Comparison of Stock Price Risk Measurement of BUMN Banks

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ABSTRACT

Currently, most people around the world suffered and has changing the ways of their lives. This resulted in a slowdown in global economic growth in 2020. This also affected stock markets in Indonesia in almost all sectors. In addition, the stock market performance of the financial industry was also significantly affected, including state-owned banks. This study aims to analyze the potential loss from investing in the stock market of the state bank for the next 15 days by reviewing the risk value as a tool to measure the maximum loss. The findings show that Autoregressive AR(1)-GARCH(1) is suitable for determining the models mean and variance, which are used to calculate the Value at risk (VaR) of each bank. The VaR measurement for all banks shows a negative sign indicating the investor's maximum loss from holding one of the shares of that bank for the projected period of time. Measurement of risk will be one of the things that investors will consider when investing in financial markets.

INTRODUCTION

Since the beginning of 2020, COVID-19 has spread widely throughout the world causing many people to suffer in almost every aspect of life. In addition, this pandemic has forced people to change their activity patterns abnormally. The current extraordinary event is increasingly attracting attention, especially for financial economists in the world, because it has slowed economic growth even at negative numbers (Khan et al., 2020). In Indonesia, Hanoatubun (2020) found that the pandemic has made it difficult for Indonesians to get their basic needs and reduce their consumption, causing a decline in economic growth. As a result, governments around the world including Indonesia are trying to manipulate the way people live through stay-at-home policies to stop the spread of the virus.

The Covid-19 pandemic has also had an impact on the financial sector, especially banking (Ahadiat, 2021). State-owned banks that are members of the State Bank Association (Himbara) generally contribute 43% of the total assets of all banks in Indonesia (Financial Services Authority, 2020). In Semester 1 2020, Bank Himbara recorded a significant loss *year-to-year*. Bank BNI experienced the most significant decrease in revenue, which experienced a loss of 41.54% compared to Semester 1 2019, followed by Bank BTN whose net profit decreased significantly by 40%. Investors consider this phenomenon as the risk of investment, because the shock*(shock)*will affect the return*(return)*they are either positively or negatively when investing in the financial sector. Several studies have proven that financial data is highly volatile due to high market uncertainty (Henrawaty et al., 2021). Therefore, the measurement of investment risk becomes important to minimize losses (Rahman et al., 2020). *Value at risk* (VaR) is a tool for estimating the reduction in risk of return with a certain time horizon and confidence value.

Akhmadi et al. (2019) found that the GPD method outperformed EVT and was very close. with the capital adequacy ratio (CAR). In addition, both methods have a higher value than the other methods. As for extreme data in the financial sector, an empirical study conducted by (Budiarti, 2019) shows that the AR-GARCH-copula Tawn approach is most suitable for modeling the joint distribution of a portfolio which can be used as a basis for VaR calculations in extreme cases. Vo t al. (2019) shows the *conditional value at risk* (CVaR) in measuring extreme risk in various companies in

ASEAN as well as the Markowitz model for assessing the risk and return framework as a portfolio distribution.

Therefore, this study aims to measure the rate of return of risk by calculating the respective VaR of each daily share price of state-owned banks in Indonesia. The GARCH model is used to estimate the mean and variance parameters during periods of economic shock.

METHODS

The data in this study are the daily stock prices of state-owned banks, namely BNI and BRI, starting from the COVID-19 pandemic in early 2020 until the fourth quarter of 2020. Before calculating risk return using VaR, each bank's return volatility was measured using the GARCH model to get more accurate measurements.

Tsay (2010) tested the stationary time series data with measuring the autocorrelation function (*Autocorrelation function*) and partial stationary function (*partial autocorrelation function*), through testing the movement of the *plotting data*. Ambya et al. (2020) in his research proves that financial time series data is classified as non-stationary data. Therefore, at this stage the non-stationary data must be transformed into a stationary form by using an approach of *differencing*. This approach was first performed by Granger and Joyeux (1980), which aims to stabilize the average values*(means)*and the variance of the time series data. When the time series data is stationary, the next step can be carried out.

The next step in GARCH modeling is to test the stationary time series data whether it has heteroscedasticity problems that can cause the modeling to be inaccurate. (Engle, 1982) argues that financial time series data modeling tends to have heteroscedasticity problems. To solve this problem, (Tsay, 2010) suggests testing the effect of *Autoregressive Conditional Heteroscedasticity* (ARCH). This ARCH effect can be tested using the Lagrange Multiplier (LM) test (Lee & King, 1993). If the *p-value* in each order has a significant LM test (<0.0001), it can be concluded that there is a heteroscedasticity problem. Therefore, generalization modeling of the ARCH effect or the GARCH model should be carried out to build a forecasting model (Wong & Li, 1995).

The next step is AR(p) mean modeling and GARCH(p,q) variance modeling. The equation of the AR(p)-GARCH(p,q) modeling is as follows.

$$SP_{xt} = \vartheta + \sum_{i=1}^{p} \omega_i SP_{xt-i} + \varepsilon_t$$

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

The final step is to measure the level of risk from investing in BRI and BNI shares using the Value at Risk (VaR) approach. VaR is an approach to measure the loss threshold value of a portfolio to control internal risk and as an investment policy consideration (Meng & Taylor, 2020). Research Akhmadi et al. (2019) measures the level of risk by applying the VaR approach to estimate the maximum loss of a portfolio within a certain period and level of probability. Mathematically, the VaR equation with a certain horizon and confidence level is as follows Tsay (2010):

$$VaR_{(1-\alpha)}\,(t) = W_0 * (\mu - R)\sqrt{t}$$

Where W_0 is the initial investment value of the portfolio, R is the quantile value of the share price distribution; is the level of volatility obtained from the GARCH model equation; and t is the time horizon.

RESULTS AND ANALYSIS

The data in this study are the daily share prices of BRI and BNI in the periodization of the Covid-19 pandemic in 2020. The distribution of daily share prices for each bank is presented in the following graph.

(a) (b)

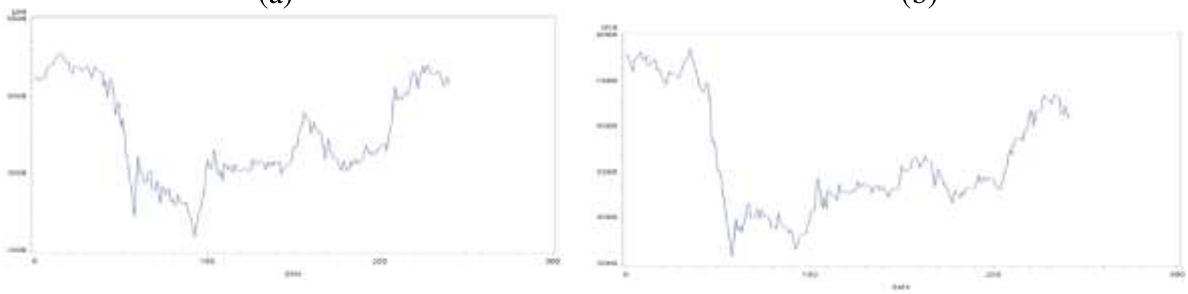

Figure 1. Plot of daily stock prices (a) Bank Rakyat Indonesia (BRI), (b) Bank Negara Indonesia (BBNI)

In general, Figures 1a and 1b show the daily stock prices of BRI and BNI fluctuated during the study period. Since the Covid-19 pandemic was announced in Indonesia in March 2020, all stock prices have decreased significantly. However, in April, the rate of return increased again due to the adjustment of government policies towards financial institutions. The implementation of the policy "*New Normal*" in the third quartile of 2020 has made daily stock price movements *less volatile*. Then in the fourth quartile of 2020, all stock prices will gradually increase again. Figures 1a and 1b also illustrate that the average value and variance of daily stock prices are not around the zero line, which indicates that the time series data is not visually stationary, and this is also proven statistically through the ADF unit root test.

Table 1. Test Augmented Dickey–Fuller daily share price of BRI and BNI in Indonesia

Bank Code	Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	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	0.8592	2.DF2.DF

The unit root test result statistically shows that the probability value for all stock prices is more than 0.0001, which means that the null hypothesis is not rejected, indicating non stationary. Then, non-stationary time series data is also proven through ACF and PACF graphs (Figure 2).

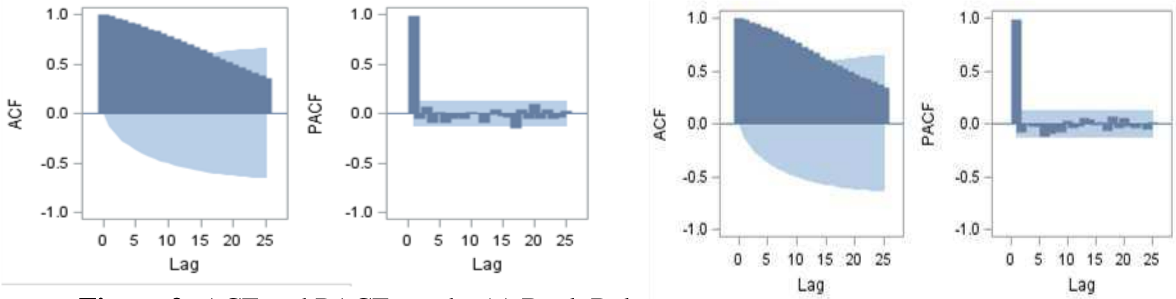

Figure 2: ACF and PACF graphs (a) Bank Rakyat Indonesia (b) Bank Negara Indonesia

Figure 2 shows a slow moving ACF graph which indicates the distribution of time series data is not around zero, causing the data to be non-stationary. Furthermore, the PACF graph is also not around zero which proves that the data set is not stationary. Therefore, we carry out the next step through aapproach *differencing*.

Data Set Transformation

The data set in this study is indicated as non-stationary data, so the next step is to transform the data set into a stationary one by applying the method of *differencing*. Table 2 shows the ADF unit root test after *differencing* lag 1 (d=1). Statistically, the probability value after *differencing* d=1 is <0.0001, so the data set has become stationary.

Table 2. Unit Root Test Augmented Dickey–Fuller after differencing 1 (d = 1)

Bank Code	Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
BBRI	Zero Mean	3	-220.345	0.0001	-7.49	<.0001		
	Single Mean	3	- 220 352	0.0001	-7.47	<.0001	27.94	0.0010
	Trend	3	-243 970	0.0001	-7.65	<.0001	29.27	0.0010
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

To verify this transformation Figures 3a and 3b show trends and correlation analysis after d = 1, which indicates that the residual data sets distributed around zero. The ACF and PACF charts also show a fast movement after lag=1, thus proving that the data set has turned stationary.

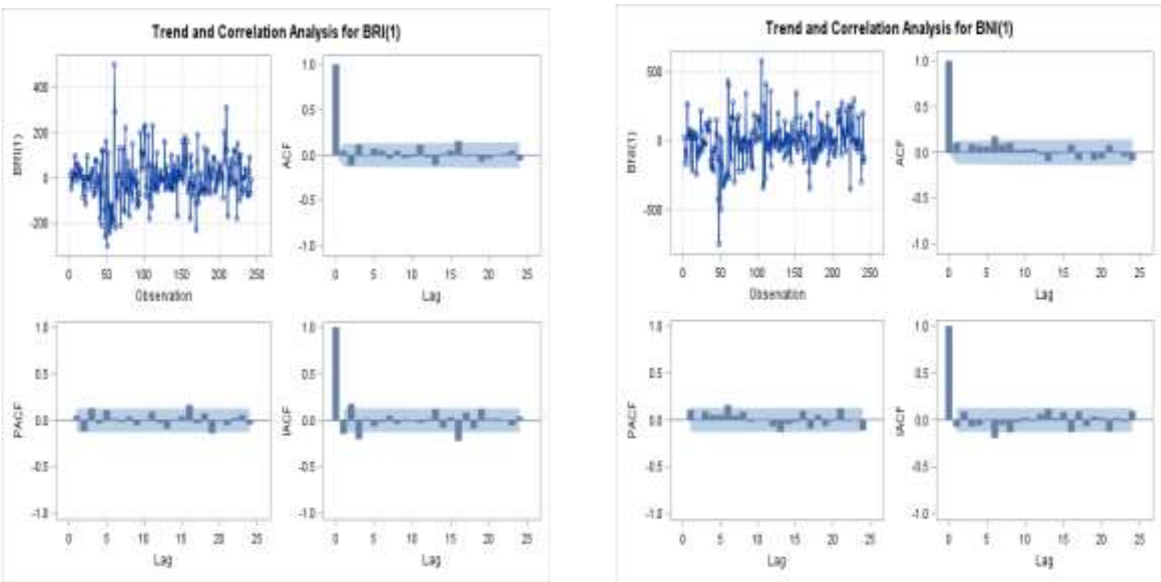

Figure 3. Graph of Trends and Correlation (a) Bank Rakyat Indonesia (b) Bank Negara Indonesia

Identification of ARCH Effects

The next step in GARCH modeling is to determine whether the stationary time series data has heteroscedasticity problems or not. Table 3 shows that the Pormanteau Q test and the LM test have a significance level of <0.0001, which indicates that there is a heteroscedasticity problem. So the model must be generalized through the application of the GARCH model to estimate the level of volatility.

Table 3: ARCH Effect Test

BBRI					BBNI				
Order	Q	Pr > Q	LM	Pr > LM	Order	Q	Pr > Q	LM	Pr > LM
1	238,885	<.0001	208,725	<.0001	1	249,215	<.0001	215,266	<.0001
2	442,009	<.0001	208.95	<.0001	2	469,538	<.0001	215,673	<.0001
3	620.94	<.0001	209,407	<.0001	3	665,988	<.0001	215,774	<.0001
4	777,806	<.0001	209,473	<.0001	4	840.811	<.0001	215,794	<.0001
5	915,914	<.0001	209.501	<.0001	5	998.464	<.0001	215.89	<.0001
6	1036.34	<.0001	209.543	<.0001	6	1136.97	<.0001	216.325	<.0001
7	1139.72	<.0001	209.561	<.0001	7	1255.85	<.0001	216.375	< .0001
8	1228.21	<.0001	209.578	<.0001	8	1356.44	<.0001	216.453	<.0001
9	1306.76	<.0001	209.677	<.0001	9	1441.9	<.0001	216.455	<.0001
10	1377.28	<.0001	209.677	<.0001	10	1517.44	< .0001	216,626	<.0001
11	1441.27	<.0001	209.706	<.0001	11	1584.63	<.0001	216,631	<.0001
12	1499.14	<.0001	209.734	<.0001	12	1645.36	<.0001	216,659	<.0001

GARCH modeling

Conditional *heteroscedasticity* is crucial in formation of a good forecasting model. The AR(p)-GARCH(p,q) model can then be applied, where AR(p) is a condition for having a model mean and GARCH(p,q) is a model of variance.

Table 4. Parameter estimation AR(1)-GARCH(1,1)

BBRI						BBNI					
Variable	DF	Estimate	Standard Error	t Value	Appro. Pr > |t|	Variable	DF	Estimate	Standard Error	t Value	Approx. Pr > |t|
Intercept	1	4240	945.4457	4.49	<.0001	Intercept	1	6395	791.5428	8.08	<.0001
AR1	1	-0.9911	0.008566	-115.7	<.0001	AR1	1	-0.9958	0.00588	-169.3	<.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	<.0001	GARCH1	1	0.6575	0.1152	5.71	<.0001
GARCH1	1	0.3623	0.1053	3.44	0.0006	GARCH1	1	0.7301	0.0719	10.15	<.0001

Table 4 shows the estimated parameters of the model building AR (1)-GARCH(1,1) from BRI and BNI. The model is believed to be a good measurement model in making a forecast, because the probability value of each bank is less than 5%. This indicates that AR(1) can estimate the mean value and GARCH(1,1) can estimate the variance value. The AR(1)-GARCH(1,1) model equation for each bank can be modeled as follows.

AR(1): $BBRI_t = 4240–0.9911\ BBRI_{t-1}$
GARCH(1.1): $\sigma_t^2 = 856.162 + 0.2055\varepsilon^2{}_{t-1} + 0.711\sigma_{t-1}^2$

AR(1): $BBNI_t = 6395–0.9958\ BBNI_{t-1}$
GARCH(1,1): $\sigma_t^2 = 4209 + 0.1751\varepsilon^2{}_{t-1} + 0.6575\sigma_{t-1}^2$

Measurement of Bank Risk Value Using VaR

Model AR(1)-GARCH(1,1) can then be used as the basis for calculating VaR, where AR(1) is used to calculate the mean value and GARCH(1,1) is used to determine the variance value. From Appendix 1, data on t-1 from each bank is obtained: $BBRI_{242} = 4180$ and $BBNI_{242} = 6305$.

Thus, the average value for the 243rd year (t_{234}) is as follows.
$BBRI_{243} = 97{,}202$; and $BBNI_{243} = 116.48$

Then, the volatility values are implied volatilities for BRI is $\sigma_{243} = 95.22$; and for BNI is $\sigma_{243} = 148.03$

Calculation of the two models above are then used to form the VaR of each of the daily value of shares of BRI and BNI with a confidence interval 5%, 1.65 standard deviation and a time horizon of 15 days as shown in Table 5.

Table 5: VaR calculation for the next 15 days with 95% confidence interval

Bank	Mean Value	Volatility	VaR
BBRI	97,202	95.22	-232.03
BBNI	116,481	148.03	-494.84

DISCUSSION

Table 5 represents the VaR value of each daily stock price for the next 15 days. With *a confidence interval* 95%, all stock prices are believed to decrease with a maximum decline of Rp. 232.03 for BRI, and Rp. 494.84 for BNI. The decline in stock prices in the banking sector was due to unstable global economic conditions, including in Indonesia. The results of the VaR calculations confirm the financial statements they have published in 2020, where the Covid-19 pandemic has slowed economic activity which has caused most creditors to be unable to pay their obligations that are due to banks.

VaR measurement can then be used as a basis for investors in determining investments to be made on the stock exchange. Table 5 shows stock prices that have a downward trend over the next 15 days. Then it can be recommended for investors with characteristics *risk taker* to "sell", and for investors with characteristics *risk averse* to keep their investments and wait until the trend returns to increase. Therefore, it can be concluded that the VaR calculation of the daily share prices of BRI and BNI can assist investors in deciding to "*go long*" or "*go short*" of a portfolio investment to minimize risk.

CONCLUSION

The Covid-19 pandemic has shocked everyone in the world, which makes everyone have to be able to adjust their way of life. This extraordinary event of course also had an impact on the Indonesian banking sector. This economic instability has caused banks in Indonesia to experience a significant decline in profits, so studies regarding potential losses in investing in the Indonesian banking sector need to be measured.

VaR is used to measure the maximum value of future losses with *aconfidence interval* certainusing the GARCH model to estimate the average and variance models. The AR(1,1)-GARCH(1,1) model is believed to be the best model in forming the mean and variance which are elements in calculating the VaR value. The calculation results find that the VaR values are different for BRI and BNI, namely the maximum potential loss for BRI is Rp.232.03 and BNI is Rp.494.84. The results of this study are considered for investors who wish to invest in the Indonesian banking sector.

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