Dynamic Model of Forecasting Stock Prices

Fajrin Satria Dwi Kesumah, Ernie Hendrawaty, Mustofa Usman, Edwin Russel, Rialdi Azhar, Widiarti and Prayudha Ananta

Department of Management, Faculty of Economics and Business, Department of Accounting, Faculty of Economics and Business, Department of Economics Development, Faculty of Economics and Business, Department of Mathematics, Faculty of Mathematics and Sciences, Universitas Lampung, Bandar Lampung, Indonesia

Abstract: Sharia based investments currently become more popular in Indonesia as an alternative for those who have a long-term horizon and are seeking an Islamic way in investing their money. However, such long-term investment allows the existence of heteroscedasticity or heterogeneous variances in the time series data. To come up with this issue, one way to model the Autoregressive Conditional Heteroscedasticity (ARCH) effect is GARCH Model. The objective of this study is to obtain the best model estimating the parameters, to forecast the stock prices and to present its predicted volatility. The results show that the best model as fitted data is AR (1)-GARCH (1,1). The implication of this model is to predict the share price of Indofood CBP Sukses Makmur Tbk, Indonesia, for the next 2 months (60 days) and it shows a very reasonable result as the percentage of error is less than the mean.

Key words: Volatility forecasting, GARCH, ARCH effect, stock price forecasting, parameters, investment

INTRODUCTION

Charles (2008) in his study stated that the model of volatile returns in finance is fundamentally a crucial aspect to deal with financial activities such as derivative pricing and hedging, market making, risk management and portfolio selection. One way to run the forecast of financial time series data is by using its past data (Warsono et al., 2019a; Tsay, 2005). This statistic approach has been widely used by many financial analysts to predict the share price. The activity of individuals particularly in forecasting the volatility of share price has affected the aggregate market of stock value by approximately 50% (Lundholm and Rogo, 2015). Beaver et al. (1980) stated that analysts of finance and association management might do a forecasting in assisting the company to both evaluate and value the financial statement quality because some current raised incomes are expected from that forecasting activity.

Volatility, generally is defined as the movement of stock prices and it could be a gain (selling price exceeds buying price) or otherwise a loss. The situation of the volatility relies on the risk preference from investors, either risk takers or risk averse. High volatility means to persuade a high return but consequently is followed by a high risk or risk takers, in contrast, for those who have the patience in gaining from the difference from buying and selling price have such long-term horizon called risk averse (Chan and Fong, 2000). Hull (2015) mentioned this condition in his study as high risk, high return while Virginia et al. (2018) called this as risk and return trade-off.

The study in forecasting the volatility share price was initially introduced widely by Engle (1982) named ARCH Model which was then developed by Bollerslev (1986) by generalized it known as Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model. Fuess et al. (2007) examined the GARCH-type VaR that might enable in tracing the process of actual return by including the conditional time varying more effectively. On the other hand, Kristjanpoller and Minutolo (2015) argued that forecasting volatility only using GARCH method still has relatively high errors, so, they conducted the extended method to predict the volatility by combining GARCH Model and Artificial Neural Networks (ANN). Their finding is the 25% reduction in the mean average error by using ANN-GARCH Model compared to GARCH Model alone.

MATERIALS AND METHODS

Data and statistical modeling: In this study, we surf the data of share price for Indofood CBP Sukses Makmur, Tbk from its Initial Public Offering (IPO) in 2000 to the end of year 2018. However, it was just listed in Jakarta Islamic Index (JII), the 30-most valuable sharia stock in Indonesia, in June, 2011 (code: ICBP). ICBP is also recognised as one of established and leading company in miscellaneous sector with engagement in diverse business categories.

The first step in this study is checking the stationarity of time series data. This can be done by running
Augmented Dicky Fuller (ADF) test which can be described mathematically as follows (Warsono et al., 2019a, b):

$$ICBP_t = \mu + \delta L ICBP_{t-1} + \sum_{k=1}^{p-1} \Delta ICBP_{t-k} + \varepsilon_t$$  \hspace{1cm} (1)

With the hypothesis:
- $H_0 = \delta = 0$ (Non stationary)
- $H_1 = \delta < 1$ (Stationary)

In addition, the unit-root ADF test:
$$\tau = \frac{\delta}{Sc_{\varepsilon}}$$  \hspace{1cm} (2)

where, according to Brockwell and Davis (2002), we reject $H_0$ if $\tau < -2.57$ or if $p < 0.05$ with significant level of $\alpha = 0.05$.

**Autocorrelation Function (ACF) and normal distribution:** Brockwell and Davis (2002) stated that autocorrelation coefficient at lag n in such large number observation is approximate to be distributed normally with mean 0 and variance $1/T$ which is:

$$\tau_n \approx N\left(0, \frac{1}{T}\right)$$  \hspace{1cm} (3)

Equation 3 creates the autocorrelation hypothesis of lag m $H_0: \omega_m = 0$ against $H_1: \omega_m \neq 0$ and now it allows to use the statistical test as follows:

$$X = \frac{\tau_n}{\sqrt{1/T}} = \tau \sqrt{T}$$  \hspace{1cm} (4)

$H_0$ is rejected if $|X| > X_{\alpha/2}$ or p-value $< 0.05$ and the slow decay movement of ACF can detect the stationarity.

**ARCH effect test:** Virginia et al. (2018) stated that before analysing the framework of GARCH Model, it is necessary to conduct the Langrange Multiplier (LM) test to check the ARCH effect. The Order of Autoregressive AR (p), Moving Average MA(q)-ARMA Model. The general equation for AR (p) is:

$$ICBP_t = \beta + \phi_1 ICBP_{t-1} + \phi_2 ICBP_{t-2} + \ldots + \phi_p ICBP_{t-p} + \varepsilon_t$$  \hspace{1cm} (5)

**MA (q):**

$$ICBP_t = \mu + \varepsilon_t - \phi_1 \varepsilon_{t-1} - \phi_2 \varepsilon_{t-2} - \ldots - \phi_q \varepsilon_{t-q}; \varepsilon_t \sim N(0, \sigma^2)$$  \hspace{1cm} (6)

Equation 5 and 6 is combined into:

$$ICBP_t = \beta + \gamma \varepsilon_{t-1} + \phi_1 ICBP_{t-1} + \phi_2 ICBP_{t-2} + \ldots + \phi_p ICBP_{t-p} + \varepsilon_t$$  \hspace{1cm} (7)

**Langrange Multiplier (LM) test:** Engle (1982) studied that heteroscedasticity (ARCH Effect) could be detected by using ARCH-LM test which below is the steps:

- Regress the time series data:
  $$ICBP_t = \beta + \theta_1 ICBP_{t-1} + \theta_2 ICBP_{t-2} + \ldots + \theta_p ICBP_{t-p} + \varepsilon_t$$

- Test the q ARCH by squaring the residuals and regressing the variance $t$:
  $$\sigma_t^2 = \theta_0 + \theta_1 \varepsilon_{t-1}^2 + \theta_2 \varepsilon_{t-2}^2 + \ldots + \theta_q \varepsilon_{t-q}^2$$

- Test the hypothesis:
  $$H_0: \theta_0 = \theta_1 = \ldots = \theta_q = 0$$
  $$H_1: \text{not all equal to } 0$$

- Statistical test:
  $$LM = TR^2$$

Where, $R^2$ is R-squares.

**GARCH Model:** The GARCH Model allows the conditional variance from prior lag that is correspond to the conditional variance, thus, here is Eq. 8:

$$\sigma_t^2 = \alpha + \sum_{k=1}^{q} \gamma_k \varepsilon_{t-k}^2 + \sum_{l=1}^{p} \phi_k \varepsilon_{t-l}^2$$  \hspace{1cm} (8)

Hence, Eq. 8 presents the GARCH Model:

$$ICBP_t = \beta + \sum_{l=1}^{p} \phi_l ICBP_{t-l} + \varepsilon_t - \sum_{k=1}^{q} \gamma_k \varepsilon_{t-k}^2$$  \hspace{1cm} (9)

**RESULTS AND DISCUSSION**

The study investigates the time series of stock prices of PT Indofood CBP Sukses Makmur Tbk (Code: ICBP) from 2000-2018 as the second highest market share company at the sector of miscellaneous industry.
listed on Jakarta Islamic Index (JII). It is clearly seen on Fig. 1 that from the beginning of its Initial Price Offering (IPO) in October, 2000 the data of ICBP remained stable up to about its first 200th. The next 1000 data, the series experienced a gradual increase while it soared for the first time at approximately 3000, 200th data. Later on, before reaching its second highest peak on the 4000th, the data were fluctuating but indicating an upward trend. After that however, a downward trend happened and fluctuated prior to reaching its top peak on the last data December, 2018.

Therefore, from this plotting data, it can be judged subjectively that the series are not stationary due to it behaves at no constant movement around certain number.

To test statistically the nonstationary data, ADF test can be run by using a software of SAS to confirm it. The hypothetical test is to reject $H_0$ if p-value less than a significant confidence of 0.05 or tau statistic is < -2.57.

From Table 1, the stationarity is confirmed by p-value which is more than 5% confidence interval and the value of tau which is larger than tau statistic. Hence, we fail to reject $H_0$, so as to the series are statistically non-stationary.

Furthermore, to convince the non-stationary data, Autocorrelation Function (ACF) graph depicted on Fig. 2 enables us to judge it. The picture suggests us the gradual decrease indicating statistically is non-stationary. In addition, the residuals are not normally distributed in all areas as Fig. 3 shows that there is a high deviation data compared to others.

**Differencing the series of ICBP stock prices:** The non-stationary data may not be financially effective to forecast the data set. The differencing then is conducted by transforming it into stationary data. Differencing with lag = 1 ($d = 1$) is run to have stationary and it can be visible from Fig. 4 showing the observations now are around zero.
Table 1: Test of ADF unit root

| Types      | Lags | Rho    | Pr<Rho | Tau    | Pr<Tau | f-values | Pr>F  |
|------------|------|--------|--------|--------|--------|----------|-------|
| Zero mean  | 3    | 2.8016 | 0.9981 | 2.8557 | 0.9991 |          |       |
| Single mean| 3    | 2.0617 | 0.9981 | 1.5511 | 0.9994 | 4.4180   | 0.0606|
| Trend      | 3    | -3.4252| 0.9179 | -1.1263| 0.9232 | 3.2181   | 0.5297|

Table 2: Test of ADF unit-root after differencing (d = 1)

| Types      | Lags | Rho    | Pr<Rho | Tau    | Pr<Tau | f-values | Pr>F  |
|------------|------|--------|--------|--------|--------|----------|-------|
| Zero mean  | 3    | -8373.22| 0.0001 | -38.41 | <0.0001|          |       |
| Single mean| 3    | -8518.07| 0.0001 | -38.52 | <0.0001| 742.00   | 0.0010|
| Trend      | 3    | -8637.90| 0.0001 | -38.61 | <0.0001| 745.41   | 0.0010|

The stationary data also is proved by the normal distribution graph on Fig. 5 that is currently diagnosed normally, since, the residuals are in all areas of observation.

The approval of the transformation of the stationarity also is observable on the autocorrelation analysis as depicted on Fig. 6. The ACF graph experiences a very strong decline that satisfies the observation as stationary data.

To make it more reliable data stationary, Table 2 justifies that the ADF unit-root test has a significant proof with p-value as well as tau-statistic of <0.0001, respectively.

From those confirmed evidences in stationarity shift, it, therefore, allows us to go further to conduct autocorrelation models and for the sake of this study is aiming to examine which AR (p) is the best model to fit with.

Test of ARCH effect: To make AR(p) as the best model, it is suggested that there should be no heteroscedasticity issue in the estimation of forecasted series data. The GARCH Model then can be a solver to cope with that concern but prior to conducting it ARCH-LM test is computed.

Table 3 confirms that the existence of heteroscedasticity is noticeable. The results of Q and LM tests from the past squared residuals show the significant p-value (p<0.0001) indicating H_0 is rejected. As the availability of ARCH effect, this means that GARCH (p, q) framework can be applied to forecast the volatility of ICBP share prices.

AR(p)-GARCH(p, q) Model: The finding of the best estimation model from the data analysis shown on Table 4 is that the mean model of AR(1) and the variance framework of GARCH(1, 1).

Thus, below is the presentation of the model estimation of AR(1)-GARCH(1, 1):
Mean model AR(1):

\[ ICBP_t = 387.4519 - 1.0006 ICBP_{t-1} + \epsilon_t \]

Variance model GARCH(1, 1):

\[ \sigma_t^2 = 2219 + 1.839 \epsilon_{t-1}^2 + 0.0438 \sigma_{t-1}^2 \]

The estimation model of AR(1) can be interpreted that holding all other variables constant ICBP, is estimated of 387.4519 averagely while a 1 unit increase of ICBP, would effect on the decrease of ICBP, by 1.0006 on average if other is constant.

In addition to Table 4 and 5 presents the data analysis from computing AR(1)-GARCH(1, 1) in which the model explains 99% of the variable given the \( R^2 \) 0.9994. The RMSE, on the other hand is 71.108 indicating very far number comparable to share-price prediction (PoSP) in Table 6. This comparison makes it clear that the model estimation is well-predicted. Furthermore, it is supported by the significantly small MAPE of 1.710 that enables the model accurately forecasting the variable.

Figure 7 supports Table 6 where it shows the gradual incline of the ICBP share prices in the upcoming 60 days.
Table 4: Estimation parameter model of AR(1)-GARCH(1, 1)

| Variable | df | Estimate  | SE        | t-values | Approximately Pr>|t| |
|----------|----|-----------|-----------|---------|-----------------|
| Intercept| 1  | 387.4519  | 82.512000 | 4.70    | <0.0001         |
| AR1      | 1  | -1.0006   | 0.0000708 | 14135   | <0.0001         |
| ARCH0    | 1  | 42.013300 | 52.82     | 0.063400| 28.99           |
| ARCH1    | 1  | 1.8390    | 0.3288    | 13.32   | <0.0001         |
| GARCH1   | 1  | 0.4348    | 0.032880  | 13.32   | <0.0001         |

Table 5: GARCH estimates for ICBP

| Fit statistic | Mean |
|---------------|------|
| R2            | 0.999|
| RMSE          | 71.108|
| MAPE          | 1.710|
| Max APE       | 18.809|
| Max AE        | 36.890|
| Normalized BIC| 681.935|

Table 6: Forecasts for variable ICBP (the next two months)

| Observations | PoSP  | SE       | Confidence limits (95%) | Observations | PoSP  | SE       | Confidence limits (95%) |
|--------------|-------|----------|-------------------------|--------------|-------|----------|-------------------------|
| 4579         | 10298.9 | 71.2817 | 10195.2 10438.7 | 4609 | 10369.0 | 383.202 9617.97 11120.1 |
| 4580         | 10309.9 | 98.6391 | 10116.6 10503.2 | 4610 | 10371.3 | 389.319 9608.29 11134.4 |
| 4581         | 10310.5 | 120.494 | 10068.3 10540.6 | 4611 | 10373.4 | 395.345 9598.55 11148.3 |

However, although, it relies on the risk preference of the investors, it is noticeably seen from the graph that the increase trend is also followed by the wider risk. If only the investors are risk taker in the short-term duration then it is highly recommend to take buy action on ICBP share price but for those who have a long-term horizon in investment it is should be suggested to deal with other factors that affect the volatility of ICBP risks.

CONCLUSION

The model estimation of AR(p)-GARCH(p, q) is considerably used in this study as a tool to predict the share price of ICBP as the most market capitalization company in miscellaneous sector at JII. The series data is initially not stationary so to transform the stationarity, the process of differencing with lag = 1 (d = 1) is computed and the data then switch to stationary.

The test of ARCH-LM is computed to measure heteroscedasticity issue (ARCH Effect) prior to model the estimation of AR(p)-GARCH(p, q). The result of the test indicates that it has ARCH effect, so, the next step in modeling the series data might be conducted.

The AR(1)-GARCH(1, 1) is the fit model in this study as having a significant R-square of 99%. Ability of the model for prediction the share price is also quite good.

The test of ARCH-LM is computed to measure heteroscedasticity issue (ARCH Effect) prior to model the estimation of AR(p)-GARCH(p, q). The result of the test indicates that it has ARCH effect, so, the next step in modeling the series data might be conducted.
significant with the RMSE 71.3442. Therefore, the model is applicable for forecasting the ICBP share price for the next 2 months.

ACKNOWLEDGEMENT

The researcher would like to thank JII Jakarta for providing the data in this study. The authors would also like to thank Universitas Lampung for financially supporting this study through scheme research professor under contract No: 2835/UN26.21/PN/2019.

REFERENCES

Beaver, W., R. Lambert and D. Morse, 1980. The information content of security prices. J. Account. Econ., 2: 3-28.
Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. J. Econ., 31: 307-327.
Brockwell, P.J. and R.A. Davis, 2002. Introduction to Time Series and Forecasting. 8th Edn., Springer, Berlin, ISBN: 978-0-387-95351-9, Pages: 469.
Chan, K. and W.M. Fong, 2000. Trade size, order imbalance and the volatility-volume relation. J. Financial Econ., 57: 247-273.
Charles, A., 2008. Forecasting volatility with outliers in GARCH models. J. Forecasting, 27: 551-565.
Engle, R.F., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50: 987-1007.
Fuess, R., D.G. Kaiser and Z. Adams, 2007. Value at risk, GARCH modelling and the forecasting of hedge fund return volatility. J. Derivatives Hedge Funds, 13: 2-25.
Hull, J.C., 2015. Risk Management and Financial Institutions. 4th Edn., John Wiley & Sons, Hoboken, New Jersey, USA., ISBN: 9781118955956, Pages: 752.
Kristjanpoller, W. and M.C. Minutolo, 2015. Gold price volatility: A forecasting approach using the artificial neural network-GARCH model. Expert Syst. Appl., 42: 7245-7251.
Lundholm, R.J. and R. Rogo, 2015. Do analyst forecasts vary too much?. J. Financial Reporting, 1: 101-123.
Tsay, R.S., 2005. Analysis of Financial Time Series. 2nd Edn., Wiley-Interscience, New York.
Virginia, E., J. Ginting and F.A. Elfaki, 2018. Application of GARCH model to forecast data and volatility of share price of energy (Study on Adaro Energy Tbk, LQ45). Int. J. Energy Econ. Policy, 8: 131-140.
Warsono, W., E. Russel, W. Wamiliana, W. Widiarti and M. Usman, 2019a. 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). Int. J. Energy Econ. Policy, 9: 240-247.
Warsono, W., E. Russels, W. Wamiliana, W. Widiarti and M. Usman, 2019b. Vector autoregressive with exogenous variable model and its application in modeling and forecasting energy data: Case study of PTBA and HRUM energy. Int. J. Energy Econ. Policy, 9: 390-398.