Integrated Early Warning Prediction Model for Islamic Banks: The Malaysian Case

Jaizah Othman[a] & Mehmet Asutay[b]

a) Visiting Professor in Finance at Princess Nourah Bint Abdulrahman University (PNU), Riyadh Saudi Arabia
b) Professor of Middle Eastern and Islamic Political Economy & Finance, Durham University Business School, Durham University, UK

Abstract

It is increasingly becoming important to predict the performance of Islamic banks in order to anticipate a problem before it materializes and negatively affects banks' performance and financial standing. Benefiting from the earlier research on the subject, this study aims to develop a preliminary integrated early warning model for Islamic banks in Malaysia to assess their financial standing by using quarterly data for the 2005 to 2010 period. Factor analysis and three parametric models (discriminant analysis, logit analysis, and probit analysis) are used in this study. Out of 29 variables used in the early stage of study, only 13 were selected as predictor variables in this study. Results show that, overall, 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. Based on these results, therefore, 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 healthy and non-healthy Islamic banks, thus reducing the expected cost of bank failure.

Keywords: Early Warning System; Principal Component Analysis; Discriminant Analysis; Logit; Probit; Islamic Banks; Malaysia.

INTRODUCTION

The current crisis in financial markets has demonstrated, in the worst possible way, how the central role of banks in the economy can affect various stakeholders. In contrast to past crises, this one began in developed countries and their economies have been influenced adversely. Governments, urgently seeking a way out of the crisis, have announced various fiscal initiatives, including what is in all but name the partial nationalization of several banks – a measure that substantially increases the debt to GDP ratio. The way the crisis unfolded has highlighted the need for early warning models that can help monitor banks and avoid similar problems in the future.[1]

The recent financial crisis has generated a new round of discussions among practitioners regarding the adequacy of the regulatory environment. Numerous studies have been carried out to try and explain the reasons behind the crisis and how its recurrence can be avoided in the future.[1] Most central banks have for years been using different early warning systems to monitor the risk of banks. 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—indicate that safeguarding the banking system is no easy task.[2]

It is a fact that in the last ten years we have witnessed dramatic changes in the Islamic financial landscape, which has now become a reality in the financial system of more than seventy-five countries. While Islamic banks and financial institutions have enjoyed high growth rates, they have not been immune to the impact of financial crises despite an overemphasised discourse on the 'resilience of Islamic finance'. Such developments, therefore, have necessitated predicting the performance of Islamic banks with the objective of anticipating a problem before it materializes and negatively affects banks' performance and financial standing. Prevention lowers the costs that follow from bad performance and failure in respect of depositors and owners and the economy generally.[3] Thus, there is a need for an early warning system in Islamic banking as well to identify the possible causes of bad performance, detect potential problem banks, and facilitate supervision of banks as well as scheduling the remedial procedures.

This study, therefore, aims to examine distress levels of Islamic banks through the use of preliminary integrated early warning models for the prediction of their performance level with the objective of identifying any potential difficulties with their financial standings; thereby an attempt is made to develop a reliable and efficient insolvency prediction model for Islamic banks in Malaysia. To do so, the available models and methodologies in the literature have been utilised in developing a model for the Malaysian Islamic banks based on data from the period 2005 quarter 4 to 2010 quarter 3. As Malaysia has become a leading country in Islamic financial development, the research presented in this study should be considered as making an important contribution to the field.

The paper proceeds as follows: Section 2 provides a review of the literature on banks' failure prediction models and Section 3 presents a brief review on Islamic banking in Malaysia. Research methodology in terms of the sample and variable selection, Islamic banks ranking and grouping, and factor analysis/principal component analysis results are all presented in Section 4, followed by empirical results of each models in the form of MDA, logit and probit in Section 5. Lastly, Section 6 summarises the results of the integrated models and the accuracy of the models by concluding the paper.

ISLAMIC BANKING AND FINANCIAL DISTRESS

The Islamic finance industry in Malaysia has been in existence for over 30 years. The enactment of the Islamic Banking Act 1983 enabled the country's first Islamic Bank to be established and thereafter, with the liberalisation of the Malaysian financial system, more Islamic banks and financial institutions were established. Malaysia's long track record of building a successful domestic Islamic financial industry on solid foundations adds to the richness, diversity and maturity of the financial system.[4]

The historical records, however, show that the Malaysian financial system is not resilient against financial crises. The Asian financial crisis of 1997-1998, for example, has led the Malaysian banking system into a major financial crisis that resulted in falling share prices and declining property prices, thus affecting the asset values as well as the collateral; additionally, it caused an increase in the number of non-performing loans or financings that led to financial distress of the related financial institutions. It should be noted that the effect of the 1997-1998 crisis started when some banks were categorised as ‘ill’. Consequently, the Central Bank of Malaysia (Bank Negara Malaysia) intervened and created a plan to put those affected institutions into mergers in order to improve the soundness of the financial system. However, as there was only one fully-fledged Islamic bank (Bank Islam Malaysia Berhad-BIMB) during this period, this did not yield any consequences for Islamic banking. The post-Asian financial crisis, however, resulted in an increasing role for Islamic banks and financial institutions, with their share reaching about 20% of the financial system by 2011 with 17 Islamic banks.

During this period, Islamic banks have shown a robust development, but also occasional difficulties with financial standing. For example, in the FYs June 2005 and June 2006, BIMB suffered hefty pre-tax losses of RM478 million and RM1.2 million due to sizeable financing-loss charges. The bank’s 3 months-past-due ratio at the end of June 2006 has hit a high of 30%, suggesting this was as a result of its historically weak practices. The credit problem in the bank’s financing portfolio had earlier emerged during the Asian financial crisis in 1997-1998, but the significant amount of losses during 2005/2006 cast doubt on the effectiveness of Malaysia’s regulatory and supervisory control of its financial system. The earlier investigation suggested that the problem arose due to the bank’s poor credit evaluation and poorly established risk management framework. Furthermore, the huge number of non-performing financing occurred due to the lending activities to housing, car financing as well as corporate financing. In addition to Malaysian case, there are other examples of Islamic financial and banking institutions which experienced difficulties with their financial performance. These incidences, therefore, have revealed potential problems in the financing standing of Islamic banks that should be taken into consideration not only by the banks’ management but also by the relevant authorities.

Furthermore, a series of failures of conventional financial institutions due to the recent global financial crisis has shifted the attention of many industry players towards the Islamic financial system as another alternative for the existing conventional banking system. The principles of Islamic finance suggest that the Islamic financial sector should be more resilient to financial crises. However, in a recent study, Hassan and Dridi found that the recent global financial crisis led to a larger decline in profitability in some of Islamic banks compared to the conventional banks.[5] This suggests that, although the impact was not significant, an effective checks and balances system has to be constructed that will help to keep the financial distress of Islamic banks at a controllable level.

Considering such events, this paper attempts to examine the financial distress of Malaysian Islamic banks to develop an integrated early warning system for Islamic banks with a given set of predictors that will help the banks' management as well as the relevant authorities in making accurate decisions before the banks fall into the 'unhealthy' category. Since none of the previous studies have really examined financial distress in the case of Islamic banks, nor explored early warning systems for Islamic banks, this paper will contribute to the body of literature on Islamic banks' prediction models, especially for Malaysian Islamic banks.

BANK PREDICTION MODELS: LITERATURE REVIEW

The earliest failure prediction models developed since 1970s were mostly constructed using classical statistical techniques such as multivariate discriminant analysis (MDA). Later studies also used neural networks, split-population survival time model, Bayesian belief networks, and isotonic separation. In fact, some of these models have been consistently used in the regulatory practices of banking organizations. [6]

Furthermore, the prediction of failure for banks has been extensively researched since the late 1960s. A variety of statistical, such as linear discriminant analysis (LDA), multivariate discriminant analysis (MDA), quadratic discriminant analysis (QDA), multiple regressions, logistic regression (logit), probit, and factor analysis (FA), and other methods such as neural network topologies have been applied to solve bankruptcy prediction problems in banks and firms.[7]

Predicting the default risk for banks, loans, and securities is a classic, yet timely issue. Since the work of Altman,[8] who suggested using the so-called 'Z-Score' to predict default risk, hundreds of research articles have studied this issue.[9] Several have shown that intelligence modelling techniques used in operation research can be applied to predict bank failures and crises.

In order to create an accurate bank failure prediction model, several independent variables need to be included in the analysis as shown in the following section. This study used the following earlier studies on bankruptcy prediction models as a benchmark for choosing explanatory variables: Beaver,[10] Altman,[8] Zmijewski,[11] Thompson,[12] Kolari *et al.,*[13] Lanine *et al*.,[14] Swicegood and Clark,[15] Tung *et al.,*[16] Zhao *et al.,*[6] Boyacioglu *et al*.,[7] Jagtiani *et al.,*[17] Chung *et al.,*[18] Ravi and Pramodh,[19] Gunsel,[20] Al-Osaimy and Bamakhramah,[3] and Canbas *et al.*[21] As shown in the earlier studies, the most commonly used financial ratios can forecast potential failures really well. In fact, some of those studies also included a few financial ratios that are infrequently used but proven to be significant to the models. Thus, this study included 29 financial ratios as utilised in the previous studies.

METHODOLOGY

This study uses statistical methods with particular focus on multivariate discriminant analysis (MDA) and logistic regression methods. The next section will discuss in detail the methodology and applications of these methods in previous studies and their application for the development of a new prediction model for Islamic banks in Malaysia.

This section presents the procedures and results of the study. The first step is to look at the explanatory efficacy of the independent variables, followed by the correlation between them. The next step is to test the estimated models in order to find the most accurate and reliable ones by looking at the misclassification results. Since this section focuses more on the integrated model instead of every single model, the accuracy of those three estimated models (discriminant, logit and probit) was taken as a pool result.

Sample

For this study, data collected through annual reports of the selected ten Islamic banks (Affin Islamic, BIMB, CIMB Islamic, EONCap Islamic, Hong Leong, Kuwait Finance House, Maybank Islamic, Muamalat, Public Islamic Bank, and RHB Islamic) out of sixteen Islamic banks currently operating in the country. The sample selection was determined by the availability of data, as most of the Islamic banks have only recently been established, making it difficult to gather historical data. The data for this study, hence, covers the 2005-2010 period.

Variable Selection

The test of the relevance of the independent variables is done in two ways. First, the mean between 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 strong explanation power of the insolvency model. 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 was done using the discriminant, logit, and probit models.

At this stage, the main objective is to determine the most suitable variables for constructing an efficient insolvency early warning model. To achieve this, the collected data were 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 average values of the ratios in healthy and non-healthy groups.[18]

Using the independent t-test on financial ratios, the results are shown in Table 1, which presents descriptive statistics of the financial ratios for the two groups (healthy and non-healthy banks), and significance tests for the equality of group means for each ratio. The ratios are presented in ascending order according to the significance levels, *i.e.* according to the significance level of F statistics, with each ratio as shown in one of the columns in Table 1. As a result, out of 29 ratios used in the early stage of analysis, only 13 are established to be statistically significant at <10%. Hence, the null hypothesis that the two group means are equal is rejected at 10% significance level of these ratios. The rest of the ratios, with higher significance level (>10%), were excluded from the analysis due to inability to split the Islamic banks into healthy and non-healthy. In other words, the equality of group means for these remaining ratios cannot be rejected at 10% significance level.

Table 1 here

Ranking the Banks in the Islamic Banking Sector by their Financial Performance

Following the method used in Al-Osaimy (2004), we distinguished 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

The banks were ranked by their financial performance from 1 to 10, with 1 being the banks that obtained the lowest value of the selected ratios and vice versa, depending on the type of financial ratio measured. The classification of the selected 10 Malaysian Islamic banks into the healthy or non-healthy group was 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. Those banks with average 6 points or less were classed as healthy, while those banks scoring more than 5 were classed as non-healthy. Thus, based on these findings, 4 of the Malaysian Islamic banks were classed as healthy banks and 6 banks were classed as non-healthy.

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, this technique has three main uses: to understand the structure of a set of selected variables; to construct a questionnaire to measure the underlying variable; and to reduce a data set to a more manageable size while retaining as much of the original information as possible.[23] This technique is often used in data reduction to identify a small number of factors that explain most of the variance observed in a much large number of variables. In fact, factor analysis also can be used to generate hypotheses regarding causal mechanisms or to screen variables for subsequent analysis.

The correlation matrix shows all pairs of correlation coefficients for a set of variables. 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 2 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. 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 on the pattern of relationships among the variables.

Table 2 here

Based on Table 2, most of the variables show mediocre correlations among them. CR5 and CR6 overall show a medium correlation with the other variables, except correlation between CR5 and PR3, which shows a strong performance between them. AQ1 shows high correlation with the liquidity group of variables (LR1, LR2, LR3, and LR4) but a medium correlation with the others.

Table 3 depicts the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy, and Bartlett's test of sphericity.[22] The former 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. 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 a clear and reliable factor.[23] According to Kaiser, 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.[22] According to Hutcheson and

Sofroniou, any values between 0.5 and 0.7 are considered as mediocre, values between 0.7 and 0.8 are considered as good, values between 0.8 and 0.9 are great, and values of more than 0.9 superb.[24] As Table 3 shows, for these data, the value is 0.676, which falls into the mediocre range so that it can be concluded that the sample size was sufficient for factor analysis.

Table 3 here

Another indicator of the strength of the relationship among variables is Bartlett's test of sphericity, which is a test 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 presented in Table 3, a significant test shows that the correlation matrix is not an identity matrix; therefore, there are some relationships between the selected variables. Based on this, it can be concluded that the strength of the relationship among variables is strong and it is appropriate to proceed with factor analysis.

Table 4 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 4 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.

Table 4 here

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 results in Table 4, 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.

Based on the results from factor analysis, the ratios with 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 and thus to a lower failure risk of Islamic banks. The second factor (F2) consists of asset quality ratios (AQ1) and liquidity ratio (LR4). Both of these ratios have positive loadings, thus the greater the value, the greater the financial strength of the 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 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 5 here

Based on the component score of coefficient matrix in Table 5, factor scores for each Islamic bank are calculated for 19 quarters. Factor scores can be defined as a single score from an individual entity or sample representing performance on some latent variable. The score can be computed as follows.

$$F_1 = 0.456CR6 + 0.708AQ2 + 0.858AQ3 + 0.472LR1 + 0.754LR2 + 0.042LR3 + 0.843M1$$

and,

$$F_2 = 0.87AQ1 + 0.897LR4$$

and,

$F_3 = 0.624CR5 + 0.618PR3 + 0.878IE3 + 0.923PR4$

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 were then tested on the factors scores for the rest of the quarters (from Q2 2010 to Q3 2005) before the benchmark quarter.

EMPIRICAL PROCESS AND FINDINGS

After identifying the methodology of the study, this section presents the empirical findings through particular methods utilised.

The Discriminant Model

Discriminant analysis builds a predictive model for groups of the selected sample. The model is composed of a discriminant function, in this case two groups – healthy and non-healthy banks – based on linear combinations of the predictor variables that provide the best discrimination between the groups. Discriminant analysis, also known as discriminant function analysis (DFA), can be used after MANOVA to see how the dependent variables discriminate the groups. DFA identifies the combination of the dependent variables and also shows, from the table labelled Wilks' lambda, how many variates are significant. If the value of the significance level is less than 0.5, then the variate is significantly discriminating the groups. Once the significant variate is identified, standardized canonical discriminant function coefficient is used to find out how the dependent variables contribute to the variates. 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. (The detailed output and 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 measurements of three independent variables (factors).[1] For two populations, the healthy and non-healthy Islamic banks, it is assumed that the independent variables are distributed within each group according to multivariate normal distribution with different means but equal dispersion matrices.

It should be noted that 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.[1]

Table 6 here

In order to evaluate the effectiveness of the estimated discriminant model, the model statistics were calculated using SPSS as shown in Table 6. The eigenvalue statistic, as shown in Table 6, is the ratio of the between-groups to within-groups sum of squares of D score. A large eigenvalue (1.575) shows that the estimated discriminant model has high discriminating ability. The canonical correlation (0.782) is the measure of 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 depicts 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 D-score of the groups.

Table 7 here

Table 8 here

Table 8 shows the standardized canonical discriminant function coefficient. These coefficient values are used to find out how the dependent variable contributes to the variates. On the one hand, the higher scores indicate that a dependent variable is important for a variate (F2 = .762, F3 = .909) and vice versa (F1 = -.127). On the other hand, variables with positive or negative coefficients are contributing to the variate in opposite ways.

Since discriminant analysis identifies and describes the discriminant function variates of a set of variables, below are the outputs of discriminant analysis. Discriminant function variates are a linear combination of variables created such that the differences between group means on the transformed variable are maximized.[23] It takes the general form:

$D_a = b_1 x1 + b_2 x_2 + ...$

where

b_i is the coefficient value for each factor and x_i is the variable included under each factor.

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 in the equation that defines the variate in question.[23] The linear combination of the factor scores for each Islamic bank *a* provides a D-score, according to the estimated canonical discriminant model below:

$D_a = - 0.127F_1 + 0.080762F_2 + 0.909F_3$

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 on factor analysis. This discriminant model was estimated using SPSS software.

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

$C = (N_A D_A + N_B D_B) / (N_A + NB)$

where

C cut-off score

N_A number of the healthy Islamic bank

N_B number of the non-healthy Islamic bank

D_A average score for healthy Islamic bank

D_B average score for non-healthy Islamic bank

So,

$C = [(4 \times 272.32045) + (6 \times 145.30406)] / 10$

$= 196.1106$

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 healthy Islamic bank, and if the D-score is more than the cut-off point, the Islamic bank is classified as a non-healthy Islamic bank. Based on the results in Table 10, the estimated discriminant model correctly classified the Islamic banks into 2 groups, healthy and non-healthy, 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 70% accuracy in classifying the Islamic banks into the two groups (with maximum of 30% error or misclassification).

The Logit Model

As explained in the literature section, logit regression has been used widely in bank failure prediction. It gives accurate estimates and is a user-friendly tool for analysing bankruptcies. The advantage of the logit model is its ability to use the explanatory power of 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 generally such data are not normally distributed.

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

$P_{La} = 1 / (1 + e^{-(Z_{La})})$

where:

$Z_{LA} = \beta_1 F_{1a} + \beta_2 F_{2a} + \beta_3 F_{3a}$

Based on the probability above, an Islamic bank is classified as healthy or non-healthy by using the cut-off probability, attempting to minimize the Type I and Type II errors.

Table 9 presents the calculated test statistics for the estimated coefficient for logit model. Based on the table above, all the coefficients of the logit model are statistically significant according to the observed significant level of z-statistic corresponding to the standard errors of the coefficients. Maximization of the log-likelihood function provided the following Z_{La} equation in the logit analysis as estimated by using Eviews software:

$$Z_{La} = 12.89634 + 0.293625F_1 - 0.155630F_2 - 0.022004F_3$$

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 on factor analysis.

Table 9 here

Based on the equation above, the logit scores (Z_{La}) for each Islamic bank for each quarter are calculated. An Islamic bank is classified as healthy or non-healthy according to the estimated logit model, based on the cut-off probability of 0.5 (P_c = 0.5) and the calculated probability of logit scores. If the probability of logit score (P_{La}) is less than the cut-off probability (P_c), the Islamic bank is classified in the healthy group. But if the probability of logit score (P_{La}) is more than or equal to the cut-off probability (P_c), the Islamic bank is classified in the non-healthy group, thus indicating a higher probability of failure.

Table 10 here

The results in Table 10 show that the estimated logit model correctly classifies the Islamic banks into 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 80% accuracy in classifying the Islamic banks into two groups (with maximum of 20% error or misclassification), thus indicating the equal performance between the estimated discriminant model and the estimated logit model.

The Probit Model

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:

Table 9 presents the calculated test statistics for the estimated coefficient for probit model. Based on the table, all the coefficients of the logit model are statistically significant according to the observed significant level of z-statistic corresponding to the standard errors of the coefficients. Maximization of the log-likelihood function provided the following Z_{Pa} equation in the probit analysis as estimated using Eviews software:

$$Z_{Pa} = 50.17517 + 0.880147F_1 - 0.612051F_2 - 0.108021F_3$$

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 on factor analysis. This estimated probit model applies the probit transformation, the inverse of the cumulative standard normal distribution function to the probit scores. Based on equation above the probit scores (Z_{Pa}) for each Islamic bank for each quarter are calculated.

An Islamic bank is classified in 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 score (P_{Pa}) is less than the cut-off probability (P_c), the Islamic bank is classified in the healthy group. But if the probability of probit score (P_{Pa}) is more than or equal to the cut-off probability (P_c), the Islamic bank is classified in the non-healthy group, thus indicating a higher probability of failure.

Based on the results in Table 10, we see that the estimated probit model correctly classifies the Islamic banks into 2 groups, healthy and non-healthy, 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 80% accuracy in classifying the Islamic banks into the two groups (with maximum of 20% error or misclassification), thus again this indicates the equal performance between the three estimated models, discriminant, logit and probit.

THE INTEGRATED EARLY WARNING SYSTEM FOR ISLAMIC BANKS: CONCLUDING REMARKS

In responding to the aims of the paper stated in the introduction section, 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. In doing so, this study makes use of the earlier research on the subject to develop a preliminary model for the prediction of the performance level of Islamic financial institutions, which used factor analysis and three parametric models (discriminant analysis, logit analysis and probit analysis). The model is presented in Figure 1, which can serve as an analytical tool to support decision-making in Islamic bank supervision and examination.

Figure 1 here

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 standardized and the three factor scores are determined by using the factor score coefficient matrix calculated using SPSS. Then these factor scores are used in calculating the discriminant score, logit and probit probability of failure for the Islamic bank.

Applying all the three estimated models above to the sampled banks' data one quarter prior to the benchmark quarter and computing the respective score enables the models to function as a predictor of performance of the bank for the following quarter. Testing the predicting accuracy of the model is usually done by using the holdout sample that has not been used in deriving the functions in the above models. Various methods have been proposed in the literature in handling the issue of absence of a holdout sample. The most commonly used test, especially for small samples as in this case, is the Lachenbruch method. This method uses the original sample as a holdout sample. Thus, aapplying this method to the observations of this study, produced the results as shown in Table 11.

Table 11 here

The results indicate that out of 4 healthy banks and 6 non-healthy banks, the estimated MDA model correctly classified all 4 healthy banks and 6 non-healthy bank. The classification accuracy for the healthy bank is 100% while the mis-classification is 0%. Using the estimated Logit model, the model correctly classified 2 out of 4 healthy banks with the classification accuracy of 50% while the mis-classification rate, the Type I error *i.e* classifying a healthy bank as non-healthy is 50%. For the non-healthy banks, the estimated Logit model has correctly classified all the banks.

Finally, using the estimated Probit model, all the healthy banks were correctly classified. As for the non-healthy banks, out of 6 non-healthy banks, the model correctly classified 4 banks. The classification accuracy for the non-healthy banks is 67%, while the mis-classification rate, the Type II error *i.e* classifying a non-healthy bank as healthy bank, is only 33%. The overall accuracy for this integrated model is 87%, which is comparable to most of the models used in the previous studies.

Table 10, hence, presents the classification results according to the estimated discriminant, logit, and probit models respectively for the rest of the quarters. For the estimated MDA model, the variables included into the model correctly classified the non-healthy banks prior to the benchmark quarter for most of the quarters but misclassified two healthy banks from Q42008 onwards. Thus, the Type I error was eliminated and Type II error was increased. The estimated Logit model, similar with the MDA model, correctly classified the non-healthy banks throughout the study period and mis-classified two healthy banks throughout the study period. As for the estimated Probit model, in contrast to the above models, correctly classified the healthy banks and misclassified two non-healthy banks. Thus, the Type II error was eliminated and Type I error was increased.

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 presented in this study can serve as an analytical tool to support the decision-making process in Islamic bank supervision and examination, as it shows the process flow of the integrated model, *i.e.* the estimated models and their parameters. Based on this integrated model, when evaluating bank performance, only the ratios of the evaluated bank change whilst all the system parameters remain unchanged.

The model can be used by regulators to monitor the performance of Islamic banks that may be experiencing serious financial problems. On the one hand, from the regulators' perspective, the ability to detect the Islamic banks' performance using the publicly available data will have a major impact on their monitoring costs, especially on-site examinations. On the other hand, this information is also valuable for other parties involved in monitoring the Islamic banks' performance or preventing their failure. If the integrated model is effectively employed in the supervision and examination of Islamic banks, it will significantly reduce restructuring costs in the long term. Importantly, it would be possible to prevent huge economic and financial losses in an economy. Considering that the authentic characters of the Islamic banks, which provides partial resilience to Islamic banks, are withering away due to convergence with the conventional banking model, it is essential that early warning mechanisms to predict distress should be developed and proactively applied in Islamic banking to prevent big losses.

REFERENCES AND NOTES

(1) Ioannidis, C., Pasiouras, F. & Zopounidis, C. (2009) Assessing bank soundness with classification techniques. *Omega* 38(5): 345-357.

(2) Demyanyk, Y. & Hasan, I. (2010) Financial Crises and Bank Failures: A review of Prediction Methods. *Omega The International Journal of Management Science* 38: 315-324.

(3) Al-Osaimy, M. H. & Bamakhramah, A. S. (2004) An Early Warning System for Islamic Banks Performance. *Islamic Economics* 17(1): 3-14.

(4) See http://www.inceif.org/islamic-finance/industry-growth

(5) Hasan, M. & Dridi, J. (2010) The Effects of the Global Crisis on Islamic and Conventional Banks: A Comparative Study. IMF Working Paper, WP/10/201. Washington, D.C.: IMF.

(6) Zhao, H.; Sinha, A. P. & Ge, W. (2009) Effects of feature construction on classification performance: An empirical study in bank failure prediction. *Expert Systems with Applications* 36(2): 2633-2644.

(7) Boyacioglu, M. A.; Kara, Y. & Baykan, Ö. (2009) Predicting bank financial failures using neural networks, support vector machines and multivariate statistical methods: A comparative analysis in the sample of savings deposit insurance fund (SDIF) transferred banks in Turkey. *Expert Systems with Applications* 36(2): 3355-3366.

(8) Altman, E. I. (1968) Financial Ratios, Discriminant Analysis and The Prediction of Corporate Bankruptcy. *Journal of Finance* 23(4): 589-609.

(9) Kumar, P. Ravi & Ravi, V. (2007) Bankruptcy prediction in banks and firms via statistical and intelligent techniques-a review. *European Journal of Operational Research* 180(1): 1-28.

(10) Beaver, W. H. (1966) Financial Ratios as Predictors of Failure. *Journal of Accounting Research* 4: 71-111.

(11) Zmijewski, M. E. (1984) Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research* 22: 59-82.

(12) Thomson, J. B. (1991) Predicting bank failures in the 1980s. *Economic Review* 27: 9-20.

(13) Kolari, J.; Glennon, D.; Shin, H. & Caputo, M. (2002) Predicting large US commercial bank failures. *Journal of Economics and Business* 54(4): 361-387.

(14) Lanine, G. & Vennet, R. V. (2006) Failure prediction in the Russian bank sector with logit and trait recognition models. *Expert Systems with Applications* 30(3): 463-478.

(15) Swicegood, P. & Clark, J. A. (2001) Off-site monitoring systems for predicting bank underperformance: A comparison of neural networks, discriminant analysis, and professional human judgment. *International Journal of Intelligent Systems in Accounting, Finance & Management* 10(3): 169-186.

(16) Tung, W. L.; Quek, C. & Cheng, P. (2004) GenSo-EWS: a novel neural-fuzzy based early warning system for predicting bank failures. *Neural Networks* 17(4): 567-587.

(17) Jagtiani, J.; Kolari, J.; Lemieux, C. & Shin, H. (2003) Early warning models for bank supervision: Simpler could be better. *Economic Perspectives* 27(3): 49-60.

(18) Chung, K. C.; Tan, S. S. & Holdsworth, D. K. (2008) Insolvency Prediction Model Using Multivariate Discriminant Analysis and Artificial Neural Network for the Finance Industry in New Zealand. *International Journal of Business and Management* 39(1): 19-28.

(19) Ravi, V. & Pramodh, C. (2008) Threshold accepting trained principal component neural network and feature subset selection: Application to bankruptcy prediction in banks. *Applied Soft Computing* 8(4): 1539-1548.

(20) Gunsel, N. (2005) Financial ratios and the probabilistic prediction of bank failure in North Cyprus. *European Journal of Scientific Research* 18(2): 191-200.

(21) Canbas, S.; Cabuk, A. & Kilic, S. B. (2005) Prediction of commercial bank failure via multivariate statistical analysis of financial structures: the Turkish case. *European Journal of Operational Research* 166(2): 528-546.

(22) Kaiser, H. F. (1974) An index of factorial simplicity. *Psychometrika*. 39(1): 31-36.

(23) Field, A. P. (2009) Discovering statistics using SPSS: And sex and drugs and rock’n’roll. London: Sage.

(24) Hutcheson, G. D. & Sofroniou, N. (1999) The Multivariate Social Scientist. London: Sage.

TABLES

Table 1: Test of equality of group means for the financial ratios

Code	Definition	Healthy Banks		Non Healthy Banks		Test statistics			Accept/ Reject
		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 Assets	.239581	.0876397	.116843	.2988128	0.08	3.107	0.086	Reject*

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	Acceptt
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

Table 2: 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

Table 3: 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

Table 4: 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.									

Table 5: 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.			

Table 6: Result on Eigenvalues

Eigenvalues				
Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.575[a]	100.0	100.0	.782

Note: (a) First 1 canonical discriminant functions were used in the analysis.

Table 7: Result on Wilks' Lambda

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

Table 8: Standardized Canonical Discriminant Function Coefficients

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

Table 9: Test Statistics for the estimated logit and probit model

Logit				
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
Probit				
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

Table 10: Summary of Classification Results Using Estimated MDA, Estimated Logit and Estimated Probit Models

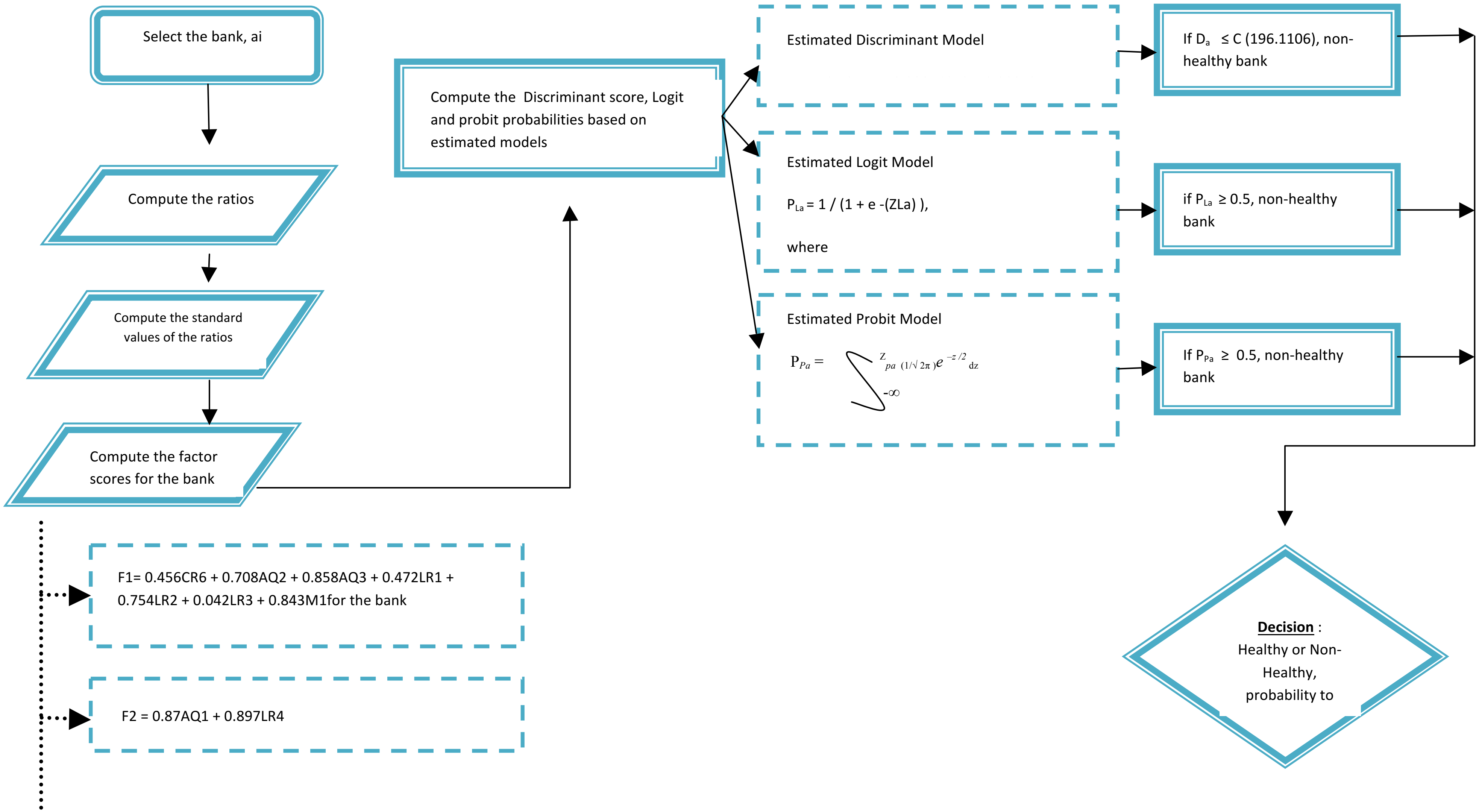
Estimated Models	**Q2 2010**	**Q1 2010**	**Q42009**	**Q3 2009**	**Q2 2009**	**Q1 2009**	**Q4 2008**	**Q3 2008**	**Q2 2008**	**Q1 2008**
Discriminant Analysis	100%	100%	100%	100%	100%	100%	80%	80%	80%	80%
Logit Model	80%	80%	80%	80%	80%	80%	80%	80%	80%	80%
Probit Model	80%	80%	80%	80%	80%	80%	80%	80%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

Table 11: Classification Results of Islamic Banks Performance for One Quarter Prior to Benchmark Quarter (Q3 2010)

Performance Group	**No of Cases**	**Correct Classification**	**%**	**Misclassification**	**%**
Discriminant Model					
Healthy	4	4	100	0	0
Non-Healthy	6	6	100	0	0
Overal	**10**	**10**	**100**	**0**	**0**
Logit Model					
Healthy	4	2	50	2	50
Non-Healthy	6	6	100	0	0
Overall	**10**	**8**	**80**	**2**	**20**
Probit Model					
Healthy	4	4	100	0	0
Non-Healthy	6	4	67	2	33
Overall	**10**	**8**	**80**	**2**	**20**

Average %			**87**		**13**

Figure 1: Integrated Model Process Flow



F3 = 0.624CR5 + 0.618PR3 + 0.878IE3 + 0.923PR4