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Risk Measurement and Stock Prices during the COVID-19 Pandemic: An Empirical Study of State-Owned Banks in Indonesia*

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Abstract

The current COVID-19 pandemic has changed the way people live their lives around the world. More than a decade after the global financial crisis, the world is struggling with the health and economic effects of a profound new crisis caused by the COVID-19 pandemic. It also affected the Indonesian stock market in almost every sector. Besides, the performance of the stock market of financial industries has also been significantly affected, particularly four state-owned banks. This study aimed to analyze the potential loss from investing in the stock market of such government banks for the next 15 days by revisiting value at risk (VaR) as a tool for measuring the maximum loss. The findings suggest that Autoregressive AR (1)-GARCH (1) is a good fit for the determination of the mean and variance model, which were used to calculate the VaR of each bank. VaR measurement for all banks shows a negative sign that indicates the maximum loss of investors from holding any of those banks' stocks for a projected time horizon. Risk measurement will be one of the things that will be considered by investors when investing in the financial market. The results of the study suggest that investors who have funds in state-owned banks should reconsider their investments.

Keywords: Value at Risk, COVID-19, GARCH Model, Investment, Risk Management

JEL Classification Code: C58, G21, G32

1. Introduction

Since early 2020, COVID-19 has been widely spreading around the globe. It has caused people to suffer in many aspects of life. Besides, it forced people to stop performing their activities normally. Amidst the recovery and containment, the world economic system is characterized as experiencing significant, broad uncertainty. Economic forecasts and consensus among macroeconomics experts show significant disagreement on the overall extent, long-term effects, and projected recovery (Khan et al., 2020). Hanoatubun (2020) found that this pandemic made it difficult for Indonesians to obtain their basic needs; it also reduced their consumption, thus decreasing economic growth. Consequently, governments worldwide have attempted to change the way people live by strongly urging them to stay at home to stop the spread of the virus. This policy has also been implemented in Indonesia being one of the countries greatly affected by the virus, especially in the area of banking.

The big four state-owned banks listed on the Indonesia Stock Exchange (IDX) are Bank Rakyat Indonesia (BBRI), Bank Negara Indonesia (BBNI), Bank Mandiri (BMRI) and Bank Tabungan Negara (BBTN). Together, they account for 43% of the total assets of all banks in Indonesia (Otoritas Jasa Keuangan, 2020). They also suffered as the pandemic was announced by the World Health Organization (WHO). This condition has been reflected in their respective semi-annual financial report. In Semester 1 2020, all four banks recorded a significant loss on a year-to-year basis. BBNI had the most significant drop in earning; it suffered a loss

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of 41.54% compared with that in Semester 1 2019, followed by BBTN, whose net profit significantly decreased by 40%. Furthermore, BBRI as the most capitalized state-owned bank included in the IDX also experienced a net profit loss of 36.88%. BMRI also recorded a decrease in earnings of 23.94%, which was similar to that in Semester 1 2019. In the credit measurement, the non-performing loan (NPL) increased to more than 3% for the state-owned banks, except for BBTN, whose NPL decreased from 2.42% to 2.40% in June 2020. Although the ratio is still at a normal rate, it indicates that the shocks might affect the lack of ability of creditors to repay their debts.

Investors might perceive this phenomenon as an investment risk, as the shock is likely to influence their returns either positively or negatively at a specific case when investing in financial sectors. Investment risk can be defined as the probability or likelihood of occurrence of losses relative to the expected return on any particular investment. Some studies have proven that financial data is highly volatile as market uncertainty is quite high (Hendrawaty et al., 2021). Therefore, the measurement of investment risk is important to minimize the loss (Rahman et al., 2020) risk, and cost-inefficiency for a sample of 30 commercial banks in Bangladesh from 2006 to 2018. To conduct the analysis, we used the Generalized Methods of Moments (GMM. Value at Risk (VaR) a statistical tool to measure and quantify financial risk within a firm or portfolio over a specific time frame. This metric is often used by Banks to determine the extent and probability of occurrence of a potential loss on the advances.

To some extent, in the measurement of market risk, Emenogu et al. (2020) defined volatility as the statistical measurement of the return distribution on a provided security that can be evaluated by using standard deviation or variance among the returns. In this case, the application of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) statistically provides a more accurate model of variance. Bollerslev (1986) first introduced the GARCH model to avoid the high order of autoregressive conditional heteroscedasticity (ARCH), which was previously available to model variance (Engle, 1982).

Akhmadi et al. (2019) estimated VaR using the extreme value theory (EVT) and generalized Pareto distribution (GPD) for state-owned bank enterprises in Indonesia after the occurrence of the global financial crisis (GFC) in 2008. They suggested that the GPD method outperforms the EVT and is very close to the banks' capital adequacy ratio (CAR); moreover, the two methods have a higher value compared with the other methods. Meanwhile, for extreme data in the financial sector, the empirical study conducted by Budiarti (2019) demonstrated that the AR-GARCH-copula Tawn approach is the best fit for modeling the joint distribution of a portfolio that can be used as the basis for the calculation of the VaR in extreme cases. Vo et al. (2019) return and portfolio diversification at the industry level in four member countries of the ASEAN for which required data are available: Vietnam, Thailand, Malaysia, and Singapore. Market indices are examined for 10 industries from 2007 to 2016, comprising different economic periods, including 2007–2009 (crisis used conditional value at risk (CVaR) to measure extreme risk. Markowitz's risk-return framework is utilized to determine the optimal weight of industries in the portfolio.

Furthermore, some previous studies have employed the econometric model of GARCH to estimate the volatility of variance to calculate the percentage of the maximum loss from the return of the given portfolio. In Indonesia, Sitorus (2018) stated that one consideration for investors to make an investment decision in stock instruments by monitoring the daily volatility movement and the trend. From the risk perspective, measuring the maximum probability of risk level in the future can be a consideration in making stock investment decisions that have the same movements and characteristics. Risk projection based on historical data with a certain time period can be calculated with Value at Risk (VaR) with a certain level of confidence. Thus the investment decision will be optimal. The Value at Risk model will calculate the expected losses. This research will show that volatility that looks the same but has a different level of risk. Mutia et al. (2018) used the ARMA-GARCH model to determine the VaR of the portfolio of combined stock prices from five companies included in the IDX. She noticed that BBNI has the riskiest assets in the portfolio. Conversely, Sukono et al. (2019) used the ARMA-FIGARCH model to measure the VaR of some IDX stocks and found that BBRI has the highest VaR compared with the other companies included in the sample. Furthermore, in the study conducted by Denkowska and Wanat (2020), the C-DCC-GARCH model was used to measure conditional variances to determine the systematic risks of European insurances during the crisis in 2020, while Le and Tran (2021) used that model to measure the effects of US stock market on both Vietnamese and Philippines Stock Markets.

Therefore, this study aims to measure the risk returns by computing the respective VaRs of the daily stock price of state-owned banks in Indonesia. The GARCH model was used to estimate the parameters of means and variances during the economic shock period.

2. Research Methods

In this study, the daily stock prices of state-owned banks in Indonesia from the COVID-19 pandemic in early 2020 until the fourth quarter of 2020 were observed. Prior to computing the risk-return using the VaR, the return volatility of each bank was measured using the GARCH model to obtain a more accurate measurement in the ES approach. The stages of the GARCH model are as follows.

2.1. Stationarity of Data

In the GARCH model, the time-series data should be stationary, or the means and variances should fluctuate around zero. A stationary test could be conducted visually by reading the plotting data and statistically using the augmented Dickey-Fuller (ADF) test, which was initially introduced by Dickey and Fuller (1979), Y_2, ..., Y_n be generated by the model Rao (1961). Mathematically, the equation of the ADF test is as follows:

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

The above formula was used to construct the following hypothesis:

H0: $\mathrm{DF}_\tau > 2.57$ = Non-stationary
H1: $\mathrm{DF}_\tau < 2.57$ = Stationary (Brockwell & Davis, 2002)

Tsay (2010) developed the measurement of stationarity data in which he tested stationary time-series data by computing its autocorrelation function (ACF) and partial autocorrelation function (PACF). The indication of stationary time-series data can be studied from the data movement of the ACF and PACF graphs, in which the slow movement of data indicates non-stationarity.

However, Ambya et al. (2020) FNG price is categorised as a time series data with volatility in both variance and mean, as well as most likely in some cases having heteroscedasticity problem. To come up with an estimated prediction model, some analysis tools, such as autoregressive integrated moving average (ARIMA proved that financial data is classified as non-stationary data. Hence, in this stage, non-stationary data need to be transformed into stationary data. One of the ways to do this is by employed differencing approach. Such an approach was initially conducted by Granger and Joyeux (1980). The aim of this process was to stabilize the means and variances of the time-series data, particularly financial data, by doing changes in the time-series data (Hyndman & Athanasopoulos, 2018). Once the data is already stationary, the next step will be performed.

2.2. ARCH Effect Test

One concern in modeling financial data is heteroscedasticity (Engle, 1982), which renders the model prediction less accurate. To solve this issue, Tsay (2010) suggested conducting a test on the ARCH effect. To determine whether the ARCH effect is included in the model, the Lagrange Multiplier (LM) test should be conducted (Lee & King, 1993). If at any lag of order the p-value obtained from the LM test is significant (<0.001), then it can be concluded that heteroscedasticity exists. Therefore, we need longer lags and generalize it into a proper model (Wong & Li, 1995), which is the GARCH model.

2.3. Mean Model of AR (*p*) and Variance Model of GARCH (*p*, *q*)

The GARCH model is computed by squaring the past residuals to estimate the variances as it has a long memory process and involves heteroscedasticity (Tsay, 2010). The mean model of AR (p) is defined as order lag p, and the variance model of GARCH (p, q) is defined as conditional variances and squared residuals (Tsay, 2010). The equation for the AR (p)-GARCH (p, q) model is as follows:

$$\mathrm{SP}_{xt} = \vartheta + \sum_{i=1}^{p} \omega_i \mathrm{SP}_{xt-i} + \varepsilon_t \tag{2}$$

$$\sigma_t^2 = c + \sum_{i=1}^{q} \gamma_i {\varepsilon^2}_{t-i} + \sum_{j=1}^{p} \theta_j \sigma_{t-j}^2 \tag{3}$$

where SP_{xt} denotes each state-owned bank's daily stock prices at time t; ϑ, constant; and ω_i, coefficient regression of AR (p) with $i = 1, 2, 3, \ldots, p$; c is constant, and γ_i is the coefficient regression of MA (q) with $i = 1, 2, 3, \ldots, q$.

2.4. Value at Risk (VaR) Measurement

Value at risk is a measure of the risk of loss for investments. It estimates how much a set of investments might lose, given normal market conditions, in a set time period such as a day. VaR has become a common tool for risk measurement in financial agencies. The formal definition of VaR can be as a measurement of portfolio value that might be considered a loss for any given probability level. Thus, measuring the downside risk is important to control the internal risk and to make financial regulations (Meng & Taylor, 2020). The study by Akhmadi et al. (2019) demonstrated that measuring risk level by applying the VaR approach can be defined as the estimated maximum losses for portfolio investments at a certain period and probability level. Tsay (2010) mathematically demonstrates the measurement of VaR with a certain time horizon and confidence level as follows:

$$\mathrm{VaR}_{(1\text{-}\alpha)}(t) = W_0 \times (\mu - R)\sqrt{t} \tag{4}$$

where W_0 denotes the initial investment value or portfolio; R, the quantile value α^{th} from the distribution of stock prices; σ, volatility; and t, time horizon.

3. Results

3.1. Data Description

The data obtained for this study includes the daily stock prices from four state-owned banks in Indonesia from the start of the COVID-19 pandemic in January 2020 to the fourth quarter of 2020. The distribution of the daily stock prices for each bank is described in Figure 1.

Overall, Figure 1 demonstrates that the daily stock prices of all state-owned banks in Indonesia during the study period have fluctuated. Since the COVID-19 pandemic has been announced in Indonesia in March 2020, all stock prices have significantly decreased. However, in April, the returns have increased again due to the adjustments made by the government for the Indonesian financial institutions. The implementation of the 'New Normal' policy in the early third quarter of 2020 has made the movements of stock prices less volatile for all banks. In the fourth quarter of 2020, it can be noticed that all stock prices gradually increased due to market makers' beliefs.

The graphs also demonstrate that the means and variances of the stocks are not maintained at around zero, indicating that all the data sets are visually non-stationary. It can be statistically proven by employing the ADF unit-root test.

Statistically, the results of the ADF test presented in Table 1 demonstrate that the probability values for all returns are more than 0.0001. This means that we do not reject the null hypothesis. It implies that the time-series data are not yet stationary in terms of the means and variances. Therefore, it is important to perform the next step of differencing. The non-stationary time series can also be proven using the graph of the ACF and PACF for each bank, which can be illustrated by the following graphs.

Figure 2 demonstrates that all the ACF graphs exhibit a slow movement, indicating that after lag 1, the data set distributions are not on the circle of zero, of which it is confirmed non-stationary data set. Besides, the data sets on the PACF graphs at lag 1 are not at around zero which assigns time series as non-stationary data set.

3.2. Stationarity Transformation

Since the data sets have been statically indicated as non-stationary data, the next step is to transform them into stationary data by employing the differencing method. Table 2 demonstrates that the ADF test once differencing lag 1 ($d = 1$) was conducted for all data set to obtain stationary data.

To verify this transformation, Figure 3 presents the graphs for the trend and correlation analysis of all the data sets. It can be observed from the figures that differencing 1 ($d = 1$) makes the data set have the behavioral of residual distributions at around zero mean. It can also be seen that the ACF and PACF graphs exhibit a delayed movement, indicating stationarity.

3.3. ARCH Effect Identification

To successfully create an accurate GARCH model, it is important to determine whether or not the stationary data set of the daily stock prices of all four banks have issues

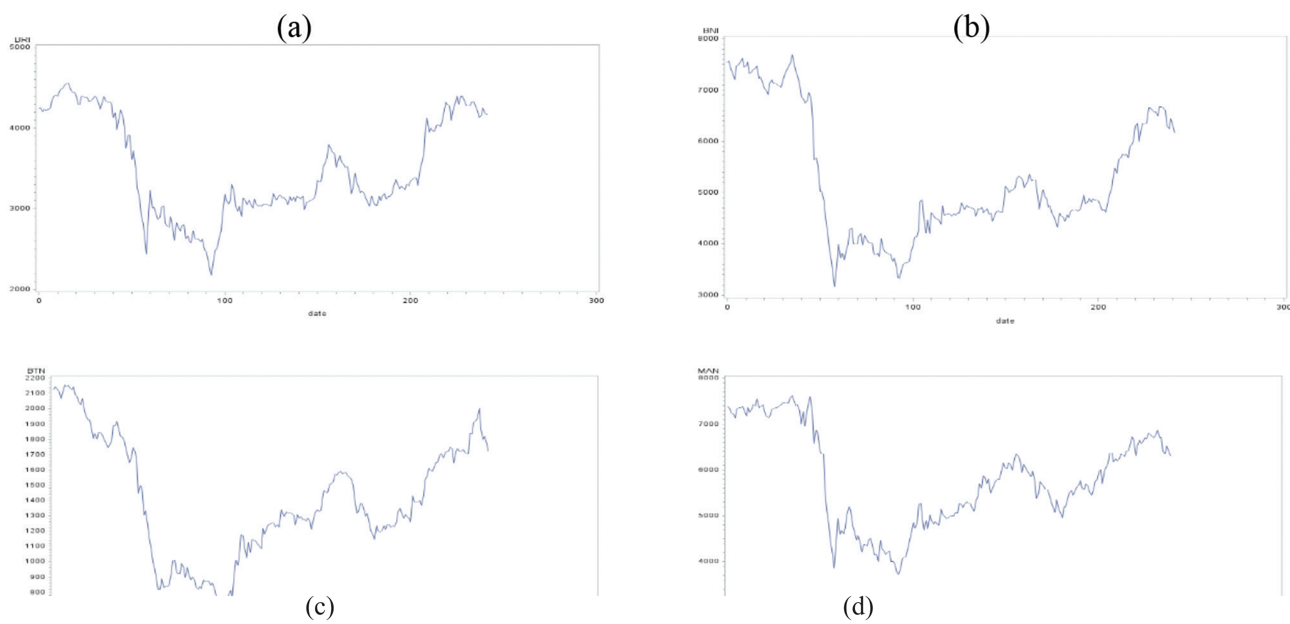


Figure 1: Distribution of the Daily Stock Prices for (a) Bank Rakyat Indonesia (Code: BBRI), (b) Bank Negara Indonesia (Code: BBNI), (c) Bank Tabungan Negara (Code: BBTN) and (d) Bank Mandiri (Code: BMRI)

Table 1: Augmented Dickey-Fuller Test for all State-Owned Banks in Indonesia

Bank Code	Type	Lags	*ρ*	Pr < *ρ*	*τ*	Pr < *τ*	*F*	Pr > *F*
BBRI	Zero Mean	3	–0.1181	0.6554	–0.2507	0.5953		
	Single Mean	3	–3.8374	0.5552	–1.3620	0.6012	0.9276	0.8344
	Trend	3	–3.4103	0.9174	–1.2630	0.8940	1.9691	0.7842
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
BBTN	Zero Mean	3	–0.5682	0.5548	–0.790	0.3741		
	Single Mean	3	–5.1422	0.4187	–1.812	0.3739	1.6985	0.6380
	Trend	3	–4.6320	0.8445	–1.789	0.7077	3.0579	0.5664
BMRI	Zero Mean	3	–0.2802	0.6185	–0.548	0.4779		
	Single Mean	3	–5.0159	0.4307	–1.673	0.4433	1.4350	0.7051
	Trend	3	–4.5470	0.8503	–1.5420	0.8123	1.8164	0.8147

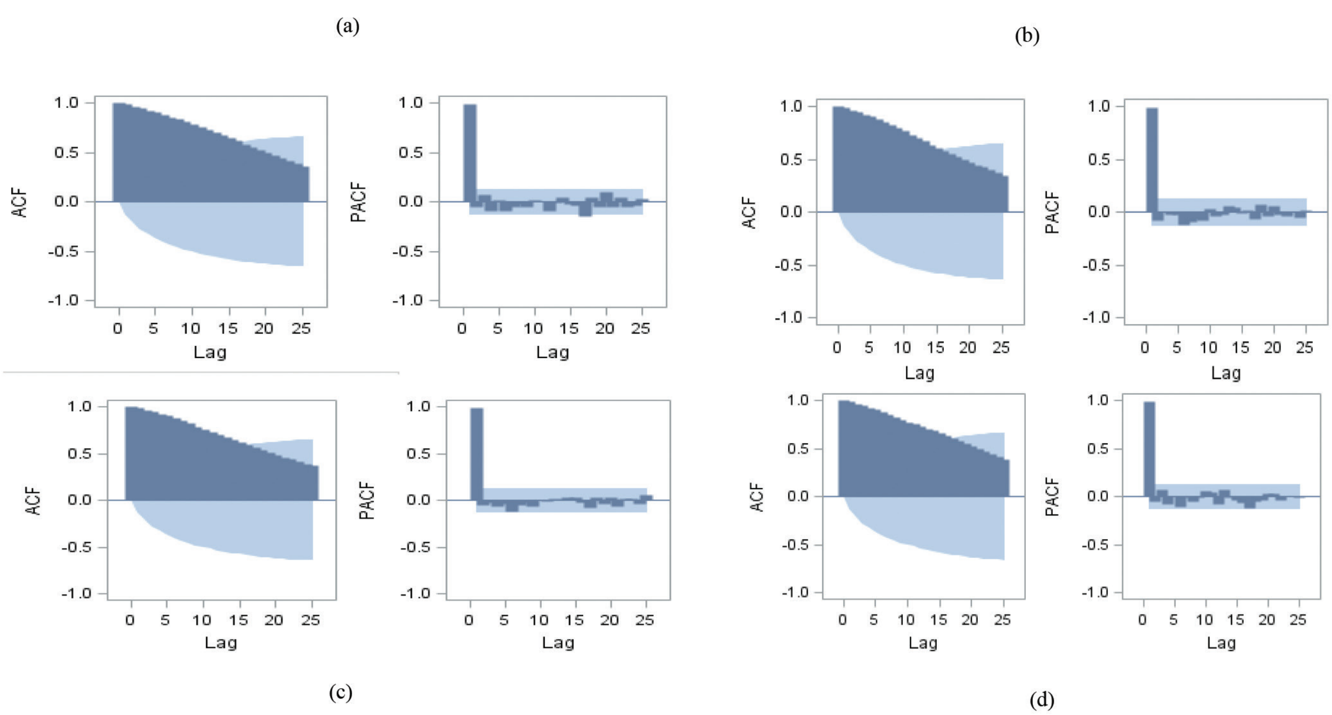


Figure 2: ACF and PACF graphs for (a) Bank Rakyat Indonesia (Code: BBRI), (b) Bank Negara Indonesia (Code: BBNI), (c) Bank Tabungan Negara (Code: BBTN) and (d) Bank Mandiri (Code: BMRI)

with heteroscedasticity. Table 3 presents the Portmanteau Q and LM test with all data set having a significant value of <0.00001 that conclude in having the issue. Therefore, the outcomes suggest that residual data sets can be applied to the GARCH(p,q) model to estimate their volatility.

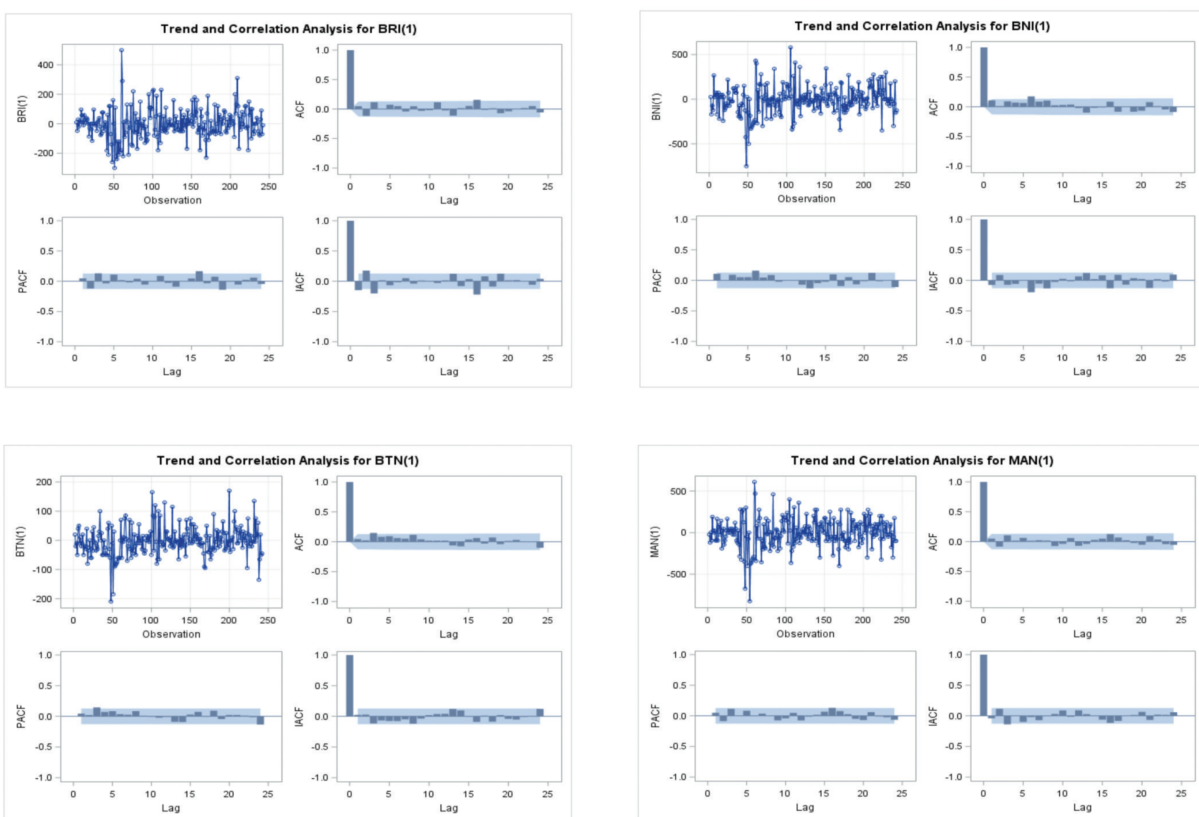
3.4. GARCH Model

Conditional heteroscedasticity is important to create a good-fit forecasting model. The AR (*p*)-GARCH (*p*, *q*) model can then be run to do so, where AR (*p*) is conditional

Table 2: Augmented Dickey-Fuller Test for all State-Owned Banks in Indonesia After Differencing 1 (d = 1)

Bank Code	Type	Lags	ρ	Pr < ρ	τ	Pr < τ	F	Pr > F
BBRI	Zero Mean	3	–220.345	0.0001	–7.49	<0.0001		
	Single Mean	3	–220.352	0.0001	–7.47	<0.0001	27.94	0.0010
	Trend	3	–243.970	0.0001	–7.65	<0.0001	29.27	0.0010
BBNI	Zero Mean	3	–137.438	0.0001	–6.57	<0.0001		
	Single Mean	3	–138.101	0.0001	–6.56	<0.0001	21.51	0.0010
	Trend	3	–156.960	0.0001	–6.76	<0.0001	22.91	0.0010
BBTN	Zero Mean	3	–114.588	0.0001	–6.14	<0.0001		
	Single Mean	3	–115.108	0.0001	–6.13	<0.0001	18.82	0.0010
	Trend	3	–134.974	0.0001	–6.38	<0.0001	20.41	0.0010
BMRI	Zero Mean	3	–194.059	0.0001	–7.25	<0.0001		
	Single Mean	3	–194.712	0.0001	–7.24	<0.0001	26.23	0.0010
	Trend	3	–206.894	0.0001	–7.33	<0.0001	26.88	0.0010

(3a) (3b)



(3c) (3d)

Figure 3: Trend and Correlation Analysis Graphs For (a) Bank Rakyat Indonesia (Code: BBRI), (b) Bank Negara Indonesia (Code: BBNI), (c) Bank Tabungan Negara (Code: BBTN) and (d) Bank Mandiri (Code: BMRI)

Table 3: Tests for ARCH Disturbances Based on Residuals for Each Bank

Order	*Q*	Pr > *Q*	LM	Pr > LM	Order	*Q*	Pr > *Q*	LM	Pr > LM
BBRI					**BBNI**				
1	238.885	<0.0001	208.725	<0.0001	1	249.215	<0.0001	215.266	<0.0001
2	442.009	<0.0001	208.95	<0.0001	2	469.538	<0.0001	215.673	<0.0001
3	620.94	<0.0001	209.407	<0.0001	3	665.988	<0.0001	215.774	<0.0001
4	777.806	<0.0001	209.473	<0.0001	4	840.811	<0.0001	215.794	<0.0001
5	915.914	<0.0001	209.501	<0.0001	5	998.464	<0.0001	215.89	<0.0001
6	1036.34	<0.0001	209.543	<0.0001	6	1136.97	<0.0001	216.325	<0.0001
7	1139.72	<0.0001	209.561	<0.0001	7	1255.85	<0.0001	216.375	<0.0001
8	1228.21	<0.0001	209.578	<0.0001	8	1356.44	<0.0001	216.453	<0.0001
9	1306.76	<0.0001	209.677	<0.0001	9	1441.9	<0.0001	216.455	<0.0001
10	1377.28	<0.0001	209.677	<0.0001	10	1517.44	<0.0001	216.626	<0.0001
11	1441.27	<0.0001	209.706	<0.0001	11	1584.63	<0.0001	216.631	<0.0001
12	1499.14	<0.0001	209.734	<0.0001	12	1645.36	<0.0001	216.659	<0.0001
BBTN					**BMRIC**				
1	254.448	<0.0001	218.78	<0.0001	1	18.9965	<0.0001	16.7291	<0.0001
2	487.935	<0.0001	218.917	<0.0001	2	29.9033	<0.0001	21.1674	<0.0001
3	702.121	<0.0001	218.917	<0.0001	3	53.4595	<0.0001	32.9516	<0.0001
4	894.715	<0.0001	219.123	<0.0001	4	60.0424	<0.0001	33.0737	<0.0001
5	1069.08	<0.0001	219.173	<0.0001	5	68.5733	<0.0001	34.495	<0.0001
6	1223.33	<0.0001	219.583	<0.0001	6	152.502	<0.0001	83.9577	<0.0001
7	1357.96	<0.0001	219.65	<0.0001	7	168.825	<0.0001	84.018	<0.0001
8	1475.76	<0.0001	219.65	<0.0001	8	172.851	<0.0001	85.3611	<0.0001
9	1577.67	<0.0001	219.676	<0.0001	9	177.051	<0.0001	89.1447	<0.0001
10	1667.05	<0.0001	219.721	<0.0001	10	179.448	<0.0001	89.1453	<0.0001
11	1744.94	<0.0001	219.74	<0.0001	11	182.625	<0.0001	89.3905	<0.0001
12	1812.52	<0.0001	219.74	<0.0001	12	196.204	<0.0001	90.5953	<0.0001

to have a mean model and GARCH (p, q) is to have a model of variances and squared residuals for each data set.

Table 4 presents the parameter estimates for the construction of the AR (1)-GARCH (1, 1) model for each bank. The models are believed to have a good-fit measurement to make forecasting as probability values for all banks stated in Table 4 are less than the confidence interval of 5%. This indicates that AR (1) and GARCH (1, 1) estimate the means and variances, respectively, of the four banks. For each bank, the AR (1)-GARCH (1, 1) model is applied as follows:

a. BBRI mean and variance models
AR (1): $BBRI_t = 4240 - 0.9911\ BBRI_{t-1}$
GARCH (1, 1):

$$\sigma_t^2 = 856.162 + 0.2055\varepsilon_{t-1}^2 + 0.711\sigma_{t-1}^2$$

b. BBNI mean and variance models
AR (1): $BBNI_t = 6395 - 0.9958\ BBNI_{t-1}$
GARCH (1, 1):

$$\sigma_t^2 = 4209 + 0.1751\varepsilon_{t-1}^2 + 0.6575\sigma_{t-1}^2$$

c. BBTN model
AR (1): $BBTN_t = 1715 - 0.9937\ BBTN_{t-1}$
GARCH (1, 1):

$$\sigma_t^2 = 1008 + 0.2605\varepsilon_{t-1}^2 + 0.3623\sigma_{t-1}^2$$

Table 4: Estimation of the Parameters of AR (1)–GARCH (1, 1) For Each Bank

Variables	df	Estimate	Standard Error	*t*-value	Approx. Pr > |*t*|	Variables	df	Estimate Error	Standard	*t*-value Pr > |*t*|	Approx.
BBRI						**BBNI**					
Intercept	1	4240	945.4457	4.49	<0.0001	Intercept	1	6395	791.5428	8.08	<0.0001
AR1	1	–0.9911	0.008566	–115.7	<0.0001	AR1	1	–0.9958	0.00588	–169.3	<0.0001
ARCH0	1	856.162	398.0918	2.15	0.0315	ARCH0	1	4209	2085	2.02	0.0435
ARCH1	1	0.2055	0.0691	2.97	0.0029	ARCH1	1	0.1751	0.0476	3.68	0.0002
GARCH1	1	0.711	0.0901	7.89	<0.0001	GARCH1	1	0.6575	0.1152	5.71	<0.0001
BBTN						**BMRI**					
Intercept	1	1715	240.5458	7.13	<0.0001	Intercept	1	6540	794.1411	8.24	<0.0001
AR1	1	–0.9937	0.005699	–174.4	<0.0001	AR1	1	–0.9898	0.00817	–121.1	<0.0001
ARCH0	1	1008	214.1995	4.71	<0.0001	ARCH0	1	2029	964.408	2.1	0.0354
ARCH1	1	0.2605	0.0903	2.88	0.0039	ARCH1	1	0.2107	0.0774	2.72	0.0065
GARCH1	1	0.3623	0.1053	3.44	0.0006	GARCH1	1	0.7301	0.0719	10.15	<0.0001

d. BMRI model
AR (1): $BMRI_t = 6540 - 0.9898\ BMRI_{t-1}$
GARCH (1, 1):

$$\sigma_t^2 = 2029 + 0.2107\varepsilon_{t-1}^2 + 0.7301\sigma_{t-1}^2$$

3.5. Measurement of VaR

The AR (1)-GARCH (1, 1) models are then applied as the basis for the computation of VaR, where AR (1) is used to calculate the means and GARCH (1,1) to determine the variances. From Appendix 1, the t–1 data of each bank can be obtained: $BBRI_{242} = 4180$; $BBNI_{242} = 6305$; $BBTN_{242} = 1725$; and $BMRI_{242} = 6325$. Thus, the mean values for $t = 243$ are as follows:

a. $BBRI_{243} = 4240 - 0.9911\ BBRI_{242}$
$BBRI_{243} = 4240 - 0.9911\ (4180)$
$BBRI_{243} = 97.202$

b. $BBNI_{243} = 6395 - 0.9958\ BBNI_{242}$
$BBNI_{243} = 6395 - 0.9958\ (6305)$
$BBNI_{243} = 116.48$

c. $BBTN_{243} = 1715 - 0.9937\ BBTN_{242}$
$BBTN_{243} = 1715 - 0.9937\ (1725)$
$BBTN_{243} = 0.8675$

d. $BMRI_{243} = 6540 - 0.9898\ BMRI_{242}$
$BMRI_{243} = 6540 - 0.9898\ (6325)$
$BMRI_{243} = 279.511$

The volatility values are as follows:

a. Volatility value for BBRI

$$\sigma_{243}^2 = 856.162 + 0.2055\varepsilon_{242}^2 + 0.711\sigma_{242}^2.$$

$$\sigma_{243}^2 = 856.162 + 0.2055(4180) + 0.711(10253)$$

$$\sigma_{243}^2 = 9067.94$$

$\sigma_{243} = 95.22$

b. Volatility value for BBNI

$$\sigma_{243}^2 = 4209 + 0.1751\varepsilon_{t-1}^2 + 0.6575\sigma_{t-1}^2$$

$$\sigma_{243}^2 = 4209 + 0.1751(6305) + 0.6575(25247.2)$$

$$\sigma_{243}^2 = 21913.04$$

$\sigma_{243} = 148.03$

c. Volatility value for BBTN

$$\sigma_{243}^2 = 1008 + 0.2605\varepsilon_{t-1}^2 + 0.3623\sigma_{t-1}^2$$

$$\sigma_{243}^2 = 1008 + 0.2605(1725) + 0.3623(2672.55)$$

$$\sigma_{243}^2 = 2425.62$$

$\sigma_{243} = 49.25$

d. Volatility value for BMRI

$$\sigma_{243}^2 = 2029 + 0.2107\varepsilon_{t-1}^2 + 0.7301\sigma_{t-1}^2$$

Table 5: VaR Computation for 15 days Ahead with 95% Confidence Interval

Bank Code	Mean Value	Volatility	VaR
BBRI	97.202	95.22	–232.03
BBNI	116.481	148.03	–494.84
BBTN	0.867	49.25	–311.36
BMRI	279.515	183.70	–91.36

$$\sigma_{243}^2 = 2029 + 0.2107(6325) + 0.7301(34284.7)$$

$$\sigma_{243}^2 = 33748.3$$

$$\sigma_{243} = 183.70$$

The above calculations enable the construction of VaR for each selected stock price with a 5% confidence interval (a 1.65 standard deviation) and time horizon of 15 days, as shown in Table 5.

4. Discussion

Table 5 presents the VaR of the stock prices for the next 15 days. With a confidence interval of 95%, all stock prices are believed to decrease by a maximum of Rp232.03 for BBRI, Rp494.84 for BBNI, Rp311.36 for BBTN, and Rp91.36 for BMRI. The decrease in the stock prices in the banking sector is caused by the unstable economic condition around the globe, most particularly in Indonesia. The VaR results confirmed what the banks published in their annual report, i.e. in 2020, the COVID-19 pandemic has slowed down economic activities, causing many creditors to fail in their obligations to the banks.

VaR measurement can be a consideration for investors when putting their funds on the stock market. Table 5 demonstrates that the stock prices have maintained a downward trend for 15 days. Thus, it can be a recommendation for investors with risk-taker characteristics to go short, or keep that investment and wait until some expecting increasing trends occurring for risk-averse investors. Therefore, it can be deduced that the calculation of VaR in stock prices for state-owned banks in Indonesia is to help investors making decisions either to go long or short for their portfolios to minimize the risk of risk.

5. Conclusion

The COVID-19 pandemic has shocked the people worldwide, forcing them to adjust the way they live or implement the 'New Normal' policy. This is the government's way to restabilize economic activities in Indonesia, and it is relatively working to some extent. The COVID-19 pandemic has affected financial institutions. With the unstable economy in Indonesia, all state-owned banks suffered from a significant profit drop, as people have less activity in the banking industries. Thus, it is important to study the potential loss when investing in the Indonesian banking sector.

The VaR is used to measure the maximum loss that might occur in the next couple of days with a certain confidence interval using the GARCH model to estimate the means and variances. AR (1, 1)-GARCH (1, 1) is believed to be a good-fit model for constructing the means and variances, which are accurate elements for the measurement of the VaR. The finding suggests that the VaR varies among banks' stock prices, with the largest maximum potential drop occurring in BBNI (494.84); BMRI has the smallest value of VaR, i.e. 91.36. The results of the study suggest that investors who have funds in state-owned banks should reconsider their investments.

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