Forecasting Model for State-Owned Bank Stock Prices During Pandemic: GARCH Model Application

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Abstract. Since Covid-19 was announced as pandemic by Indonesian authorities, it had many negative effects, more particularly on banking sector. The aim of this study is to measure the impacts of Covid-19 on Bank Negara Indonesia stock prices and to find the best-fit model to forecast its daily stock prices for the next 30 days. The application of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model was applied to measure the residual of mean and variance. The finding is to apply AR(1)-GARCH(1,1) model to forecast the future stock prices as the R-square of the model is more than 98%, indicating more accuracy. The forecast shows gradual increase of stock prices indicating that economic growth tends to come out from recession gradually.

Keywords: Covid-19 Pandemic, Banking Sector, GARCH Model, Forecasting.

1 Introduction

Corona Virus 2019 (Covid-19) was spread globally in late 2019, and it started affecting Indonesia officially announced by authority in March 2020. Since then, many Indonesians have suffered to survive, as many aspects of life have been restricted such as economic activities have not been run as usual. [1] argued in his empirical study that the pandemic has caused slowing down the financial economics and so does economic growth around the world. Moreover, International Monetary Fund (IMF) in 2020 stated that the pandemic caused worse economic crisis than what happened in 2008. Indonesia composite index (IHSG) was also significantly dropped, of which it touched its lowest level of Rp3,911.71 for the first time. The Financial Authority Service (OJK) and Indonesia Stock Exchange (IDX) issued some policies to stabilize market condition by reducing the trading hour of 1.5 hour since 30th March 2020 and by loosening the investors to buy back without approval from General Meeting of Stockholders, and by implementing a policy of pausing trading for 30 minutes in case of a 5% decline in intraday trading.

Furthermore, [2] found the pandemic caused global banking sector having detrimental impacts, such as default risk, liquidity risk and asset risk. The negative impacts as global pandemic occurred in Chinese's banking particularly are included in short term, long term, and systemic risks [3]. They suggested that credit supports from Chinese government is highly essential to prevent from high economic recession, such as interest rate deduction, and digital transformation. Meanwhile, Indonesian banking is also threatened to have some risks since the

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Covid 19 pandemic, including default risk in Medium and Small Enterprises (UMKM) sector that might not enable to repay their obligation, market risk as weakening exchange rate, and liquidity risk as debitters experiencing some difficulties in their business and income [4]. As risk increasing, stock prices drop [5].

Bank Negara Indonesia (code: BBNI) is one of state-owned banks in Indonesia that also suffers from the negative impacts during the pandemic. It was reflected on their semi-annual financial report in Semester 1 2020, which showed a significant loss in a year-to-year basis. [6] found that BBNI had the most significant drop in earning, in which it suffered a loss of 41.54% compared with that in Semester 1 2019. This decreased earning is believed to decrease in BBNI stock prices as evidently showing in their financial report. Thereby, the volatility in price movement in stocks is essential to measure market risk in accordance to provide more insight for investors [7].

To some extent, volatility is the statistical measurement of the return distribution on a provided security that can be evaluated by implementing standard deviation among returns [8]. Of which, [9] introduced Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model to measure the high volatility. The model has been widely used in various economic aspects to have its forecasting data. A model of AR(4)-GARCH(1,1) is applied to forecast volatility stock prices in Indika Energy (INDI) [10]. Besides, the model also is applied to predict the prices of some commodities, for example [11] estimated the future prices of future natural gas (FNG); [12] measured the forecasted daily oil prices by modelling GARCH (1,1).

Therefore, the study is to measure the future daily prices of BBNI stocks as the Covid-19 outbreak occurred in 2020 by implementing the application of GARCH model.

2 Methodology and Data Analysis

2.1 Transformation of Stationary Data

The first stage before modelling GARCH is to ensure the data set is in stationary. To do so, it can be done first by visually checking the data plot; second by statistically testing Augmented Dickey-Fuller (ADF Test); and third by computing autocorrelation function (ACF) and the partial autocorrelation (PACF). In ADF test, [13] proposed the equation statistically to check stationary data, which is as follows.

$$DF_{\tau} = \frac{\gamma_i}{\widehat{Se}_{\gamma_1}} \tag{1}$$

The hypothesis is defined as.

H0 : 〖DF〗_τ > 2.57 = non-stationary

H0 : 〖DF〗_τ < 2.57 = stationary

However, Gunarto et al. (2020) stated that in financial data series stationary data set are not found both in mean and variance, so they suggested to apply differencing method.

2.2 Differencing Method

It was [14] offered the transformation tool to change the non-stationary data set into stationary by differencing data set to stabilize the mean and volatility.

$$a(B) = (1-B)^{d} \tag{2}$$

where B is defined as backward operator; d is the number of differencing; and a(B) is the integrating filter of order d. [15] explained by implementing differencing method and the data set has been stationary, then GARCH model can be applied.

2.3 ARCH-effect Test

Heteroscedasticity in financial data set has been an issue in modelling time series data [16] or having an Autoregressive Conditional Heteroscedasticity (ARCH) effect, of which can make parameter estimate for forecasting model inaccurate. ARCH effect can be measured by examining Lagrange Multiplier (LM) test [17], and the order of ARCH can be determined by applying the Portmanteau test [18]. When LM test has a probability of 0.5, the model involves heteroscedasticity. Thereby to generalise it, GARCH(p,q) model can be applied [15].

2.4 AR(p)-GARCH(p,q) Model

The model can be equated as follows.

$$BBNI_t = \alpha + \sum_{i=1}^{p} \vartheta_i BBNI_{t-i} + \varepsilon_t \tag{4}$$

$$\sigma_t^2 = \beta + \sum_{i=1}^{q} \gamma_i \epsilon^2{}_{t-i} + \sum_{j=1}^{p} \vartheta_j BBNI_{t-j} \tag{5}$$

This model combines the m^{th}-order autoregressive error model with the GARCH (p,q) variance model, which is denoted as the AR (m) - GARCH (p,q) regression model.

3 Results and Discussion

In this study, we observed daily data of stock prices from Bank Negara Indonesia (BBNI) in 2020. There are 242 data collection during the study period and to be analysed to obtain the fitted model for its daily forecasting. The graph below shows the plot for BBNI stock prices.

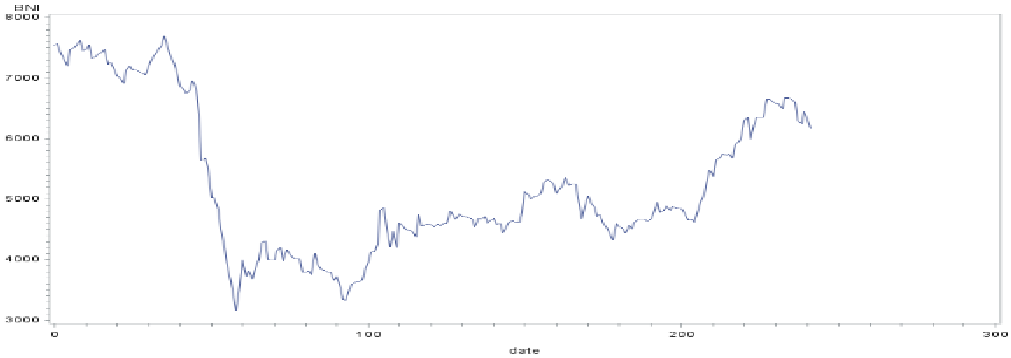

Fig. 1. Distribution of the Daily Stock Prices for Bank Negara Indonesia

Generally, Figure 1 shows that the daily stock prices of BBNI during the study period have fluctuated. The fluctuation was quite normal in early 2020, but after Indonesian government officially announced pandemic in March 2020, BBNI stock price dropped significantly at the lowest level. Afterwards, the movement of BBNI stock price was in upward trend, although it was not that high. It was because authorities have implemented the "new normal" policy that encourage the economic growth. However, the graph shows as non-stationary because mean and variance are not at around zero. In addition, statistically this visual measurement can be proven by applying ADF test as follows.

Table 1. Augmented Dickey–Fuller (ADF) test for BBNI Stock Prices

Bank Code	Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
BBNI	Zero Mean	3	-0.4072	0.5899	-0.6734	0.4249		
	Single Mean	3	-4.7006	0.4618	-1.7011	0.4294	1.4931	0.6903
	Trend	3	-3.7265	0.9008	-1.3976	0.8592	2.2395	0.7301

Table 1 shows the probability from ADF test in BBNI stock prices is more than 0.5, so we do not reject null hypothesis, or the data set is statistically non-stationary in mean and variance. This measurement also is supported by the examining ACF and PACF graphs as follows.

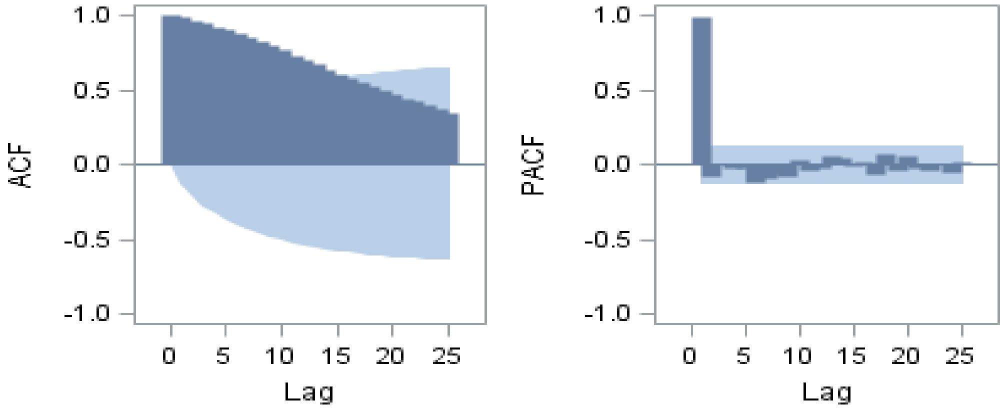

Fig.2. ACF and PACF graphs for Bank Negara Indonesia

Figure 2 presents the slow movement in ACF indicating after lag 1 the data set distributions are not at around zero or non-stationary data set. In addition, the data sets on the PACF graph at lag 1 are also not at around zero which assigns time series as non-stationary data set.

3.1 Stationary Data

As data sets are non-stationary, the next stage is to transform it into stationary data by employing the differencing method. Table 2 shows ADF test after differencing lag 1 (d = 1) was conducted.

Table 2. ADF test for BBNI after differencing 1 (d = 1)

Bank Code	Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
BBNI	Zero Mean	3	-137.438	0.0001	-6.57	<.0001		
	Single Mean	3	-138.101	0.0001	-6.56	<.0001	21.51	0.0010
	Trend	3	-156.960	0.0001	-6.76	<.0001	22.91	0.0010

Table 2 indicates data set has been stationary in mean and variance once differencing lag 1 (d=1) conducted, where its probability is significant of 0.001. Figure 2 verifies this transformation. The distribution of residual in ACF graph shows is at around zero in mean and variance, while PACF graph has a delay movement.

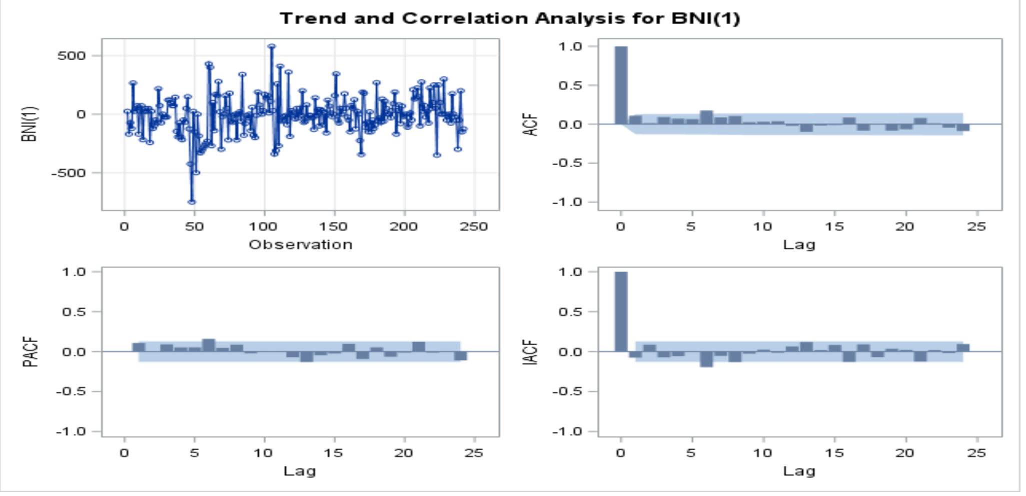

Fig. 3. Trend and correlation analysis graphs for BBNI

3.2 ARCH Effect Identification

Before modelling data set, heteroscedasticity issue should be solved by checking the involvement of ARCH effect. Table 3 measures Portmanteau Q and LM test that have probability value of <0.0001. Therefore, to generalize heteroscedasticity problem GARCH(p,q) model can be applied.

Table 3. Tests for ARCH disturbances based on residuals for BBNI

Order	Q	Pr > Q	LM	Pr > LM
1	249.215	<.0001	215.266	<.0001
2	469.538	<.0001	215.673	<.0001
3	665.988	<.0001	215.774	<.0001
4	840.811	<.0001	215.794	<.0001
5	998.464	<.0001	215.89	<.0001
6	1136.97	<.0001	216.325	<.0001
7	1255.85	<.0001	216.375	<.0001
8	1356.44	<.0001	216.453	<.0001
9	1441.9	<.0001	216.455	<.0001
10	1517.44	<.0001	216.626	<.0001
11	1584.63	<.0001	216.631	<.0001
12	1645.36	<.0001	216.659	<.0001

3.3 GARCH Model

Conditional heteroscedasticity is crucial to have a good-fit forecasting model. The AR(p)-GARCH(p,q) model allows to do so, where AR(p) is conditional to have a mean model and GARCH(p,q) is to have a model of variances and squared residuals for BBNI data set.

Table 4. Estimation of the parameters of AR(1)-GARCH(1,1) for BBNI

Variable	DF	Estimate	Standard Error	t Value	Approx. Pr > |t|
Intercept	1	6395	791.5428	8.08	<.0001
AR1	1	-0.9958	0.00588	-169.3	<.0001
ARCH0	1	4209	2085	2.02	0.0435
ARCH1	1	0.1751	0.0476	3.68	0.0002
GARCH1	1	0.6575	0.1152	5.71	<.0001

Table 5. Statistic Description for AR(1)-GARCH(1,1) model

SSE	6297864.61	**Observations**	242
MSE	26024	**Uncond Var**	25147.2474
Log Likelihood	-1557.1677	**Total R-Square**	0.9825
SBC	3141.78008	**AIC**	3124.33539
MAE	115.602233	**AICC**	3124.58963
MAPE	2.36031843	**HQC**	3131.36274
		Normality Test	24.0827
		Pr > ChiSq	<.0001

The model of AR(1)-GARCH(1,1) model is equated as follows.

Mean model of AR (1): $BBNI_t = 6395 – 0.9958\ BBNI_{t-1}$

Variance model of GARCH (1,1): $\sigma_t^2 = 4209 + 0.1751\varepsilon^2{}_{t-1} + 0.6575\sigma_{t-1}^2$

The equation models statistically fit the data set, as in Table 5 total R-square is 98.25%, indicating a strong explanation for the forecasting model. Further, the disturbances of conditional variance are constant because from the Table 4 it can be noticed that the sum of ARCH and GARCH coefficients is approaching one. Therefore, the model is confidently to forecast the daily stock prices of BBNI as follows.

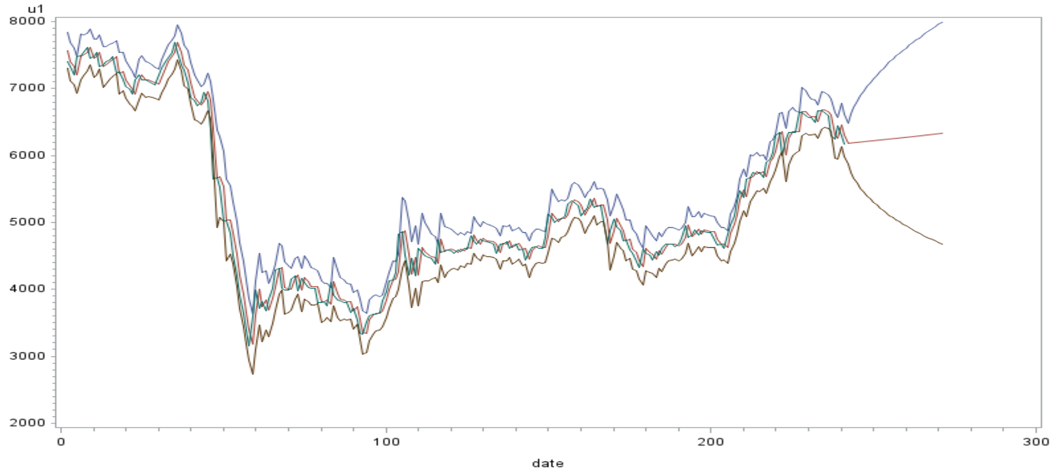

Fig. 4. Predicted Data of BBNI Stock Prices for 30 Days

From the model, the expected estimation in the next 30 days of BBNI shows a gradual increase, as shown in Figure 4. This is believed as the authorities have been struggling to stabilize economic condition, such as providing assistance to business actors, providing tax incentives, relaxing and restructuring loans, expanding working capital financing, product support, and e-learning training [19]. Globally, [3] argued that the gradual increase in any sector during pandemic is to support MSEs by facilitating them with special credit lines, interest rate reduction on loans, deferred repayments, and digital transformation. When MSEs are excited again with various program support from the government, indirectly the role of banks in intermediation can be more stretched and result in better growth for the financial sector.

4 Conclusion

In our final section, the study that has been completed describes the performance of the econometric model in forecasting daily stock price for BBNI. Our study found an econometric model that can be used in designing BBNI's future stock prices. AR(1)-GARCH(1,1) came out as the best. This model shows excellence with very applicable evidence in forecasting the future of BBNI. In more detail, we found that the stock prices of BBNI show a gradual performance but is not significant. Therefore, as an economic driver in Indonesia, BBNI should take a proper supporter for government to stabilize Indonesian economy.

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