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Application of Short-term Forecasting Models for Energy Entity Stock Price: Evidence from Indika Energi Tbk, Jakarta Islamic Index

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ABSTRACT

Share price as one kind of financial data is the time series data that indicates the level of fluctuations and heterogeneous variances called heteroscedasticity. The method that can be used to overcome the effect of autoregressive conditional heteroscedasticity effect is the generalised form of ARCH (GARCH) model. This study aims to design the best model that can estimate the parameters, predict share price based on the best model and show its volatility. In addition, this paper discusses the prediction-based investment decision model. The findings indicate that the best model corresponding to the data is AR(4)-GARCH(1,1). The model is implemented to forecast the stock prices of Indika Energy Tbk, Indonesia, for 40 days and significantly presented good findings with an error percentage below the mean absolute.

Keywords: Autoregressive Conditional Heteroscedasticity Effect, Generalised Form of Autoregressive Conditional Heteroscedasticity Model, Volatility, Share Price Forecasting, Investment Decision
JEL Classifications: C5, C53, Q4, Q47

1. INTRODUCTION

A method that can be used to predict the future based on previous data is forecasting (Warsono et al., 2019a). It is also literally crucial in forecasting financial data. Analysts implement the financial forecasting data as an early information to be usable for making a decision. Gleason and Lee (2003) and Call (2008) stated that the role of analysts is extremely vital in spreading the information regarding the prediction of the company share price. The forecasting conducted by financial analysts also serves as a standard company evaluation to increase market value in the future.

Generally, the movement of the company share price is known as volatility. It can have an impact on the capital gain, the difference of buying and selling price, of investors. A low share price movement means low volatility, indicating that investors need a long term to maximally gain in the market. By contrast, a high share price volatility gives a warning to traders in trading their stocks on short-term investments. Virginia et al. (2018) termed the situation of volatility and high return as 'risk and return trade-off'. Provided the high daily volatility on the share price, the increase or decrease in share prices emerges, which allows speculators to gain from the different opening and closing prices or high risk and high return (Hull, 2015). Risk takers will greatly consider the high volatility with proper strategic plans to gain from the trading, whereas risk-averse investors will hold the investment up to a long period as they believe that the stock price will gradually go up in the future (Chan and Wai-Ming, 2000).

The study focuses on forecasting an energy company as it significantly affects the economic growth (Warsono et al., 2019b).

Polyakova et al. (2019) related an investment on the energy field to economic growth in Russia that shows a positive correlation between investment and GDP. Taiwo and Apanisile (2015) investigated the impact of the volatility of oil price on economic growth in 20 sub-Saharan African countries, which are divided into two groups (oil-exporting and -non-exporting countries). The findings show that volatility in group A (oil-exporting countries) has a positive and significant effect on economic growth, whereas the oil price volatility has a positive but insignificant impact on the economic growth in group B (non-oil-exporting countries). In addition, Kongsilp and Mateus (2017) stated that asset pricing and important information are fundamental considerations for investments.

2. DATA AND STATISTICAL MODELLING

The data used in this study were obtained from Indika Energy Tbk from 2016 to 2018. The company has been actively exploring, producing and processing coal with an ownership interest in mining enterprises that provide energy resources for Indonesia and many countries around the globe (Indika Energy Tbk, 2018). Indika Energy, Tbk (code: INDY) has been listed in Jakarta Islamic Index (JII) since June 2018. JII is categorised an index for 30 blue-chip Sharia Stocks.

Before analysing the dynamics of time series data, the behaviours should be checked and classified as either stationary or non-stationary. One way to do so is to plot the data and examine how the graph behaves. The other way is through a statistical test, which checks the stationarity by testing the unit root and applying augmented Augmented Dicky–Fuller (ADF) test. The ADF test process can be presented as follows (Tsay, 2005; Warsono et al., 2019a; 2019b).

Let $IE_1, IE_2, IE_3, \ldots, IE_n$ be the series of data from Indika Energy Tbk and $\{IE_t\}$ follows the AR(p) model with mean μ. The mathematical equation can be presented as

$$IE_t = \mu + \gamma_1 IE_{t-1} + \sum_{k=1}^{p-1} \gamma_k \Delta IE_{t-1} + \varepsilon_t \tag{1}$$

Where γ_i denotes the parameters and ε_t is the white noise with mean 0 and variance σ_ϵ^2. This test is conducted through the calculation of the value of τ statistic as follows (Virginia et al., 2018):

$H_0 = \gamma_1 = 0$ (non-stationary)

$H_1 = \gamma_1 < 1$ (stationary)

ADF Test:

$$\tau = \frac{\gamma_i}{Se_{\gamma 1}} \tag{2}$$

Reject H_0 if $\tau < -2.57$ or if $P < 0.05$ with a significant level of $\alpha = 0.05$ (Brockwell and Davis, 2002. p. 195).

2.1. Autocorrelation Function (ACF) and White Noise Inspection

White noise is a time series consisting of uncorrelated data and has a constant variance (Montgomery et al., 2008). If it is so, then the distribution of the sample autocorrelation coefficient at lag k in a large sample is approximately a normal distribution with mean 0 and variance $1/T$, where T is the number of observations (Brockwell and Davis, 2002). Equation (3) presents

$$r_k \sim \mathrm{N}\left(0, \frac{1}{T}\right) \tag{3}$$

From Equation (3), the hypothesis of the autocorrelation of lag k H_0: $\theta_k = 0$ against H_1: $\theta_k \neq 0$ can be conducted by using the following test statistic:

$$Y = \frac{r_k}{\sqrt{1/T}} = r_k \sqrt{T} \tag{4}$$

We reject H_0 if $|Y| > Y_{\alpha/2,}$ where $Y_{\alpha/2}$ is the upper $\alpha/2$ percentage point of the standard normal distribution or reject H_0 if $P < 0.05$. In addition, ACF and partial ACF (PACF) can be implemented by using the test statistic from Equation (4) (Wei, 2006). Non-stationary data can be indicated with the ACF decaying very slowly.

Furthermore, to solve the issue as the time series indicated white noise when jointly evaluating autocorrelations, the Box–Pierce statistic (Box and Pierce, 1970) can used as a solution:

$$Q_{BP} = \mathrm{T} \sum_{k=1}^{K} r_k^2 \tag{5}$$

Q_{BP} is distributed as chi-squares with K degree of freedom and under null hypothesis that the time series is white noise (Montgomery et al., 2008). H_0 is rejected if $Q_{BP} > x^2_{\alpha,K}$ and $P < 0.05$, and then it is concluded that the series is not white noise.

When the data are still non-stationary, the use of differencing and transformation processes is applied. However, when the data are already stationary in the mean, the estimation of the order of autoregressive moving average (ARMA) is set by applying ACF and PACF.

2.2. Test of the Autoregressive Conditional Heteroscedasticity (ARCH) Effect

The first idea in modelling volatility assumes that conditional heteroscedasticity can be modelled using an ARCH (Engle, 1982). Atoi (2014) mentioned that this model associates with the conditional variance of the disturbance term to the linear combination of the squared disturbance in the past. To convince the existence of the ARCH effect, the selected best ARMA model should be checked by using the Lagrange multiplier (LM) test (Virginia et al., 2018).

2.3. ARMA(p,q) Model

Wold (1938) was the first scholar who introduced the combination of AR and MA schemes and showed that it can model all stationary time series provided the appropriate order of p and q. Aside from selecting the best model of ARMA, the parameters should be estimated via various smallest values in the selection criteria (Khim and Liew, 2004), such as Aikaike information criterion (AIC) (Akaike, 1973), Schwarz information criterion (Schwarz, 1978) and Hannan–Quinn information criterion (HQC) (Hannan and Quinn, 1978). In general, the AR(p) model form can be written in Equation (6):

$$IE_t = \beta + \Phi_1 IE_{t-1} + \Phi_2 IE_{t-2} + \Phi_3 IE_{t-3} + \ldots + \Phi_p IE_{t-p} + \varepsilon_t \quad (6)$$

MA(q) is presented as follows:

$$IE_t = \mu + \varepsilon_t - \lambda_1 \varepsilon_{t-1} + \lambda_2 \varepsilon_{t-2} + \lambda_3 \varepsilon_{t-3} + \ldots + \lambda_q \varepsilon_{t-q}; \varepsilon_t \sim N\left(0, \sigma^2\right) \quad (7)$$

Equations (6) and (7) can be generally formulated as

$$IE_t = \beta + \Phi_1 IE_{t-1} + \Phi_2 IE_{t-2} + \Phi_3 IE_{t-3} + \ldots + \Phi_p IE_{t-p} + \varepsilon_t - \ddot{e}_1 \varepsilon_{t-1} - \ddot{e}_2 \varepsilon_{t-2} + \ldots + \ddot{e}_q \varepsilon_{t-q} = \beta + \sum_{i=1}^{p} \Phi_i IE_{t-i} + \varepsilon_t - \sum_{k=1}^{q} \ddot{e}_k \varepsilon_{t-i} \quad (8)$$

where the variable is at lag t; β indicates the constants of AR(p); Φ_i is the regression coefficient; $i = 1,2,3,\ldots, p$; p is the order of AR; λ_k denotes the model parameter of MA, $k = 1,2,3,\ldots, q$; q is the order of MA; and ε_t is the error term at time t.

2.4. LM Test

Heteroscedasticity can be an issue involved in time series data that has autocorrelation problem (Engle, 1982). Eagle mentioned at the same year that to detect heteroscedasticity, the ARCH effect can use the ARCH-LM test. The stages are as follows:

1. Consider a linear regression of time series:

$$IE_t = \vartheta + \gamma_1 IE_{t-1} + \gamma_2 IE_{t-2} + \ldots + \gamma_p IE_{t-p} + \varepsilon_t$$

2. Test the q ARCH by squaring the residuals and regressing the variance t:

$$\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 \varepsilon_{t-2}^2 + \gamma_3 \varepsilon_{t-3}^2 + \ldots + \gamma_q \varepsilon_{t-q}^2$$

3. Conduct the hypothesis:

$$H_0 = \gamma_1 = \gamma_2 = \ldots = \gamma_q = 0;$$

$$H_1 \ldots \gamma_1 \neq 0 \text{ or } \gamma_2 \neq 0 \text{ or } \ldots \text{ or } \gamma_q \neq 0$$

4. Statistical test:

$$LM = TR^2,$$

Where,

$$R^2 = \frac{\sum_{i=1}^{n} (\hat{x}_i - \bar{x})^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \quad (9)$$

T is the total data, and R^2 refers to R-squared with χ^2 (q) distribution.

2.5. Generalised Form of ARCH (GARCH) Model

Bollerslev (1986) introduced the GARCH model to avoid the high order of ARCH model. The model is applicable for observing some residual relationships that also depend on some previous residuals. Due to the conditional variance associated with the conditional variance of previous lag that is allowed in the GARCH model, the equation is presented as follows:

$$\sigma_t^2 = \varpi + \sum_{i=1}^{q} \varrho_i \varepsilon_{t-i}^2 + \sum_{k=1}^{p} \varsigma_j \varepsilon_{t-j}^2 \quad (10)$$

Figure 1: Data of Indika Energy Tbk share price from 2016 to 2018

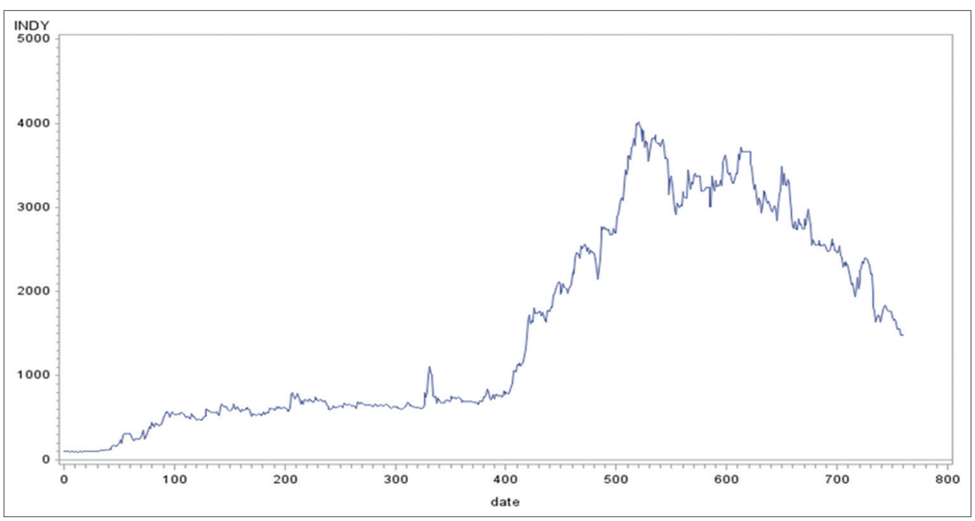


Table 1: ADF unit-root tests

Type	Lags	Rho	Pr<Rho	Tau	Pr<Tau	F	Pr>F
Zero mean	3	−0.2350	0.6294	−0.2295	0.6039		
Single mean	3	−2.1532	0.7602	−1.2825	0.6402	1.0629	0.7989
Trend	3	−0.9103	0.9893	−0.3025	0.9905	0.9420	0.9747

ADF: Augmented Dicky–Fuller

Wang (2009) stated that heteroscedasticity of time-varying conditional variance of the GARCH model is on AR and MA, in which q lag from the square residual and the p lag of the conditional variance is equated as GARCH(p,q).

Therefore, Equation (11) shows the GARCH model as

$$IE_t = \beta + \sum_{i=1}^{p} \Phi_i IE_{t-i} + \varepsilon_t - \sum_{k=1}^{q} \lambda_k \varepsilon_{t-i}$$

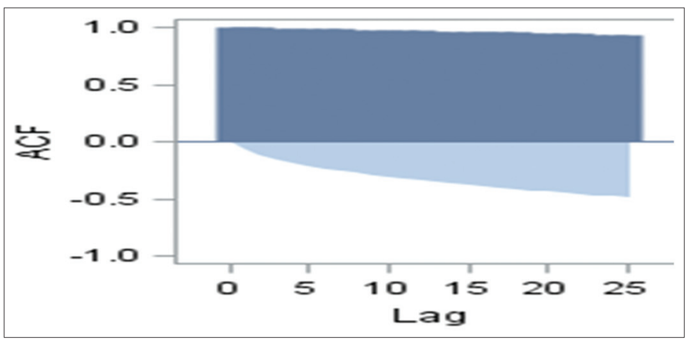
$$\varepsilon_t \sim N(0, var(IE)^2) \tag{11}$$

$$\sigma_t^2 = \varpi + \sum_{i=1}^{q} \varrho_i \varepsilon_{t-i}^2 + \sum_{k=1}^{p} \varsigma_j \varepsilon_{t-j}^2$$

3. RESULTS AND DICUSSION

On this study, we investigate the data of the adjusted closing share price of Indika Energy Tbk (JII Code: INDY) from 2016 to 2018, as one of the largest market capitalization in Indonesia energy companies (IDX Statistic, 2018). Figure 1 reveals that the plotted data are non-stationary. It is due to the gradual increase observed in the first 400 data, and the trend significantly increases up to above 500 data and plummets up to the final data observed. This phenomenon therefore indicates that Indika Energy Tbk share price data are not constantly moving around a specific number.

Figure 2: Correlation analysis of Indika Energy Tbk data



To ensure that the series of data are non-stationary, ADF unit-root test statistic, ACF and PACF tests, and white noise inspection are conducted for non-stationary data.

Table 1 shows the ADF test with a $P > 0.05$ and Tau value above the tau statistic, which confirms that we do not have enough evidence to reject H_0 and that the data of Indika Energy Tbk are non-stationary. Meanwhile, the parameter of intercept estimation (H_0: intercept = 0) shown in Table 2 is obviously significant with $P < 0.0001$, meaning that it is different from zero.

Furthermore, autocorrelation analysis for the data is performed to examine whether the data are stationary or not. As shown in Figure 2, as the ACF moderately declines, the data series becomes non-stationary. Hence, to have a stationary data, the white noise behaviour should be checked, in which it tests the approximation of the hypothesis for a statistical test that up to examined lag of data series are different from zero significantly. As shown in Table 3, as expected, the data series is non-stationary due to the autocorrelation checked in a group of six with a white noise where to reject H_0 very significantly the $P < 0.0001$.

Table 2: Parameter estimates for the intercept (Constant value)

Variable	DF	Estimate	Standard error	t-value	Approx Pr>|t|
Intercept	1	1551	43.2228	35.89	<0.0001

3.1. Differencing the Data Series of Indika Energy Tbk

The following stage of this study transforms the non-stationary to stationary data by differencing of Indika Energy Tbk data. The implementation is performed by computing differencing with lag = 2 ($d = 2$) to obtain the stationary, which is observable in Figure 3. The residual data behaviour after differencing is distributed in a circle of zero. In addition, the ACF plot is also declining very fast.

3.2. Trend and Correlation Analysis for INDY(2)

Furthermore, after convincing that the data series of Indika Energy Tbk is stationary by all means, the examination of the autocorrelation patterns for residuals is computed by using the Box–Jenkins methodology to have the adequacy of estimated ARMA model of the series. As shown in Figure 3, PACF Figure 4 also assists in identifying the proper ARMA model, whereby the differencing makes it appropriate to the series.

Table 3: Autocorrelation check for white noise of Indika Energy Tbk

To lag	Chi-square	DF	Pr>Chi-square	Autocorrelations					
6	4517.14	6	<0.0001	0.998	0.995	0.993	0.990	0.987	0.984
12	8914.68	12	<0.0001	0.981	0.978	0.975	0.972	0.970	0.967
18	9999.99	18	<0.0001	0.965	0.962	0.960	0.958	0.955	0.952
24	9999.99	24	<0.0001	0.950	0.947	0.944	0.941	0.938	0.934

Table 4: Autocorrelation check for white noise of Indika Energy Tbk after differencing (d=2)

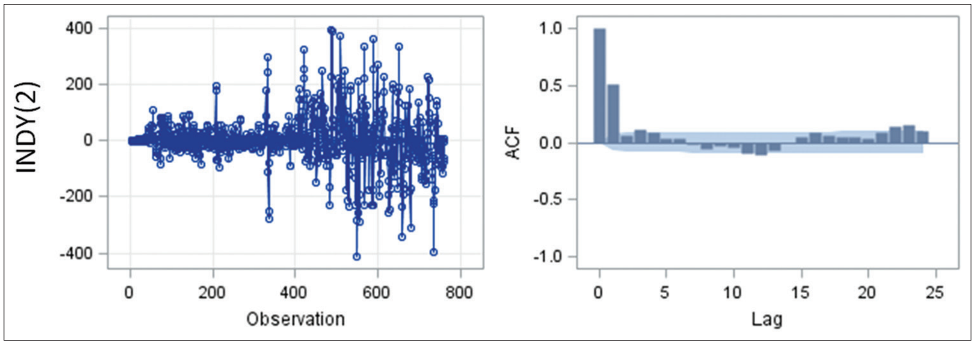
To lag	Chi-square	DF	Pr>Chi-square	Autocorrelations					
6	221.13	6	<0.0001	0.513	0.061	0.117	0.083	0.038	0.039
12	242.57	12	<0.0001	−0.018	−0.056	−0.032	−0.044	−0.094	−0.112
18	259.60	18	<0.0001	−0.070	−0.006	0.054	0.091	0.063	0.044
24	309.56	24	<0.0001	0.050	0.040	0.084	0.137	0.155	0.099

Table 5: ADF unit-root tests after differencing (d=2)

Type	Lags	Rho	Pr<Rho	Tau	Pr<Tau	F	Pr>F
Zero mean	3	−549.964	0.0001	−12.58	<0.0001		
Single mean	3	−554.143	0.0001	−12.59	<0.0001	79.30	0.0010
Trend	3	−569.165	0.0001	−12.69	<0.0001	80.47	0.0010

ADF: Augmented Dicky–Fuller

Figure 3: Residuals and autocorrelation function plotting after differencing with d = 2 for Indika Energy Tbk data



In addition, transforming the data series with d = 2 improves the white noise of the data as illustrated in Table 4. After differencing (d = 2), the series data also became stationary. This finding is also supported by the ADF test results (d = 2) shown in Table 5.

Table 5 proves that the hypothesis of ADF test (H_0) is significantly rejected as the P-value and Tau value are both <0.0001. Thus, the data series of INDY is now stationary. Therefore, we may conduct autocorrelation models, and in this study, we examine either AR(1), AR(2), AR(3) or AR(4) as a good candidate to fit with the process.

3.3. ARCH Effect Test

The existence of heteroscedasticity in a time series data can be a problem that makes the estimation inefficient. To cope with this issue, an adequate method should be applied, such as the GARCH model. It therefore needs to confirm whether the heteroscedasticity exists or not by using the ARCH-LM test prior to find the best model of the GARCH(p,q).

The confirmation of the existence of nonlinear dependencies is evident in Table 6, which clearly suggests that H_0 is rejected as the portmanteau (Q) and LM tests calculated from the squared residuals have a very significant p-value (P < 0.0001). This finding indicates that the ARCH effect for the data residuals of Indika Energy Tbk is applicable in the GARCH(p,q) model in forecasting volatility.

3.4. AR(p)–GARCH(p,q) Model

The following step aims to find the best model based on the AIC, AICC, SBC, HQC and its mean square error (MSE) criteria for AR(1)–GARCH(1,1), AR(2)–GARCH(1,1), AR(3)–GARCH(1,1) and AR(4)–GARCH(1,1), of which the model volatility is presented on Figure 5. Table 7 shows the information criteria.

The information criteria above (Table 7) evidently show two candidate models with the smallest AIC, AICC, SBC and HQC. AR(1)–GARCH(1,1) model has the smallest SBC and HQC, whereas AR(4)–GARCH(1,1) is the best model with the smallest AIC and AICC criteria. Nevertheless, between the AR(1)–GARCH(1,1) and AR(4)–GARCH(1,1) models, the latter has the smallest MSE. This finding indicates that to perform the next prediction and study analysis, the best model that should be used is AR(4)–GARCH(1,1).

Figure 4: Partial autocorrelation function plotting after differencing with d = 2 for Indika Energy Tbk data

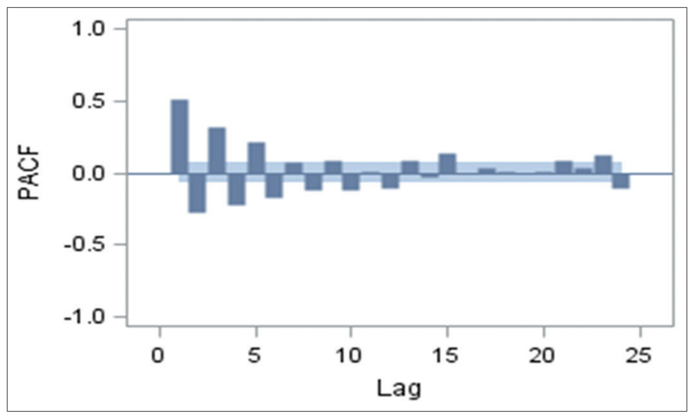


Table 8 shows that the parameter estimate for AR(2) is insignificant as the t-value is 1.28 and P = 0.2016, indicating indifference with zero, whereas the other parameters have a significance of P < 0.05. Thus, according to the analysis results of AR(4)–GARCH(1,1), the model estimation can be presented as follows:

- Mean Model AR(4):

$$IE_t = 97.9901 - 1.0596IE_{t-1} + 0.0796IE_{t-2} - 0.1526IE_{t-3} + 0.1327IE_{t-4} \quad (12)$$

- And the variance model, GARCH(1,1):

$$\sigma_t^2 = 20.1405 + 0.3360\varepsilon_{t-1}^2 + 0.7583\sigma_{t-1}^2 \quad (13)$$

From the model estimate of AR(4), on average, holding all variables constant, IE_t is 97.9901. On average, if IE_{t-1} increases

Figure 5: Volatility of the AR(4)–GARCH(1,1) Model of Indika Energy Tbk data

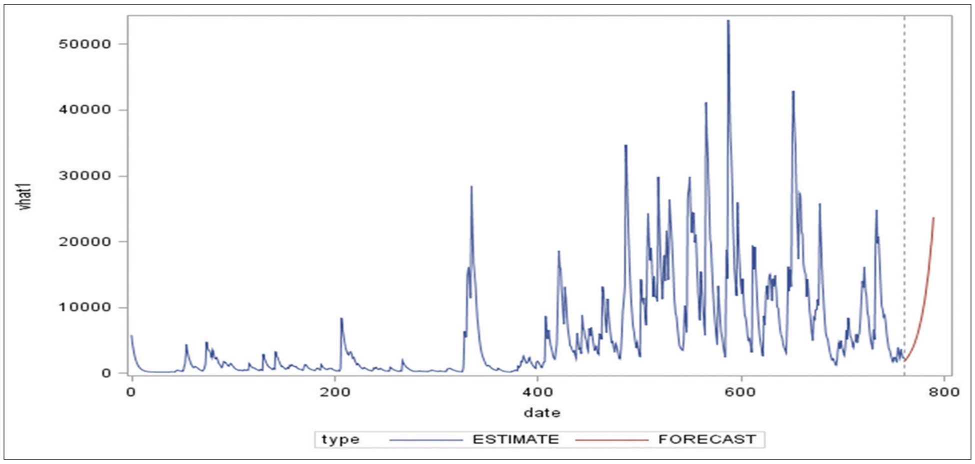


Table 6: ARCH-LM test for Indika Energy Tbk data

Order	Q	Pr>Q	LM	Pr>LM
1	757.2733	<0.0001	741.7637	<0.0001
2	1480.1593	<0.0001	741.7653	<0.0001
3	2170.7237	<0.0001	741.7771	<0.0001
4	2822.4403	<0.0001	742.4999	<0.0001
5	3434.7345	<0.0001	742.8902	<0.0001
6	4011.2627	<0.0001	742.9341	<0.0001
7	4550.1352	<0.0001	743.0223	<0.0001
8	5054.6188	<0.0001	743.0249	<0.0001
9	5527.5168	<0.0001	743.0265	<0.0001
10	5971.4245	<0.0001	743.1121	<0.0001
11	6387.4615	<0.0001	743.1148	<0.0001
12	6778.7317	<0.0001	743.1154	<0.0001

ARCH: Autoregressive conditional heteroscedasticity, LM: Lagrange multiplier

Table 7: Information criteria for the AR(1)–GARCH(1,1), AR(2)–GARCH(1,1), AR(3)–GARCH(1,1) and AR(4)–GARCH(1,1) models and their MSE

Model	AIC	AICC	SBC	HQC	MSE
AR(1) – GARCH(1,1)	8001.89	8001.97	8025.07	8010.82	4046
AR(2) – GARCH(1,1)	8002.69	8002.81	8030.50	8013.40	4044
AR(3) – GARCH(1,1)	8004.60	8004.75	8037.05	8017.09	4045
AR(4) –GARCH(1,1)	7997.81	7998.00	8034.88	8012.08	4008

AIC: Aikaike information criterion, HQC: Hannan–Quinn information criterion, MSE: Mean square error

1 unit, then IE_t decreases by 1.059 and all variables are constant. On the other hand, when IE_{t-2} has 1 unit increase, then IE_t will increase by 0.0796 on average, considering all other variables constant. For an increase of 1 unit of IE_{t-3} on average, the mean IE_t will decline by 0.1526. However, the mean IE_t will increase on average by 0.1327 if IE_{t-4} increases by 1 unit on average and other variables are constant.

Furthermore, according to the data analysis results of the AR(4)–GARCH(1,1) model, as shown in Table 9, the R-square is 0.99, indicating that the variable explained 99% by the model. Likewise, MSE = 4008, allowing to compute the root MSE (RMSE). An RMSE of 63.6 is significantly small compared with the forecasted

Table 8: Parameter estimates of the AR(4)–GARCH(1,1) model

Variable	DF	Estimate	Standard error	t-value	Approx Pr>|t|
Intercept	1	97.9901	4180	0.02	0.9813
AR1	1	−1.0596	0.0432	−24.51	<0.0001
AR2	1	0.0796	0.0623	1.28	0.2016
AR3	1	−0.1526	0.0657	−2.32	0.0203
AR4	1	0.1327	0.0429	3.09	0.0020
ARCH0	1	20.1405	3.5569	5.66	<0.0001
ARCH1	1	0.3360	0.0216	15.59	<0.0001
GARCH1	1	0.7586	0.009078	83.56	<0.0001

AR: Autoregressive, GARCH: Generalised form of ARCH, ARCH: Autoregressive conditional heteroscedasticity

Table 9: Statistical estimation of GARCH for Indika Energy Tbk data

SSE	3049846.42	Observations	761
MSE	4008	Uncond. var.	
Log likelihood	−3990.9061	Total R-square	0.9972
SBC	8034.88919	AIC	7997.81212
MAE	38.6131864	AICC	7998.00361
MAPE	2.93060988	HQC	8012.08898
		Normality test	977.9273
		Pr>Chi-Sq.	<0.0001

AIC: Aikaike information criterion, HQC: Hannan–Quinn information criterion, MSE: Mean square error, AR: Autoregressive, GARCH: Generalised form of autoregressive conditional heteroscedasticity

stock prices (F_SP) in Table 10, showing that the model has a good prediction ability. In addition, in Table 9, MAE has a relatively very small statistic from the prediction stock price (F_SP) (Table 10), whereas the accuracy of forecasting is very good as a representative of a very small mean absolute percentage error (MAPE) of 2.93.

3.5. Behaviour of the Forecasting Model of AR(4)–GARCH(1,1)

The figure above depicts the conditional variance of Indika Energy Tbk along with its prediction for 40 days later. The graph illustrates that a relative constant variance was achieved in around the first 300 data before becoming very volatile and reaching its peak just before the 600 data. The forecasting trend of the risk however shows an indication of an increasing pattern as shown by the red line.

Table 10: Prediction of data share price of Indika Energy Tbk for 40 days

Obs.	F-SP	Std. error	95% confidence limits		Obs.	F-SP	Std. error	95% confidence limits	
762	1483.3322	63.7656	1358.3539	1608.3104	782	1510.7817	296.8898	928.8883	2092.675
763	1485.1947	90.9271	1306.9808	1663.4085	783	1512.6447	303.8874	917.0363	2108.253
764	1486.0767	111.6767	1267.1943	1704.9591	784	1513.5266	310.7274	904.5121	2122.5412
765	1487.9397	129.1344	1234.8409	1741.0384	785	1515.3896	317.4201	893.2576	2137.5217
766	1488.8217	144.498	1205.6107	1772.0326	786	1516.2716	323.9746	881.2931	2151.2502
767	1490.6847	158.3783	1180.269	1801.1003	787	1518.1346	330.399	870.5644	2165.7048
768	1491.5667	171.1364	1156.1455	1826.9878	788	1519.0166	336.7009	859.095	2178.9383
769	1493.4297	183.0073	1134.742	1852.1173	789	1520.8796	342.887	848.8335	2192.9258
770	1494.3117	194.1537	1113.7775	1874.8459	790	1521.7616	348.9635	837.8058	2205.7175
771	1496.1747	204.694	1094.9818	1897.3676	791	1523.6246	354.9359	827.9631	2219.2862
772	1497.0567	214.7176	1076.218	1917.8954	792	1524.5066	360.8095	817.3331	2231.6802
773	1498.9197	224.2936	1059.3122	1938.5271	793	1526.3696	366.589	807.8685	2244.8708
774	1499.8017	233.4772	1042.1947	1957.4086	794	1527.2516	372.2787	797.5987	2256.9046
775	1501.6647	242.313	1026.7398	1976.5895	795	1529.1146	377.8829	788.4778	2269.7514
776	1502.5467	250.8378	1010.9136	1994.1797	796	1529.9966	383.4051	778.5365	2281.4568
777	1504.4097	259.0822	996.6178	2012.2015	797	1531.8596	388.8489	769.7299	2293.9894
778	1505.2917	267.0723	981.8397	2028.7436	798	1532.7416	394.2175	760.0895	2305.3937
779	1507.1547	274.8301	968.4976	2045.8117	799	1534.6046	399.514	751.5716	2317.6377
780	1508.0367	282.3749	954.5921	2061.4812	800	1535.4866	404.7412	742.2085	2328.7648
781	1509.8997	289.7233	942.0525	2077.7468	801	1537.3496	409.9017	733.9571	2340.7422

F-SP: Forecasted stock prices

Figure 6: Forecasting Indika Energy Tbk plot with its confidence interval

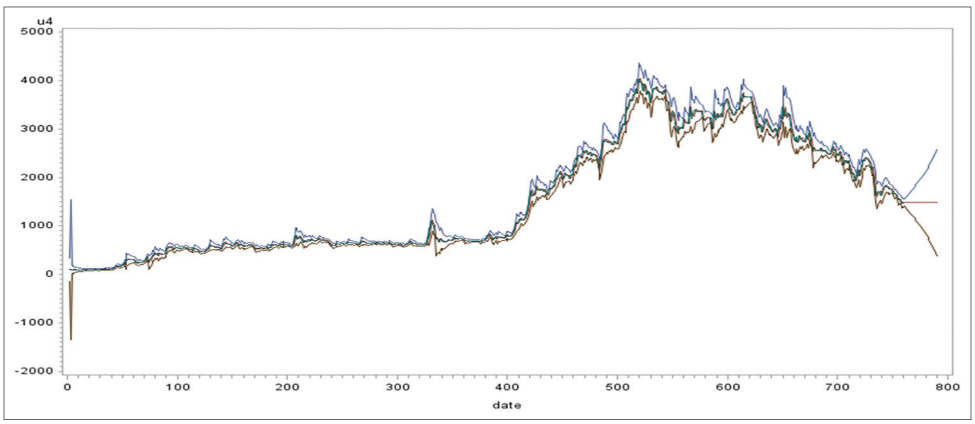
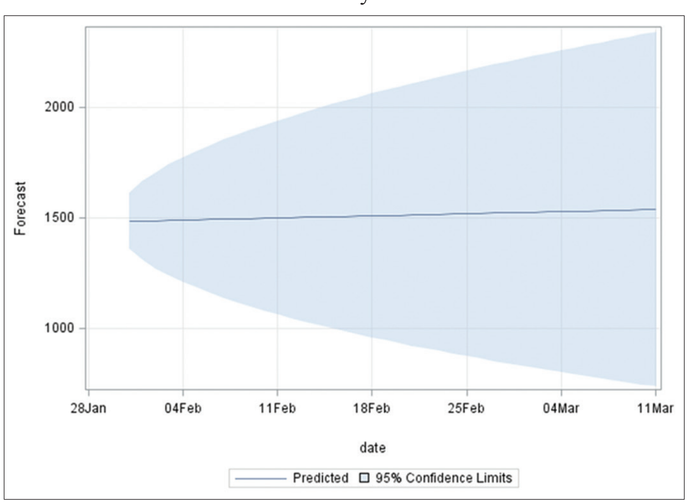


Figure 7: Forecasting Indika Energy Tbk share price for the next 40 days



The aim of this study is to identify the best time in making investment decisions on INDY after computing the best model with the smallest residual value for AR(4)–GARCH(1,1). Figure 6 suggests that the prediction share prices for 40 days experience a gradual upside trend, and it also supports the forecasting with its upper and lower limits. The graph illustrates that the prediction has an increasing pattern with a slow movement as shown in the red line. The risk however is high as presented with the blue line (upper limit) and brown line (lower limit).

Figure 7 supports the data in Figure 6, showing that the stock price of INDY gradually increases. The forecast in this study however only for short-term period as we can see the risk for longer period increases significantly over time.

According with the data forecasting of the AR(4)–GARCH(1,1) model, which has the ability to accurately predict with a lower error level (< 0.0001), investors can decide the timing for their investments on INDY. In this case, by analysing the trend, which shows a moderate upside pattern, investors should buy stocks on INDY.

By contrast, the share price movement is influenced by some factors, such as profit and loss, exchange rate and company value. Based on another previous research, the share price is positively affected by the net profit margin (Djamaluddin et al., 2018), earnings per share (Utami and Darmawan, 2019) and debt-to-equity ratio (Atihira and Yustina, 2017). Finally, with correlation and residual factor on previous years, it presents that the AR(4)–GARCH(1,1) model is adequately accurate in forecasting the share prices.

4. CONCLUSION

At present, investors with the intention of owning a long-term horizon have an opportunity to put their investments in a sharia stock market. The most reliable measurement of sharia index in Indonesia is JII, which consists of only 30 selected companies. One of the 30 companies is Indika Energy Tbk (code: INDY), which has been listed at JII since May 2017 and has become one of the most liquid energy-based stocks. The time series data are analysed by using AR(p)–GARCH(p,q). Their stationarity initially are non-stationary so as to it is simply doing the differencing process with lag = 2 (d = 2) to make them stationary. ARCH-LM test then is computed to examine whether heteroscedasticity (ARCH effect) exists or not before modelling AR(p)–GARCH(p,q). From the test, it is concluded that the series has the ARCH effect, so the model can be applied to model the data.

AR(4)–GARCH(1,1) model is then considered the best model for the time series data of INDY as it is significant with the 99% of R-square. Furthermore, a MAPE of only 2.93% makes AR(4)–GARCH(1,1) as the best prediction model. Finally, the model is applicable for forecasting the stock price for the next 40 days.

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REFERENCES

Akaike, H. (1973), Information theory and the maximum likelihood principle. In: Petrov, B.N., Cs ä ki, F., editors. 2nd International Symposium on Information Theory. Budapest: Akademiai Ki à do.

Atihira, A.T., Yustina, A.I. (2017), The influence of return on asset, debt to equity ratio, earnings per share, and company size on share return. Journal of Applied Accounting and Finance, 1(2), 128-146.

Atoi, N.V. (2014), Testing volatility in Nigeria stock market using GARCH models. CBN Journal of Applied Statistics, 5(2), 65-93.

Bollerslev, T. (1986), Generalized autoregressive conditional heteroscedasticity. Journal of Econometrics, 31, 307-327.

Box, G.E.P., Pierce, D.A. (1970), Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. Journal of American Statistics Association, 65, 1509-1526.

Brockwell, P.J., Davis, R.A. (2002), Introduction to Time Series and Forecasting. New York: Springer-Verlag.

Call, A.C. (2008), Analysts' Cash Flow Forecasts and the Predictive Ability and Pricing of Operating Cash Flows. Working Paper.

Chan, K., Wai-Ming, F. (2000), Trade size, order imbalance, and the volatility-volume relation. Journal of Financial Economics, 78, 193-225.

Djamaluddin, S., Resiana, J., Djumarno, D. (2018). Analysis the effect of Npm, der and per on return share of listed company in Jakarta Islamic index (Jii) period 2011-2015. International Journal of Business and Management Invention (IJBMI), 7(2), 58-66.

Engle, R. (1982), Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50, 987-1007.

Gleason, C., Lee, C. (2003), Analyst forecast revisions and market price discovery. The Accounting Review, 78, 193-225.

Hannan, E.J., Quinn, B.G. (1978), The determination of the order of an autoregression. Journal of Royal Statistical Society, 41, 190-195.

Hull, J.C. (2015), Risk Management and Financial Institutions. Hoboken, New Jersey: John Wiley and Sons, Inc.

IDX Annual Statistic. (2018), Available from: https://www.idx.co.id/media/4842/idx-annual-statistics-2018.pdf. [Last accessed on 2019 Jun 01].

Khim, V., Liew, S. (2004), Autoregressive Order Selection Criteria. Faculty of Economics and Management, Universiti Putra Malaysia. Working Paper.

Kongsilp, W., Mateus, C. (2017), Volatility risk and stock return predictability on global financial crises. China Finance Review International, 7(1), 33-66.

Montgomery, D., Jennings, C., Kulachi, M. (2008), Introduction Time Series Analysis and Forecasting. Hoboken, New Jersey: John Wiley and Sons Inc.

Polyakova, A.G., Ramakrishna, S.A., Kolmakov, V.V., Zavylalov, D.V. (2019), A model of fuel and energy sector contribution to economic growth. International Journal of Energy Economics and Policy, 9(5), 25-31.

PT Indika Energy Tbk. (2018), Available from: https://www.finance.yahoo.com/quote/INDF.JK/history?p=INDF.JK. [Last accessed on 2019 Jun 01].

Schwarz, G. (1978), Estimating the dimension of a model. Annals of Statistics, 6, 461-464.

Taiwo, A., Apanisile, O. (2015), The impact of volatility of oil price on the economic growth in Sub-Saharan Africa. British Journal of Economics, Management and Trade, 5, 338-349.

Tsay, R.S. (2005), Analysis of Financial Time Series. Hoboken, New Jersey: John Wiley and Sons, Inc.

Utami, M.R., Darmawan, A. (2019), Effect of DER, ROA, ROE, EPS and MVA on stock prices in sharia Indonesian stock index. Journal of Applied Accounting and Taxation, 4(1), 15-22.

Virginia, E., Ginting, J., Elfaki, F.A.M. (2018), Application of GARCH model to forecast data and volatility of share price of energy (study on adaro energy Tbk, LQ45). International Journal of Energy Economics and Policy, 8(3), 131-140.

Wang, P. (2009), Financial Econometrics. 2nd ed. New York: Routledge, Taylor and Francis Group.

Warsono, W., Russel, E., Wamiliana, W., Usman, M. (2019a), Vector autoregressive with exogenous variable model and its application in modeling and forecasting energy data: Case study of PTBA and HRUM energy. International Journal of Energy Economics and Policy, 9(2), 390-398.

Warsono, W., Russel, E., Wamiliana, W., Usman, M. (2019b), Modeling and forecasting by the vector autoregressive moving average model for export of coal and oil data (case study from Indonesia over the years 2002-2017). International Journal of Energy Economics and Policy, 9(4), 240-247.

Wei, W.W. (2006), Time Series Analysis: Univariate and Multivariate Methods. 2nd ed. New York: Pearson.

Wold, H. (1938), A Study in the Analysis of Stationary Time Series. Uppsala: Stockholm.