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Determination of Value-at-Risk in UNVR Stocks Using ARIMA-GJR-GARCH Model

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Abstract

Stocks are investment instruments that are in great demand by investors as a basis for storing finances. The most important thing in investing is the return and risk of loss obtained from investing in stocks. Risk measurement is carried out using *Value-at-Risk* and *Conditional Value-at-Risk*. The stock movements used are historical data and in the form of time series, so that a model can be formed to predict the next movement of stocks and risk measurements can be carried out. The purpose of this study is to determine the value of risk obtained by investors using time series analysis. The data used in this study is the daily closing price of stocks for 3 years. The stages of the analysis carried out to predict stock movements are to determine the ARIMA model for the mean model and the GJR-GARCH model for the volatility model. The mean value and variance are used to calculate the risk value of *VaR*. Based on the results of the *Value-at-Risk* calculation obtained, UNVR shares have a risk value of 0.01217. This means that if an investment is made in UNVR shares of IDR 100,000,000.00, the estimated maximum loss of potential loss that occurs is estimated to reach IDR 1,217,000.

Keywords: Risk, ARIMA, GJR-GARCH, *Value-at-Risk*

1. Introduction

Investment is an activity of placing funds that are carried out at this time in the hope of obtaining benefits in the future. Investing money in various alternative assets, one of which is stocks is one of the activities related to investment (Tandelilin, 2010). Stocks are the most popular securities today to trade. In investing, an investor must often monitor the movement of stocks on the exchange as a whole (Ali, 2022).

Every investment has several important things, namely risk and rate of return. Return is the level of profit obtained by investors in investing. Risks in investing are sometimes unavoidable. There are several types of investment risks, namely business risk, financial risk, inflation risk, liquidity risk, country risk, currency risk, market risk, and interest risk (Sulistianingsih, et al., 2021). There are various ways to estimate risks such as Value-at-Risk and Conditional Value-at-Risk. In this study, risk measurement was carried out using Value-at-Risk using a time series model.

Time series models are widely used to analyze time series with different types of data. Some of the previous studies used the ARIMA-GJR-GARCH time series model. Xu *et al.* (2015) used the ARIMA-GJR-GARCH model to forecast the exchange rate of the Renminbi (Chinese currency) against the Hong Kong dollar. The GJR-GARCH model can be used for asymmetric data in the variance equation. Based on the analysis of the paper, the ARIMA model (1,1,1)-GJR-GARCH (1,1) is the best model for exchange rates and forecasting. Su & Lin (2011) determines *Value-at-Risk* using the GJR-GARCH model against financial ownership. The result obtained is that Model GJR-GARCH is good for *VaR* forecasting.

There are some flaws in the models that have been carried out by some previous researchers. Among others Xu *et al.* (2015) have not linked their research to the determination of *VaR* values, Su & Lin (2011) have not determined the value of risk using *Conditional Value-at-Risk* (*CVaR*).

Based on these deficiencies, the study used the ARIMA-GJR-GARCH model and the Genetic Algorithm to estimate the size of the risk. The purpose of this study was to apply the ARIMA-GJR-GARCH model to estimate the risk of UNVR shares. This study used the help of Excel software, *Eviews 10*.

2. Literature Review

2.1. Return

Return is the amount of profit made by investors in investing. According to Tsay (2005), there are several definitions of *returns* including assuming that the selected shares do not pay dividends. the *return* formula used is:

$$r_t = \frac{P_t - P_{(t-1)}}{P_{(t-1)}} \tag{1}$$

where r_t represents the value of the time return to-t, P_t represents the value of the time return to-t, and $P_{(t-1)}$ represents the time stock price$-(t-1)$ or the share price one period before the time-t.

2.2. Mean Model

Model ARIMA (p, d, q) introduced by Box and Jenkins, where p is an AR operator, d is an order *differencing*, and q is an MA operator. In general, the ARIMA model (p, d, q) is as follows:

$$\phi_p(B)(1-B)^d Z_t = \theta_0 + \theta_q(B)\alpha \tag{2}$$

where ϕ_p is the coefficient of the AR model parameter that depends on lag, θ_q is the coefficient of the parameters of the MA model that depends on lag, $(1-B)^d$ is operator *differencing*, Z_t is data at the time to t, B is the operator step back, and d is a *differencing* rate for the process to be stationary.

2.3. Volatility Model

The GARCH model is a generalization of the ARCH model developed by Bollerslev in 1986. Based on its development, the GARCH model is a supporter of *time series* analysis of the capital market by providing volatility estimators. Model GARCH (p, q) is as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \theta_i a_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + u_t \tag{3}$$

The GARCH equation above shows that the conditional si variant is volatility (ARCH) and the previous variance (GARCH) is seen from residual squares (p) and the previous residual variant (q) (Olowe, 2010). The things that are nature of the GARCH model are the GARCH model in its low-accuracy volatility forecasting and on many stock data, stock *returns* have an asymmetric influence that is not detected by the GARCH model (Dwipa, 2016).

This GJR model (Glosssten, Jagannathan, and Runkle) is another asymmetric GARCH model that is a common form of the GJR-GARCH model (p, q). Model GJR-GARCH (p, q) defined as follows (Hidayana *et al.*, 2022):

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \theta_i a_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \gamma_i I_{t-i} a_{t-i}^2 \tag{4}$$

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

where I_{t-i} is a *dummy* variable which means I_{t-i} is a functional index of value 0 ketika ε_{t-i} positive and worth 1 when ε_{t-i} negative. If the parameter $\gamma_i > 0$ then the negative *error* does not work which means that the influence of *bad news* is greater than the influence of *good news* (Dritsaki, 2017).

2.4. *VaR*

Value-at-Risk (*VaR*) is one of the instruments for measuring risk. So that the equation becomes (Dokov *et al.*, 2008):

$$VaR = \inf\{x | F_l(x) \geq \alpha\}$$

The standard method assumes that *the return on* univariate-distributed assets *is normal*, having two parameters namely the average (*mean*) μ and standard deviation σ. *VaR* estimation is performed using the following equation:

$$VaR = -1 \cdot \left(\mu + \sigma_t F^{-1}(\alpha)\right) \tag{5}$$

3. Result and Discussion

In this section, data analysis is carried out using the mean model and volatility models. Then the *Value-at-Risk* calculation is carried out using the average value and variance that has been obtained.

3.1. Data

The data used in this study is daily historical data on stock closures starting in the period from December 17 2018 to December 14, 2021. The data is obtained from the website https://finance.yahoo.com/. Data analysis is carried out with the help of *Eviews* and Excel software.

3.2. Statistic Descriptive

The descriptive statistics of the data used based on the value of stock returns that can be calculated using equation (1) are shown in Table 1.

Table 1. Data descriptive statistics

Kode	Samples	Mean	Median	Maximum	Minimum	Standard deviation
UNVR	746	-0.0007	-0.00056	0.19383	-0.0692	0.02056

Then a stationary test was carried out based on the return value using the Eviews software, it was obtained that the original data was stationary. So, it can be concluded that the model used is the ARMA model (p, q) or the ARIMA model (p, d, q) with the order d in the model is worth 1.

3.3. Mean Model Estimation

After stationary data, it further determines the average model. Based on section 2.2, the best average model was obtained, namely ARMA (2,0,3). The model has a white noise diagnostic test result with a Ljung-Box value (44.958991) less than $\chi^2_{\alpha;k-m}$ (44.98534) and residual is normal. Therefore, the ARIMA model (2,0,3) is said to be significant. The UNVR stock model estimates according to equation (2) which is as follows

$$Z_t = -0.248710Z_{t-1} - 0.782618Z_{t-2} - 0.839945a_{t-1} + 0.551698a_{t-2} - 0.709946a_{t-3} + a_t.$$

3.4. Volatility Model Estimation

Before determining the volatility model, the first thing to do is to check the effect of ARCH on the selected average model. After testing ARCH-LM using Eviews software, it was obtained that the average model had an ARCH effect. The selected model is said to be significant after validating normally distributed white noise and residual diagnostic tests. GARCH model estimation is as follows

$$\sigma_t^2 = 1.40 \times 10^{-5} + 0.155901a_{t-1}^2 + 0.814572\sigma_{t-1}^2 + u_t.$$

Furthermore, checking the symmetrical effect on the GARCH model was carried out, and it was found that the GARCH model had an asymmetric effect. Therefore, an estimate of the GJR-GARCH model for the volatility model was carried out. So, a significant model was obtained, namely GJR-GARCH (1,1). Based on section 2.3 the volatility model estimates are as follows

$$\sigma_t^2 = 1.05 \times 10^{-5} + 0.092302a_{t-1}^2 + 0.151156a_{t-1}^2 \mathrm{I}_{t-1} + 0.707198\sigma_{t-1}^2 + \varepsilon_t.$$

3.5. *VaR* Estimation

The *value-at-Risk* calculation is based on the results of estimated averages and variances. There are several parameters used to calculate *VaR*, namely the average $\hat{\mu}$ and standard deviation $\hat{\sigma}$ which refers to section 2.4. Then a Backtesting calculation is carried out to determine *VaR* performance where the value obtained is no more than the range [0, 2]. *VaR* results can be seen in Table 2.

Table 2. *Value-at-Risk* and QPS calculation results

Kode	$\hat{\mu}_t$	$\hat{\sigma}_t^2$	$\hat{\sigma}_t$	VaR_t	QPS
UNVR	0.002266	0.000077	0.008781	0.012177	0.328758

4. Conclusions and Suggestions

The conclusion obtained is the average model, namely ARIMA (2,0,3), while the volatility model for UNVR stocks is GJR-GARCH (1.1). Then the results of the *Value-at-Risk* calculation obtained using the ARIMA(2,0,3)-GJR-GARCH(1,1) model were 0.01217. This means that if an investment is made in UNVR shares of IDR 100,000,000.00, the estimated maximum loss of potential loss that occurs is estimated to reach IDR 1,217,000. The suggestion proposed for further research is to be able to use other time series models to improve the average and volatility models.

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