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Dynamic Model of Forecasting Stock Prices

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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

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Augmented Dicky Fuller (ADF) test which can be described mathematically as follows (Warsono *et al*., 2019a, b):

$$ICBP_t = \mu + \delta_1 ICBP_{t-1} + \sum_{k=1}^{p-1} \delta_k \Delta ICBP_{t-1} + \varepsilon_t \quad (1)$$

With the hypothesis:

- $H_0 = \delta_1 = 0$ (Non stationary)
- $H_1 = \delta_2 < 1$ (Stationary)

In addition, the unit-root ADF test:

$$\tau = \frac{\delta_i}{Se_{\delta_1}} \quad (2)$$

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:

$$r_n \sim N\left(0, \frac{1}{T}\right) \quad (3)$$

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:

$$X = \frac{r_n}{\sqrt{1/T}} = r_n \sqrt{T} \quad (4)$$

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:

$$ICBP_t = \beta + \vartheta_1 ICBP_{t-1} + \vartheta_2 ICBP_{t-2} + \vartheta_3 ICBP_{t-3} + \ldots + \vartheta_p ICBP_{t-p} + \varepsilon_t \quad (5)$$

MA (q):

$$ICBP_t = \mu + \varepsilon_t - \varphi_1 \varepsilon_{t-1} + \varphi_2 \varepsilon_{t-2} + \varphi_3 \varepsilon_{t-3} + \ldots + \varphi_q \varepsilon_{t-q};\ \varepsilon_t \sim N(0, \sigma^2) \quad (6)$$

Equation 5 and 6 is combined into:

$$\begin{aligned} ICBP_t &= \beta + \vartheta_1 ICBP_{t-1} + \vartheta_2 ICBP_{t-2} + \\ &\vartheta_3 ICBP_{t-3} + \ldots + \vartheta_p ICBP_{t-p} + \varepsilon_t - \varphi_1 \varepsilon_{t-1} + \\ &\varphi_2 \varepsilon_{t-2} + \varphi_3 \varepsilon_{t-3} + \ldots + \varphi_q \varepsilon_{t-q} = \beta + \sum_{i=1}^{p} \Phi_i IE_{t-i} + \varepsilon_t - \sum_{k=1}^{q} \lambda_k \varepsilon_{t-1} \end{aligned} \quad (7)$$

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:

$$\sigma_t^2 = \theta_0 + \theta_1 \varepsilon_{t-1}^2 + \theta_2 \varepsilon_{t-2}^2 + \theta_3 \varepsilon_{t-3}^2 + \ldots + \theta_q \varepsilon_{t-q}^2$$

- Test the hypothesis:

H_0: $\theta_1 = \theta_2 = , \ldots , = \theta_q = 0$
H_1: 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:

$$\sigma_t^2 = \alpha + \sum_{i=1}^{q} x_i \varepsilon_{t-i}^2 + \sum_{k=1}^{p} g_j \varepsilon_{t-j}^2 \quad (8)$$

Hence, Eq. 8 presents the GARCH Model:

$$\begin{aligned} ICBP_t &= \beta + \sum_{i=1}^{p} \vartheta_i ICBP_{t-i} + \varepsilon_t - \sum_{n=1}^{q} \varphi_n \varepsilon_{t-i} \\ \sigma_t^2 &= \alpha + \sum_{i=1}^{q} x_i \varepsilon_{t-i}^2 + \sum_{n=1}^{p} g_j \varepsilon_{t-j}^2 \end{aligned} \quad (9)$$

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

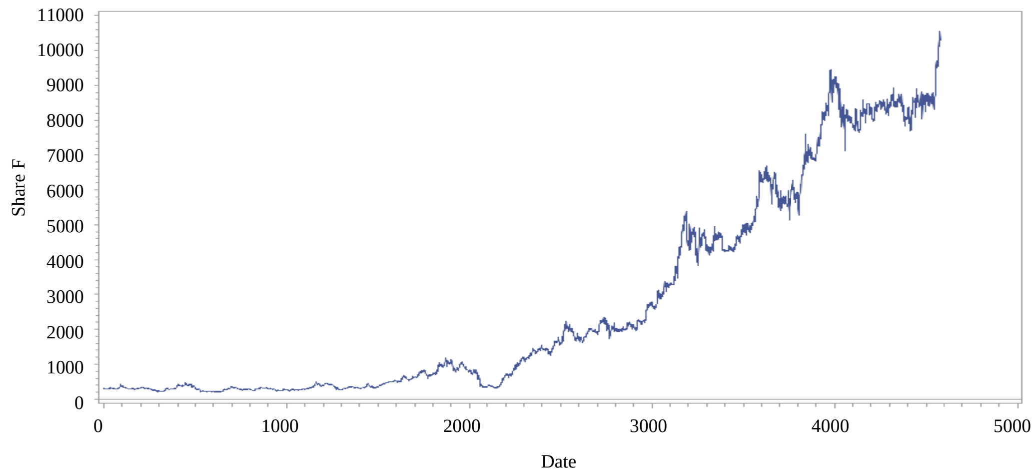

Fig. 1: Daily stock prices of ICBP 2000-2018

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

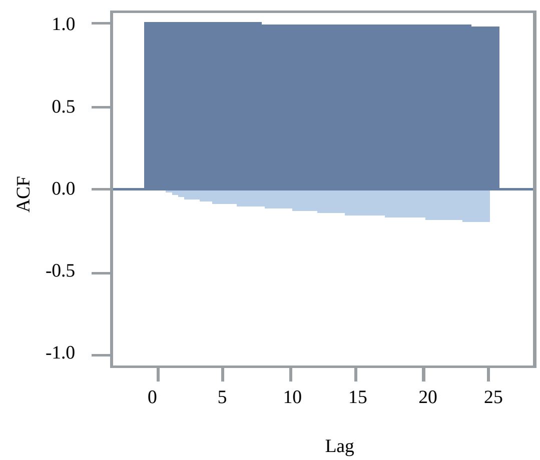

Fig. 2: ACF of ICBP data

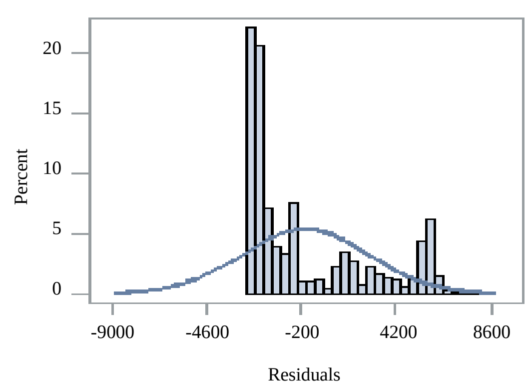

Fig. 3: Normal distribution of ICBP data

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

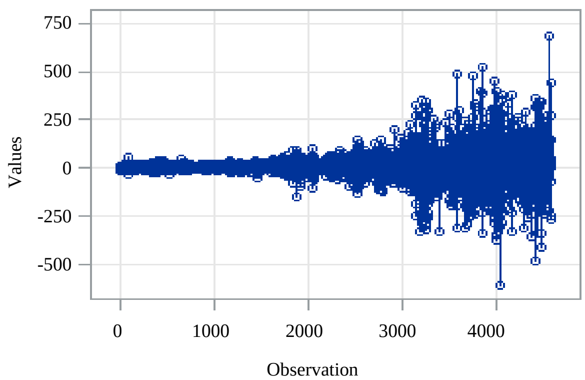

Fig. 4: Residuals plotting after differencing with d = 1 for ICBP

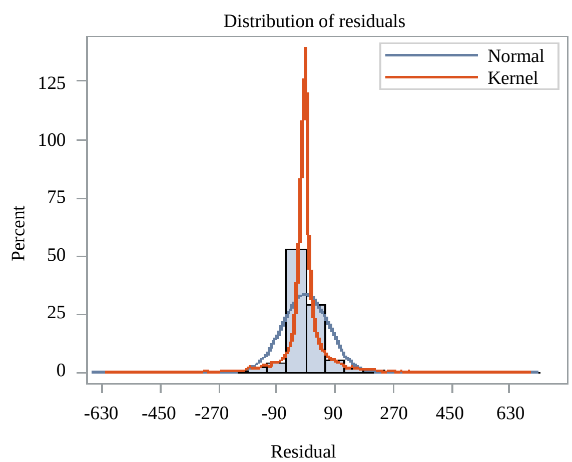

Fig. 5: Residual normality diagnostics of ICBP after differencing (d = 1)

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.

Table 3: Tests for ARCH-LM disturbances

Order	Q	Pr>Q	LM	Pr>LM
1	4497.8818	<0.0001	4480.5342	<0.0001
2	8902.0297	<0.0001	4481.2368	<0.0001
3	13215.0354	<0.0001	4481.5764	<0.0001
4	17472.5527	<0.0001	4482.8544	<0.0001
5	21668.4032	<0.0001	4482.9660	<0.0001
6	25806.7436	<0.0001	4483.1159	<0.0001
7	29879.5676	<0.0001	4483.1840	<0.0001
8	33893.2486	<0.0001	4483.2499	<0.0001
9	37855.7390	<0.0001	4483.2499	<0.0001
10	41765.2393	<0.0001	4483.4235	<0.0001
11	45622.0008	<0.0001	4483.4284	<0.0001
12	49425.8450	<0.0001	4483.4509	<0.0001

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_o 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):

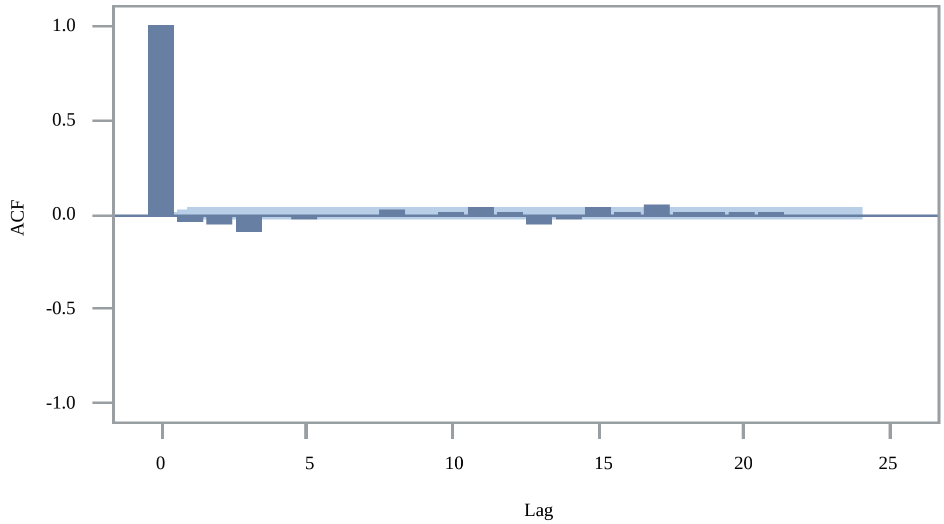

Fig. 6: ACF plotting of ICBP after differencing (d = 1)

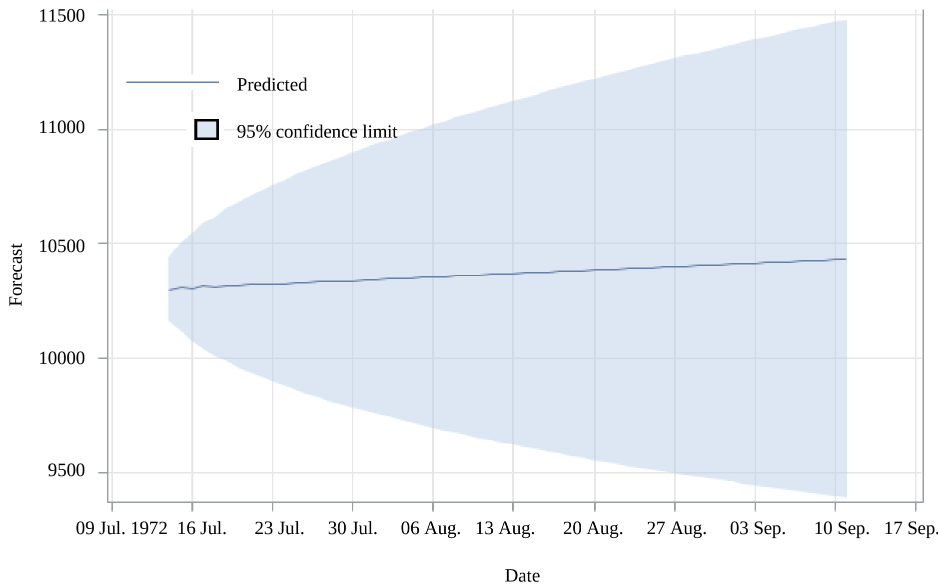

Fig. 7: Forecasting of ICBP share price for the next 60 days

- Mean model AR(1):

$$ICBP_t = 387.4519\text{-}1.0006ICBP_{t\text{-}1}+\varepsilon_t$$

- Variance model GARCH(1, 1):

$$\sigma_t^2 = 2219+1.839\varepsilon_{t-1}^2+0.0438\sigma_{t-1}^2$$

The estimation model of AR(1) can be interpreted that holding all other variables constant $ICBP_t$ is estimated of 387.4519 averagely while a 1 unit increase of $ICBP_{t\text{-}1}$ would effect on the decrease of $ICBP_t$ 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	00.0000708	-14135	<0.0001
ARCH0	1	2219	42.0133000	52.82	<0.0001
ARCH1	1	1.8390	0.0634000	28.99	<0.0001
GARCH1	1	0.0438	0.0032880	13.32	<0.0001

Table 5: GARCH estimates for ICBP

Fit statistic	Mean
R^2	0.999
RMSE	71.108
MAPE	1.710
Max APE	18.809
MAE	36.890
Max AE	681.935
Normalized BIC	8.534

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

			Confidence limits (95%)					Confidence limits (95%)	
Observations	PoSP	SE	------------------------------		Observations	PoSP	SE	------------------------------	
4579	10298.9	71.2817	10159.2	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	10304.5	120.494	10068.3	10540.6	4611	10373.4	395.345	9598.55	11148.3
4582	10313.3	138.536	10041.7	10584.8	4612	10375.7	401.277	9589.21	11162.2
4583	10309.7	154.809	10006.3	10613.1	4613	10377.8	407.125	9579.84	11175.7
4584	10316.9	169.270	9985.11	10648.6	4614	10380.0	412.889	9570.8.0	11189.3
4585	10314.7	182.796	9956.43	10673.0	4615	10382.2	418.575	9561.78	11202.6
4586	10320.7	195.22	9938.05	10703.3	4616	10384.4	424.183	9553.02	11215.8
4587	10319.6	207.037	9913.78	10725.4	4617	10386.5	429.719	9544.3.0	11228.8
4588	10324.6	218.101	9897.13	10752.1	4618	10388.8	435.184	9535.82	11241.7
4589	10324.3	228.725	9876.01	10772.6	4619	10390.9	440.582	9527.38	11254.4
4590	10328.6	238.798	9860.61	10796.7	4620	10393.1	445.913	9519.15	11267.1
4591	10329.0	248.529	9841.85	10816.1	4621	10395.3	451.183	9510.98	11279.6
4592	10332.8	257.837	9827.41	10838.1	4622	10397.5	456.391	9502.97	11292.0
4593	10333.5	266.868	9810.48	10856.6	4623	10399.6	461.541	9495.04	11304.2
4594	10336.9	275.564	9796.85	10877.0	4624	10401.8	466.633	9487.26	11316.4
4595	10338.1	284.026	9781.37	10894.7	4625	10404.0	471.671	9479.55	11328.5
4596	10341.2	292.216	9768.43	10913.9	4626	10406.2	476.655	9471.98	11340.4
4597	10342.5	300.206	9754.15	10930.9	4627	10408.4	481.588	9464.48	11352.3
4598	10345.4	307.969	9741.82	10949.0	4628	10410.6	486.471	9457.11	11364.0
4599	10347.0	315.558	9728.52	10965.5	4629	10412.7	491.305	9449.80	11375.7
4600	10349.7	322.954	9716.73	10982.7	4630	10414.9	496.092	9442.61	11387.3
4601	10351.4	330.197	9704.26	10998.6	4631	10417.1	500.834	9435.49	11398.7
4602	10354.0	337.274	9692.97	11015.1	4632	10419.3	505.531	9428.48	11410.1
4603	10355.8	344.214	9681.20	11030.5	4633	10421.5	510.185	9421.53	11421.4
4604	10358.3	351.010	9670.37	11046.3	4634	10423.7	514.796	9414.68	11432.6
4605	10360.3	357.682	9659.21	11061.3	4635	10425.8	519.367	9407.90	11443.8
4606	10362.7	364.228	9648.79	11076.5	4636	10428.0	523.898	9401.20	11454.8
4607	10364.6	370.662	9638.16	11091.1	4637	10430.2	528.39	9394.58	11465.8
4608	10367.0	376.982	9628.13	11105.9	4638	10432.4	532.844	9388.03	11476.7

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 if 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 significant with the RMSE 71.3442. Therefore, the model is applicable for forecasting the ICBP share price for the next 2 months.

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