An investment decision-making model to predict the risk and return in stock market: An Application of ARIMA-GJR-GARCH

Rizki Apriva Hidayana[a*], Herlina Napitupulu[b] and Sukono[b]

[a]Master's Program of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran, Jatinangor, West Java, Indonesia
[b]Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran, Jatinangor, West Java, Indonesia

CHRONICLE	ABSTRACT
	In deciding to invest in stocks traded in the capital market, investors need to predict which stocks provide the prospect of return and the risks to be faced. This paper aims to predict the return and risk of stock asymmetry using a time series model approach. Predicting stock returns and risk is based on the Autoregressive Integrated Moving Average-Glosten Jagannatan Runkle-Generalized Autoregressive Conditional Heteroscedasticity (ARIMA-GJR-GARCH) model. In contrast, the largest risk potential measurement is performed using the Value-at-Risk (VaR) model. The data analyzed are the best ten stocks according to the criteria that apply on the IDX, the period between 17 December 2018 to 14 December 2021, which includes the names of stock BBCA, BBNI, BBRI, BMRI, ASII, ICBP, PGAS, PTBA, TLKM, and UNVR. The analysis results show that of the best ten stocks, based on the ratio between the predicted values of the average return and Value-at-Risk, those with relatively better performance are PTBA, TLKM, UNVR and BBCA stocks. Based on the results of this analysis, it can be used as a reference in making investment decisions for investors, specifically investing in the ten stocks analyzed.

1. Introduction

Investment is an activity of placing funds that are carried out at this time to obtain benefits in the future. In the object of investment, assets are generally divided into real and financial assets. Real assets are related to infrastructure, and financial assets are related to stocks (Dwipa, 2016). Investors choose to invest in stocks in a company based on the desire to earn profits in the future, which can be seen from the number of stock returns. Investing in stocks is faced with risk because stock returns are volatile. Stock returns can change quickly, so the stock index value can also change; this movement is known as stock return volatility. High volatility indicates high risk, as well as low volatility results in low risk. Therefore, it needs to be overcome by using a mathematical model.

Several researchers have used various time series models, one of which is the ARCH model introduced by Engle in 1982. According to Dwipa (2016), stock returns have three characteristics. The first is volatility grouping, meaning that very large changes occur at certain times and small changes at other periods. The second is fat tailedness which means that stock returns display a greater sharpness than the normal distribution. Third, there is a leverage effect, a condition where bad news and good news have an asymmetric effect on return volatility. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model has a more flexible structure to accommodate the stock's volatility (Bollerslev, 1986). Tamilselvan and Vali (2016) used the GARCH model to research Muscat stocks on the security market by concluding that the GARCH (1,1) model is the best estimate for symmetrical data. There is no leverage effect on the data used. However,

the GARCH model cannot be used on data with a leverage effect. Ali (2013) used the EGARCH, GJR-GARCH, TGARCH, AVGARCH, NGARCH, IGARCH, and APARCH models to determine the functional relationship of the time series pathogenic indicators to activate reactions on the coast. However, the TGARCH model is marginally better than other models in capturing the response of the variable pathogen indicator. Mittnik, Paolella, and Rachev (2002) used the EGARCH, GJR-GARCH, TGARCH, AVGARCH, NGARCH, IGARCH, and APARCH models to determine the functional relationship of the time series of pathogenic indicators to activate reactions at the coast. However, the TGARCH model is slightly better than other models in capturing the pathogen variable indicator responses (Lee, 2007).

Measurement of risk in this study is using Value-at-Risk (VaR). According to Bakhtiar et al. (2020), VaR is one of the most popular tools used by investors in measuring risk. VaR is used as a measuring tool to assess the worst losses in investing at a particular time and level of confidence. Several levels of risk measurement use VaR. Sukono et al. (2019) examine the ARIMA-GARCH model used to estimate and expect a shortfall of several stocks in the Indonesian capital market. Based on the analysis, selected stocks are obtained. Bank Mandiri stocks have the lowest risk level, and Mustika Ratu stocks have the highest level of risk, with the VaR of the stock generally smaller than the expected shortfall value. Bucevska (2013) conducted a relative test of the selected GARCH type model in terms of the ability to estimate volatility and extended empirical research on VaR estimation in financial markets. Nilsson (2017) finds the best APARCH model to estimate volatility, while to estimate VaR the best model is APARCH, GJR-GARCH, or EGARCH, depending on the VaR level used.

From the research described, there are still some shortcomings in these models. Among others, Tamilselvan and Vali (2016) examined Muscat stocks using the GARCH model on symmetric data, but the GARCH model cannot be used if the data is asymmetrical. One solution for asymmetric data is the GJR-GARCH model. Sukono et al. (2019) determined VaR using the time series model but did not use the GJR-GARCH model. Based on this gap, this study uses the Autoregressive Moving Average-Glosten Jagannatan Runkle-Generalized Autoregressive Conditional Heteroscedasticity (ARIMA-GJR-GARCH) model to determine the VaR value on stock returns. The ARIMA model is an average model assuming constant volatility, while the GJR-GARCH model is a variance model with the data characteristics used having an asymmetric effect. The asymmetric effect changes the magnitude of the volatility when the stock returns. Calculating risk value using VaR requires a component, namely volatility, which can be estimated using time series analysis. Therefore, this study aims to predict the return and risk of stock asymmetry using a time series model approach. Researchers want to know the magnitude of the risk obtained in the ten stocks analyzed. So, it is hoped that the results of this study will be useful for investors in helping investment decisions, especially in the ten stocks analyzed in this study.

2. Literature Review

Capital market in Indonesia. Stocks are investment instruments that are in great demand by investors as a basis for saving finances. In investing, there are several important things: risk and rate of return (return). Return is the level of profit obtained by investors in investing. According to Campbell, Lo, and MacKinley (1998), the use of returns has two main reasons. First, for the average investor, financial markets can be considered highly competitive, so the investment size does not affect price changes. Second, in theory, the return series is easier to handle than the price series because it has more interesting statistical properties, such as stationarity. The Indonesia Stock Exchange defines the capital market as long-term financial instruments that can be traded, such as bonds, stocks, mutual funds, derivative instruments, and others. The capital market is a means of funding for companies and other institutions (e.g., the government) and as a means for investing activities. Thus, the capital market can facilitate various buying and selling activities and other activities (IDX, 2021).

The best ten stock's criteria. The criteria for determining the ten best stocks on the IDX include being listed on the IDX for at least 3 months, including 10 stocks based on transaction value in the regular market, high liquidity and large market capitalization, as well as financial condition and growth prospects.

Investment decision theory. The investment decision is to invest one or more assets to get profits in the future (Hartono and Wahyuni, 2017). These decision-makers can learn about different types of investments and encourage people to make investment decisions or try investing. Ummah et al. (2021) examined student investment decisions as an intermediary variable, with the results obtained that intentions or interests influence student investment decisions. Therefore, if someone is interested in investing, it will encourage them to make investment decisions.

3. Materials and methods

3.1 Materials

The research object is return data obtained from daily data closing stock prices. The data used is secondary data between 17 December 2018 to 14 December 2021, including the names of stock BBCA, BBNI, BBRI, BMRI, ASII, ICBP, PGAS, PTBA, TLKM, and UNVR. This stock price data are obtained from the website https://finance.yahoo.com/. The software used in this research is Eviews 10 and MS. Excel.

3.2   Methods

3.2.1.   Return

According to Rupert (2011) and Kalfin et al. (2019), return is the return on the results obtained from investing. In general, the return formula is as equation (1).

$$r_t = \ln\left(\frac{S(t_i)}{S(t_{i-1})}\right) \tag{1}$$

where r_t is stock return at time t, $S(t_i)$ is the stock price in period t_i and $S(t_{i-1})$ is the stock price at period t_{i-1}.

3.2.2.   Stationarity

The stationarity test is the underlying assumption in the statistical procedures used in time series analysis. According to Tsay (2005), the data stationarity test can use the Augmented Dickey-Fuller (ADF) test. The Augmented Dickey-Fuller (ADF) test is a stationary test on average, where the ADF test statistics are seen in Eq. (2).

$$ADF = \frac{\hat{\delta}}{SE(\hat{\delta})} \tag{2}$$

where $SE(\hat{\delta})$ is the standard error for $\hat{\delta}$. The decision-making criteria are if the $ADF < \alpha$ then reject H_0 in other words, the data is stationary. If the ADF value $> \alpha$ then accept H_0 in other words, the data is not stationary.

3.2.3.   ARMA Modeling

The ARMA model aims to discuss the average model in the time series. The Autoregressive Moving Average (ARMA) model can be expressed in the following Eq. (3).

$$r_t = \omega + \sum_{i=1}^{p} \phi_i r_{t-i} + a_t - \sum_{j=1}^{q} \theta_j a_{t-j} \tag{3}$$

where r_t is the return value at time t, a_t is a white noise process or error at time t (Sukono et al., 2017).

ARMA modeling process. In general, the ARMA modeling process is: (i) Model identification by determining p and q values with autocorrelation function (ACF) and partial autocorrelation function (PACF) from correlogram plots. (ii) Parameter estimation can use the method of least squares or maximum likelihood. (iii) Diagnostic test with white noise and non-correlation test on residuals using Box-Pierce or Ljung-Box. If the model is suitable (iv), Forecasting can be used for recursive predictions.

3.2.4.   ARCH effect test

The ARCH model used to estimate volatility was introduced by Engle (1982). This model is used when the error variance in the model follows the autoregressive (AR) form. To model the time series using the ARCH process (p).

$$a_t = \sigma_t v_t, \quad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2 \tag{4}$$

where v_t is the order of independent and identically distributed (iid), a_t is the residual return from the average model, σ_t^2 is the residual variance squared at time t, and $\alpha_1 a_{t-1}^2$ is the ARCH component.

ARCH effect test. The most widely used test to detect the effect of ARCH is the Lagrange Multiplier (LM). Based on equation (4), the ARCH effect test (p) is based on the null hypothesis $H_0: \alpha_1 = \alpha_2 = \cdots = \alpha_p = 0$ it means that there is no ARCH effect and $H_1: \exists \alpha_i \neq 0, i = 1,2, \ldots, p$ means that there is an ARCH effect. The test statistics used are as Eq. (5).

$$LM = nR^2 \tag{5}$$

where n is the number of data and R^2 s the coefficient of determination in the previous regression model.

3.2.5.   GARCH Modeling

Bollerslev (1986) developed the ARCH model into a GARCH model (p, q) where q is the order ARCH and p is the order GARCH. In general, the GARCH model is as Eq. (6).

$$a_t = \sigma_t v_t, \quad \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{6}$$

where ϵ_t is the order of independent and identically distributed (iid), σ_t^2 is the residual variance at time$-t$, ω is the constant component, α_i is the i-th parameter of ARCH, a_{t-i}^2 is the square of the residual at a time to $(t - i)$, β_j is the-j parameter of GARCH, σ_{t-j}^2 is the variance of the residual at a time to $(t - j)$. Equation (3) shows that the conditional variance is a past shock as seen from the squared residual (p) and the past residual variance (q) (Olowe and Ayodeji, 2010).

The volatility modeling process. The volatility modeling process is: (i) Estimated ARMA model with time series model. (ii) Use the residuals from the ARMA model to test the ARCH effect. (iii) If there is an ARCH effect, the estimation of the volatility model and the combined estimates form the ARMA model and the volatility model. (iv) Perform diagnostic tests to observe the suitability of the model. (v) If the model already fits, use it to predict based on recursive predictions.

3.2.6. Asymmetry

According to Bakhtiar et al. (2020), the asymmetric test is a property that shows an imbalance in certain conditions or objects. The asymmetric nature is called the leverage effect or high volatility in the time series. To determine the nature of asymmetry, namely by skewness and kurtosis. Skewness is a degree of imbalance in the distribution. The asymmetric test can be done by using the cross-correlation between the lag residual (ε_t) and the squared residual (ε_t^2).

According to Brooks (2008), asymmetric testing can be tested by testing the sign bias in the regression equation as Eq. (7).

$$\hat{u}_t^2 = \phi_0 + \phi_1 S_{t-1}^- + \phi_2 S_{t-1}^- u_{t-1} + \phi_3 S_{t-1}^+ u_{t-1} + v_t \tag{7}$$

where S_{t-1}^- is a dummy indicator with a value of 1 if $\hat{u}_{t-1} < 0$ and 0 for others, v_t is an error, $S_{t-1}^+ = 1 - S_{t-1}^-$ which is a positive observation, ϕ_1 is a sign bias parameter (positive or negative effect), ϕ_2 and ϕ_3 are size of bias parameter.

Eq. (7) can be used to see the effect of asymmetry on the model by looking at the probability value of the dummy multiplication with the residual GARCH model. Reject H_0 if the probability value of the dummy multiplication with the GARCH model residual $< \alpha$, then the residual is asymmetric.

3.2.7. GJR-GARCH Modeling

Glosten Jagannathan and Runkle (1993) introduced the asymmetric GARCH model, namely the GJR-GARCH model. The GJR-GARCH model and the GARCH model is that the GJR-GARCH model has parts representing asymmetric properties. The GJR-GARCH model is as equation (8) and (9). The advantage of the GJR-GARCH model is that it can measure volatility due to the different effects of bad news and good news.

$$a_t = \sigma_t \epsilon_t, \qquad \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \gamma_i I_{t-i} a_{t-i}^2 \tag{8}$$

and

$$I_{t-i} = \begin{cases} 1, a_{t-i} < 0 \\ 0, a_{t-i} \geq 0 \end{cases} \tag{9}$$

where α_i is the parameter to i of ARCH, β_j is the parameter to j of GARCH and γ_i is the parameter to i of the leverage effect, I_{t-i} is a dummy variable which means a functional index that is zero when a_{t-i} positive and one when a_{t-i} negative. If the parameter $\gamma_i > 0$ then the negative error does not work, which means that the effect of bad news will be greater than the effect of good news (Dritsaki, 2017).

GJR-GARCH modeling process: (i) Estimation of GARCH model with time series model. (ii) Use the residuals from the GARCH model to test the ARCH effect. (iii) Conducting diagnostic tests to observe the suitability of the model. (iv) Test for asymmetric effects. (v) If there is an asymmetric effect, it can be used to predict based on recursive prediction.

3.2.8. Value-at-Risk

According to Dwipa (2016), VaR is the maximum potential loss in a certain period with a certain level of confidence in normal (market) conditions. VaR at the confidence level $(1 - \alpha)$ and time interval t can be formulated as Eq. (10).

$$VaR = \inf\{r_t | F_l(r_t) \geq \alpha\} \tag{10}$$

where F_l is the distribution function of return r_t. Then the VaR for the next period with a confidence level of α can be formulated as Eq. (11).

$$VaR = \mu + \sigma_t F^{-1}(\alpha) \tag{11}$$

where μ is the mean, σ^2 is the variance, and σ is the standard deviation (Sukono et al., 2018).

3.2.9. Backtesting

Back-test is a method used to measure the estimated VaR performance. Suppose r_t represents gain or loss at time t and VaR_t is a prediction of VaR at time t. In 1998 Lopez introduced a model of the size-adjusted frequency approach as Eq. (12).

$$C_t = \begin{cases} 1 + (r_t - VaR_t)^2, & r_t > VaR_t \\ 0, & r_t \leq VaR_t \end{cases} \tag{12}$$

The statistic used to test the VaR risk performance uses the quadratic probability score (QPS). The QPS equation is as Eq. (13).

$$QPS = \left(\frac{2}{n}\right) \sum_{i=1}^{n} (C_t - p)^2 \tag{13}$$

where n is the number of data, p is the probability value. The QPS value is between the range [0, 2] where 0 is the minimum value that occurs when $r_t \leq VaR_t$ and 2 is the maximum value that occurs when $r_t > VaR_t$. VaR performance is good when the small QPS is close to 0 (Sukono et al., 2019).

4. Results and Discussion

4.1. Results

4.1.1. Descriptive Statistics of Stock Return

Descriptive statistics explain the average, maximum and minimum values in rupiah. ICBP stocks obtained the highest average closing price with an average of IDR9,830,127.346.00. Then the maximum price of the ten highest stocks is ICBP stocks with IDR12,400,000,000.00. The highest minimum price was also obtained for ICBP stocks at IDR7,750,000,000.00. Descriptive statistics in detail can be seen in Table 1.

Table 1
Descriptive Statistics of Stock Data

No	Code	Mean (IDR)	Maximum Value (IDR)	Minimum Value (IDR)
1	BBCA	6,167,332,440	7,750,000,000	4,430,000,000
2	BBNI	6,598,063,003	9,850,000,000	3,160,000,000
3	BBRI	3,937,012,342	4,890,000,000	2,170,000,000
4	BMRI	6,576,226,542	8,150,000,000	3,720,000,000
5	ASII	6,032,138,070	8,475,000,000	3,280,000,000
6	ICBP	9,830,127,346	12,400,000,000	7,750,000,000
7	PGAS	1,586,939,597	2,650,000,000	605,000,000
8	PTBA	2,643,986,577	4,470,000,000	1,485,000,000
9	TLKM	3,566,899,329	4,470,000,000	2,560,000,000
10	UNVR	7,547,533,512	10,005,000,000	3,820,000,000

Furthermore, the calculation of stock returns uses equation (1). Because the stock return calculation uses Eq. (1), the movement of the stock return value is on average 0. So, it can be seen that the data is stationary. Next is the stationarity test of the data in section 4.1.2.

4.1.2. Stationarity Test

A stationary test is conducted by using Dickey-Fuller with a probability value of 5%. The formula used for this stationary test uses Eq. (2). Stationary testing in this study using Eviews 10 software, so that the stationarity test results are given in Table 2.

Table 2
Stock return stationary test

No	Name	ADF Value	Critical Value	Probability	Stationary
1.	BBCA	-28.26384	-2.8652	0.0000	Stationer
2.	BBNI	-25.57169	-2.8652	0.0000	Stationer
3.	BBRI	-20.95871	-2.8652	0.0000	Stationer
4.	BMRI	-26.58175	-2.8652	0.0000	Stationer
5.	ASII	-28.67779	-2.8652	0.0000	Stationer
6.	ICBP	-28.91462	-2.8652	0.0000	Stationer
7.	PGAS	-25.62396	-2.8652	0.0000	Stationer
8.	PTBA	-28.19626	-2.8652	0.0000	Stationer
9.	TLKM	-23.31614	-2.8652	0.0000	Stationer
10.	UNVR	-14.48223	-2.8652	0.0000	Stationer

Based on the stationary test in Table 2, the probability value obtained is less than the probability value used, which is 5%, meaning that the stock return data for BBCA, BBNI, BBRI, BMRI, ASII, ICBBP, PGAS, PTBA, TLKM, and UNVR are stationary. Then proceed with the ARIMA model and diagnostic testing.

4.1.3. ARIMA modeling and Diagnostic Test

The stock return data, which has been stationary, is continued by identifying the ARIMA model. The ARIMA model can be identified by looking at the ACF and PACF on the correlogram plot. Based on Table 1, for the data on the ten stocks, the differencing process was not carried out because the ten stocks were stationary at the level. So, the differencing process used is 0 and the modeling process uses Eq. (3). The model equation is obtained based on the output of Eviews 10 as shown in Table 3 and the model obtained can be seen in Table 4.

Table 3
ARIMA Model Estimation

No	Name	Parameter	Parameter Estimation	t-statistic	P-value
1.	BBCA	AR (1)	-0.514166	-26.21417	0.0000
		MA (3)	0.117129	5.097995	0.0000
2.	BBNI	AR (1)	0.064438	3.036586	0.0025
		MA (1)	-0.999472	-45.34951	0.0000
3.	BBRI	AR (1)	-0.417325	-16.34477	0.0000
		MA (3)	0.081640	2.453917	0.0144
4.	BMRI	AR (2)	0.338607	2.124245	0.0340
		MA (2)	-0.474612	-2.973079	0.0030
5.	ASII	AR (1)	-0.053180	-2.230933	0.0260
		AR (2)	-0.060206	-2.192661	0.0286
		MA (1)	-0.999636	-32.09550	0.0000
6.	ICBP	AR (4)	-0.740712	-5.270208	0.0000
		MA (4)	0.657000	4.105697	0.0000
7.	PGAS	AR (1)	-0.944571	-69.00926	0.0000
		MA (2)	-0.929149	-68.69278	0.0000
8.	PTBA	AR (4)	0.156793	6.586803	0.0000
		MA (3)	0.090062	3.636374	0.0003
9.	TLKM	AR (1)	-1.066740	-42.21242	0.0000
		AR (2)	-1.058787	-40.64755	0.0000
		AR (3)	-0.063695	-2.493440	0.0129
		MA (3)	-0.984652	-75.62536	0.0000
10.	UNVR	AR (1)	-0.248710	-2.559542	0.0107
		AR (2)	-0.782618	-9.999477	0.0000
		MA (1)	-0.839945	-7.690707	0.0000
		MA (2)	0.551698	3.811751	0.0001
		MA (3)	-0.709946	-8.403299	0.0000

Table 3 shows parameter estimates, t-statistical values, and p-values. The results of p-value obtained is less than the probability value of 5%, so a model can be made according to the parameters in the output results of Table 3.

Table 4
ARIMA Modeling

No	Name	ARIMA Model	Model Equation
1.	BBCA	ARIMA (1,0,3)	$r_t = -0,514166r_{t-1} + 0,117129a_{t-3} + a_t$
2.	BBNI	ARIMA (1,0,1)	$r_t = -0,064438r_{t-1} - 0,999472a_{t-2} + a_t$
3.	BBRI	ARIMA (1,0,3)	$r_t = -0,417325r_{t-1} + 0,081640a_{t-3} + a_t$
4.	BMRI	ARIMA (2,0,2)	$r_t = 0,338607r_{t-2} - 0,474612a_{t-2} + a_t$
5.	ASII	ARIMA (2,0,1)	$r_t = -0,053180r_{t-1} - 0.060206z_{t-2} - 0.999636a_{t-1} + a_t$
6.	ICBP	ARIMA (4,0,4)	$r_t = -0.740712r_{t-4} + 0.657000a_{t-4} + a_t$
7.	PGAS	ARIMA (1,0,2)	$r_t = -0.944571r_{t-1} - 0.929149a_{t-2} + a_t$
8.	PTBA	ARIMA (4,0,3)	$r_t = 0.156793r_{t-4} + 0.090062a_{t-3} + a_t$
9.	TLKM	ARIMA (3,0,3)	$r_t = -1.066740r_{t-1} - 1.058787z_{t-2} - 0.063695r_{t-3} - 0.984652a_{t-3} + a_t$
10.	UNVR	ARIMA (2,0,3)	$r_t = -0.248710r_{t-1} - 0.782618z_{t-2} - 0.839945a_{t-1} + 0.551698a_{t-2} + 0.709946a_{t-3} + a_t$

After obtaining the ARIMA model as shown in Table 4, then the significance test of the model is in Table 4. The significance results can be used using the p-value shown in Table 3 because decision-making is seen from the p-value. If p-value $> \alpha$ then H_0 is don't reject and H_1 is rejected, if p-value $< \alpha$ then H_0 is rejected and H_1 is don't reject. The t-test results were obtained in the models in Table 3 with a probability value of < 0.05, meaning that the lag obtained in each model has a significant effect on stock return data. After that, a diagnostic test was carried out on the model in Table 4 to see that the model obtained was good to use. The diagnostic test carried out is the white noise test; this test is used to see whether the model is good or not. White noise testing is good if the model obtained has a probability value of more than $\alpha = 0.05$. Diagnostic test results and normality can be seen in Table 5.

Table 5
Diagnostic Test and Normality

No	Name	ARIMA Model	Diagnostic Test	Normal Residual
1.	BBCA	ARIMA (1,0,3)	White noise	Normal
2.	BBNI	ARIMA (1,0,1)	White noise	Normal
3.	BBRI	ARIMA (1,0,3)	White noise	Normal
4.	BMRI	ARIMA (2,0,2)	White noise	Normal
5.	ASII	ARIMA (2,0,1)	White noise	Normal
6.	ICBP	ARIMA (4,0,4)	White noise	Normal
7.	PGAS	ARIMA (1,0,2)	White noise	Normal
8.	PTBA	ARIMA (4,0,3)	White noise	Normal
9.	TLKM	ARIMA (3,0,3)	White noise	Normal
10.	UNVR	ARIMA (2,0,3)	White noise	Normal

The diagnostic test obtained in Table 5 is that the ten models have white noise, and the residuals are normally based on the output of Eviews 10, so it can be said that the model fits. These results indicate that there is no correlation between residuals. From the ten models, it can be continued to the next stage, namely the heteroscedasticity test.

4.1.4.   Heteroscedasticity Test

A heteroscedasticity test was conducted to see whether the model has a constant or non-constant residual. This test can use Eq. (5) with the hypothesis that if the p-value $< \alpha$ then there is an ARCH effect and if the p-value is $> \alpha$, then there is no ARCH effect and cannot be continued for further model testing. The results of heteroscedasticity carried out on ten stocks are shown in Table 6.

Table 6
Heteroscedasticity test on the average model

No	Name	P-Value	Test results
1.	BBCA	0.0004	There is an ARCH effect
2.	BBNI	0.0000	There is an ARCH effect
3.	BBRI	0.0000	There is an ARCH effect
4.	BMRI	0.0000	There is an ARCH effect
5.	ASII	0.0000	There is an ARCH effect
6.	ICBP	0.0000	There is an ARCH effect
7.	PGAS	0.0000	There is an ARCH effect
8.	PTBA	0.0000	There is an ARCH effect
9.	TLKM	0.0000	There is an ARCH effect
10.	UNVR	0.0160	There is an ARCH effect

Table 6 shows that the ten models obtained with *p-value* $< \alpha$ are 5%. It means that the residual variance of each model is not homogeneous, so GARCH modeling is carried out using the ARIMA model approach.

4.1.5.   GARCH Modeling and Diagnostic Test

GARCH modeling was carried out on ten stock data containing heteroscedasticity properties. The next process is GARCH estimation by looking at the ACF and PACF plots, and the modeling process is carried out using equation (6). The model equation can be seen from the output results of Eviews 10, which are listed in Table 7 and the GARCH modeling can be seen in Table 8.

Table 7 is a parameter estimation table for the GARCH model. Based on the output obtained in Table 7, the p-value of each model is less than 5%. Then, the parameters obtained are used to create a model. The p-value is used to see whether each parameter used is significant or not. From Table 7, a GARCH model can be made from Table 8.

Table 7
GARCH Model Estimation

No	Name	Parameter	Parameter Estimation	z-statistic	P-value
1.	BBCA	ω	3.55×10^{-5}	5.998938	0.0000
		α_1	0.297815	7.024272	0.0000
		β_1	0.643384	17.50368	0.0000
2.	BBNI	ω	1.08×10^{-5}	3.101068	0.0019
		α_1	0.101445	6.481046	0.0000
		β_1	0.883664	57.42953	0.0000
3.	BBRI	ω	1.31×10^{-5}	4.455161	0.0019
		α_1	0.101445	6.545144	0.0000
		β_1	0.883664	44.08548	0.0000
4.	BMRI	ω	4.01×10^{-5}	4.947399	0.0000
		α_1	0.148979	5.985380	0.0000
		β_1	0.821305	38.59841	0.0000
5.	ASII	ω	1.13×10^{-5}	2.819046	0.0048
		α_1	0.052065	5.352401	0.0000
		β_1	0.924575	62.09474	0.0000
6.	ICBP	ω	0.000219	11.85928	0.0000
		α_1	0.571363	8.353831	0.0000
		β_1	0.151660	3.689371	0.0002
7.	PGAS	ω	4.28×10^{-5}	3.955612	0.0001
		α_1	0.091825	5.217514	0.0000
		β_1	0.863369	38.377773	0.0000
8.	PTBA	ω	0.000140	5.244338	0.0000
		α_1	0.238700	6.105710	0.0000
		β_1	0.664758	15.32815	0.0000
9.	TLKM	ω	1.08×10^{-5}	3.707499	0.0002
		α_1	0.061793	6.464341	0.0000
		β_1	0.911388	71.91348	0.0000
10.	UNVR	ω	1.40×10^{-5}	4.895856	0.0000
		α_1	0.155901	9.706558	0.0000
		β_1	0.814572	50.41685	0.0000

Table 8
GARCH Model

No	Name	GARCH Model	Model Equation
1.	BBCA	GARCH (1,1)	$\sigma_t^2 = 3.55 \times 10^{-5} + 0.297815a_{t-1}^2 + 0.643384a_{t-1}^2 + u_t$
2.	BBNI	GARCH (1,1)	$\sigma_t^2 = 1.08 \times 10^{-5} + 0.101445a_{t-1}^2 + 0.883664a_{t-1}^2 + u_t$
3.	BBRI	GARCH (1,1)	$\sigma_t^2 = 1.31 \times 10^{-5} + 0.113634a_{t-1}^2 + 0.862452a_{t-1}^2 + u_t$
4.	BMRI	GARCH (1,1)	$\sigma_t^2 = 4.01 \times 10^{-5} + 0.148979a_{t-1}^2 + 0.821305a_{t-1}^2 + u_t$
5.	ASII	GARCH (1,1)	$\sigma_t^2 = 1.13 \times 10^{-5} + 0.148979a_{t-1}^2 + 0.924575\sigma_{t-1}^2 + u_t$
6.	ICBP	GARCH (1,1)	$\sigma_t^2 = 0.000219 + 0.571363a_{t-1}^2 + 0.151660\sigma_{t-1}^2 + u_t$
7.	PGAS	GARCH (1,1)	$\sigma_t^2 = 4.28 \times 10^{-5} + 0.091825a_{t-1}^2 + 0.863369\sigma_{t-1}^2 + u_t$
8.	PTBA	GARCH (1,1)	$\sigma_t^2 = 0.000140 + 0.238700a_{t-1}^2 + 0.664758\sigma_{t-1}^2 + u_t$
9.	TLKM	GARCH (1,1)	$\sigma_t^2 = 1.08 \times 10^{-5} + 0.061793a_{t-1}^2 + 0.911388\sigma_{t-1}^2 + u_t$
10.	UNVR	GARCH (1,1)	$\sigma_t^2 = 1.40 \times 10^{-5} + 0.155901a_{t-1}^2 + 0.814572\sigma_{t-1}^2 + u_t$

Table 7 displays the ten tested models for significance using the t-test and diagnostic test. Decision-making is seen from the p-value contained in Table 7. If p-value $> \alpha$ then H_0 is don't reject and H_1 is rejected, if p-value $< \alpha$ then H_0 is rejected and H_1 is don't reject. The p-value results obtained are probability values < 0.05, meaning that the lag obtained in each model significantly affects stock return. Table 8 is the GARCH model formed based on the parameter estimates obtained. After that, a diagnostic test was carried out on the model shown in Table 9.

Table 9
Diagnostic Test and Normality

No	Name	GARCH Model	Diagnostic Test	Normal Residual
1.	BBCA	GARCH (1,1)	White noise	Normal
2.	BBNI	GARCH (1,1)	White noise	Normal
3.	BBRI	GARCH (1,1)	White noise	Normal
4.	BMRI	GARCH (1,1)	White noise	Normal
5.	ASII	GARCH (1,1)	White noise	Normal
6.	ICBP	GARCH (1,1)	White noise	Normal
7.	PGAS	GARCH (1,1)	White noise	Normal
8.	PTBA	GARCH (1,1)	White noise	Normal
9.	TLKM	GARCH (1,1)	White noise	Normal
10.	UNVR	GARCH (1,1)	White noise	Normal

The diagnostic test results on the GARCH (1,1) model for each stock show that the model has white noise. There is no correlation between the residuals and the model is said to be suitable, so the GARCH (1,1) model for all stocks used can be continued to the next stage, namely the ARCH effect test.

4.1.6. ARCH Effect Test

The ARCH effect test is the same as the heteroscedasticity test to see whether the model has a constant or non-constant residual. This test shows that if the *p-value* > α then the GARCH (1,1) model has no ARCH effect. Based on the results obtained using the Eviews 10 software, the GARCH (1,1) model for ten stocks has a value greater than (5%) and can be seen in Table 10.

Table 10
Heteroscedasticity test on the volatility model

No	Name	P-Value	Test results
1.	BBCA	0.9535	No ARCH Effect
2.	BBNI	0.4848	No ARCH Effect
3.	BBRI	0.7723	No ARCH Effect
4.	BMRI	0.6576	No ARCH Effect
5.	ASII	0.9461	No ARCH Effect
6.	ICBP	0.8677	No ARCH Effect
7.	PGAS	0.4424	No ARCH Effect
8.	PTBA	0.5881	No ARCH Effect
9.	TLKM	0.9748	No ARCH Effect
10.	UNVR	0.7954	No ARCH Effect

Table 10 shows that the *p-value* of the ten models is greater than α (5%). There is no ARCH effect on all models, meaning that the residual variance of each model is homogeneous. It proves that the test can be continued to the next stage, namely the asymmetric GARCH method.

4.1.7. Asymmetry Test

This asymmetric test is also known as the cross-correlation test, which means the multiplication between the lag residual (u_t) and the residual squared (u_t^2). Multiplication is done to see whether the GARCH model in Table 7 has asymmetric properties or not. To check the cross-correlation using the first Eviews 10 software by looking at the multiplication value between the residuals and the squared residuals. The cross-correlation between the residuals and the squared residuals in the ten models is that there is no value equal to zero, so the data used is asymmetrical. It means that the condition of bad news and good news has an asymmetric effect on volatility. Second, the asymmetric test results using Eq. (7) produce values in Table 11.

Table 11
Asymmetry Test

No	Name	GARCH Model	The probability value of dummy multiplication with residual GARCH model
1.	BBCA	GARCH (1,1)	0.0000
2.	BBNI	GARCH (1,1)	0.0000
3.	BBRI	GARCH (1,1)	0.0000
4.	BMRI	GARCH (1,1)	0.0000
5.	ASII	GARCH (1,1)	0.0000
6.	ICBP	GARCH (1,1)	0.0000
7.	PGAS	GARCH (1,1)	0.0000
8.	PTBA	GARCH (1,1)	0.0000
9.	TLKM	GARCH (1,1)	0.0000
10.	UNVR	GARCH (1,1)	0.0000

Table 11 is the result of the dummy multiplication with the residual GARCH model. The rejection criterion is to reject H_0 if the probability value of the dummy multiplication with the GARCH model residual < α then the residual is asymmetric. Based on Table 10 the probability value obtained is $0.0000 < \alpha$, the data used has an asymmetric effect. Furthermore, from the asymmetrical GARCH model, modeling of the GJR-GARCH is carried out as in point 4.1.8.

4.1.8. GJR-GARCH Modeling

GJR-GARCH modeling can be done if you already know the asymmetrical nature of the GARCH model contained in Table 8. The parameter estimation of the GJR-GARCH model is carried out using equation (8) with the help of Eviews 10 software. The modeling results are presented in Table 12.

Table 12

GJR-GARCH Model

No	Name	GJR-GARCH (1,1) Model
1.	BBCA	$\sigma_t^2 = 8.53 \times 10^{-6} + 0.038909a_{t-1}^2 + 0.159906a_{t-1}^2 I_{t-1} + 0.861201\sigma_{t-1}^2 + \varepsilon_t$
2.	BBNI	$\sigma_t^2 = 7,73 \times 10^{-6} + 0,041698a_{t-1}^2 + 0,064183a_{t-1}^2 I_{t-1} + 0,916975\sigma_{t-1}^2 + \varepsilon_t$
3.	BBRI	$\sigma_t^2 = 9,48 \times 10^{-6} + 0,041375a_{t-1}^2 + 0,126782a_{t-1}^2 I_{t-1} + 0,885933\sigma_{t-1}^2 + \varepsilon_t$
4.	BMRI	$\sigma_t^2 = 2,22 \times 10^{-5} + 0,072777a_{t-1}^2 + 0,136036a_{t-1}^2 I_{t-1} + 0,826186\sigma_{t-1}^2 + \varepsilon_t$
5.	ASII	$\sigma_t^2 = 8,31 \times 10^6 + 0,065700a_{t-1}^2 I_{t-1} + 0,953184\sigma_{t-1}^2 + \varepsilon_t$
6.	ICBP	$\sigma_t^2 = 9,21 \times 10^{-5} + 0,094863a_{t-1}^2 + 0,211101a_{t-1}^2 I_{t-1} + 0,488967\sigma_{t-1}^2 + \varepsilon_t$
7.	PGAS	$\sigma_t^2 = 4,31 \times 10^{-5} + 0,063100a_{t-1}^2 + 0,063350a_{t-1}^2 I_{t-1} + 0,864486\sigma_{t-1}^2 + \varepsilon_t$
8.	PTBA	$\sigma_t^2 = 3,31 \times 10^{-5} + 0,072700a_{t-1}^2 + 0,056582a_{t-1}^2 I_{t-1} + 0,852711\sigma_{t-1}^2 + \varepsilon_t$
9.	TLKM	$\sigma_t^2 = 9,84 \times 10^{-6} + 0,036302a_{t-1}^2 + 0,070058a_{t-1}^2 I_{t-1} + 0,909500\sigma_{t-1}^2 + \varepsilon_t$
10.	UNVR	$\sigma_t^2 = 1,05 \times 10^{-5} + 0,092302a_{t-1}^2 + 0,151156a_{t-1}^2 I_{t-1} + 0,707198\sigma_{t-1}^2 + \varepsilon_t$

Table 12 shows the asymmetric value obtained from each of these models is not equal to zero, which means that there is a shock so that the volatility of the return value for the leverage effect has a significant effect. The results of the four models have a greater influence on bad news received in return volatility than on good news.

4.1.9. Value-at-Risk and Backtesting

Before determining the Value-at-Risk value, the average value and volatility of stock returns for the next period are predicted. The Value-at-Risk value is determined based on the ARIMA model results for the calculated average of $\hat{\mu}_t = \hat{r}_t$ and GJR-GARCH for the volatility (variance) calculated from $\hat{\sigma}_t^2 = \sigma_t^2$. The estimates of the mean and the volatility (variance) σ^2 are in Table 13. Before determining the Value-at-Risk value, the average value and volatility of stock returns for the next period are predicted. Using the average and volatility model of stock returns, the values of $\hat{\mu}_t = \hat{r}_t$ and $\hat{\sigma}_t^2 = \sigma_t^2$ are calculated. These results can be seen in Table 13.

Table 13

Mean, variance, VaR and QPS

No	Name	$\hat{\mu}_t$	$\hat{\sigma}_t^2$	$\hat{\sigma}_t$	VaR_t	QPS
1.	BBCA	0.006608	0.001072	0.032741	0.047088	0.026745
2.	BBNI	0.000261	0.000523	0.022869	0.037244	0.10406
3.	BBRI	0.010326	0.01012	0.100598	0.154655	0.007416
4.	BMRI	0.002055	0.004064	0.063749	0.102494	0.012248
5.	ASII	0.000263	0.000549	0.023431	0.038398	0.087148
6.	ICBP	0.001464	0.001773	0.042107	0.06801	0.012248
7.	PGAS	0.000811	0.000241	0.015524	0.024804	0.292517
8.	PTBA	0.00958	0.000445	0.021095	0.025227	0.222450
9.	TLKM	0.003263	0.000118	0.010863	0.014661	0.357752
10.	UNVR	0.002266	0.000077	0.008781	0.012222	0.328758

Based on the results obtained in Table 13 in the column $\hat{\mu}_t$ it can be seen that the maximum average value is in BBRI stocks with a value of 0.010326 and the minimum is in BBNI stocks with a value of 0.000261. In column $\hat{\sigma}_t$ or standard deviation, it can be seen that the maximum standard deviation value is obtained in BBRI stocks with a value of 0.100598 and the minimum standard deviation is in BBNI stocks with a value of 0.022869. If the probability value is 5%, then the normal distribution value is $z_{0.05} = -1.65$ and the investment assumption is $S_0 = 1$ unit, then the Value-at-Risk value is obtained using Eq. (11) and the results are following Table 13 in the VaR_t column.

Value-at-Risk value is measured using back-testing to see whether the Value-at-Risk performance is good or not. The back-testing calculation using QPS starts from obtaining the C_t value or loss indicator which is worth 0 and 1. Then the C_t t results are used to calculate the QPS value referring to equation (13). Thus, the QPS results are obtained in Table 13 in the QPS column. It can be seen that the QPS value obtained on BBCA stocks is 0.026745, BBNI stocks are 0.10406, BBRI stocks are 0.007416, BMRI stocks are 0.012248, ASII stocks are 0.087148, ICBP stocks are 0.012248, PGAS stocks are 0.292517, PTBA stocks are 0.222450, TLKM stocks are 0.357752, and UNVR's stocks are 0.328758. The maximum QPS is in TLKM stocks with a value of 0.357752 and the minimum QPS is in BBRI stocks with a value of 0.007416. The QPS results obtained for the ten stocks are not more than the range [0, 2] and tends to approach 0, which means that the ARIMA-GJR-GARCH Value-at-Risk performance is good for use in the analyzed stock return data.

4.2. Discussion

High volatility results indicate high risk and low volatility, which results in low risk. Tamilselvan and Vali (2016) used the GARCH model to test Muscat stocks in the securities market by concluding that the GARCH (1,1) model is the best estimate for symmetric data with no leverage effect on the data used. The volatility obtained in this study is relatively high. In other words, the greater the volatility obtained, the greater the risk. The data used in this study are the best ten stock data based on the IDX. The ten stocks used are good stocks for long-term investments. This study uses the ARIMA-GJR-GARCH

model. The ARIMA model estimation is used to get the mean value and the GJR-GARCH model estimate is used to get the variance value. So the Value-at-Risk value obtained from each stock is shown in Table 13. It can be explained that the maximum risk obtained by investors with an initial investment of IDR100,000,000.00 and invest in ten stocks, for example, BBCA stocks, which are IDR4,708,800,000. The results of this study can be used to assist investors in making investment decisions by knowing the maximum risk obtained for each stock.

Furthermore, based on the data presented in Table 13, if a comparison (calculated ratio) is made between the mean values of $\hat{\mu}_t$ with risk values measured using variance $\hat{\sigma}_t^2$ each stock return, then the results can be presented in a histogram as shown in Fig. 1.
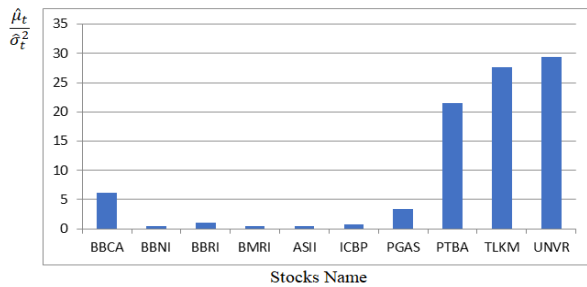
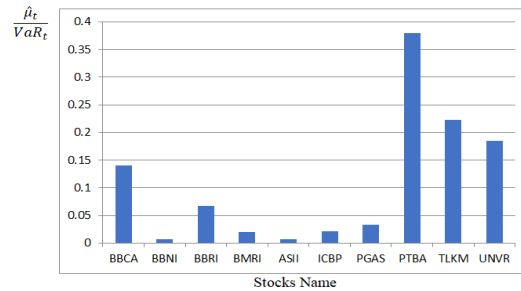**Fig. 1.** Histogram Ratio of Mean to Variance

Fig. 2. Histogram Ratio of Mean to Value-at-Risk

Fig. 1 captures only four stocks of the ten best stocks on the IDX that have relatively good performance. The four stocks are UNVR with a predicted mean return of 0.002266 and a risk (variance) of 0.000077; TLKM mean return is 0.003263 and variance is 0.000118; PTBA mean return is 0.00958 and variance is 0.000445; followed by BBCA stock with a mean return of 0.006608 and a variance of 0.001072. For investors who pay attention to risk measured by variance, these comparison values (ratio) can be used as a reference in making investment decisions.

Next, also from the data presented in Table 13, if a comparison (ratio) is made between the mean values of $\hat{\mu}_t$ to the values of Value-at-Risk VaR_t each stock return, the ratio calculation results can be presented in the form of a histogram, as shown in Fig. 2. The figure shows that of the ten best stocks on the IDX that have relatively good performance, there are only four stocks. The four stocks are PTBA with a predicted mean return of 0.00958 and a Value-at-Risk of 0.025227; TLKM mean return is 0.003263 and Value-at-Risk is 0.014661; UNVR mean return is 0.002266 and Value-at-Risk is 0.012222; followed by BBCA stock with a mean return of 0.006608 and Value-at-Risk of 0.047088. For investors who pay attention to risk measured by Value-at-Risk with a confidence level of 5%, these comparison values (ratio) can be used to make investment decisions.

5. Conclusion

In this study, an estimation of the Value-at-Risk value has been carried out using a time series model. The data analyzed are BBCA, BBNI, BBRI, and BMRI stock return data. The models obtained from each stock are ARIMA(1,0,3)-GJR-GARCH(1,1) BBCA stocks, ARIMA(1,0,1)-GJR-GARCH(1,1) BBNI stocks, ARIMA(1,0,3)-GJR-GARCH(1,1) BBRI stocks, ARIMA(2,0,2)-GJR-GARCH(1,1) BMRI stocks, ARIMA(2,0,1)-GJR -GARCH(0,1) ASII stocks, ARIMA(4,0,4)-GJR-GARCH(1,1) ICBP stocks, ARIMA(1,0,2)-GJR-GARCH(1,1) PGAS stocks, ARIMA(4,0,3)-GJR-GARCH(1,1) PTBA stocks, ARIMA(3,0,3)-GJR-GARCH(1,1) TLKM stocks, and ARIMA(2,0,3)- GJR-GARCH(1,1) UNVR stocks. The Value-at-Risk values obtained from the four stocks are 0.047088 for BBCA, 0.037244 for BBNI, 0.154655 for BBRI, 0.102494 for BMRI, 0.038398 for ASII, 0.06801 for ICBP, 0.024804 for PGAS, 0.025227 for PTBA, 0.014661 for TLKM, and 0.012222 for UNVR. The QPS, which is relatively small and in the range of values [0, 2], shows that risk measurement using Value-at-Risk on the analyzed stocks has good performance. This research can estimate the value of volatility with data that has an asymmetric effect using a time series model and can determine the value of Value-at-Risk with ARIMA-GJR-GARCH model. Based on the ten stocks data used, there is an asymmetric effect on the data. It means that the data has a greater influence of bad news on the volatility of stock returns. Value-at-Risk results can be used to determine the estimated maximum risk of loss. This research is useful for investors in making investment decisions in the stock sector. Thus, this research can assist investors in choosing stocks that have a small investment loss risk.

246

References

Ali, G. (2013). EGARCH, GJR-GARCH, TGARCH, AVGARCH, NGARCH, IGARCH and APARCH models for pathogens at marine recreational sites. *Journal of Statistical and Econometric Methods*, *2*(3), 57-73.

Bakhtiar, S. M., Syata, I., Alwi, W., Ibnas, R., & Anugrawati, S. D. (2021, May). Estimation of Average Value at Risk (AVaR) on Sharia Joint-Stock Index Using Glosten, Jaggnathan and Runkle (GJR) model. In *1st International Conference on Mathematics and Mathematics Education (ICMMEd 2020)* (pp. 143-149). Atlantis Press.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, *31*(3), 307-327.

Brooks, C. (2008). RATS Handbook to accompany introductory econometrics for finance. *Cambridge Books*.

Bucevska, V. (2013). An Empirical evaluation of GARCH models in value-at-risk estimation: Evidence from the Macedonian stock exchange. *Business Systems Research: International journal of the Society for Advancing Innovation and Research in Economy*, *4*(1), 49-64.

Campbell, J. Y., Lo, A. W., MacKinlay, A. C., & Whitelaw, R. F. (1998). The econometrics of financial markets. *Macroeconomic Dynamics*, *2*(4), 559-562.

Dritsaki, C. (2017). An empirical evaluation in GARCH volatility modeling: Evidence from the Stockholm stock exchange. *Journal of Mathematical Finance*, *7*(2), 366-390.

Dwipa, N. M. S. (2016). GLOSTEN JAGANNATHAN RUNKLE-GENERALIZED AUTOREGRESSIVE CONDITIONAL HETEROSCEDASTICS (GJR-GARCH) METHODE FOR VALUE AT RISK (VaR) FORECASTING. *Proceeding of ICMSE*, *3*(1), M-63.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the econometric society*, 987-1007.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The journal of finance*, *48*(5), 1779-1801.

Hartono, E. F. & Wahyuni, D. U. (2017). Analisis faktor-faktor keputusan investasi pada perusahaan property dan real estate. *Jurnal Ilmu dan Riset Manajemen, 6*(6).

Bursa Efek Indonesia. (2021). IDX Stock Index Handbook. Jakarta: BEI.

Kalfin, Sukono, & Carnia, E. (2019). Portfolio Optimization of the Mean-Absolute Deviation Model of Some Stocks using the Singular Covariance Matrix. *International Journal of Recent Technology and Engineering (IJRTE)*, Volume-8 Issue-3, 7818-7822.

Lee, O. (2007). A study on Box-Cox transformed threshold GARCH (1, 1) process. *Communications for Statistical Applications and Methods*, *14*(1), 141-146.

Mittnik, S., Paolella, M. S., & Rachev, S. T. (2002). Stationarity of stable power-GARCH processes. *Journal of Econometrics*, *106*(1), 97-107.

Nilsson, C. (2017). Forecasting Swedish stock market volatility and value-at-risk: A comparison of EWMA and GARCH models.

Olowe, R.A. (2010). Oil Price Volatility. *Global Financial Crisis and The Mont of The Year Effect*. International Journal of Business and Management. Vol 5.

Rupert, D. (2011). *Statistics and Data Analysis for Financial Engineering*. 2nd ed., Spinger text in statistics, New York.

Sukono., Soeryana, E., and Simanjuntak, A. (2019). ARIMA-GARCH Model for Estimation of Value-at-Risk and Expected shortfall of Some Stocks in Indonesia Capital Market. *Proceedings of the International Conference on Industrial Engineering and Operations Management Riyadh*. Saudi Arabia.

Sukono., Susanti, D., Najmia, M., Lesmana, E., Napitupulu, H., Supian, S., and Putra, A.S. (2017). Analysis of stock investment selection based on CAPM using covariance and genetic algorithm approach. *IOP Conference Series: Materials Science and Engineering.* 332 012046.

Sukono, Kartiwa, A., Subartini, B., Hidayat, Y., & Bon, A.T. (2018). Estimation of Conditional Value-at-Risk under Assets Liability Model with Non Constant Volatility. *Proceedings of the International Conference on Industrial Engineering and Operations Management, Bandung, Indonesia*, March 6-8, 2018, 2726-2733.

Tamilselvan, M., & Vali, S. M. (2016). Forecasting stock market volitility-evidence from muscat security market using garch models. *International Journal of Commerce and Finance*, *2*(1), 37-53.

Tsay, R.S. (2005). *Analysis of financial time series*. 2nd ed., Chicago: John Wiley & Sons. Inc. University of Chicago.

Ummah, A., Ahsan, M., & Anas, A. (2021). Students' investment decisions with intention as an intervening variable. *Equilibrium: Jurnal Ekonomi Syariah, 9*(1), 135-152.