and a feed forward neural network for predicting bank performance in Malaysia. Data from thirteen Malaysian banks from the period 2001 to 2006 was used in their study. As a measure of bank performance, the return on assets (ROA) ratio was used as a dependent variable for the multiple linear regressions. As in the case of independent variables, seven variables were selected: liquidity; credit risk; cost to income ratio; size; concentration ratio; inflation; and GDP. Results from the multiple linear regression show that credit risk and cost to income ratio are significant in determining bank performance. Mean square prediction error has been used as a measure of the performance for both methods. They concluded that an artificial neural network is more capable of predicting bank performance.

During the same period, another study of bank failure prediction was conducted by Boyacioglu *et al.* (2009). Their study applied various neural network techniques, support vector machines and multivariate statistical methods to the bank failure prediction models in the Turkish banking system. Twenty financial ratios are selected as predictor variables in their study. These ratios are from six feature groups: capital adequacy, assets quality, management quality, earnings, liquidity and sensitivity to market risks (CAMELS). In the neural networks category, they employed four different architectures: multi-layer perceptron, competitive learning, self organising map and learning vector quantisation. As for the multivariate statistical methods, multivariate discriminant analysis, k-means cluster analysis and logistic regression analysis are examined. Boyacioglu *et al.* (2009) concluded that multi-layer perceptron and learning vector quantisation can be deemed to be the most successful models in predicting the financial failure of banks.

2.4 LITERATURE REVIEW ON DEFAULT ISSUES AND COMPOSITION OF DEPOSITS

This section will cover the literature of the issues related to the analysis of the fourth empirical chapter. The first one is the literature on the issue of banks' defaults and is followed by the literature on deposit composition. First of all, let us look at the definition of liquidity risk and defaults. According to the definition of the Basel Committee on Banking Supervision (1997), liquidity risk arises from the inability of a bank to accommodate decreases in liabilities or to fund increases in assets. When a bank has inadequate liquidity, it cannot obtain sufficient funds, either by increasing liabilities or by converting assets promptly, at a reasonable cost, thereby affecting its profitability. Decker (2000), in his research, suggested that liquidity risk can be divided into funding liquidity risk and market liquidity risk. Funding liquidity risk is the risk that the bank will be unable to meet its obligations as they fall due because of an inability to liquidate assets or obtain adequate funding sources. However, market liquidity risk is where banks cannot easily unwind or offset specific exposures without significantly lowering market prices because of inadequate market depth or market disruptions.

Basel I and Basel II have set out regulatory standards for Credit risk, market risk, and operational risk, but did not mention liquidity risk. In fact, there are few studies in the literature that discuss liquidity risk. Landskroner and Paroush (2008), in their study also have the same opinion on this issue. According to them, there have been discussions on credit risk, market risk and operational risk among the academicians and regulators but less attention has been paid to liquidity risk, until recently when it has become one of the major risks faced by banks and financial institutions. In their study they constructed a bank management model with the asset and liability structure as the key factor that influences the banks' exposure to liquidity risk. They found that liquidity risk increases when the competition in the credit market increases. At the same time, an increase in competition in the deposit market will have an impact on the liquidity position of the banks.

Worth discussing in this section is the related literature of liquidity risk that focuses on bank failures in previous studies especially those related to determinants of bank profitability or net interest margin (e.g. Bourke, 1989; Molyneux and Thornton, 1992; Demirgüç-Kunt and Huizinga, 1999; Shen *et al*., 2001; Pasiouras and Kosmidou, 2007; Athanasoglou *et al*., 2008; Naceur and Kandil, 2009, Shen *et al*., 2009; Bordeleau and Graham, 2010; Hussein, 2010, Akhtar *et al*., 2011; Olson and A.Zoubi, 2011; and Millon Cornett *et al*., 2011).

The study by Bourke (1989) reviews the performance of banks in Europe, North America and Australia, and examines the internal and external factors affecting profitability. A few years later, another study by Molyneux and Thornton (1992) replicated the same methods used by Bourke (1989) by examining the determinants of bank performance across 18 European countries between 1986 and 1989. This study conforms to the traditional US concentration and bank profitability studies.

Demirgüç-Kunt and Huizinga (1999) present evidence on the impact of financial development and the bank performance structure using bank-level data for developed and developing countries. They found that for countries with an under-developed financial system, any changes made to move towards a more developed financial system diminished the bank profitability and margins. A study by Shen *et al*. (2001) stated that classical models of the interest margins have the assumption that all banks belong to an identical banking system in a country. The idea that two or more kinds of banking systems can possibly exist at the same time in one country is called the Partial Banking System, and it can be divided into two classes: the separated banking system and the universal banking system. According to their study they found that the net interest margins in the separated banking system are affected by credit risk, interest rate risk, the leverage level as well as the quality of management. Whilst for the universal banking system, the net interest margins are vulnerable to credit risk and leverage level.

By using bank level data, Pasiouras and Kosmidou (2007) examine how a bank's specific characteristics and the overall banking environment affect the profitability of banks in 15 European countries operating during 1995 and 2001. They found that, besides a bank's specific characteristics, the financial market structure and the macroeconomic conditions do affect the profitability of both domestic and foreign banks. Another study conducted by Athanasoglou *et al*. (2008) also examined the effect of bank-specific, industry-specific and macroeconomic variables on the profitability level of Greek banks for a period between 1985 and 2001. They found that all bank-specific determinants affect bank profitability and the business cycle does have a positive impact on bank profitability, especially in the upper phase of the cycle. Naceur and Kandil's (2009) study, on the other hand, examined the effect of regulations on the cost of intermediation and profitability. A higher capital requirement, the reduction in implicit cost, and an increase in management efficiency, are among the factors that play a positive part in the banks' profitability in the post-regulation period. However, any reduction in economic activity had opposite effects on the banks' profitability. This conforms to the earlier findings (*e.g.* Pasiouras and Kosmidou, 2007; Athanasoglou *et al*., 2008).

Liquidity ratios have been commonly used to measure the bank liquidity position. However, Shen *et al*. (2009) investigate cases of liquidity by using alternative liquidity risk measures besides the liquidity ratio. They found that liquidity risk is the endogenous determinant of bank performance. They also found that liquidity risk may reduce bank profitability due to the higher cost of funds, but it will increase a bank's net interest margins. The causes of liquidity risk are comprised of: components of liquid assets and dependence on external funding. They also found that liquidity risk is negatively related to bank performance in a market-based financial system and it has no effect in a bank-based financial system.

The recent crisis has highlighted the significance of sound bank liquidity management. Thus, regulators around the world are continuously developing new liquidity standards for a more stable and resilient financial system. Among the current studies focusing on this issue are studies by Bordeleau and Graham (2010), Hussein (2010), and Cornett *et al*. (2011). Bordeleau and Graham (2010), in their paper, investigate the impact of holding liquid assets on bank profitability in U.S. and Canada. They found that holding some liquid assets will increase a bank's profitability, but holding too many liquid assets will eventually reduce the bank's profitability. However, this relationship may differ depending on the business model and the economic cycle. Although holding more liquid assets proved to have a significant impact on bank performance, the banks must also consider the trade-off between resilience to liquidity risk and the cost that the banks have to bear due to holding liquid assets that do not generate much profit to the bank. Thus, holding too many liquid assets may reduce the bank's ability to generate more income, to increase capital, as well as to extend more credit.

Since most of the earlier studies focus on only conventional banks, Hussein (2010) examines the behaviour of the key bank-level stability factors of liquidity, capital, risk-taking and consumer confidence in not only conventional banks but also in Islamic banks operating in Gulf Cooperation Countries between 2000 and 2007. The study concluded that although bank liquidity is not determined by the bank's product mix, non-performing assets do have a positive and significant impact on the bank's liquidity position. This means that Islamic banks are inclined to take more stringent strategies during the crisis as opposed to conventional banks. The consumer confidence level, as measured by deposits and consumer funding over liabilities, was shown to be higher in Islamic banks than conventional banks. Cornett *et al*. (2011), on the other hand, examined the effect of the financial crisis on the credit supply during the financial crisis of 2007 to 2009. They found that banks that relied more heavily on core deposit and equity capital financing tended to lend more to other banks, whereas banks that held more illiquid assets on their balance sheet tended to reduce lending. Thus, it can be concluded that, during the crisis, an effort by banks in managing their liquidity crisis will eventually lead to a decline in credit supply. A study by Akhtar *et al.* (2011) also does comparison analysis, this time on liquidity management between Islamic banks and conventional banks in Pakistan. This study examines the liquidity risk associated with the solvency of financial institutions by evaluating the liquidity risk management (LRM). They found that there was a positive but insignificant relationship of the size of the banks and the net-working capital to net assets with liquidity risk. Additionally, they found that the capital adequacy ratio in conventional banks and return on assets in Islamic banks is positive and significant at the 10% significance level.

Previously, regulators required banks to focus more on credit and operational risk, but not on liquidity risk. The subprime mortgage crisis caused a severe effect on the banking system, and the credit crunch in 2007 reminded banks of the vital nature of the liquidity risk effect. Formerly, liquidity ratios have been considered as the best practice to measure the liquidity position of the bank. But, liquidity ratios alone are not enough to measure liquidity and were not the only solution.

As mentioned earlier, the recent financial crisis during 2007–2009 reminded many banks around the world of the importance of liquidity risk management. Although liquidity risk can lead to bank failure, banks can protect themselves from liquidity risk (Davis, 2008). According to Davis (2008), liquidity risks are common to banks. Liquidity risk can give rise to a risk of bank failures, thus the most appropriate action that should be taken is by having an appropriate liquidity policy in place. Ideally, on the asset side, the bank should hold a significant number of liquid assets such as cash, whilst government securities can be used as readily as collateral. Whilst on the liability side, diversifying the source of funding is advisable in order to reduce liquidity risk.

To depict the effect of the macroeconomic condition, the commonly used macroeconomic variables are the annual percent change of GDP and the annual percent change of inflation. Besides these, some researchers will also take into consideration the lagged effects in variables selection. Based on previous studies in this area it can be concluded that economic growth (GDP) has a positive effect on a bank's performance (*e.g.* Kosmidou *et al*., 2005; Pasiouras and Kosmidou, 2007; Athanasoglou *et al*., 2008, Anbar and Alper, 2011; Derbali, 2011). On the other hand, the impact of inflation on a bank's performance, based on previous studies has been divided into two; a positive relationship (*e.g.* Kosmidou *et al*., 2005; Athanasoglou *et al*., 2006; Pasiouras and Kosmidou, 2007; Athanasoglou *et al*., 2008) or a negative relationship (*e.g.* Kosmidou, 2008).

Kosmidou *et al.* (2005) investigate the impact of bank-specific characteristics, the macroeconomic conditions and the financial market structure on UK owned commercial banks' profit during the period from 1995 to 2002. They found that bank-specific determinants positively influenced the profitability of banks when macroeconomics and the financial market measures of bank performance are included. A study by Pasiouras and Kosmidou (2007) investigates how bank-specific characteristics and the overall banking environment can affect the profitability of commercial and foreign banks in selected EU countries. They found that the profitability of those banks was not only been affected by bank-specific characteristics but also by macroeconomic conditions as well as the financial market structure. Similar results are also found by Athanasoglou *et al*. (2008) which examine the effect of bank-specific, industry specific, and macroeconomic determinants of bank profitability. They found that all the bank-specific determinants significantly affect bank profitability as predicted. Besides, the upper phase of the business cycle also has a positive and significant effect on bank profitability. A study by Alper and Anbar (2011) investigates the bank-specific and macroeconomic determinants of the bank's profitability in Turkey for a period between 2002 and 2010. Their results confirm the previous studies. They found that asset size and non-interest income have a positive and significant effect on profitability, while the size of the credit portfolio and the loans under follow-up have a negative and significant effect on profitability. In the case of the macroeconomic determinants, only the real interest rate has positive effects on profitability. Thus, they concluded that increasing the bank size and non-interest income as well as decreasing the credit/asset ratio can boost profitability probability. Another study by Derbali (2011) examines the profitability indicators of commercial banks in Tunisian banks. He found that the size, composition of assets, credit risk, concentration, and market capitalisation have positively influenced the profitability. The latest study done in the US is by Hoffmann (2011) and examines the determinants of banks' profitability during the period 1995 to 2007. He found that there was a negative relationship between the capital ratio and the profitability which means that the banks are operating by carefully disregarding the prospective opportunities in making profit.

As in the case of inflation and bank performance, some studies found a positive relationship between inflation and bank profitability whereas others found otherwise. A study by Pasiouras and Kosmidou (2007) found that inflation is positively related to domestic bank performance while on the other hand foreign bank inflation has a negative relationship with bank profitability due to an increase of costs over revenues. Thus these mixed results could be ascribed to the different levels of the macroeconomic conditions in each country as well as the anticipation with regard to the inflation rate between domestic and foreign banks. This result corresponds with work done by Athanasoglou *et al*. (2008), who found that inflation positively and significantly affects profitability. In contrast to the above findings, the study by Kosmidou (2008) found that inflation negatively and significantly affects the banks' performance.

2.4.1 Default Issues

According to Altman (1993) failure, insolvency, default and bankruptcy are four different terms and they all mean that a business is in distress. Bankruptcy may be the worst case scenario for certain companies, but default also can cause problems to the business' stakeholders. Some studies therefore do not try to predict bankruptcy, but failure instead.

Ideally, failure, insolvency, default and bankruptcy can be defined in different ways (E. I. Altman, 1993). Failure in economic terms means that a business has a rate of return on invested capital that is significantly and continuously lower than that of similar investments, which means that the company cannot meet their obligations to the shareholders. In other words it simply means that the company cannot give enough return on its shares. Insolvency, on the other hand, can be divided into two categories: technical insolvency and insolvency in a bankrupt sense. Technical insolvency is more to do with the short term obligations and can be temporary. Otherwise, insolvency in a bankrupt sense is worse than technical insolvency because it means that something is continually wrong with the business, which normally happens when the total liabilities are bigger than the total assets (Mous, 2005). Default happens when a company cannot meet their obligation to the creditors. For example, when a company is not paying the periodical interest or settling the debt when it is due. When this happens it is a serious sign that the company is in trouble, although it may not lead to bankruptcy. Finally, bankruptcy occurs when a company files for bankruptcy. These definitions give a clear distinction between each category and make it easier for the researcher to distinguish between failed and non-failed companies based on the above criteria.

Besides bankruptcy and financial distress, there are several other economic definitions of failure used in the previous research on corporate failure such as cash insolvency and loan default (Balcaen and Ooghe, 2006). According to Laitinen (1994), cash insolvency simply means that the firm is unable to pay its financial obligations when the payments become due. Ward and Foster (1997) are of the opinion that loan default is a better way of defining failure because loan default definition is more consistent with economic reality. According to Hayden (2003) some default events, as described in the new framework of Basel II, are defined as credit loss when they are associated with any delay in payment of more than 90 days or with a distressed restructuring involving the forgiveness or postponement of principal amounts or interest by financial institutions. However, this definition is not suitable when analysing business failure which is due to a purely credit-oriented failure definition (Balcaen and Ooghe, 2006).

In Austria, with the same time frame and samples, both Hayden and Bauer (2004) and Halling and Hayden (2006) carried out studies which investigated the factors behind the problems encountered by around 150 Austrian banks during the period 1995 to 2002. Hayden and Bauer (2004), in their study, defined default as a situation where a bank is facing a serious problem and there is little chance of survival unless the government or other agencies intervene. This definition of default is followed suit by Halling and Hayden (2006) in their later research. In their study, Halling and Hayden (2006) recommended a multi-period logit that includes an indicator measuring market share as bank size relative to total bank size in the home region, and the ratio of net interest income to the number of employees as an indicator of management quality. They concluded that the size relative to the rival banks may be a sign of quality of management.

Previously, many banks' default studies have been conducted to determine the factors that might be the determinants of the event in the study, be it systemic crisis or financial institution distress. Econometric and statistical techniques have been applied and the most often used methods used are, among others, Logit and Probit regression models, discriminant analysis, and hazard-function models. Thus, for an analysis to determine the systemic crisis, macroeconomic variables have often been used. A study by Demirguc-Kunt and Detragiache (1998) during 1980 and 1994, examines the determinants of the banking crisis in a number of developed and developing countries using a multivariate logit econometric model. They found that countries with a low GDP growth, high real interest rates, high inflation, higher likelihood of balance-of-payment crisis and explicit deposit insurance are more likely to face a crisis. In fact, their study in 2002, based on evidence from 61 countries in 1980 to 1997, confirms the significance of deposit insurance as a risk factor for banks' stability.

Thus, based on previous discussion in the literature on forecasting the banks' failure, distress and closure, this study will focus on the early identification on banks' financial distress based on financial statements as well as macroeconomic variables. Studies in this area have been developed since the early 1970s and Altman *et al*. (1981) gave a comprehensive review of the early stage literature. The most updated review of the literature on prediction methods for financial crises and bank failures is based on the study by Demnyanyk and Hassan (2009). They analysed the financial and economic conditions linked to the crisis of subprime mortgages in the US and the global financial crisis. Previously, Wheelock and Wilson (2000) also conducted a study to analyse the bank-specific factors that help to explain banks' default in the US during the period 1984 to 1993. They found that the probability of failure is higher for banks with lower capitalisation, profitability, and poor assets quality. Another comparable study conducted by Bongini *et al*. (2001) also looks at the distress condition in financial institutions during the Asian financial crisis during the late 1990s. They found that CAMEL type financial data does predict the financial distress as well as the policy of "Too big to Fail" impact on those financial institutions.

The earlier study by Diamond and Dybvig (1983) developed a model to explain why banks choose to issue deposits that are more liquid than their assets. They specifically investigated bank liquidity and found out that lack of it may lead to a bank run. A bank run is the sudden and unexpected increase in bank deposit withdrawals. Besides, the model has been widely used to understand bank runs and other types of financial crises, as well as ways to prevent such crises. Later, Goldgerg and Hudgins (2002) examined the role played by uninsured deposits as a source of thrift funding and what the depositors' response will be to market forces. The study found that failed institutions showed a declining trend of uninsured deposits-to-total deposits prior to failure. Moreover, these deteriorating institutions draw less deposit from uninsured depositors prior to failure as compared to solvent institutions. In fact, a study by Gatev *et al*. (2007), showed results that reverse the standard notion of liquidity risk at banks, where runs from depositors had been observed as one of the causes of the bank's problem.

According to Wagner (2006) an increase in a bank's liquidity, in actual fact, might well increase banking instability. Although higher asset liquidity may lead to banking stability, it may also make banking crises less damaging. Consequently, banks may opt to take on new risk more than assess the positive impact on banking stability. During the same period, Porath (2006) conducted a study on financial distress and the financial strength of German savings and cooperative banks. The study estimated a default prediction model and also analysed the impact of macroeconomic information on forecasting banks' defaults. Although, in bank's risk assessment, most of the findings for U.S. have shed some doubt on the value of macroeconomics information, but Porath (2006) found out that macroeconomics information does notably enhance the default predictions.

By using the US banks data from 1980 to 1992, Cole and Wu (2009) presented a dynamic hazard model and a probit model as an early warning system (EWS). They compare the accuracy of the time varying hazard model that was developed by

Shumway (2001) and the one-period probit model used by Cole and Gunther (1998). The study found that smaller banks with high non-performing loan and deposits as their main sources of funding are more likely to fail and vice versa. They also concluded that a one-period probit model outperformed the time-varying hazard model in predicting the bank's failure and this model, that was fitted to the 1980s data, is performing astonishingly well in forecasting bank failures during 2009-2010. Subsequently, a study by Cole and White (2010) investigated why commercial banks failed during the recent financial crisis. They found that traditional proxies for the CAMELS components, as well as measures of commercial real estate investments, did an excellent job in explaining the failures of banks that were closed during 2009, just as they did in the previous banking crisis of 1985–1992. Surprisingly, they did not find that residential mortgage-backed securities played a significant role in determining which banks failed and which banks survived. These results offer support for the CAMELS approach to judging the safety and soundness of commercial banks, but call into serious question the current system of regulatory risk weights and concentration limits on commercial real estate loans.

Earlier, Shen *et al*. (2009) utilised the alternative liquidity measures in addition to the traditional liquidity ratios and looked into the causes of liquidity risk. By applying the data instrumental variable regression using two-stage least squares (2SLS) estimators to assess bank liquidity risk and the performance model, they found that liquidity risk is the endogenous determinant of bank performance. Among the main causes of liquidity risk in banks are: the components of liquid assets and reliance on external funding, supervisory and regulatory factors, and macroeconomics factors. Moreover, the study found that the higher cost of funds may reduce the bank profitability, and liquidity risk is negatively related to bank performance in a market-based financial system, but has no effect in a bank-based financial system.

For Islamic banks, risk and liquidity management has become a big issue for all banks as well as for the regulators of those banks. A study by Mounira and Anas (2009) gave a brief description of Islamic banks' performance and explained the risks to which Islamic banks are exposed. At the same time, this study also tried to identify the mitigating practices used in these banks.

The recent global financial crisis has emphasised the importance of good bank liquidity management. By analysing the impact of liquid asset holdings on bank profitability for US and Canadian banks, a study by Bordeleau and Graham (2010) proposed that banks that hold some liquid assets are in a better profitability position, although holding too many liquid assets may also diminish the banks' profitability.

Another research on predicting banks' defaults was a study by Van der Ploeg (2010). This study, based on US bank data from 1987 to 2008, examines and compares the predictive performance of multiple default prediction models (logit, probit, hazard and neural networks) and gauges the capability of those models to correctly predict credit rating transition. The study found that all the models have a satisfactory performance in the prediction of banks' defaults. Another study concentrating on the factors behind the Canadian banks' relative resilience during the credit turmoil was conducted by Huang and Ratnovski (2010). The study found that high depository funding as compared to wholesale funding, and a number of regulatory as well as structural factors in the Canadian market, make the banks less motivated to take too many risks. Subsequently, Huang and Ratnovski (2011) conducted another study that looked into wholesale funding. According to this study, short-term wholesale financiers have less motivation to do their own monitoring thus leaving their decision to withdraw based on negative public signals, triggering inefficient liquidations.

A study by Berger and Turk-Ariss (2011) examines the importance of regulatory and market discipline during the recent global financial crisis. They tested the presence of depositor discipline effects in the period leading up to the global financial crisis in the US and EU. The study found a significant impact on the depositor discipline in both the US and EU, but it emerged that depositor discipline in US banking organisations was stronger for the largest institutions thus consistent with the fact that these organisations rely more on uninsured deposits. Furthermore, the study found that depositors seemed to respond more consistently to equity ratios than to measures of loan portfolio performance.

As mentioned in the earlier section, Cornett *et al*. (2011) examined the effect of the financial crisis on the credit supply during the financial crisis of 2007 to 2009. They found that banks that relied more heavily on core deposit and equity capital financing tended to lend more to other banks, whereas banks that held more illiquid assets on their balance sheet tended to reduce lending. Thus, it can be concluded that, during the crisis, an effort by banks in managing their liquidity crisis will eventually lead to a decline in credit supply. From a different perspective, Derbali (2011) examined the profitability indicators of Tunisian commercial banks and the study found that profitability was positively influenced by the size of the banks, assets composition, credit risk, concentration, market capitalisation, with net interest margin as profitability measures.

The most recent study was conducted by Kao *et al*. (2012). According to Kao *et al*. (2012), short-term financing such as asset-backed commercial paper (ABCP) or repurchase agreements (repo) was prevalent prior to the 2007-2008 financial crises. Banks funded by short-term debts, however, are exposed to rollover risk as the banks are unable to raise sufficient funds to finance their long-term assets. Under such circumstance, the banks' equity holders need to absorb the rollover loss. Both deteriorating collateral assets fundamentals and market illiquidity are important drivers of the rollover risk. In their study, they developed a structural default model based on Leland (1994), in which default is an endogenously determined decision made by equity holders to analyse the joint effect of market liquidity and interest rate sensitive fundamentals of collateral assets on the survival times of banks relying on day-to-day short-term finance. They proposed a model that provides an explanation of the empirically observed phenomenon that banks default even when the quality of their fundamentals is still high.

2.4.2 Composition of Deposits

Deposits play and essential role as one of the banks' sources of funding and a major fraction of the banks' assets is usually financed by their customer deposits. Thus, this led to more research in this area related to deposits and their role for the banks. An earlier study was conducted by Diamond and Dybvig (1983). They argued that deposits are subject to bank runs and can be costly for banks due to assets and liability maturity mismatches. Flannery (1998), and Cook and Spellman (1994) are further examples of studies which claim that depositors may still continue to monitor their banks even when the deposits are insured, this could be due to feeling not totally protected by the existing insurance scheme.

As mentioned in the study conducted by Bologna (2011), short-term wholesale funding has shown a positive effect towards supplementing the retail deposits, mostly during the years prior to the global financial crisis. Earlier, Calomiris (1991) found that wholesale funding permits investors to monitor their banks, provide market discipline, and take advantage of investment opportunities without been restricted to the availability of the deposit supply. The recent global financial crisis has emphasised the effect of an excessive dependence on short-term wholesale funding, as shown in the recent studies by Acharya *et al*., 2008; Huang and Ratnovski, 2009; and Goldsmith-Pinkham and Yorulmazer, 2010. According Acharya *et al*. (2008), the debt capacity of an asset is the maximum amount that can be borrowed using the asset as collateral and they showed that a small change in the asset's primary value can be linked with a disastrous drop in the debt capacity, such as the market freeze observed during the crisis in 2007 to 2008.

Another study concentrating on the factors behind the Canadian banks' relative resilience during the credit turmoil was conducted by Huang and Ratnovski (2010). Their study found that high depository funding as compared to wholesale funding, and a number of regulatory as well as structural factors in the Canadian market, make the banks less motivated to take too many risks. Subsequently, Huang and Ratnovski (2011) conducted another study that looked into wholesale funding. According to this study, short-term wholesale financiers have less motivation to do their own monitoring thus leaving their decision to withdraw based on negative public signals, triggering inefficient liquidations. Goldsmith-Pinkham and Yorulmazer (2010) on the other hand, analysed the UK based bank, Northern Rock. This study looked at the significant effect of both the bank run and the subsequent bailout announcement on the UK banking system. These were measured by looking at the abnormal returns of the stock prices of those banks. Thus, the effects were a sensible response by investors towards the news of the bank's liability side of its balance sheets, with significant effect on those banks that relied heavily on funding from the wholesale markets. Another study on wholesale funding by Huang and Ratnovski (2011) showed that short-term wholesale financiers have less motivation to do their own monitoring thus leaving their decision to withdraw based on negative public signals, triggering inefficient liquidations.

A number of studies have proved the effect of monitoring efforts and disciplining by customer depositors and a number of these studies were conducted in the US (Park and Peristiani, 1998; Billet *et al*., 1998; Jordan *et al*., 1999; Jagtiani and Lemieux, 2001; Gilbert and Vaughn, 2001; Goldberg and Hudgins, 2002; and Berger and Turk-Ariss, 2011). Studies by Park and Peristiani (1998), Billet *et al*. (1998), and Berger and Turk-Ariss (2011), found that depositors have a disciplining effect on banks, while studies by Gilbert and Vaughn (2001), Jordan *et al*. (1999), and Jagtiani and Lemieux (2001) found opposite results.

A study by Park and Peristiani (1998) examined the effect of the depository institutions' risk on the pricing and growth of uninsured deposits through the occurrence of depositor discipline, and this study supported the presence of market discipline and found that qualitative results are similar for fully insured deposits. Billet *et al*. (1998) also found that insured deposit financing does protect banks from the full cost of market discipline. Furthermore, an increase in risk resulted in banks employing more of their insured deposits, thus reflecting the doubt on the ability of capital market participants to successfully discipline bank behaviour within the current regulatory environment. Billet *et al*. (1998) also highlighted the potential for regulation to undermine market discipline regulated industries. Later, Berger and Turk-Ariss's (2011) study found a significant impact of depositors discipline in both the US and EU, but it emerged that depositor discipline in the US banking organisations is stronger for the largest institutions thus consistent with the fact that these organisations rely more on uninsured deposits. Furthermore, the study found that depositors seemed to respond more consistently to equity ratios than to measures of loan portfolio performance.

In contrast, Gilbert and Vaughn (2001) showed no evidence of abnormal deposit withdrawals following the announcements of formal actions, thus suggesting that any public announcement of enforcement actions did not initiate bank runs or enhance deposit discipline. Another study with contrasting results was conducted by Jordan *et al.* (1999), and examined the impact of requiring the release of supervisory information on troubled banks during a critical banking crisis. The study found that even with the improvised disclosure in US banks during the financial crisis, it still did not stabilise and grant good conditions for market discipline to work more effectively.

Thus this study supported the public policy proposal of enhanced bank disclosure even during the banking crisis period. Jagtiani and Lemieux (2001) studied the pricing behaviour of bonds issued by bank holding companies in the period preceding the failure of their subsidiaries. The results show that bond prices are related to the financial condition of the issuing bank holding companies, and the spreads began to rise as early as six quarters prior to the failure. Furthermore, those troubled banks' bond spreads are many times different from those of the healthy banks. They concluded that bond spreads could possibly be valuable for bank supervisors as a warning signal from the financial markets, and proposed bank holding companies to issue publicly traded debt in large amounts that likely will enhance market discipline in the banking system whenever it is needed.

The recent study by Rasiah (2010) conducted research to identify the determinants of profitability of commercial banks, and the profitability determinants were mainly divided into two categories: the internal determinants and external determinants. The internal determinants include management controllable factors such as liquidity, investment in securities and subsidiaries, loans and non-performing loans, overhead expenses, types of deposits (savings, current and fixed), total capital and capital reserves, and money supply. Whereas the external determinants include factors that are beyond management control such as interest rates, inflation rates, market growth as well as market share.

Sawada (2010) investigated the impact of liquidity shock caused by depositors' behaviour on bank portfolio management during the financial crisis in the absence of deposit insurance in the system. The study found that banks responded to the liquidity shock sensitively via an increase in cash possessions by selling securities in the financial market and not by liquidating bank loans. Furthermore, banks that were exposed to the local contagion adjusted the liquidity of their portfolio by being involved in the financial market, and there was no evidence to conclude that the role of lender of last resort was part of the mitigation measure to solve the liquidity constraints in the bank portfolio.

Hussein (2010) examines the behaviour of the key bank-level factors of liquidity, capital, risk-taking and consumer confidence in Islamic and conventional banks in Gulf Cooperation Countries. He found that the liquidity position is not determined by the bank's product mix, but is rather attributed to systemic factors. On the other hand, non-performing assets do have a significant relationship with liquidity, thus suggesting that the Islamic banks are inclined to take rigorous risk strategies during the crisis as compared to the conventional banks. In addition to that, although conventional banks had higher averages of liquidity as compared to Islamic banks, consumers do have a higher confidence level in Islamic banks as they are more capitalised. The consumer confidence level or depositors' discipline, as substituted by deposits and customer funding over liabilities, usually emerges to be higher in Islamic banks than conventional banks.

It is interesting to note that most of the existing literature in this area examines the role of deposits without being able to distinguish between insured and non-insured ones, while economics perspectives point out that these two groups of depositors should be expected to behave differently. Furthermore, from the Islamic banks perspective, it will be useful to consider the different types of depositors according to their types of contracts in further research.

2.5 CONCLUSION

A lot of effort has been put into developing bankruptcy prediction models since the early 1960s and the trend continues through to today. Most of the available information on bankruptcy prediction models is based on published research by academicians and a few from the practitioners or experts from the banking industry. Generally, there are two main approaches in bankruptcy prediction research: empirical research and statistical methods research (Ahmad, 2005). Empirical research is the most often used approach in bankruptcy prediction, and means the empirical search for predictors (financial ratios) that may lead to the lowest misclassification rates. On the other hand, the second approach concentrates on the search for the statistical methods that may improve the prediction accuracy. According to Ahmad (2005), bankruptcy prediction models are generally known as the measure of financial distress. According to him, there are three stages in the development of financial distress measure: univariate analysis, multivariate analysis, and logit analysis.

In 2004, Aziz and Dar compiled an extensive literature review on 46 articles reporting 89 empirical studies predicting corporate bankruptcy. They investigated the accuracies of three different types of prediction models: statistical models, artificial intelligent expert system models, and theoretical models. Statistical analysis category consists of univariate analysis, multiple discriminant analysis, logit analysis, linear probability model, probit model, cumulative sums procedure, and partial adjustment process. The Artificial Intelligent Expert System (AIES) category consists of a recursively partitioned decision tree, a case-based reasoning model, neural networks, genetic algorithms, and rough sets models. Finally, the theoretic category consists of a balance sheet decomposition measure, gambler's ruin theory, cash management theory, and credit risk theories. According to their study, out of 46 articles reviewed, 64% of all authors used statistical techniques, 25% used artificial intelligent expert systems, and 11% of them used theoretical models in predicting corporate bankruptcy.

Furthermore, based on the previous studies, many ratios have been identified as the important predictors in bankruptcy prediction models. However, there was no ultimate decision on which ratios were the most beneficial in predicting the likelihood of failure. In fact, the importance of each ratio is not clear as most of the previous studies cited different ratios being the most important indicator of bankruptcy. According to Altman (1993), the most important predictors in bankruptcy prediction models are the ratios that measure liquidity, profitability, solvency and cash flow. As for the other researchers, they selected financial ratios as the predictors of bankruptcy based on the popularity and predictive ability of the ratios in previous bankruptcy research studies (Muller, Steyn-Bruwer and Hamman, 2009).

Amongst the most popular financial ratios used by previous researchers were: net income to total assets, total liabilities to total assets, size, changes in net income, cash flow ratios, financial expenses to sales, debt coverage, and receivables turnover. From the Malaysian banking system perspective, during the period 1996 to 1997, Low *et al*. (2001) found that cash flow ratios were significant in explaining bankruptcy. In the much earlier period, during 1987 to 1997, Mohamed *et al.* (2001) found that the leverage ratio and efficiency ratio were significant in explaining bankruptcy. Another study conducted by Zulkarnain *et al*. (2001), using the sample from the period 1980 to 1996, found that total liabilities to total assets, sales to current assets, cash to current liabilities, and market value to debt were significant in explaining financial distress.

Chapter 3
ISLAMIC BANKING IN MALAYSIA: AN INTRODUCTION

3.1 INTRODUCTION

Islamic finance is now among the fastest growing segment in the global financial industry. After the challenging events of the recent financial crisis, Islamic finance still managed to show a remarkably strong growth. Islamic finance has maintained an average annual growth of 15% to 20%, with the size of assets amounting to more than USD1trillion. Islamic mutual funds as well as takaful industry had also shown a significant growth of 23% per annum and 13% per annum respectively.

To some extent, Islamic finance has not only attracted Muslim nations but also non Muslim. In other words, Islamic finance is no longer a second choice after conventional banking, instead it has grown to be an attractive option to the conventional banking system. With the 1.5 million people of the Muslim population, this is a market that cannot be disregarded. In fact, a number of established financial centres in the world such as London, Hong Kong, Singapore and Tokyo have also taken steps to become Islamic Financial Centres.

Malaysia has already taken a step ahead to be an International Islamic Financial hub. The development of Islamic finance in Malaysia has occurred at a significant pace both on the domestic as well as on the international front. With the significant achievements for the targets set in the Financial Sector Masterplan 2001 and the newly launched Financial Sector Blueprint 2011-2020, an important role was played by Bank Negara Malaysia in promoting Islamic Finance. Furthermore, it has also contributed towards achieving a more efficient, effective, stable and resilient financial system. This is substantiated by a significant transformation of the financial system that is now more diversified with a well developed financial market as well as broadened product offerings. Recently, Bank Negara Malaysia has allowed for greater foreign participation in the financial markets and this is shown by an increase in the numbers of players.

The development of the Malaysian Islamic financial system has now evolved the Malaysian Islamic finance industry into a progressive, comprehensive and competitive component of the overall financial sector. The Islamic banking industry has shown impressive and steady growth over the last eleven years from 6.9% in 2000 to 22% of the banking sector at the end of 2011 (BNM, 2012). In fact, this growth is way beyond the target of 20% as mentioned in the Financial Sector Master Plan. Domestic Islamic banks accounted for about 85% of the market share in the Islamic banking sector. Among the main factors that contributed to the massive development of Islamic finance in Malaysia is a comprehensive legal, tax, accounting, regulatory and supervisory framework. Other factors that should also be taken into consideration are the willingness of the players and developers of Islamic finance to explore new initiatives, willingness to use the existing resources so long as it does not contravene any *Shari'ah* principle, and the willingness of the *Shari'ah* scholars to practice *ijtihad*.

The recently launched Bank Negara Malaysia's New Financial Sector Blue Print (FSBP) 2011-2020 has set another path for the country's economic development, establishing the financial sector as a key driver and means for economic growth. The new Financial Sector Blueprint is careful not to include any performance or market share targets as previously set during the Financial Sector Master Plan 2000-2010 (BNM, 2012).

For the last ten years, Islamic finance has experienced a tremendous growth and major transformation in its financial landscape. Perhaps, this transformation can be proved by looking at three major components. Firstly, Islamic finance has developed into a complete and more competitive financial intermediary by serving not only Muslim but also non-Muslim customers. In fact, realizing the opportunities in this market, several established conventional players have taken a major step by entering the Islamic financial industry, resulting in more competition for market share and in more varieties of product range being offered (BNM, 2010).

Secondly, significant milestones have been achieved in the development of the Islamic financial infrastructure for Islamic finance. Worthy of mention is the establishment of the Islamic Financial Services Board (IFSB) in 2002. IFSB was established as an ‘international prudential standard setting body’ for Islamic finance. Since its establishment, several standards have been developed by taking into account the specificities of Islamic finance. Among the standards developed by IFSB are the capital adequacy requirement and standards for governance and risk management. Another notable achievement is in the area of talent development. Several programmes and certifications focused on Islamic finance are being offered by higher learning institutions, professional entities, training agencies, and industry groups (BNM, 2010).

Finally, the enhanced international dimension of Islamic Finance has increased the form of intermediation that facilitates the linkages between emerging economies, thus contributing to more efficient mobilisation of funds across regions. In fact, this has drawn more participation by the more established financial centres to form stronger financial linkages with Asia and the Middle East regions. In other words, with the international dimension of Islamic finance, international participation in Islamic finance in the different jurisdictions has increased (BNM, 2010).

3.2 MALAYSIAN ISLAMIC FINANCIAL SYSTEM

A financial system consists of instruments, institutions, markets and regulations on how to channel the excess funds from the buyer to the seller and from the lender to the borrower. Financial systems can be defined as an area where the trading of funds between the borrower and the lender takes place. In other words a financial system is a set that consists of the market, the individual and the organisation.

The Islamic Financial system in Malaysia consists of Islamic banking, the Islamic capital market, takaful operators, savings and developmental finance institutions. Simultaneously, non-Islamic companies are also allowed to offer ranges of Islamic financial products. In Malaysia, Islamic banking and conventional banking coexist alongside each other in the financial system, thus this is called a dual banking system. In fact, this distinctive concept of dualism adopted in the Malaysian financial system has made it different from the solely conventional system adopted in other jurisdictions. Some other Muslim countries, such as Pakistan, Sudan and Iran, have converted their whole financial system into a fully Islamic system.

The path for the development of Islamic finance started as far back as 1983. From the building of the foundation of the legal, regulatory and *Shari'ah* framework, and the Islamic Banking Act (1983), to the formation of the first Islamic bank and Takaful Company to institute the Islamic windows concept for banking institutions and encouraging competition amongst the Islamic financial institutions in the nineties (1990s), and to establishing key infrastructures and institutional arrangements such as the *Shari'ah* Advisory Council and the Islamic Money Market, Malaysia is on a mission to be the centre for Islamic finance.

The next section will discuss further the development of the Islamic financial system in Malaysia, with a focus on Islamic banking.

3.2.1 Islamic Banking

As mentioned earlier, Malaysia has implemented a dual banking system where the Islamic banking and conventional banking co-exist side by side in the financial system. In fact, this model has been acknowledged by other countries.

There are currently seventeen fully-fledged domestic and foreign Islamic banks operating in Malaysia. This significant development can be traced back to 1969 when the Pilgrims Management and Fund Board (Tabung Haji) was established with the main function of assisting Muslims to perform a pilgrimage in Makkah, saving their money as well as encouraging them to participate in some investments. In fact, the establishment of Tabung Haji has been acknowledged by others as the first in the world (Mohammed Seidu, 2002).

Based on this experience, Malaysia then introduced a well coordinated and systematic process of implementing the Islamic financial system. The progress of this implementation can be divided into three main phases. The summary of these phases is given as follows.

The first phase is regarded as the period of adaptation (1983-1992). The Malaysian Government had formed a National Steering Committee on the establishment of an Islamic bank in 1981. The task was given to the Central Bank of Malaysia to prepare the relevant documents with regard to the possibility of establishing an Islamic bank during that period. After two years, the effort was considered successful with the establishment of the first Islamic bank in the country, Bank Islam Malaysia Berhad (BIMB). During the same period the Bank Islam Act (IBA) 1983 was officially enacted. Operating for 10 years without any competition made it possible for the bank to grow and develop many new products. The significant growth can be evidenced by examining the growth of total deposits, total assets, and total loans during this 10 years period. These monopolistic years, 1983 to 1993, allowed BIMB to operate efficiently without any competition in the market. This was in fact considered a successful effort by the Government of Malaysia in implementing a dual banking system.

The second phase, from 1993 to 2003, was aimed at constructing a favourable environment for more competition among the banks. Besides creating more awareness among the public with regards to Islamic banking, the Malaysian Government had taken a further step by introducing Skim Perbankan Tanpa Faedah (SPTF) or interest free banking in 1993. Under this scheme the conventional banks were allowed to offer similar Islamic banking facilities as those offered by the full-fledged Islamic bank. Among the reasons behind the introduction of Islamic windows were: to increase competition in the market by increasing number of players, to find the fastest ways to spread Islamic banking nationwide, to optimise the existing banking infrastructure, resources and services, to increase the level of sophistication in terms of product and services, and finally to facilitate the achievement of economies of scale, synergies and critical mass.

In 1998, the term of SPTF or the interest free banking scheme was replaced by the Skim Perbankan Islam (SPI) or the Islamic Banking Scheme (IBS). In fact, during this time all banking institutions that had an Islamic banking unit were obliged to upgrade to the Islamic banking division instead. The second fully-fledged Islamic banking was established: the Bank Muamalat Malaysia Berhad was a result of a merger between the Bank Bumiputera Malaysia Berhad and the Bank of Commerce Malaysia Berhad. This set up saw the Islamic banking operations of those two banks merged to establish a new Islamic bank.

The final phase, which commenced in 2004, was the period for further liberalisation of Islamic banking in Malaysia. In fact this financial liberalisation, which was initially planned in 2007, was brought forward by the government of Malaysia. During this period a number of new licences, notably for the foreign Islamic banks, were issued by the Central Bank of Malaysia. The idea behind this liberalisation was to create more competition among the banks, to take advantage of the new growth opportunity, and finally to increase the performance of the Islamic banking industry as a whole.

Among the first fully-fledged foreign Islamic banks operating in Malaysia were the Kuwait Finance House, the Al-Rajhi Banking and Investment Corporation, and a consortium led by the Qatar Islamic Bank (Bank Negara Malaysia, 2004). In order to further strengthen the Islamic banking industry, all the Islamic windows were allowed to be set up as fully-fledged Islamic banks. Currently, there are 16 fully-fledged Islamic banks, and five International Islamic banks participating in the Islamic banking industry in Malaysia (Bank Negara Malaysia, 2012). In fact, in order to promote strategic alliances, the foreign equity ceiling has been raised to 49 percent. Another effort taken by the Central Bank of Malaysia was to allow for the Islamic banking business in foreign currencies that can be conducted by the co-called international currency business units (ICBUs) to be set up within the existing financial institutions.

3.2.2 Islamic Interbank Money Market

Generally, the financial market can be divided into two distinct markets, the money market and the capital market. These two markets work as channels in which an enormous amount of funds flows, based on demand and supply. Likewise, in Malaysia, the Securities Commission (SC) has divided the Islamic capital market (ICM) into two main markets which are the equity market and the Islamic debt market. In fact, these two markets have played an important role in the development of the Islamic banking industry in Malaysia by providing a place for liquidity management.

The establishment of the Islamic Money Market (IMM) was another success story behind the development of the Islamic financial system in Malaysia. The IMM was established in 1994 and was considered to be the first of its kind in this region during that time. It functions as a systematic system that permits banks with surplus units to invest in the deficit units of other banks, this is called the *mudharabah* interbank investment. With the introduction of IMM, the Islamic banks can undoubtedly manage their liquidity position without being involved in the conventional money market. Among the short term instruments used are Islamic Acceptance Bills (IAB) and Bank Negara Negotiable Notes (BNNN).

3.2.3 Islamic Capital Market

Generally, the term capital market refers to an institution that provides a channel for the borrowing and lending of long term funds (Rose, 2000). As compared to the money market, this capital market will channel funds of more than one year. The Securities Commission defined the Islamic Capital Market as a market that carried out a transaction that complies with the *Shari'ah* law (www.sc.com.my). In other words, all transactions in the Islamic capital market must be free from the involvement of activities which are prohibited in Islam, so that no elements of *usury* (riba), gambling (*maisir*) and ambiguity (*gharar*) are involved. Due to this, the Securities Commission has formed the *Shari'ah* Advisory Council (SAC) to advise SC on matters not only concerning *Shari'ah* issues but also on any other issues relating to the Islamic Capital Market (Muhammad Hasib, 2007).

The Islamic Capital Market is divided into two markets; the equity market and the Islamic debt market. The equity market is further sub-divided into four main types. The first type is Bursa Malaysia and MESDAQ. Currently about 88% of the securities listed on Bursa Malaysia are *Shari'ah*-compliant and this represents two-thirds of Malaysia's market capitalisation. A long list of *Shari'ah* approved securities across diversified industries will give Muslim investors more opportunities to be involved in the equity market without any doubt. The list is updated twice yearly in order to ensure transparency and that the securities comply with the *Shari'ah* Advisory Council ruling. These *Shari'ah* approved securities have been put through qualitative and quantitative screening measures. Secondly, the Islamic unit trust funds industry. For those investors who would prefer to invest for a long term and have their money managed by competent and professional managers in accordance to the *Shari'ah* principles, the Islamic unit trust is the best choice. Ideally, there are options for those investors to invest their money in Islamic unit trust funds; either they invest in Islamic equity funds, sukuk funds, or any other funds managed by fund managers (Muhammad Hasib, 2007).

Thirdly there is the benchmark index. As for the benchmark, the FTSE Bursa Malaysia EMAS *Shari'ah* index (FBM EMAS *Shari'ah*) and the FTSE Hijrah *Shari'ah* Index (FBM Hijrah *Shari'ah*) will give a broad benchmark for the investors if they wish to invest in any of the compliant securities. Lastly, Islamic stock broking companies were formed to facilitate the necessary transaction to trade and invest in the *Shari'ah* approved securities (Muhammad Hasib, 2007).

The recent establishment of Bursa *Suq Al-Sila*' is another significant development in the Islamic Capital Market. Bursa *Suq Al-Sila'* is a commodity trading platform specifically dedicated to facilitating Islamic liquidity management and financing by Islamic banks. This fully electronic web based platform provides industry players with an avenue to undertake multi commodity and multi currency trades from all around the world (Bursa Malaysia, 2010). In effect, Bursa *Suq Al-Sila'* integrates the global financial and capital markets together with the commodity market.

3.2.4 Takaful

Another remarkable development in the Malaysian Islamic financial system is the establishment of Islamic insurance companies. Syarikat Takaful Malaysia Berhad was established a year after the Takaful Act 1984 was enacted. The second takaful company, Takaful Nasional Sdn Bhd was established in 1993 and this has proven to be another milestone in the Insurance industry based on *Shari'ah* principles (Muhammad Hasib, 2007). Currently there are 12 takaful operators, four retakaful operators and one international takaful operator (BNM, 2012).

3.2.5 Other Facilitatory Arrangments and Institutions

3.2.5.1 Islamic Banking Act 1983

The Malaysian Islamic banking industry is governed by the Islamic Banking Act 1983, which provides for the licensing, regulation and supervision of the Islamic banking and financial business to ensure that such businesses are maintained at all times in accordance with *Shari'ah* principles. This Act, which came into force on 7th April 1983, was enacted to provide for the licensing and regulations of Islamic banking business and governed by the Central Bank of Malaysia. This Act rules that the Islamic banking business must not become involved with prohibited activities according to Islam.

3.2.5.2 *Shari'ah* Advisory Council (SAC)

Similar to the Islamic Capital Market, Islamic banking and takaful also have their own dedicated *Shari'ah* Advisory Councils. The *Shari'ah* Advisory Council of Bank Negara Malaysia is responsible to advise on matters in relation to Islamic banking and takaful businesses, or any other Islamic finance area that is supervised and regulated by the Central Bank of Malaysia (www.mifc.com). The Council consists of prominent scholars, jurist and market practitioners. These members of the council are those who are qualified individuals who can present *Shari'ah* opinions and have vast experience in banking, finance, and law, with much stress on those experts in the areas of Islamic economics and finance.

The *Shari'ah* Advisory Council is responsible for analysing issues on Islamic banking and takaful matters, in order to ensure that the aspects of operation of Islamic financial institutions are in accordance with the *Shari'ah* interpretations. On top of that, the role of the *Shari'ah* advisory council is to examine and approve the validity of application of *Shari'ah* in Islamic financial products submitted by Islamic banks, and issue *Shari'ah* resolutions and decisions relating to their relevant jurisdictions from time to time. The Central Bank of Malaysia has issued their SAC *Shari'ah* Resolution, which has been translated into various languages and is being used as a reference point.

3.2.5.3 Rating Agencies

The Rating Agency Malaysia Berhad (RAM) and the Malaysian Rating Agency Berhad (MARC) are two independent rating agencies established in Malaysia. The functions of these two rating agencies are to create transparency and instil market confidence in the rating of bonds and financial institutions. These two rating agencies have shown an astonishing role in the significant development of conventional private debt securities and Islamic Private debt securities.

3.2.5.4 Derivatives Market

A derivative transaction as defined by Culp (2002) is “a bilateral contract whose value is derived from the value of some underlying asset, reference rate, or index”. In conventional terms, Culp (2002) adds that derivatives which are primarily used for risk transfer can be an effective tool in fine-tuning the risk transfer process so that specific risks can be targeted for disposition by the firm. However, Obiyathullah (1999) defines a derivative instrument as simply a financial instrument or an asset that derives its value from the value of some other underlying asset. He argues that with the vast potential that can be reaped from this exciting range of instruments, ignoring it will be a loss to the Islamic banking and finance industry which is currently lacking in the generation of innovative *Shari'ah*-compliant financial instruments. Three main instruments that are viable for ICM are the forwards, futures and options.

In this respect, the Malaysian government has initiated the establishment of the Kuala Lumpur Commodity Exchange (KLCE) in 1980 under the provision of the commodities Futures Trading Act 1980. Although it is a relatively thin market, the government anticipated the potential of derivatives through the establishment of the Kuala Lumpur Options and Financial Futures exchange (KLOFFE) in 1995 which was legislated under the Futures Industry Act 1993. Simplifying the trading of derivatives under one roof has led the government to integrate all derivatives exchange into one. The establishment of the Malaysia Derivatives Exchange (MDEX) in 2002 was in fact quite timely. MDEX offers a large array of derivatives products and services including the KLSE composite Index Futures and Options, Crude Palm Oil futures and Kuala Lumpur Inter-Bank Offered Rate Futures.

3.2.5.5 Labuan Offshore Financial Services Authority (LOFSA)

The establishment of the Labuan Offshore Financial Services Authority (LOFSA) in 2002 demonstrates Malaysia’s seriousness in projecting itself as the forerunner of the centre for international Islamic finance. LOFSA is used as a platform to make headway in “spurring the development of Islamic banking and financial activities such as retakaful business, developing and strengthening the capital market, e-commerce and other ancillary activities” (LOFSA, 2002).

3.2.5.6 Islamic Financial Services Board (IFSB)

The establishment of the Islamic Financial Services Board (IFSB) was another milestone in the history of Malaysia's conscientious effort at establishing itself as the key player in the ICM and Islamic banking and finance. Formed in Nov 2002, with headquarters in Malaysia, the IFSB serves as an association for central banks, monetary authorities and other institutions that are responsible for the regulation and supervision of the Islamic financial services industry (IFSB, 2002). Its establishment completes the infrastructure needed to realise Malaysia's aspiration to be the centre for Islamic banking and finance.

3.2.5.7 International *Shari'ah* Research Academy for Islamic Finance (ISRA)

ISRA was established in 2008 to provide a platform for greater engagement amongst practitioners, scholars, regulators, academicians in the area of *Shari'ah* and to promote applied research for contemporary issues in Islamic finance. Their efforts have contributed to the harmonisation of *Shari'ah* interpretations and thus the standardisation of *Shari'ah* applications and practices in Islamic finance. ISRA has now become an important repository of knowledge for *Shari'ah* views or fatwas.

3.3 CENTRAL BANK OF MALAYSIA: REGULATORY CONTRIBUTIONS

BNM, the Central Bank of Malaysia, was set up in 1959. The initial task was to set into motion the process of institutional building. The next task was to exercise its power to regulate all banking and licensed financial institutions involved in credit and finance under the Banking and Financial Institutions Act, 1989 (BAFIA) as well as Islamic banks licensed under the Islamic banking Act, 1983 (IBA). In other words, the Central Bank of Malaysia is responsible for maintaining the stability of the Malaysian financial system. An equally uphill task faced by the BNM was to realise the successful implementation of the ten-year Financial Sector Masterplan (FSMP) unveiled in 2000 which acts as a roadmap for the future development of the financial system in Malaysia, and which has been proven to be successful recently. And, with the recently launched Financial Sector Blueprint 2011-2020 this will give BNM another major task to achieve for another 10 year period.

3.3.1 Financial Sector Masterplan 2001-2010 and Financial Sector Blueprint 2011-2020

The Financial Sector Masterplan (FSMP), formulated by the Central Bank of Malaysia in early 2001, has drawn another big agenda in the Malaysian financial system. FSMP sets from medium to longer term strategies to build a financial sector that is resilient, efficient and competitive, and responsive to the changing economic environment. Spanning over three phases, FSMP has provide sufficient time for gradual, sequenced and comprehensive development of the financial sector for the next ten years since the launching of FSMP in 2001. This FSMP agenda covers not only the banking sector but the insurance sector, the Islamic banking sector, development financial institutions, alternative modes of financing, as well as the Labuan International Offshore Financial Centre.

After FSMP 2001, another 10-year masterplan was launched recently (November 2011) by Bank Negara Malaysia. The new Financial Sector Blue Print (FSB) 2011-2020 was launched with a new theme: “Strengthening Our Future - Strong, Stable, Sustainable" (BNM, 2012). This new 10-year plan provides a motivational method for Malaysia’s economic development and establishes the financial sector as one of the keys for future economic growth. As mentioned earlier, the previous FSMP 2001 targeted a 20% market share for the industry, but this new Financial Sector Blueprint 2011-2020 excludes any performance or market share targets. The new plan maps the future direction for the Malaysian financial system, setting it towards becoming a key factor contributing to the growth of the Malaysian economy. At the same time, it also positions the country to reap the benefits of increasing regional economic and financial integration; its leadership in Islamic finance will develop Malaysia as an international Islamic financial centre and aid the growing internationalisation of the Islamic finance industry. It is predicted that by 2020, the Malaysian financial system is expected to achieve six times of GDP as compared to the current 4.3 times of GPD. Furthermore, the financial sector contribution to the nominal GDP is forecasted to increase by around 10% to 12% in 2020 as compared to the current rate of 8.6%. Half of the financing in 2020 will be raised through financial markets, and Islamic finance will continue to increase in prominence, being expected to grow at a faster pace to account for 40% of the total financing. The blueprint will also continue the internationalisation of Islamic finance to facilitate more cross-border Islamic financial activities, and for all institutions offering Islamic financial services in Malaysia, the integration of the existing national-level *Shari'ah* Councils into a single apex authority on *Shari'ah* matters will be established (BNM, 2012).

3.3.2 Malaysia International Islamic Financial Centre (MIFC)

Another significant milestone in the Malaysian Islamic financial system is the establishment of the Malaysia International Islamic Financial Centre (MIFC). The comprehensive MIFC initiative places Malaysia firmly at the centre of global developments in the industry. In realizing its agenda of becoming the International Islamic Financial Centre, Malaysia has exploited every existing infrastructure available in order to make Malaysia function as a one stop centre, in other words, to be the most effective Islamic financial centre.

As a yardstick, a comparison with an established financial centre like London was undertaken. The success story of London as one of the established financial centres for international finance should be taken into account in establishing Malaysia as an international centre for Islamic banking and finance.

3.3.3 Islamic Financial Services Board (IFSB)

The last few years have shown a significant growth and importance in Islamic finance. This growth continued further during the 2000s with more developments. Among the major developments was the establishment of the Islamic Financial Services Board (IFSB), which was established to deal with the regulatory and supervisory, and corporate government issues of the Islamic financial industry (to address systematic stability and governance and regulatory issues relating to the Islamic financial services industry). The standards developed by the IFSB are for governing the operations of Islamic financial institutions. The role of the IFSB is not only to harmonise the standards but also to play a vital role towards the consistent development of Islamic finance in different jurisdictions.

3.4 REGULATIVE ROLE OF THE CENTRAL BANK OF MALAYSIA AND ITS STRATEGIES ON MONITORING FINANCIAL DISTRESS

Bank Negara Malaysia (the Central Bank of Malaysia), as mentioned above, was established with the main function of providing the licensing and regulation of the banking business. The Banking and Financial Institution Act (BAFIA) set up in 1989 extended the authority of Bank Negara Malaysia for the supervision and regulation of the financial institutions engaged in deposit taking and in the extension of finance and credit facilities. As a matter of fact, the Finance Companies Act, 1969 and the Banking Act 1989 have been revoked with the introduction of BAFIA 1989. There are three main regulators in the Malaysian Financial System: Bank Negara Malaysia which controls the banking institutions, insurance companies as well as the selected development financial institution; the Securities Commission of Malaysia (SC) which controls the capital markets; and finally the Labuan Off-shore Financial Services Authority (LOFSA) which regulates the offshore financial services.

When it comes to dealing with problem banks with the lowest cost possible, Malaysia has established the Malaysia Deposit Insurance Corporation or Perbadanan Insuran Deposit Malaysia (PIDM) in 2005 enacted under the Malaysia Deposit Insurance Act 2005. Ideally, deposit insurance serves as a safety net in maintaining the stability of the financial system. However, Bank Negara Malaysian remains the main regulator for declaring whether a bank has failed or not, and whether the bank should be transferred to PDIM.

With the fast changing financial landscape worldwide, the Central Banks from every jurisdiction have played their part in maintaining the stability of their own financial system. A major transformation has taken place almost everywhere due to globalisation, liberalisation, financial innovation as well as the significant development in technologies. These factors, as a matter of fact, have changed the regulators perspective in managing risk. From the Malaysian financial system perspective, Bank Negara Malaysia has played a major role in encouraging more competition and efficiency among the players as well as maintaining the stability of the financial system at the same time.

The Asian financial crisis in 1997 resulted in a major impact to the financial liberalisation in many South East Asian countries. In fact, Malaysia had already taken the necessary measures to minimise the systemic risk during that time. In fact, the crisis increased the awareness among the regulators of the necessity of building up a more responsive, resilient and efficient financial system. Perhaps, Bank Negara Malaysia has played its role in ensuring that each bank has its own risk management system as well as holding adequate capital that is commensurate with their risk profile. At the same time, Bank Negara Malaysia has always reviewed and monitored the practices of banks as well as intervened when necessary.

Bank Negara Malaysia, therefore, introduced a few measures and standards in order to maintain the stability of the financial system, such as the regulations on risk management capabilities, governance standards and transparency. These measures were taken in tandem with further growth in the financial landscape, with greater focus on the bank's internal control and risk management systems. For each player in the industry, their overall performance and financial condition will be assessed regularly to ensure the early detection of any weaknesses in the industry that could affect the stability of the financial system. In fact, Bank Negara Malaysia opted for an enhanced risk-based approach in 2007 for monitoring the safety and soundness of each player in the industry.

The Central Bank of Malaysia Act 2009 came into force in November 2009 and this Act empowered Bank Negara Malaysia to address challenges in a rapidly changing environment. This Act will enable Bank Negara Malaysia to manage effectively the emerging risks and challenges in performing its role and responsibilities (BNM, 2009). The Act incorporated an explicit mandate that included risks that disrupted the financial intermediation process, or which effected public confidence. Whenever the risks of disruption are identified, the BNM will be in a position to act using a number of intervention tools such as by requesting any supervisory authority or government agency to provide necessary information in the interest of safeguarding financial stability. Furthermore, Central Bank of Malaysia Act 2009 also mandates the establishment of a new Financial Stability Executive Committee that has been given the power to propose its own procedures and be able to consider specific intervention and resolution proposals related to financial institutions. Most importantly perhaps, the new legal framework also reinforces BNM's power to provide liquidity assistance to financial institutions and enter the arrangements with other central banks. Thus, this will create a buyer of last resort of illiquid assets if those come to threaten the health of the financial system. In other words, it creates an effective safety net for orderly resolution of financial institutions that will reduce threats to the financial system. This new Act will force the banks to follow more stringent prudential rules, which are part of a proper risk management practices (The Report: Malaysia 2010, 2010).

3.4.1 Problem Bank Identification

3.4.1.1 Risk-Based Approach in CAMELS Framework

Prior to 2007, Bank Negara Malaysia adopted the CAMELS framework as its supervisory rating system to assess the financial soundness of the financial system. This framework focused on the key risks of the bank portfolio that would intimidate the safety and soundness of the financial institutions, with greater concern on the institutions' credit market and operational risks. The framework consists of on-site and off-site monitoring tasks. The off-site function works with the review of reports submitted by the financial institutions to Bank Negara Malaysia as an early detection if problems occur. On the other hand, the on-site assessment focuses more on the risk profiles, activities, and size of each bank. Generally, based on supervisory ratings, banks will be reviewed every one to three years. For banks with more supervisory concern, more frequent on-site examination will be conduct as compared to those with less supervisory concern (Rajoo, 2008).

3.4.1.2 Enhanced Risk-Based Supervisory Approach

Early 2007 has seen tremendous changes in the supervisory approach to monitoring the financial institutions in Malaysia. Bank Negara Malaysia has chosen to adopt the enhanced risk-based supervisory approach in assessing the safety and soundness of the financial institutions. Each bank will be assessed based on the impact of risks on their earnings and capital before being accorded with a Composite Risk Rating (CRR). This supervisory rating will be reviewed annually but is subject to change at any time. With greater complexity in the financial industry, regulators found that there is a need for better collaboration with financial institutions to further understand the capability of each bank in their risk management activities (Rajoo, 2008).

In monitoring each bank, financial data as well as non-financial data are the main key indicators in assessing the banks' growth rates, risk profiles, and the banks' concentration profiles. In fact, this information is vital in assessing the soundness and vulnerability of each bank. In practice, each financial institution in Malaysia is required to submit periodic returns through the Financial Institutions Statistical Systems. This system captures the major categories of ratios such as capital adequacy, liquidity and profitability ratios. These periodic reports consist of weekly, monthly, quarterly, and annual reports. In fact, this database is useful in the off-site assessment of financial institutions (Rajoo, 2008).

According to Rajoo (2008), besides depending on the financial and non-financial data, other macro elements should be taken into consideration. Based on previous experience during the Asian financial crisis in 1997, there was found to be a correlation between the performances of financial institutions and the economic conditions. Therefore, supervisors have taken extra steps by taken into consideration the external threats that may affect the stability of the financial system. Bank Negara Malaysia's assessment methods applied both qualitative and quantitative data. Among the techniques used are static and trend analysis, scenario and sensitivity analysis, and stress testing.

3.4.2 Problem Bank Intervention and Resolution

Bank Negara Malaysia has the supervisory power to intervene and instruct the banks to take the corrective actions whenever it finds it necessary. Under BAFIA, section 73 mentioned that the BAFIA authorises the Bank to exercise formal enforcement actions over the bank, the bank's directors, officers, as well as the related companies whenever the need arises. In fact, supervisory rating affects the response by the supervisor (Rajoo, 2008).

The worst action that can be taken against the problem financial institutions is revocation of the bank's license and the winding up of the institutions. Otherwise, the formal enforcement actions are the issuance of orders by Bank Negara Malaysia for the corrective actions to be taken not only by bank but the management as well within a certain time frame. The corrective measures should be taken against the problem banks in order to correct the identified weaknesses, to improve the overall condition, and to restore the bank to the safe and sound condition as soon as possible before things get worse. However, the bank will be subject to more heavy supervision if a bank's financial condition continues to weaken after taking the necessary actions (Rajoo, 2008:116).

Another party which is worthy of mention in this section is the Malaysia Deposit Insurance Corporation or Perbadanan Insuran Deposit Malaysia (PIDM). The statutory power given to PIDM allows them to lend to its member institutions, guarantee deposits, loans or advances to a member institution for short-term liquidity support (Rajoo, 2008).

In circumstances where the problem banks do not restore their sound and safety condition, the intensified action that can be taken by regulators is to consider and implement bank failure contingency scenarios. Bank Negara Malaysia is responsible for supervising the resolution of critical problem banks through resolution management (Rajoo, 2008).

3.5 MALAYSIA EXPERIENCE AND CONCLUSION

The Asian financial crisis in 1997 had a major and lasting impact on the Malaysian financial landscape. The crisis originally started with the currency crisis and gradually affected the economic sector as well, including the corporate sector. This has resulted in an increase in non-performing loans in the banking sector due to the inability of the corporate sector to service their debts with the banks. Measures were needed to warrant the stability of the financial system during that time. Among the major developments during this period were the establishment of Danaharta as an asset management company, Danamodal as the special purpose vehicle, and the Corporate Debt Restructuring Committee (CDRC) with a task to restructure corporate debt (Rajoo, 2008).

Furthermore, due to the major impact of the Asian financial crisis of 1997 on the Malaysian financial landscape, regulators have taken extra precautions regarding the impact of the external elements on the stability of the financial system. Actions have been taken and policies have been strengthened to ensure that they are ready for the next crisis. This experience has heightened the importance of early detection of the vulnerabilities in the financial institutions. However, with the dynamics of the changing financial landscape, it is inevitable that there are new types of risks in the system. The risks arising from the innovation of new products pose new challenges for supervisors to understand and manage them. What should be taken into consideration now is the detection and prevention measures which stop institutions from turning into problem banks, rather than managing the crisis. Equally important is the quality and transparency of financial reporting and disclosure in the Islamic finance industry. The practice differs significantly from one regulatory jurisdiction to another.

Chapter 4
RESEARCH METHODOLOGY AND MODELLING

4.1 INTRODUCTION

This chapter consists of two discussion sections. The first part of this chapter presents the various aspects of research methodology and research design used for this study. Whereas, the second part of this chapter will discuss the existing prediction models, the statistical models available as well as the selection of appropriate models for this study.

Among the main objectives of this study is to build an insolvency prediction model for Islamic financial institutions. In other words, this study tries to identify another set of promising explanatory variables in predicting the insolvency of Islamic financial institutions.

Predicting the default risk for banks, loans and securities is a classic, yet timely issue. Since the work of Altman (1968), who suggested using the so-called "*Z*-score" to predict firms' default risk, hundreds of research articles have studied this issue (refer to Kumar and Ravi, 2007; Fethi and Pasiouras, 2010). Several studies have shown that the intelligence modelling techniques used in operational research can be applied for predicting bank failures and crises.

This chapter presents the various aspects of research methodology and research design for this study. It describes the methods used and how the data was collected to address the aims and questions of the research. This section begins with some definitions of research methodology follow by a few different types of research. Further discussion detailing the research strategy of this research, starting with some definitions and types of research strategy continues. Research design, definition and types, is also discussed in the section on discussions of the methods of data collection, the selected techniques use in data analysis as well as the selected variables. The limitations and difficulties in conducting this research are discussed in the final part of this section.

4.2 RESEARCH METHODOLOGY

Research is defined as a process of finding solutions to a problem after a thorough study and analysis of the situational factors (Sekaran and Bougie, 2009). It can also be defined as a process for collecting, analysing and interpreting information to answer the research questions. According to Gray *et al*. (2007), research methodology is defined as the study of research process; the principles, procedures, and strategies in gathering, analysing and interpreting the results.

According to Kumar (2005), in order to qualify as research, this process must possess as far as possible certain characteristics: the procedures used to find the answer to questions are relevant, appropriate and justifiable; procedures adopted are systematic; the conclusion of the findings is correct and is verifiable; and procedures used have undergone critical scrutiny.

Research can be classified into two major types of category based on the approaches the process has taken to find the answer to the research questions: quantitative research and qualitative research.

Quantitative research is a more structured and rigid methodology in nature in which the design of the research strategy is usually to produce the findings in the form of numerical data. The analysis of the data subjects variables to frequency distributions, cross-tabulations or other statistical methods appropriate for the research (Kumar, 2005). The final conclusion of this type of research will be more analytical in nature and it makes inferences and conclusions by means of testing the degree and strength of relationships among the selected variables.

Qualitative research, on the other hand, is a more unstructured type of research with a more flexible methodology. This type of research gives more emphasis to words in the collecting and analyzing of data as compared to quantitative research (Bryman, 2008). Investigating the experiences, meaning, feeling, and perceptions are the main concern in this type of research. The final conclusion will be more descriptive and narrative in nature (Kumar, 2005).

This study follows quantitative research methodology, as the aim is to construct a statistical model and analyse collected data through statistical and econometric models by developing relationship between variables. The researcher obtained the necessary data from secondary sources, from the annual reports as well as the interim financial statements reported every quarter for the selected sample of banks.

4.3 RESEARCH STRATEGY

Research strategy can be defined as a proper plan by which the activity of searching for the relevant data and assessing the data is carried out in order to answer the research questions (Saunders *et al.,* 2007).

Research strategy can be distinguished into two types: deductive approach or an inductive approach. The deductive approach works from the more general to the more specific (Sekaran and Bougie, 2009; Bryman, 2001). Deductive is an approach to the relationship between theory and research in which the research is conducted with reference to hypotheses and ideas inferred from the theory (Bryman, 2001).

On the other hand, the inductive approach works the other way round. The inductive approach starts from more specific observations and moves to broader generalisations and theories (Sekaran and Bougie, 2009; Bryman, 2001). Contrary to deductive approach, inductive approach is also an approach to the relationship between theory and research but the the theory is generated out of the research (Bryman, 2001).

Comparing these two approaches, an inductive approach is more open-ended and exploratory, while a deductive approach is narrower in nature and is concerned more with testing or confirming the hypotheses.

Albeit certain studies may look like they are purely deductive, but most of the social science research undertaken may involve both inductive and deductive approaches at certain levels in the research project (Sekaran and Bougie, 2009). As for the present research, deductive research strategy is employed, as this study aims to test a number of models that have already been formulated in the literature with the data collected from the cases.

4.4 RESEARCH DESIGN

Research design can be defined as the strategy used to put together the different elements of certain research projects in a cohesive and coherent way. In other words, it is meant to structure certain research projects in order to address defined research questions (De Vaus, 2001). For some researchers, research design is treated as a roadmap in doing their research. Some important elements that the researcher needs to keep in mind in designing their research are the scope of the study, the sources of information or data, and the methods to be used.

There are four main types of research design: exploratory, descriptive, hypothesis testing (analytical and predictive), and case study analysis.

An exploratory study is normally undertaken when not much is known about the situation in hand, or no information is available on how similar problems or research issues have been solved in the past. In such cases, extensive preliminary work needs to be done to gain familiarity with the phenomenon in the situation, and understand what is occurring, before developing a model and setting up a rigorous design for comprehensive investigation. In other words, exploratory studies are carried out to better understand the nature of the problem, since very few studies might have been conducted in that area. Data collection through surveys or observations is exploratory in nature. When the data reveals certain patterns regarding the phenomena of interest, theories are developed and hypotheses are formulated for subsequent testing. Exploratory studies are also necessary when some facts are known, but more information is needed for developing a viable theoretical framework. In sum, exploratory studies are important for obtaining a good grasp of the phenomena of interest and for advancing knowledge through subsequent theory building and hypothesis testing (Sekaran and Bougie, 2009).

Another type of research design is the descriptive study. Descriptive study is undertaken to ascertain and be able to describe the characteristics of the variables of interest in a situation. The main goal of descriptive study is to offer to the researcher a profile or to describe relevant aspects of the phenomena of interest from an individual, organisational, industrial-oriented, or other perspective (Sekaran and Bougie, 2009). Hypothesis testing, on the other hand, aims to explain the nature of certain relationships, establish the differences among groups, or the independence of two or more factors in situation. In other words, hypothesis testing offers an enhanced understanding of the relationship that exists among variables and it can be done with both qualitative and quantitative data (Sekaran and Bougie, 2009).

Finally, the case study involves in-depth, contextual analysis of matters relating to similar situations in other organisations. Case studies are generally qualitative in nature and are sometimes used as a tool in managerial decision making (Sekaran and Bougie, 2009).

As for the present research design, this research is a case study as it is focused on Malaysian Islamic banking. In addition, it also benefits from explanatory design, as the study aims to explain and examine a particular issue, and that is the efficiency of a particular insolvency prediction model for Islamic financial institutions in the case of Malaysia.

4.5 RESEARCH METHODS

Most research requires the researcher to use specific techniques in collecting and analysing the collected data in order to answer the initially established research questions (Robson, 2002).

Research methods can be defined as a simple set of instruments that are used for data collection and data analysis (Cohen, Manion, and Morisson, 2007). The selection of methods must be based on the types of data that are required, from whom, and under what condition (Robson, 2002).

There are two categories of research methods that are worth discussing here: quantitative method and qualitative method. The quantitative method is more suitable for any research which has the intention of obtaining measurable findings, or maybe evaluating them. Due to this, the data involved will be more quantitative in nature such as numbers or attributes that can be measured in terms of scales. The survey is one of the main research tools that has been employed by many researchers nowadays (Arksey and Knight, 1999), but econometric and statistical studies are mainly classified as quantitative studies.

On the other hand, for a researcher with the motive of exploring further in their area of interest, the qualitative method will be the more suitable method to use. In fact, most of the data collected through the qualitative method is mostly spoken or written data, which aims to express preferences, opinions and understandings, and therefore it is absolutely not capable of numerical interpretation. Among the methods that directly relate to the qualitative research method are qualitative interviewing, focus group interviews, and participant observations (Bryman, 2008).

For this study, a quantitative method is used, as the aim is to use a particular model to test its validity in the case of Islamic banks with the primary data collected through obtaining financial data for the selected Islamic banks in Malaysia.

4.5.1 Data Collection: Secondary Data

There are two types of data, primary data and secondary data. The primary data are collected for the specific purpose of answering the problem at hand. However, secondary data are obtained from publicly available databases or media to be used in quantitative research, such as this study.

The data collection for this research will involve secondary data as mentioned above. For example, the secondary data that can be obtained includes company records or archives, government publications, industry analysis offered by the media, and a few others. For the purposes of the present research, the secondary data will be collected from the annual reports and the interim financial reports made public every quarter. Out of 17 fully-fledged Islamic banks, 10 of them have been selected as a sample for this study. Annual reports and quarterly financial reports have been obtained for those banks.

4.5.2 Data Analysis: Statistical and Econometric Methods

The data analysis for this research is quantitative in nature and involves statistical and econometric methods: amongst these are Multivariate Discriminant Analysis (MDA), Logit and Probit, and Factor Analysis. Statistical Package for the Social Sciences (SPSS) and Eviews (Econometric Views), are the two main statistical packages for windows used in this study.

4.6 RESEARCH MODELLING: SURVEY

This section reviews the available prediction modelling research. It provides an overview of prediction models and how they have been used. Highlights are given of each study methodology and its findings. However, the following review of the prediction modelling literature is not intended to be comprehensive in nature. The studies included in this review are chosen to be representative of the rich body of literature that exists. They represent some of the best and most widely cited research articles that relate to the development and application of prediction models. And, to add more, only the statistical method applied in the Early Warning System will be discussed in this chapter due to the nature of the research.

There is an increasing demand for predicting the performance of Islamic banks due to the vital importance of any problem that may face these banks before it materialises and negatively affects their performance and their financial status. This will save on the costs of bad performance or failure to depositors, owners and the economy. Thus, a need arises for an early warning system which will identify the possible causes of bad performance, detect potential problem banks, and facilitate the surveillance of banks as well as scheduling the remedial procedures. This research aims at benefiting from the previous research efforts on the subject to develop a preliminary model for the prediction of the performance level of Islamic financial institutions, hoping that this will be a cornerstone for further development and improvisation, specially as more information and data become available or accessible.

According to Al-Osaimy and Bamakhramah (2004), among the reasons for an increasing demand for early warning systems are: identifying the possible causes of bad performance, facilitating the surveillance of banks and reducing its costs, and the proper timing of examining problem banks and scheduling the remedial procedures.

The current crisis has demonstrated, in the worst possible way, that banks play a central role in the economy which is of crucial importance for various stakeholders. In contrast to past crises, the current crisis began in developed countries and their economies have been influenced adversely. Unemployment has increased substantially, investments and consumption has decreased and all the governments are looking at possible ways to exit the crisis. Consequently, several of them have already announced fiscal initiatives, which include in all but name the partial nationalisation of several banks, and which increases substantially the debt to GDP ratio. Such developments illustrate the need for early warning models that will help to monitor banks and avoid similar problems in the future (Ioannidis *et al*., 2009).

The recent crisis has highlighted, once again, the importance of early warning models to forecast banking crises and assess the soundness of individual banks (Ioannidis *et* *al*., 2009). In fact, the recent events have generated a new round of discussion among the experts as well as the regulators regarding the adequacy of the regulatory environment. A number of studies have been conducted in an attempt to explain the reasons behind the crises and how these crises could be avoided in the future.

Most central banks have employed various early warning systems to monitor the risk of banks for years. However, the repeated occurrence of banking crises during the past two decades such as the Asian crisis, the Russian bank crisis, and the Brazilian bank crisis indicates that safeguarding the banking system is no easy task. According to the Federal Deposit Insurance Corporation Improvement Act of 1991, regulators in the United States must conduct on-site examinations of bank risk every 12-18 months. Regulators use a rating system (the CAMELS rating) to indicate the safety and soundness of banks. The CAMELS ratings consist of six parts: capital adequacy, asset quality, management expertise, earnings strength, liquidity and sensitivity to market risk (Demyanyk and Hasan, 2009).

Among the statistical techniques analysing and predicting bank failures, discriminant analysis (DA) was the leading technique for many years. There are three subcategories of discriminant analysis: linear, multivariate, and quadratic.

The variables that are commonly used by researchers in their bankruptcy prediction models are shown in Table 4.1. According to (Du Jardin, 2009), the total is greater than 100 as several types of variables may have been used at the same time.

Table 4.1: List of Explanatory Variables Commonly Used by Bankruptcy Prediction Models

Variables		Frequency (decreasing order) of use in the 190 studies
1	Financial ratio (ratio of two financial variables)	93%
2	Statistical variable (mean, standard deviation, variance, logarithm, factor analysis scores… calculated with ratio or financial variables)	28%
3	Variation variable (evolution overtime of a ratio or a financial variable)	14%
4	Non-financial variable (any characteristic of a company or its environment other than those related to its financial situation)	13%
5	Market variable (ratio or variable related to stock price, stock return)	6%
6	Financial market variable (data coming a balance sheet, an income statement or any financial documents)	5%

Source: Du Jardin (2009: 39–46)

The first type of variable, and historically the most commonly used, is of course the financial ratio, which expresses the relationship between any two items on a balance sheet, income statement, or other financial document. Despite this pitfall, ratios are still the favoured indicators of financial health. Indeed, more than 93% of the 190 studies were analysed using ratios, and the remaining 7% use other types of variables. Moreover, over 53% of these studies include only ratios in their models and almost 78% include ratios used either alone or in conjunction with another type of variable.

Aside from ratios, there are five other types of variables that play secondary roles that are not entirely negligible. In the second place is a statistical variable and financial market data was considered the least favourable to previous researchers due to the limited predictive value.

The following table gives the criteria used to select explanatory variables for inclusion in a bankruptcy model (Du Jardin, 2009):

Table 4.2: Criteria Used to Select Explanatory Variables for Inclusion in Bankruptcy Model

Criteria Used	Percentage (%)
Popularity in the literature or predictive ability assessed in previous studies	40%
Univariate analysis : t-test, F-test, correlation test, signs of coefficients	17%
Stepwise search + Wilks's lambda	16%
Stepwise search + likelihood criterion	10%
Genetic algorithms, special algorithms (Relief, Tabu)	6%
Expert	4%
Methods that fit non-linear modeling techniques (such as neural networks)	3%
Other (multiple regression, regression tree, theoretical model)	4%

Source: Du Jardin (2009: 39–46)

4.6.1 Existing Models for Measuring Financial Distress

Several bank failure prediction models have been developed since the mid 1970s. Most of the earlier models were built using classical statistical techniques, such as multivariate discriminant analysis (MDA). Later studies have also used neural networks, split-population survival time model, Bayesian belief networks, and isotonic separation. Some of these models have been routinely applied in the regulatory practices of banking agencies. Most of these models predict likely bank failures based on a set of high-level constructs called financial ratios, instead of low-level accounting variables. These financial ratios are usually constructed based on publicly available balance and income data that commercial banks are required to report to regulatory authorities on a regular basis. They are designed to reflect the soundness of a commercial bank in several aspects. Given the importance of the subject, extensive research has been devoted to the design and identification of such financial ratios in the last three decades. As a result, a large set of financial ratios has been identified and applied in regulatory practices. These financial ratios are believed to be more effective explanatory variables than the raw accounting data in the call reports in predicting and explaining bank failures (Zhao *et al*., 2009).

The prediction of failure for banks has extensively been researched since the late 1960s. A variety of statistical methods and other methods such as neural network topologies have been applied to solve bankruptcy prediction problem in banks and firms. Among the statistical methods that have been used are linear discriminant analysis (LDA), multivariate discriminant analysis (MDA), quadratic discriminant analysis (QDA), multiple regressions, logistic regression (logit), probit and factor analysis (FA).

This study generally will focus more on the statistical methods with more attention to statistical methods such as multivariate discriminant analysis (MDA), the logistic regression method and the probit method. The next section will discuss in detail the methodology and the application of these methods in previous studies and the possibility of application to the development of a new prediction model for Islamic banks in Malaysia.

4.6.1.1 Statistical models

According to Aziz and Dar (2004), this category can be divided into two types of analyses, univariate and multivariate analyses, and statistical models always look at the symptoms of failures. Unlike multivariate analysis, univariate analysis examines and observes each variable one after the other.

4.6.1.1.1 Linear Discriminant Analysis (LDA)

Linear discriminant analysis is one of the methods used in statistic, pattern recognition and machine learning to find a linear combination of features which characterise or separate two or more classes of objects or events. LDA is closely related to the analysis of variance and regression analysis which also attempts to express one dependent variable as a linear combination of other features or measurements. Logistic regression and probit regression are similar to LDA, as they explain categorical variables. LDA is also closely related to factor analysis and principal component analysis in that both look for linear combinations of variables which explain the data. LDA explicitly attempts to model the difference between the classes of data but principal component analysis on the other hand does not take into account any difference between the classes' data, and factor analysis builds the feature combination based on differences rather than similarities.

4.6.1.1.2 Multivariate Discriminant Analysis (MDA)

MDA is concerned with the classification of distinct sets of observations and it tries to find the combination of variables that predicts the group to which an observation belongs. The combination of predictor variables is called the linear discriminant function, and this function can be used to classify new observations whose group membership is unknown. The linear discriminant function is as follows:

$$D = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots\dots + \beta_n X_n$$

where:
D is the discriminant score,
B_0 is an estimated constant,
B_n are the estimated coefficients, and
X_n are the variables

Based on this discriminant function score, an observation is classified into the appropriate group.

Altman (1968) is the first researcher who used discriminant analysis to predict the failures of firms from different industries. Sinkey (1975) also employed discriminant analysis to predict bank failures. Altman (1977) in a later study developed discriminant model to predict the failures of the Savings and Loan Association for the period of 1966 to 1973 using 32 ratios as explanatory variables. Lam and Moy (2002) combined several discriminant models, and performed simulation analysis to enhance the accuracy of classification results for classification problems in discriminant analysis. Another multivariate statistical method that is used to predict bank failures is multiple regression analysis. Meyer and Pifer (1970) are the first researchers who used this method to predict bank failures.

The *Z*-score formula for predicting bankruptcy published in 1968 was among the pioneers in bankruptcy modelling. During the earlier years, Altman developed a formula which can be used to predict the probability that a firm will go into bankruptcy within two years. The *Z*-score uses multiple corporate income and balance sheet values to measure the financial health of a company. Altman's work built upon research by the accounting researcher William Beaver and others. In the 1930s and onwards, Mervyn and a few other researchers had collected matched samples and assessed that various accounting ratios appeared to be valuable in predicting bankruptcy. In fact, Altman's *Z*-score model is a customised version of the discriminant analysis technique used by the earlier researcher, Fisher (1936). William Beaver's work, which was published in 1966 and 1968, was another milestone in bankruptcy modelling. Beaver's work was the first to apply a statistical method, t-tests to predict bankruptcy for a pair-matched sample of firms. This method was used to evaluate the importance of each of several accounting ratios based on univariate analysis, using each accounting ratio at one time. A major improvement made by Altman was to apply discriminant analysis instead of univariate analysis. This is due to the fact that discriminant analysis could take into account multiple variables concurrently instead of evaluating each ratio one after another.

The *Z*-score is a linear combination of four or five common ratios, weighted by coefficients. These coefficients were estimated by identifying a set of firms which had declared bankruptcy and then collecting a matched sample of firms which had survived, with matching by industry and approximate size in terms of assets. In the earlier stage, Altman applied the statistical method of discriminant analysis to a dataset of publicly held manufacturers. The original data sample consisted of 66 firms with 33 of those companies having filed for bankruptcy. The sample included all manufacturers except those small companies with an asset of less than US$1 million. From the original 22 variables, five were selected as doing the best overall job together in the prediction of bankruptcy (Altman, 1968). As such, the original *Z*-score bankruptcy model was as follows:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$$

where;

X_1: working capital/total assets,

X_2: retained earnings/total assets,

X_3: earnings before interest and taxes/total assets,

X_4: market value equity/book value of total liabilities,

X_5: sales/total assets,

Using this formula, one inserts the more commonly written percentage, for example, 0.10 for 10%, for the first four variables (X_1-X_4) and rounds the last coefficient off to equal 1.0 (from 0.99). As such, the final version of *Z*-score model is as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

The cut-off values for the *Z*-score involve three zones that permit one to assess whether this model identifies the company as safe, in the gray area, or troubled. Any score greater than or equal 2.99 is considered safe, a score between 1.82 and 2.98 is in the grey area, and finally any score below 1.81 is considered as a troubled company.

The *Z*-score model has gained wide acceptance by many users such as auditors and management accountants. Although the model was originally designed for publicly held manufacturing companies, this model also has been used in a variety of contexts and countries. Since the earlier model was based on data from publicly held manufacturers, this model has been re-estimated since then based on other sets of data.

Later variations by Altman were designed to be applicable to privately held companies (*Z'*-score) and non-manufacturing companies (*Z"*-score). As for the privately held companies *Z'*-score model, Altman has done a complete re-estimation of the model by substituting the market value in X_4 with the book values of equity (Altman, 1993). The result of the revised *Z'*-score model is as follows:

$$Z' = 0.717(X_1) + 0.847(X_2) + 3.107(X_3) + 0.420(X_4) + 0.998(X_5)$$

There have been some slight changes to the cut-off values for the *Z'*-score. Any score greater than or equal to 2.9 is considered safe, a score between 1.23 and 2.9 is in the grey area, and finally any score below 1.23 is considered to be in a distressed zone.

Further modification of the *Z*-score can be seen in the *Z"*-score model for the non-manufacturing companies. In order to minimise the potential industry effect, Altman developed this model without X_5 (sales/total assets). This model has been used by Altman to assess the financial health of non-US corporates. Similarly with the *Z'*-score, the book value of equity was used in the *Z"*-score model (Altman, 1993). The *Z"*-score model is as follows:

$$Z'' = 6.56\ (X1) + 3.26\ (X2) + 6.72\ (X3) + 1.05\ (X4)$$

All of the coefficients for variables X_1 to X_4 are changed as are the group means and cut-off scores. Any score greater than or equal to 2.6 is considered safe, a score between 1.1 and 2.6 is in the grey area, and finally any score below 1.1 is considered to be in a distressed area.

After considering a few research projects done in the past, neither of the Altman models nor any other models are recommended for use with financial firms especially Islamic financial institutions. This may be due to the fact that most of these financial firms are always involved with off-balance sheet activities. There are market-based formulas used to predict the default of financial firms but are of very limited predictive value due to much reliance on market data to predict the market event.

4.6.1.1.3 Quadratic Discriminant Analysis (QDA)

Quadratic discriminant analysis has been used in statistical classification or as a quadratic classifier in machine learning. QDA is closely related to linear discriminant analysis, where it is assumed that there are only two classes of points and that the measurements are normally distributed.

4.6.1.1.4 Multiple Regression

The general purpose of multiple regressions (the term was first used by Pearson, 1908) is to learn more about the relationship between several independent or predictor variables and a dependent or criterion variable.

4.6.1.1.5 Logistic Regression Analysis (Logit)

Logistic regression analysis is a form of regression which is used when the dependent is a dichotomy and the independents are of any type. In logit models, the dependent variable is usually binary which can take the value 1 with a probability of success $P(Zi)$, or the value 0 with probability of failure $1- P(Zi)$. An explanation of the relationship between independent variables and a binary dependent begins with the following non-linear function:

$$P(Z_i) = e^{Zi} / (1 + eu^{Zi})$$

$$= 1 / (1 + eu^{-Zi})$$

where $P(Z_i)$ is a cumulative probability function that takes value between 0 and 1.

The input is Z_i and the output is $P(Z_i)$. The logistic function is useful because it can take as input any value from negative infinity to positive infinity whereas the output is confined to values between 0 and 1. The variable Z_i represents the exposure to some of the independent variables, while $P(Z_i)$ represents the probability of a particular outcome, given that set of explanatory variables. The variable Z_i is a measure of the total contribution of all the independent variables used in the model and is known as logit. The variable Z_i is usually defined as follows:

$$Z_i = \beta_0 + \beta_1 F_1 + \beta_2 F_2 + \ldots\ldots + \beta_m F_m$$

where;

β_0 is the constant of the equation or also known as an intercept and,

β_m are the coefficient of the predictor variables or regression coefficients.

The constant or intercept is the value of Z_i when the value of all independent variables is zero. Each of the coefficients of regression variables describes the size of the contribution of risk factor. A positive coefficient means that the explanatory variables increase the probability of the outcome, whereas a negative coefficient means that the variable decreases the probability of the outcome. Meanwhile, a larger value of coefficient means that the risk factor has strongly influenced the probability of the outcome; while a near-zero regression coefficient means that the risk factor has little influence on the probability of the outcome.

Logistic regression, also known as th logistic model or logit model, is used in statistics for the prediction of the probability of occurrence of an event by fitting data to a logic function curve. It is a generalised linear model used for binomial regression. Like many forms of regression analysis, it makes use of several predictor variables that may be either numerical or categorical. Logistic regression is a useful way of describing the relationship between one or more independent variables and a binary response variable, expressed as a probability that has only two possible values, such as fail or non-fail.

The main aim of the logit model is to correctly predict the group of outcome for individual observations using the most parsimonious model. A model is created that includes all predictor variables that are useful in predicting the response variable (Boyacioglu *et al.*, 2009).

Logistic regression analysis is considered as amongst the most famous methods in statistical modelling. Among the earliest researchers to employ logistic regression to predict banks and firms failure are Martin (1977) and Ohlson (1980). Thomson (1991) conducted a study on bank failures in the United States only during the 1980s whereas Gonzalez-Hermosillo (1999) examined bank failures in the United States, Mexico and Colombia during the 1980s and 1990s.

A study by Kolari *et al*. (2002) developed an early warning system based on logit analysis and trait recognition for large United States banks. In Turkey, Canbas *et al*. (2005) proposed an integrated early warning system by combining discriminant analysis, logistic regression, probit and principal component analysis. In th Russian banking industry, Konstandina (2006) used logit analysis to predict Russian bank failures (Boyacioglu *et al*., 2009).

4.6.1.1.6 Probit

Another type of statistical model is known as the Probit model. A probit model is a popular specification for an ordinal or binary response model which employs a probit link function. This model is most often estimated using the standard maximum likelihood procedure, such an estimation being called a probit regression.

Similar to the logit model, the response variable Y is binary; there can be only two possible outcomes which can be denoted as the value *0* or *1*. Thus *Y* may represent certain outcomes such as success or failure. This model also has a vector regressor *X* that will influence the outcome of *Y*. This can be explained in the following form of model:

$$Pr\ (Y = 1 \mid X) = \Phi\ (X'\beta)$$

Where Pr denotes probability and Φ is the Cumulative Distribution Function (CDF) of the standard normal distribution. The parameters β are typically estimated by maximum likelihood.

4.6.1.1.7 Factor Analysis

Another method which is worth discussing in this chapter is Factor Analysis. Factor analysis is a statistical method used to describe variability among observed variables in terms of a potentially lower number of unobserved variables called factors (Schreiber *et al*.. 2006). Factor analysis searches for joint variations in response to unobserved latent variables. The observed variables are modelled as linear combinations of the potential factors, plus error terms. The information gained about the interdependencies between observed variables can be used later to reduce the set of variables in a dataset (Field, 2009). Factor analysis is closely related to principal component analysis, but the two are differ in the communality estimates that are used. This is due to the fact that principal component analysis decomposes the original data into a set of linear variates. Furthermore, principal component analysis is concerned only with establishing which linear components exist within the data and how a particular variable might contribute to that component. On the contrary, factor analysis derives a mathematical model from which factors are estimated (Field, 2009).

There are a few types of well known factor analysis. Among the popular ones are Exploratory factor analysis (EFA), Confirmatory factor analysis (CFA), Principal component analysis (PCA), Canonical factor analysis , and Common factor analysis which is also known as Principal factor analysis (PFA) or Principal axis factoring (PAF). Exploratory factor analysis is used to uncover the underlying structure of a relatively large set of variables with an assumption that any indicator could possibly be associated with any other factor. Perhaps this is among the most common form of factor analysis (Fabrigar *et al.*, 1999). Another type of factor analysis is confirmatory factor analysis which seeks to decide if the number of factors and loadings of measures variables match with what is expected on the basis of pre-established theory. After selecting the indicator variables, the factor analysis is used to see if they load as forecasted on the number of factors with an assumption that each factor is linked with a specified subset of indicator variables (Schreiber *et al*.. 2006). Principal component analysis is another common form of factor analysis. Principal component analysis seeks for a linear combination of variables such that the maximum variance is extracted from the variables. This variance then will be removed and PCA seeks for a second linear combination which explains the maximum proportion of the remaining variance, and so on (Field, 2009; Velicer and Jacksons, 1990).

4.7 MODEL SELECTION

This section will discuss in detail the selection of models and the rationale behind the selection. Multivariate statistical methods have been selected to analyse the data as well as to come up with the new prediction models for Islamic banks in Malaysia in one of the empirical chapters in this research. These methods are multivariate discriminant analysis, logistic regression analysis and probit analysis, and principal component analysis. The integration between these four methods hopefully will produce higher prediction accuracy as compared to individual models. Among the previous bank failure studies which employed multivariate statistical analysis, those employing discriminant analysis include Sinkey (1975), those using logistic regression models includes Rose and Kolari (1985); Pantolone and Platt (1987), and those using a probit model include Cole and Gunther (1998). It should be noted that these studies have used financial ratios as independent variables to estimate the models.

Recent studies showed a new development in the modelling of bank failure prediction with new approaches such as the combination of non-parametric approaches with the discriminant or logit analysis (Canbas *et al*, 2005). For example, Tam and Kiang (1992) introduced a neural network approach to perform discriminant analysis. Years later, Jo and Han (1996) introduced an integrated model for bankruptcy prediction using discriminant analysis and two artificial intelligence methods, neural networks and case-based forecasting, and came to the conclusion that the integrated models performed better in term of higher prediction accuracy as compared to individual models. Another work on bank failure prediction models was by Kolari *et al*. (2002), who used both the parametric method of logit analysis and the non-parametric approach of trait recognition in order to develop a classification of early warning system models to identify large bank failures based on the original samples, and tested the effectiveness of these models based on their prediction accuracy by using the holdout samples. They concluded that both logit and trait recognition performed well in terms of classification test results. During the same period, Lam and Moy (2002) combined several discriminant methods and they performed a simulation analysis to improve the accuracy of classification results for classification problems in discriminant analysis.

After reviewing each of these models, it should be noted that this research combines three well known parametric models that are discriminant, probit and logit analysis, together with another parametric model, principal component analysis, in order to develop an integrated prediction model. Besides using the three well known approaches, principal component analysis helps the researcher to explore and understand the underlying patterns of relationship between the selected financial ratios, and by applying this method to the financial data, any important ratios that could explain any significant changes in the bank's financial condition will be explored. Then, financial factor components will be selected and factor scores will be estimated for each of the sample banks. These scores later will be used as independent variables in estimating the discriminant, logit and probit models. Finally, the most important part in this research will be the construction of the integrated prediction models by combining all the parametric models together. This integrated modelling is discussed further in Chapter 7 as one of the empirical chapters that analyse those statistical methods carried out on the actual quarterly data from Islamic banks in Malaysia.

The application of multivariate statistical methods such as discriminant analysis in this study will require uncorrelated variables. Thus, Pearson Correlation coefficients were calculated in order to determine the correlation between the variables. Factor analysis will be applied to the selected financial ratios in order to decide the best combinations of ratios that will be useful for the new integrated prediction model. In fact, the main objective of factor analysis is to explain the covariance relationship among many variables, but for certain reasons the suitability of factor analysis to the selected banks' financial data should be tested either by using Kaiser-Meier-Olkin (KMO) or Bartlett's test of Sphericity. Then, the principal component analysis will be applied to the banks, data set where the selected financial variables will be used.

Numerous studies have been conducted based on the three well known parametric methods as explained above. For this study, the researcher will refer to the three established models that were developed by Altman (1968), Ohlson (1980), and Zmijewski (1984). These three models are based on accounting data or variables from the financial statements of selected samples.

Multiple discriminant analysis, binary choice models (logit and probit) and proportional hazard models are among the most commonly used methods for the analysis of financial ratios. Thus, the empirical research continues in Chapter 7 with the utilisation of the logit model to analyse the role of the funding structure of the Islamic banks' assets. This empirical chapter also analyses the role of deposits, macroeconomic variables and other alternative bank-specific variables in explaining the Islamic banks' performance. The second empirical chapter (Chapter 6) employs discriminant analysis in predicting the Islamic banks and conventional banks' failure. Specifically, this second empirical chapter analyses whether the well known Altman's Emerging Market *Z*-score model can predict bankruptcy and at the same time measure the financial performance of Islamic and conventional banks in Malaysia.

Table 4.3 summarizes the empirical models and the variables employed. This table explains the types of models, the model specification, the variables and their descriptions.

Table 4.3: The Empirical Models and the Employed Variables

Model	Formula	Variable Description
Altman (1968) Mutiple-Discriminant Analysis		X_1 = Net working capital/total assets X_2 = Retained earnings/total asset X_3 = Earnings before interest and tax/total assets X_4 = Market value of equity/book value of total liabilities X_5 = Sales/total assets
Ohlson (1980) Logit model	$P\ (Z_i) \quad = e^{Zi} / (1 + eu^{Zi})$ $\qquad\quad = 1 / (1 + eu^{-Zi})$ Where $P(Z_i)$ is a cumulative probability function that takes value between 0 and 1.	Size Total liabilities/total assets Working capital/total assets Current liabilities/current assets 1 if total liabilities exceed total assets, 0 otherwise Net income/total assets Funds provided by operation/total liabilities 1 if net income was negative for the last 2 years, 0 otherwise Change in net income
Zmijewski (1984) Probit model	$Pr\ (Y = 1 \mid X) = \Phi\ (X'\beta)$ Where Pr denotes probability and Φ is the Cumulative Distribution Function (CDF) of the standard normal distribution. The parameter β are typically estimated by maximum likelihood.	Net income/total liabilities Total liabilities / total assets Current assets/current liabilities

This research consists of four main empirical chapters and each chapter involves different statistical and econometric methods. Further explanations on the methods involved are as follows:

4.7.1 First Empirical Chapter – Evaluating the Performance of Islamic Banks: Descriptive Quantitative Analysis (Chapter 5)

The first empirical chapter provides a comprehensive descriptive analysis of selected financial ratios in terms of the estimated means and standard deviations for selected Islamic banks in Malaysia.

For the purpose of this research, 24 financial ratios have been selected and classified into five main categories, which are capital ratios, asset quality ratios, liquidity ratios, profitability ratios, and income-expenditure structured ratios. The SPSS statistical software package has been utilised in analysing these ratios. The selections of these financial ratios were based on past similar research in this study area. The financial ratios used in this research are given in Table 4.4 below.

Table 4.4: Selected Financial Ratios

Category	Ratios	Definition	Used By
Capital Ratios	**CR1**	(Shareholders' Equity + Total Income)/Total Assets	Lanine, and Vennet (2006); Swicegood and Clark (2001); Tung *et al.* (2004); Ravi *et al.* (2008); Zhao *et al.* (2008); Boyacioglu *et al.* (2009); Jagtiani *et al.* (2003)
	CR2	(Shareholders' Equity + Total Income) / (Deposits and non-deposit Funds)	Ravi and Pramodh (2008)
	CR3	Net Working Capital/Total Assets	Chung et al. (2008); Ravi and Pramodh (2008)
	CR4	(Shareholders' Equity + Total Income)/(Total Assets + Contingencies and Commitments)	Ravi and Pramodh (2008)
	CR5	Forex Position/Shareholders' Equity	Boyacioglu *et al.* (2009
	CR6	Capital/Assets	Gunsel (2007); Lanine and Vennet (2006)
Asset Quality Ratios	**AQ1**	Loans/Total Assets	Gunsel (2007); Lanine and Vennet (2006); Swicegood and Clark (2001); Ravi *et al.* (2008); Zhao *et al.* (2008); Boyacioglu *et al.* (2009); Moin (2008)
	AQ2	Non-performing Loans/Loans	Tung *et al.* (2004); Zhao *et al.* (2008)
	AQ3	Permanent Assets/Total Assets	Boyacioglu *et al.* (2009)
	AQ4	Forex Assets/Forex Liabilities	Boyacioglu *et al.* (2009
Liquidity Ratios	**LR1**	Liquid Assets/Total Assets	Gunsel (2007); Lanine and Vennet (2006); Ravi and Pramodh (2008); Jagtiani *et al.* (2003)
	LR2	Liquid Assets/(Deposits and non-deposit Funds)	Gunsel (2007); Lanine and Vennet (2006); Ravi and Pramodh (2008); Jagtiani *et al.* (2003)
	LR3	Forex Liquid Assets/Forex Liabilities	Boyacioglu *et al.* (2009
Profitability Ratios	**PR1**	Net Income(Loss)/Average Total Assets	Gunsel (2007); Chung *et al.* (2006); Swicegood and Clark (2001); Ravi *et al.* (2008); Zhao *et al.* (2008); Boyacioglu *et al.* (2009); Jagtiani *et al.* (2003); Al-

			Osaimy and Bamakhramah (2004); Moin (2008)
	PR2	Net Income(Loss)/Average Shareholders' Equity	Chung *et al.* (2006); Zhao *et al.* (2008); Boyacioglu *et al.* (2009); Moin (2008)
	PR3	Net Income (Loss)/Average Share	Tung *et al.* (2004)
	PR4	Net Income before Tax/Average Total Assets	Chung *et al.* (2006); Zhao *et al.* (2008); Boyacioglu *et al.* (2009)
	PR5	Provision for Loan Losses/Loans	Tung *et al.* (2004)
	PR6	Provision for Loan Losses/Total Assets	Jagtiani *et al.* (2003)
Income-Expenditure Structured Ratios	**IE1**	Net Interest Income After Provision/Average Total Assets	Ravi *et al.* (2008)
	IE2	Interest Income/Interest Expenses	Zhao *et al.* (2008); Ravi and Pramodh (2008).
	IE3	Non-Interest Income/Non-Interest Expenses	Ravi and Pramodh (2008)
	IE4	Total Income/Total Expenses	Zhao *et al.* (2008); Moin (2008)
	IE5	Interest Income/Average Profitable Assets	Ravi and Pramodh (2008).
	IR6	Interest Expenses/Average Non-Profitable Assets	Ravi and Pramodh (2008).
	IE7	Interest Expenses/Average Profitable Assets	Ravi and Pramodh (2008).
	IE8	Interest Income/Total Income	Zhao *et al.* (2008)
	IE9	Non-Interest Income/Total Income	Ravi and Pramodh (2008)
	IE10	Interest Expenses/Total Expenses	Ravi and Pramodh (2008)

4.7.2 Second Empirical Chapter – Predicting Banking Distress: A Comparative Study on Islamic and Conventional Banks in Malaysia (Chapter 6)

The second empirical chapter analyses whether Altman's Emerging Market (EM) *Z*-score model can predict bankruptcy and at the same time measure the financial performance of Islamic and conventional banks in Malaysia. The main objective of this study is to introduce to the Malaysian banking industry the EM *Z*-score developed by Altman (2002) as a valuable analytical tool in finding the possible reasons that may lead to a deterioration of a bank's performance as well as providing an insight on Islamic and conventional performance. As opposed to the other empirical chapters, this research examines 13 Islamic banks and 10 conventional banks, during the period of 2005 – 2010 by using those banks' annual financial reports. This is significant since the study also look at the impact of the recent global crisis on Islamic and conventional banks in Malaysia. The methodology used in this chapter is based on the *Z*-score model for emerging markets developed by Altman (2002). Most of the previous studies have proved that the EM-score model has more than 80 percent accuracy and have confirmed that it is robust tool and valuable in assessing and predicting the potential distress condition of companies. In this study, the EM *Z*-score for each Islamic and conventional bank for the past three years has been calculated by examining the financial statements of each of these banks. By Applying the Emerging Market *Z*-score, this study investigated whether the EM *Z*-score model can predict the Islamic and conventional banks performance for a period of up to three years earlier.

The modified version of Altman's Emerging Market *Z*-score Model (Altman, 2002) is applied in the analysis, and the model is as follows:

$$Z'' = 6.56\,(X_1) + 3.26\,(X_2) + 6.72\,(X_3) + 1.05\,(X_4) + 3.25$$

Thus, any banks with score greater than or equal to 2.6 are considered as having a low probability of bankruptcy, a score below 1.1 is considered as having a high probability of bankruptcy, and a score between 1.1 and 2.6 is in the grey area. Table 4.5 below shows the definition and EM *Z*-score classification.

Table 4.5: Description and Classification of EM *Z*-score Model

Ratios	Description	Coefficient
X_1	Working Capital to Total Assets	6.56
X_2	Retained Earnings to Total Assets	3.26
X_3	EBIT to Total Assets	6.72
X_4	Net Worth to Total Liabilities	1.05
Cut-off value:		
Above 2.66	Safety Zone	
Between 2.66 and 1.1	Grey Area	
Below 1. 1	Distressed Area	

4.7.3 Third Empirical Chapter – Integrated Early Warning Prediction Model for Islamic Banks: Multiple Regression Analysis (MDA, Logit & Probit) (Chapter 7)

The third empirical chapter provides further significant results in modelling early prediction models for Islamic banks in Malaysia. This chapter is the continuation of the chapter Five by utilising all the financial ratios selected with some additional ratios as suggested in previous studies. Thus, for the purpose of this empirical chapter, 29 financial ratios have been selected and classified into seven categories. Management and leverage ratios were included in this chapter as suggested by a few researchers (refer to Chung *et al*., 2008; Moin, 2008). The proposed model includes most of the explanatory variables that have been applied in the previous studies as can be found in the literature or appeared in the previous literature. The additional financial ratios used in this research are given in Table 4.6 below.

Table 4.6: Selected Financial Ratios

Category	Ratios	Definition	Used By
Management	M1	Operating Expenses/Total Assets	Gunsel (2007); Ravi *et al.* (2008), Zhao *et al.* (2008), Boyacioglu *et al.* (2009).
	M2	Interest Expenses/Total Deposits	Gunsel (2007)
Leverage	LE1	Total Liabilities/Total Equity	Chung *et al.* (2006); Moin (2008)
	LE2	Total Liabilities/Total Assets	Chung *et al.* (2006); Moin (2008)
	LE3	Total Assets/Total Equity	Chung *et al.* (2006)

The selection of the variables that can help predict the bank failure is still an ongoing issue. In the early stage of developing the prediction model, accounting data has been used due to the public availability of the data. Nowadays, current researchers in this area have also included other available data in the prediction models, such as the capital market information from the stock or bond markets, credit rating, and deposit insurance premium. Some researchers have even included the macroeconomics variables assuming that the business cycle conditions also resulted in a bank distress condition. For the purpose of this study, the researcher will only focus on micro data in the form of financial data from the selected Islamic banks in Malaysia.

The Multivariate Discriminant Analysis, Logistic regression analysis, and probit analysis are employed in this research. As in the case of the explanatory variables, accounting data from the selected banks are used. Quarterly data for each Islamic bank has been used with the opinion that the high frequency of the availability of the relevant data will accurately reflect any changes in the financial condition of the banks.

This research attempts to build an integrated early warning prediction model for Islamic banks in Malaysia, based on three selected techniques: Multivariate Discriminant Analysis, Logistic Regression Analysis, and Probit Analysis. In other words, this research attempts to develop an insolvency prediction model based on multivariate discriminant analysis, logit analysis, and probit analysis to analyse the determinant of banks to become insolvent and also to test the predictive accuracy of these methods. Besides SPSS statistical software package, Eviews software has also been employed in analysing these ratios.

4.7.4 Fourth Empirical Chapter – Alternative Measures: Funding Mix, Deposits, Macroeconomics &Alternative Bank-Specific Variables (Chapter 8)

The final empirical research will be amongst the first studies investigating the Malaysian Islamic banks' funding structure in predicting their defaults. Besides the funding structure, the composition of deposits, macroeconomic variables as well as other alternative bank-specific variables were also taken into consideration in modelling the prediction model. The best alternative models were also recommended in this chapter based on the tests conducted on the models developed earlier. In addition to the previous literature review chapter, this empirical chapter looks in-depth at a few literatures that relate to the analysis of this study; *i.e.* literatures on default issues and deposit composition. Based on the previous study conducted by Bologna (2011) and statistics results by Aziz and Dar (2004), the logit model is used in this chapter. Table 4.7 below depicts the definition of variables used in the original models (Model 1), funding structure model (Model 2), and deposits structure model (Model 3). While, Table 4.8 gives some definition on the variables that are used in the robustness tests, by giving the list of alternative bank-specific variables as well as macroeconomics variables. Eviews software is used in this study.

Table 4.7: Definition of Variables Included in the Models

No.	Variable	Description
1	Asset Quality	Non Performing Financing / Total Financing
2	Capital Adequacy	Risk-Weighted Capital Ratio
3	Profitability	Net Income/Total Equity Ratio
4	Financing Rate	Base Financing Rate
5	Funding Structure	Financing / Deposit Ratio
6	*Mudharabah* Deposits	*Mudharabah* Deposits/Total Deposits Ratio
7	Non-*Mudharabah* Deposits	Non-*Mudharabah* Deposits/Total Deposits
8	Demand Deposits	Demand Deposits/Total Deposits Ratio
9	Savings Deposits	Savings Deposits/Total Deposits Ratio
10	General Investment Deposits	General Investment Deposits/Total Deposits Ratio
11	Special Investment Deposits	Special Investment Deposits/Total Deposits Ratio
12	Negotiable Investment Deposits	Negotiable Investment Deposits/Total Deposits Ratio

Table 4.8: Definition of Bank-specific and macroeconomic Variables used in the Alternative Models

Original Model Variable Name	Definition	Alternative Model Variable Name	Definition
Asset Quality	Non-Performing Financing Ratio	Asset Quality	Reserve to total Assets ratio
Capital Adequacy	Risk-Weighted Capital Ratio	Capital Adequacy	Tangible Common Equity Ratio
Profitability	Net Income to Total Equity Ratio	Profitability (ROA)	Net Income Before Tax to Total Assets Ratio
Lending Rate (BFR)	Base Financing Rate	Lending Rate (BFR)	Base Financing Rate
		GDP	GDP growth rate
		Inflation	Consumer Price Index
		Unemployment	Unemployment Rate

4.8 LIMITATIONS AND DIFFICULTIES OF THE RESEARCH

There is no perfect study and the present research study is no exception. Therefore, this section will discuss some limitations in this research, which include:

(i) The data collection method was limited to secondary sources of data. Only the quarterly financial data from the selected sample is used in this study.

(ii) The number of banks in the sample. Out of 17 fully-fledged Islamic banks only 10 Islamic banks were selected for this study with an expectation that these banks would represent the whole population of the Islamic financial institutions in Malaysia.

In addition to the limitations mentioned above, a few difficulties were encountered during the course of this research. These include:

(i) Assessing the Data

The publicly available data offers the researcher certain advantages over a high quality of data; therefore considerable time and expense can be saved. But, for certain cases, the data for the selected period of the research was not available online and this impacted the data collection process and the number of observations as well.

(ii) Absence of key variables.

Since secondary data entails the collection or the compilation of the financial data carried out by banks for reporting purposes, it may be that a few key variables for this research will not be available. For example, for the composition of assets and liabilities according to certain Islamic contracts, the researcher needs to resort to the notes of the accounts in the respective financial reports. Failure to examine the significance or otherwise of the theoretically important variables can be annoying when it emerges that those variables are among the important variables to differentiate between Islamic banking and conventional banking operations, and could be among the significant factors that affect the insolvency of Islamic banks.

(iii) Quality of secondary data

The researcher has no control over the quality of the data collected since it is publicly available data and subject to manipulation. The quality of data should never be taken for granted, and in some cases the data available may not meet the requirement of the researcher since it was compiled based on certain standard formats required by certain authorities.

4.9 CONCLUSION

Recent times have seen an increase in the number of prediction of business performance or failures studies. Discriminant analysis is one of the most utilised statistical techniques for the prediction of the performance of business firms. It was originally developed to classify certain variables into two or more pre-specified groups according to the most statistically significant distinguishing characteristics. The discriminant analysis technique usage is extended to the prediction of the status of such variables in the future, based on the results of the discriminant function several years before, mostly between one and two years prior to the performance or problem or failure occurrence, and the testing of the classification power of such a function (Altman and Brenner, 1981).

Discriminant analysis, though not the oldest technique for the evaluation and prediction of business performance, being superseded by the Financial Ratios Analysis, is more preferred to the latter because it gives a summary index of performance, takes into consideration the possible interrelationships among the independent variables as they explain the variations in the groupings of the dependent variable and last, but not least, the discriminant analysis can include other non-financial factors, such as managerial, political, or social factors, that may affect the behaviour of the dependent variable (Altman and Brenner, 1981; Sinkey, 1975).

Lately, discriminant analysis has also been applied to the prediction of the performance and/or failure of financial institutions, markets and instruments (e.g. commercial banks and investment companies, bond markets and investment portfolios among others). Although still undergoing fine-tuning improvements, so far the record of such studies is generally impressive. This was evident from the favourable scores they acquired in the statistical testing of their classification results and predictive powers (Altman and Brenner, 1981; Sinkey, 1975).

The focus of this research is on the continuing body of work that attempts to develop early warning systems for detecting deterioration in a bank's financial condition. While mandatory on-site examination provides supervisors with the opportunity to review all the information and to develop a periodic view of the institution's financial condition, supervisors need a means of identifying at-risk institutions so that supervisory actions can be taken during the period between examinations. Regulators currently have early warning system models, which attempt to flag troubled institutions that are likely to fail and can intervene whenever needed. However, as an important remark it should be emphasised that the model that is going to be developed in this study cannot and should not replace the judgement of experienced bank supervisors, rather it could assist them by providing objective information that can be useful in assessing the status of individual banks.

Chapter 5
EVALUATING THE PERFORMANCE OF ISLAMIC FINANCIAL INSTITUTIONS: DESCRIPTIVE QUANTITATIVE ANALYSIS

5.1 INTRODUCTION

This chapter provides a comprehensive descriptive analysis of selected financial ratios in terms of the estimated means and standard deviations for the selected Islamic banks in Malaysia. Financial ratios have been used as a practical way to keep track of a bank's financial condition. In monitoring the financial condition of the financial institutions, the CAMELS approach was used by many regulators around the world. The acronym CAMELS stands for; Capital Adequacy, Asset Quality, Management, Earnings, Liquidity, and Sensitivity to Market Risk. As far as this study is concern, most of the selected variables are from these categories.

A study by Gunsel (2007) has employed the multivariate logit model in order to identify the determinants of the likelihood of bank failure in Cyprus. The study used the CAMELS rating system in a bank failure model and found the CAMELS approach to be appropriate for identifying weaknesses specific to individual banks. The study also suggests that inadequate capital, poor asset quality, high interest expenses, low profitability, low liquidity and small asset size are among the significant variables that can determine the likelihood of failure in the case of Cyprus banks.

Another study that applied the CAMELS approach is by Nurazi and Evans (2005). The study investigates whether the CAMELS ratios can be used to predict bank failure in the Indonesian banking industry. Multivariate logistic regression was used to do the analysis due to its flexibility and it being relatively free of restrictions, and multivariate discriminant analysis was carried out to evaluate for consistency. The study found that logistic regression in tandem with multiple discriminant analysis could function as an early warning system for identifying bank failure. Furthermore, they found that among the variables that are statistically significant in explaining bank failure are equity capital to total assets, Earning before income tax to productive assets, net income to total assets, operating expense to operating income, cash and bank to total deposit, and the natural logarithm for bank size. Therefore, these variables should be taken into consideration in identifying and solving the problems in banks.

As discussed in the previous chapter, due to the absence of any theory to guide the selection of the variables, this study takes an informal approach to the selection of financial ratios as potential indicators of insolvency. The selection of the ratios is based on a few categories as follows:

(i) The selection of ratios are based on the predictive variables used in the previous studies,

(ii) The selected ratios have some potential in this study, and

(iii) The availability of data from the selected sample of banks.

It may be the case that some of the important data needed for the models are inaccessible to the researcher, thus the decision to exclude some of the ratios is inevitable.

5.2 DESCRIPTIVE ANALYSIS

Considerable attention has been devoted to financial ratio analysis for classifying failed and non-failed companies, or for assessing the business performance of a company, and as in this case for the Islamic banks in Malaysia. This section discusses in detail the descriptive analysis by means of the selected ratios for the whole sample after defining the meaning of each ratio.

5.2.1 Capital Ratios

Capital adequacy is a measurement of a bank to determine if solvency can be maintained due to risks that have been incurred as a course of business. Capital allows a financial institution to grow, establish and maintain both public and regulator confidence, and also provide a cushion to be able to absorb any future potential losses. Earlier studies by Gunther (1995) and Thomson (1991), as discussed in the literature review chapter, use various balance-sheet and income statement variables in developing their early warning models to predict bank failure. It was found that capital adequacy is highly significant in those models.

Among the key ratios for examining capital adequacy, as mentioned in the Basel II framework, are: equity capital ratio, Tier 1 leverage ratio, Tier 1 risk-based capital ratio, Tier 2 risk-based capital ratio or Tier risk capital ratio, and Taxes ratio. Further details on these ratios can be found in the Basel II Capital Accord.

A study by Estrella *et al*., (2000) compares the effectiveness of different types of capital ratios in predicting bank failure. They found that the simple ratios, such as the leverage ratio and the ratio of capital to gross revenue, are able to predict bank failure as well as the more complex ratios such as risk weighted ratios over a longer time period. Their finding suggests that bank regulators may find that these simple ratios contain useful information required in designing the regulatory capital framework, specifically as an indicator of the need for prompt supervisory action.

For this study, the capital ratios selected are based on the variables that have been used in the previous research.

5.2.1.1 Capital Ratio 1 (CR1)

CR1 as the initial ratio shows the fraction of total assets that has been financed by equity and total income, and is calculated as follows:

CR1= (Shareholders' Equity + Total Income) / Total Assets

In addition, this ratio also shows the fraction that has been financed by loans and other non-equity shares. A high equity and total income to assets ratio means that a big fraction of capital consists of equity, whilst a lower ratio means much of the business is financed by loans or other non-equity shares. Thus, for analysis purposes, the higher the ratio the better, due to the fact that the operation is financed by equity as opposed to loans or other non-equity shares which is more risky.

5.2.1.2 Capital Ratio 2 (CR2)

CR2 shows the proportion of total deposits as compared to the equity and total income, as is calculated in the following format:

CR2= (Shareholders' Equity + Total Income) / (Deposits and non-deposit Funds)

In this case, a high equity and total income to total deposits ratio means a bank does not depend on loans or non-equity shares to cover for any sudden withdrawal by depositors. A lower ratio means a bank will need to resort to loans or other non-equity shares to cover for sudden withdrawal by depositors. The higher the ratio the better for the bank solvency.

5.2.1.3 Capital Ratio 3 (CR3)

Net working capital to total assets is defined as the net current assets of a bank expressed as a percentage of its total assets, and is calculated as follows:

CR3 = Net Working Capital / Total Assets

Working capital measures the financial health of a particular business based on the current cash flow. Generally, net working capital is calculated by subtracting the current liabilities from the current assets. On the other hand, total assets can be defined as a combination of cash, account receivable, marketable securities, and other cash equivalents. Thus, the net working capital to total assets ratio can be used to measure the bank's ability to cope with its financial obligation. A positive net working capital to total assets ratio means the bank is operating efficiently and vice versa.

5.2.1.4 Capital Ratio 4 (CR4)

Another ratio worth discussing in this chapter is the equity and total income to total assets including contingencies and commitments. This ratio shows the proportion of total assets including contingencies and commitments to the equity, and is calculated in the following format:

CR4 = (Shareholders' Equity + Total Income) / (Total Assets + Contingencies and Commitments)

A high equity and total income to total assets including contingencies and commitments means a bank does not depend on loans or other non-equity shares to cover for any obligations due or for emergency purposes.

5.2.1.5 Capital Ratio 5 (CR5)

A bank capital to asset ratio is a measure for estimating how much capital a bank needs to maintain as a cushion against credit risks. In other words, it is a measure of a bank's financial condition and should be maintained at a certain level as prescribed in Basel II. Capital ratios measure the amount of a bank's capital in relation to the amount of risk it is taking. The main idea, as detailed in Basel II, is that all banks must ensure that a certain percentage of their risk is covered by their permanent capital. This ratio is calculated as follows:

CR5 = Capital/Assets

This ratio is expected to be negatively related to the probability of failure. Thus, the higher the capital to assets ratio a bank has, the greater the level of unexpected losses it can absorb before becoming insolvent, in other words the less risky it should be. In other words, the higher this ratio is indicates that there is sufficient capital to absorb unexpected losses, hence the lower the probability that the bank will fail.

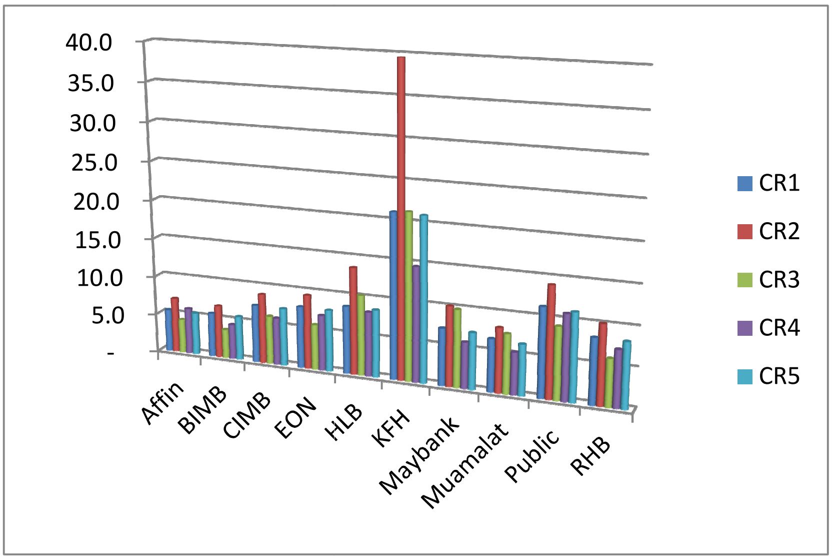
Another capital ratio that is worthy of mention is the ratio of total loans to total equity capital. As a matter of fact, any increase in the value of non-performing loans or financing may lead to a significance decrease in bank capital.

The estimated capital ratios for the sample Islamic banks in Malaysia are presented in table 5.1.

Table 5. 1: Mean Values of Selected Capital Ratios (Dec 2005 –Sept 2010)

Banks	CR1	CR2	CR3	CR4	CR5
Affin	5.5	7.1	4.3	5.9	5.4
BIMB	5.7	6.7	3.7	4.5	5.6
CIMB	7.4	8.9	6.2	6.0	7.4
EON	7.9	9.5	5.8	7.1	7.9
HLB	8.7	13.7	10.3	8.2	8.6
KFH	21.1	39.5	21.3	14.6	21.0
Maybank	7.3	10.2	9.9	5.9	7.2
Muamalat	6.7	8.2	7.6	5.4	6.5
Public	11.4	14.1	9.2	10.9	11.2
RHB	8.4	10.1	6.0	7.2	8.3

Figure 5.1: Capital Ratios



By looking at the results from the ratios calculated for the selected banks in Table 5.1 and Figure 5.1, it can be concluded that most of the samples have about the same average mean in each ratio. The conspicuous difference in this case is the mean ratios for the Kuwait Finance House. The means for all four ratios under this category have shown a significant difference as compared to the mean for other banks. In fact, the most significant difference is in the shareholders' equity and total income to deposits and non-deposit funds. Ideally, the higher this ratio is for Islamic banks delineates that Islamic banks can provide a better equity buffer against any claim on liabilities, especially during economic downturns where depositors panic about losing their savings and will try to evacuate all their savings, which is also known as 'bank run'.

This result connotes that the KFH does have a higher figure of equity and income as compared to total deposits, and in fact the KFH is the largest Islamic bank in terms of capital. The KFH started their operation five years ago, with their targets more on wholesale banking instead of retailing, which is shown in the lower figure of deposits and non-deposit funds. Under their new five-year plan which ends in 2014, the KFH target is to grow in both retail and wholesale banking.

The recent financial stability report issued by Bank Negara Malaysia 2010 has reported that the Risk Weighted Capital Ratio (RWCR) for the Islamic banking system in Malaysia has decreased from 15.6% in 2009 to 14.9% in 2010. Likewise, the Core Capital Ratio has decreased from 13.2% to 12.7% during the same period. According to the guidelines issued by Bank Negara Malaysia on the Risk Weighted Capital Adequacy Framework for Islamic Banks, for Islamic banking licensed under Banking and Financial Institutions Act 1989 (BAFIA) with Islamic banking operations, the minimum RWCR of 8% has to be complied with at the conventional banking, Islamic banking, and overall entity level.

5.2.2 Asset Quality Ratios

Asset quality evaluates risk, controllability, adequacy of loan loss reserve, and acceptable earnings; and the effect of off-balance sheet earnings and loss. The quality of the bank assets depends on the ability of the bank to collect it during and at maturity. In other words, as loans are one of the main types of asset with a high default risk, an increase in the number of non-performing loans will have a big impact on the quality of the bank's assets. If this figure keeps increasing it may cause a big impact on the bank's assets quality, affecting the bank's profitability and the capital of the bank. In fact, all these may lead to bank failure.

It is also necessary for the bank to determine the liquidity and maturity structure of their assets. Ideally, banks invest in assets in order to earn some returns. But checks and balances on how those assets are performing need to be conducted in order to avoid mismatch and liquidity problems in the future.

The assets of a bank are: cash, trading portfolio, securities available for sale and held to term, loans of various maturities, and fixed assets.

Among the key ratios for examining asset quality, as mentioned in the Basel II Capital Accord, are: Loan-loss reserve to total loans ratio, Coverage ratio, Overdue loans to total loan ratio, 90-day Overdue loans to total loans ratio. For this study, the researcher will focus more on the ratios that have been mentioned in the previous research.

5.2.2.1 Asset Quality Ratio 1 (AQ1)

This ratio is utilized to measure the quality of assets and is calculated as follows:

AQ1 = Total Financing / Total Assets

One of the main concerns in a bank is the growth in the riskiest assets that may cause the bank to underestimate non-performing financing. Higher leverage may be reflected on poorer asset quality. Consequently, an increase in the total financing to total assets ratio is likely to increase the probability of bank failure. In other words the higher the total financing to total assets ratio, the more risky the bank. The higher the ratio denotes that higher total assets are tied to net financing. This ratio should be as close to 1 as possible, but any figure that is bigger than a 1.1 ratio indicates that the bank gives more financing than it has in deposits.

5.2.2.2 Asset Quality Ratio 2 (AQ2)

Non-performing financing, also known as non-performing loans, is a form of financing that is no longer producing income for the bank that owns the loans. Generally, financing becomes non-performing when borrowers stop servicing their financing and the financing becomes default. The exact classification of non-performing financing may vary from one jurisdiction to another. In the Malaysian banking system, financing is considered to be non-performing after it has been default for three consecutive months.

This ratio is reported by banks as a measure of the quality of their outstanding financing and it indicates the percentage of non-performing financing a bank has on its books and is calculated as follows:

AQ2 = Non-performing Financing / Total Financing

Ideally, this ratio should be a small percentage and a figure of more than 10 percent indicates that the bank does have serious problems in collecting their debts. A smaller ratio indicates smaller losses, while a higher ratio means higher losses for the banks, thus increasing the probability of bank failure. In fact, this also means larger losses for the banks since the banks will have to write off bad financing.

5.2.2.3 Asset Quality Ratio 3 (AQ3)

This ratio presents the percentage of permanent assets relative to the total assets of the bank and is calculated in the following format:

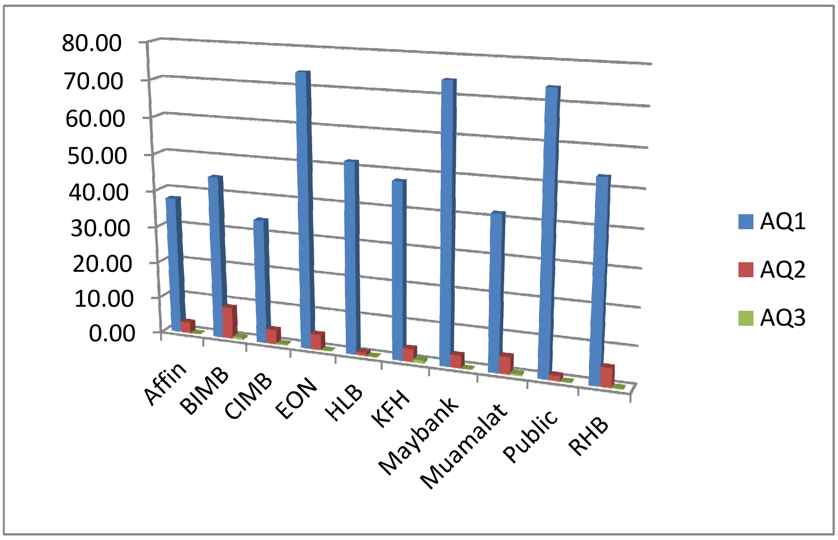
$$AQ3 = Permanent\ Assets\ /\ Total\ Assets$$

Table 5.2 depicts the mean values of assets quality ratios for the sampled banks.

Table 5. 2: Mean Values of Selected Assets Quality Ratios (Dec 2005 – Sept 2010)

Banks	AQ1	AQ2	AQ3
Affin	37.71	2.88	0.03
BIMB	44.59	8.64	0.54
CIMB	33.98	3.88	0.29
EON	74.03	4.14	0.05
HLB	51.83	0.83	0.03
KFH	47.81	3.48	0.74
Maybank	74.21	3.35	0.00
Muamalat	41.74	4.71	0.40
Public	73.96	1.30	0.00
RHB	53.15	5.17	0.19

Figure 5.2: Asset Quality Ratios



As depicted in Table 5.2 and Figure 5.2, after analysing these three ratios for assets quality it can be concluded that among all the selected banks, with regards to the mean for non-performing financing to financing and of permanent assets to total assets, there was not much difference between them. The significant difference in this category of ratio is on the total financing to total assets ratio for three selected banks, EonCap Islamic Bank, Maybank Islamic and Public Islamic Bank, which shows a tremendous difference in means as compared to the others. This may be due to the high figure of total financing of those banks, which is likely increase the probability of the bank's failure. The main concern of most of the banks is the growth in their riskiest assets that consequently may cause them to underestimate non-performing financing. If that is the case here, those banks should review their policy on financing.

According to the 2010 Financial Stability Report issued by Bank Negara Malaysia, the total financing allocated by the Islamic banking industry in Malaysia increased from RM186.86 billion at the end of 2009 to RM222.28 billion at the end of 2010; this is equivalent to 22.7% of the market share. As at the end of 2010, the total outstanding banking system financing increased by 12.7% at the end of 2009 to RM883.3 billion, equivalent to 115.3% of the gross domestic product (GDP). The total outstanding financing to both business and households has recorded a robust growth of 9.4% and 13.4% respectively (BNM Financial Stability Report, 2010).

Similarly, in terms of the market shares of assets, deposits and financing for the total banking sector in Malaysia, the Islamic banking industry has reached a remarkable average of just over 22% at the end of 2010, which is well above the 20% target set by the Financial Sector Master Plan of Malaysia for the Islamic banking sector. Furthermore, the net non-performing financing ratio reported in the Financial Stability Report issued by the Bank Negara Malaysia has shown a slightly decreased percentage at the end of 2010 as compared to the previous year, that is 2.2% at the end of 2009 to 2.0% at the end of 2010 (BNM Financial Stability Report, 2010).

5.2.3 Liquidity Ratios

The liquidity position of a bank is when the bank is able to meet certain financial obligations. In other words, the bank has the ability to repay their depositors and other creditors without incurring too much cost. Sometimes this is also referred to as liquidity risk which arises because the bank issues short-term liquid liabilities to fund longer-term financing that is less liquid. The major source of funding for banks is their customers' deposit accounts. This is the least expensive source of fund as compared to the more expensive sources of funds such as borrowing funds or liquidating investment securities portfolios.

Generally, the term liquidity refers to the bank's cash, securities, a bank's ability to convert an asset into cash, and their unused lines of credit position. The faster the conversion, the more liquid are the bank's assets. On the other hand, illiquidity risk is the concern of most of the banks. Illiquidity means the bank is unable to convert their assets into cash during a crucial period. Banks need to make sure that they are able to meet their obligations whenever needed. In fact it is poor liquidity, as opposed to poor asset quality or inadequate capital, which leads to most bank failures.

Liquidity ratios are expected to be both positively and negatively related to the likelihood of bank failure. On the one hand, a high ratio of liquidity may suggest to the depositors that the bank is liquid, thus increasing the depositors confidence towards the bank. In fact, this can also be related to a lower probability of bank failure. On the other hand, higher liquidity can be described in terms of the weak financial investment activities of a bank, thus increasing the probability of bank failure. To measure the overall liquidity risk two ratios are used in this study, i.e. the ratio of liquid assets to total assets, and the ratio of liquid assets to total deposits.

5.2.3.1 Liquidity Ratio 1 (LR1)

The first liquidity ratio is the ratio of liquid assets to total assets (LR1) and can be calculated in the following format:

$$LR1 = Liquid\ Assets / Total\ Assets$$

A liquid asset is defined as the cash and short-term funds, deposits and placement with other banks and financial institutions, and the securities available for sale. This LR1 ratio means that the higher the ratio of liquid assets to total assets implies a greater capacity to discharge bank liabilities. Thus, the lower the ratio means the higher the probability of bank failure. This ratio is an important liquidity management tool on an ongoing basis as it measures the extent to which liquid assets can support the bank's asset base. Thus, a low liquid asset to total assets ratio can be hazardous to the bank's financial health and survival.

5.2.3.2 Liquidity Ratio 2 (LR2)

The second liquidity ratio selected for this study is the ratio of liquid assets to total deposits (LR2) calculated as follows:

LR2 = Liquid Assets / (Deposits and Non-deposit Funds)

A bank with more liquidity is in a better position to deal with any unexpected deposit runs. Among the major risks faced by banks is liquidity risk. This liquidity risk can be defined as the risk that depositors will withdraw a large amount of their deposits, thus leaving a bank with the problem of not having enough liquid assets to cover depositors' withdrawals. It will not be the case if banks have enough liquid assets to cover such unexpected withdrawals by depositors. In other words, when the amount of liquid assets is great enough it will save the bank from the liquidity problem mentioned here.

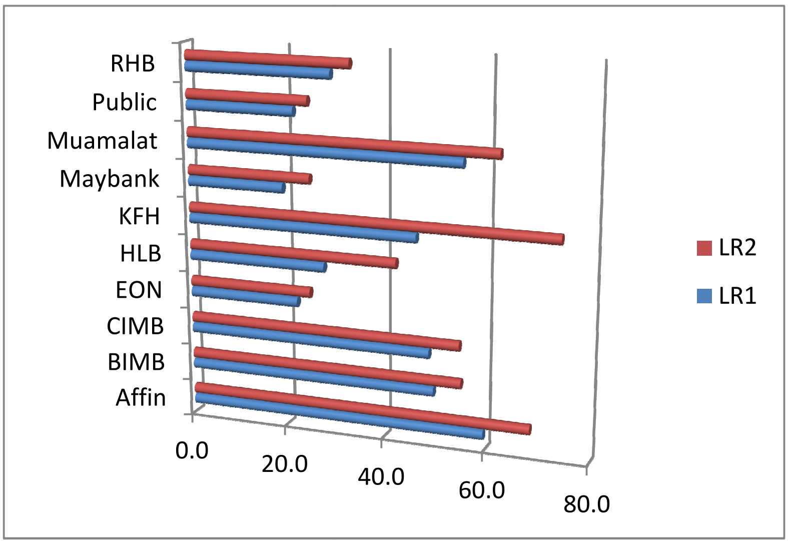
In the case of a company, their ability to turn short term assets into cash to cover their debts is of the greatest significance when their creditors are asking for their payments. Liquidity ratios were frequently used by bankruptcy analysts and mortgage originators to determine the survival of a company. Thus, the higher the ratios, the lower the probability that the company is a going concern due to the larger margin of safety that the company has to cover its short term debts.

The mean values of the the two selected liquidity ratios are presented in Table 5.3.

Table 5.3: Mean Values of Selected Liquidity Ratios (Dec 2005 – Sept 2010)

	LR1	LR2
Affin	59.5	68.5
BIMB	49.7	55.1
CIMB	48.8	54.8
EON	22.2	24.9
HLB	27.8	42.2
KFH	46.2	73.8
Maybank	19.5	25.0
Muamalat	55.2	62.2
Public	21.8	24.7
RHB	29.4	33.1

Figure 5.3: Liquidity Ratios



The third category of analysis focuses on the liquidity ratios, liquid assets to total assets and liquid assets to total deposits and non-deposit funds. Figure 5.3 shows that there are three banks having higher means on these ratios, *i.e.* Affin Islamic Bank, Kuwait Finance House, and Bank Muamalat. This means that those banks are more liquid than the rest of the Islamic banks. In other words, these Islamic banks have a larger margin of safety to cover their short-term obligations than the rest of the banks. It is suggested that those banks with lower LR1 and LR2 should be monitored closely due their lower liquidity position.

In general, out of ten banks selected for this study, three of these banks showed a good liquidity position as compared to the others. But, it is worth discussing in detail this liquidity position for certain banks. The significant difference in liquidity ratios for KFH as compared to the other banks can be specifically attributed to their operation during the early years of their establishment in Malaysia when they only focused on wholesale banking and thus not much in the way of deposits or non-deposits funds was involved here.

Generally, by looking at the above average ratios, it can be construed that Islamic banks seem to have a reasonable liquidity position. According to Haron (2004), Islamic banks experienced excess liquidity given the lack of Islamic financial instruments in the market for Islamic banks to invest. Similarly, higher liquidity may be due to the stringent financing of Islamic banks such that Islamic banks must comply with *Shari'ah*, contrasting with the practice of conventional banks.

5.2.4 Profitability Ratios

Profitability determines the ability of a bank to increase capital through retained earnings, absorbing loan losses, supporting the future growth of assets, and providing a return to investors. For most of the banks, the largest source of income is the net interest revenue, or net profit, from the financing activities. Other sources of income for the bank come from various activities such as investment, foreign exchange trading, and commission or transaction fees.

There is a requirement for the banks to charge provisions for loan losses against earnings which can also reduce the banks' profitability. It is the responsibility of the banks' management to look at what types of loans are in the portfolio, the performance of such a portfolio as well as the economic conditions. In some cases, if the economic conditions are deteriorating and the bank does not provision for anticipated losses in order to maintain profitability then problems may develop during the next fiscal period and vice versa.

Ideally, earning is among the most important component in measuring the performance of a bank. Among the well known ratios under this category to measure the profitability of banks are the ratio of net income to total assets (well known with return on assets) and the ratio of net interest income to total assets. The higher of these ratios will be negatively related to the probability of failure. In other words, the higher these ratios are the lower the probability that the bank will fail.

This category of ratios measures the company's ability to generate earnings and this profit is one of the important sources of funds from the company's operation. The more the profit generated by the bank's operation, the higher will be the source of funds as well as the liquidity position of the bank. Based on a previous study, many companies face financial distress when they have negative profits and they found that profit is often used as one of the predictors in developing their financial distress prediction models (Khunthong, 1997).

Among the key ratios for examining profitability as detailed in the Basel II framework are; Net interest margin, Return on average assets, Return on average equity, Return on earning assets, Operating profit margin, Non-interest income to average assets ratio, average collection of interest, overhead ratio, and efficiency ratio. For this study, six types of profitability ratios are used, namely: Return on assets, Return on Equity, Return on average share, Income before Tax to total assets, Provision for financing losses to total financing and provision to financing losses to total assets.

5.2.4.1 Profitability Ratio 1 (PR1)

Net Income is the net operating income after taxes and zakat. Average total assets are the assets for the last four quarters divided by four, for a given fiscal year. The PR1 ratio, generally known as the return on asset ratio (ROA), measures how profitable a bank is relative to its total assets, and is calculated as follows:

$$PR1 = Net\ Income\ (Loss) / Average\ Total\ Assets$$

ROA gives an idea as to how efficient the bank is in managing its assets to generate income. In other words it tells us what incomes were generated from invested capital. For the investors, the ROA figure gives an idea of how effectively the company is converting the money it has to invest into net income. The higher this ratio, the better, because then the bank is earning more profit on less investment.

As discussed in Altman (1968), earnings before interest and taxes to total assets is a measure of the true productivity of the firm's assets independent of any tax and leverage factors and it was found that ROA is a significant factor in explaining financial failure. This finding is supported by other studies conducted by Altman, Haldeman, and Narayanan (1977). Martin (1977) and Thomson (1991) are among those researchers who concluded that the ratio of net income to total assets is negatively related to the probability of failure which means that by holding all other variables constant, an increase in the ratio of net income to total assets can be expected to decrease the probability of failure.

5.2.4.2 Profitability Ratio 2 (PR2)

The average shareholders' equities are the total of shareholders' equity for four quarters for a given fiscal year divided by four. The PR2 ratio is particularly important because the vital objective of bank management is to maximise their shareholder wealth. The net income definition is the same as mentioned above but for the Shareholders' equity, it does not include preferred shares.

This ratio measures the ability of the bank to expand capital internally and pay a dividend and is calculated using the following format:

PR2 = Net Income (Loss) / Average Shareholders' Equity

It is also a measurement for return on the shareholders' equity, although this is not considered as an effective measure of earnings performance from the bank's point of view. Generally known as return on equity, this ratio measures how much profit can be generated with the money shareholders have invested. Thus, the higher this ratio is, the better because then the bank is earning more profit from the invested shareholders' money.

5.2.4.3 Profitability Ratio 3 (PR3)

Return on equity may also be calculated by dividing the net income by the average share. The average share is calculated by adding the total of shares (common and preferred shares) for the four quarters during the given fiscal year and dividing by four (four quarters). This is the measure of operations as if the operations were totally funded by equity. Thus, the higher the PR3 ratio is the better, because the bank is then earning more profit from the invested money in common and preferred shares. This ratio is calculated using the following format:

PR3 = Net Income (Loss) / (Common Stocks and Preferred Stocks/4)

5.2.4.4 Profitability Ratio 4 (PR4)

The next ratio selected for this research is the net income before tax divided by the average assets, and is calculated as follows:

PR4 = Net Income Before Tax/Average Total Assets

The main difference here, as compared to the previous return on asset ratio, is that the net Income figure is the net operating income before taxes and zakat. Average total assets are the assets for the last four quarters divided by four, for a given fiscal year. Thus, the higher the PR4 ratio, the better, because the bank is then earning more profit before tax and zakat on less investment.

5.2.4.5 Profitability Ratio 5 (PR5)

Provision for financing losses is a reserve account created to cover for the unexpected defaults on financing by borrowers. These are generally referred to as non-performing financing or non-performing loans from the conventional banks' perspective. The higher the non-performing financing figure, the higher will probably be the provision for financing loss. Although this might guarantee a bank's solvency and capitalisation if and when the defaults occur, it will also reduce the net income and earnings per share of the bank. A bank making a high number of risky financing moves will have a high financing loss provision as compared to a bank with a smaller number of risky financing options.

The higher the PR5 ratio means that a bank is protecting itself from insolvency by having a high financing loss provision. Thus, the higher the provision for financing losses to financing ratio, the better it is for bank's solvency. PR5 is calculated as follows:

PR5 = Provision for financing Losses/Total financing

5.2.4.6 Profitability Ratio 6 (PR6)

Another ratio which is quite similar to the previous ratio is provision for financing losses divided by total assets, as calculated in the following format:

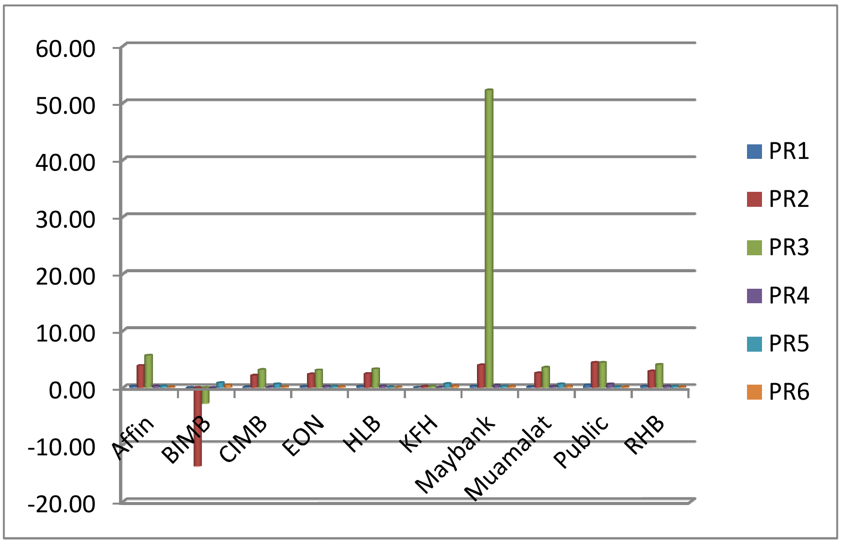
$$PR6 = Provision\ for\ financing\ Losses/Total\ Assets$$

The main difference is the denominator for the ratio. Instead of total financing, this denominator is replaced with total assets. The higher the non-performing financing is, the higher the provision for financing losses should be. Consequently, this also will have an effect on the earnings of the banks. A higher ratio is better for the bank's solvency. The estimated profitability ratios are depicted in Table 5.4.

Table 5.4: Mean Values of Selected Profitability Ratios (Dec 2005 – Sept 2010)

	PR1	PR2	PR3	PR4	PR5	PR6
Affin	0.23	3.86	5.65	0.30	0.30	0.12
BIMB	-0.17	-13.79	-2.78	-0.14	0.83	0.46
CIMB	0.11	2.14	3.15	0.08	0.63	0.18
EON	0.19	2.38	3.06	0.26	0.25	0.18
HLB	0.21	2.44	3.28	0.29	0.10	0.05
KFH	0.02	0.22	0.25	0.04	0.67	0.33
Maybank	0.28	3.96	52.22	0.38	0.28	0.21
Muamalat	0.15	2.56	3.54	0.22	0.63	0.26
Public	0.45	4.39	4.39	0.62	0.15	0.11
RHB	0.24	2.87	4.05	0.30	0.24	0.13

Figure 5.4: Profitability Ratios



As can be seen from Table 5.4 and Figure 5.4 above, on average there is not much significant difference in the mean of the profitability ratios for all banks except in two cases. In the case of BIMB, the bank reported a loss before zakat and tax in two consecutive years. During FY2005, the bank reported a total loss of nearly RM500million and in FY2006 a total loss of RM1.28 billion. These losses have been considered among the biggest for local banks in recent years. The bank has been reported has having RM1.16 billion of non-performing financing on its books, which is more than double than the industry average. This is proved by the figure shown on the ROE for the bank. This is an indicator about how BIMB is managing its equity and its ability to generate profits as a percentage of this equity. In other words, the ROE measures the amount of profit that the banks generate with the money shareholders have invested. The bank bounced back during FY2007 with a profit before zakat and tax of RM255.49 million, recorded as the highest profit ever in its 24 years history thus marking the bank's full recovery from the previous two years' of losses. The bank performance improved significantly and began earning positive returns on equity rather than negative returns during FY2005 and FY2007.

In contrast to the performance of BIMB and all other banks in the study sample, Maybank Islamic Berhad has shown a magnificent performance throughout the study period. In the banking sector in general, a low equity ratio signalled an increase in bankruptcy risk as less equity is available to cover the demand for funds and deposit withdrawal and vice versa.

In the case of KFH, the bank has reported losses for six consecutive quarters prior to the fourth quarter of 2010. And this is due to the more challenging operating environment in 2010, as the group and the bank moved forward with their business realignment and restructuring plans in early 2010.

The Financial Stability Report 2010 issued by Bank Negara Malaysia reported that the Return on Assets for the Islamic banking sector has decreased from 1.3% at the end of 2009 to 1.2% at the end of 2010 (BNM Financial Stability Report 2010). For the Islamic banks, the lower ROA and ROE are due to the low net financing and asset quality that they have, which demand close monitoring by regulators. In fact, the higher provision for financing losses may give some impact on the bank's profits.

5.2.5 Income-Expenditure Structured Ratios

The final category of ratios selected for this study is the income-expenditure structured ratios. Under this category five ratios have been selected for further research, namely: net interest income after provision to average total assets, interest income to interest expenses, total income to total expenses, interest income to total income, and interest expenses to total expenses.

5.2.5.1 Income-Expenditure Structured Ratio 1(IE1)

Net interest income can be defined as the difference between the income generated by the banks interest bearing assets and the expenses that the banks have to bear in servicing their liabilities. In other words, net interest income is the difference between the interest payments the bank receives on loans outstanding and the interest payments the bank makes to customers on their deposits. The assets for banks include commercial and personal loans, mortgages, and other types of loans. On the other hand, banks liabilities consist mainly of customers' deposits.

It is expected that a higher IE1 ratio will be negatively related to the probability of a bank's failure. A higher ratio is better for the bank's financial condition, thus avoiding insolvency. IE1 is calculated as follows:

IE1 = Net Interest Income After Provision/Average Total Assets

5.2.5.2 Income-Expenditure Structured Ratio 2 (IE2)

Interest income, as defined above, is the interest payments that the bank receives on loans outstanding, and interest expenses are the interest payments the bank makes to their existing depositors. This IE2 ratio measures the fraction of interest income that the bank receives as against the total interest that the bank has to make to their depositors, as calculated using the following format:

IE2 = Interest Income/Interest Expenses

A higher ratio is better for the banks' performance.

5.2.5.4 Income-Expenditure Structured Ratio 4 (IE4)

The third type of ratio under this category is IE4 and is calculated as follows:

IE4 = Total Income/Total Expenses

Total income includes not only the interest income but also other non-interest income. Sources of non-interest income include fees for services, penalty charges, asset sales, property leasing and others. Unlike interest income, this type of income is unlikely to be affected by the economic and financial market cycle and is generally not controlled by law or regulation. On the other hand, total expenses consist of not only the expense associated with attracting and keeping their depositors' funds but also include almost all operating and overhead expenses such as salaries and employee benefits, insurance, operation and maintenance of facilities, equipment, furniture, and vehicles.

5.2.5.5 Income-Expenditure Structured Ratio 8 (IE8)

Interest income is the interest payments that the bank receives on loans outstanding, and total income is defined as the interest and non-interest income that the bank receives. This ratio measures the fraction of income that the bank receives from their interest bearing assets to the total income that includes interest and non-interest income, and is calculated in the following format:

IE8 = Interest Income/Total Income

A higher ratio is better for the bank's health.

5.2.5.6 Income-Expenditure Structured Ratio 10 (IE10)

And finally, the last type of ratio under Income-Expenditure Structured ratios is IE10 and is calculated as follows:

IE10 = Interest Expenses/Total Expenses

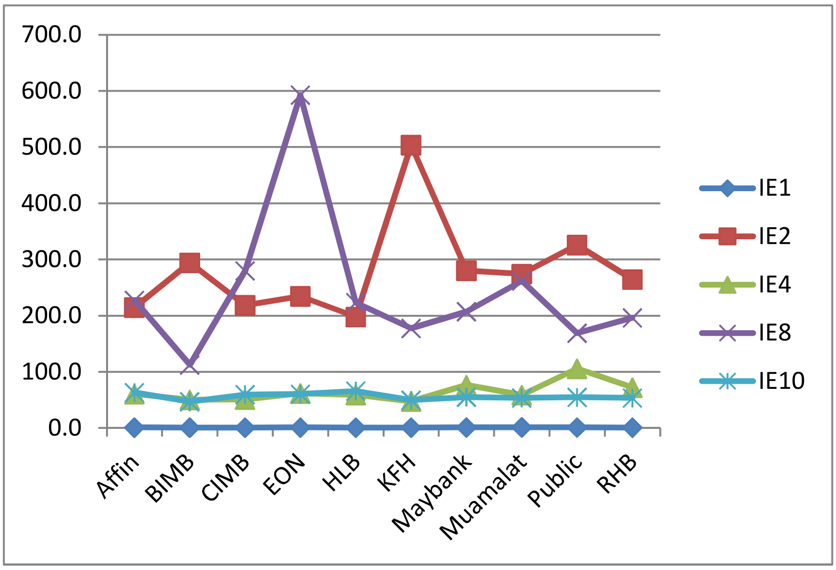
The Interest expenses to total expenses ratio measures the proportion of the total expenses that the bank has to spend in order to keep their depositors' fund as well as attracting more depositors.

The estimated income-expenditure structured ratios are presented in Table 5.5:

Table 5.5: Mean Values of Selected Income-Expenditure Structured Ratios (Dec 2005-Sept 2010)

	IE1	IE2	IE4	IE8	IE10
Affin	1.1	214.6	60.8	227.6	63.3
BIMB	0.9	294.4	50.6	112.6	47.0
CIMB	1.0	218.9	51.2	280.0	59.8
EON	1.2	61.9	61.9	592.8	60.5
HLB	1.1	197.8	59.2	223.4	66.0
KFH	1.1	503.6	47.8	177.5	49.8
Maybank	1.2	280.4	76.8	207.5	55.2
Muamalat	1.5	274.3	59.1	262.0	53.9
Public	1.2	325.9	105.8	169.1	54.9
RHB	1.1	264.5	72.2	196.3	53.7

Figure 5.5: Income-Expenditure Structured Ratios



The final analysis in this chapter is an analysis of the mean performance of income-expenditure structured ratios for the selected banks. As depicted in Table 5.5 and Figure 5.5, the IE1, IE4 and IE10 have shown a consistent performance among the sample banks. The interest income to interest expenses and interest income to total income ratios, shows various performance among the banks as compared to the abovementioned ratios. The interest income to interest expenses ratio measures the percentage of interest income that the bank receives from their outstanding financing as against the total interest that the bank needs to pay out to their existing depositors.

And the interest income to total income ratio measures the fraction of income that the bank receives from their interest bearing assets to the total income that includes interest and non-interest income. Thus, the higher these two ratios are is better for the bank's health.

The significant difference in the interest income to interest expenses ratio for KFH, as compared to the other banks, can be specifically attributed to the low interest expenses since the bank was involved more in wholesale banking during their early years of operations.

5.3 CONCLUSION

Generally, financial ratios have been used as a cost efficient and practical way of keeping track of a bank's financial condition. Various studies have utilised statistical techniques with financial ratios in examining corporate bankruptcy or financial distress since the late 1960s. Sinkey (1975), Meyer and Pifer (1970), Martin (1977), Espahbodi (1991), and Thomson (1991) are among those who have employed financial and accounting information as ratio analysis, and found that the financial and accounting information is an efficient way of showing the characteristics of failed and non-failed financial institutions. Amongst the most widely used bank-specific indicators are financial ratios that have been used to measure CAMELS's six categories of information.

Since there is little agreement among researchers regarding the best accounting ratios in predicting financial failure, most researchers who use financial ratios in their prediction models take an ad hoc approach by selecting the ratios based on their popularity in the literature. In other words, there is no basic rule or theory for choosing which variables to be included in the study. Furthermore, in the case of the Islamic banking industry in Malaysia, there was very little information about bankruptcy due to the industry being in its infancy. In fact, there is no figure on bankruptcy in Islamic banking in Malaysia: only the low performance of the banks was reported. Most of the bankruptcy studies were about bankruptcy in the US, Latin America, UK and Australia banking industries.

This chapter, so far, provided a comprehensive description of selected financial ratios in terms of the estimated means and standard deviations for the selected Islamic banks in Malaysia. From the finding on Capital ratios, most of the samples have about the same average mean in each ratio except for the Kuwait Finance House. These results imply that the KFH does have a higher figure in equity and income as compared to total deposits due to the fact that the KFH started their business operation in Malaysia focused only on wholesale banking instead of retail, thus having a lower figure for deposits and non-deposit funds.

In terms of asset quality ratios, it can be concluded that among all the selected banks, there was not much difference between the mean of non-performing financing to financing and of permanent assets to total assets. But, there was a significant difference in total financing to total assets ratio for three banks, and this could be due to the high figure in total financing for those banks. The main concern is the quality of the financing. A lower quality of financing can be depicted by higher non-performing financing which in turn attracts higher unearned income and loan loss impairment. The higher unearned income and loss impairment may result in lower profitability.

Findings from liquidity ratios show that there are three banks having a higher mean on these ratios*, i.e*. Affin Islamic Bank, the Kuwait Finance House, and Bank Muamalat. This means that those banks are more liquid than the rest of the Islamic banks. In other words, these Islamic banks have a larger margin of safety to cover their short-term obligations than the rest of the banks. It is suggested that those banks with lower LR1 and LR2 should be monitored closely due their lower liquidity position. The Liquidity position of banks can be related to fewer total assets that are tied to net financing and more liquid assets available for meeting deposit and short-term funding demands.

The findings on profitability ratios show that on average there is not much significant different in the mean of profitability ratios for all banks except in two cases, BIMB and KFH. In the case of BIMB, the bank reported a loss before zakat and tax in two consecutive years, FY2005 and FY2006. In the case of the KFH, the bank has reported losses for six consecutive quarters prior to the fourth quarter of 2010. And this is due to the more challenging operating environment in 2010 as the group and the bank carried out their business realignment and restructuring plans in early 2010. In contrast to the performance of BIMB and all the other banks in the study sample, Maybank Islamic Berhad has shown a magnificent performance throughout the study period. This could be due to the increase in financing and higher asset quality.

Finally, income-expenditure structured ratios have shown a consistent performance among the sample banks. The significant difference in interest income to interest expenses ratio for the KFH, as compared to the other banks, can be specifically attributed to the low interest expenses since the bank was involved more in wholesale banking during their early years of operations.

The next chapter discusses in detail the modelling of the integrated early warning system for Islamic banks in Malaysia.

Chapter 6

PREDICTING BANKING DISTRESS: A COMPARATIVE STUDY OF ISLAMIC AND CONVENTIONAL BANKS IN MALAYSIA

6.1 INTRODUCTION

Bank failures threaten the economic system as a whole. Therefore, it is crucial to predict bank financial failures in order to prevent or minimise the negative effects on the economic system. Due to this, this second empirical chapter analyses whether the well known Altman Emerging Market *Z*-score model can predict bankruptcy and at the same time measure the financial performance of Islamic and conventional banks in Malaysia. This empirical analysis examines 13 Islamic banks and 10 Conventional banks in Malaysia, during the period 2005-2010. This is significant since the study also looks at the impact of the global financial crisis on the Islamic and conventional banks' performance.

This chapter is structured as follows: section 2 presents the literature reviews on Altman *Z*-score models; Section 3 describes the methodological issues pertaining to data collection, the variables and the statistical methods adopted in the paper; Section 4 presents the analysis of the results and a summary; finally, Section 5 concludes the study.

6.2 LITERATURE REVIEW

The prediction of failure for financial firms especially banks has been an extensively researched area since the late 1960s. The past forty years have seen an increasingly rapid development in the field of failure prediction models. There are various statistical and neural networks methods that have been used in bankruptcy prediction problems for banks and firms. Among the statistical methods that have been applied include multivariate discriminant analysis, linear discriminant analysis, quadratic discriminant analysis, multiple regressions, logistic regression, probit and factor analysis. As for neural networks, among the methods used include: multi-layer perception, radial basis function network, probabilistic neural network, auto-associative neural network, self-organising neural network, learning vector quantisation and a few other artificial intelligence techniques (Ravi Kumar and Ravi, 2007).

6.2.1 Multivariate Discriminant Analysis (MDA)

Until the 1980s, the technique of MDA dominated the literature on corporate failure models. After the 1980s, its use decreased (Dimitras *et al*., 1996), but the MDA method is frequently used as a 'baseline' method for comparative studies (Altman and Narayanan, 1997). In other words, MDA seems to be generally accepted as a standard method.

MDA is concerned with the classification of distinct sets of observations and it tries to find the combination of variables that predicts the group to which an observation belongs. The combination of predictor variables is called the linear discriminant function, and this function can be used to classify new observations whose group membership is unknown. The linear discriminant function is as follows:

$$D = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots + \beta_n X_n$$

where:

D is the discriminant score,

B_0 is an estimated constant,

B_n are the estimated coefficients, and

X_n are the variables

Based on this discriminant function score, an observation is classified into the appropriate group.

Altman (1968) is the first researcher who used discriminant analysis to predict the failures of firms from different industries. Sinkey (1975) also employed discriminant analysis to predict bank failures. Altman (1977) in a later study developed a discriminant model to predict the failures of the Savings and Loan Association for the period of 1966 to 1973 using 32 ratios as explanatory variables. Lam and Moy (2002) combined several discriminant models, and performed simulation analysis to enhance the accuracy of classification results for classification problems in discriminant analysis. Another multivariate statistical method that is used to predict bank failures is multiple regression analysis. Meyer and Pifer (1970) are the first researchers who used this method to predict bank failures.

6.2.2 Altman *Z*-score Models

The *Z*-score formula for predicting bankruptcy, published in 1968, was amongst the pioneers in bankruptcy modelling. During the earlier years, Altman developed a formula which can be used to predict the probability that a firm will go into bankruptcy within two years. The *Z*-score uses multiple corporate income and balance sheet values to measure the financial health of a company. Altman's work built upon research by accounting researcher Beaver and others. In the 1930s and onwards, Mervyn and a few other researchers had collected matched samples and assessed that various accounting ratios appeared to be valuable in predicting bankruptcy. In fact, Altman's *Z*-score model is a customised version of the discriminant analysis technique used by the earlier researcher, Fisher (1936). Beaver's work, which was published in 1966 and 1968, was another milestone in bankruptcy modelling. Beaver's work was the first to apply a statistical method, t-tests, to predict bankruptcy for a pair-matched sample of firms. This method was used to evaluate the importance of each of several accounting ratios based on univariate analysis, using each accounting ratio one at a time. A major improvement introduced by Altman was to apply discriminant analysis instead of univariate analysis. This is due to the fact that discriminant analysis could take into account multiple variables concurrently instead of evaluating each ratio one after another.

The *Z*-score is a linear combination of four or five common ratios, weighted by coefficients. These coefficients were estimated by identifying a set of firms which had declared bankruptcy and then collecting a matched sample of firms which had survived, matching by industry and approximate size in terms of assets. In the earlier stage, Altman applied the statistical method of discriminant analysis to a dataset of publicly held manufacturers. The original data sample consisted of 66 firms, where 33 of those companies had filed for bankruptcy. The sample only included manufacturers except those small companies with an asset of less than USD$1 million. From the original 22 variables, five were selected as doing the best overall job together in the prediction of bankruptcy (Altman, 1968). As such, the original *Z*-score bankruptcy model was as follows:

$$Z = 0.012(X_1) + 0.014(X_2) + 0.033(X_3) + 0.006(X_4) + 0.999(X_5)$$

where:

X_1 : working capital/total assets,

X_2 : retained earnings/total assets,

X_3 : earnings before interest and taxes/total assets,

X_4 : market value equity/book value of total liabilities,

X_5 : sales/total assets, and

Using this formula, one inserts the more commonly written percentage, for example, 0.10 for 10%, for the first four variables (X_1-X_4) and rounds the last coefficient off to equal 1.0 (from 0.99). As such, the final version of *Z*-score model is as follows:

$$Z = 1.2(X_1) + 1.4(X_2) + 3.3(X_3) + 0.6(X_4) + 1.0(X_5)$$

The cut-off values for the *Z*-score involve three zones that permit one to assess whether this model identifies the company as safe, in the gray area, or troubled. Any score greater than or equal to 2.99 is considered safe, a score between 1.82 and 2.98 is in the grey area, and finally any score below 1.81 is considered as a troubled company.

The *Z*-score model has gained wide acceptance by many users such as auditors and management accountants. Although the model was originally designed for publicly held manufacturing companies, this model has also been used in a variety of contexts and countries. Since the earlier model was based on data from publicly held manufacturers, this model has been re-estimated since then based on other sets of data.

Later variations by Altman were designed to be applicable to privately held companies (*Z*'-score) and non-manufacturing companies (*Z*"-score). As for the privately held companies Z'score model, Altman has done a complete re-estimation of the model by substituting the market value in X_4 with the book values of equity. The result of the revised Z'-score model is as follows:

$$Z' = 0.717(X_1) + 0.847(X_2) + 3.107(X_3) + 0.420(X_4) + 0.998(X_5)$$

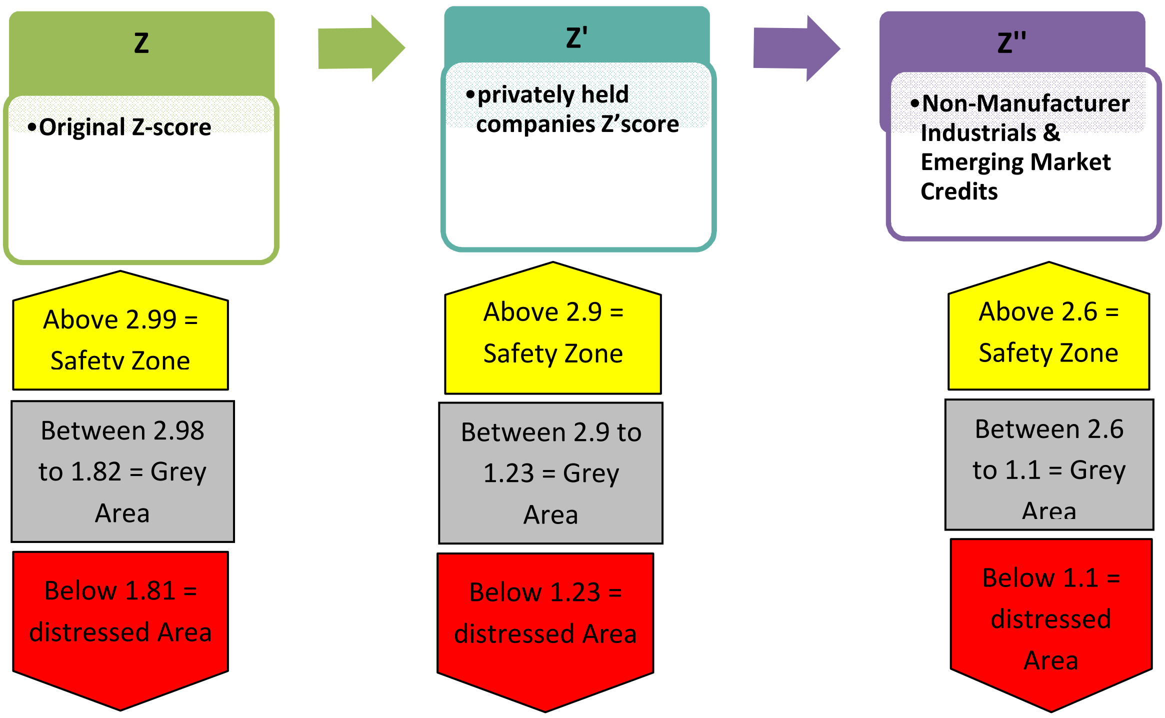
There has been some slight changes to the cut-off values for the *Z'*-score. Any score greater than or equal to 2.9 is considered safe, a score between 1.23 and 2.9 is in the grey area, and finally any score below 1.23 is considered as in the distressed zone.

Further modification of the *Z*-score can be seen in the Z"-score model for the non-manufacturing companies. In order to minimise the potential industry effect, Altman developed this model without X_5 (sales/total assets). This model has been used by Altman to assess the financial health of non-US corporates. Similarly with the Z'-score, the book value of equity was used in the Z"-score model. The Z"-score model is as follows:

$$Z'' = 6.56(X_1) + 3.26(X_2) + 6.72(X_3) + 1.05(X_4)$$

All of the coefficients for variables X_1 to X_4 are changed as are the group means and cut-off scores. Any score greater than or equal to 2.6 is considered safe, a score between 1.1 and 2.6 is in the grey area, and finally any score below 1.1 is considered as in the distressed area.

Figure 6.1: Altman *Z*-score Models



After considering a few research studies done in the past, neither of the Altman models nor any other models are recommended for use with financial firms especially Islamic financial institutions. This may be due to the fact that most of these financial firms are always involved with off-balance sheet activities. There are market-based formulas used to predict the default of financial firms, but these have a very limited predictive value due to much reliance on market data to predict the market event.

6.3 METHODOLOGY

6.3.1 Data

For testing the financial distress of Islamic and conventional banks in Malaysia, Altman's Emerging Market *Z*-score model (EM *Z*-score) has been used in this study which is based on secondary data. The data from the published sources is the basis for analysis. The required balance sheet and income statement items for EM *Z-score* analysis is obtained from Ibisonline Database and Bankscope. The financial data used are annual and cover the period 2005-2010 encompassing 13 Islamic banks and 10 conventional banks.

6.3.2 Tool for Data Analysis

The methodology that will be used in this study is based on the *Z*-score model for emerging markets developed by Altman (2002). Most of the previous studies have proved that the EM *Z*-score model has more than 80 percent accuracy and confirmed that it is a robust tool and valuable in assessing and predicting the potential distress condition of companies. In this study, the EM *Z*-score for each Islamic and conventional bank for the past six years was calculated by examining the financial statements of each of these banks. These *Z*-scores were then will compared with the *Z*''-score for the current year. By Applying the Emerging Market *Z*-score, this study investigated whether the EM *Z*-score model can predict the Islamic and conventional banks performance for a period of up to six years earlier.

Several bank failure prediction models have been developed since the mid 1970s. Most of the earlier models were built using classical statistical techniques, such as multivariate discriminant analysis (MDA). Later studies have also used neural networks, split-population survival time model, Bayesian belief networks, and isotonic separation. Some of these models have been routinely applied in the regulatory practices of banking agencies. Most of these models predict likely bank failures based on a set of high-level constructs called financial ratios, instead of low-level accounting variables. These financial ratios are usually constructed based on publicly available balance and income data that commercial banks are required to report to regulatory authorities on a regular basis. They are designed to reflect the soundness of a commercial bank in several aspects. Given the importance of the subject, extensive research has been devoted to the design and identification of such financial ratios in the last three decades. As a result, a large set of financial ratios has been identified and applied in regulatory practices. These financial ratios are believed to be more effective explanatory variables than the raw accounting data in the call reports in predicting and explaining bank failures (Zhao *et al.*, 2009).

As such, the original Altman *Z*-score bankruptcy model was as follows:

$$Z \quad = \quad 1.2(X_1) + 1.4(X_2) + 3.3(X_3) + 0.6(X_4) + 1.0(X_5)$$

where:

X_1 : working capital/total assets,

X_2 : retained earnings/total assets,

X_3 : earnings before interest and taxes/total assets,

X_4 : market value equity/book value of total liabilities,

X_5 : sales/total assets, and

The cut-off values for the *Z*-score involve three zones that permit one to assess whether this model identifies the company as safe, in the gray area, or troubled. Any score greater than or equal to 2.99 is considered safe, a score between 1.82 and 2.98 is in the grey area, and finally any score below 1.81 is considered as a troubled company.

Some modification of the original *Z*-score can be seen in the Z”-score model for the non-manufacturing companies. In order to minimise the potential industry effect, Altman developed this model without X_5 (sales/total assets). This model has been used by Altman to assess the financial health of non-US corporates. The *Z*”-score model is as follows:

$$Z'' \quad = \quad 6.56(X_1) + 3.26(X_2) + 6.72(X_3) + 1.05(X_4)$$

All of the coefficients for variables X_1 to X_4 are changed as are the group means and cut-off scores. Any score greater than or equal to 2.6 is considered safe, a score between 1.1 and 2.6 is in the grey area, and finally any score below 1.1 is considered as in a distressed area.

As for this study, the modified version (Altman, 2002) of the Emerging Market *Z*-score Model is applied in the analysis. Thus, the model is as follows:

$$Z'' = 6.56(X_1) + 3.26(X_2) + 6.72(X_3) + 1.05(X_4) + 3.25$$

Altman (2002) added a constant term of + 3.25 so as to standardize the scores with a score of zero (0) equated to a D (default) rated bond (Altman, 2002). In other words, +3.25 is a scale factor that equates 0 to a benchmark typical of other corporations that have defaulted on their corporate bonds. Thus, any banks with a score greater than or equal to 2.6 are considered as having a low probability of bankruptcy, a score below 1.1 is considered as having a high probability of bankruptcy, and a score between 1.1 and 2.6 is in the grey area. Banks with *Z*-scores within this range are considered an uncertain credit risk and should be carefully observed before it is too late for any remedial or recovery action by the relevant authorities.

Table 6.1: Description and Classification of EM *Z*-score Model

Ratios	Description	Coefficient
X_1	Working Capital to Total Assets	6.56
X_2	Retained Earnings to Total Assets	3.26
X_3	EBIT to Total Assets	6.72
X_4	Net Worth to Total Liabilities	1.05
	Cut-off value:	
Above 2.66	Safety Zone	
Between 2.66 and 1.1	Grey Area	
Below 1. 1	Distressed Area	

As depicted in Table 6.1 above, X_1 variable can be defined as the working capital to total assets. This variable examines the net liquid assets of a firm as compared to the total assets of the company. In other words, it measures the liquidity of the assets in relation to the firm's size. It shows the ability of the company in managing their liquidity position and the net working capital is a result of subtracting the current total liabilities from current assets.

The next variable is X_2, which can be defined as the retained earnings to total assets. This variable examines the retained earnings as compared to the total assets. This variable measures the cumulative profitability of a company.

The third variable, X_3, can be defined as return to total assets. This variable is calculated by dividing earnings before interest and taxes (EBIT) by total assets. It observes the ability of the company in generating profits from their assets base. In fact, this variable is important in assessing the survival of a company.

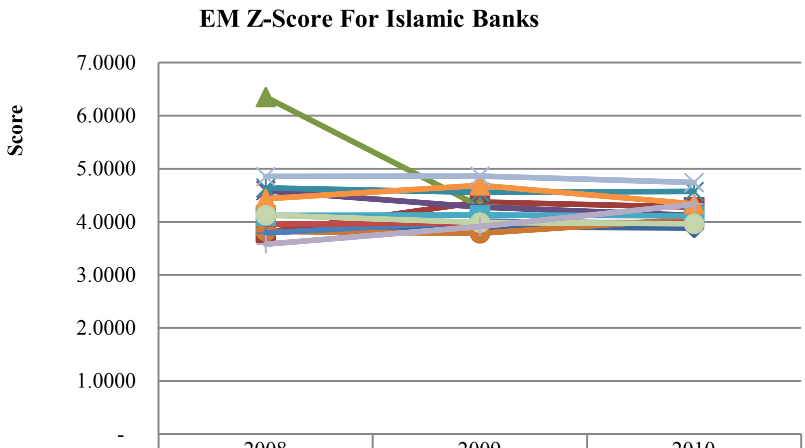
The fourth variable X_4, is defined as the company's net worth or market value of equity to total liabilities. Thus, the higher the score the less likely the company is to go bankrupt.

6.4 RESULTS AND DISCUSSION

According to a study conducted by Al-Zaabi (2011), the modified Altman *Z*-score model (EM *Z*-score) can be used to measure the distance to default, although this technique can be considered a non-traditional way of measuring the financial performance of banks. By applying the same methods, this study will focus on the comparative performance between Islamic banks and conventional banks in Malaysia. Table 6.2 and Figure 6.2 below depict the overall results of the EM *Z*-score for the Islamic banks and conventional banks. Based on the EM *Z*-score model, any score below 1.1 means that the banks are unhealthy and close to insolvency, while banks with a score above 2.6 are considered as healthy banks with a low probability of bankruptcy. On the other hand, any bank with a score falling between 1.1 and 2.6 is considered to be facing serious financial problems.

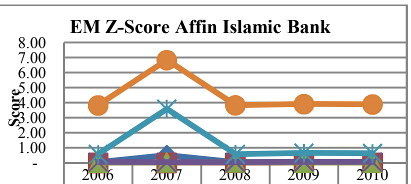
Initially, the data for Islamic banks from 2008 to 2010 was reconstructed in order to calculate the *Z*-score for each Islamic bank. Based on the EM *Z*-score for each Islamic bank, as shown in Figure 6.2, it was concluded that all Islamic banks falls in the healthy area of the scale. The EM *Z*-score for each Islamic bank significantly exceeded the cut-off value of 2.6. In spite of this, Figure 6.3 provides an insight into each Islamic bank's performance throughout the study period. Alliance Islamic Bank, AmIslamic Bank, Asian Finance Bank, Hong Leong Islamic Bank, HSBC Amanah, and the Kuwait Finance House are among the top 6 Islamic banks that have achieved an average EM *Z*-score of more than 4.0. For the rest of the Islamic banks, most of their EM *Z*-scores are well above the cut-off point of 2.6. Based on Figure 6.3 which gives the individual performance for each Islamic bank, most have shown a fluctuation in their performance during his period, thus suggesting that the global financial crisis did affect Islamic bank performance. On the other hand, the EM *Z*-score for Standard Chartered Saadiq starts escalating from 2008, indicating the improvement of their financial position and financial performance whilst the rest are having a downturn in performance.

Figure 6.2: EM *Z*-score for Islamic Banks

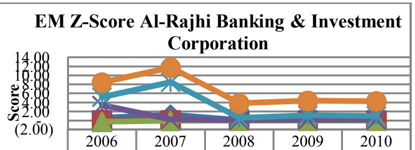


	2008	2009	2010
Affin Islamic Bank Berhad	3.8234	3.9031	3.8824
Al Rajhi Banking & Investment Corporation (Malaysia) Berhad	3.7983	4.3715	4.2727
Alliance Islamic Bank Berhad	6.3491	4.2850	4.0880
AmIslamic Bank Berhad	4.5851	4.2753	4.1180
Asian Finance Bank Berhad	4.6361	4.5551	4.5696
Bank Islam Malaysia Berhad	3.8201	3.7814	4.0533
Bank Muamalat Malaysia Berhad	3.7844	4.0113	3.9622
EONCAP Islamic Bank Berhad	3.9489	3.9827	3.9829
Hong Leong Islamic Bank Berhad	4.1171	4.1217	4.1136
HSBC Amanah Malaysia Berhad	4.4320	4.6869	4.3326
Kuwait Finance House (Malaysia) Berhad	4.8504	4.8603	4.7381
RHB Islamic Bank Berhad	4.1220	3.9842	3.9622
Standard Chartered Saadiq Berhad	3.5792	3.9065	4.3315

Figure 6.3: Analysis of EM-*Z*-score each Islamic Bank

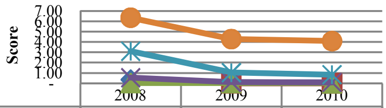


	2006	2007	2008	2009	2010
X1	0.05	0.51	0.04	0.06	0.06
X2	0.00	0.01	0.01	0.01	0.01
X3	0.02	0.03	0.03	0.02	0.02
X4	0.05	0.04	0.05	0.06	0.06
Original Z"-Score	0.57	3.58	0.57	0.65	0.63
EM Z"-Score	3.82	6.83	3.82	3.90	3.88



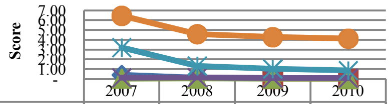
	2006	2007	2008	2009	2010
X1	0.55	1.30	0.06	0.13	0.12
X2	-	-	-	0.00	0.00
X3	(0.29)	(0.04)	0.01	0.02	0.01
X4	3.38	0.20	0.08	0.16	0.14
Original Z"-Score	5.20	8.48	0.55	1.12	1.02
EM Z"-Score	8.45	11.73	3.80	4.37	4.27

EM Z-Score Alliance Islamic Bank



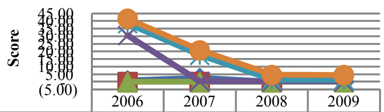
	2008	2009	2010
X1	0.35	0.11	0.09
X2		0.01	0.01
X3	0.03	0.03	0.02
X4	0.54	0.12	0.09
Original Z"-Score	3.10	1.04	0.84
EM Z"-Score	6.35	4.29	4.09

EM Z-Score AmIslamic Bank



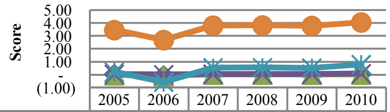
	2007	2008	2009	2010
X1	0.42	0.13	0.09	0.08
X2			0.01	0.01
X3	0.04	0.05	0.04	0.04
X4	0.12	0.15	0.10	0.08
Original Z"-Score	3.21	1.34	1.03	0.87
EM Z"-Score	6.46	4.59	4.28	4.12

EM Z-Score Asian Finance



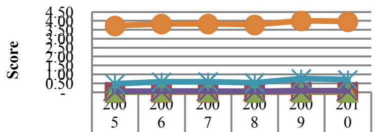
	2006	2007	2008	2009
X1	0.96	2.62	0.17	0.16
X2	(0.01)	(0.01)	(0.01)	
X3	(0.01)	0.01	0.01	0.01
X4	30.69	0.38	0.22	0.19
Original Z"-Score	38.38	17.59	1.39	1.31
EM Z"-Score	41.63	20.84	4.64	4.56

EM Z-Score Bank Islam Malaysia



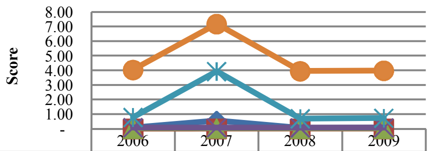
	2005	2006	2007	2008	2009	2010
X1	0.04	(0.02)	0.05	0.05	0.05	0.08
X2						
X3	(0.02)	(0.06)	0.02	0.03	0.02	0.03
X4	0.05	0.02	0.06	0.06	0.06	0.09
Original Z"-Score	0.21	(0.56)	0.55	0.57	0.53	0.80
EM Z"-Score	3.46	2.69	3.80	3.82	3.78	4.05

EM Z-Score Bank Muamalat Malaysia



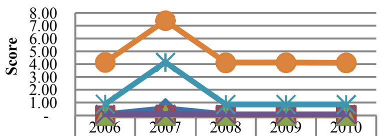
	2005	2006	2007	2008	2009	2010
X1	0.05	0.05	0.05	0.05	0.07	0.07
X2	0.01	0.01	0.01	0.01	0.01	0.01
X3	0.02	0.03	0.03	0.02	0.02	0.02
X4	0.05	0.06	0.06	0.05	0.09	0.08
Original Z"-Score	0.48	0.59	0.59	0.53	0.76	0.71
EM Z"-Score	3.73	3.84	3.84	3.78	4.01	3.96

EM Z-Score EONCap Islamic Bank



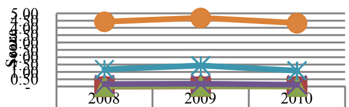
	2006	2007	2008	2009
Series1	0.08	0.55	0.06	0.07
Series2	0.00	0.00	0.00	0.01
Series3	0.03	0.03	0.03	0.02
Series4	0.09	0.08	0.07	0.08
Series5	0.79	3.93	0.70	0.73
Series6	4.04	7.18	3.95	3.98

EM Z-Score Hong Leong islamic Bank

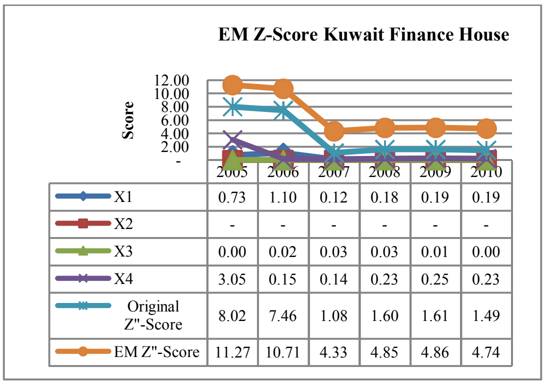


	2006	2007	2008	2009	2010
X1	0.08	0.57	0.08	0.08	0.08
X2	0.00	0.01	0.01	0.01	0.02
X3	0.03	0.04	0.03	0.03	0.03
X4	0.09	0.11	0.09	0.09	0.09
Original Z"-Score	0.89	4.15	0.87	0.87	0.86
EM Z"-Score	4.14	7.40	4.12	4.12	4.11

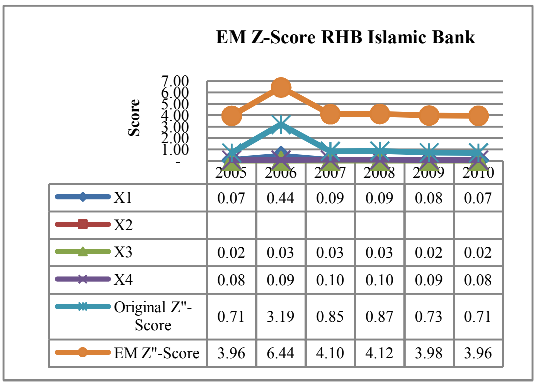
HSBC Amanah



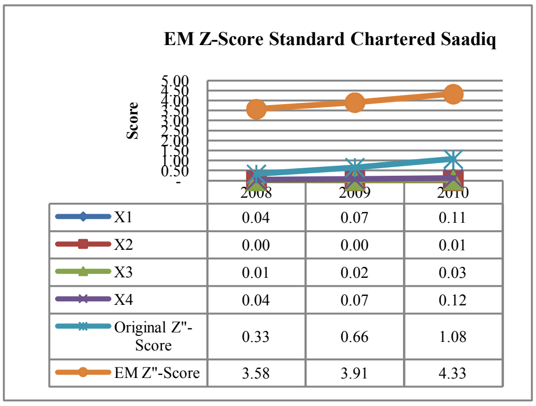
	2008	2009	2010
X1	0.14	0.15	0.11
X2	0.00	0.01	0.01
X3	0.02	0.03	0.02
X4	0.16	0.18	0.13
Original Z"-Score	1.18	1.44	1.08
EM Z"-Score	4.43	4.69	4.33



	2005	2006	2007	2008	2009	2010
X1	0.73	1.10	0.12	0.18	0.19	0.19
X2	-	-	-	-	-	-
X3	0.00	0.02	0.03	0.03	0.01	0.00
X4	3.05	0.15	0.14	0.23	0.25	0.23
Original Z"-Score	8.02	7.46	1.08	1.60	1.61	1.49
EM Z"-Score	11.27	10.71	4.33	4.85	4.86	4.74



	2005	2006	2007	2008	2009	2010
X1	0.07	0.44	0.09	0.09	0.08	0.07
X2						
X3	0.02	0.03	0.03	0.03	0.02	0.02
X4	0.08	0.09	0.10	0.10	0.09	0.08
Original Z"-Score	0.71	3.19	0.85	0.87	0.73	0.71
EM Z"-Score	3.96	6.44	4.10	4.12	3.98	3.96



	2008	2009	2010
X1	0.04	0.07	0.11
X2	0.00	0.00	0.01
X3	0.01	0.02	0.03
X4	0.04	0.07	0.12
Original Z"-Score	0.33	0.66	1.08
EM Z"-Score	3.58	3.91	4.33

Table 6.2: Analysis of EM *Z*-score individual ratio (Islamic Banks)

Ratios	2008	2009	2010
X1 (Working Capital/Total Assets)	11.13%	10.05%	9.94%
X2 (Retained Earning/Total Assets)	0.15%	0.53%	0.44%
X3 (EBIT/Total Assets)	2.43%	2.38%	2.20%
X4 (Book Value of Equity/Total Liabilities)	14.07%	11.74%	11.50%

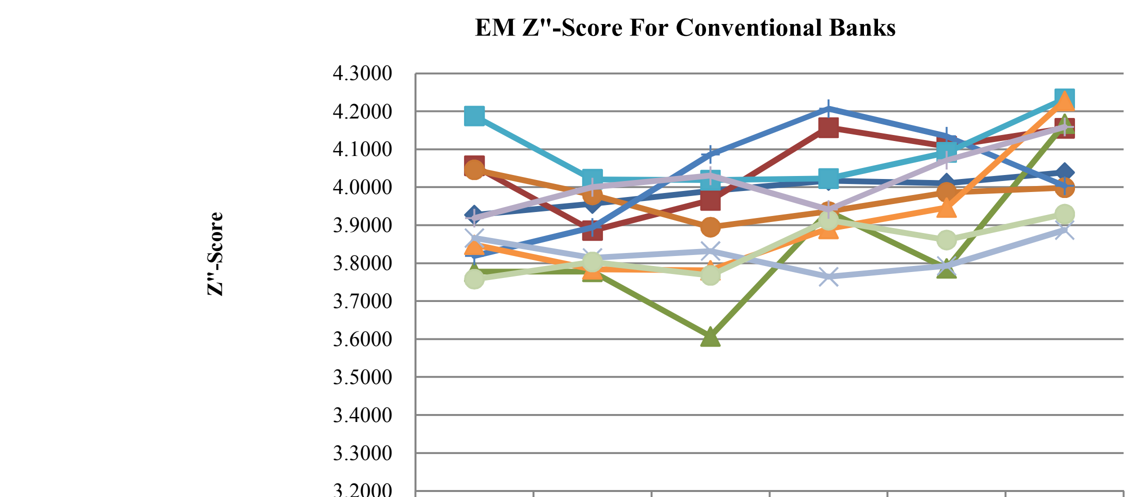
Source: Author's own estimate

For most of the EM *Z*-score results for the Islamic banks, the X_1 ratio was one of the important ratios for the score. The X_1 ratio measures the proportion of working capital in the total assets, thus giving an idea of the banks' underlying operating efficiency. Generally, any money that is tied in the inventory, or money that customers still owe to the bank, cannot be used to settle the bank's financial obligations. Thus, an increase in working capital might be due to the inefficient practice of banks in their operation, and the better the bank manages its working capital the less they will use external debts. Table 6.2 depicts an average ratio of $X_{1,}$ showing that the X_1 ratios for all Islamic banks have shown a deteriorating trend starting in 2008. The content of working capital in the total assets (X_1) has slightly decreased from 11.13% in 2008 to 10.05% in 2009 and further decreased in 2010 to 9.94%. It indicates the less moderate use of working capital over those three years, although this is more favourable for the financial health of the banks. On the other hand, a declining trend in working capital ratio over a longer time period could give a signal to those banks to carry out further analysis of their operations. A declining usage of working capital may cause liquidity problems but at the same time it also implies the bank's overall efficiency due to having less debtors.

Furthermore, X_2 and X_3 ratios measure the banks' operating efficiency or in other words the ability of Islamic banks to generate profits from the sale of their products as well as using the existing assets to produce sales. The X_2 ratio, retained earnings to total assets, measures the banks' ability in accumulating profits by using its assets. It denotes the extent to which assets have been paid for by bank profits. A 100% retained earnings to total asset ratio denotes that growth has been financed through profits not debts. Any X_2 ratio lower than 100% means growth may not be sustainable as it is financed through an increase in debts. Conversely, an increase in retained earnings to total assets ratio is a good sign as it indicates that the bank is more stable and constantly retains more earnings. In this study, the retained earnings to total assets ratio (X_2) was recorded as 0.15% in 2008, increasing to 0.53% in 2009, and dropping off to 0.44% in 2010. An increase in 2009 showed that the Islamic banks are able to generate adequate reserves for the future prospects of the banking operation. Furthermore, it may also mean that the Islamic banks are able to pay off a major portion of their assets out of reinvested profits, this being a good sign for the Islamic banking industry. Meanwhile, the earnings before interest to total assets (X_3) has gradually decreased from 2.43% in 2008 to 2.38% and 2.20% in 2009 and 2010 respectively. This ratio measures the effectiveness of banks in using their assets to generate profits before the contractual obligations must be paid, without being affected by management financing decisions. The bigger banks' earnings in comparison to its total assets means that the banks efficiently managed their assets to generate more income. In addition to that, this ratio is the measure of overall efficiency of banks wherein leads to the success of the banks. Therefore, this study showed that Islamic banks are having a decreasing trend in their X_3 ratio and the management of the banks should be cautious enough to boost the ratio to avoid further deterioration in banks' performance.

Finally, X_4, the ratio of equity fund to total liabilities, which measures the long term financial stability of banks, also showed a declining rate from 14.07% in 2008, to 11.74% in 2009 and to 11.50% in 2010. This ratio shows how much the banks' assets can decline in value before it becomes insolvent. Based on those ratios, it was revealed that the equity fund was less than the total liabilities; hence it indicates that more debts were used in the banks' operations as compared to equity funds. The fraction of equity and debts used had a direct impact on the banks' performance. Thus, to protect banks from adverse financial performance, banks should change their financial structure and the banks' management should monitor it with caution.

Figure 6.4: EM *Z*-score for Conventional Banks

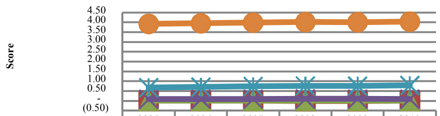


	2005	2006	2007	2008	2009	2010
Affin Bank Berhad	3.9272	3.9567	3.9906	4.0176	4.0108	4.0389
Alliance Bank Malaysia Berhad	4.0564	3.8858	3.9654	4.1568	4.1078	4.1554
AmBank (M) Berhad	3.7777	3.7777	3.6073	3.9360	3.7864	4.1676
Hong Leong Bank Berhad	4.0459	3.9800	3.8949	3.9361	3.9865	3.9988
HSBC Bank Malaysia Berhad	3.8190	3.8942	4.0865	4.2073	4.1342	4.0038
Malayan Banking Berhad	4.1877	4.0210	4.0187	4.0227	4.0918	4.2329
OCBC Bank (Malaysia) Berhad	3.8486	3.7837	3.7814	3.8907	3.9465	4.2279
Public Bank Berhad	3.8661	3.8139	3.8321	3.7641	3.7929	3.8871
Standard Chartered Bank Malaysia Berhad	3.7579	3.8033	3.7678	3.9133	3.8610	3.9293
United Overseas Bank (Malaysia) Berhad	3.9185	4.0001	4.0304	3.9415	4.0714	4.1587

As for Conventional banks, the data from 2005 to 2010 was also reconstructed in order to calculate the *Z*-score for each conventional bank and the EM *Z*-score for each conventional bank as shown in Figure 6.4. Based on these results, it can be concluded that all conventional banks falls into the healthy area of the scale. The EM *Z*-score for these banks significantly exceeded the cut-off value of 2.6. Figure 6.5 will provide an insight into each conventional bank's performance throughout the study period. Eventually, all of these banks achieved an average EM *Z*-score of more than 3.6. Based on Figure 6.5, considering the individual performance for each conventional bank, most of these banks have shown a fluctuation in their performance during this period thus signifying the impact of the global financial crisis on the banks' performance.

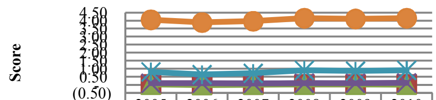
Figure 6.5: Analysis of EM *Z*-score for each Islamic Bank

EM Z-Score Affin Bank



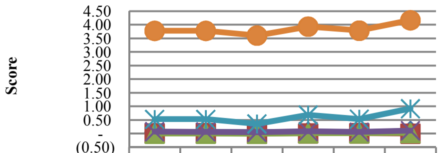
	2005	2006	2007	2008	2009	2010
X1	0.07	0.08	0.08	0.09	0.09	0.08
X2	0.01	0.01	0.01	(0.00)	(0.00)	0.01
X3	0.01	0.01	0.01	0.02	0.01	0.02
X4	0.09	0.09	0.10	0.10	0.10	0.10
Original Z"-Score	0.68	0.71	0.74	0.77	0.76	0.79
EM Z"-Score	3.93	3.96	3.99	4.02	4.01	4.04

EM Z-Score Alliance Bank



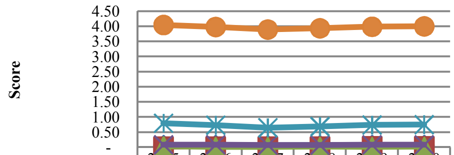
	2005	2006	2007	2008	2009	2010
X1	0.08	0.08	0.08	0.09	0.09	0.10
X2	0.03	0.02	0.02	0.03	0.03	0.03
X3	0.01	(0.01)	0.01	0.02	0.01	0.01
X4	0.10	0.10	0.09	0.11	0.10	0.11
Original Z"-Score	0.81	0.64	0.72	0.91	0.86	0.91
EM Z"-Score	4.06	3.89	3.97	4.16	4.11	4.16

EM Z-Score Ambank



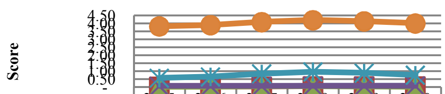
	2005	2006	2007	2008	2009	2010
X1	0.06	0.06	0.05	0.07	0.05	0.10
X2	0.01	0.02	0.01	0.01	0.02	-
X3	0.00	0.01	(0.00)	0.01	0.01	0.02
X4	0.07	0.07	0.05	0.08	0.06	0.11
Original Z"-Score	0.53	0.53	0.36	0.69	0.54	0.92
EM Z"-Score	3.78	3.78	3.61	3.94	3.79	4.17

EM Z-Score Hong Leong Bank



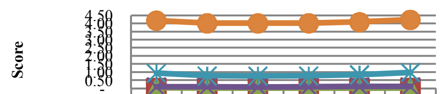
	2005	2006	2007	2008	2009	2010
X1	0.07	0.07	0.06	0.07	0.07	0.07
X2	0.02	0.02	0.02	0.02	0.03	0.03
X3	0.03	0.01	0.01	0.01	0.01	0.01
X4	0.08	0.09	0.07	0.08	0.08	0.08
Original Z"-Score	0.80	0.73	0.64	0.69	0.74	0.75
EM Z"-Score	4.05	3.98	3.89	3.94	3.99	4.00

EM Z-Score HSBC Bank

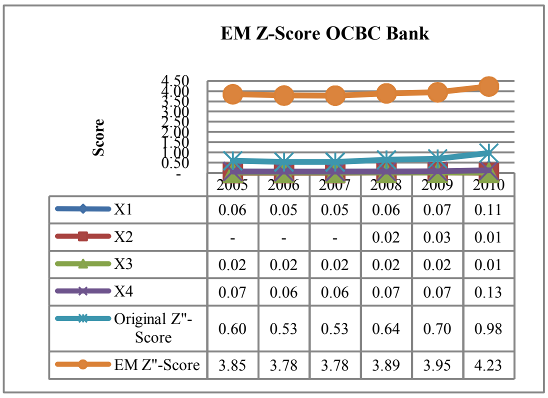


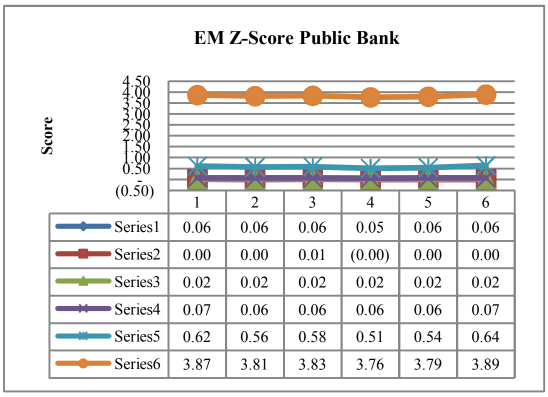
	2005	2006	2007	2008	2009	2010
X1	0.05	0.05	0.05	0.06	0.06	0.06
X2	0.03	0.03	0.03	0.04	0.04	0.04
X3	0.01	0.02	0.05	0.05	0.04	0.02
X4	0.07	0.07	0.06	0.07	0.07	0.07
Original Z"-Score	0.57	0.64	0.84	0.96	0.88	0.75
EM Z"-Score	3.82	3.89	4.09	4.21	4.13	4.00

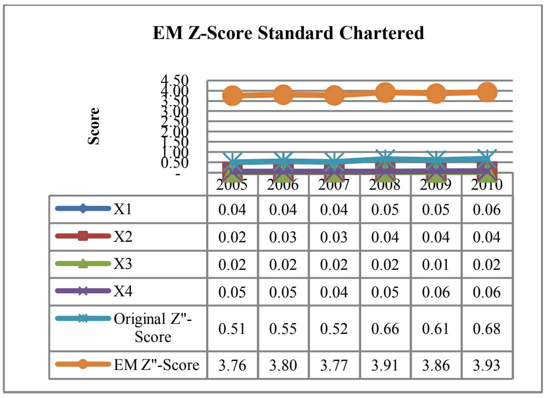
EM Z-Score Maybank



	2005	2006	2007	2008	2009	2010
X1	0.08	0.07	0.07	0.07	0.09	0.10
X2	0.03	0.03	0.03	0.03	0.02	0.03
X3	0.03	0.02	0.02	0.02	0.01	0.02
X4	0.09	0.08	0.08	0.09	0.10	0.11
Original Z"-Score	0.94	0.77	0.77	0.77	0.84	0.98
EM Z"-Score	4.19	4.02	4.02	4.02	4.09	4.23







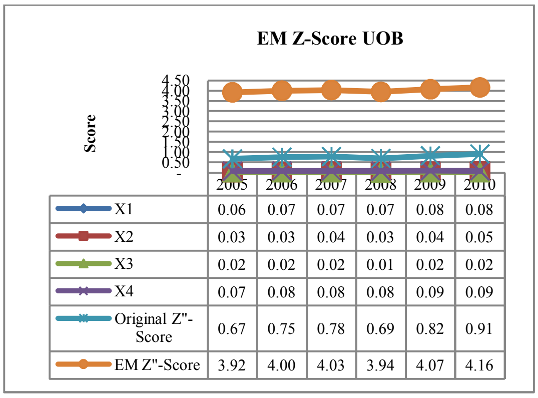


Table 6.3: Analysis of EM *Z*-score individual ratio (Conventional Banks)

Ratios	2005	2006	2007	2008	2009	2010
X_1 (Working Capital/Total Assets)	6.46%	6.38%	6.17%	6.80%	7.00%	8.20%
X_2 (Retained Earning/Total Assets)	1.82%	1.96%	1.89%	2.10%	2.45%	2.55%
X_3 (EBIT/Total Assets)	1.59%	1.20%	1.58%	1.95%	1.57%	1.64%
X_4 (Book Value of Equity/Total Liabilities)	7.70%	7.50%	7.14%	7.86%	8.05%	9.39%

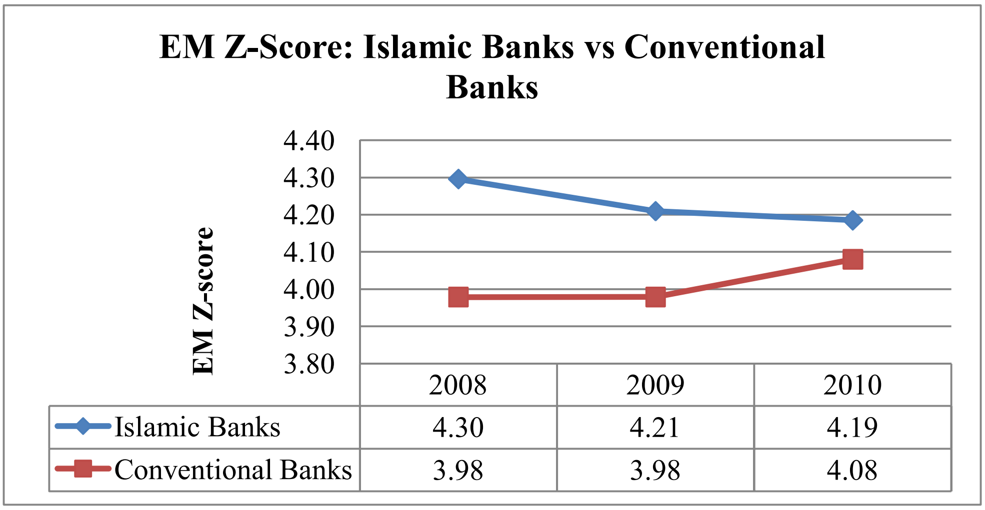
Source: Author's own estimate

For most of the EM *Z*-score results for conventional banks, the X_1 ratio was one of the important ratios for the score. Table 8.3 shows that the X_1 ratios for all conventional banks have shown an escalating trend starting in 2008. The content of working capital in the total assets *(*X_1*)* has slightly decreased from 6.46% in 2005 to 6.38% in 2006, and further decreased in 2007 to 6.17%. The ratio starts to escalate to 6.8%, 7% and 8.20% in 2008, 2009 and 2010 respectively. Thus, this indicates that conventional banks have a better liquidity position as opposed to Islamic banks especially during the global financial crisis.

Further analysis on retained earnings to total assets (X_2) for conventional banks recorded an increasing performance from 2.10% in 2008 to 2.45% and 2.55% in 2009 and 2010 respectively. As discussed earlier, an increasing trend in this ratio denotes that conventional banks are able to generate sufficient reserves for the future prospects of the banking operation as well as being a good sign of the conventional banks' performance. Meanwhile, the earnings before interest to total assets ratios (X_3) for conventional banks have showed fluctuated performance during the study period. The ratio fluctuates from 1.59% in 2005 to 1.20%, 1.58%, 1.95%, 1.57% and 1.64% in 2006, 2007, 2008, 2009 and 2010 respectively. These ratios are much lower as compared to the ratios for the Islamic banks although they are not showing the decreasing trend as experienced by the Islamic banks. However, based on these results, the management of conventional banks should monitor closely this ratio in order to avoid further relapse in the banks' performance that will lead to bank failure.

Lastly, the equity fund to total liabilities ratio (X_4) for conventional banks showed a declining trend from 7.70% in 2005 to 7.50% and 7.14% in 2006 and 2007 correspondingly. However, starting from 2008, X_4 has escalated from 7.86% in 2008 to 8.05% in 2009 and 9.39% in 2010, thus showing that conventional banks do opt for more debts in their banking operations as compared to equity. Therefore, the banks' management should monitor closely their financial structure in order to avoid further weaknesses that may lead to serious financial performance.

Figure 6.6: EM *Z*-score: Islamic Banks vs Conventional Banks



Finally, Figure 6.6 illustrates the comparison of EM *Z*-score performance between the Islamic and conventional banks. Based on these results, it shows that Islamic banks are on a declining trend during 2008 - 2010, whilst for conventional banks, they are on an escalating trend. Thus, this suggests that the recent global financial crisis did have some impact on the performance of the banking industry in Malaysia even though it is not that significant. In terms of profitability, according to the study conducted by Hassan and Dridi (2010), it is suggested that, in general, Islamic banks fared better than conventional banks during the global financial crisis. However, their comparison will not lead to reliable conclusions about financial stability and the resilience of the Islamic banking sector due to a lack of appropriate controls on varying conditions across the financial system in countries where Islamic banks operate. For instance, this study might not reflect the moderate impact of the global financial crisis on certain countries such as GCC, Jordan, and Malaysia. In terms of asset growth, they found that Islamic banks maintained stronger asset growth compared to conventional banks in almost all countries, growing on average more than twice that of conventional banks during 2007-2009. This indicates that the market share of Islamic banks is likely to continue forward.

6.5 CONCLUSION

The prediction of corporate distress is a common issue in developed countries but has only recently emerged in developing countries. Numerous studies have attempted to further improve as well as replicate the initial model developed by Altman (1968) in different markets worldwide. However, this topic, especially the prediction of banking distress, was less well-researched in emerging markets, such as Malaysia. Therefore, this study is important, especially from the Malaysian perspective, as it has revealed the results of the EM *Z*-score model developed by Altman (2002) as tested on the Islamic and conventional banks.

The main objective of this study is to introduce to the Malaysian banking industry the EM *Z*-score developed by Altman (2002) as a valuable analytical tool in finding the possible reasons that may lead to deterioration of banks' performance as well as providing an insight on Islamic and conventional performance. This study significantly indicates that both Islamic banks and conventional banks are financially healthy and sound. The EM-*Z*-score for all banks are well above the cut-off point of 2.6, although for Islamic banks the EM *Z*-scores are showing a declining trend whilst those for conventional banks are showing an increasing trend. This empirical evidence is important for the banks since it provides a warning signal to the banks' management as well as the related parties in the planning, controlling and decision making processes. If the declining trend continues, the management as well as the relevant authorities could take early remedial actions to reduce the likelihood of bankruptcy.

This model is not the only model that can be tested to analyse banks performance, however it can be used to complement the existing models used by banks in monitoring their performance. Thus based on the presented results, it can be concluded that in order for Islamic banks and conventional banks to sustain themselves in the banking industry they should concentrate on their past performance in order to predict their future position in the banking industry.

Finally, as for future research, although the Islamic banking industry in Malaysia has grown tremendously during the recent period, as shown in term of the number of players, the availability of the data is still the main concern for the researcher since most of the updated reports on financial performance are not available online. Thus, this has some effect on the number of samples as well as the maximum outcome of this study. It is recommended that, for future research, the coefficient values of each ratio in this EM *Z*-score model are updated based on the inputs from the Conventional and Islamic banking industry in Malaysia, thus giving some true values for better prediction of the banking distress condition.

Chapter 7

INTEGRATED EARLY WARNING PREDICTION MODEL FOR ISLAMIC FINANCIAL INSTITUTIONS: MULTIPLE REGRESSION ANALYSIS (MDA, LOGIT & PROBIT)

7.1 INTRODUCTION

After presenting the descriptive empirical results in the first empirical chapter, this chapter present the empirical modelling and the results of the third empirical study. This chapter develops a preliminary model for the prediction of the performance level of Islamic financial institutions for the period of December 2005 to September 2010 by using the quarterly data for ten selected Islamic banks in Malaysia. The first section describes the procedures and results for the ranking and grouping of Islamic banks into two groups, healthy and non-healthy Islamic banks. This is followed by an analysis of the independent variables by using analysis of variance (ANOVA) to compare the means of two or more samples by using an F-distribution in order to determine the variables which are most suitable for constructing an efficient prediction model. Factor analysis is deliberated further in the next section of this chapter followed by the empirical findings of the integrated models (discriminant, logit and probit). The section on integrated models will describe the results of the estimated models (discriminant, logit and probit) and the classifications. These estimated classification results were compared with the actual classifications to look into the issue of misclassifications, or in other words to study the accuracy of the estimated models. Finally, the chapter will be concluded with a comparison of the three estimated models.

7.2 EMPIRICAL RESULTS

In order to create an accurate bank failure prediction model, several independent variables need to be included in the analysis as shown in the next section. As mentioned and discussed in the methodology and literature chapter, this study used the following previous studies on bankruptcy prediction models as a benchmark in choosing explanatory variables, such as Beaver (1966), Altman (1968), Zmijewski (1984), Thomson (1991), Kolari *et al.* (1996), Lanine *et al.* (2006), Swicegood and Clark (2001), Tung *et al*. (2004), Zhao *et al*. (2008), Boyacioglu *et al*. (2009), Jagtiani *et al*. (2003), Chung *et al*. (2008), Ravi and Pramodh (2008), Gunsel (2007), Al-Osaimy and Bamakhramah (2004) and Canbas *et al.* (2005). As discussed in the literature review chapter, the most commonly used financial ratios can forecast the potential failure really well. In fact, some studies also included a few financial ratios that are infrequently used but proved to be significant to the models. Thus, this study includes only 29 financial ratios used in the previous studies, as has been discussed in the research methodology and modelling chapter.

This section will analyse the procedures and the results of the study. The main aim of this study is to construct a reliable insolvency prediction model for Islamic banks in Malaysia. Thus, the first step is to look at the explanatory power of the independent variables followed by studying the correlation between those variables. The next step is to test the estimated models in order to find the most accurate and reliable models by looking at the misclassification results. Since this section focuses more on the integrated model instead of on every single model, the accuracy of the three estimated models (discriminant, logit and probit) were taken as a pool result.

7.2.1 Ranking the Banks in the Islamic Banking Sector by Their Financial Performance

This study uses the method of Al-Osaimy (2004) to distinguish the two groups according to the summary index composed of the following financial ratios:

Profitability = Net Profit / Total Assets.
Productivity = Total Income / Total Assets.
Efficiency = Total Income / General and Administrative Expenses
Leverage = Customers Deposits / Shareholders Equity

Concerning the ranking of banks by their financial performance, this study used the rank from 1 to 10, where 1 will be granted to the banks that obtained the lowest value of the selected ratios and vice versa, depending on the type of financial ratios measured. The classification of the selected 10 Malaysian Islamic Banks between the healthy and non-healthy groups is based on the ranking of each bank according to each of the above four financial ratios, summing the ranking scores of each bank and calculating the average score. Those banks with 5 points or less were classified into healthy banks, while those banks scoring more than 5 are classified into non-healthy banks. Thus, based on these findings, 4 Malaysian Islamic banks were classified into healthy banks group and 6 banks were classified as non-healthy.

The grouping of the banks according to their financial performance during the benchmark period (September 2010) is presented in Table 7.1.

Table 7.1: The ranking Scores and Grouping of Healthy and Non-Healthy Banks

Banks	Profitability	Rank	Productivity	Rank	Efficiency	Rank	Leverage	Rank	Total score	Average Score	Position
Kuwait Finance House	-0.047063481	10	0.875749875	9	232.8802956	10	195.6583223	1	30	7.5	Non-Healthy
Public Bank	0.422001767	2	1.270871694	2	665.0319159	2	875.0829288	2	8	2	Healthy
EONCap Islamic	0.436428972	1	1.343466518	1	453.8009614	4	932.8256919	3	9	2.25	Healthy
RHB Islamic	0.222774254	6	1.085275475	7	363.8625657	6	964.8975184	4	23	5.75	Non-Healthy
Maybank	0.320507716	3	1.206257152	4	439.4592017	5	979.4425622	5	17	4.25	Healthy
Hong Leong	0.146939926	8	0.787848502	10	503.1091077	3	1048.992666	6	27	6.75	Non-Healthy
Muamalat	0.239013492	5	1.235338114	3	307.6388239	7	1060.435935	7	22	5.5	Non-Healthy
BIMB	0.194218881	7	1.141655552	6	252.6779158	9	1124.334832	8	30	7.5	Non-Healthy
Affin	0.012864621	9	0.925987754	8	293.4542554	8	1310.156695	9	34	8.5	Non-Healthy
CIMB	0.25747054	4	1.157348369	5	735.4198975	1	1708.678458	10	20	5	Healthy
Cut-off point: >5											

Notes: Healthy : Public bank, EonCap Islamic, Maybank, CIMB
Non-Healthy: KFH, RHB, Hong Leong, Muamalat, BIMB, Affin

7.2.2 Analysis of the Independence Variables

The test of the relevance of the independent variables is done in two ways. First, the mean between the healthy and non-healthy banks' financial ratios is studied for all 20 quarters. The validity of the variables is studied using the ANOVA test at the 10 percent significance level. In the early stage of model development, 29 variables were selected based on previous studies on bankruptcy prediction models. The ANOVA test was conducted on these 29 variables in order to gain a strong explanatory power for the insolvency model. The results of this test will be discussed further in the next section.

The second way to test the fitness of the variables is to explore how well one variable at the time predicts the probability of a bank failure. This is done by using discriminant, logit and probit models. This will be discussed in the following section of this chapter.

7.2.2.1 Analysis of Variance (ANOVA)

In statistics, one way analysis of variance (One-way ANOVA) is a technique used to compare the means of two or more samples by using the F-distribution (Field, 2009). The ANOVA tests the null hypothesis that samples in two or more groups are drawn from the same population.

The formula for the one-way ANOVA F-test statistic is:

$$F = \frac{explained\ variance}{unexplained\ variance}$$

or

$$F = \frac{between - group\ variability}{within - group\ variability}$$

The "explained variance", or "between group variability" is

$$\sum_i \frac{n_i(\bar{Y}_{i-} - \bar{Y})^2}{(K-1)}$$

where $\bar{Y}_{i-}$ denotes the sample mean in the ith group, n_i is the number of observations in the ith group, and $\bar{Y}$ denotes the overall mean of the data.

The “unexplained variance”, or “within group variability” is

$$\sum_{i} \frac{\left(Y_{ij} - \bar{Y}_{i-}\right)^2}{(N-K)}$$

where Y_{ij} is the jth observation in the ith out of K groups and N is the overall sample size. This F-statistic follows the F-distribution with K-1, N-K degrees of freedom under the null hypothesis. The statistic will be large if the between-group variability is large relative to the within-group variability, which is unlikely to happen if the population means of the groups all have the same value.

At this stage, the main objective is to determine the variables which are most suitable for constructing an efficient early warning model for insolvency. To achieve this, the data was analysed using the SPSS statistical software package, where the individual discriminating ability of 29 financial ratios was tested by comparing the equality of group means using Wilk’s lambda and associated F-test. This test compared the difference between the average values within each group. The smaller the Wilk’s lambda, the greater the differences between the averages values of the ratios in healthy and non-healthy groups.

By using the independent t-test on financial ratios, the results are presented in Table 7.2.

Table 7.2: Test of Equality of Group Means for the Financial Ratios

Code	Definition	Healthy Banks		Non Healthy Banks		Test statistics			Accept H_0/ Reject H_0
		Mean	Std. Deviation	Mean	Std. Deviation	R^2	F	Sig.	
CR1	Shareholders' Equity /Total Assets	8.402633	2.2412743	9.234678	2.4889663	0.03	1.234	0.274	Accept
CR2	Shareholders' Equity / (Deposits and non-deposit Funds)	9.931081	2.9956406	13.467037	10.9716562	0.05	1.933	0.173	Accept
CR3	Net Working Capital/Total Assets	7.771799	2.7656042	8.811924	3.8140332	0.03	0.975	0.33	Accept
CR4	Shareholders' Equity/(Total Assets + Contingencies and Commitments)	6.950892	2.0480445	6.815665	1.9487232	0.00	0.046	0.832	Accept
CR5	Financing/Shareholder's equity	892.260495	205.0004287	540.436306	215.9991685	0.42	27.916	0.00	Reject***
CR6	Shareholder's Equity / Total Financing	14.336730	4.3535285	20.588139	9.2883727	0.16	7.428	0.01	Reject***
AQ1	Loans/Total Assets	66.107239	5.4538328	46.157535	2.6992707	0.85	214.954	0.00	Reject***
AQ2	Non-performing Loans/Loans	3.171078	1.4126553	4.276396	1.4335836	0.14	6.032	0.019	Reject**
AQ3	Permanent Assets/Total Assets	.086702	.1344406	.320438	.1027328	0.50	38.167	0.00	Reject***
AQ4	Specific Provision / Total Financing	.310601	.2010536	.466968	.4264991	0.05	2.2	0.146	Accept
LR1	Liquid Assets/Total Assets	28.069266	3.3683832	44.600878	2.4612094	0.89	314.067	0.00	Reject***
LR2	Liquid Assets/(Deposits and non-deposit Funds)	32.320545	3.3707487	55.742877	15.2149878	0.54	45.179	0.00	Reject***
LR3	Total Deposits / Total Loans	153.720709	30.5638476	194.464830	16.1704114	0.42	27.769	0.00	Reject***
LR4	Total Financing / Total Deposits	78.058721	8.7322843	57.328726	15.3191682	0.42	27.642	0.00	Reject***
PR1	Net Income(Loss)/Total Assets	.227913	.0855760	.110102	.3080823	0.07	2.715	0.108	Accept
PR2	Net Income(Loss)/Shareholders' Equity	3.096351	1.2440997	5.805571	15.0513533	0.02	0.644	0.427	Accept
PR3	Net Income (Loss)/Total Share (CS/PS)	15.694408	12.0891294	2.133943	5.0513580	0.36	21.424	0.00	Reject***
PR4	Net Income before Tax/Average Total	.239581	.0876397	.116843	.2988128	0.08	3.107	0.086	Reject*

	Assets								
PR5	Provision for Loan Losses/Total Assets	.171237	.0802411	.231295	.2401977	0.03	1.125	0.296	Accept
IE1	Net Interest Income After Provision/Average Total Assets	1.143738	.1647074	1.147397	.4772256	0.00	0.001	0.974	Accept
IE2	Interest Income/Interest Expenses	264.971248	30.3472291	291.700425	173.8756642	0.01	0.459	0.502	Accept
IE3	Total Income/Total Expenses	130.858696	8.9479444	113.894736	19.6912588	0.24	12.303	0.001	Reject***
IE4	Interest Income/Total Income	115.239729	8.3663485	135.011602	73.4372799	0.04	1.431	0.239	Accept
IE5	Interest Expenses/Total Expenses	57.612975	5.3179638	55.613202	4.7099555	0.04	1.585	0.216	Accept
M1	Operating Expenses / Total Assets	.298167	.1176054	.386923	.0894355	0.16	7.217	0.011	Reject**
M2	Interest Expenses / Total Deposits	.606021	.1393208	.699111	.2599084	0.05	1.993	0.166	Accept
LE1	Total Liabilities / Total Equity	1298.563254	367.4474433	1133.351891	393.8376001	0.05	1.882	0.178	Accept
LE2	Total Liabilities / Total Assets	91.522191	2.3238423	90.037952	4.0682014	0.05	2.007	0.165	Accept
LE3	Total Assets / Total Equity	1399.487450	366.5533913	1242.874123	393.9420879	0.04	1.694	0.201	Accept

Notes: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

In the initial stage of analysis, the univariate analysis of variance (ANOVA) test was applied to the 29 ratios of the selected Islamic banks, and 13 ratios were determined as the early warning indicators which have the discriminating ability for healthy and non-healthy banks.

Table 7.2 presents means and standard deviations of the financial ratios for the two groups (healthy and non-healthy banks), and significance tests for the equality of group means for each ratios. The ratios are presented in ascending order according to the significance levels, *i.e.* according to the significance level of the F statistics of each ratio as shown in one of the columns in Table 7.2. As a result, out of 29 ratios used in the early stage of analysis, only 13 have the small significance level (<10%). Hence, the null hypothesis that the two group means are equal is rejected at the 10% significance level of these ratios. For the rest of the ratios, with bigger significance level (>10%), these were excluded from the analysis due to the inability to split the Islamic banks into the healthy and non-healthy groups. In other words, the equality of the group means these remaining ratios cannot be rejected at the 10% significance level.

7.2.3 Factor Analysis

Factor analysis attempts to identify underlying variables, or factors, that explain the pattern of correlations within a set of observed variables. In other words, it is a technique that is used for identifying groups or clusters of variables. According to Field (2009), this technique has three main uses: to understand the structure of a set of selected variables, to construct a questionnaire to measure the an underlying variable, and to reduce a data set to a more manageable size, at the same time still retaining as much as the original information as possible. This technique is often used in data reduction to identify a smaller number of factors that explain most of the variance observed in a much larger number of variables. In fact, factor analysis also can be used to generate hypotheses regarding causal mechanisms or to screen variables for subsequent analysis.

In the following section, the results on factor analysis will be discussed in detail.

7.2.3.1 Descriptive Analysis

Table 7.3 contains the descriptive statistics for each of the selected variables in terms of their mean, standard deviation and number of observations (*N*).

Table 7.3: Descriptive Analysis

Descriptive Statistics			
Variables	**Mean**	**Std. Deviation**	**Analysis *N***
CR5	716.348400	273.7553707	40
CR6	17.462435	7.8284747	40
AQ1	56.132387	10.9585277	40
AQ2	3.723737	1.5121868	40
AQ3	.203570	.1671989	40
LR1	36.335072	8.8630746	40
LR2	44.031711	16.0929627	40
LR3	174.092769	31.7513669	40
LR4	67.693724	16.1761070	40
PR3	8.914175	11.4359577	40
IE3	122.376716	17.3694218	40
M1	.342545	.1124940	40
PR4	.178212	.2260629	40

7.2.3.2 Correlation Matrix

The correlation matrix is the table that shows all pairs of correlation coefficients for a set of variables. In other word, it shows the correlation coefficients between each pair, for several variables, arranged so that each variable is identified on each row and on each column, with the coefficient listed in the cells and defined by the rows and columns. In SPSS, before finding a solution to a set of variables to make it more sensible, factor analysis is conducted in order to look at the intercorrelation between variables.

Table 7.4 below shows the *R*-Matrix or correlation matrix produced using the coefficients option. This table contains the Pearson correlation coefficient between all pairs of selected variables. In order to do factor analysis, all selected variables should be correlated fairly well, but not perfectly correlated. Any variables that do not correlate with any other variables should be eliminated from the study. Thus, this correlation matrix table can be used to check the pattern of relationships among the variables.

Based on Table 7.4, most of the variables have shown mediocre correlations among them. CR5 and CR6, overall have shown a medium correlation with the other variables except the correlation between CR5 and PR3 which has shown a strong performance between them. AQ1 shows high correlation with the liquidity group of variables (LR1, LR2, LR3, and LR4) but shows a medium correlation with the others.

Table 7.4: Correlation Matrix

Correlation Matrix[a]														
		CR5	**CR6**	**AQ1**	**AQ2**	**AQ3**	**LR1**	**LR2**	**LR3**	**LR4**	**PR3**	**IE3**	**M1**	**PR4**
Correlation	CR5	1.000	-.599	.589	-.506	-.694	-.607	-.485	-.541	.387	.844	.627	-.413	.524
	CR6	-.599	1.000	-.400	.379	.502	.379	.531	.397	.255	-.585	-.539	.301	-.470
	AQ1	.589	-.400	1.000	-.410	-.536	-.960	-.790	-.802	.711	.485	.522	-.260	.222
	AQ2	-.506	.379	-.410	1.000	.522	.367	.571	.236	-.189	-.544	-.181	.383	-.009
	AQ3	-.694	.502	-.536	.522	1.000	.636	.750	.174	-.190	-.704	-.415	.793	-.374
	LR1	-.607	.379	-.960	.367	.636	1.000	.807	.757	-.683	-.512	-.488	.423	-.252
	LR2	-.485	.531	-.790	.571	.750	.807	1.000	.451	-.295	-.436	-.419	.605	-.200
	LR3	-.541	.397	-.802	.236	.174	.757	.451	1.000	-.603	-.420	-.475	-.007	-.200
	LR4	.387	.255	.711	-.189	-.190	-.683	-.295	-.603	1.000	.259	.314	.000	.092
	PR3	.844	-.585	.485	-.544	-.704	-.512	-.436	-.420	.259	1.000	.593	-.480	.506
	IE3	.627	-.539	.522	-.181	-.415	-.488	-.419	-.475	.314	.593	1.000	-.167	.881
	M1	-.413	.301	-.260	.383	.793	.423	.605	-.007	.000	-.480	-.167	1.000	-.247
	PR4	.524	-.470	.222	-.009	-.374	-.252	-.200	-.200	.092	.506	.881	-.247	1.000

a. Determinant = 1.59E-009

7.2.3.3 Inverse Correlation Matrix

Table 7.5 below shows the inverse of the correlation matrix (R^{-1}), which is used in various calculations including the factor scores. The diagonal element of the inverse correlation matrix measures the extent to which the variables are linear combinations of other variables. Large diagonal elements indicate that variables are highly correlated.

Table 7.5: Inverse Correlation Matrix

Inverse of Correlation Matrix													
	CR5	CR6	AQ1	AQ2	AQ3	LR1	LR2	LR3	LR4	PR3	IE3	M1	PR4
CR5	11.663	13.833	14.061	-1.058	6.782	-4.458	1.739	3.169	-17.461	-.717	-.301	.294	1.967
CR6	13.833	37.263	39.509	-5.306	4.452	-4.920	9.458	-1.181	-45.143	1.530	-1.356	2.316	8.691
AQ1	14.061	39.509	84.627	-6.444	3.743	17.209	26.171	2.646	-54.523	-1.856	-3.734	-6.277	11.552
AQ2	-1.058	-5.306	-6.444	4.241	-.114	5.011	-6.611	-.430	8.359	2.036	-1.424	.280	-1.136
AQ3	6.782	4.452	3.743	-.114	14.980	-9.382	-2.617	7.859	-6.841	3.743	-.753	-1.905	.920
LR1	-4.458	-4.920	17.209	5.011	-9.382	39.560	-6.350	-9.050	11.525	-.089	-7.354	-3.540	4.206
LR2	1.739	9.458	26.171	-6.611	-2.617	-6.350	24.686	2.726	-19.523	-6.246	8.188	-5.297	-2.999
LR3	3.169	-1.181	2.646	-.430	7.859	-9.050	2.726	9.668	-1.702	.882	2.430	-1.244	-2.411
LR4	-17.461	-45.143	-54.523	8.359	-6.841	11.525	-19.523	-1.702	60.551	.138	-1.345	-.960	-8.500
PR3	-.717	1.530	-1.856	2.036	3.743	-.089	-6.246	.882	.138	6.773	-3.676	1.992	2.123
IE3	-.301	-1.356	-3.734	-1.424	-.753	-7.354	8.188	2.430	-1.345	-3.676	16.027	-3.597	-12.699
M1	.294	2.316	-6.277	.280	-1.905	-3.540	-5.297	-1.244	-.960	1.992	-3.597	6.025	3.162
PR4	1.967	8.691	11.552	-1.136	.920	4.206	-2.999	-2.411	-8.500	2.123	-12.699	3.162	13.481

7.2.3.4 KMO and Bartlett's Test

Table 7.6 shows the important part of the factor analysis output, that is the Kaiser-Meyer-Olkin measure of sampling adequacy, and Bartlett's test of sphericity. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is an index used to examine the appropriateness of factor analysis. The KMO statistic varies between 0 and 1. High values, between 0.5 and 1.0, indicate that factor analysis is appropriate while values below 0.5 imply that factor analysis may not be appropriate. On one hand, a value of 0 indicates that the sum of partial correlations is large relative to the sum of correlations, indicating diffusion in the pattern of correlation; hence factor analysis may not be appropriate. On the other hand, a value close to 1 indicates that the patterns of correlations are relatively compact and factor analysis should generate clear and reliable factors. According to Kaiser (1974), any values greater than 0.5 are barely acceptable and any value smaller than this should lead the researcher to either add more data or reconsider the selection of variables. According to Hutcheson and Sofroniou (1999), any values between 0.5 and 0.7 are consider as mediocre, values between 0.7 and 0.8 are considered as good, values between 0.8 and 0.9 are great, and values more than 0.9 are superb. For this data the value is 0.676, which falls into the range of being mediocre, so it can be concluded that the sample size is sufficient for factor analysis.

Another indicator of the strength of the relationship among variables is Bartlett's test of sphericity. Bartlett's test of sphericity is a test in statistics used to examine the hypothesis that the variables are uncorrelated in the population. In other words, the population matrix is an identity matrix; each variable correlates perfectly itself ($r=1$) but has no correlation with the other variables ($r=0$). The observed significance level is .0000 and this is small enough to reject the hypothesis. Based on the results depicted in Table 6.6, a significant test shows that the correlation matrix is not an identity matrix, therefore, there is some relationship between the selected variables. Based on that, it can be concluded that the strength of the relationship among variables is strong and it is appropriate to proceed with factor analysis.

Table 7.6: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.676
Bartlett's Test of Sphericity	Approx. Chi-Square	685.542
	df	78
	Sig.	.000

7.2.3.5 Total Variance Explained

Table 7.7 shows the eigenvalues associated with each linear component or factor before extraction, after extraction and after rotation. Before extraction, SPSS has identified 13 linear components or factors within the data set. The eigenvalues associated with each factor represent the variance explained by that particular linear component or factor. The SPSS output in Table 7.7 also shows the eigenvalue in terms of the percentage of variance explained. Factor 1 explains 27.920% of the total variance, factor 2 explains 27.190% of the total variance, and factor 3 explains 24.274% of the total variance. These 3 factors combined explain 79.384% of the total variance. The first few factors explain relatively large amounts of variance, especially factor 1 and 2, whereas subsequent factors explain smaller amounts of variance.

SPSS extracts all factors with eigenvalues greater than 1 and excludes factors with eigenvalues less than 1, thus leaving this study with 3 factors. The eigenvalues associated with these factors are again displayed, together with the percentage of variance explained, in the columns labelled Extraction Sum of Squared Loadings. The values in this part of the table are the same as the values before extraction, in the initial eigenvalues, except that the values for the discarded factors are ignored, hence the table is blank after the third factor. In the Rotation Sums of Squared Loadings column, the eigenvalues of the factors after rotation are displayed.

According to the result in Table 7.7, factor 1 accounted for considerably more variance than the other 2 factors (51.194% compared to 15.582% and 12.609%) before rotation but it accounts for only 27.920% of variance (compared to 27.190% and 24.274% respectively) after the rotation.

Table 7.7: Total Variance Explained

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.655	51.194	51.194	6.655	51.194	51.194	3.630	27.920	27.920
2	2.026	15.582	66.775	2.026	15.582	66.775	3.535	27.190	55.110
3	1.639	12.609	79.384	1.639	12.609	79.384	3.156	24.274	79.384
4	.906	6.972	86.356						
5	.796	6.122	92.479						
6	.456	3.510	95.988						
7	.219	1.688	97.676						
8	.145	1.118	98.794						
9	.064	.496	99.290						
10	.045	.348	99.638						
11	.025	.193	99.831						
12	.016	.124	99.956						
13	.006	.044	100.000						
Extraction Method: Principal Component Analysis.									

7.2.3.6 Component Matrix and Rotated Component Matrix

Table 7.8 shows the component matrix before rotation. This matrix contains the loadings of each variable onto each factor. Although this matrix is not particularly important for further elaboration, it is interesting to know that before rotation most of the selected variables load highly onto the first factor, as shown by the total variance explained in Table 7.7 (51.194% before rotation as compared to 27.920% total variance after rotation).

Table 7.8: Component Matrix

Component Matrix[a]			
	Component		
	1	2	3
CR5	-.854	-.131	.151
CR6	.643	.443	-.185
AQ1	-.849	.472	-.076
AQ2	.575	.141	.438
AQ3	.801	.352	.324
LR1	.868	-.393	.143
LR2	.811	-.012	.383
LR3	.666	-.552	-.215
LR4	-.485	.755	.019
PR3	-.803	-.277	.101
IE3	-.712	-.097	.614
M1	.550	.453	.474
PR4	-.525	-.353	.674
Extraction Method: Principal Component Analysis.			
a. 3 components extracted.			

Table 7.9 shows the rotated component matrix which is a matrix of the factor loadings for each variable onto each factor. This matrix contains the same information as the component matrix in Table 7.8, except that it is calculated after rotation. Based on these two tables (Table 7.8 and Table 7.9), there is not much different in factor loadings for each variable.

Table 7.9: Rotated Component Matrix

Rotated Component Matrix[a]			
	Component		
	1	2	3
CR5	-.481	.384	.624
CR6	.456	-.009	-.660
AQ1	-.383	.870	.213
AQ2	.708	-.201	-.041
AQ3	.858	-.160	-.331
LR1	.472	-.815	-.205
LR2	.754	-.463	-.147
LR3	.042	-.839	-.298
LR4	.022	.897	-.025
PR3	-.544	.234	.618
IE3	-.070	.342	.878
M1	.843	.070	-.125
PR4	-.019	.028	.923
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			
a. Rotation converged in 5 iterations.			

Table 7.10 presents the results of the factor analysis, and the ratios with the large loadings on the same factors are grouped. The first factor (F1) consists of one capital ratio (CR6), two asset quality ratios (AQ2 and AQ3), three liquidity ratios (LR1, LR2 and LR3), and one management ratio (M1). All the ratios grouped under this factor have positive loadings. Hence, an increase in the value of these ratios will lead to an increase in the factor score, thus the lower the failure risk of Islamic banks. The second factor (F2) consists of an asset quality ratio (AQ1) and a liquidity ratio (LR4). Both of these ratios have positive loadings, thus the greater the value, the greater the financial strength for an Islamic bank, and the lower the risk of failure. The third factor (F3) consists of two profitability ratios (PR3 and PR4), one capital ratio (CR5), and one Income-expenditure ratio (IE3). All the four ratios grouped under this factor have positive loadings. This means that any increase in the value of these ratios will lead to an increase in the factor score, thus lowering the risk of Islamic bank failure.

Table 7.10: Results on Factor Analysis

Ratios	Definition	Component			Category
		1	2	3	
CR6	Shareholder's Equity / Total Financing	0.456	-0.009	-0.66	Capital
AQ2	Non-performing Loans/Loans	0.708	-0.201	-0.041	Asset Quality
AQ3	Permanent Assets/Total Assets	0.858	-0.16	-0.331	Asset Quality
LR1	Liquid Assets/Total Assets	0.472	-0.815	-0.205	Liquidity
LR2	Liquid Assets/(Deposits and non-deposit Funds)	0.754	-0.463	-0.147	Liquidity
LR3	Total Deposits / Total Loans	0.042	-0.839	-0.298 asset	Liquidity
M1	Operating Expenses / Total Assets	0.843	0.07	-0.125	Management
AQ1	Loans/Total Assets	-0.383	0.87	0.213	Asset Quality
LR4	Total Financing / Total Deposits	0.022	0.897	-0.025	Liquidity
CR5	Financing/Shareholder's equity	-0.481	0.384	0.624	Capital
PR3	Net Income (Loss)/Total Share (CS/PS)	-0.544	0.234	0.618	Profitability
IE3	Total Income/Total Expenses	-0.07	0.342	0.878	Income-Expenditure
PR4	Net Income before Tax/Average Total Assets	-0.019	0.028	0.923	Profitability

7.2.3.7 Component Score Coefficient Matrix

Table 7.11 shows the component score matrix from which the factor scores are calculated.

Table 7.11: Component Score of Coefficient Matrix

Component Score Coefficient Matrix			
	Component		
	1	2	3
CR5	-.044	.023	.163
CR6	.074	.121	-.223
AQ1	-.015	.263	-.059
AQ2	.261	.015	.124
AQ3	.278	.079	.013
LR1	.059	-.232	.072
LR2	.229	-.069	.110
LR3	-.137	-.284	-.043
LR4	.116	.348	-.100
PR3	-.090	-.042	.165
IE3	.165	.031	.355
M1	.336	.144	.081
PR4	.155	-.087	.417
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Component Scores.			

7.2.3.8 Estimated Factor Scores for Each Bank

Based on the component score of the coefficient matrix in Table 7.11 above, factor scores for each Islamic bank for 19 quarters are calculated. Factor scores can be defined as a single score from an individual entity or sample representing their performance on some latent variable. Table 7.12 shows the results of factor scores for each bank for each quarter calculated. The score can be computed as follows.

$$F_1 = 0.074CR6 + 0.261AQ2 + 0.278AQ3 + 0.059LR1 + 0.229LR2 - 0.137LR3 + 0.336M1$$

and,

$$F_2 = 0.263AQ1 + 0.348LR4$$

and,

$$F_3 = 0.163CR5 + 0.165PR3 + 0.355IE3 + 0.417PR4$$

Table 7.12: Estimated Factor Scores for Each Bank

	Q2 2010			Q1 2010			Q42009			Q3 2009		
Banks	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**
Affin	(8.68)	29.81	166.27	(9.26)	29.44	170.22	(9.16)	28.70	156.31	(11.47)	26.30	154.47
BIMB	(12.64)	24.28	119.98	(10.23)	26.00	119.92	(9.84)	25.68	122.15	(10.27)	25.54	129.19
CIMB	(11.62)	38.79	436.68	(13.01)	40.09	369.51	(14.14)	37.26	343.40	(14.11)	34.02	282.23
EONCap Islamic	(6.08)	39.85	188.48	(5.89)	43.51	190.69	(7.18)	42.01	184.37	(6.48)	47.46	188.74
Hong Leong	(16.63)	27.68	127.52	(15.04)	29.01	128.77	(16.10)	28.71	131.98	(16.62)	29.50	130.96
Kuwait Finance House	0.25	53.79	80.32	2.85	47.99	55.93	2.16	45.13	66.78	(1.44)	49.97	97.64
Maybank	(5.30)	52.94	228.98	(6.28)	53.15	243.18	(6.35)	54.11	246.08	(7.01)	54.38	224.57
Muamalat	(7.64)	28.31	131.99	(9.83)	25.86	121.45	(7.92)	27.42	125.92	(7.07)	27.53	123.68
Public Bank	(8.52)	38.67	197.07	(9.28)	36.57	208.69	(8.11)	40.49	203.35	(8.35)	40.79	208.26
RHB Islamic	(9.11)	36.43	157.50	(9.59)	36.25	145.73	(8.88)	34.13	164.36	(9.60)	34.33	145.52

	Q22009			Q12009			Q42008			Q32008		
Banks	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**
Affin	(10.40)	27.33	175.57	(13.33)	24.30	174.87	(11.99)	26.08	193.72	(12.99)	24.73	187.80
BIMB	(14.06)	22.58	143.06	(11.36)	24.30	148.31	(9.60)	26.41	140.79	(8.01)	28.72	154.43
CIMB	(14.29)	30.86	232.66	(18.24)	27.12	203.95	(26.27)	20.25	171.13	(35.60)	14.80	129.55
EONCap Islamic	(6.87)	46.40	202.84	(7.08)	45.23	199.29	(7.49)	43.12	208.55	(7.69)	44.82	213.31
Hong Leong	(16.14)	27.62	132.00	(12.82)	32.79	132.24	(14.66)	32.72	138.63	(13.98)	34.60	144.88
Kuwait Finance House	(1.98)	53.23	92.42	(2.12)	45.77	101.26	(2.49)	46.50	95.93	(5.12)	40.64	124.73
Maybank	(5.01)	51.96	217.72	(5.20)	51.32	236.88	(3.95)	51.33	230.99	(6.11)	52.49	263.41
Muamalat	(5.46)	30.49	120.43	(5.11)	30.84	118.06	(8.96)	27.56	177.76	(7.49)	31.44	185.60
Public Bank	(8.25)	38.12	202.84	(9.13)	47.27	225.03	(8.56)	47.52	252.92	(8.27)	54.39	151.12
RHB Islamic	(11.24)	31.94	141.92	(10.32)	37.65	138.38	(11.78)	37.65	150.25	(11.78)	38.96	156.57

	Q22008			Q12008			Q42007			Q32007		
Banks	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**
Affin	(16.01)	22.74	184.24	(18.32)	21.10	178.20	(23.08)	17.70	161.50	(22.28)	18.07	152.31
BIMB	(9.73)	25.26	183.47	(7.97)	27.74	160.09	(8.99)	26.82	166.68	(7.80)	28.97	174.56
CIMB	(48.97)	10.92	98.58	(36.14)	13.26	99.89	(29.96)	14.63	89.70	(30.50)	14.24	73.21
EONCap Islamic	(7.57)	45.89	198.57	(6.95)	46.81	226.64	(7.90)	48.57	208.00	(8.30)	51.19	209.83
Hong Leong	(10.59)	34.87	148.65	(8.68)	38.56	152.84	(10.00)	39.82	149.50	(9.40)	41.43	146.48
Kuwait Finance House	(6.12)	38.73	135.57	(6.17)	34.42	124.04	(5.19)	34.74	104.70	(5.55)	28.85	88.04
Maybank	(6.96)	53.10	255.33	(6.81)	54.58	247.76	(7.92)	52.25	264.45	(5.22)	56.30	201.88
Muamalat	(8.30)	30.16	175.67	(8.10)	29.83	171.31	(9.81)	26.30	163.63	(9.29)	27.00	162.76
Public Bank	(7.52)	50.62	144.91	(6.24)	46.95	145.69	(9.01)	50.71	150.34	(7.71)	50.25	152.17
RHB Islamic	(10.58)	37.31	144.06	(11.27)	36.32	141.99	(10.24)	35.87	142.94	(11.05)	40.64	151.15

	Q22007			Q12007			Q42006			Q32006		
Banks	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**
Affin	(28.04)	15.01	141.32	(16.35)	20.23	148.27	(10.61)	21.94	159.18	(12.93)	23.16	158.28
BIMB	(9.12)	28.37	176.64	(8.40)	29.64	179.25	(7.24)	31.11	208.41	(8.29)	36.63	(529.78)
CIMB	(20.15)	16.65	87.73	(21.59)	17.04	94.65	(14.25)	22.71	113.87	(17.67)	18.68	75.61
EONCap Islamic	(8.51)	50.22	205.06	(8.63)	52.68	203.11	(8.98)	51.73	195.13	(8.20)	52.82	197.03
Hong Leong	(10.00)	39.52	143.94	(11.04)	35.25	148.24	(9.83)	39.82	149.50	(10.34)	40.24	156.46
Kuwait Finance House	(8.67)	27.16	107.51	(9.26)	25.71	84.06	(18.31)	17.80	75.57	(7.90)	19.05	56.18
Maybank	(3.92)	54.25	186.73	(7.97)	53.13	198.68	(5.72)	49.54	207.07	(6.08)	62.07	202.93
Muamalat	(9.02)	27.26	150.60	(9.87)	26.35	147.86	(12.00)	24.63	161.26	(13.56)	24.50	163.39
Public Bank	(7.92)	52.59	149.82	(7.14)	49.36	153.07	(8.96)	59.92	148.98	(4.30)	56.96	153.26
RHB Islamic	(11.09)	41.67	164.90	(11.04)	34.21	150.65	(10.96)	33.74	152.93	(13.72)	27.71	151.00

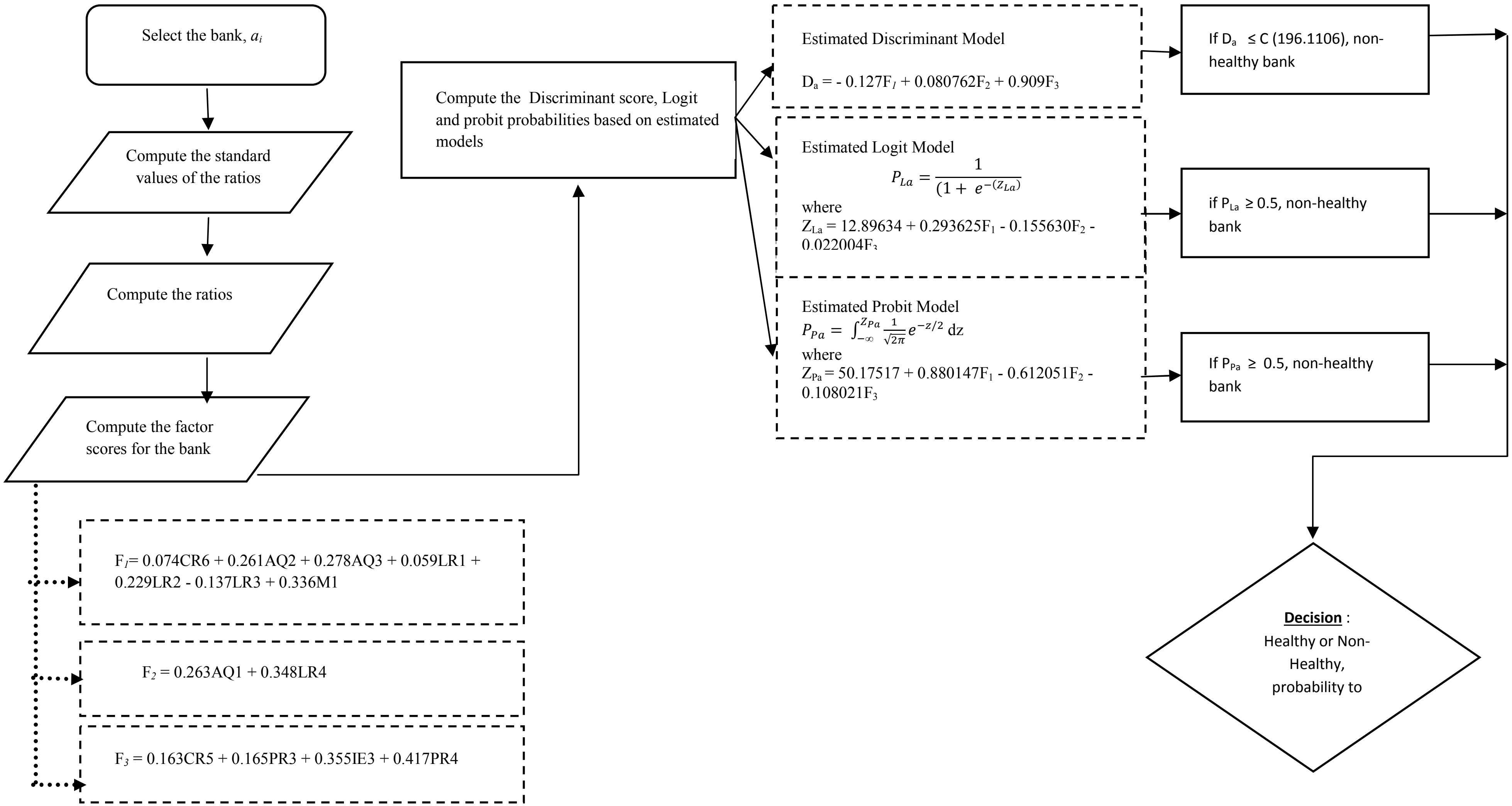
	Q22006			Q12006			Q42005		
Banks	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**
Affin	(6.12)	31.63	162.16	(2.39)	30.04	132.38	12.83	34.99	128.55
BIMB	(10.93)	35.78	(654.22)	(6.20)	40.64	178.38	(5.36)	37.22	179.04
CIMB	(7.84)	24.55	58.22	(0.22)	40.61	96.55	12.06	48.73	72.69
EONCap Islamic	(9.46)	57.06	203.32	(9.05)	57.05	176.85	(8.71)	58.24	189.28
Hong Leong	(11.32)	39.65	159.38	53.02	183.64	158.21	(10.99)	38.38	158.73
Kuwait Finance House	4.95	19.91	45.76	(3.44)	12.32	37.34	92.64	0.00	43.99
Maybank	(3.82)	58.07	220.43	(1.41)	55.29	228.43	(3.43)	56.93	253.16
Muamalat	(13.50)	24.50	163.91	(13.44)	24.50	164.62	(12.96)	24.50	167.67
Public Bank	(7.83)	57.89	151.42	(8.35)	61.13	155.29	(7.70)	64.73	163.59
RHB Islamic	(14.12)	28.40	149.47	(13.58)	29.52	146.65	(13.29)	29.64	144.06

After grouping the factors and calculating the factor scores, an integrated model (discriminant, logit and probit) was estimated using these findings. In this study, the scores of the three factors determined by factor analysis (principal component analysis) in one quarter (Q2 2010) before the benchmark quarter (Q3 2010) were used as the independent variables in the estimation of the estimated models. These estimated models then were tested on the factors scores for the rest of the quarters (from Q2 2010 to Q3 2005) before the benchmark quarter.

7.3 INTEGRATED EARLY WARNING MODEL

The factor analysis and three parametric models (discriminant analysis, logit analysis and probit analysis) have been used in this study to construct an integrated prediction model for Islamic banks in Malaysia. This integrated model can be an analytical tool for decision support in Islamic bank supervision and examination. This system of the integrated model can be used as presented in Figure 7.1 and it shows the process flow of the integrated model *i.e.* the estimated models and their parameters. These parameters include the means and standard deviations of the selected financial ratios, the factor score coefficients of the three factors obtained by factor analysis, and finally the estimated coefficients of the discriminant, logit and probit models. Based on this integrated model, when evaluating bank performance, all the system parameters will remain unchanged and only the ratios of the evaluated bank will change. These ratios are the 13 early warning indicators that were determined in the previous section using factor analysis (principal component analysis). In the early stage, all these 13 ratios are standardised and the three factor scores are determined by using the factor score coefficient matrix as calculated in Table 7.11 using SPSS. Table 7.12 shows the factor scores for each bank for each quarter calculated. Then these factor scores are used in calculating the discriminant score, logit and probit probability of failure for the Islamic bank. The results are discussed in detail in the next section below.

Figure 7.1:Integrated Model Process Flow



7.3.1 Discriminant Analysis (SPSS)

Discriminant analysis builds a predictive model for the groups of the selected sample. The model is composed of a discriminant function, two groups in this case; healthy and non-healthy, based on linear combinations of the predictor variables that provide the best discrimination between the groups (Balcaen and Ooghe, 2006). Discriminant analysis, also known as Discriminant Function Analysis (DFA), can be used after MANOVA to see how the dependent variable discriminate the groups. Discriminant function analysis identifies the combination of the dependent variables and also determines how many variates are significant by looking at the table labelled Wilks's lambda. If the value of the significance level is less than 0.5 then the variable is significantly discriminating the groups. Once the significant variable has been identified, the standardised canonical discriminant function coefficient will be used to find out how the dependent variable contribute to the variate. High scores indicate that a dependent variable is important for a variate, and variables with positive and negative coefficients are contributing to the variate in opposite ways (Canbas *et al.*, 2005). The detailed output explanation of the discriminant analysis is provided in the next section.

In discriminant analysis it is considered that any bank *a* is characterized by a vector of elements that are the measurements of three independent variables (factors). For two populations, the healthy and non-healthy Islamic banks, it is assumed that the independent variables are distributed within each group according to a multivariate normal distribution with different means but equal dispersion matrices (Canbas *et al.*, 2005).

The objective of this method is to obtain the linear combination of the independent variables that maximizes the variances between the populations relative to within-group variance.

7.3.1.1 Group Statistics

Table 7.13: Group Statistic for Discriminant Analysis

Group Statistics					
y		Mean	Std. Deviation	Valid N (list wise)	
				Unweighted	Weighted
1	F1	-9.075632	5.6396283	6	6.000
	F2	33.384220	10.7639410	6	6.000
	F3	130.597012	30.4902847	6	6.000
2	F1	-7.881615	2.8456126	4	4.000
	F2	42.560858	6.9386208	4	4.000
	F3	262.803199	117.2199206	4	4.000
Total	F1	-8.598025	4.5551094	10	10.000
	F2	37.054875	10.1426007	10	10.000
	F3	183.479487	98.7804293	10	10.000

7.3.1.2 Summary of Canonical Discriminant Function

In order to evaluate the effectiveness of the estimated discriminant model, the model statistics were calculated using SPSS as shown in Table 7.14. The eigenvalue statistic as shown in Table 7.14, is the ratio of the between-groups to within-groups sum of squares of the D score. A large eigenvalue (1.575) shows that the estimated discriminant model is of high discriminating ability. The canonical correlation (0.782) is the measure of the degree of association between D-scores and the group variable that is coded 0 for healthy Islamic banks and 1 for non-healthy Islamic banks.

Table 7.14: Result on Eigenvalues

Eigenvalues				
Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.575[a]	100.0	100.0	.782
a. First 1 canonical discriminant functions were used in the analysis.				

Table 7.15 shows the result on Wilks' Lambda. A small Wilks' Lambda (0.388) means that most of the total variability is attributable to differences between the means of the D-score of the groups.

Table 7.15: Result on Wilks' Lambda

Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.388	6.147	3	.105

Table 7.16: Standardised Canonical Discriminant Function Coefficients

Standardised Canonical Discriminant Function Coefficients	
	Function
	1
F1	-.127
F2	.762
F3	.909

Table 7.16 shows the standardised canonical discriminant function coefficient. These coefficient values are used to find out how the dependent variable contributes to the variates. On one hand, the higher the scores indicates that a dependent variable is important for a variate (F_2 = .762, F_3 = .909) and vice versa (F_1 = -.127). On the other hand, variables with positive or negative coefficients are contributing to the variate in opposite ways.

Table 7. 17: Canonical Discriminant Function Coefficients

Canonical Discriminant Function Coefficients	
	Function
	1
F1	-.026
F2	.080
F3	.012
(Constant)	-5.400
Unstandardized coefficients	

Table 7.17 shows the first canonical discriminant function coefficients or the unstandardised version of the standardised coefficients as described in above. These

values are less useful as compared to the standardised version, but they do show where the standardised version came from.

7.3.2 Empirical Results for Discriminant Analysis

7.3.2.1 Discriminant Function

Discriminant analysis, also known as discriminant function analysis, identifies and describes the discriminant function variates of a set of variables. Below are the outputs of discriminant analysis. The combination of predictor variables is called as a linear discriminant function, and this function can then be used to classify new observations whose group membership is unknown (Boyacioglu *et al.*, 2009). The linear discriminant function takes the general form:

$$D_a = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots .. + \beta_n X_n$$

Where D_a is a discriminant score, β_0 is an estimated constant, β_n are the estimated coefficients, and for each factor and X_n are the variables included under each factor (Boyacioglu *et al.*, 2009).

The Discriminant score is a score for an individual case on a particular discriminant function variate obtained by replacing that case's scores on the measured variables into the equation that defines the variate in question. The linear combinations of the factor scores provide each Islamic bank a D-score, according to the estimated canonical discriminant model below:

$$D_a = - 0.127F_1 + 0.080762F_2 + 0.909F_3 \qquad (7.1)$$

In the equation above, D_a is the discriminant score for bank *a,* and F_1, F_2, and F_3 represent the selected factors as discussed in the previous section of factor analysis. This discriminant model was estimated by using SPSS software.

7.3.2.2 Discriminant Scores Using Estimated Discriminant Model for Each Islamic Bank

Table 7.18 below presents the estimated scores for each Islamic bank for each quarter based on the Discriminant function developed above.

Table 7.18: Estimated Discriminant Scores for Each Bank

	Q2 2010	Q1 2010	Q42009	Q3 2009	Q2 2009	Q1 2009	Q4 2008	Q3 2008	Q2 2008	Q1 2008
Banks	**D**	**D**	**D**	**D**	**D**	**D**	**D**	**D**	**D**	**D**
Affin	174.96074	178.3444	165.1149	161.9063	181.7392	179.1676	197.4879	191.2077	186.8286	180.3859
BIMB	129.17641	130.1137	131.8586	138.1956	149.0287	154.7725	149.3276	163.278	187.2551	167.6713
CIMB	427.97728	368.0877	342.3397	284.2688	236.8227	208.3728	174.3237	133.5539	104.1519	105.4922
EONCap Islamic	202.46541	207.2369	200.5118	208.5524	220.608	216.5232	223.3887	229.0294	216.434	242.5687
Hong Leong	139.11597	141.0609	143.8971	143.6353	143.0847	146.8225	152.8074	159.841	163.0421	169.4173
Kuwait Finance House	113.96333	87.0415	94.816	127.0173	124.821	127.1938	122.9474	144.9979	153.5253	139.7652
Maybank	249.15876	262.3467	265.7206	246.461	238.1409	255.0951	249.5836	280.2125	273.4482	267.6732
Muamalat	142.52491	131.351	136.3617	134.3039	133.3953	131.4626	183.7262	193.6181	183.7168	179.479
Public Bank	209.68034	218.7475	216.7314	221.4528	214.48	241.7327	267.2037	179.8634	171.2499	169.007
RHB Islamic	172.08303	161.3144	176.5412	159.652	154.7642	155.7874	166.7667	173.5041	160.7299	158.1724

	Q4 2007	Q3 2007	Q2 2007	Q1 2007	Q4 2006	Q3 2006	Q2 2006	Q1 2006	Q4 2005
Banks	**D**	**D**	**D**	**D**	**D**	**D**	**D**	**D**	**D**
Affin	163.2284	155.0444	143.459	152.2762	162.7593	163.1612	172.277	143.5293	141.8788
BIMB	173.0912	181.7436	183.3416	186.5941	214.0644	-452.606	-566.027	193.9074	191.7849
CIMB	96.49056	81.27199	94.99761	101.7619	122.6215	85.21068	72.62067	118.7326	101.6789
EONCap Islamic	227.0871	230.7929	225.7511	225.87	217.9334	220.3884	229.4939	205.3814	217.5369
Hong Leong	167.5124	165.9154	162.2287	163.01	167.4928	174.1962	176.5261	277.0144	174.923
Kuwait Finance House	122.2999	102.7199	119.5213	97.17619	84.57942	66.58669	56.1394	43.77046	28.22363
Maybank	281.2076	227.0726	211.5676	222.1017	226.7004	232.5363	245.1083	249.9475	273.9364
Muamalat	170.0188	169.703	158.8077	155.7372	166.879	168.9136	169.3822	170.0169	172.7327
Public Bank	176.4428	177.5922	177.2597	177.6595	182.2159	183.2579	182.7498	188.7951	199.0019
RHB Islamic	158.5635	169.764	183.054	164.4142	166.1087	160.1183	159.3033	157.5229	155.2274

7.3.2.3 Classification Using Discriminant Scores

Based on the Discriminant score and the calculated cut-off score, an Islamic bank is classified into the healthy or non-healthy group. The optimum cut-off score is calculated as approximately equal to zero, and is the weighted average of the Discriminant score of the healthy and non-healthy Islamic bank groups:

$$C \quad = \quad (N_A D_A + N_B D_B) / (N_A + N_B)$$

where

C : cut-off score
N_A : number of the healthy Islamic banks
N_B : number of the non-healthy Islamic banks
D_A : average score for a healthy Islamic bank
D_B :average score for a non-healthy Islamic bank

So,

$$C \quad =[(4 \text{ x } 272.32045) + (6 \text{ x } 145.30406)] / 10$$

$$=196.1106$$

Based on the cut-off score calculated above, if the D-score is less than the cut-off score, the Islamic bank is classified as a non-healthy Islamic bank, and if the D-score is more than the cut-off point, the Islamic bank is classified as a healthy Islamic bank.

Table 7.19 shows the calculated D-scores using the estimated discriminant model and classification results for each of the Islamic banks.

Table 7.19: Discriminant Scores Using Estimated Discriminant Model and Classification Results

	Actual Class	Q2 2010		Q1 2010		Q42009		Q3 2009		Q2 2009	
Banks		**D**	**Prediction**	**D**	**Prediction**	**D**	**Prediction**	**D**	**Prediction**	**D**	**Prediction**
Affin	1	174.96	1	178.34	1	165.11	1	161.91	1	181.74	1
BIMB	1	129.18	1	130.11	1	131.86	1	138.20	1	149.03	1
CIMB	0	427.98	0	368.09	0	342.34	0	284.27	0	236.82	0
EONCap Islamic	0	202.47	0	207.24	0	200.51	0	208.55	0	220.61	0
Hong Leong	1	139.12	1	141.06	1	143.90	1	143.64	1	143.08	1
Kuwait Finance House	1	113.96	1	87.04	1	94.82	1	127.02	1	124.82	1
Maybank	0	249.16	0	262.35	0	265.72	0	246.46	0	238.14	0
Muamalat	1	142.52	1	131.35	1	136.36	1	134.30	1	133.40	1
Public Bank	0	209.68	0	218.75	0	216.73	0	221.45	0	214.48	0
RHB Islamic	1	172.08	1	161.31	1	176.54	1	159.65	1	154.76	1
	Actual Class	**Q1 2009**		**Q4 2008**		**Q3 2008**		**Q2 2008**		**Q1 2008**	
Banks		**D**	**Prediction**	**D**	**Prediction**	**D**	**Prediction**	**D**	**Prediction**	**D**	**Prediction**
Affin	1	179.17	1	197.49	0*	191.21	1	186.83	1	180.39	1
BIMB	1	154.77	1	149.33	1	163.28	1	187.26	1	167.67	1
CIMB	0	208.37	0	174.32	1*	133.55	1*	104.15	1*	105.49	1*
EONCap Islamic	0	216.52	0	223.39	0	229.03	0	216.43	0	242.57	0
Hong Leong	1	146.82	1	152.81	1	159.84	1	163.04	1	169.42	1
Kuwait Finance House	1	127.19	1	122.95	1	145.00	1	153.53	1	139.77	1
Maybank	0	255.10	0	249.58	0	280.21	0	273.45	0	267.67	0
Muamalat	1	131.46	1	183.73	1	193.62	1	183.72	1	179.48	1
Public Bank	0	241.73	0	267.20	0	179.86	1*	171.25	1*	169.01	1*
RHB Islamic	1	155.79	1	166.77	1	173.50	1	160.73	1	158.17	1
	Actual Class	**Q4 2007**		**Q3 2007**		**Q2 2007**		**Q1 2007**		**Q4 2006**	

Banks		D	Prediction	D	Prediction	D	Prediction	D	Prediction	D	Prediction
Affin	1	163.23	1	155.04	1	143.46	1	152.28	1	162.76	1
BIMB	1	173.09	1	181.74	1	183.34	1	186.59	1	214.06	0*
CIMB	0	96.49	1*	81.27	1*	95.00	1*	101.76	1*	122.62	1*
EONCap Islamic	0	227.09	0	230.79	0	225.75	0	225.87	0	217.93	0
Hong Leong	1	167.51	1	165.92	1	162.23	1	163.01	1	167.49	1
Kuwait Finance House	1	122.30	1	102.72	1	119.52	1	97.18	1	84.58	1
Maybank	0	281.21	0	227.07	0	211.57	0	222.10	0	226.70	0
Muamalat	1	170.02	1	169.70	1	158.81	1	155.74	1	166.88	1
Public Bank	0	176.44	1*	177.59	1*	177.26	1*	177.66	1*	182.22	1*
RHB Islamic	1	158.56	1	169.76	1	183.05	1	164.41	1	166.11	1

	Actual Class	Q3 2006		Q2 2006		Q1 2006		Q4 2005	
Banks		D	Prediction	D	Prediction	D	Prediction	D	Prediction
Affin	1	163.16	1	172.28	1	143.53	1	141.88	1
BIMB	1	(452.61)	1	(566.03)	1	193.91	1	191.78	1
CIMB	0	85.21	1*	72.62	1*	118.73	1*	101.68	1*
EONCap Islamic	0	220.39	0	229.49	0	205.38	0	217.54	0
Hong Leong	1	174.20	1	176.53	1	277.01	0*	174.92	1
Kuwait Finance House	1	66.59	1	56.14	1	43.77	1	28.22	1
Maybank	0	232.54	0	245.11	0	249.95	0	273.94	0
Muamalat	1	168.91	1	169.38	1	170.02	1	172.73	1
Public Bank	0	183.26	1*	182.75	1*	188.80	1*	199.00	0
RHB Islamic	1	160.12	1	159.30	1	157.52	1	155.23	1

*Note: * Misclassification*

As depicted in Table 7.19 above, the estimated discriminant model correctly classifies the Islamic banks into 2 groups, healthy and non-healthy Islamic banks, for the six quarters (Q2 2010, Q1 2010, Q4 2009, Q3 2009, Q2 2009 and Q1 2009) before the benchmark quarter (Q3 2010). For the rest of the quarters, the estimated discriminant model showed at least a 70% accuracy in classifying the Islamic banks into the two groups (with a maximum of 30% error or misclassification).

7.3.3 Logit

As explained in the literature chapter, the Logit regression has been used considerably in bank failure prediction. It gives accurate estimates and is a user-friendly tool for analysing bankruptcies. Another reason why logistic regression is preferable compared to other accurate predicting models is its easiness to use, as statistical software for the logit model is available. In this study Eviews software is employed although some researchers will also use Stata software to run the logit regression. The advantage of the logit model is its capability for providing explanatory power for all the independent variables. The logit model has the statistical property of not assuming multivariate normality among the independent variables, contrary to the probit model that does assume a normal distribution of the data. This can be seen as an advantage when analysing banking data, as it is generally not normally distributed (Andersen, 2008).

The logit analysis is based on a cumulative logistic function; it provides the probability of an Islamic bank belonging to one of the prescribed groups, given by the financial characteristics of the Islamic bank (Canbas *et al.*, 2005). In the logit method the probability of an Islamic bank *a* of going non-healthy (P_{La}) is calculated using the cumulative logistic function:

$$P_{La} = \frac{1}{(1+ e^{-(Z_{La})}} \qquad (7.2)$$

where

$$Z_{La} \quad = \quad \beta_1 F_{1a} + \beta_2 F_{2a} + \beta_3 F_{3a} \qquad (7.3a)$$

Based on the probability above, an Islamic bank is classified as healthy or non-healthy by using the cut-off probability, attempting to minimise the Type I and Type II errors (Canbas *et al.,* 2005).

7.3.3.1 Test Statistics for Logit Model

Table 7.20: Test Statistics for Logit Model

Dependent Variable: Y				
Method: ML - Binary Logit (Quadratic hill climbing)				
Sample: 1 190				
Included observations: 190				
Convergence achieved after 5 iterations				
Covariance matrix computed using second derivatives				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	12.89634	1.894401	6.807609	0.0000
F1	0.293625	0.056922	5.158338	0.0000
F2	-0.155630	0.027897	-5.578766	0.0000
F3	-0.022004	0.006403	-3.436398	0.0006
McFadden R^2	0.412720	Mean dependent var		0.600000
S.D. dependent var	0.491192	S.E. of regression		0.319718
Akaike info criterion	0.832597	Sum squared resid		19.01285
Schwarz criterion	0.900956	Log likelihood		-75.09676
Hannan-Quinn criter.	0.860288	Deviance		150.1935
Restr. deviance	255.7444	Restr. log likelihood		-127.8722
LR statistic	105.5509	Avg. log likelihood		-0.395246
Prob(LR statistic)	0.000000			

Table 7.20 presents the calculated test statistics for the estimated coefficient for the logit model. Based on the table above, all the coefficients of the logit model are statistically significant according to the observed significant level of the z-statistic corresponding to the standard errors of the coefficients. Maximisation of the log-likelihood function provided the following Z_{La} equation in the logit analysis as estimated by using Eviews software:

$$Z_{La} \quad = \quad 12.89634 + 0.293625F1 - 0.155630F2 - 0.022004F3 \qquad (7.3b)$$

In the equation above, Z_{La} is the logit score for bank *a,* and F_1, F_2, and F_3 represent the selected factors as discussed in the previous section of factor analysis.

Based on the equation 7.3b above the logit scores (Z_{La}) for each Islamic bank for each quarter are calculated as shown in Table 7.21 below.

7.3.3.2 Results: Z_{La}

Table 7.21: Logit Scores Z_{La}

	Q2 2010	Q1 2010	Q42009	Q3 2009	Q2 2009	Q1 2009	Q4 2008	Q3 2008	Q2 2008	Q1 2008
Banks	Z_{La}	Z_{La}	Z_{La}	Z_{La}	Z_{La}	Z_{La}	Z_{La}	Z_{La}	Z_{La}	Z_{La}
Affin	2.049215776	1.849055697	2.300061792	2.035930234	1.726766086	1.351697885	1.053135905	1.099707196	0.603103724	0.312693382
BIMB	2.764432998	3.20640579	3.320882948	3.064278908	2.105938607	2.51528855	2.867607403	2.675947882	2.071833997	2.716235882
CIMB	-6.16174742	-5.294383119	-4.611761912	-2.752041405	-1.223264955	-1.168674015	-1.735728071	-2.709006662	-5.350782751	-1.975677551
EONCap Islamic	0.763273068	0.199064743	0.19244919	-0.544790948	-0.804771183	-0.608034201	-0.604386403	-1.031228045	-0.838300099	-1.416014262
Hong Leong	0.898603459	1.132295405	0.795436345	0.54438703	0.953449206	1.118082229	0.448871608	0.218579316	1.088140764	0.984008957
Kuwait Finance House	2.831406889	5.034018046	5.038454649	2.54745235	1.998705662	2.9208394	2.817388654	2.322980878	2.086854486	2.999015544
Maybank	-1.938570367	-2.569168741	-2.803886754	-2.565188459	-1.453385899	-1.831717047	-1.335863256	-2.86356825	-3.030488438	-3.048852015
Muamalat	3.343370399	3.314216055	3.531882495	3.813230731	3.897988021	3.998204246	2.06416546	1.718751139	1.899971745	2.105443221
Public Bank	0.039577009	-0.113254695	-0.262578077	-0.48519919	0.076657244	-2.091536477	-2.577216115	-1.321966883	-0.378244505	0.550069354
RHB Islamic	1.086559712	1.232457512	1.359972471	1.534879098	1.503629607	0.96136804	0.270742855	-0.070181864	0.812306604	0.811315181
	Q4 2007	**Q3 2007**	**Q2 2007**	**Q1 2007**	**Q4 2006**	**Q3 2006**	**Q2 2006**	**Q1 2006**	**Q4 2005**	
Banks	Z_{La}	Z_{La}	Z_{La}	Z_{La}	Z_{La}	Z_{La}	Z_{La}	Z_{La}	Z_{La}	
Affin	-0.190776866	0.192124147	-0.782767113	1.684182774	2.863065877	2.013230286	2.610311727	4.605506363	8.39055198	
BIMB	2.414753172	2.255789193	1.915804622	1.871739271	1.343871539	16.41886137	18.51268691	0.826363393	1.589425536	
CIMB	-0.150026796	0.114400321	2.457232353	1.823103304	2.672250249	3.135839248	5.492584108	4.387613853	7.253576327	
EONCap Islamic	-1.559605284	-2.123124579	-1.930975216	-2.30642815	-2.085001697	-2.068068755	-3.234279048	-2.532853198	-2.888905864	
Hong Leong	0.473598792	0.464922685	0.64282992	0.907812815	0.52257206	0.155792307	-0.105612482	-3.597991925	0.204374556	
Kuwait Finance House	3.663108845	4.838717453	3.758355623	4.325456725	3.085683605	6.374987463	10.24596836	9.14696473	39.12838756	
Maybank	-3.378498359	-1.838993242	-0.805888347	-2.085679004	-1.048407154	-3.014566848	-2.113341271	-1.148423563	-2.540521737	
Muamalat	2.323697275	2.384276334	2.691038237	2.645422066	1.991841494	1.506274447	1.511553918	1.513544068	1.587703865	
Public Bank	-0.948867895	-0.53427123	-0.908811134	-0.250107394	-2.338319478	-0.602209489	-1.744327143	-2.487068504	-3.037765273	
RHB Islamic	1.16211781	0.00093409	-0.474499254	1.014821331	1.063522581	1.231880334	1.041879451	1.087763403	1.210435667	

7.3.3.3 Results: e $^{-Za}$

Table 7.22 depicts the e $^{-Za}$ results based on the equation 7.2.

Table 7.22: e $^{-Za}$

	Q2 2010	**Q1 2010**	**Q42009**	**Q3 2009**	**Q2 2009**	**Q1 2009**	**Q4 2008**	**Q3 2008**	**Q2 2008**	**Q1 2008**
Banks	e^{-Za}	e^{-Za}	e^{-Za}	e^{-Za}	e^{-Za}	e^{-Za}	e^{-Za}	e^{-Za}	e^{-Za}	e^{-Za}
Affin	0.1288359	0.1573857	0.1002526	0.1305589	0.1778586	0.2588004	0.3488421	0.3329685	0.5471109	0.7314741
BIMB	0.0630118	0.0405019	0.0361209	0.0466875	0.1217313	0.0808395	0.0568347	0.0688415	0.1259545	0.0661231
CIMB	474.25607	199.21469	100.66135	15.674597	3.3982648	3.2177231	5.6730566	15.014353	210.77321	7.2115041
EONCap Islamic	0.4661382	0.8194968	0.8249362	1.7242478	2.2361847	1.8368170	1.8301289	2.8045077	2.3124327	4.1206637
Hong Leong	0.4071378	0.3222926	0.4513842	0.5801973	0.3854093	0.3269061	0.6383480	0.8036597	0.3368421	0.3738095
Kuwait Finance House	0.0589298	0.0065125	0.0064837	0.0782808	0.1355105	0.0538884	0.0597618	0.0979810	0.1240768	0.0498361
Maybank	6.9488096	13.054967	16.508687	13.003108	4.2775734	6.2445997	3.80327773	17.523945	20.707344	21.091118
Muamalat	0.0353177	0.0363625	0.0292498	0.0220767	0.0202826	0.0183485	0.1269241	0.1792899	0.1495728	0.1217916
Public Bank	0.9611959	1.1199171	1.3002779	1.6244985	0.9262072	8.097347	13.160449	3.7507914	1.4597198	0.5769098
RHB Islamic	0.3373751	0.291575	0.2566678	0.2154817	0.2223217	0.3823694	0.7628126	1.0727032	0.4438331	0.4442733

	Q4 2007	**Q3 2007**	**Q2 2007**	**Q1 2007**	**Q4 2006**	**Q3 2006**	**Q2 2006**	**Q1 2006**	**Q4 2005**
Banks	e^{-Za}	e^{-Za}	e^{-Za}	e^{-Za}	e^{-Za}	e^{-Za}	e^{-Za}	e^{-Za}	e^{-Za}
Affin	1.2101893	0.8252044	2.1875170	0.1855960	0.0570934	0.1335565	0.0735116	0.0099966	0.000227
BIMB	0.0893894	0.1047908	0.1472233	0.1538558	0.2608338	7.4025E-08	9.121E-09	0.4376379	0.2040427
CIMB	1.1618653	0.8919008	0.0856717	0.1615237	0.0690965	0.0434632	0.0041171	0.0124303	0.0007076
EONCap Islamic	4.7569432	8.3572094	6.8962322	10.038504	8.0446051	7.9095331	25.388061	12.589374	17.973633
Hong Leong	0.62275706	0.62818367	0.52580234	0.40340558	0.59299337	0.8557369	1.11139111	36.5248162	0.81515699
Kuwait Finance House	0.0256526	0.0079172	0.0233220	0.0132275	0.0456987	0.0017036	3.55E-05	0.0001065	1.0157E-1
Maybank	29.326699	6.2902023	2.2386843	8.0500556	2.8531029	20.380261	8.2758469	3.1532181	12.686288

Muamalat	0.0979109	0.0921556	0.0678105	0.0709753	0.1364439	0.2217345	0.2205669	0.2201284	0.2043943
Public Bank	2.5827840	1.7062043	2.4813707	1.2841633	10.363805	1.8261492	5.7220500	12.025970	20.858577
RHB Islamic	0.3128229	0.9990663	1.6072091	0.3624671	0.3452375	0.2917434	0.3527910	0.3369693	0.2980673

7.3.3.4 Results: P_{La}

Finally, Table 7.23 shows the probability of logit scores for each bank for each quarter as according to the equation given (7.2).

Table 7.23: Probability of Logit Scores P_{La}

	Q2 2010	Q1 2010	Q42009	Q3 2009	Q2 2009	Q1 2009	Q4 2008	Q3 2008	Q2 2008	Q1 2008
Banks	P_{La}	P_{La}	P_{La}	P_{La}	P_{La}	P_{La}	P_{La}	P_{La}	P_{La}	P_{La}
Affin	0.8858683	0.8640161	0.9088821	0.8845182	0.8489983	0.7944070	0.7413766	0.7502052	0.6463660	0.5775425
BIMB	0.9407233	0.9610746	0.9651383	0.955395	0.8914790	0.9252066	0.9462217	0.9355923	0.8881353	0.9379779
CIMB	0.0021041	0.0049946	0.0098365	0.0599714	0.2273623	0.2370947	0.1498563	0.0624439	0.0047220	0.1217803
EONCap Islamic	0.6820639	0.5496024	0.5479643	0.3670737	0.3090058	0.3525077	0.3533408	0.2628460	0.3018929	0.1952871
Hong Leong	0.7106624	0.7562622	0.6889974	0.6328323	0.7218083	0.7536328	0.6103709	0.5544283	0.7480314	0.7279029
Kuwait Finance House	0.9443495	0.9935295	0.9935580	0.9274021	0.8806611	0.9488670	0.9436082	0.9107625	0.8896189	0.9525296
Maybank	0.125805	0.0711492	0.0571145	0.0714127	0.1894810	0.1380338	0.2081911	0.0539841	0.0460673	0.0452670
Muamalat	0.9658870	0.9649133	0.9715814	0.9784001	0.9801205	0.9819820	0.8873711	0.8479679	0.8698883	0.8914311
Public Bank	0.5098929	0.4717165	0.4347300	0.3810251	0.5191549	0.1099221	0.0706192	0.2104912	0.4065503	0.6341516
RHB Islamic	0.7477333	0.7742484	0.7957552	0.8227190	0.8181152	0.7233956	0.5672752	0.4824617	0.6926008	0.6923896
	Q4 2007	**Q3 2007**	**Q2 2007**	**Q1 2007**	**Q4 2006**	**Q3 2006**	**Q2 2006**	**Q1 2006**	**Q4 2005**	
Banks	P_{La}	P_{La}	P_{La}	P_{La}	P_{La}	P_{La}	P_{La}	P_{La}	P_{La}	
Affin	0.4524499	0.5478838	0.3137238	0.8434576	0.9459901	0.8821791	0.9315222	0.9901023	0.9997730	
BIMB	0.9179454	0.9051487	0.8716698	0.8666594	0.7931258	1.0000	1.0000	0.6955854	0.8305352	
CIMB	0.4625634	0.5285689	0.9210887	0.8609380	0.9353692	0.9583471	0.9958996	0.9877222	0.9992928	
EONCap Islamic	0.1737032	0.1068694	0.1266426	0.0905919	0.1105631	0.1122393	0.0378959	0.0735869	0.0527047	

Hong Leong	0.6162351	0.6141813	0.6553928	0.7125523	0.627749	0.5388694	0.4736213	0.0266490	0.5509165	
Kuwait Finance House	0.9749889	0.9921449	0.9772094	0.9869451	0.9562983	0.9982992	0.9999645	0.9998934	1.000000	
Maybank	0.0329742	0.1371704	0.3087673	0.1104965	0.2595310	0.0467721	0.1078068	0.2407771	0.0730658	
Muamalat	0.9108207	0.9156204	0.9364957	0.9337282	0.8799378	0.8185084	0.8192913	0.8195858	0.8302928	
Public Bank	0.2791125	0.3695212	0.2872431	0.4377970	0.0879986	0.3538383	0.1487641	0.0767697	0.0457486	
RHB Islamic	0.7617173	0.5002335	0.3835518	0.7339626	0.7433631	0.7741475	0.7392124	0.7479603	0.7703760	

7.3.3.5 Classification Using Estimated Logit Model

Table 7.24 shows the classification result based on the estimated logit model. An Islamic bank is classified into the healthy or non-healthy group according to the estimated logit model, based on the cut-off probability of 0.5 ($P_c = 0.5$) and the calculated probability of the logit scores as shown below. If the probability of the logit score (P_{La}) is less than the cut-off probability (P_c), the Islamic bank is classified into the healthy group. But, if the probability of the logit score (P_{La}) is more than or equal to the cut-off probability (P_c), the Islamic bank is classified into the non-healthy group, thus increasing the probability of failure.

Table 7.24:Classification Using Estimated Logit Model

Banks	Actual Class	Q2 2010		Q1 2010		Q42009		Q3 2009		Q2 2009	
		P_{La}	Prediction	P_{La}	Prediction	P_{La}	Prediction	P_{La}	Prediction	P_{La}	Prediction
Affin	1	0.88586835	1	0.86401619	1	0.90888216	1	0.88451821	1	0.8489983	1
BIMB	1	0.94072331	1	0.96107463	1	0.96513831	1	0.955395	1	0.89147904	1
CIMB	0	0.00210413	0	0.00499464	0	0.00983658	0	0.05997146	0	0.22736239	0
EONCap Islamic	0	0.68206393	1*	0.54960249	1*	0.54796435	1*	0.36707379	0	0.30900584	0
Hong Leong	1	0.71066243	1	0.75626226	1	0.68899743	1	0.63283236	1	0.72180831	1
Kuwait Finane House	1	0.94434959	1	0.99352955	1	0.99355801	1	0.92740217	1	0.88066111	1
Maybank	0	0.125805	0	0.07114922	0	0.0571145	0	0.07141271	0	0.18948102	0
Muamalat	1	0.96588707	1	0.9649133	1	0.97158144	1	0.97840012	1	0.98012053	1
Public Bank	0	0.50989296	1*	0.47171655	0	0.43473007	0	0.38102517	0	0.51915493	1*
RHB Islamic	1	0.74773334	1	0.77424841	1	0.79575522	1	0.82271906	1	0.8181152	1

Banks	Actual Class	Q1 2009		Q4 2008		Q3 2008		Q2 2008		Q1 2008	
		P_{La}	Prediction	P_{La}	Prediction	P_{La}	Prediction	P_{La}	Prediction	P_{La}	Prediction
Affin	1	0.79440707	1	0.74137662	1	0.75020524	1	0.64636607	1	0.57754255	1
BIMB	1	0.92520668	1	0.94622173	1	0.93559238	1	0.8881353	1	0.93797792	1
CIMB	0	0.23709475	0	0.14985636	0	0.06244398	0	0.00472203	0	0.12178037	0
EONCap Islamic	0	0.35250775	0	0.3533408	0	0.26284609	0	0.30189292	0	0.19528718	0
Hong Leong	1	0.75363282	1	0.61037092	1	0.5544283	1	0.74803145	1	0.72790296	1
Kuwait Finane House	1	0.94886704	1	0.94360827	1	0.91076251	1	0.88961892	1	0.95252963	1
Maybank	0	0.13803385	0	0.20819117	0	0.05398418	0	0.04606736	0	0.04526706	0
Muamalat	1	0.98198204	1	0.88737115	1	0.84796791	1	0.86988833	1	0.89143111	1
Public Bank	0	0.10992216	0	0.07061922	0	0.21049124	0	0.40655037	0	0.63415168	1*
RHB Islamic	1	0.72339563	1	0.56727527	1	0.48246173	0*	0.69260081	1	0.69238969	1

	Actual	Q4 2007		Q3 2007		Q2 2007		Q1 2007		Q4 2006	

Banks	Class	P_{La}	Prediction	P_{La}	Prediction	P_{La}	Prediction	P_{La}	Prediction	P_{La}	Prediction
Affin	1	0.45244991	0*	0.54788384	1	0.31372382	0*	0.84345761	1	0.94599016	1
BIMB	1	0.91794541	1	0.90514873	1	0.87166986	1	0.8666594	1	0.79312589	1
CIMB	0	0.46256349	0	0.52856893	1*	0.92108873	1*	0.86093808	1*	0.9353692	1*
EONCap Islamic	0	0.17370329	0	0.10686947	0	0.12664268	0	0.09059198	0	0.11056315	0
Hong Leong	1	0.61623519	1	0.61418132	1	0.65539289	1	0.71255239	1	0.627749	1
Kuwait Finane House	1	0.97498896	1	0.99214499	1	0.97720946	1	0.98694518	1	0.95629833	1
Maybank	0	0.03297424	0	0.1371704	0	0.30876736	0	0.11049656	0	0.25953109	0
Muamalat	1	0.91082071	1	0.91562041	1	0.93649576	1	0.93372827	1	0.87993782	1
Public Bank	0	0.27911255	0	0.36952124	0	0.28724318	0	0.43779707	0	0.08799869	0
RHB Islamic	1	0.76171732	1	0.50023352	1	0.38355188	0*	0.73396263	1	0.74336314	1

	Actual Class	Q3 2006		Q2 2006		Q1 2006		Q4 2005	
Banks		P_{La}	Prediction	P_{La}	Prediction	P_{La}	Prediction	P_{La}	Prediction
Affin	1	0.88217919	1	0.93152228	1	0.9901023	1	0.99977305	1
BIMB	1	1.0000	1	1.0000	1	0.69558544	1	0.83053526	1
CIMB	0	0.95834711	1*	0.99589969	1*	0.98772226	1*	0.99929286	1*
EONCap Islamic	0	0.11223933	0	0.03789592	0	0.0735869	0	0.05270472	0
Hong Leong	1	0.53886949	1	0.47362139	0*	0.02664903	0*	0.55091653	1
Kuwait Finane House	1	0.99829926	1	0.9999645	1	0.99989347	1	1.000000	1
Maybank	0	0.04677211	0	0.10780687	0	0.24077714	0	0.07306583	0
Muamalat	1	0.81850842	1	0.81929138	1	0.81958584	1	0.83029281	1
Public Bank	0	0.35383836	0	0.14876414	0	0.07676971	0	0.04574863	0
RHB Islamic	1	0.77414751	1	0.73921248	1	0.74796032	1	0.77037603	1

* Misclassification

As depicted in Table 7.24 above, the estimated logit model correctly classifies the Islamic banks into 2 groups, healthy and non-healthy Islamic banks, for all of the quarters before the benchmark quarter (Q3 2010) with a minor error or misclassification. Based on these results, the estimated logit model showed at least 70% of accuracy in classifying the Islamic banks into two groups (with a maximum of 30% error or misclassification), thus indicates the equal performance between the estimated discriminant model and the estimated logit model.

7.3.4 Probit

In the probit method the probability (P_{pa}) of a bank falling under one of the two groups is given a cumulative standard normal distribution function as follows:

$$P_{Pa} = \int_{-\infty}^{Z_{Pa}} \frac{1}{\sqrt{2\pi}} e^{-z/2}\, dz \qquad (7.4a)$$

Table 7.25: Test Statistics for Probit Model

Dependent Variable: Y				
Method: ML - Binary Probit (Quadratic hill climbing)				
Sample: 1 100				
Included observations: 100				
Convergence achieved after 7 iterations				
Covariance matrix computed using second derivatives				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	50.17517	20.59124	2.436724	0.0148
F1	0.880147	0.363078	2.424129	0.0153
F2	-0.612051	0.255239	-2.397954	0.0165
F3	-0.108021	0.048524	-2.226154	0.0260
McFadden R^2	0.934430	Mean dependent var		0.600000
S.D. dependent var	0.492366	S.E. of regression		0.125351
Akaike info criterion	0.168259	Sum squared resid		1.508427
Schwarz criterion	0.272465	Log likelihood		-4.412927
Hannan-Quinn criter.	0.210433	Deviance		8.825855
Restr. deviance	134.6023	Restr. log likelihood		-67.30117
LR statistic	125.7765	Avg. log likelihood		-0.044129
Prob(LR statistic)	0.000000			

Table 7.25 presents the calculated test statistics for the estimated coefficient for the probit model. Based on the table above, all the coefficients of the logit model are statistically significant according to the observed significance level of the z-statistic corresponding to the standard errors of the coefficients. Maximisation of the log-

likelihood function provided the following Z_{Pa} equation in the probit analysis as estimated by using Eviews software:

$$Z_{Pa} = 50.17517 + 0.880147F_1 - 0.612051F_2 - 0.108021F_3 \quad (7.4b)$$

In the equation above, Z_{Pa} is the probit score for bank *a,* and F_1, F_2, and F_3 represent the selected factors as discussed in the previous section of factor analysis. In this estimated probit model, it applies the probit transformation, the inverse of the cumulative standard normal distribution function, to the probit scores. The results of this transformation are shown in Table 7.27 (cumulative standard normal distribution function) and Table 7.28 (the inverse of the cumulative standard normal distribution function).

Based on the equation 7.4b above the probit scores (Z_{Pa}) for each Islamic bank for each quarter are calculated as shown in Table 7.26 below.

7.3.4.1 Results: Z_{Pa}

Table 7.26: Probit scores

	Q2 2010	Q1 2010	Q42009	Q3 2009	Q2 2009	Q1 2009	Q4 2008	Q3 2008	Q2 2008	Q1 2008
Banks	Z_{Pa}	Z_{Pa}	Z_{Pa}	Z_{Pa}	Z_{Pa}	Z_{Pa}	Z_{Pa}	Z_{Pa}	Z_{Pa}	Z_{Pa}
Affin	0.95843	0.86911	1.06956	0.95007	0.81994	0.65094	0.52283	0.54258	0.31339	0.17738
BIMB	1.26675	1.46853	1.52373	1.41006	0.98094	1.17136	1.32560	1.24239	0.98912	1.26681
CIMB	-2.67085	-2.31884	-2.01604	-1.19186	-0.51296	-0.50148	-0.77553	-1.24656	-2.48611	-0.92504
EONCap Islamic	0.36057	0.09421	0.08929	-0.25888	-0.36750	-0.27678	-0.26480	-0.46223	-0.38517	-0.63459
Hong Leong	0.40138	0.50824	0.35492	0.23645	0.43008	0.49747	0.19198	0.08638	0.49160	0.43982
Kuwait Finance House	1.21778	2.23148	2.24626	1.10517	0.84142	1.28818	1.23517	1.03678	0.93839	1.36054
Maybank	-0.88589	-1.16845	-1.27686	-1.18197	-0.66730	-0.82793	-0.60231	-1.28937	-1.37354	-1.39003
Muamalat	1.53651	1.51983	1.62114	1.74975	1.78153	1.82567	0.97747	0.81612	0.89532	0.98804
Public Bank	0.03333	-0.02556	-0.10546	-0.20566	0.05558	-0.94964	-1.15536	-0.65796	-0.21837	0.21888
RHB Islamic	0.49440	0.55398	0.63004	0.69738	0.68453	0.42067	0.10900	-0.04682	0.35621	0.35601

	Q4 2007	Q3 2007	Q2 2007	Q1 2007	Q4 2006	Q3 2006	Q2 2006	Q1 2006	Q4 2005
Banks	Z_{Pa}	Z_{Pa}	Z_{Pa}	Z_{Pa}	Z_{Pa}	Z_{Pa}	Z_{Pa}	Z_{Pa}	Z_{Pa}
Affin	-0.06185	0.10844	-0.34582	0.79329	1.34441	0.94777	1.21237	2.11872	3.86155
BIMB	1.13340	1.06153	0.90648	0.88569	0.65917	7.11201	7.99555	0.38124	0.74137
CIMB	-0.08855	0.02297	1.11488	0.82522	1.22244	1.41723	2.48684	1.97372	3.27079
EONCap Islamic	-0.71747	-0.98195	-0.89459	-1.07430	-0.97568	-0.96840	-1.51189	-1.20558	-1.36385
Hong Leong	0.19867	0.18968	0.27369	0.40706	0.22137	0.05560	-0.06245	-1.93494	0.08299
Kuwait Finance House	1.65403	2.19741	1.71349	1.96221	1.39549	2.90401	4.68919	4.18718	18.10901
Maybank	-1.52685	-0.86489	-0.39324	-0.97594	-0.48293	-1.41914	-0.98198	-0.52421	-1.15473
Muamalat	1.08994	1.11615	1.24925	1.22776	0.93739	0.71407	0.71689	0.71832	0.75486
Public Bank	-0.47914	-0.28486	-0.46424	-0.15097	-1.14025	-0.32737	-0.85966	-1.20684	-1.46250
RHB Islamic	0.52007	-0.02066	-0.23306	0.46020	0.48521	0.57247	0.48210	0.49941	0.55420

7.3.4.2 Results: *NORMSDIST*

Table 7.27: NORMSDIST

	Q2 2010	Q1 2010	Q42009	Q3 2009	Q2 2009	Q1 2009	Q4 2008	Q3 2008	Q2 2008	Q1 2008
Banks	P_{Pa}	P_{Pa}	P_{Pa}	P_{Pa}	P_{Pa}	P_{Pa}	P_{Pa}	P_{Pa}	P_{Pa}	P_{Pa}
Affin	0.831076	0.807606	0.857591	0.828961	0.793875	0.742456	0.699452	0.706289	0.623009	0.570395
BIMB	0.897377	0.929019	0.936211	0.920738	0.83669	0.879274	0.907514	0.892954	0.838698	0.897388
CIMB	0.003783	0.010202	0.021898	0.116658	0.30399	0.308016	0.219014	0.106279	0.006457	0.177473
EONCap Islamic	0.640789	0.537527	0.535576	0.397865	0.356624	0.390975	0.39558	0.321957	0.350058	0.262848
Hong Leong	0.655929	0.694359	0.638674	0.593458	0.666432	0.690573	0.57612	0.534417	0.688499	0.669966
Kuwait Finance House	0.888346	0.987175	0.987656	0.865457	0.799943	0.901158	0.891616	0.85008	0.825977	0.913171
Maybank	0.187837	0.121312	0.100825	0.118609	0.252289	0.203856	0.273484	0.098635	0.084792	0.08226
Muamalat	0.937794	0.935724	0.947507	0.959919	0.962587	0.96605	0.835831	0.792785	0.814693	0.838434
Public Bank	0.513295	0.489804	0.458006	0.418527	0.522161	0.171148	0.123971	0.255281	0.413571	0.58663
RHB Islamic	0.689488	0.710204	0.735667	0.757217	0.753181	0.663002	0.543399	0.481327	0.639157	0.639085
	Q4 2007	**Q3 2007**	**Q2 2007**	**Q1 2007**	**Q4 2006**	**Q3 2006**	**Q2 2006**	**Q1 2006**	**Q4 2005**	
Banks	P_{Pa}	P_{Pa}	P_{Pa}	P_{Pa}	P_{Pa}	P_{Pa}	P_{Pa}	P_{Pa}	P_{Pa}	
Affin	0.475341	0.543176	0.36474	0.786197	0.910592	0.828376	0.887314	0.982943	0.999944	
BIMB	0.871476	0.855775	0.817659	0.812108	0.745106	1.000000	1.00000	0.648488	0.770767	
CIMB	0.464718	0.509162	0.867549	0.795376	0.889229	0.921791	0.993556	0.975793	0.999464	
EONCap Islamic	0.236541	0.163061	0.185504	0.141343	0.164612	0.166421	0.065282	0.113989	0.086307	
Hong Leong	0.578741	0.575219	0.60784	0.658019	0.587599	0.522168	0.475104	0.026499	0.533071	
Kuwait Finance House	0.95094	0.986004	0.956689	0.975131	0.918565	0.998158	0.999999	0.999986	1.0000	
Maybank	0.063399	0.19355	0.34707	0.164547	0.314573	0.077929	0.163054	0.300067	0.124101	
Muamalat	0.86213	0.867822	0.894213	0.890231	0.825721	0.762409	0.763279	0.763719	0.774832	
Public Bank	0.315919	0.387876	0.32124	0.439998	0.12709	0.371694	0.194988	0.113748	0.071802	
RHB Islamic	0.698494	0.491759	0.407857	0.677314	0.686237	0.716498	0.685132	0.691255	0.710278	

7.3.4.3 Results: *NORMSINV*

Table 7. 28: NORMSINV

Banks	**Q2 2010**	**Q1 2010**	**Q42009**	**Q3 2009**	**Q2 2009**	**Q1 2009**	**Q4 2008**	**Q3 2008**	**Q2 2008**	**Q1 2008**
Affin	0.958427	0.869109	1.069561	0.950066	0.819941	0.650936	0.522825	0.542575	0.313392	0.177381
BIMB	1.266747	1.468527	1.523726	1.410056	0.980944	1.171365	1.325603	1.242394	0.989119	1.266808
CIMB	-2.67085	-2.31884	-2.01604	-1.19186	-0.51296	-0.50148	-0.77553	-1.24656	-2.48611	-0.92504
EONCap Islamic	0.360569	0.094205	0.089294	-0.25888	-0.3675	-0.27678	-0.2648	-0.46223	-0.38517	-0.63459
Hong Leong	0.401378	0.508244	0.354917	0.236449	0.430082	0.497474	0.191978	0.086377	0.491599	0.439819
Kuwait Finance House	1.217777	2.231484	2.246264	1.105169	0.841418	1.288177	1.235166	1.036776	0.938386	1.360543
Maybank	-0.88589	-1.16845	-1.27686	-1.18197	-0.6673	-0.82793	-0.60231	-1.28937	-1.37354	-1.39003
Muamalat	1.536515	1.519834	1.621144	1.749747	1.781529	1.825675	0.977467	0.816121	0.895324	0.98804
Public Bank	0.033332	-0.02556	-0.10546	-0.20566	0.055577	-0.94964	-1.15536	-0.65796	-0.21837	0.218884
RHB Islamic	0.4944	0.553981	0.630044	0.697377	0.684534	0.42067	0.108999	-0.04682	0.356207	0.356014
Banks	**Q4 2007**	**Q3 2007**	**Q2 2007**	**Q1 2007**	**Q4 2006**	**Q3 2006**	**Q2 2006**	**Q1 2006**	**Q4 2005**	
Affin	-0.06185	0.108438	-0.34582	0.793294	1.34441	0.947769	1.212365	2.118724	3.861548	
BIMB	1.133396	1.06153	0.90648	0.885689	0.659168	7.112011	7.981697	0.381242	0.741374	
CIMB	-0.08855	0.022967	1.114879	0.825217	1.22244	1.417225	2.486837	1.973718	3.270786	
EONCap Islamic	-0.71747	-0.98195	-0.89459	-1.0743	-0.97568	-0.9684	-1.51189	-1.20558	-1.36385	
Hong Leong	0.198675	0.189676	0.273694	0.407063	0.221373	0.055597	-0.06245	-1.93494	0.082991	
Kuwait Finance House	1.654034	2.19741	1.71349	1.962215	1.395486	2.904013	4.68919	4.187185	4.753424	
Maybank	-1.52685	-0.86489	-0.39324	-0.97594	-0.48293	-1.41914	-0.98198	-0.52421	-1.15473	
Muamalat	1.08994	1.116155	1.249248	1.227759	0.93739	0.714072	0.716891	0.718315	0.754855	
Public Bank	-0.47914	-0.28486	-0.46424	-0.15097	-1.14025	-0.32737	-0.85966	-1.20684	-1.4625	
RHB Islamic	0.520075	-0.02066	-0.23306	0.4602	0.485213	0.572469	0.482098	0.49941	0.554198	

7.3.4.4 Classification Using Estimated Probit Model

Table 7.29 shows the classification results based on the estimated probit model. An Islamic bank is classified into the healthy or non-healthy group according to the estimated probit model, based on the cut-off probability of 0.5 ($P_c = 0.5$) and the calculated probability of probit scores as shown below. If the probability of probit scores (P_{Pa}) is less than the cut-off probability (P_c), the Islamic bank is classified into the healthy group. But, if the probability of the probit score (P_{Pa}) is more than or equal to the cut-off probability (P_c), the Islamic bank is classified into the non-healthy group, thus increasing the probability of failure.

Table 7.29: Classification Using Estimated Probit Model

Banks	Actual Class	Q2 2010		Q1 2010		Q42009		Q3 2009		Q2 2009	
		P_{pa}	Prediction	P_{pa}	Prediction	P_{pa}	Prediction	P_{pa}	Prediction	P_{pa}	Prediction
Affin	1	0.958427	1	0.869109	1	1.069561	1	0.950066	1	0.819940811	1
BIMB	1	1.266747	1	1.468527	1	1.523726	1	1.410056	1	0.980944345	1
CIMB	0	-2.67085	0	-2.31884	0	-2.01604	0	-1.19186	0	-0.51295905	0
EONCap Islamic	0	0.360569	0	0.094205	0	0.089294	0	-0.25888	0	-0.367498368	0
Hong Leong	1	0.401378	0*	0.508244	1	0.354917	0*	0.236449	0*	0.430082435	0*
Kuwait Finance House	1	1.217777	1	2.231484	1	2.246264	1	1.105169	1	0.841417981	1
Maybank	0	-0.88589	0	-1.16845	0	-1.27686	0	-1.18197	0	-0.667304546	0
Muamalat	1	1.536515	1	1.519834	1	1.621144	1	1.749747	1	1.781529323	1
Public Bank	0	0.033332	0	-0.02556	0	-0.10546	0	-0.20566	0	0.055577285	0
RHB Islamic	1	0.4944	0*	0.553981	1	0.630044	1	0.697377	1	0.684534151	1
Banks	**Actual Class**	**Q1 2009**		**Q4 2008**		**Q3 2008**		**Q2 2008**		**Q1 2008**	
		P_{pa}	Prediction	P_{pa}	Prediction	P_{pa}	Prediction	P_{pa}	Prediction	P_{pa}	Prediction
Affin	1	0.650936	1	0.522825	1	0.542575	1	0.313392	0*	0.177381018	0*
BIMB	1	1.171365	1	1.325603	1	1.242394	1	0.989119	1	1.266808073	1
CIMB	0	-0.50148	0	-0.77553	0	-1.24656	0	-2.48611	0	-0.925039541	0
EONCap Islamic	0	-0.27678	0	-0.2648	0	-0.46223	0	-0.38517	0	-0.634590444	0
Hong Leong	1	0.497474	0*	0.191978	0*	0.086377	0*	0.491599	0*	0.439818976	0*
Kuwait Finance House	1	1.288177	1	1.235166	1	1.036776	1	0.938386	1	1.360542994	1
Maybank	0	-0.82793	0	-0.60231	0	-1.28937	0	-1.37354	0	-1.390030232	0
Muamalat	1	1.825675	1	0.977467	1	0.816121	1	0.895324	1	0.988040382	1
Public Bank	0	-0.94964	0	-1.15536	0	-0.65796	0	-0.21837	0	0.218883741	0
RHB Islamic	1	0.42067	0*	0.108999	0*	-0.04682	0*	0.356207	0*	0.356013701	0*

Banks	Actual Class	Q4 2007		Q3 2007		Q2 2007		Q1 2007		Q4 2006	
		P_{pa}	Prediction	P_{pa}	Prediction	P_{pa}	Prediction	P_{pa}	Prediction	P_{pa}	Prediction
Affin	1	-0.06185	0*	0.108438	0*	-0.34582	0*	0.793294	1	1.344410458	1
BIMB	1	1.133396	1	1.06153	1	0.90648	1	0.885689	1	0.659167543	1
CIMB	0	-0.08855	0	0.022967	0	1.114879	1*	0.825217	1*	1.222440179	1*
EONCap Islamic	0	-0.71747	0	-0.98195	0	-0.89459	0	-1.0743	0	-0.975677583	0
Hong Leong	1	0.198675	0*	0.189676	0*	0.273694	0*	0.407063	0*	0.221373206	0*
Kuwait Finance House	1	1.654034	1	2.19741	1	1.71349	1	1.962215	1	1.395486402	1
Maybank	0	-1.52685	0	-0.86489	0	-0.39324	0	-0.97594	0	-0.482927961	0
Muamalat	1	1.08994	1	1.116155	1	1.249248	1	1.227759	1	0.93739017	1
Public Bank	0	-0.47914	0	-0.28486	0	-0.46424	0	-0.15097	0	-1.140254295	0
RHB Islamic	1	0.520075	1	-0.02066	0*	-0.23306	0*	0.4602	0*	0.485213309	0*

Banks	Actual Class	Q3 2006		Q2 2006		Q1 2006		Q4 2005	
		P_{pa}	Prediction	P_{pa}	Prediction	P_{pa}	Prediction	P_{pa}	Prediction
Affin	1	0.947769	1	1.212365	1	2.118724	1	3.861548	1
BIMB	1	7.112011	1	7.981697	1	0.381242	0*	0.741374	1
CIMB	0	1.417225	1*	2.486837	1*	1.973718	1*	3.270786	1*
EONCap Islamic	0	-0.9684	0	-1.51189	0	-1.20558	0	-1.36385	0
Hong Leong	1	0.055597	0*	-0.06245	0*	-1.93494	0*	0.082991	0*
Kuwait Finance House	1	2.904013	1	4.68919	1	4.187185	1	4.753424	1
Maybank	0	-1.41914	0	-0.98198	0	-0.52421	0	-1.15473	0
Muamalat	1	0.714072	1	0.716891	1	0.718315	1	0.754855	1
Public Bank	0	-0.32737	0	-0.85966	0	-1.20684	0	-1.4625	0
RHB Islamic	1	0.572469	1	0.482098	0*	0.49941	0*	0.554198	1

As depicted in Table 7.29 above, the estimated probit model correctly classifies the Islamic banks into 2 groups, healthy and non-healthy Islamic banks, for almost all of the quarters before the benchmark quarter (Q3 2010) with a minor error or misclassification. Based on these results, the estimated probit model showed at least 60% of accuracy in classifying the Islamic banks into two groups (with a maximum of 40% error or misclassification), thus again this indicates the equal performance between the three estimated models, the discriminant, logit and probit models.

7.3.4.5 Integrated Model Findings

Based on the above results, the combination of principal component analysis and the three parametric models (discriminant, logit and probit) can be very useful as an analytical decision support tool in bank supervision and examination. This integrated model consists of the estimated models and their parameters. These parameters are the means and standard deviations of the financial ratios, the factor score coefficient of the three factors that were obtained by principal component analysis, and finally the estimated coefficients of the discriminant model, logit model and probit model.

When evaluating a new bank according to the integrated model above, all the parameters will remain unchanged, and only the ratios of the evaluated bank will change. These ratios are the 13 early warning indicators that were determined as shown in Table 7.2 above. Hence, input to this integrated model consists of 13 early warning ratios. Initially, these ratios are standardised and the three factor scores are determined by using the factor score coefficient matrix calculated in Table 7.11. Then these factor scores are used in calculating the discriminant score, logit and probit probability of failure for the bank. This integrated model provides early warning signals for each of the discriminant, logit and probit models. Hence, the use of this integrated model provides better information about the future prospects of Islamic banks.

Tables 7.19, 7.24 and 7.29 present the classification results according to the estimated discriminant, logit and probit models respectively. Overall, classification accuracy is relatively high in the first few quarters before the benchmark quarter for all the estimated models. Correct classification rates are high during the first few quarters and decrease subsequently. Thus, based on these results it is obvious that the first few quarters before the benchmark quarter are the most important period for the correct prediction. These results show the predictive ability of the integrated model. It shows the ability of the integrated model in differentiating between the healthy and non-healthy Islamic banks, thus reducing the expected cost of bank failure.

7.4 CONCLUSION

This study has constructed an integrated model using the publicly available data for Islamic banks in Malaysia. Thus, this new integrated model can be easily used by regulators in monitoring the performance of Islamic banks that are experiencing any serious financial problems. On the one hand, from the regulators' perspective, the ability to detect the Islamic banks' performance by using the publicly available data will have a major impact on their monitoring cost especially for the on-site examinations. On the other hand, this information is also valuable for other parties that are involved in monitoring Islamic banks' performance or preventing the Islamic banks from failure. If the integrated model was effectively employed in Islamic bank supervision and examination, it would reduce the amount of restructuring cost significantly in the long term.

Table 7.30 presents the classification results according to the estimated discriminant, logit and probit models respectively. Overall, classification accuracy is relatively high in the first few quarters before the benchmark quarter for all the estimated models. Correct classification rates are high during the first few quarters and decrease subsequently. Thus, based on these results it is obvious that the first few quarters before the benchmark quarter are the most important for making a correct prediction. These results show the predictive ability of the integrated model to differentiate the healthy and non-healthy Islamic banks, thus reducing the expected cost of bank failure.

Table 7.30: Summary of Classification Results Using Estimated MDA, Estimated Logit and Estimated Probit Models

Estimated Models	Q2 2010	Q1 2010	Q42009	Q3 2009	Q2 2009	Q1 2009	Q4 2008
Discriminant Analysis	100%	100%	100%	100%	100%	100%	80%
Logit Model	80%	90%	90%	100%	90%	100%	100%
Probit Model	90%	100%	90%	90%	90%	90%	90%
Average Correct classification	**90%**	**97%**	**93%**	**97%**	**93%**	**97%**	**90%**
Estimated Models	**Q3 2008**	**Q2 2008**	**Q1 2008**	**Q4 2007**	**Q3 2007**	**Q2 2007**	**Q1 2007**
Discriminant Analysis	80%	80%	80%	80%	80%	80%	80%
Logit Model	90%	100%	90%	90%	90%	80%	90%
Probit Model	90%	80%	80%	80%	80%	70%	90%
Average Correct classification	**87%**	**87%**	**83%**	**83%**	**83%**	**77%**	**87%**
Estimated Models	**Q4 2006**	**Q3 2006**	**Q2 2006**	**Q1 2006**	**Q4 2005**		
Discriminant Analysis	70%	80%	80%	70%	90%		
Logit Model	90%	90%	80%	80%	90%		
Probit Model	90%	90%	90%	70%	80%		
Average Correct classification	**83%**	**87%**	**83%**	**73%**	**87%**		

Chapter 8
ALTERNATIVE MEASURES FOR PREDICTING FINANCIAL DISTRESS: FUNDING MIX, DEPOSITS, MACROECONOMICS & ALTERNATIVE BANK SPECIFIC VARIABLES

8.1 INTRODUCTION

As discussed in the previous chapter, the integrated model developed was more concentrated on the internal financial performance of Islamic banks. Out of 29 variables or financial ratios selected based on the previous studies, only 13 were determined as the early warning indicators which have the discriminating ability for healthy and non-healthy Islamic banks. Thus, in this chapter, the process in selecting the explanatory variables that have the discriminating power continues but is more concentrated on other measures such as the funding structure, the composition of deposits, macroeconomic variables, and the alternative bank-specific variables of Islamic banks.

The recent financial crisis still has an impact on the financial system around the world. In fact, funding liquidity has been mentioned as one of the main concerns during that period (Bologna, 2011). Based on a study by Bologna (2011), this study further extended research by looking into the impact and to what extent the funding structure of Islamic banks and other variables could play a part in explaining the financial condition of Islamic banks. In other words, this chapter investigates and tries to discover if any specific funding structure for Islamic banks, as well as other predictors, can be taken into account as explanatory variables in predicting the failure of Islamic banks.

Since most of the studies in this area were from the conventional banks' perspective, which are mostly in the US, this empirical chapter will be among the very first studies investigating the capability of the Malaysian Islamic banks' funding structure in predicting their default. Besides, in analysing Islamic banks' deposits, this study will look in detail at the effects of the deposits composition in accordance with the Islamic contracts used in the Islamic banks' performance, the effect of selected macroeconomic variables as well as other bank-specific variables.

The contribution of this empirical analysis can be divided into two: it is one of the first few studies that examine the role of the funding structures of Islamic banks in their performance, and also to examine the effect of deposit composition, especially the *mudharabah* and non-*mudharabah* deposits, on an Islamic banks' performance. This chapter proceeds as follows. After a brief introduction, the next section in this chapter provides some input on research methodology especially on the selection of appropriate models and the definition of variables included in the models. This is followed by the analysis of the results and the robustness test of the model by testing the model using other alternatives measures, such as macroeconomics variables and the alternative bank specific variables. This section also recommends the best alternative model(s) to measure Islamic banks' distress. The final section presents the conclusion of this chapter.

8.2 SELECTION OF THE APPROPRIATE MODEL

Multiple discriminant analysis, binary choice models (logit and probit) and proportional hazard models are among the most commonly used methods for the analysis of financial ratios. By referring to the statistics reported by Aziz and Dar (2006) it can be concluded that more than 30 percent of the research was examined using multiple discriminant analysis, while another 21 percent preferred the logit model. And more than 77 percent of all studies on corporate bankruptcy prediction use statistical models.

Thus, based on the above statistics and the study done by Bologna (2011), the logit model is used to analyse the role of funding in explaining Islamic banks' defaults. As mentioned previously in the literature chapter and the integrated model chapter, the logit model has been used frequently in previous bank failure prediction studies. The logit model is based on a cumulative logistic function; it provides the probability of an Islamic bank belonging to one of the prescribed groups, given by the financial characteristics of the Islamic bank. In this study, the binary dependent variable $Y_{a,t}$ is a variable representing the status of Islamic bank a at time t. When $Y_{a,t} = 0$ a bank is in healthy condition and when $Y_{a,t}$ = 1 a bank is in non-healthy condition The classification of banks into healthy and non-healthy has been discussed in the previous chapter (refer to Table 7.1).

Table 8.1: Definition of Variables Included in the Models

No.	Variable	Description	Symbol Used
1	Asset Quality	Non Performing Financing / Total Financing	NPF
2	Capital Adequacy	Risk-Weighted Capital Ratio	RWCR
3	Profitability	Net Income/Total Equity Ratio	ROE
4	Financing Rate	Base Financing Rate	BFR
5	Funding Structure	Financing / Deposit Ratio	FTD
6	*Mudharabah* Deposits	*Mudharabah* Deposits/Total Deposits Ratio	MD
7	Non-*Mudharabah* Deposits	Non-*Mudharabah* Deposits/Total Deposits	NMD
8	Demand Deposits	Demand Deposits/Total Deposits Ratio	DD
9	Savings Deposits	Savings Deposits/Total Deposits Ratio	SD
10	General Investment Deposits	General Investment Deposits/Total deposits Ratio	GID
11	Special Investment Deposits	Special Investment Deposits/Total Deposits Ratio	SID
12	Negotiable Investment Deposits	Negotiable Investment Deposits/Total Deposits Ratio	NID

Figure 8.1: Process Flow of the Alternative Measures

Step 1
- Compute all the relevant financial ratios

Step 2
- Model 1: Original Model
- $Y_{a,t} = \beta_1 + \beta_2 NPF_{a,t-1} + \beta_3 RWCR_{a,t-1} + \beta_4 ROE_{a,t-1} + \beta_5 BFR_{t-2} + \mu_a$

Step 3
- Model 2: Funding Structure Model
- $Y_{a,t} = \beta_1 + \beta_2 NPF_{a,t-1} + \beta_3 RWCR_{a,t-1} + \beta_4 ROE_{a,t-1} + \beta_5 BFR_{t-2} + \beta_6 FTD_{a,t-j} + \mu_a$

Step 4
- Model 3:Deposits Structure Model
- $Y_{a,t} = \beta_1 + \beta_2 NPF_{a,t-1} + \beta_3 RWCR_{a,t-1} + \beta_4 ROE_{a,t-1} + \beta_5 BFR_{t-2} + \beta_6 D_{a,k,t-j} + \mu_a$

Step 5
- Model 4: Alternative Macroeconomics Variables Model
- $Y_{a,t} = \beta_1 + \beta_2 NPF_{a,t-1} + \beta_3 RWCR_{a,t-1} + \beta_4 ROE_{a,t-1} + \beta_5 ME_{t-j} + \beta_6 FTD_{a,t-3} + \mu_a$

Step 6
- Model 5: Alternative Bank Specific Variables Model
- $Y_{a,t} = \beta_1 + \beta_2 RTA_{a,t-1} + \beta_3 TCE_{a,t-1} + \beta_4 ROA_{a,t-1} + \beta_5 BFR_{t-2} + \beta_6 FTD_{a,t-3} + \mu_a$

Step 7
- Model 6: Funding Mix Model
- $Y_{a,t} = \beta_1 + \beta_2 NPF_{a,t-1} + \beta_3 RWCR_{a,t-1} + \beta_4 ROE_{a,t-1} + \beta_5 BFR_{t-2} + \beta_6 ATD_{a,t-2} + \mu_a$

Step 8
- The best Alternative Model(s) to Measure Islamic Banks' distress

Based on the Bologna (2011) result, the Multivariate Logit model has been identified and estimated, but with some changes to the definition of the variables due to the characteristics of Islamic banks:

$$Y_{a,t} \ = \ \beta_1 + \ \beta_2 \, NPF_{a,t-1} + \ \beta_3 \, RWCR_{a,t-1} + \ \beta_4 \, ROE_{a,t-1} + \ \beta_5 \, BFR_{t-2} + \ \mu_a$$

(Model 1)

where;

$Y_{a,t}$ being the status of each Islamic bank *a* at time *t*, $NPF_{a,t-1}$, $RWCR_{a,t-1}$, $ROE_{a,t-1}$ being respectively the non-performing financing ratio, the risk-weighted capital ratio, and the return on equity for Islamic bank *a* at time *t-1*. BFR_{t-2} is the based financing rate.

The original model above, Model 1, as shown in Figure 8.1, has been modified to test whether types of funding (financing and deposits) can be considered as a significant indicator of banks' risky conditions. This can be done by testing Model 2 and Model 3 as depicted in Figure 8.1 above.

Based on Model 2, the financing-to-deposit ratio (FTD) has been inserted into the original model. This ratio provides a measure of the funding mix used by a bank to finance their financing portfolio. The higher the financing-to-deposit ratio means the less the bank is using their customer deposits to finance their loan portfolio. According to Bologna (2011), if the theory of different monitoring levels by different banks' creditors is correct, with depositors relying more on bank supervision and deposit insurance to look after them, it can be concluded that depositors are more stable sources of funding than other credits. Moreover, the more reliant the bank is on non-deposits funding the more vulnerable it is to defaults. If the findings show that the bank relies heavily on loans instead of deposits, this will increase the possibility of the bank's default. Moreover, a large share of financed funds in banks' assets is fundamentally more unstable as compared to deposits, thus boosting the possibility of default. Based on this, the modified model is shown below.

$$Y_{a,t} \ = \ \beta_1 + \ \beta_2 \, NPF_{a,t-1} + \ \beta_3 \, RWCR_{a,t-1} + \ \beta_4 \, ROE_{a,t-1} + \ \beta_5 \, BFR_{t-2} + \beta_6 \, FTD_{a,t-j} + \ \mu_a$$

(Model 2)

As for the third model (Model 3), this looks at the types of deposits which can be considered to be potentially more volatile. In particular, in this study, the composition of deposits at bank level was examined as well as the types of deposits according to the types of Islamic contracts used. According to Bologna (2011), the levels of awareness of depositors and their stability should vary amongst different kind of depositors. Although, as mentioned in Bologna's (2011) study, brokered deposit has been found to be a significant variable in explaining banks' default in the US, but as a proxy, this study used *mudharabah* and non-*mudharabah* deposits in explaining the effect of these deposits on banks' defaults. Thus, this study examines the impact of different types of deposits in Islamic banks in Malaysia and their probability of defaults. The modified model is as follows:

$$Y_{a,t} = \beta_1 + \beta_2 \, NPF_{a,t-1} + \beta_3 \, RWCR_{a,t-1} + \beta_4 \, ROE_{a,t-1} + \beta_5 \, BFR_{t-2} + \beta_6 \, D_{a,k,t-j} + \mu_a$$

(Model 3)

where;

D is the deposits, and *k* for different subset of deposits.

Next, based on the logit models presented above, the robustness test was conducted on the use of different sets of macroeconomic variables and alternative bank specific variables. The fourth model was based on Model 2 above, where a number of macroeconomic variables were tested in alternative specifications of this model by replacing the Based Financing Rate (*BFR*) previously used with the GDP growth rate, unemployment rate, and inflation rate. The estimated Model 4 is as follows:

$$Y_{a,t} = \beta_1 + \beta_2 \, NPF_{a,t-1} + \beta_3 \, RWCR_{a,t-1} + \beta_4 \, ROE_{a,t-1} + \beta_5 \, ME_{t-j} + \beta_6 \, FTD_{a,t-3} + \mu_a$$

(Model 4)

The fifth model (Model 5) modified Model 2 by replacing the original banks variables with the alternative variables: reserve to total assets ratio, tangible to common equity ratio, net income before tax to total assets ratio. The estimated model is as follows:

$$Y_{a,t} = \beta_1 + \beta_2\, RTA_{a,t-1} + \beta_3\, TCE_{a,t-1} + \beta_4\, ROA_{a,t-1} + \beta_5\, BFR_{t-2} + \beta_6\, FTD_{a,t-3} + \mu_a$$

(Model 5)

Finally, to test the robustness of the models, the sixth model is based on Model 2, but has been modified to replace the financing-to-deposits ratio with the assets-to-deposits ratio. The equation including the alternative funding mix is estimated as follows:

$$Y_{a,t} = \beta_1 + \beta_2\, NPF_{a,t-1} + \beta_3\, RWCR_{a,t-1} + \beta_4\, ROE_{a,t-1} + \beta_5\, BFR_{t-2} + \beta_6\, ATD_{a,t-2} + \mu_a$$

(Model 6)

8.4 EMPIRICAL RESULTS

8.4.1 Model 1: The Original Model

The basic results confirm the findings of the literature on banks' defaults, which shows a clear evidence of the relationship between the probability of default and capital adequacy, profitability, and asset quality. Based on the results of the original model, only the capital adequacy variable is significant in explaining banks' defaults in the Malaysian Islamic Banks between 2007 and 2010 (Table 8.2).

Table 8.2: Basic Determinants of Bank's Defaults [1] (Original Model)

Constant	-7.496466 (2.998356)**
Non-performing financing (NPF_{t-1})	0.044961 (0.077388)
Capital Adequacy ($RWCR_{t-1}$)	0.421491 (0.093899)***
Profitability (ROE_{t-1})	-0.064945 (0.098620)
Lending Rate (BFR_{t-2})	0.339785 (0.396053)
McFadden R^2	0.202170
Log likelihood	-64.46694

Note: **, *** significant at 5 percent and 1 percent respectively

[1] Dependent variable is Islamic banks' status (healthy/non-healthy)

Thus, based on the results for original model (Model 1) above, the model can be described as follows:

$$Y_{a,t} = -7.496466 + 0.044961\, NPF_{a,t-1} + 0.421491\, RWCR_{a,t-1} - 0.064945\, ROE_{a,t-1} + 0.339785\, BFR_{t-2}$$

(Model 1a)

The McFaddden R^2 value for Model 1 is 0.20, meaning that the model is satisfactory. As a rule of thumb for McFadden R^2, for any value between 0.20 and 0.40 the model can be considered to have an excellent fit (McFadden, 1979). In this model, the variables used in Model 1 predicted 20% of the variability in the performance of Islamic banks.

8.4.2 Model 2: Funding Structure

The second model examined the role of funding in predicting the financial distress of Islamic banks. The results, as depicted in Table 8.3, clearly indicate that funding does play an important role in determining Islamic banks' distress position. It is found that the extent to which a bank was funding its assets through deposits, rather than using other forms of funding, played an important role in explaining the financial distress condition of Islamic banks. By controlling the bank-specific variables such as asset quality, capital adequacy, profitability, and financing rate, the financing-to-deposit ratio was found to be relevant to this model. In particular, high reliance on other forms of funding than deposits may significantly increase the probability of banks' default. For instance, high reliance on loans may increase the probability of defaults even after one quarter of such increase, as shown by the McFadden R^2 results for three quarters before the event. Thus, it is important for Islamic banks to achieve a balanced funding position in a structural and stable manner.

Table 8.3: Introducing Funding: The impact of the financing-to-deposit ratio on Banks' defaults[1]

	2a	2b	2c
Constant	-3.162300 (3.325317)	-3.520866 (3.293417)	-4.065606 (3.308965)
Non-Performing Financing (NPF_{t-1})	-0.001847 (0.077876)	0.015296 (0.077292)	0.028780 (0.077898)
Capital Adequacy ($RWCR_{t-1}$)	0.376595 (0.096912)***	0.373724 (0.096647)***	0.381333 (0.098657)***
Profitability (ROE_{t-1})	-0.123903 (0.102838)	-0.108346 (0.103119)	-0.103349 (0.105641)
Lending Rate (BFR_{t-2})	0.320057 (0.432431)	0.345037 (0.431606)	0.399313 (0.437503)
Financing to Desposit (FTD_{t-1})	-0.052468 (0.012094)***		
Financing to Desposit (FTD_{t-2})		-0.050633 (0.011562)***	
Financing to Desposit (FTD_{t-3})			-0.049973 (0.010967)***
McFadden R^2	0.328166	0.332842	0.344773
Log likelihood	-63.30129	-62.86070	-61.73653

Note: *** significance at 1 percent
[1] Dependent variable is Islamic banks' status (healthy/non-healthy)

Thus, based on the results for Model 2, the model can be described as follows according to the different lags of the *FTD* data:

$$Y_{a,t} = -3.162300 - 0.001847\,NPF_{a,t-1} + 0.376595\,RWCR_{a,t-1} - 0.123903\,ROE_{a,t-1} + 0.320057\,BFR_{t-2} - 0.052468\,FTD_{a,t-1} + \mu_a$$

(Model 2a)

or

$$Y_{a,t} = -3.520866 + 0.015296\,NPF_{a,t-1} + 0.373724\,RWCR_{a,t-1} - 0.108346\,ROE_{a,t-1} + 0.345037\,BFR_{t-2} - 0.050633\,FTD_{a,t-2} + \mu_a$$

(Model 2b)

or

$$Y_{a,t} = -4.065606 + 0.028780\, NPF_{a,t-1} + 0.381333\, RWCR_{a,t-1} - 0.103349\, ROE_{a,t-1} + 0.399313\, BFR_{t-2} - 0.049973\, FTD_{a,t-3} + \mu_a$$

(Model 2c)

Furthermore, the McFadden R^2 values for Model 2a, Model 2b, and 2c are 0.33, 0.33, and 0.34 respectively. Based on the rule of thumb for McFadden R^2, these values are well above the minimum value for satisfactory results, thus this means that all three models above have an excellent fit. In other words, the variables used in the three models predicted more than 33% of the variability in Islamic banks' performance.

8.4.3 Model 3 (Deposit Structure)

The third model looked at the role of different types of deposits in predicting the distress of Islamic banks in Malaysia. Generally, not all types of deposits contribute equally to the banks' funding stability. Based on the results of this study, it was shown that each type of deposit has a different effect on the banks' performance, thus suggesting that heavy reliance on more volatile sources of deposits may contribute to the risky position of the banks. In this study, five types of deposits in Islamic banks were considered to be included in Model 3: demand deposits, savings deposits, general investment deposits, special investment deposits, and negotiable investment deposits. Furthermore, this third model also examined the effects of *mudharabah* and non-*mudharabah* deposits on the banks' performance.

As depicted in Table 8.4 below, the results show that all types of deposits, except negotiable investment deposits, do play a significant role in Islamic banks' performance. In other words, those deposits appear to be correlated to the default risk. Demand deposits (DD_{t-1}, DD_{t-2}, and DD_{t-3}) and general investment deposits (GID_{t-3}) are significant at the 1% level, while the rest of the deposits are significant at the 5% level, thus suggesting that deposits do play an important role in predicting the Islamic banks' distress in Malaysia. For instance, high reliance on demand deposits as bank funding may increase the probability of defaults even after one quarter of such an increase, while for general investment deposits, the probability of default can be predicted only after three quarters of such an increase. This result is in contrast with the study conducted by Bologna (2011) who found that large demand deposits are not a significant factor with a negative sign, which suggests more active monitoring by large demand depositors.

Table 8.4: Banks' Defaults[1]: Does Deposit Composition Matter? Effect of *Mudarabah* Deposits and Non-*Mudarabah* Deposits, Demand Deposits, Savings Deposits, General Investment Deposits, Special Investment Deposits, and Negotiable Investment Deposits

	a	b	c	d	e	f	g	h
Constant	-31.08948 (7.998538)	-28.79092 (7.431765)	-30.61056 (7.578344)	-10.65138 (3.690568)	-10.73648 (3.715674)	-10.58415 (3.708147)	-7.590468 (4.031467)	-7.479467 (4.028405)
Non-Performing Financing (*NPF* $_{t-1}$)	-0.108951 (0.138377)	-0.022308 (0.126824)	0.046823 (0.131425)	0.108803 (0.105393)	0.089839 (0.107172)	0.087868 (0.107500)	0.177381 (0.112390)	0.179896 (0.115140)
Capital Adequacy (*RWCR* $_{t-1}$)	1.359098 (0.293912)***	1.248961 (0.262392)***	1.207964 (0.248658)***	0.545835 (0.122985)***	0.550741 (0.124280)***	0.549527 (0.124566)***	0.502079 (0.123551)***	0.508721 (0.123549)***
Profitability (*ROE* $_{t-1}$)	-0.095423 (0.157462)	-0.088748 (0.160007)	-0.128530 (0.182605)	0.047489 (0.124591)	0.053006 (0.123419)	0.049600 (0.123478)	-0.148511 (0.126852)	-0.147356 (0.126388)
Lending Rate (*BFR* $_{t-2}$)	1.243409 (0.724882)*	1.154280 (0.705776)	1.524483 (0.729082)**	0.653371 (0.471356)	0.670295 (0.474348)	0.650039 (0.472972)	0.324379 (0.489028)	0.306641 (0.494824)
Demand Deposits $_{t-1}$	0.295927 (0.066328)***							
Demand Deposits $_{t-2}$		0.262829 (0.058649)***						
Demand Deposits $_{t-3}$			0.250849 (0.055058)***					
Savings Deposits $_{t-1}$				-0.086996 (0.035342)**				
Savings Deposits $_{t-2}$					-0.091338 (0.035603)**			
Savings						-0.091175		

Deposits $_{t-3}$						(0.035656)**		
General Investment Deposits $_{t-1}$							-0.029356 (0.013505)**	
General Investment Deposits $_{t-2}$								-0.032649 (0.013628)**
McFadden R^2	0.620974	0.610535	0.623739	0.339952	0.344607	0.344196	0.327858	0.335548
Log likelihood	-30.61070	-31.45372	-30.38740	-53.30638	-52.93045	-52.96368	-54.28316	-53.66205

Note: *, **, *** significance at 10 percent, 5 percent and 1 percent respectively
[1] Dependent variable is Islamic banks' status (healthy/non-healthy)

Table 8.4b: Continued

	i	j	k	l	m	n	o	p
Constant	-7.400255 (3.962952)	-11.12111 (3.801171)	-11.19909 (3.848293)	-11.06230 (3.839384)	-11.79885 (3.908678)	-11.54476 (3.849284)	-11.59348 (3.851675)	-7.567306 (3.879919)
Non-Performing Financing (*NPF* $_{t-1}$)	0.193711 (0.117119)	0.138727 (0.105954)	0.113578 (0.109958)	0.105896 (0.110622)	0.130904 (0.107455)	0.135040 (0.107820)	0.127761 (0.109521)	0.193145 (0.110563)*
Capital Adequacy (*RWCR* $_{t-1}$)	0.505710 (0.122171)***	0.513574 (0.126139)***	0.520884 (0.127195)***	0.520523 (0.127066)***	0.589173 (0.135801)***	0.581495 (0.134192)***	0.586705 (0.135977)***	0.572481 (0.124423)***
Profitability (*ROE* $_{t-1}$)	-0.153602 (0.127344)	-0.077754 (0.117931)	-0.066930 (0.117539)	-0.065526 (0.117365)	-0.033454 (0.117287)	-0.036807 (0.117322)	-0.035147 (0.117248)	-0.137860 (0.124529)
Lending Rate (*BFR* $_{t-2}$)	0.313924 (0.493269)	0.621036 (0.472450)	0.619429 (0.476989)	0.600201 (0.477075)	0.661637 (0.481362)	0.631571 (0.475601)	0.635615 (0.474132)	0.292692 (0.481124)
General Investment Deposits $_{t-3}$	-0.036395 (0.013953)***							
Special		0.028816						

Investment Deposits $_{t-1}$		(0.014693)**						
Special Investment Deposits $_{t-2}$			0.030848 (0.014835)**					
Special Investment Deposits $_{t-3}$				0.032044 (0.014905)**				
Negotiable Instruments of Deposit $_{t-1}$					-0.010538 (0.012872)			
Negotiable Instruments of Deposit $_{t-2}$						-0.008646 (0.012960)		
Negotiable Instruments of Deposit $_{t-3}$							-0.010035 (0.013164)	
Mudarabah Deposit $_{t-1}$								-0.032145 (0.015691)**
McFadden R^2	0.344131	0.321499	0.324654	0.326716	0.300580	0.299204	0.300023	0.326299
Log likelihood	-52.96892	-54.79668	-54.54187	-54.37535	-56.48614	-56.59727	-56.53110	-54.40905

Note: *, **, *** significance at 10 percent, 5 percent and 1 percent respectively

[1] Dependent variable is Islamic banks' status (healthy/non-healthy)

Table 8.4c: Continued

	q	r	s	t	u
Constant	-7.755431 (3.811845)	-8.265643 (3.721329)	-10.78180 (3.683827)	-11.20752 (3.726036)	-11.72063 (3.741796)
Non-Performing Financing (*NPF* $_{t-1}$)	0.217755 (0.111369)*	0.233541 (0.113049)**	0.193145 (0.110563)*	0.217755 (0.111369)*	0.233541 (0.113049)**
Capital Adequacy (*RWCR* $_{t-1}$)	0.584063 (0.125313)***	0.588208 (0.124757)***	0.572481 (0.124423)***	0.584063 (0.125313)***	0.588208 (0.124757)***
Profitability (*ROE* $_{t-1}$)	-0.143860 (0.125832)	-0.138850 (0.124693)	-0.137860 (0.124529)	-0.143860 (0.125832)	-0.138850 (0.124693)
Lending Rate (*BFR* $_{t-2}$)	0.309295 (0.479557)	0.369792 (0.475178)	0.292692 (0.481124)	0.309295 (0.479557)	0.369792 (0.475178)
Mudarabah Deposit $_{t-2}$	-0.034521 (0.015483)**				
Mudarabah Deposit $_{t-3}$		-0.034550 (0.014530)**			
Non-*Mudarabah* Deposit $_{t-1}$			0.032145 (0.015691)**		
Non-*Mudarabah* Deposit $_{t-2}$				0.034521 (0.015483)**	
Non-*Mudarabah* Deposit $_{t-3}$					0.034550 (0.014530)**
McFadden R^2	0.332263	0.337086	0.326299	0.332263	0.337086
Log likelihood	-53.92740	-53.53790	-54.40905	-53.92740	-53.53790

Note: *, **, *** significance at 10 percent, 5 percent and 1 percent respectively
[1] Dependent variable is Islamic banks' status (healthy/non-healthy)

The models based on the estimated logit results are as follows:

$$Y_{a,t} = \beta_1 + \beta_2\, NPF_{a,t-1} + \beta_3\, RWCR_{a,t-1} + \beta_4\, ROE_{a,t-1} + \beta_5\, BFR_{t-2} + \beta_6\, D_{a,k,t-j} + \mu_a$$

(Model 3)

Based on results shown in Table 8.4, the estimated models with the respective coefficient values are as follows:

Demand Deposits

$$Y_{a,t} = -31.08948 - 0.108951\, NPF_{a,t-1} + 1.359098\, RWCR_{a,t-1} - 0.095423\, ROE_{a,t-1} + 1.243409\, BFR_{t-2} + 0.295927\, DD_{a,t-1} + \mu_a$$

(Model 3a)

and,

$$Y_{a,t} = -28.79092 - 0.022308\, NPF_{a,t-1} + 1.248961\, RWCR_{a,t-1} - 0.088748\, ROE_{a,t-1} + 1.154280\, BFR_{t-2} + 0.262829\, DD_{a,t-2} + \mu_a$$

(Model 3b)

and,

$$Y_{a,t} = -30.61056 + 0.046823\, NPF_{a,t-1} + 1.207964\, RWCR_{a,t-1} - 0.128530\, ROE_{a,t-1} + 1.524483\, BFR_{t-2} + 0.250849\, DD_{a,t-3} + \mu_a$$

(Model 3c)

Savings Deposits

$$Y_{a,t} = -10.65138 + 0.108803\, NPF_{a,t-1} + 0.545835\, RWCR_{a,t-1} - 0.047489\, ROE_{a,t-1} + 0.653371\, BFR_{t-2} - 0.086996\, SD_{a,t-1} + \mu_a$$

(Model 3d)

and,

$$Y_{a,t} = -10.73648 + 0.089839\, NPF_{a,t-1} + 0.550741\, RWCR_{a,t-1} + 0.053006\, ROE_{a,t-1} + 0.670295\, BFR_{t-2} - 0.091338\, SD_{a,t-2} + \mu_a$$

(Model 3e)

and,

$$Y_{a,t} = -10.58415 + 0.087868\, NPF_{a,t-1} + 0.549527\, RWCR_{a,t-1} + 0.049600\, ROE_{a,t-1} + 0.650039\, BFR_{t-2} - 0.091175\, SD_{a,t-3} + \mu_a$$

(Model 3f)

General Investment Deposits

$$Y_{a,t} = -7.590468 + 0.177381\, NPF_{a,t-1} + 0.502079\, RWCR_{a,t-1} - 0.148511\, ROE_{a,t-1} + 0.324379\, BFR_{t-2} - 0.029356\, GID_{a,t-1} + \mu_a$$

(Model 3g)

and,

$$Y_{a,t} = -7.479467 + 0.179896\, NPF_{a,t-1} + 0.508721\, RWCR_{a,t-1} - 0.147356\, ROE_{a,t-1} + 0.306641\, BFR_{t-2} - 0.032649\, GID_{a,t-2} + \mu_a$$

(Model 3h)

and,

$$Y_{a,t} = -7.400255 + 0.193711\, NPF_{a,t-1} + 0.505710\, RWCR_{a,t-1} - 0.153602\, ROE_{a,t-1} + 0.313924\, BFR_{t-2} - 0.036395\, GID_{a,t-3} + \mu_a$$

(Model 3i)

Special Investment Deposits

$$Y_{a,t} = -11.12111 + 0.138727\, NPF_{a,t-1} + 0.513574\, RWCR_{a,t-1} - 0.077754\, ROE_{a,t-1} + 0.621036\, BFR_{t-2} - 0.028816\, SID_{a,t-1} + \mu_a$$

(Model 3j)

and,

$$Y_{a,t} = -11.19909 + 0.113578\, NPF_{a,t-1} + 0.520884\, RWCR_{a,t-1} - 0.066930\, ROE_{a,t-1} + 0.619429\, BFR_{t-2} - 0.030848\, SID_{a,t-2} + \mu_a$$

(Model 3k)

and,

$$Y_{a,t} = -11.06230 + 0.105896\, NPF_{a,t-1} + 0.520523\, RWCR_{a,t-1} - 0.065526\, ROE_{a,t-1} + 0.600201\, BFR_{t-2} - 0.032044\, SID_{a,t-3} + \mu_a$$

(Model 3l)

Negotiable Instruments of Deposits

$$Y_{a,t} = -11.79885 + 0.130904\,NPF_{a,t-1} + 0.589173\,RWCR_{a,t-1} - 0.033454\,ROE_{a,t-1} + 0.661637\,BFR_{t-2} - 0.010538\,NID_{a,t-1} + \mu_a$$

(Model 3m)

and,

$$Y_{a,t} = -11.54476 + 0.135040\,NPF_{a,t-1} + 0.581495\,RWCR_{a,t-1} - 0.036807\,ROE_{a,t-1} + 0.600201\,BFR_{t-2} - 0.631571\,NID_{a,t-2} + \mu_a$$

(Model 3n)

and,

$$Y_{a,t} = -11.59348 + 0.127761\,NPF_{a,t-1} + 0.586705\,RWCR_{a,t-1} - 0.035147\,ROE_{a,t-1} + 0.635615\,BFR_{t-2} - 0.010035\,NID_{a,t-3} + \mu_a$$

(Model 3o)

***Mudharabah* Deposits**

$$Y_{a,t} = -7.567306 + 0.193145\,NPF_{a,t-1} + 0.572481\,RWCR_{a,t-1} - 0.137860\,ROE_{a,t-1} + 0.292692\,BFR_{t-2} - 0.032145\,MD_{a,t-1} + \mu_a$$

(Model 3p)

and,

$$Y_{a,t} = -7.755431 + 0.217755\,NPF_{a,t-1} + 0.584063\,RWCR_{a,t-1} - 0.143860\,ROE_{a,t-1} + 0.309295\,BFR_{t-2} - 0.034521\,MD_{a,t-2} + \mu_a$$

(Model 3q)

and,

$$Y_{a,t} = -8.265643 + 0.233541\,NPF_{a,t-1} + 0.588208\,RWCR_{a,t-1} - 0.138850\,ROE_{a,t-1} + 0.369792\,BFR_{t-2} - 0.034550\,MD_{a,t-3} + \mu_a$$

(Model 3r)

Non-*Mudharabah* Deposits

$$Y_{a,t} = -10.78180 + 0.193145\,NPF_{a,t-1} + 0.572481\,RWCR_{a,t-1} - 0.13786\,ROE_{a,t-1} + 0.292692\,BFR_{t-2} - 0.032145\,NMD_{a,t-1} + \mu_a$$

(Model 3s)

and,

$$Y_{a,t} = -11.20752 + 0.217755\, NPF_{a,t-1} + 0.584063\, RWCR_{a,t-1} - 0.143860\, ROE_{a,t-1} + 0.309295\, BFR_{t-2} - 0.034521\, NMD_{a,t-2} + \mu_a$$

(Model 3t)

and,

$$Y_{a,t} = -11.72063 + 0.233541\, NPF_{a,t-1} + 0.588208\, RWCR_{a,t-1} - 0.138850\, ROE_{a,t-1} + 0.369792\, BFR_{t-2} - 0.034550\, NMD_{a,t-3} + \mu_a$$

(Model 3u)

Consequently, based on the results described above, it can be concluded that all the models developed based on Model 3 have shown a high satisfactory performance. This implied that an inclusion of deposits variables into the models is significant in explaining banks' defaults. The most excellent fit model is Model 3a, 3b, and 3c with a McFadden R^2 range from 0.61 to 0.62. This implies that about 61% to 62% of the total variations in the performance of Islamic banks are explained by the explanatory variables included in Model 3a, Model 3b or Model 3c, which consist of NPF_{t-1}, $RWCR_{t-1}$, ROE_{t-1}, BFR_{t-2}, and DD_{t-1}/ DD_{t}-2/DDt$_{-3}$. And in fact, Demand Deposits and General Investment Deposits are statistically significantly associated with Islamic banks' performance and the probabilities of defaults. Such a relation appears to be stable and persistent, which is proved by the significant performance of those variables from one to three quarters before the current bank conditions which are either healthy or non-healthy. Furthermore, it also evident that the Islamic banks' funding choices do affect the probability of default and clearly indicate the banks' decreasing conditions well ahead of the actual failure.

Next, this study continues with the modification of Model 2 by adding or replacing the existing variable(s) with alternative variables. Table 8.5 below presents the alternative variables used in the robustness test models.

Table 8.5: Definition of Bank-specific and macroeconomics Variables used in the Alternative Models

Original Model Variable Name	Definition	Alternative Model Variable Name	Definition
Asset Quality	Non-Performing Financing Ratio	Asset Quality	Reserve to total Assets ratio
Capital Adequacy	Risk-Weighted Capital Ratio	Capital Adequacy	Tangible Common Equity Ratio
Profitability	Net Income to Total Equity Ratio	Profitability (ROA)	Net Income Before Tax to Total Assets Ratio
Lending Rate (BFR)	Base Financing Rate	Lending Rate (BFR)	Base Financing Rate
		GDP	GDP growth rate
		Inflation	Consumer Price Index
		Unemployment	Unemployment Rate

8.4.4 Robustness Test 1 – Using Alternative Macroeconomics Variables

The first robustness test was carried out using the alternative macroeconomics variables and was based on the existing Model 2. Table 8.5 above, has defined the alternative macroeconomic variables used in this test: GDP growth rate, unemployment rate, and inflation rate. The Logit model (Model 4) has been tested for robustness in the use of an alternative set of macroeconomic variables. The macroeconomic variables have been tested in alternative specifications of the model by replacing the base financing rate previously used with the GDP growth rate, the unemployment rate, and the inflation rate and the results are presented in Table 8.6 below.

Table 8.6: Banks' Defaults and Funding Relevance: Testing for Robustness to Alternative Macroeconomics Variables

	a	b	c	d	e	f	g
Constant	-3.371087* (1.907113)	-5.550646 (1.754000)***	-9.049192 (1.971264)***	-3.845781 (2.014208)*	-5.952425 (1.866811)***	-9.210538 (1.993634)***	-2.053784 (3.405087)
Non-Performing Financing (NPF_{t-1})	0.112137 (0.106561)	0.210235 (0.108892)	0.210235 (0.108892)	0.110343 (0.107641)	0.198949 (0.109544)	0.198949 (0.109544)*	0.109111 (0.106825)
Capital Adequacy ($RWCR_{t-1}$)	0.524377 (0.130039)***	0.581392 (0.127653)***	0.581392 (0.127653)***	0.532885 (0.130387)***	0.575218 (0.124862)***	0.575218 (0.124862)***	0.521888 (0.128343)***
Profitability (ROE_{t-1})	-0.097248 (0.118284)	-0.146598 (0.122420)	-0.146598 (0.122420)	-0.089651 (0.120637)	-0.133235 (0.126207)	-0.133235 (0.126207)	-0.098946 (0.118407)
GDP growth rate $_{t-1}$	-0.021233 (0.051749)	-0.036572 (0.050740)	-0.036572 (0.050740)				
Inflation $_{t-1}$				0.072992 (0.085052)	0.065221 (0.081425)	0.065221 (0.081425)	
Unemployment $_{t-3}$							-0.404547 (0.907183)
FTD_{t-2}	-0.053375 (0.014544)***			-0.052544 (0.014512)***			-0.053094 (0.014461)***
Mudharabah Deposit Ratio $_{t-1}$		-0.034985 (0.015341)**			-0.032581 (0.015557)**		
Non-*Mudharabah* Deposit Ratio $_{t-1}$			0.034985 (0.015341)**			0.032581 (0.015557)**	
McFadden R^2	0.395443	0.327258	0.327258	0.399022	0.328023	0.328023	0.395627
Log likelihood	-48.82490	-54.33161	-54.33161	-48.53582	-54.26977	-54.26977	-48.81002

Note: *, **, *** significance at 10 percent, 5 percent and 1 percent respectively

[1] Dependent variable is Islamic banks' status (healthy/non-healthy)

Table 8.6b: Banks' Defaults and Funding Relevance: Testing for Robustness to Alternative Macroeconomics Variables (continued)

	h	i	j	k	l
Constant	-4.822487 (3.263847)	-8.204495 (3.509311)**	-3.761433 (3.823389)	-0.777587 (4.318909)	-6.210779 (4.450459)
Non-Performing Financing (*NPF* $_{t-1}$)	0.202062 (0.109342)	0.202062 (0.109342)	0.112444 (0.107089)	0.110966 (0.120320)	0.110966 (0.120320)
Capital Adequacy (*RWCR* $_{t-1}$)	0.565430 (0.122951)***	0.565430 (0.122951)***	0.553019 (0.136479)***	0.604844 (0.156608)***	0.604844 (0.156608)***
Profitability (*ROE* $_{t-1}$)	-0.146290 (0.123470)	-0.146290 (0.123470)	-0.071221 (0.123573)	-0.204597 (0.140710)	-0.204597 (0.140710)
GDP growth rate $_{t-1}$			-0.039385 (0.055997)	-0.039820 (0.060492)	-0.039820 (0.060492)
Inflation $_{t-1}$			0.091636 (0.095274)	0.038936 (0.102966)	0.038936 (0.102966)
Unemployment $_{t-3}$	-0.210131 (0.873739)	-0.210131 (0.873739)	-0.100586 (0.965809)	0.089045 (1.062434)	0.089045 (1.062434)
FTD $_{t-2}$			-0.052067 (0.014547)***	-0.063060 (0.016026)***	-0.063060 (0.016026)***
Mudharabah Deposit Ratio $_{t-1}$	-0.033820 (0.015410)**			-0.054332 (0.019965)***	
Non-*Mudharabah* Deposit Ratio $_{t-1}$		0.033820 (0.015410)**			0.054332 (0.019965)***
McFadden R^2	0.324356	0.324356	0.402407	0.463808	0.463808
Log likelihood	-54.56594	-54.56594	-48.26248	-43.30363	-43.30363

Note: *, **, *** significance at 10 percent, 5 percent and 1 percent respectively
[1] Dependent variable is Islamic banks' status (healthy/non-healthy)

The models based on the estimated logit results are as follows:

$$Y_{a,t} = \beta_1 + \beta_2\, NPF_{a,t-1} + \beta_3\, RWCR_{a,t-1} + \beta_4\, ROE_{a,t-1} + \beta_5\, ME_{t-j} + \beta_6\, FTD_{a,t-3} + \mu_a$$

(Model 4)

Based on the results shown in Table 8.6 above, the estimated models with the respective coefficient values are as follows:

GDP growth rate

$$Y_{a,t} = -3.371087 + 0.112137\, NPF_{a,t-1} + 0.524377\, RWCR_{a,t-1} - 0.097248\, ROE_{a,t-1} + 0.021233\, GDP_{t-1} - 0.053375\, FTD_{a,t-3} + \mu_a$$

(Model 4a)

and,

$$Y_{a,t} = -5.550646 + 0.210235\, NPF_{a,t-1} + 0.581392\, RWCR_{a,t-1} - 0.146598\, ROE_{a,t-1} + 0.036572\, GDP_{t-1} - 0.034985\, MD_{a,t-1} + \mu_a$$

(Model 4b)

and,

$$Y_{a,t} = -9.049192 + 0.210235\, NPF_{a,t-1} + 0.581392\, RWCR_{a,t-1} - 0.146598\, ROE_{a,t-1} + 0.036572\, GDP_{t-1} + 0.034985\, NMD_{a,t-1} + \mu_a$$

(Model 4c)

Inflation rate

$$Y_{a,t} = -3.845781 + 0.110343\, NPF_{a,t-1} + 0.532885\, RWCR_{a,t-1} - 0.089651\, ROE_{a,t-1} + 0.072992\, INF_{t-1} - 0.052544\, FTD_{a,t-3} + \mu_a$$

(Model 4d)

and,

$$Y_{a,t} = -5.952425 + 0.198949\, NPF_{a,t-1} + 0.575218\, RWCR_{a,t-1} - 0.133235\, ROE_{a,t-1} + 0.065221\, INF_{t-1} - 0.032581\, MD_{a,t-1} + \mu_a$$

(Model 4e)

and,

$$Y_{a,t} = -9.210538 + 0.198949\, NPF_{a,t-1} + 0.575218\, RWCR_{a,t-1} - 0.133235\, ROE_{a,t-1} + 0.065221\, INF_{t-1} - 0.032581\, NMD_{a,t-1} + \mu_a$$

(Model 4f)

Unemployment Rate

$$Y_{a,t} = -2.053784 + 0.109111\, NPF_{a,t-1} + 0.521888\, RWCR_{a,t-1} - 0.098946\, ROE_{a,t-1} - 0.404547\, UNEMPLOY_{t-1} - 0.053094\, FTD_{a,t-3} + \mu_a$$

(Model 4g)

and,

$$Y_{a,t} = -4.822487 + 0.202062\, NPF_{a,t-1} + 0.565430\, RWCR_{a,t-1} - 0.146290\, ROE_{a,t-1} - 0.210131\, UNEMPLOY_{t-1} - 0.033820\, MD_{a,t-1} + \mu_a$$

(Model 4h)

and,

$$Y_{a,t} = -8.204495 + 0.202062\, NPF_{a,t-1} + 0.565430\, RWCR_{a,t-1} - 0.146290\, ROE_{a,t-1} - 0.210131\, UNEMPLOY_{t-1} - 0.033820\, NMD_{a,t-1} + \mu_a$$

(Model 4i)

As a conclusion for these alternative models, the introduction of macroeconomic variables into the models does not provide significant results. This is in contrast with the results in Bologna (2011) that showed a statistically significant impact of *GDP, INF*, unemployment and alternative lending rate in the model. The only variables that are significant to the model throughout the analysis are the capital adequacy variable and funding variables. In other words, the capital adequacy variable and funding variables remain highly significant, thus confirming the robustness of the estimates.

This robustness test applied the GDP as a measure of cyclical input effects on Islamic banks' performance, with the expectation that GDP has a negative relationship with the Islamic bank's distress condition. It is predicted that when GDP shows a decreasing trend especially during recession, it will have some impact on credit quality which will lead to defaults and decreasing banks' profits. The results show that GDP has a negative relationship with the banks' distress condition, or in other words GDP has a positive relationship with Islamic banks' performance. This result is similar to the study by Kosmidou (2008), Athanasoglou *et al.* (2008), and Wasiuzzaman and Tarmizi (2010).

As in the case of the inflation effect on the banks' distress condition, the results of this study found that inflation is positively related to the banks' distress condition, but it is not statistically significant. In other words, there is a negative relationship between inflation and bank performance. This result is similar to Kosmidou (2008) who found that inflation has a significant negative impact on banks' profits. Inflation rate is used as a proxy to measure how microenvironment risk can have some impact on Islamic banks' performance. Inflation rate measures the overall percentage of increment in the consumer price index for all goods and services. A study by Athanasoglou *et al.* (2008) found that inflation positively and significantly affects the profitability of Greek banks, and this may be due to the ability of those banks to satisfactorily predict future inflation which in turn implies that interest rates have been adjusted accordingly.

In addition, a study by Vong and Chan (2009) examined the impact of bank characteristics as well as macroeconomics and the financial structure variables on the performance of the Macao banking industry; this suggested that high inflation is often associated with higher costs and higher income. As the income increases more than the inflation cost, this will increase the probability of high profits, however, there will be a negative correlation if the cost increases faster than the income does. With regards to the macroeconomics variables effect on banks' performance in the Macao banking industry, this study found that only the rate of inflation shows a significant relationship. As from the Malaysian banking perspective, Sufian (2009) found that a higher inflation rate has a positive impact on Malaysian banks' profitability. Wasiuzzaman and Tarmizi (2010) also found that inflation has positively influenced Islamic bank profitability, thus their results are in contrast with the results of this study.

Finally, the robustness test using the unemployment rate as one of the predictors shows that the unemployment rate is not positively significant in predicting the Islamic banks' distress condition. In other words, unemployment has a negative impact on Islamic banks' performance. A study by Abreu and Mendes (2002) found that the unemployment rate positively affects the profitability of banks, and this was confirmed by Heffernan and Fu (2008), and these are in constrast with the results of this study.

Since the results of this robustness test found that all macroeconomic variables, *i.e. GDP*, inflation rate and unemployment rate, do not show a significant impact on the model as opposed to the previous studies, this requires further explanation. The recent global financial crisis and the Euro zone sovereign debt crisis have impacted on the economic growth of many countries including Malaysia. But, a stronger domestic economy, and strength from regional trade and investment activities has reinforced the effect on the Malaysian economy. Furthermore, the low unemployment rate, not over leveraged, as well as the availability of credit from the resilient financial sectors, are also among the contributing factors to the stability of the Malaysian economy.

8.4.5 Robustness Test 2 – Using Alternative Bank Specific Variables

The second robustness test is done by using the alternative bank specific variables, based on the existing Model 2. As defined in Table 8.5, the alternative bank specific variables used in this test are as follows: reserve to total assets ratio, tangible common equity ratio, and net income to total assets ratio. The logit model (Model 5) has been tested for robustness in the use of an alternative set of bank specific variables. The alternative bank specific variables, as mentioned above, have been tested in alternative specifications of the model by replacing it with the non-performing financing, risk-weighted capital ratio, and return on equity previously used in Model 2. The results of the tests are presented in Table 8.7 below.

Table 8.7: Banks' Defaults and Funding Relevance: Testing for Robustness to Alternative Bank Specific Variables [1]

	a	B	c	d	e	f
Constant	3.793483 (4.26328)	2.117683 (3.07938)	1.281841 (2.61868)	3.676086 (3.84480)	-0.673056 (2.70059)	-1.435215 (2.73310)
Alternative Asset Quality (RTA_{t-1})	1.331114 (0.30395) ***	0.117537 (0.12559)	0.117537 (0.12559)	1.335266 (0.30528) ***	0.120118 (0.12533)	0.120118 (0.12533)
Alternative Capital Adequacy Ratio (TCE_{t-1})	0.961721 (0.20778) ***	0.307605 (0.09967) ***	0.307605 (0.09967) ***	0.956175 (0.20312) ***	0.304999 (0.09910) ***	0.304999 (0.09910) ***
Alternative Profitability (ROA_{t-1})	-3.383255 (2.19952)	-6.126502 (1.88911) ***	-6.126502 (1.88911) ***	-3.312009 (2.21502)	-6.087059 (1.87851) ***	-6.087059 (1.87851) ***
Lending Rate (BFR_{t-2})	-0.082239 (0.63881)	-0.229156 (0.41032)	-0.229156 (0.41032)			
Unemployment rate $_{t-3}$				-0.126175 (1.12669)	0.385399 (0.76826)	0.385399 (0.76826)
FTD_{t-2}	-0.153844 (0.02918) ***			-0.153445 (0.02882) ***		
MD_{t-1}		-0.008358 (0.014420)			-0.007622 (0.014225)	
NMD_{t-1}			0.008358 (0.014420)			0.007622 (0.014225)
McFadden R^2	0.532479	0.168980	0.168980	0.532453	0.168603	0.168603
Log likelihood	-37.75767	-67.11437	-67.11437	-37.75971	-67.14476	-67.14476

Note: *, **, *** significance at 10 percent, 5 percent and 1 percent respectively
[1] Dependent variable is Islamic banks' status (healthy/non-healthy)

The models based on the estimated logit results are as follows:

$$Y_{a,t} = \beta_1 + \beta_2\, RTA_{a,t-1} + \beta_3\, TCE_{a,t-1} + \beta_4\, ROA_{a,t-1} + \beta_5\, BFR_{t-2} + \beta_6\, FTD_{a,t-2} + \mu_a$$

(Model 5)

Based on the results shown in Table 8.7 above, the estimated models with the respective coefficient values are as follows:

With BFR_{t-2}

$$Y_{a,t} = 3.793483 + 1.331114\, RTA_{a,t-1} + 0.961721\, TCE_{a,t-1} - 3.383255\, ROA_{a,t-1} - 0.082239\, BFR_{t-2} - 0.153844\, FTD_{a,t-2} + \mu_a$$

(Model 5a)

and,

$$Y_{a,t} = 2.117683 + 0.117537\, RTA_{a,t-1} + 0.307605\, TCE_{a,t-1} - 6.126502\, ROA_{a,t-1} - 0.229156\, BFR_{t-2} - 0.008358\, MD_{a,t-1} + \mu_a$$

(Model 5b)

and,

$$Y_{a,t} = 1.281841 + 0.117537\, RTA_{a,t-1} + 0.307605\, TCE_{a,t-1} - 6.126502\, ROA_{a,t-1} - 0.229156\, BFR_{t-2} - 0.008358\, NMD_{a,t-1} + \mu_a$$

(Model 5c)

Furthermore, the robustness test using a set of alternative bank specific variables continues by replacing the BFR_{t-2} with $UNEMPLOY_{t-3}$

With $UNEMPLOY_{t-3}$

$$Y_{a,t} = 3.676086 + 1.335266\, RTA_{a,t-1} + 0.956175\, TCE_{a,t-1} - 3.312009\, ROA_{a,t-1} - 0.126175\, UNEMPLOY_{t-3} - 0.153844\, FTD_{a,t-2} + \mu_a$$

(Model 5d)

and,

$$Y_{a,t} = -0.673056 + 0.120118\,RTA_{a,t-1} + 0.304999\,TCE_{a,t-1} - 6.087059\,ROA_{a,t-1} + 0.385399\,UNEMPLOY_{t-3} - 0.007622\,MD_{a,t-1} + \mu_a$$

(Model 5e)

and,

$$Y_{a,t} = -1.435215 + 0.120118\,RTA_{a,t-1} + 0.304999\,TCE_{a,t-1} - 6.087059\,ROA_{a,t-1} + 0.385399\,UNEMPLOY_{t-3} - 0.007622\,NMD_{a,t-1} + \mu_a$$

(Model 5f)

Based on the results above, the robustness of the results concerning the sensitivity of the banks' default probability to their funding conditions is also confirmed when using a different set of bank-specific variables to represent capital adequacy, asset quality, and profitability. The results show that in all cases there is no loss of significance of the funding variables (Model 5a). Model 5a showed that RTA_{t-1}, TCE_{t-1}, and FTD_{t-3} are significant at the 1% significance level and McFadden R^2 is 0.53, meaning that the model is an excellent fit or highly satisfactory. In other words, the variables used in this model (Model 5a) have predicted 53% of the variability in the performance of Islamic banks. This is confirmed also when jointly substituting the banks' specific variables and the macroeconomic variables by replacing the based financing rate with the rate of unemployment. In this specification of the alternative model, all control variables have been replaced in the original model and still all three significant funding variables (Financing–to-deposits ratio, *mudharabah* deposits ratio, and non-*mudharabah* deposits ratio) confirm their level of significance as depicted in Table 8.7 above. However, the other main finding here is that with this alternative specified set of bank's specific variables, the non-performing financing and the return on equity previously used in the original model, were never significant, but when they are replaced with reserve-to-total assets and return on assets the new variables are significant in explaining the banks' default probability. The McFadden R^2 value for model 5a and 5d is 0.53, which is much better than the original 0.20 value. This means that the model has improved further with the introduction of alternative banks' specific variables.

8.4.6 Funding Mix Model

Subsequently, results are also robust to the use of alternative specifications of the banks' funding mix. In the funding structure model (Model 2), the financing to deposits ratio (*FTD*) has been used as the best proxy for funding composition, and the results showed the FTD as a significant factor in explaining the banks' financial distress in the Islamic banking system. Besides *FTD*, alternative variables can also be used to measure the bank funding mix. Thus, the asset-to deposit ratio is the most common factor used as an alternative to *FTD*. Based on Table 8.8 below, results show that the asset-to deposit ratio is as significant as the *FTD* ratio in explaining the financial distress of Islamic banks in Malaysia.

Table 8.8: Testing for Robustness of Results of an Alternative Measure of Funding Mix [1]

Variables	Model 6
Constant	-3.414083 (5.352768)
Non-performing Financing (NPF_{t-1})	0.133085 (0.103524)
Capital Adequacy ($RWCR_{t-1}$)	0.612658 (0.137402) ***
Profitability(ROE_{t-1})	-0.077564 (0.117568)
Lending rate (BFR_{t-2})	0.750520 (0.479274)
Alternative Measure of Funding Mix (ATD_{t-2})	-0.081888 (0.045636) *
McFadden R^2	0.318685
Log likelihood	-55.02398

Note: *, **, *** significance at 10 percent, 5 percent and 1 percent respectively

[1] Dependent variable is Islamic banks' status (healthy/non-healthy)

$$Y_{a,t} = \beta_1 + \beta_2\, NPF_{a,t-1} + \beta_3\, RWCR_{a,t-1} + \beta_4\, ROE_{a,t-1} + \beta_5\, BFR_{t-2} + \beta_6\, ATD_{a,t-2} + \mu_a$$

(Model 6)

$$Y_{a,t} = -3.414083 + 0.133085\, NPF_{a,t-1} + 0.612658\, RWCR_{a,t-1} - 0.077564\, ROE_{a,t-1} + 0.750520\, BFR_{t-2} - 0.081888\, ATD_{a,t-2} + \mu_a$$

(Model 6)

Table 8.8 above depicts that $RWCR_{t-1}$ is significant at the 1% sig level, and ATD_{t-2} is significant at the 10% level, while the McFadden R^2 result is 0.32. This means that Model 6 is an excellent fit or has a high satisfactory performance. In other words, the variables used in this model (Model 6) predicted 32% of the variability in the performance of Islamic banks.

8.4.7 Final Model

Finally, based on the models discussed above, this study took the most significant variables to be the explanatory variables for the final models. This study suggested two final models as follows:

$$Y_{a,t} = \beta_1 + \beta_2\, RWCR_{a,t-1} + \beta_3\, BFR_{t-2} + \beta_4\, FTD_{a,t-2} + \beta_5\, DD_{a,t-3} + \beta_6\, MD_{a,t-1} + \mu_a$$

(Model 7a)

and,

$$Y_{a,t} = \beta_1 + \beta_2\, RTA_{a,t-1} + \beta_3\, TCE_{a,t-1} + \beta_4\, BFR_{t-2} + \beta_5\, FTD_{a,t-2} + \beta_6\, DD_{a,t-3} + \beta_7\, MD_{a,t-1} + \mu_a$$

(Model 7b)

Table 8.9: Final Models [1]

Variables	Model 7a	Model 7b
Constant	-21.22802 (8.600198)**	-7.969269 (7.455780)
Capital Adequacy ($RWCR_{t-1}$)	1.295227 (0.289061)***	
Alternative Asset Quality (RTA_{t-1})		1.915017 (0.538334)***
Alternative Capital Adequacy Ratio (TCE_{t-1})		1.540563 (0.363095)***
Lending rate (BFR_{t-2})	0.988050 (0.865238)	0.480843 (0.929985)
FTD_{t-2}	-0.073624 (0.022217)***	-0.224483 (0.052258)
MD_{t-1}	-0.056580 (0.026019)**	0.051192 (0.028152)
DD_{t-3}	0.276188 (0.068882)***	0.234497 (0.064928)
McFadden R^2	0.721201	0.689368
Log likelihood	-22.51622	-25.08707

Note: *, **, *** significance at 10 percent, 5 percent and 1 percent respectively
[1] Dependent variable is Islamic banks' status (healthy/non-healthy)

Based on results shown in Table 8.9 above, the estimated models with the respective coefficient values are as follows:

$$Y_{a,t} = -21.22802 + 1.295227\, RWCR_{a,t-1} + 0.988050\, BFR_{t-2} - 0.073624\, FTD_{a,t-2} + 0.276188\, DD_{a,t-3} - 0.056580\, MD_{a,t-1} + \mu_a$$

(Model 7a)

and,

$$Y_{a,t} = -7.969269 + 1.915017\, RTA_{a,t-1} + 1.540563\, TCE_{a,t-1} + 0.480843\, BFR_{t-2} + 0.224483\, FTD_{a,t-2} + 0.234497\, DD_{a,t-3} + 0.051192\, MD_{a,t-1} + \mu_a$$

(Model 7b)

Based on the results described above, it can be concluded that both final models, developed based on the results from all the models developed earlier, have shown a high satisfactory performance. This means that the inclusion of selected significant variables from the previous models has proved to be momentous to the performance of the final models. This study recommends two final models: the first model (Model 7a) includes $RWCR_{t-1}$, BFR_{t-2}, FTD_{t-2}, DD_{t-3}, and MD_{t-1} as explanatory variables, and the second model (Model 7b) includes RTA_{t-1}, TCE_{t}-1, BFR_{t-2}, FTD_{t-2}, DD_{t-3}, and MD_{t-1}. With McFadden R^2 values of 0.721201 (Model 7a) and 0.689368 (Model 7b), this means that both models are an excellent fit and about 72% or 68% of the total variations in the performance of Islamic banks are explained by the explanatory variables included in both models. These McFadden R^2 values are considered as extremely high.

8.5 SUMMARY OF THE RESULTS AND CONCLUSION

The recent financial crisis has shown how critical liquidity conditions can affect banks' operations under stress and their probability of survival. The evidence from this study confirms that funding liquidity conditions significantly affect Islamic banks' risk profile and the probability of defaults. This is in line with the recent empirical study conducted in the U.S. by Bologna (2011), who found that liquidity conditions did affect the U.S. banks risk profile, thus suggesting that the relevant supervisory and regulatory authorities should better supervise and regulate the banks' liquidity conditions The study also signifies the importance of tighter regulation and supervision of banks liquidity, not only focussing on U.S. banks but extending to other countries as well.

Table 8.10 below depicts the summary of the tested models.

Table 8.10: Summary of the Results/Models

Model		**Significance Variables**	**McFadden R^2**
Model 1		$RWCR_{t-1}$***	0.202170
Model 2	Model2a	$RWCR_{t-1}$***, FTD_{t-1}***	0.328166
	Model2b	$RWCR_{t-1}$***, FTD_{t-2}***	0.332842
	Model2c	$RWCR_{t-1}$***, FTD_{t-3}***	0.344773
Model 3	Model 3a	$RWCR_{t-1}$***, BFR_{t-2}*, DD_{t-1}***	0.620974
	Model 3b	$RWCR_{t-1}$***, DD_{t-2}***	0.610535
	Model 3c	$RWCR_{t-1}$***, BFR_{t-2}**, DD_{t-3}***	0.623739
	Model 3d	$RWCR_{t-1}$***, SD_{t-1}**	0.339952
	Model 3e	$RWCR_{t-1}$***, SD_{t-2}**	0.344607
	Model 3f	$RWCR_{t-1}$***, SD_{t-3}**	0.344196
	Model 3g	$RWCR_{t-1}$***, GID_{t-1}**	0.327858
	Model 3h	$RWCR_{t-1}$***, GID_{t-2}**	0.335548
	Model 3i	$RWCR_{t-1}$***, GID_{t-3}***	0.344131
	Model 3j	$RWCR_{t-1}$***, SID_{t-1}**	0.321499
	Model 3k	$RWCR_{t-1}$***, SID_{t-2}**	0.324654
	Model 3l	$RWCR_{t-1}$***, SID_{t-3}**	0.326716
	Model 3m	$RWCR_{t-1}$***	0.300580
	Model 3n	$RWCR_{t-1}$***	0.299204
	Model 3o	$RWCR_{t-1}$***	0.300023
	Model 3p	$RWCR_{t-1}$***, NPF_{t-1}*,MD_{t-1}**	0.326299
	Model 3q	$RWCR_{t-1}$***, NPF_{t-1}*,MD_{t-2}**	0.332263
	Model 3r	$RWCR_{t-1}$***, NPF_{t-1}**,MD_{t-3}**	0.337086
	Model 3s	$RWCR_{t-1}$***, NPF_{t-1}*,NMD_{t-1}**	0.326299
	Model 3t	$RWCR_{t-1}$***, NPF_{t-1}*,NMD_{t-2}**	0.332263
	Model 3u	$RWCR_{t-1}$***, NPF_{t-1}**,NMD_{t-3}**	0.337086
Model 4	Model4a	$RWCR_{t-1}$***, FTD_{t-2}***	0.395443
	Model4b	$RWCR_{t-1}$***, MD_{t-1}**	0.327258
	Model4c	$RWCR_{t-1}$***, NMD_{t-1}**	0.327258
	Model4d	$RWCR_{t-1}$***, FTD_{t-2}***	0.399022
	Model4e	$RWCR_{t-1}$***, MD_{t-1}**	0.328023
	Model4f	$RWCR_{t-1}$***, NMD_{t-1}**	0.328023
	Model4g	$RWCR_{t-1}$***, FTD_{t-2}***	0.395627
	Model4h	$RWCR_{t-1}$***, MD_{t-1}**	0.324356
	Model4i	$RWCR_{t-1}$***, NMD_{t-1}**	0.324356
	Model4j	$RWCR_{t-1}$***, FTD_{t-2}***	0.402407
	Model4k	$RWCR_{t-1}$***, FTD_{t-2}***,	0.463808

		MD_{t-1}***	
	Model4l	$RWCR_{t-1}$***, FTD_{t-2}***, NMD_{t-1}***	0.463808
Model 5	Model5a	RTA_{t-1}***, TCE_{t-1}***, FTD_{t-2}***	0.532479
	Model5b	TCE_{t-1}***, ROA_{t-1}***	0.168980
	Model5c	TCE_{t-1}***, ROA_{t-1}***	0.168980
	Model5d	RTA_{t-1}***, TCE_{t-1}***, FTD_{t-2}***	0.532453
	Model5e	TCE_{t-1}***, ROA_{t-1}***	0.168603
	Model5f	TCE_{t-1}***, ROA_{t-1}***	0.168603
Model 6		$RWCR_{t-1}$***, ATD_{t-2}*	0.318685
Model 7	Model 7a	$RWCR_{t-1}$***, FTD_{t-2}***, DD_{t-3}***, MD_{t-1}**	0.721201
	Model 7b	RTA_{t-1}***, TCE_{t-1}***, FTD_{t-2}***, DD_{t-3}***, MD_{t-1}*	0.689368

Note: *, **, *** significance at 10 percent, 5 percent and 1 percent respectively

Based on Table 8.10, the original model (Model 1) has been enhanced further with the inclusion of funding variables (Model). The McFadden R^2 has increased from 0.20 in Model 1 to the highest value of 0.34 in Model 2. Based on the McFadden rule of thumb, any value between 0.20 and 0.40 means that the model can be considered as having an excellent fit. Based on Model 2, it seems that only *RWCR* and *FTD* are statistically significant at the 1% level. Thus, it can be concluded that the inclusion of *FTD* into the model has increased the goodness-of-fit of the model.

Next, all models under Model 3 have shown a better performance as compared to Model 2 and Model 1. A maximum McFadden R^2 value of 0.62 for Model 3c implies that about 62% of the total variations in the performance of Islamic banks are explained by the explanatory variables included in Model 3c, consisting of NPF_{t-1}, $RWCR_{t-1}$, ROE_{t-1}, BFR_{t-2}, and DD_{t-3}. It is acceptably high, particularly for logit and probit models where evidence of goodness-of-fit points to a range of 0.20 and 0.40 (Harper *et al*., 1990). Moreover, the results show that $RWCR_{t-1}$ and DD_{t-3} are statistically significance at the 1% level, and BFR_{t-2} is marginally significant (5% significant level). Thus, the inclusion of the deposits structure into Model 3 does increase the goodness-of-fit of the model. In addition, all the models under Model 3 do show a steady performance with McFadden R^2 ranging from 0.299204 (Model 3n) to 0.623739 (Model 3c), which is much higher than the McFadden R^2 for the original model (Model 1).

Model 4 is the first robustness test to use the macroeconomic variables as the explanatory variables in the model. As mentioned earlier in the results section, the macroeconomic variables have been tested in alternative specifications of the model by replacing the financing rate previously used with the GDP growth rate, the unemployment rate, and the consumer price index. All the models under Model 4 have shown similar performance as shown by Model 3. The McFadden R^2 ranged from the lowest 0.324356 (Model 4h, Model 4i) to the highest 0.463808 (Model 4k, Model 4l). A maximum McFadden R^2 value of 0.46 for Model 4k and Model 4l means that 46% of the total variations in the performance of Islamic banks are explained by the explanatory variables included in Model 4k and 4l, which consist of NPF_{t-1}, $RWCR_{t-1}$, ROE_{t-1}, GDP_{t-1}, $INFLATION_{t-1}$, $UNEMPLOY_{t-3}$, FTD_{t-2}, MD_{t-1} (Model4k), and NMD_{t-1}(Model4l). The results show that $RWCR_{t-1}$, FTD_{t-2}, MD_{t-1} (Model4k), and NMD_{t-1} (Model4l) are statistically significant at the 1% level, while the rest of the variables are not significant.

Based on model 4d, 4e and 4f, with the inclusion of inflation as the determining factor, this study found that inflation has a positive impact on bank performance although it is not significant. This means that the higher the inflation rate the higher the probability of the banks' default. The relationship between inflation and performance is ambiguous. According to Perry (1992), the relationship between inflation and performance does depend on whether inflation expectations are fully anticipated. An inflation fully anticipated by the banks' management entails that the banks can properly adjust their interest rates to increase their profits faster than costs. Thus, unanticipated inflation will result in faster increases in banks' costs and subsequently have a negative effect on the banks' profitability. This is similar with the other macroeconomic variables; GDP_{t-1} and $UNEMPLOY_{t-3}$, where neither of these two variables significantly affect the performance of Islamic banks.

The second robustness test is done by replacing the original bank variables previously used in Model 2 with the alternative set of banks' specific variables; RTA_{t-1}, TCE_{t-1}, and ROA_{t-1}. In this last specification of the alternative model, all control variables have been replaced from the original model showing their level of significance. In the original model, only $RWCR_{t-1}$ has shown a consistent significance performance throughout the study. However, in this last specification of the alternative model, all alternative variables have shown a significant performance. In other words, the main different here is that with this alternatively specified set of banks' specific variables - the RTA_{t-1}(replaced NPF_{t-1}) and ROA_{t-1}(replaced ROE_{t-1}), it transpires that the original variables used previously were never significant, but the model becomes somewhat significant in explaining the banks' default probability once replaced with the alternative set of banks' specific variables. Moreover, the only variables that remain highly significant are $RWCR_{t-1}$ and FTD_{t-2}, thus confirming the robustness of the estimates. A maximum McFadden R^2 value of 0.532479 for model 5a implies that about 53% of the total variations in the performance of Islamic banks are explained by the explanatory variables included in Model 5a consisting of RTA_{t-1}, TCE_{t-1}, ROA_{t-1}, BFR_{t-2}, and FTD_{t-2}. The results from Model 5a show that RTA_{t-1}, TCE_{t-1} and FTD_{t-2} are statistically significant at the 1% level. While for Model 5b, a McFadden R^2 value of 0.532453 implies that about 53% of the total variations in the performance are explained by the explanatory variables included consisting of RTA_{t-1}, TCE_{t-1}, ROA_{t-1}, $UNEMPLOY_{t-3}$, and FTD_{t-2}, showing that RTA_{t-1}, TCE_{t-1} and FTD_{t-2} are statistically significant at the 1% level.

Subsequently, FTD_{t-2} has been replaced with the asset-to-deposit ratio (ATD_{t-2}) as an alternative for the bank funding mix. The results proved that ATD_{t-2} can also be used as an alternative measure of funding mix besides FTD_{t-2} although the FTD_{t-2} is significant at the 1% level while ATD_{t-2} is only significant at the 10% level when used in the model. In other words, it seems that FTD_{t-2} is statistically significant at the 1% level, but ATD_{t-2} is marginally significant. However, the inclusion of ATD_{t-2} as an alternative measure for the funding mix shows that it does not much affect the McFadden values for both models (Model 2 and Model 6).

Finally, based on the models above, the variables that showed a significant performance were selected as explanatory variables for the final models. This study suggested two final models and the results of McFadden R^2 for both recommended final models showed an excellent fit to predict Islamic banks' performance. The inclusion of the significant variables into the final models has proved to have a major impact on the performance of the models as suggested by the values of McFadden R^2 for Model 7a and Model 7b, which are 0.721201 and 0.689368 respectively. This study recommended these final two models as part of the monitoring process of

Islamic banks in Malaysia and will complement the existing methods used by the relevant authorities in monitoring the banks' performance, instead of replacing the current practices.

This study used the funding mix variable, composition of deposits variables, macroeconomic variables, alternative banks' specific variables as well as the alternative funding mix variable, to investigate the variables that can affect the banks' performance. This study found that the funding mix variable (FTD_{t-2}), composition of deposits (*DD, SD, GID, SID, MD* and *NMD*), alternative banks' specific variables (RTA_{t-1}, TCE_{t-1} and ROA_{t-1}), and alternative funding mix (ATD_{t-2}), are statistically significant in the models. In contrast, none of the macroeconomic variables tested show as a significant factor in the models, thus suggesting that performance of Islamic banks in Malaysia is not affected by the economic conditions throughout the study period. Furthermore, the Inflation rate, *GDP* growth rate and unemployment rate in Malaysia have been consistent and did not show major movement during the study period. Thus, this may be due to the efficient regulation and supervision by the relevant authorities, in this case Bank Negara Malaysia. According to Shen *et al.* (2001), countries with greater official power and higher restrictiveness will make the banks under their purview less liable to suffer from liquidity risk. In addition, bank liquidity risk could be reduced with direct government supervision and regulation of the banks' activities. The results of this study also confirm the results found in Shen *et al.*'s (2001) study that macroeconomics has no effect on bank liquidity in a bank-based financial system, and liquidity risk has different effects on bank performance in different financial systems.

Finally, the findings of this empirical study show the relationship between banks' funding profiles and Islamic banks performance in Malaysia. The most recent new regulatory framework for liquidity risk adopted by the Basel Committee on Banking Supervision (2010) seems have all the potential and features that may help the banks to reduce the probability of high liquidity risk. This new framework has correctly distinguished the different influences of all types of deposit on the banks' performance by differentiating the treatment of these deposits, as either more stable or less-stable deposits. In the case of Islamic banks, the relevant authorities should not neglect the effect of different types of deposits to avoid further deterioration of the Islamic banks' performance ahead of any further financial crisis.

Chapter 9
CONCLUSION

9.1 INTRODUCTION

The Islamic banking sector has experienced fast growth in the last three decades and has become too large to be ignored in debates on financial stability. The impact of the global financial crisis on the performance of Islamic banks during the initial stage of the event was very minimal; however, the total resilience of the Islamic banking industry is a difficult claim to make. As mentioned in the earlier chapters, there have been a number of Islamic finance and banking distress examples in recent years, including the case of BIMB in Malaysia as well as the most recent Arcapita case. While some of the defaults and failures over the years are attributed to governance problems, some of these are mainly financing and liquidity problems as in the case of BIMB and Arcapita, as well as the GFH cases. Hence, these cases require a careful examination of financial distress in the case of Islamic banks, as the subject matter has been explored for conventional banks in an extensive manner as evidenced in the literature. This study, hence, aimed at exploring, examining and analysing financial distress in the case of Malaysian Islamic banking by using three different models and modifying them in relation to the specific aspects of the case, which are presented in the empirical chapters.

Being the conclusion chapter, this chapter first of all provides a summary of the empirical chapters presented. It highlights the aim and objectives of the study, the methods used and the results of the study. This is followed by some concluding remarks on the empirical findings. Following the summary of the empirical chapters, the limitation of the study is discussed in the next section and is followed by the recommendations for future research. The study recommends that the policy makers and all the stakeholders in the Islamic banking industry in Malaysia consider and apply the recommended integrated and alternative measure models as well as the *EM Z*-score model developed by Altman to measure the distress condition of Islamic banks in Malaysia.

9.2 REFLECTING ON THE EMPIRICAL RESULTS

This section aims to provide a summary of the empirical chapters presented in this study.

9.2.1 Evaluating the Performance of Islamic Banks: Descriptive Quantitative Analysis (Chapter Five)

Chapter Five is the first of the four empirical chapters, which analyses the secondary data collected from the selected Islamic banks based on the selected ratios. This chapter provides a comprehensive description of the selected financial ratios in terms of the estimated means and standard deviations for the selected Islamic banks in Malaysia. There are five categories of financial ratios selected for this empirical study: capital ratios, asset quality ratios, liquidity ratios, profitability ratios, and income-expenditure structured ratios.

From the finding on capital ratios, it can be stated that most of the sampled banks have about the same average mean in each ratio except for KFH. These results imply that KFH does have a higher figure in equity and income as compared to its total deposits due to the fact that KFH started their business operation in Malaysia focused only on wholesale banking instead of retail; thus its lower figure for deposits and non-deposit funds should be attributed to this fact.

In terms of asset quality ratios, it can be concluded that among all the selected banks, there was not much difference between the mean of non-performing financing to financing and of permanent assets to total assets. However, there was a significant difference in total financing to total assets ratio for three banks, which could be due to the high amount of the total financing of those banks. It should be noted that the main concern is the quality of the financing. A lower quality of financing can be depicted by higher non-performing financing, which in turn attracts higher unearned income and loan loss impairment, on the one hand, and the higher unearned income and loss impairment may result in lower profitability, on the other hand.

Findings from liquidity ratios show that there are three banks having higher means on these ratios: Affin Islamic Bank, Kuwait Finance House, and Bank Muamalat. This means that those banks are more liquid than the rest of the Islamic banks. In other words, these Islamic banks have a larger margin of safety available to cover their short-term obligations than the rest of the banks. It is suggested that those banks with lower *LR1* and *LR2* should be monitored closely due their lower liquidity position. The liquidity position of banks can be related to having fewer total assets that are tied to net financing and more liquid assets available for meeting deposit and short-term funding demands.

From the finding on profitability ratios, it was found that, on average, there are not many significant differences in the mean of the profitability ratios for all banks except in two cases, BIMB and KFH. In the case of BIMB, the bank reported a loss before *zakat* and tax in two consecutive years, FY2005 and FY2006. In the case of KFH, the bank has reported losses for six consecutive quarters prior to the fourth quarter of 2010. This can be explained by there being a more challenging operating environment in 2010, as the group and the bank carried out their business realignment and restructuring plans in early 2010. In contrast to the performance of BIMB and all other banks in the study sample, Maybank Islamic Berhad has shown a magnificent performance throughout the study period. This could be owing to the increases in financing and higher asset quality.

As regards to the income-expenditure structured ratios, they show consistent performance among the sample banks. The significant difference in the interest income to interest expenses ratio for KFH, as compared to the other banks, can be specifically attributed to the low interest expenses, since the bank was involved more in wholesale banking during its early years of operations.

9.2.2 Predicting Banking Distress: A Comparative Study on Islamic Banks and Conventional Banks in Malaysia (Chapter Six)

Chapter Six is the second part of the empirical chapters that analyses whether the Altman Emerging Market (*EM*) *Z*-score models can predict bankruptcy and at the same time measure the financial performance of Islamic and conventional banks in Malaysia. This chapter examines 13 Islamic banks and 10 conventional banks during the period of 2005-2010, which covers the impact of the global financial crisis on the Islamic banks' and conventional banks' performance. Furthermore, the results can be compared to the models that have been used in the last two empirical chapters.

The methodology used in this study is based on the *Z*-score model for emerging markets developed by Altman (2002). Most of the previous studies have proved that the Emerging Market or *EM Z*-score model has more than 80 percent accuracy and this confirms that it is a robust tool and valuable in assessing and predicting the potential distress condition of companies. In this study, the *EM Z*-score for each Islamic and conventional bank for the past three years was calculated by examining the financial statements of each of these banks. By applying the *EM Z*-score, this study investigated whether the *EM Z*-score model can predict the Islamic and conventional banks' performance for a period of up to three years earlier.

The main objective of this study is to introduce to the Malaysian banking industry the *EM Z*-score, as a valuable analytical tool in finding the possible reasons that may lead to a deterioration of the banks' performance as well as providing an insight into Islamic and conventional performance. This study established that both Islamic banks and conventional banks in Malaysia are financially robust and sound. The *EM-Z*-scores for all banks are well above the cut-off point of 2.6, although for Islamic banks the *EM Z*-scores are showing a declining trend whilst for conventional banks they are showing an increasing trend. This empirical evidence is important for the banks since it provides a warning signal to the banks' management as well as to the related parties in the planning, controlling and decision making process. If the declining trend continues, the management as well as the relevant authorities could take early remedial actions to reduce the probability of the banks going bankrupt.

Initially, the data for Islamic banks (2008-2010) and conventional banks (2005-2010) were reconstructed in order to calculate the *Z*-score for each bank. Based on the *EM Z*-score for each bank, this study concludes that all banks falls in the healthy area of the scale. The *EM Z*-score for each bank significantly exceeded the cut-off value of 2.6. However, the individual performances for each bank have mostly shown a fluctuation during his period, thus suggesting that the global financial crisis did affect Islamic bank performance.

The comparison of *EM Z*-score performance between the Islamic and conventional banks shows that the Islamic banks were exhibiting a declining trend during 2008 till 2010, whilst conventional banks were exhibiting an escalating trend. This suggests that the recent global financial crisis has had some impact on the performance of the banking industry in Malaysia, even though it is not that significant.

It should be noted that the *EM Z*-score model is not the only model that can be tested to analyse the banks' performance. However, it can be used to complement the existing models used by banks in monitoring their performance. The results presented in this empirical chapter proved the fitness of the *EM Z*-score model in predicting the distress condition of banks in Malaysia. In addition, based on the presented results it can be concluded that in order for Islamic banks and conventional banks to sustain themselves in the banking industry they should consider their past performance in order to predict their future position in the banking industry.

9.2.3 Integrated Early Warning Prediction Model for Islamic Banks: Multiple Regression Analysis (MDA, Logit & Probit) (Chapter Seven)

Chapter Seven provides the third empirical paper by adapting the existing models and developing the new early warning system for Islamic banks. It presents the newly constructed integrated model using the publicly available data for Islamic banks in Malaysia, which can be used as an alternative model for regulators in monitoring the performance of Islamic banks that are experiencing any serious financial problems. This paper develops a preliminary model for the prediction of the performance level of Islamic financial institutions for the period of December 2005 to September 2010 for ten selected Islamic banks in Malaysia.

This study makes use of earlier research on the subject to develop a preliminary model for the prediction of the performance level of Islamic financial institutions. It aims to lay a cornerstone for further development and improvement, especially as more information and data become available. Factor analysis and three parametric models (discriminant analysis, logit analysis and probit analysis) are used in this study to construct an integrated prediction model for Islamic banks in Malaysia. Out of the 29 variables used in the early stage of the study, only 13 were selected as predictor variables in this study.

The results show that, overall, the classification accuracy is relatively high in the first few quarters before the benchmark quarter (2010 Q3) for all the estimated models. Correct classification rates are high during the first few quarters and decrease subsequently. Thus, based on these results it is obvious that the first few quarters before the benchmark quarter are the most important period for making a correct prediction. These results show the predictive ability of the integrated model to differentiate between the healthy and non-healthy Islamic banks, thus reducing the expected cost of bank failure.

The integrated prediction model, constructed based on factor analysis and the other three parametric models, can serve as an analytical tool to support the decision-making process in Islamic bank supervision and examination. This integrated model can be used as presented in Figure 7.1, which shows the process flow of the integrated model, *i.e.* the estimated models and their parameters. These parameters include the means and standard deviations of the selected financial ratios, the factor score coefficients of the three factors obtained by factor analysis, and finally the estimated coefficients of the discriminant, logit and probit models. Based on this integrated model, when evaluating bank performance, all the system parameters remain unchanged and only the ratios of the evaluated bank change. These ratios are the 13 early warning indicators that were determined in the previous section using factor analysis (principal component analysis). In the early stage, all 13 ratios are standardised and the three factor scores are determined by using the factor score coefficient matrix calculated using SPSS. These factor scores are then used in calculating the discriminant score, logit and probit probability of failure for the Islamic bank by using the publicly available data for Islamic banks in Malaysia.

Hence, this new integrated model can easily be used by regulators in monitoring the performance of Islamic banks that are experiencing any serious financial problems. On the one hand, from the regulators perspective, the ability to detect the Islamic banks' performance by using the publicly available data will have a major impact on their monitoring cost especially the on-site examinations. On the other hand, this information is also valuable for other parties that are involved in monitoring Islamic banks' performance or preventing the Islamic banks from failing. If the integrated model is effectively employed in Islamic bank supervision and examination, it will reduce the amount of the restructuring cost significantly in the long term.

9.2.4 Alternative Measures: Funding Mix, Deposits, Macroeconomics and Alternative Bank Specific Variables (Chapter Eight)

Chapter Eight is the last empirical paper presented in this research, which provides the process of selecting the explanatory variables that have the discriminating power. It is more concentrated on the funding structure, composition of deposits, macroeconomic variables, and other alternative bank-specific variables. This empirical paper further explores the effect of other important variables in predicting Islamic banks' performance by using the same sample and data set for Islamic banks as in the previous empirical paper. For this, the logit model is used.

This study used the funding mix variable, composition of deposits variables, macroeconomic variables, alternative bank specific variables as well as the alternative funding mix variable, to investigate the variables that can affect the banks' performance. It was found that the funding mix variable (FTD_{t-2}), composition of deposits (*DD, SD, GID, SID, MD* and *NMD*), alternative bank specific variables (RTA_{t-1}, TCE_{t-1} and ROA_{t-1}), and the alternative funding mix (ATD_{t-2}) are statistically significant to the models.

Based on the results of all models, this study recommended two final models that showed an excellent fit for predicting Islamic banks' performance. The fit was improved by including in the final models the variables that showed significant performance as explanatory variables. These two final models are recommended, and the results of McFadden R^2 for these two final models show an excellent fit to predict Islamic banks' performance. The inclusion of the significant variables into the final models proved to have a major impact on the performance of the models as suggested by the values of McFadden R^2 for Model 7a and Model 7b, which were 0.721201 and 0.689368 respectively. This study recommended that these final two models should be used as part of the monitoring process of Islamic banks in Malaysia. They will complement the existing methods used by the relevant authorities in monitoring the banks' performance, rather than replace the current practices.

In contrast, none of macroeconomic variables tested showed a statistically significant result in the models, thus suggesting that the performance of the Islamic banks in Malaysia was not much affected by economic conditions throughout the study period. This can also be explained by the stability in the economy, as the inflation rate, GDP growth rate and unemployment rate in Malaysia have been consistent and did not show a major movement during the study period. Thus, this may be due to efficient regulation and supervision by the relevant authorities, in this case Bank Negara Malaysia. These results contradict the results of Kassim and Abd Majid's (2010) study, which suggested that Islamic banks are vulnerable to macroeconomics and financial shocks. According to Shen *et al.* (2001), countries with greater official power and higher restrictiveness will make the banks under their purview less liable to suffer from liquidity risk. In addition, bank liquidity risk could be reduced with direct government supervision and the regulation of the banks' activities. The results of this study also confirm the results found in Shen *et al.* (2001)'s study that macroeconomic magnitudes have no effect on bank liquidity in bank-based financial system, and liquidity risk has different effects on bank performance in different financial systems.

The empirical evidence produced by this study shows the relationship between the banks' funding profiles and the Islamic banks' performance in Malaysia. The most recent new regulatory framework for liquidity risk adopted by the Basel Committee on Banking Supervision (2010) seems to have all the potential and features that may help the banks to reduce the probability of high liquidity risk. This new framework has correctly distinguished the different influences that all types of deposit can have on the banks' performance by differentiating the treatment of these deposits, as either more stable or less-stable deposits. In the case of Islamic banks, the relevant authorities should not neglect the effect of different types of deposits to avoid further deterioration of the Islamic banks' performance ahead of any further financial crisis.

9.3 CONCLUDING REMARKS ON THE EMPIRICAL FINDINGS

This study presents novel empirical evidence on the determinants of Islamic bank distress in Malaysia. The evidence supports the notion that recent financial integration policies in Malaysia have led to the convergence of Islamic bank risks in Malaysia, and provides some empirical justification for introducing a more centralised system of financial regulation in Malaysia. This study suggests a number of early warning models, including a number of important variables vis-à-vis the mentioned models, which should be taken into consideration when designing early warning models for Islamic banks. This study also finds solid evidence for the importance of the funding structure, the deposits structure as well as other alternative bank-specific variables in designing the prediction models. On the contrary, the study finds an opposite effect on macroeconomic variables. Among other results, this study provides empirical evidence suggesting the importance of the systemic effect in the Malaysian banking system. Even though the effect is not highly significant, it is important to really monitor the aftermath effect on the banking system as a whole.

All of the models suggested in this study are proved to be efficient in predicting bank failure, even though these models are not fully tested by others and the sampling procedures used in this study differ significantly from those of the original researchers. The integrated models introduced in Chapter Seven and the two models in Chapter Eight have the necessary ability to predict financial distress. The results make it clear that all of the models, including the well-known *EM Z*-score, are able to predict banking distress even during the recent global financial crisis. Thus, this shows the predictive power of the models themselves, and more significantly the ability of the models to filter out banks which are in a distress condition even during the volatile period.

In this study, there is no evidence that any of the newly developed models outperformed the others in terms of failure prediction. However, in terms of identifying distressed banks, the integrated model provides some evidence that this model outperforms the other two models by estimating the distress condition of the banks as early as eight quarters prior to the year of prediction. It should be noted that the performance of those models can be unfairly judged due to the fact that each model used different types of variables as the predictors. In other words, in some cases, one model is more sensitive to the selected predictors than the other models thus affecting the possibility of selecting which model is best able to predict bank failure.

The results show that the integrated early warning system (*EWS*) model, as well as the alternative models, all produce similar results despite the varying statistical models and the wide range of financial variables used in this study. The selected variables do influence the performance of those models. The financial indicators, as well as the external variables used in the models, seem to be quite stable over the long term, thus showing the stability of the model over a long term period.

Comparing the performance of the models mentioned above, the researcher is of the opinion that the integrated prediction model developed in Chapter Seven can be considered as the best option for monitoring the Islamic banks in Malaysia, and can complement the existing ones. This integrated model can serve as an analytical tool to support decision-making in Islamic bank supervision and examination. Furthermore, it is also worthy of consideration that the two final alternative models developed in Chapter Eight have shown a high satisfactory performance. These two models take into consideration the bank variables (*RWCR*), alternative asset quality (*RTA*), alternative capital adequacy ratio (*TCE*), lending rate (*BFR*), funding structure ratios (*FTD*), and deposit composition (*MD, DD*). With McFadden R^2 values of 72% (Model 7a) and 68% (Model 7b), this shows that both models are an excellent fit, and about 72% or 68% of the total variations in the performance of Islamic banks are explained by the explanatory variables included in both models. These selected models are developed based on the true data on Islamic banks in Malaysia, thus representing the true value in those models.

9.4 LIMITATIONS OF THE RESEARCH AND SUGGESSION FOR FUTURE RESEARCH

Although the Islamic banking industry in Malaysia has grown tremendously during the recent period, as shown in terms of the number of players, the lack of data on the financial distress of Islamic banks in Malaysia is still the main concern for researchers besides the availability of the most recent financial reports. The information on the financial distress condition of Islamic banks in Malaysia is important in developing a financial distress prediction model, besides the financial variables of those banks. Thus, this has some effect on the number of samples that can be included in this study as well as the maximum outcome of this study. It is suggested that for future research, the efficiency of these models should be tied closely to the number of Islamic banks in a distress condition or failure during the given period.

From a regulator's perspective, those who are mainly concerned with the identification of the distress level of banks should consider using a combination of other statistical methods, such as MDA, logit and probit, and at the same time they should also recognise the limitation of these models. As for the screening process, models that use factors other than financial variables, such as macroeconomic variables, should also be considered. It can be assumed that any of these models can be used to predict Islamic bank distress in Malaysia; the predictive powers of those selected financial variables as well as alternative variables are stable over a relatively long period, thus allowing the application of these models during times when few distresses are occurring.

Future research can also perhaps consider how non-*Shari'ah* compliant distress can be measured. In other words, among the total financing the risk of non-*Shari'ah* compliancy can also create financial distress. Therefore, disaggregating the data with specialised financing instruments, means that each category of financing can be examined to locate non-*Shari'ah* compliant financial distress.

Finally, it is recommended that the coefficient values of each of the ratios in these models should be updated based on the most recent inputs from the Islamic banking industry in Malaysia, thus giving some true values for better prediction of banking distress conditions.

9.5 EPILOGUE

As stated in Chapter One, the thesis aimed to empirically examine and analyse the financial distress of the Malaysian Islamic banks; the effectiveness of the existing early warning statistical insolvency prediction models used in the previous studies and the models adapted by Islamic Banking Institutions (IBIs) in Malaysia were critically evaluated.

As the empirical chapters demonstrate, a few models are utilised to conduct empirical analysis in order to predict the financial distress faced by Islamic banks in Malaysia. Furthermore, an attempt is made at the modification of the existing models of early warning insolvency prediction for evaluating and analysing the Malaysian Islamic banks.

The four main empirical chapters, as discussed in the previous sections, included: a comprehensive description of the selected financial ratios; analysing whether the EM *Z*-score model can predict bankruptcy and measure Islamic and conventional banks' performance; adapting the existing models and constructing the new, integrated early warning system for Islamic banks based on factor analysis and other three parametric models; and investigating other types of variables that can affect the banks' performance. Finally, the thesis contextualised the overall findings and proposed an integrated EWS model and two alternative models developed in Chapter Eight which should be taken into consideration for further implementation by the relevant authorities in the Islamic banking industry.

As such, the thesis has achieved its aims and objectives as evidenced by the empirical chapters. It is hoped that these models can help with bringing the Islamic banking industry in general, and the Malaysian Islamic banking industry specifically, into a better way of managing their financial distress conditions. It should be noted that this study also contributes to the knowledge and understanding of managing the financial distress condition of Islamic banks in the Islamic banking literature.

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