https://dx.doi.org/10.24001/ijaems.3.8.7 ISSN: 2454-1311

Dynamic Forecasting method for *Shariah*-compliant Share Price of Healthcare sector in Malaysian Stock Exchange

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Abstract— *The healthcare sector is the category of stocks relating to medical and healthcare goods or services. The healthcare sector includes hospital management firms, health maintenance organizations (HMOs), biotechnology and a variety of medical products. The objective of this research paper is to forecast the performance of share price for healthcare sector in Malaysia. The research methodology implemented in this study is forecasting method using autoregressive integrated moving average (ARIMA). Data selection in this study is share price of healthcare company sector namely IHH Healthcare Berhad. Result shows the ARIMA(1,1,1) model exhibits r-squared value of 0.184 and Akaike Information Criterion (AIC) value is -1.112. Residual diagnostics shows ARIMA (1,1,1) is reliable model for forecasting of healthcare sector in Malaysia. The findings from this study will help economists to analyze the stock market performance especially in healthcare sector in Malaysia. This result also will help investors to decide appropriate decision in portfolio selection of capital investment.*

Keywords - Islamic Finance, share price, ARIMA model, Forecasting, Healthcare sector.

I. INTRODUCTION

Forecasting volatility of shares price plays important roles in investment market. Due to unexpected return gain by investors, forecasting technique becomes crucial area that can attract most researches and practitioners to investigate. Even there are many methods can be applied but it is critical method to identify the most accurate forecasting models among the range of forecasting models because it will affect the accuracy in forecasting (Brailsford et al., 1996)[1].

Definitely forecasting volatility exploited as risk measurement (San et al., 2011)[2]. Operational risk has always existed as one of the core risks in the financial industry and it is become more salient feature of risk (Jobst, 2007)[3].

Currently, the growing up of *shariah*-compliant companies in Malaysian market was attracted most companies to listed shares on the *shariah* board. Table 1 shows the number of *shariah*-compliant companies and non *shariah*-compliant companies listed on the Malaysian Stock Exchange (MSE). Result shows over 600 companies are listed on the *shariah* board in year 2017. Therefore, it is important to examine the performance of *shariah*-compliant companies due to outstanding demand for *shariah*-compliant companies in Malaysian market.

Table.1: Shariah-compliant and non shariah-compliant companies listed on the Bursa Malaysia

Year	*Shariah*-compliant companies	Non *Shariah*-compliant companies	Total
2011	839	107	946
2012	817	106	923
2013	653	261	914
2014	673	232	905
2015	667	234	901
2016	672	232	904

This study aim to develop forecasting model that is ARIMA model in order to examine the expected return earn by investors. ARIMA model is used to provide a forecasting model directly without resort to other procedures (Tse, 1997)[4]. This study used daily volatility of shares price for one of the *shariah*-compliant company listed on the MSE. The company is IHH Healthcare Berhad. The share price of this company is one of the 30 excellent companies in Bursa Malaysia and as one of the companies to be calculated as indicator for market capitalization in Malaysia. Therefore, the objective of this study was to investigate the performance of IHH Healthcare Berhad using a shares price data from July 2012 until July 2017.

II. LITERATURE REVIEW

Islamic finance refers to the means by which corporations in the Muslim world, including banks and other lending institutions, raise capital in accordance with Sharia, or Islamic law. It also refers to the types of investments that are permissible under this form of law. Managing assets in accordance with Islamic precepts is a bit more unique in that the practice is a form of socially responsible investing with the unique specification of avoiding interest bearing investments of any kind.

The important of understanding *shariah*-compliant companies are separately from the non *shariah*-compliant companies relates to the basic requirement of Islamic investment. According to Abu Bakar and Uzaki (2013)[5] *shariah*-compliant companies must free from any prohibited element of:

(a) Usury (*riba*) defines as an increase or excess in any exchange or sale of good or by virtue of loan without providing equivalent value to the other party.
(b) Uncertainty (*gharar*) refers to the activities that have elements of uncertainty in measure weight of goods, price of goods or deceiving the buyer on the price of goods.
(c) Gambling (*maysir*) is refers to the any activity that involves betting. The winner will take the entire bet and loser will lose his bet.
(d) Others prohibited elements, such as non-halal foods, drinks and immoral activities also must be absent.

Past study have discussed a number of volatility forecasting model such as ARIMA (Al-Shiab, 2016)[6], GARCH (Luo et al., 2010)[7] and moving average (Abu Bakar and Rosbi, 2016)[8].

In term of forecasting model Balli and Elsamadisy (2012)[9] recommended that the ARIMA model is a good estimation for short-term forecasts. Guha and Bandyopadhyay (2016)[10] used ARIMA time series model to forecast the future gold price in order to mitigate the risk in purchases of gold. While, Abu Bakar and Rosbi (2017)[11] found that ARIMA model is suitable model for data clustering. Their finding is important to economists and researchers in order to understand the dynamic behavior of currency movement. However, study from Al-Shiab (2016)[6] found that ARIMA model was not consistent with actual performance during the period of the prediction in Amman Stock Exchange. Therefore, it is important to investigate either ARIMA model is suitable to forecast *shariah*-compliant shares price in MSE or not.

Besides the study that focuses on forecasting of shares prices, gold price and currency, there are other study that used ARIMA model in forecasting the performance on their industry. Study from Tse (1997)[4] on the application of ARIMA model in real estate price provides sufficient evidence in support of the adequacy of the estimated models for office and industrial properties in Hong Kong.

Adebiyi et al. (2014)[12] presents extensive process of building stock price predictive model using the ARIMA model. Published stock data obtained from New York Stock Exchange and Nigeria Stock Exchange used with stock price predictive model developed. The results obtained revealed that the ARIMA model has a strong potential for short-term prediction and can compete favorably with existing techniques for stock price prediction.

Besides the ARIMA model, the GARCH model also one of the popular models to forecast shares price. According to Luo et al. (2010)[7] GARCH models are found to be very useful in modeling a unique stochastic process. Then, Elyasiani and Mansur (2004)[13] employs a multivariate GARCH model to investigate the relative sensitivities of the first and the second moment of bank stock return and found that short-term and long-term interest rates and their volatilities do exert significant and differential impacts on the return generation process of the bank portfolios. These findings have implications on bank hedging strategies.

Abu Bakar and Rosbi (2016)[8] forecast the share price for *shariah*-compliant companies that issues Initial Public Offerings (IPO) in year 2012. They used simple moving average and weighted moving average. The results show weighted moving average is more accurate than simple moving average. Ahmed et al. (2005) studies the efficacy of using moving average technical trading rules with currencies of emerging economies. The results support the effectiveness of the trading models, which imply the presence of strong serial correlation among currency returns for emerging markets.

III. RESEARCH METHODOLOGY

This section describes the procedure of analysis in forecasting the dynamic behavior of share price. The forecasting steps are data selection, model selection. residual diagnostics, ex-post forecasting evaluation and ex-ante forecasting.

3.1 Selection of data

The data selected in this study is a company in healthcare sector. The company is IHH Healthcare Berhad. IHH Healthcare Berhad was incorporated in May 2010 and successfully listed on MSE on 25th July 2012. This company is listed in MSE as one of the *shariah*-compliant companies.

IHH Healthcare Berhad is headquartered in Kuala Lumpur and has activities in the private hospital and health sector throughout Asia and the Middle East,

https://dx.doi.org/10.24001/ijaems.3.8.7 ISSN: 2454-1311

notably in Singapore, Brunei, China, Hong Kong, Malaysia, India, and the United Arab Emirates.

IHH Healthcare Berhad owns Singapore-based Parkway Pantai, the private hospital operator of Southeast Asia, and the International Medical University in Kuala Lumpur, and is also the majority shareholder of Acıbadem Healthcare Group, the largest Turkish private healthcare company. IHH Healthcare Berhad owns 51% of the Hyderabad-based private healthcare provider Continental Hospitals Limited in India.

Therefore, in this study, share price data for IHH Healthcare Berhad is collected from July 2012 until July 2017.The data is collected from database of Thomson Reuters Datastream.

3.2 Forecasting procedure using Autoregressive integrated moving average (ARIMA)

This study forecast the performance of share price using the statistical procedure as shown in Fig. 1. The forecasting process is start with the identification of the data model using autoregressive integrated moving average (ARIMA). In developing ARIMA model, analysis of autocorrelation function (ACF) and partial autocorrelation function (PACF) need to be performed. Then, this research need to develop estimation of the parameter for chosen ARIMA model. In validating the model, diagnostics checking need to be developed. The residual is the difference between the observed value and the estimated value of the quantity of interest (sample mean). The residual should be uncorrelated, zero mean and zero variance. Then, forecasting and error checking stage can be performed.

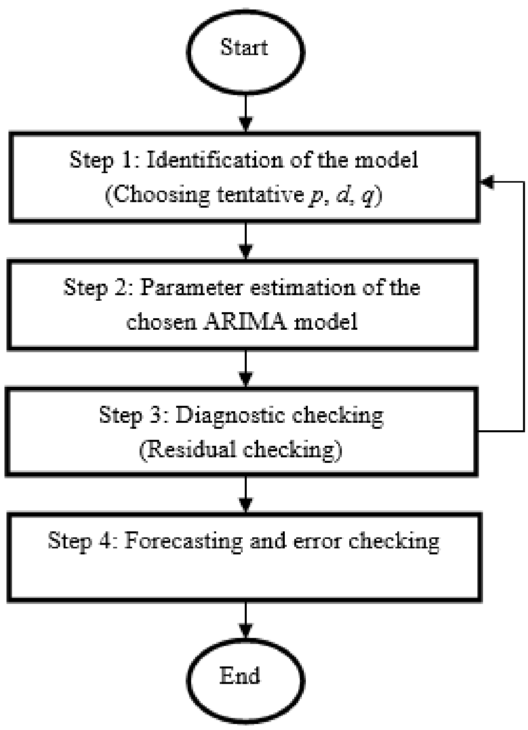


Fig. 1: Statistical forecasting procedure

3.3 Autoregressive integrated moving average (ARIMA) model development

This study modeling the data set using autoregressive integrated moving average (ARIMA). In statistics ARIMA procedure provides the identification, parameter estimation and forecasting or best fit model to forecast share price.

The AR part of ARIMA indicates that the evolving variable of interest is regressed on its own lagged values. The MA part indicates that the regression error is actually a linear combination of error terms whose values occurred contemporaneously and at various times in the past. The *I* (integrated) indicates that the data values have been replaced with the difference between their values and the previous values. The purpose of each of these features is to make the model fit the data as well as possible.

The autoregressive integrated moving average ARIMA (*p*,*d*,*q*) model is represented by Eq.(1).

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)(1-L)^d X_t = \delta + \left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t \qquad (1)$$

where L is the lag operator, ϕ_i are the parameters of the autoregressive part of the model, θ_i are the parameters of the moving average part and ε_t are error terms. The error terms ε_t are generally assumed to be independent, identically distributed variables sampled from a normal distribution with zero mean.

ARIMA models are generally denoted ARIMA (*p, d, q*) where parameters *p*, *d*, and *q* are non-negative integers, *p* is the order (number of time lags) of the autoregressive model, *d* is the degree of differencing (the number of times the data have had past values subtracted), and *q* is the order of the moving-average model.

In this study, the degree of differencing is set to one. The purpose of this step is to confirm the stationarity of the data. Therefore Eq. (1) can be represented as below:

$$\Delta X_t = \delta + \varepsilon_t + \sum_{i=1}^{q}\theta_i\varepsilon_{t-i} + \sum_{i=1}^{p}\phi_i\Delta X_{t-i} \qquad (2)$$

3.4 Autocorrelation function (ACF) statistical method

Autocorrelation, also known as serial correlation, is the correlation of a signal with a delayed copy of itself as a function of delay.

The autocorrelation of a random process is the Pearson correlation between values of the process at different times, as a function of the two times or of the time lag. Let X is set as a stochastic process, and *t* is any point in time (*t* may be an integer for a discrete-time process or a real number for a continuous-time process). Then X_t is the value (or realization) produced by a given run of the process at time *t*. Consider the process has mean μ_t and variance σ_t^2 at time *t*, for each *t*. Then the definition of the autocorrelation between times *s* and *t* is described in below equation:

$$R(s,t)=\frac{\mathrm{E}\left[\left(X_t-\mu_t\right)\left(X_s-\mu_s\right)\right]}{\sigma_t\sigma_s} \quad (3)$$

If X_t is a stationary process, then the mean μ and the variance σ^2 are time-independent, and further the autocorrelation depends only on the lag between *t* and *s*: the correlation depends only on the time-distance between the pair of values but not on their position in time. This further implies that the autocorrelation can be expressed as a function of the time-lag, and that this would be an even function of the lag $\tau = s - t$. This gives the more familiar form in Eq. (4).

$$R(\tau)=\frac{\mathrm{E}\left[\left(X_t-\mu\right)\left(X_{t+\tau}-\mu\right)\right]}{\sigma^2} \quad (4)$$

3.4 Partial autocorrelation function (PACF) statistical method

Partial correlation is a measure of the strength and direction of a linear relationship between two continuous variables whilst controlling for the effect of one or more other continuous variables (also known as 'covariates' or 'control' variables).

Formally, the partial correlation between *X* and *Y* given a set of n controlling variables $\mathbf{Z} = \{Z_1, Z_2, ..., Z_n\}$, written $\rho_{XY\cdot\mathbf{Z}}$, is the correlation between the residuals R_X and R_Y resulting from the linear regression of X with **Z** and of Y with **Z**, respectively. The first-order partial correlation (i.e. when n=1) is the difference between a correlation and the product of the removable correlations divided by the product of the coefficients of alienation of the removable correlations.

Partial autocorrelation function is described in below Eq. (5).

$$\hat{\rho}_{XY\bullet\mathbf{Z}}=\frac{N\sum_{i=1}^{N}r_{X,i}r_{Y,i}-\sum_{i=1}^{N}r_{X,i}\sum_{i=1}^{N}r_{Y,i}}{\sqrt{N\sum_{i=1}^{N}r_{X,i}^2-\left(\sum_{i=1}^{N}r_{X,i}\right)^2}\sqrt{N\sum_{i=1}^{N}r_{Y,i}^2-\left(\sum_{i=1}^{N}r_{Y,i}\right)^2}}$$

3.5 Validation of Forecasting model

In validating forecasting model, this study focuses on four factors. The factors are R-squared value, Akaike information criteria (AIC), residual diagnostics and error evaluation.

3.5.1 Validation parameter 1: R-squared value

R-squared is a statistical measure of how close the data are to the fitted regression line. It is also known as the coefficient of determination, or the coefficient of multiple determinations for multiple regressions. In statistics, the coefficient of determination is the proportion of the variance in the dependent variable that is predictable from the independent variable(s).

$$R^2=\frac{SSR}{SST}=1-\frac{SSE}{SST} \quad (6)$$

Where,

Sum of squares total, $SST=\sum\left(y-\bar{y}\right)^2$

Sum of squares regression, $SSR=\sum\left(y'-\overline{y'}\right)^2$

Sum of squares error, $SSE=\sum\left(y-y'\right)^2$

Observed data, $y=b_0+b_1x_1+b_2x_2+...+b_nx_n+\varepsilon$

Predicted data, $y'=b_0+b_1x_1+b_2x_2+...+b_nx_n$

Error, $\varepsilon=y-y'$

R-squared is a statistic used in the context of statistical models whose main purpose is either the prediction of future outcomes or the testing of hypotheses, on the basis of other related information. It provides a measure of how well observed outcomes are replicated by the model, based on the proportion of total variation of outcomes explained by the model. The coefficient of determination ranges from 0 to 1.

The higher the coefficient, the higher percentage of points the line passes through when the data points and line are plotted. A higher coefficient is an indicator of a better goodness of fit for the observations.

3.5.2 Validation parameter 2: Akaike Information Criterion (AIC)

The Akaike Information Criterion (AIC) is a measure of the relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Hence, AIC provides a means for model selection.

AIC is a goodness-of-fit measure which adjusts model chi-square to penalize for model complexity or model over parameterization). Thus AIC reflects the discrepancy between model-implied and observed covariance matrices. The AIC was developed with a foundation in information theory. Information theory is a branch of applied mathematics concerning the quantification (the process of counting and measuring) of information. In using AIC to attempt to measure the relative quality of econometric models for a given data set, AIC provides the researcher with an estimate of the information that would be lost if a particular model were to be employed to display the process that produced the data. As such, the AIC works to balance the trade-offs between the complexity of a given model and its goodness of fit, which is the statistical term to describe how well the model fits the data or set of observations.

AIC is usually calculated with software. The basic formula is defined as:

https://dx.doi.org/10.24001/ijaems.3.8.7 ISSN: 2454-1311

$$AIC = -2(log\text{-}likelihood) + 2K \quad (7)$$

In Eq. (7), K is the number of model parameters (the number of variables in the model plus the intercept) and log-likelihood is a measure of model fit. The larger value of log-likelihood indicates the better the fit of the model. The log-likelihood value is usually obtained from statistical output.

For small sample sizes $\left(\frac{n}{K} \le 40\right)$, use the second-order AIC equation.

$$AIC_c = -2(log\text{-}likelihood) + 2K + \frac{2K(K+1)}{n-K-1} \quad (8)$$

In Eq. (8), n is sample size, K is number of model parameters, and Log-likelihood value is a measure of model fit.

An alternative formula for ordinary least squares (OLS) regression type analyses for normally distributed errors:

$$AIC = n\ln(SSE/n) + 2(K+1) \quad (9)$$

In Eq. (9), *SSE* is sum of squares error.

3.5.3 Validation parameter 3: Residual diagnostics

In regression analysis, the difference between the observed value of the dependent variable (y) and the predicted value (ŷ) is called the residual (e). Each data point has one residual.

Residual = Observed value - Predicted value

$$e = y - \hat{y} \quad (10)$$

Both the sum and the mean of the residuals are equal to zero. That is, Σ e = 0 and e = 0.

3.5.4 Validation parameter 4: Mean absolute percentage error

The mean absolute percentage error (MAPE) is a measure of prediction accuracy of a forecasting method in statistics, for example in trend estimation. It usually expresses accuracy as a percentage, and is defined by the equation below:

$$M = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \quad (11)$$

where A_t is the actual value and F_t is the forecast value. The difference between A_t and F_t is divided by the actual value A_t again. The absolute value in this calculation is summed for every forecasted point in time and divided by the number of fitted points n. Multiplying by 100 makes it a percentage error.

IV. RESULTS AND DISCUSSION

This section describes result for every stage forecasting process. The result of forecasting process involved stationary checking, autocorrelation and partial correlation analysis, ARIMA model validation and residual diagnostics. Final results is regarding forecasting procedure which involved

4.1 Dynamic behavior of shares price for IHH Healthcare Berhad

Data of IHH Healthcare Berhad is collected from July 2012 until July 2017.There are 61 observations involved in this study. Figure 2 shows the dynamic behavior of shares price for IHH Healthcare Berhad. The starting value of the first month for the share price is MYR 3.098. The maximum value of the share price is MYR 6.659 in April 2016.

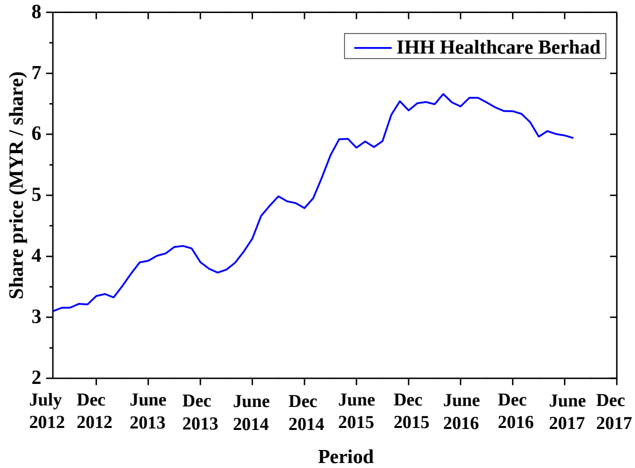
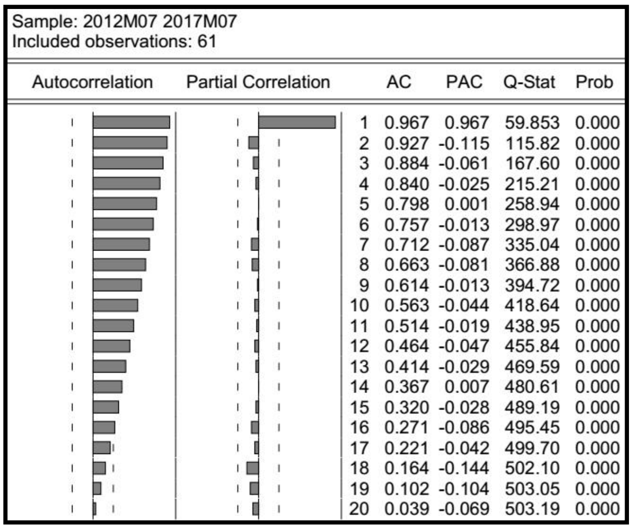


Fig. 2: Dynamic behavior of share price movement



Sample: 2012M07 2017M07
Included observations: 61

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.967	0.967	59.853	0.000
		2	0.927	-0.115	115.82	0.000
		3	0.884	-0.061	167.60	0.000
		4	0.840	-0.025	215.21	0.000
		5	0.798	0.001	258.94	0.000
		6	0.757	-0.013	298.97	0.000
		7	0.712	-0.087	335.04	0.000
		8	0.663	-0.081	366.88	0.000
		9	0.614	-0.013	394.72	0.000
		10	0.563	-0.044	418.64	0.000
		11	0.514	-0.019	438.95	0.000
		12	0.464	-0.047	455.84	0.000
		13	0.414	-0.029	469.59	0.000
		14	0.367	0.007	480.61	0.000
		15	0.320	-0.028	489.19	0.000
		16	0.271	-0.086	495.45	0.000
		17	0.221	-0.042	499.70	0.000
		18	0.164	-0.144	502.10	0.000
		19	0.102	-0.104	503.05	0.000
		20	0.039	-0.069	503.19	0.000

Fig. 3: Autocorrelation and partial correlation of share price

Then, the stationarity of the shares price is checked using correlogram of autocorrelation and partial correlation. Figure 3 shows the correlogram of shares price data. There is one significant spike in partial correlation of first lag. However, autocorrelation value decline slowly. This correlogram indicated the shares price data is non-stationary. Non-stationary is not suitable for forecasting process because mean and variance are not constant over time.

https://dx.doi.org/10.24001/ijaems.3.8.7 ISSN: 2454-1311

4.2 Stationary transformation process and evaluation

This section describes results for transforming non-stationary data to become stationary.

In developing stationary data from non-stationary, one of the common solutions is to use differenced variable for first differences:

$$\Delta y_t = y_t - y_{t-1} \qquad (12)$$

where variable y_t is value of share price at period *t*. The variable Δy_t is integrated of order one, denoted *I* (1).

Figure 4 shows the dynamic behavior of first order difference for share price. The maximum value of first order difference for share price is 0.4305 in October 2015. The minimum value for first order difference of share price is -0.2403 in March 2017.

Then, autocorrelation and partial correlation analysis is performed. Figure 4 shows the correlogram for first order difference for share price. Result shows ARIMA (*1*,*1*,*1*) model is selected for modeling the data set.

Figure 5 show a significant spike of first lag in autocorrelation (AC) and partial correlation (PCF). Therefore, it is concludes the data for first order difference of share price is a stationary data type.

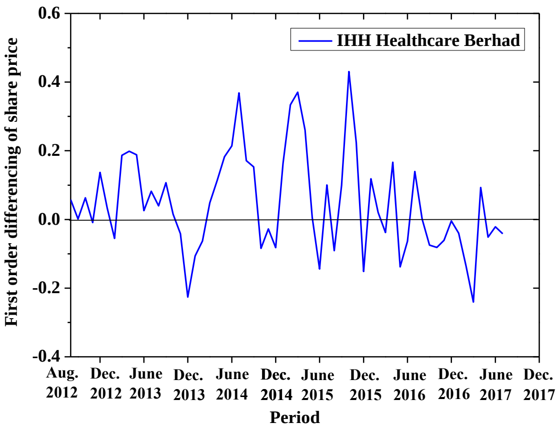
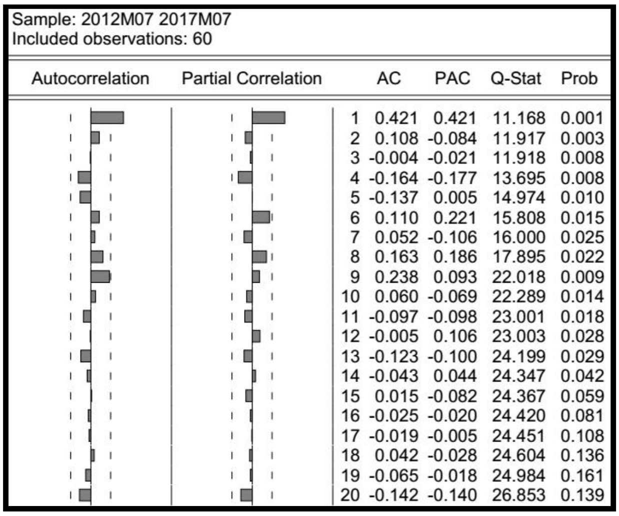


Fig. 4: First order difference of share price



Sample: 2012M07 2017M07
Included observations: 60

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.421	0.421	11.168	0.001
		2	0.108	-0.084	11.917	0.003
		3	-0.004	-0.021	11.918	0.008
		4	-0.164	-0.177	13.695	0.008
		5	-0.137	0.005	14.974	0.010
		6	0.110	0.221	15.808	0.015
		7	0.052	-0.106	16.000	0.025
		8	0.163	0.186	17.895	0.022
		9	0.238	0.093	22.018	0.009
		10	0.060	-0.069	22.289	0.014
		11	-0.097	-0.098	23.001	0.018
		12	-0.005	0.106	23.003	0.028
		13	-0.123	-0.100	24.199	0.029
		14	-0.043	0.044	24.347	0.042
		15	0.015	-0.082	24.367	0.059
		16	-0.025	-0.020	24.420	0.081
		17	-0.019	-0.005	24.451	0.108
		18	0.042	-0.028	24.604	0.136
		19	-0.065	-0.018	24.984	0.161
		20	-0.142	-0.140	26.853	0.139

Fig. 5: Autocorrelation and partial correlation of first difference for share price

Next, this study performed the normality checking. Figure 6 shows the histogram for first difference of share price. Graphical approach shows that the distribution of first difference for share price is follow normal distribution.

Figure 7 shows the normal probability plot for first order difference of share price. Figure 6 shows the data points are close to the diagonal line. Therefore, data of first difference for share price are normally distributed.

In validating the graphical approach, this study performed the numerical approach to validate the normality of the data set. Table 2 shows the value of Shapiro-Wilk normality test. The significant value of the Shapiro-Wilk Test is 0.205 which is greater than 0.05. Therefore, the data set is follow normal distribution.

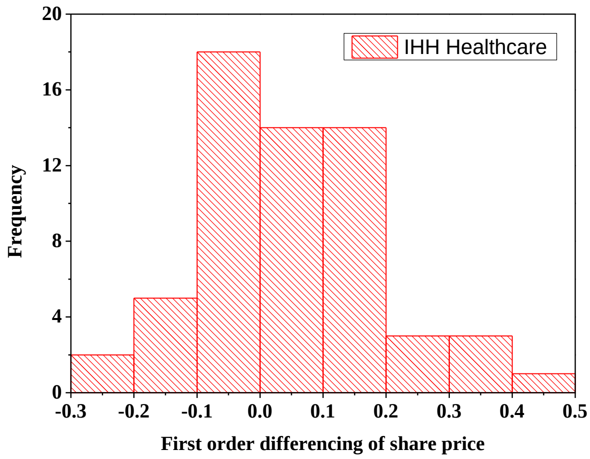


Fig. 6: Histogram of first difference for share price

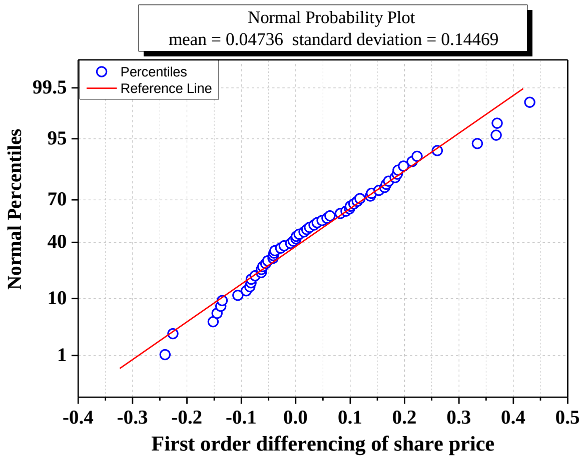


Fig. 7: Normal probability plot

Table.2: Test of normality

	Shapiro-Wilk		
	Statistics	Degree of freedom	Sig.
First order differencing of share price	.973	60	.205

https://dx.doi.org/10.24001/ijaems.3.8.7 ***ISSN: 2454-1311***

4.3 Parameter evaluation of autoregressive integrated moving average (ARIMA) model

In this section, this study analyzed the parameter for autoregressive integrated moving average (ARIMA) model. Table 3 shows the parameter for ARIMA (*1*,*1*,*1*).

Table.3: Parameter for ARIMA model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.046785	0.027719	1.687801	0.0970
AR(1)	0.243098	0.269277	0.902783	0.3705
MA(1)	0.211433	0.276606	0.764381	0.4478
SIGMASQ	0.016794	0.003725	4.508535	0.0000
R-squared	0.184239	Mean dependent var	0.047361	
Adjusted R-squared	0.140537	S.D. dependent var	0.144693	
S.E. of regression	0.134141	Akaike info criterion	-1.112060	

Therefore, the equation for autoregressive integrated moving average, ARIMA (*p*,*d*,*q*) model is described as below equation.

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)(1-L)^d\, y_t=\delta+\left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t$$

The equation for ARIMA (*1*,*1*,*1*) is described as next equation.

$$\left(1-\phi_1 L^1\right)(1-L)\,y_t=c+\left(1+\theta_1 L^1\right)\varepsilon_t$$

$$\left(1-\phi_1 L^1\right)(y_t-y_{t-1})=c+\left(1+\theta_1 L^1\right)\varepsilon_t$$

$$\left(1-\phi_1 L^1\right)\Delta y_t=c+\left(1+\theta_1 L^1\right)\varepsilon_t$$

$$\Delta y_t-\phi_1 L^1\Delta y=c+\varepsilon_t+\theta_1 L^1\varepsilon_t$$

$$\Delta y_t-\phi_1\Delta y_{t-1}=c+\varepsilon_t+\theta_1\varepsilon_{t-1}$$

$$\Delta y_t=c+\phi_1\Delta y_{t-1}+\theta_1\varepsilon_{t-1}+\varepsilon_t$$

According to parameter in Table 2, the ARIMA equation is described as below:

$$\begin{aligned}\Delta y_t &= 0.046785+0.243098\Delta y_{t-1}\\ &\quad+0.211433\varepsilon_{t-1}+0.016794\end{aligned} \qquad (13)$$

Then, ARIMA (*1*, *1*, *1*) model is validated using R-squared and Akaike Information Criterion (AIC). R-squared is a statistical measure of how close the data are to the fitted regression line. It is also known as the coefficient of determination, or the coefficient of multiple determinations for multiple regressions. AIC rewards goodness of fit (as assessed by the likelihood function), but it also includes a penalty that is an increasing function of the number of estimated parameters. The penalty discourages overfitting, because increasing the number of parameters in the model almost always improves the goodness of the fit.

From Table 2, ARIMA (*1*, *1*, *1*) model indicated the value of R-squared is 0.184 and Akaike info criterion (AIC) is -1.11.

4.4 Residual Diagnostics

Then, diagnostics checking was carried out to assess the appropriateness of the model ARIMA (*1*, *1*, *1*) by defining residuals and examining residual plots. Residual is the difference between the observed value of the dependent variable and the predicted value.

Figure 8 show the dynamic movement of residual for each of the period in time series. Residual line is calculated from the difference between actual value and fitted value. Figure 8 shows the distribution of the residual is a random distribution and following the white noise definition. White noise is regarded as a sequence of serially uncorrelated random variables with zero mean and finite variance.

Figure 9 show the correlogram analysis for residual. Figure 9 shows no significant spike for autocorrelatioan and partial correlation. Therefore, the residual for ARIMA (1,1,1) is not significant and uncorrelated random variable.

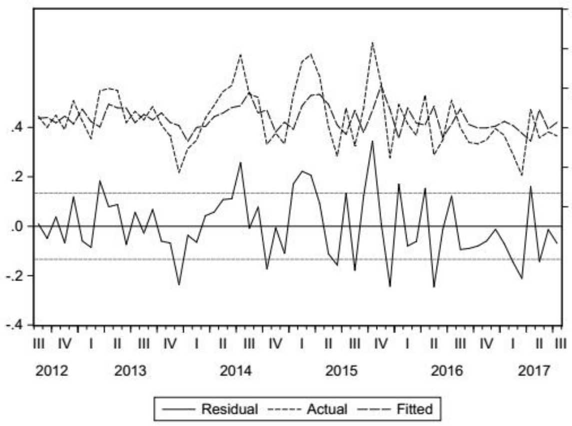
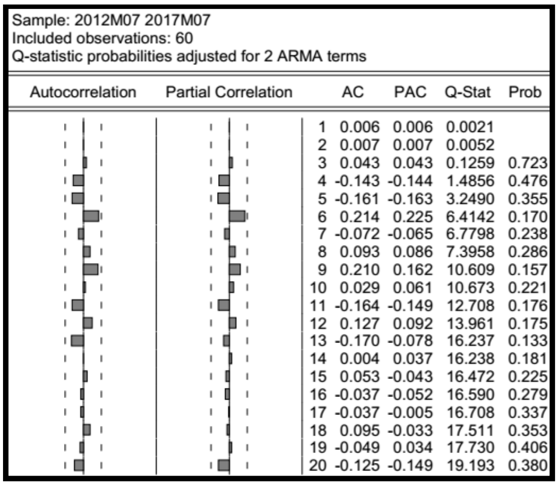


Fig. 8: Dynamic behavior of residual


Sample: 2012M07 2017M07
Included observations: 60
Q-statistic probabilities adjusted for 2 ARMA terms

	AC	PAC	Q-Stat	Prob
1	0.006	0.006	0.0021	
2	0.007	0.007	0.0052	
3	0.043	0.043	0.1259	0.723
4	-0.143	-0.144	1.4856	0.476
5	-0.161	-0.163	3.2490	0.355
6	0.214	0.225	6.4142	0.170
7	-0.072	-0.065	6.7798	0.238
8	0.093	0.086	7.3958	0.286
9	0.210	0.162	10.609	0.157
10	0.029	0.061	10.673	0.221
11	-0.164	-0.149	12.708	0.176
12	0.127	0.092	13.961	0.175
13	-0.170	-0.078	16.237	0.133
14	0.004	0.037	16.238	0.181
15	0.053	-0.043	16.472	0.225
16	-0.037	-0.052	16.590	0.279
17	-0.037	-0.005	16.708	0.337
18	0.095	-0.033	17.511	0.353
19	-0.049	0.034	17.730	0.406
20	-0.125	-0.149	19.193	0.380

Fig. 9: Correlogram for residual

Next, normality test is performed using graphical and numerical approach. Figure 10 shows the normal probabilitility plot for residual of ARIMA (1,1,1) model. Figure 10 shows only two data points is deviated from straight line. Therefore, the distribution data of residual is follow normal distribution. From the analysis, mean value is 0 and standard deviation is 0.13069.

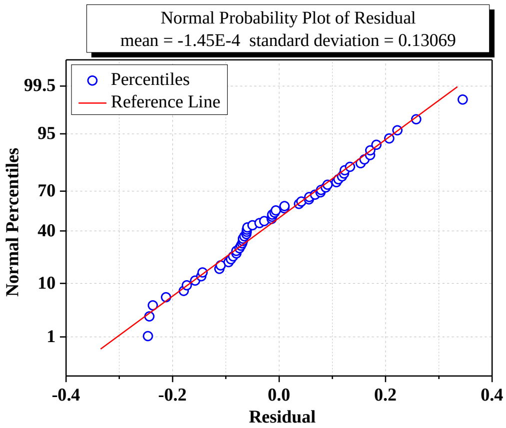


Fig. 10: Normal probability plot for residual

4.5 Forecasting validation (ex-post data set)

In this section, this study evaluated the validity of ARIMA (*1, 1, 1*) model for forecasting. The period involved in this analysis is from April 2017 until July 2017.Table 4 shows the analysis of absolute percentage error for residual. Table 3 shows the mean absolute percentage error is 1.40%. This value indicates ARIMA (*1, 1, 1*) is a reliable forecasting model.

Next, this study plots the graph for actual and forecast value. Figure 11 is the graph of forecasting model validation for ex-post data set. In Fig.10 also is plotted forecast validation range of two standard errors. Result shows mean absolute error between actual value and forecast value of share price is 0.084429. In addition, the actual value is inside the forecasting value with two standard errors. Therefore, ARIMA (1,1,1) is a reliable forecasting model.

Table.4: Parameter for ARIMA model

Period (2017)	**Actual value(A)**	**Forecast value(B)**	**Residual (A-B)**	**Absolute Percentage error (%)**
April	5.894	6.055	-0.161	2.65
May	5.913	6.003	-0.090	1.50
June	5.953	5.982	-0.029	0.49
July	5.998	5.940	0.058	0.98
Mean absolute percentage error (MAPE)				**1.40**

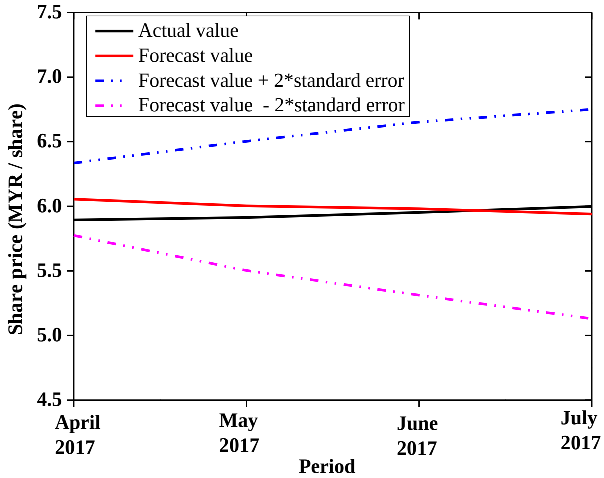


Fig. 11: Forecasting model validation (ex-post data set)

4.6 Forecasting range (ex-ante data set)

In this section, this study using ARIMA (1,1,1) to forecast from August 2017 until December 2017. Figure 12 shows the dynamic behavior of share price for IHH Healthcare Berhad. The value of share price in August 2017 is forecast as MYR 5.951. Then, the value of share price in December 2017 is forecast as MYR 6.126. The performance of the share price for IHH Healthcare Berhad is predicted increasing in December 2017 comparing to known value in July 2017.

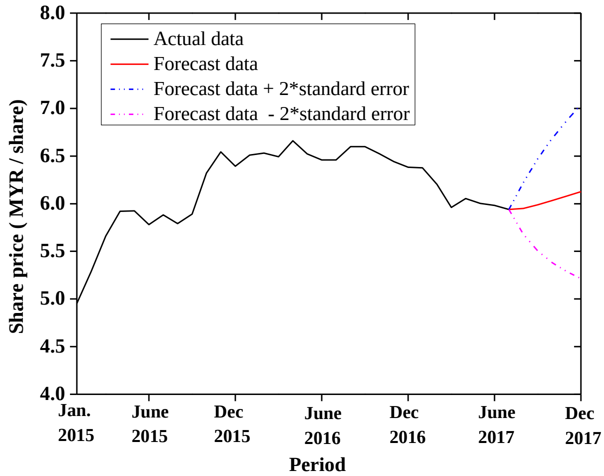


Fig. 12: Forecasting range evaluation (ex-ante data set)

V. CONCLUSION

This objective of this study is to forecast the share price of healthcare sector in Malaysia Stock Exchange. The selected company in healthcare sector is IHH Healthcare Berhad. The period involved in this analysis is from April 2017 until July 2017.The method that implemented in this study is autoregressive integrated moving average (ARIMA) model. The impact of this study is to help economists to predict the performance of healthcare sector in Malaysia. The finding also will help investors to select investment portfolio to gain more profits. The main findings from analysis of this study are:

(a) Data share price is non-stationary data set. Non stationary data set indicates mean and variance are not constant over time.

(b) The first order difference of share price is a stationary data set. Stationary data shows mean and variance are constant over time. In addition, the distribution of first difference for share price is follow normal distribution.

(c) Share price can be model using Autoregressive integrated moving average with ARIMA (*1,1,1*). This ARIMA model indicated the value of R-squared is 0.184 and Akaike info criterion (AIC) is -1.11.

(d) From correlogram residual analysis, no significant spike for autocorrelatioan and partial correlation. Therefore, the residual for ARIMA (*1,1,1*) is not significant and uncorrelated random variable.

(e) The reliability of forecasting model is checked using error checking. Mean absolute percentage error is 1.40% for ARIMA (*1,1,1*). This value indicates ARIMA(*1,1,1*) is a reliable forecasting model.

(f) The value of share price in August 2017 is forecast as MYR 5.951. Then, the value of share price in December 2017 is forecast as MYR 6.126. The performance of the share price for IHH Healthcare Berhad is predicted increasing in December 2017 comparing to known value in July 2017.

FUTHER RESEARCH

This study can be extending to investigate the determinants that contribute to dynamic behavior of share price in healthcare sector.

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