Predicting Return on Equity Based on Significant Determinants for Islamic Banks In Malaysia

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Abstract. The existence of Islamic banks that grow rapidly in every corner of the world has caused strong competition among them and other conventional banks in Malaysia. This requires the banks management to choose wisely on the determinants that make them to remain strong and relevant in the Islamic banking sector. The main purpose of this study is to predict the return on equity of some Islamic banks in Malaysia using forecast value of significant banking determinant. The significant banking determinants selected for the study include deposit ratio, operating efficiency and market concentration. The study utilized secondary data from year 2010 until year 2016 for 13 Islamic banks in Malaysia. Principal Component Analysis was applied in order to get internal and external significant determinants. The internal and external significant determinants are Bank Size and Gross Domestic Product. Then, Multiple Linear Regression was used to formulate the Bank Profit Model which shows the relationship between the Bank Size and GDP with Return on Equity. Next, Geometric Brownian Motion used to forecast the value of Bank Size and GDP. The forecast value was substitute into Bank Profit Model to calculate the Return on Equity for each bank. From the results of the study, management of bank can have focused on Bank Size and Gross Domestic Product in order to gain more profit. Besides, the Return on Equity for Islamic banks in this study in a range of 3 percent to 23.82 percent.

INTRODUCTION

There are many determinants that contribute to banks' profit. The bank management needs to choose which determinants are the most suitable for them to focus on, to deliver the best profit for the Islamic banks. The objectives of this study is to identify the internal and external significant determinants that contribute to bank profitability by using Principal Component Analysis. In this study, the profitability is a dependent variable and it can be measured by Return on Equity while the independent variables are bank size, bank capital, credit risk, liquidity, deposits ratio and operating efficiency, Gross Domestic Product, annual inflation rate and market concentration

LITERATURE REVIEW

REVIEW OF PRINCIPAL COMPONENT ANALYSIS

Principal Component Analysis (PCA) was introduced by Pearson in 1901. It has been considered as the oldest technique in multivariate analysis and modified until it was generalized by Loeve in 1963 (Ionita & Şchiopu, 2010). Jolliffe (2002) mentioned that the objective of the Principal Component Analysis (PCA) is to minimize the dimensionality of a data set that is produced by many variables which are interrelated while withholding the variability available in the data set. In addition, Wuensch (2012) explained that Principal Component Analysis is a method to extract from a set of p variables to a set of m components or factors. Besides, Principal Component Analysis is a tool to reduce multidimensional data to lower dimensions while retaining most of the information that covers standard deviation, covariance, and eigenvectors (Karamizadeh et al., 2013).

Robu and Istrate (2015) mentioned that the main advantage of using PCA is that it reduces the initial causal space to an equivalent space of less considerable dimensions. Another advantage is Principal Component Analysis does not require large computations since it will reduce multidimensional data to lower dimensions while retaining most of the information (Karamizadeh et al., 2013).

The Principal Component Analysis (PCA) can be applied to a study on the effectiveness of Principal Component Analysis in the banking domain focusing on the consumer's lending problem (Ionita & Şchiopu, 2010; Juneja, 2012). Meanwhile, Karamizadeh et al. (2013) discussed on the significance of using Principal Component Analysis method for identifying and verifying facial features in the area of facial recognition technology. In addition, Principal Component Analysis was also applied to identify the principal components of the financial statements reported by Romanian listed companies for the period 2006 to 2011 (Robu & Istrate, 2015). Assare-Kumi et al. (2016) applied the Principal Component Analysis (PCA) to compute the fifteen variables that were expected to influence the working capital management on the bank's profits of the Ghana Stock Exchange (GSE) into fifth factors.

Principal component analysis is linear combination $X_1, X_2, \dots, X_p$ which are not correlated, and whose variances $Var\ (X_i) = b_i' \sum b_i, i = 1,2, \dots, p$ are as large as possible. Given $Cov(X_i, X_k) = b_i' \sum b_k, i, k = 1,2, \dots, p,$ where $b_i' = b_{i1}, b_{i2}, \dots, b_{ip}$ are weights, then:

$$b_i'.b_i = 1$$
$$b_i'.b_j = 0\ for\ all\ i \neq j$$

The first principal component is the linear combination $b_1'X$ that maximizes $Var(b_1'X)$ subject to $b_1'b_1 = 1$. However, this accounts for the greatest variance in the data. The second principal component is also a linear combination $b_2'X$ that maximizes $Var(b_2'X)$ subject to which $b_1'b_1 = 1$ and $Cov\ (b_1'X, b_2'X) = 0$. However, this accounts for the greatest of the remaining variance in the data and so on. The number of variables in the data set is trimmed down to the rendering or analysis of the correlation among the variables when the first principal component caters for a larger share of the variances in the original.

Suppose each of the bank's financial statements is an observed variable $Y_1, Y_2, \dots, Y_P$ with weights $b_{ij}, i = 1,2, \dots, p, j = 1,2, \dots, p$, then the principal component $X_1, X_2, \dots, X_p$ are given by:

$$\begin{aligned} X_1 &= b_{11}y_1 + b_{12}y_2 + \dots + b_{1p}y_p \\ X_2 &= b_{21}y_1 + b_{22}y_2 + \dots + b_{2p}y_p \\ \vdots &\qquad \vdots \\ X_p &= b_{k1}y_1 + b_{k2}y_2 + \dots + b_{kp}y_p \end{aligned}$$

Let the random variable $Y_i (i = 1,2, \dots, p)$ have mean μ_i and the standard deviation σ_{ii}. Thus, the transformed standard variables $Z_i (i = 1,2, \dots, p)$ is given as:

$$Z_i = \frac{Y_i - \mu_i}{\sigma_{ii}}$$

Furthermore, the vector of the standardized variables could be written in matrix notation as:

$$Z = (V^{\frac{1}{2}})^{-1}(Y - \mu)$$

Where $\mu' = (\mu_1, \mu_2, \dots, \mu_k)$ and $V^{\frac{1}{2}}$ is the diagonal standard deviation matrix given by:

$$V^{\frac{1}{2}} = \begin{bmatrix} \sigma_{ii} & 0 & \cdots & 0 \\ 0 & \sigma_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_{kk} \end{bmatrix}$$

$E[Z_i] = 0, Var\ [Z_i] = 1, i = 1,2, \ldots, k\ and\ Cov\ (Z) = (V^{1/2})^{-1}\Sigma(V^{1/2})^{-1} = \rho$ where the variance-covariance matrix **Σ** and the correlation matrix ρ of Y are given by:

$$\Sigma = \begin{bmatrix} \sigma_{11}^2 & \sigma_{12}^2 & \cdots & \sigma_{1k}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 & \cdots & \sigma_{1k}^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{k1}^2 & \sigma_{k2}^2 & \cdots & \sigma_{kk}^2 \end{bmatrix}$$

$$\rho = \begin{bmatrix} 1 & \frac{\sigma_{12}^2}{\sigma_{11}\sigma_{22}} & \cdots & \frac{\sigma_{1k}^2}{\sigma_{11}\sigma_{kk}} \\ \frac{\sigma_{12}^2}{\sigma_{11}\sigma_{22}} & 1 & \cdots & \frac{\sigma_{2k}^2}{\sigma_{22}\sigma_{kk}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\sigma_{1k}^2}{\sigma_{22}\sigma_{kk}} & \frac{\sigma_{2k}^2}{\sigma_{22}\sigma_{kk}} & \cdots & 1 \end{bmatrix}$$

And

$$\rho_{ij} = \frac{\sum_{k=1}^{n}(y_{ki} - \mu_i)(y_{kj} - \mu_j)}{n}, i \neq j$$

is the covariance between variables Y_i and Y_j ,each of which has n observations.

The ρ principal components $x' = [x_1, x_2, \ldots, x_p]$ are derived from the eigenvectors of the correlation matrix of ρ of Y given by:

$$X = B'Z$$

where B= $[e_1, e_2, \ldots, e_k]$ and the $e_is, i = 1,2, \ldots, k$ are eigenvectors of ρ.

The eigenvalue-eigenvector pair $(\lambda_1, e_1), (\lambda_2, e_2), \ldots, (\lambda_1 e_k)$ of ρ are such that

$$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_k \geq 0, e_i'.e_i = 1\ and\ e_i'.e_j = 0$$

$$var(X_i) = e_i'\rho e_i = \lambda_i$$

And

$$\sum_{i=1}^{k} var\ (X_i) = \sum_{i=1}^{k} var(Z_i) = P$$

Subsequently, the proportion of the total variance in the data which is explained by the X_j is given by proportion $\frac{\lambda_j}{p}$. This is called communality.

Where $j = 1,2, \ldots, p$ and the $\lambda_j's$ are the eigenvalue of ρ.

The loading of the standardized variable Z_j which is a correlation between each principal component X_i and the corresponding standardized variable Z_j is given by:

$$Corr(X_i, Z_j) = e_{ij}.\lambda_j^{\left(\frac{1}{2}\right)}$$

Where the loading of the standardized variable Z_i is between -1 and 1 inclusive.

Therefore, this show the degree to which every Z_i affects every X_i which is conditioned on the influence of the others variable $Z_m, j \neq m$. The variable becomes more influential in naming and interpreting the component when there is a higher absolute value of loading of a variable on a component. Similarly, the size of the sample determines the significance of the magnitude of a loading. A loading of an absolute value of at least 0.30 and 0.35 with respective sample sizes of 350 and 250. This shows that a smaller sample size requires a greater absolute loading values. Assare-Kumi (2016) recommended a loading of magnitude which is more that equal to 0.50.

However, the principal component being used as an index involves the establishment of principal component scores and factor loading. The principal component scores which are the i^{th} principal component is derived by putting the standardized observed values of the variables into the equation as shown below:

$$X_i = e_i'Z$$

The number of observed variables being tested is the same as the number of components derived in the principal component analysis. This is because only the first few components account for a bigger amount of the variance in the original data. Thus, these few components are sustained, interpreted, and are involved in subsequent analysis.

REVIEW OF MULTIPLE LINEAR REGRESSION

The Multiple Linear Regression can be applied as a conventional forecasting method to examine the performance of the vector error-correction (VEC) econometric modelling technique in predicting short to medium term construction manpower demand (Wong, Chan, & Chiang, 2011). Besides, Blyth (2006) used a multiple linear regression model to forecast the cash flow of construction companies for the survival of any contractors at all stages of the work.

Assare-kumi et al. (2016) mentioned that Linear regression can be applied to model the relationship between a dependent variable and a set of independent variables by fitting a linear equation to observed data. Besides, linear relationship is said to exist between two variables when a scatter plot of the two variables shows a clustering of points which is closed to a straight line. Linear regression is divided into Simple Linear Regression and Multiple Linear Regression.

Simple Linear Regression is the most appropriate model in explaining the relationship between dependent variable and independent variable if only one independent variable exists. Below is the form of a simple linear regression model.

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

Where Y_i is dependent variable and is X_i independent variables. While, βo *and* $\beta 1$ are the regression parameters to be estimated and εi is the random error.

Subsequently, Multiple Linear Regression is the best model to explain the relationship between dependent variable and independent variable when there is more than one independent variable. The multiple linear regression model as the following:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i + \cdots + \beta_p X_p + \varepsilon_i$$

Where Y_i is dependent variable and $X_1, X_2, \ldots, X_p$ are independent variables While, $\beta o, \beta_2, \ldots, \beta_{p-1}$ are the regression parameters to be estimated by the method of least squares, and εi is the random error.

When formulating the model, there are certain assumptions that need to be established. Failure to satisfy the assumption may result in a less than satisfactory model formulation. Multicollinearity happens when more than one independent variable which appear in a regression model have a possibility to be related to or dependent on each other (Mohd Alias, 2011). Basically, if two or more independent variables are related to each other, then at least one or more variable are redundant due to their tendency to contribute overlapping information. The absence of multicollinearity problem can be detected by observing the "Variance Inflation Factor" (VIF) and Tolerance in SPSS output.

Based on Mohd Alias (2011), VIF indicates the strong correlation of an independent variable with other independent variables. VIF values above ten indicates the multicollinearity.

Tolerance is an indicator on how much the variability of independent variable is not explained by another independent variable. The value of tolerance which is less than 0.1 indicates the multicollinearity (Mohd Alias, 2011).

REVIEW IN GEOMETRIC BROWNIAN MOTION

Geometric Brownian motion (GBM) is a mathematical model in stochastic calculus that deal with uncertainty such as stock market and foreign exchange (Abidin and Jaffar, 2014). In stochastic differential equation for GBM, the relative charge is a combination of deterministic proportional growth like inflation. Otherwise, it is also described as an interest rate growth plus with a normally distributed random change. Abidin and Jaffar (2014) mentioned that GBM is an easy calculation and does not need a lot of data to forecast because the Martingale and Markov properties of GBM allow sufficient use of the short duration of data to forecast.

In this study, Geometric Brownian motion is applied as the forecasting method in order to forecast the future. GBM also used the same properties as Brownian motion. Then the stochastic integration will be discussed further by assuming a(t) and b(t) are some of the functions.

$$S(t) = a(t) + b(t)$$

The ordinary differential equation will be

$$ds = a(t)dt + b(t)dx$$

Then, the integration will be

$$\int_0^t ds = \int_0^t a(\tau)d\tau + \int_0^t b(\tau)dX(\tau)$$

$$S(t) = S_0 + \int_0^t a(\tau)d\tau + \int_0^t b(\tau)dX(\tau)$$

The technical term of mean square limit which is useful in defining the stochastic integration can be defined as

$$E\left[\left(\sum_{j=1}^{n}\left(X(t_j) - X(t_{j-1})\right)^2 - t\right)^2\right]$$

It follows the quadratic variation as $t_j = j\left(\frac{t}{n}\right)$. Since $n \to \infty$, it tends to be zero, thus

$$\sum\left(X(t_j) - X(t_{j-1})\right)^2 = t$$

According to Willmot (2007), mean square limit is often written as

$$\int_0^t (dX)^2 = t$$

Thus,

$$(dx)^2 = dt$$

Assume that the function of F(S) = ln (S) will describe the value profit as lognormal random walk. Then,

$$\frac{dF}{dS} = \frac{1}{S} \qquad (2.1)$$

$$\frac{d^2F}{dS^2} = -\frac{1}{S^2} \qquad (2.2)$$

Using Ito's Lemma by Wilmott (2007):

$$dF = \frac{dF}{dS}dS + \frac{1}{2}\frac{d^2F}{dS^2}dS^2$$

$$dF = \frac{dF}{dS}\left[\mu Sdt + \sigma SdX\right] + \frac{1}{2}\frac{d^2F}{dS^2}\left[\mu Sdt + \sigma SdX\right]^2 \qquad (2.3)$$

And

$$dX.dX = dt$$

$$(dt)^2 = dX.dt = dt.dX = 0$$

Simplify equation (2.3) to get

$$dF = \frac{dF}{dS}dS + \frac{1}{2}\sigma^2 S^2 \frac{d^2F}{dS^2}(dX)^2$$

$$dF = \frac{dF}{dS}dS + \frac{1}{2}\sigma^2 S^2 \frac{d^2F}{dS^2}dt \qquad (2.4)$$

Equations (2.1) and (2.2) is substituted in Equation (2.4) to give

$$dF = \frac{1}{S}(\mu Sdt + \sigma SdX) + \frac{1}{2}\sigma^2 S^2\left(-\frac{1}{S^2}\right)dt$$

$$dF = \frac{1}{S}(\mu Sdt + \sigma SdX) - \frac{1}{2}\sigma^2 dt$$

$$dF = \frac{1}{S}\mu S dt + \frac{1}{S}\sigma S dX - \frac{1}{2}\sigma^2 dt$$

$$dF = \mu dt + \sigma dX - \frac{1}{2}\sigma^2 dt$$

$$dF = \left(\mu - \frac{1}{2}\sigma^2\right)dt + \sigma dX$$

Then, integrate both sides

$$\int dF = \int\left(\mu - \frac{1}{2}\sigma^2\right)dt + \int \sigma dX$$

$$\ln S = \left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma(X(t) - X(0)) + c$$

$$e^{\ln S} = e^{\left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma(X(t) - X(0)) + C}$$

$$S = e^{\left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma(X(t) - X(0))} . e^{C}$$

e^c can be referred to as S (0) where S (0) is the previous time, μ is drift, σ is volatility, (X(t) – X (0)) is random value and S(t) is the asset price at time t. Drift was referred to data that have time step because of the type of data that are continuous. While, the volatility is the standard deviation of the data involved. Hence, the stochastic differential equation for ln S is

$$S(t) = S(0)e^{\left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma(X(t) - X(0))} \tag{2.5}$$

METHODOLOGY

There are five stages involved in the study. The first stage was collecting data where the data was collected from tradingeconomic.com, Datastream and financial statement of each bank from year 2010 to year 2016. The second stage was a stage of identifying the significant determinants using Principal Component Analysis. The third stage was to formulate Bank Profit Model using Multiple Linear Regression while, the fourth stage was where forecasting of the significant determinants using Geometric Brownian Motion was conducted. The final stage was to forecast the value of Return on Equity using Bank Profit Model.

DATA COLLECTION

Secondary data for return on equity, bank size, bank capital, credit risk, liquidity risk, deposit ratio, operating efficiency, and market concentration were taken from the datastream and the financial statement of each bank from year 2010 to 2016. Meanwhile, data for GDP and the annual inflation rate were taken from the tradingeconomic.com from year 2010 to 2016. In this study, return on equity is a dependent variable while the independent variables are determinants that influence bank profitability such as bank size, bank capital, credit risk, liquidity risk, deposit ratio, operating efficiency, market concentration, GDP and annual inflation rate.

As mentioned before, there are 16 Islamic banks operating in Malaysia. However, due to unavailability of data, there are only 13 Islamic banks in Malaysia involved in this study which are Bank Islam Malaysia Bhd.,CIMB Islamic Bank Bhd., Maybank Islamic Berhad, RHB Islamic Bank Berhad., Affin Islamic Bank Bhd., Bank Muamalat Malaysia Bhd., Asian Finance Bank Bhd., Hong Leong Islamic Bank Bhd., Public Islamic Bank Bhd., Standard Chartered Saadiq Berhad, OCBC Al-Amin Bank Bhd., HSBC Amanah Malaysia Berhad, and Alliance Islamic Bank Berhad.

The data were exported into SPSS software to run the Principal Component Analysis and Multiple Linear Regression. However, Geometric Brownian Motion were run using Microsoft Excel. In additional, the variables involve in this study are explain in table below.

RESULT AND DISCUSSION

IDENTIFYING THE SIGNIFICANT DETERMINANTS USING PRINCIPAL COMPONENT ANALYSIS.

Table 0.1
Kaiser-Meyer-Olkin and Bartlett's Test

Test	Results
Kaiser-Meyer-Olkin	0.547
Bartlett's Test of Sphericity	0.000

Table 4.1 shows Kaiser-Mayer-Olkin and Bartlett's Test. Based on Assare-Kumi et al. (2016), the Kaiser-Meyer- Olkin (KMO) statistic used to measure the data sampling is acceptable if the value is greater than or equal to 0.5. In this study, the KMO value is 0.547 which means that the data is adequate.

Assare-Kumi et al. (2016) also mention that when the probability value of Bartlett's Test of Sphericity is less than the significance level which is significant value 0.05, the Principal Component Analysis can be used for the analysis. Besides, in this study the Bartlett's test is significant with p= 0.000. therefore, Principal Component Analysis can be used for the analysis.

Table 0.2
Eigenvalues Explained

Component / Group	eigenvalue
Internal Component	2.852
External Component	1.476

Table 4.2 shows the Eigenvalues Explain. In this study, there were two fixed components which were extracted, one from internal component and one from external component. The validity of components can be checked via eigenvalue of one more (Pallant, 2011). This step was conducted to ensure the validity of the internal component and external component which were used in this study. So, the internal and external component is valid to use in this study.

Table 0.3
Factor Loading for each Determinants

Independent determinant	Component	
	Internal Component	External Component
Bank Capital	-0.891	
Bank Size	0.889	
Deposit Ratio	0.820	
Market Concentration	0.723	
GDP		0.774
Annual Inflation Rate		-0.716

Table 4.3 shows the Table of Factor Loading for each Determinants. Based on table above, bank capital, bank size, deposit ratio and market concentration was a fit well with each other in internal component while GDP and inflation was fit in external component. The credit risk, liquidity risk and operating efficiency was not fit for both components since the loading value was not appear in Rotated Component Matrix table in SPSS results. In addition, each of negative number show the inverse relationship factor for the component.

So, the significant determinants choose based on the highest factor loading for each component (Pallant, 2011). The highest positive factor loading for internal and external components are bank size and GDP with value 0.889 and 0.774 respectively. For overall SPSS output result for PCA was showed in the Appendix A.

FORMULATE BANK PROFIT MODEL USING MULTIPLE LINEAR REGRESSION

Table 0.4
Collinearity Statistic

	Collinearity Statistic	
	Tolerance	VIF
constant	-	-
Bank size	0.993	1.007
GDP	0.993	1.007

Table 4.4 shows the Collinearity Statistic. In this study, Tolerance value for bank size and GDP are 0.993 and 0.993. While, VIF value for bank size and GDP are 1.007 and 1.007. So, no multicollinearity has happened.

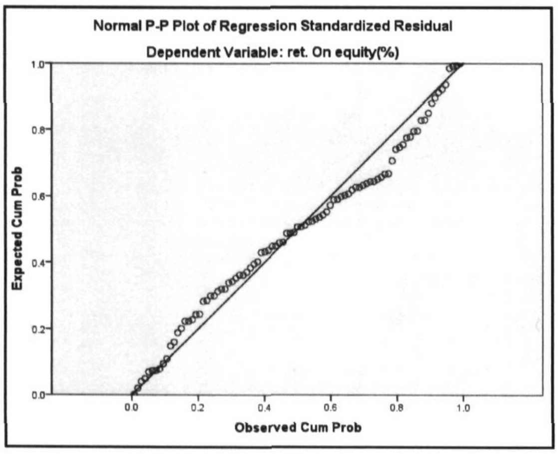

Figure 0.1: Normal P-P Plot of the Regression Standardised Residual

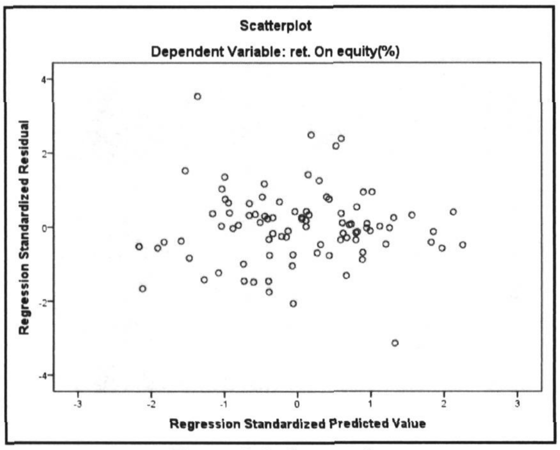

Figure 0.2: Scatterplot

Figure 4.1 shows the Normal P-P Plot of the Regression Standardised Residual. In this study, the point lies in a reasonably straight diagonal line from bottom left to top right. This suggests that there is no major deviation from normality (Pallant, 2011).

Figure 4.2 shows Scatterplot. The existence of outlier suggests some violation of assumption. Based on Pallant (2011), outlier is a cases that have a standardised residual more than 3.3 or less than -3.3 and it is not concentrated in the center along zero point. In this study, the outlier does not exist.

Table 0.5
Unstandardised Coefficients

	Unstandardised Coefficients
	B
Constant	-0.796
Bank Size	0.049
GDP	2.076

Table 4.5 shows the unstandardized Coefficients. The model of bank profit is stated as below

$$ROE = -0.796 + 0.049x_{BANKSIZE} + 2.076x_{GDP}$$

means that every increase of 0.049 bank size and 0.181 GDP annual growth rate will increase the return on equity by one unit. For overall SPSS output result for Multiple Linear Regression was showed in the Appendix B.

FORECAST THE SIGNIFICANT DETERMINANTS USING GEOMETRIC BROWNIAN MOTION

Table 0.6
Forecast value for Bank Size and GDP

Islamic Bank	Forecast value for Bank Size (% of total Asset)	Forecast value for GDP
Bank Islam Malaysia Bhd.	17.8371	0.049
CIMB Islamic Bank Bhd.	18.0181	0.049
Maybank Islamic Berhad	19.0305	0.049
RHB Islamic Bank Berhad	17.7025	0.049
Affin Islamic Bank Bhd.	16.5471	0.049
Bank Muamalat Malaysia Bhd.	16.9362	0.049
Asian Finance Bank Bhd.	14.7864	0.049
Hong Leong Islamic Bank Bhd.	17.0714	0.049
Public Islamic Bank Bhd.	17.3099	0.049
Standard Chartered Saadiq Berhad	15.8272	0.049
OCBC Al-Amin Bank Bhd.	16.4852	0.049
HSBC Amanah Malaysia Berhad	16.6165	0.049
Alliance Islamic Bank Berhad	16.1018	0.049

Table 4.7 shows forecast value for bank size and GDP for year 2017. Forecast value for GDP for each bank is same because each bank shares the same GDP and the forecast value is 0.049. The value tells that 4.9 percent of GDP give effect to the operation and performance of financial institution.

In addition, the highest forecast value of bank size is 19.0305 percent for Maybank Islamic Berhad. The higher the bank size shows that Maybank Islamic Berhad have diversification in their product and services that tends to give positive impact to their profitability. In contrast, the lowest forecast value of bank size is 14.7864 percent for Asian Finance Bank Bhd.

FORECAST VALUE OF RETURN ON EQUITY USING BANK PROFIT MODEL

Table 0.7
Forecast value for Return on Equity

Islamic Bank	Forecast value for Bank Size	Forecast value for GDP	Forecast value for Return on Equity
Bank Islam Malaysia Bhd.	17.8371	0.049	0.1797
CIMB Islamic Bank Bhd.	18.0181	0.049	0.1886
Maybank Islamic Berhad	19.0305	0.049	0.2382
RHB Islamic Bank Berhad	17.7025	0.049	0.1731
Affin Islamic Bank Bhd.	16.5471	0.049	0.1165
Bank Muamalat Malaysia Bhd.	16.9362	0.049	0.1356
Asian Finance Bank Bhd.	14.7864	0.049	0.0303
Hong Leong Islamic Bank Bhd.	17.0714	0.049	0.1422
Public Islamic Bank Bhd.	17.3099	0.049	0.1539
Standard Chartered Saadiq Berhad	15.8272	0.049	0.0813
OCBC Al-Amin Bank Bhd.	16.4852	0.049	0.1135
HSBC Amanah Malaysia Berhad	16.6165	0.049	0.1199
Alliance Islamic Bank Berhad	16.1018	0.049	0.0947

Table 4.8 shows forecast value for Return on Equity for year 2017 by using Bank Profit Model that is achieved in step two. In order to obtain forecast return on equity, forecast value of bank size and GDP is used to calculate ROE using the model below:

$$ROE = -0.796 + 0.049x_{BANKSIZE} + 2.076x_{GDP}$$

Besides, forecast value for Return on Equity for Bank Islam Malaysia Bhd. is 0.1797. This tells that in 2017, Bank Islam Malaysia Bhd. generated 17.97 percent profit on every ringgit invested by shareholders. The highest return on equity is Maybank Islamic Berhad with 23.82 percent and the lowest return on equity is Asian Finance Bank Bhd. with 3.03 percent. It is shown that the highest value of Bank Size generated the highest Return on Equity.

Ichsani and Suhardi (2015) mention that the good rate of Return on Equity is more than 12 percent. So the banks that have a good Return on Equity is Bank Islam Malaysia Bhd., CIMB Islamic Bank Bhd., Maybank Islamic Berhad, RHB Islamic Bank Berhad, Bank Muamalat Malaysia Berhad, Hong Leong Islamic Bank Bhd. and Public Islamic Bank Bhd.

CONCLUSION

Since the early existence of the Islamic banks in the banking sector, Islamic banks have a fierce competition with conventional banks in terms of the products and other services offered. Thus, the bank management of the Islamic Bank must choose wisely which determinants that they need to focus on in order to give the highest profit to the Islamic banks because some of the determinants do not really give an impact towards bank profitability. In this study, Principal Component Analysis method was used to find out the internal and external determinant which were significant. The results showed that the significant internal determinant was bank size while the significant external determinant was GDP. Hence, the first objective was achieved.

The Multiple Linear Regression was used to formulate the bank profitability model by explaining the relationship between return on equity and significant determinants. In this study, return on equity is a measurement of bank profitability. In the future, the management of bank can use this model to predict return on equity. Thus, the second objective was achieved.

Besides, to forecast the bank size and GDP for 13 Islamic banks for year 2017 Geometric Brownian Motion was used. However, the accuracy of the forecast value needs to be checked by using MAPE. The lowest MAPE value indicates the highest accuracy of the forecast values. In this study, the bank size and GDP for each bank was below ten which means the forecast value bank was highly accurate. Then the forecast value of bank size and GDP was used to calculate the Return on Equity of each Islamic Bank. Thus, the third objective was achieved.

This study recommends for the future researchers to study about prediction determinant that is significant to Net Interest Margin (NIM) as dependent determinant since this study has already incorporated Return on Equity as dependent determinant. Besides, instead of using the Geometric Brownian Motion (GBM) as in this study, the researchers can apply Levy process to estimate the future value of determinants involved. In addition, this study also can be expanded to all other Islamic banks in and outside of Malaysia.

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