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Company Stock Performance Analysis on IDX ESG Leaders Index Using the ARIMA-GARCH Model

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Abstract

Stocks are one of the most popular forms of investment. In investing stocks, it is necessary to know the movement of stock prices and the investment risks that may occur. The purpose of this study is to predict the level of risk, see the characteristics of stock returns, and whether the ESG Risk Rating makes the company's stock performance better. The models used to predict stock returns are Auto Regressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroscedasticty (GARCH), and Value at Risk (VaR) is used to predict risk. Based on the research, the potential loss for Bank BCA is IDR29.800.000,00 and Bank Mandiri is IDR33.600.000,00 with the assumption that an investor invests as much as IDR1.000.000.000,00. In addition, Bank BCA has a lower ESG Risk Rating than Bank Mandiri, but has a better performance.

Keywords: Time series analysis, ARIMA, GARCH, VaR, IDX ESGL index, stocks

1. Introduction

Investment is a commitment to place a number of funds or other resources at this time, with the aim of obtaining a number of benefits in the future (Tendelilin, 2017). Socially Responsible Investing (SRI), this is an investment strategy where investors screen their portfolios to avoid companies that do not support the development of environmental, moral, ethical, religious, and social values (Herinyanto, 2019). The Indonesian capital market in 2020 has started screening companies that meet environmental, social and governance criteria. This is evidenced by the establishment of the IDX ESGL Index by the Indonesia Stock Exchange (IDX).

Wang (2011), examines company stocks with a portfolio style approach and concludes that companies that fulfill corporate social responsibility will attract investors to invest. because seeing the company has a good image has a positive impact on the company's stock returns. Then, Sudha (2015), made predictions to see the performance of the ESG index in India using ARCH-GARCH and CAPM to see investment returns and risks. The research resulted in predictions that the ESG index has a good return rate of 27.2% compared to the Nifty and CNX 500 indexes with a return rate of 20.36% and 17.98%, with a minimal level of investment risk. In addition, several studies to predict stock returns have also been carried out by Wang (2009), using the ARIMA-GARCH model to predict stock returns on the Dow and S&P 500 indices and concluding that this model is better than the GARCH model, this is evidenced by the fit test that given by histogram QQ plot with good squared correlation. Based on Jang's research (2019), using cross-sectional regressions and multifactor models, it is concluded that the ESG value has a significant and negative effect on the economic and financial performance of European companies.

2. Literature Review

2.1 Return

Return is the profit obtained by both individuals, agencies, and companies obtained from the results of investments made. According to Tsay (2005) the return value can be calculated using the log return in equation (1).

(1)

$$r_t = \ln \frac{P_t}{P_{t-1}},$$

2.2 Uji Augmented Dickey Fuller

Makridakis (1995)., Augmented Dickey Fuller (ADF) test assumes that there is no correlation between residuals. The ADF test consists of regression estimation in equation (2).

$$\Delta Z_t = \beta_0 + \delta Z_{t-1} + \sum_{i=1}^{n} \alpha_i \Delta Z_{t-i} + a_t, \quad (2)$$

2.3 ARIMA Model

Auto Regressive Integrated Moving Average (ARIMA) or commonly called the Box-Jenkins method is a model commonly used for data forecasting analysis. The ARIMA model is a combination of 2 models, namely Auto Regressive (AR) and Moving Average (MA). The general form of the AR(p) model is as follows (Wei, 2006):

$$Z_t = \phi_1 Z_{t-1} + \cdots + \phi_p Z_{t-p} + a_t, \quad (3)$$

MA(q) is given by

$$Z_t = a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q}, \quad (4)$$

ARMA(p,q) is given by

$$Z_t = \phi_1 Z_{t-1} + \cdots + \phi_p Z_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q}, \quad (5)$$

ARIMA(p,d,q) is given by

$$W_t = \phi_1 W_{t-1} + \cdots + \phi_p W_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q}, \quad (6)$$

2.4 Identify the ARIMA Model

According to Wei (2006), identification of the ARIMA model can be done by examining the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The Autocorrelation (ACF) function can be seen in equation (7).

$$\hat{\rho}_k = \frac{\hat{\gamma}_k}{\hat{\gamma}_0} = \frac{\sum_{t=1}^{n-k}(Z_t-\bar{Z})(Z_{t+k}-\bar{Z})}{\sum_{t=1}^{n}(Z_t-\bar{Z})^2}, \quad (7)$$

$PACF$ is given by

$$P_k = \frac{cov[(Z_t-\hat{Z}_t)(Z_{t+k}-\hat{Z}_{t+k})]}{\sqrt{var(Z_t-\hat{Z}_t)}\sqrt{var(Z_{t+k}-\hat{Z}_{t+k})}} \quad (8)$$

2.5 Parameter Estimation of ARIMA Model

According to Wei (2006), one of the methods used to estimate model parameters is Maximum Likelihood Estimation. This method uses the principle of maximizing the likelihood function to estimate the parameters and in the ARIMA model. The Log Likelihood function can be seen in equation (9).

$$L = \ln P(a|\phi,\theta,\sigma_a^2) = -\frac{n}{2}\ln 2\pi\sigma_a^2 - \frac{1}{2\sigma_a^2}\sum_{t=1}^{n}(\theta_1 a_{t-1} + Z_t - \phi_1 Z_{t-1})^2 \quad (9)$$

2.6 Parameter significant test

According to Bowerman (1993) parameter testing aims to determine whether the model parameters are suitable for use in the model or not. The test hypotheses used are as follows:

$H_0: \theta_J = 0$ (parameter not sigificant)

$H_1: \theta_J \neq 0,$ (parameter significant)

where $J = 1, 2, \ldots, q$

$$t = \frac{\hat{\theta}_J}{SE(\hat{\theta}_J)}, \quad (10)$$

Critetion H_0 rejected if, $p-value < 0.05$ or $|t| > t_{\frac{\alpha}{2}, df=n-n_p}$, with n_p is the number of parameters to be estimated.

2.7 Model Diagnostic Test

To check whether the residual is white noise, this explains that a residual follows a certain distribution with a zero mean and a certain variance. The test that can be done for the assumption of white noise is the Ljung-Box test (Wei, 2006)

$H_0: \rho_1 = \rho_2 = \cdots = \rho_k$ *(white noise)*

$H_1: \rho_k \neq 0$ (not *white noise)*

Statistic test:

$$Q = n(n+2)\sum_{k=1}^{m}\frac{\hat{r}_k^2}{n-k}, \tag{11}$$

2.8 GARCH Model

The Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model is the development of the AutoRegressive Conditional Heteroskedasticity (ARCH) model introduced by Bollerslev (1986) as shown in equation (15).

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_n a_{t-n}^2 \tag{12}$$

In addition, Bollerslev (1986) proposed the GARCH model in equation (16).

$$\sigma_t^2 = \alpha_0 + \sum_{p=1}^{n}\alpha_p a_{t-p}^2 + \sum_{q=1}^{n}\beta_q \sigma_{t-q}^2 \tag{13}$$

2.9 Lagrange Multiplier

Engle (1982) developed a test used to identify whether a time series data has a heteroscedasticity effect or not, namely the Lagrange Multiplier (LM) test. The hypotheses used are:

$H_0: \alpha_1 = \alpha_2 = \cdots = \alpha_p$ (no heteroscedasticity effect)

H_1: minimal terdapat satu $\alpha_i \neq 0$ (heteroscedasticity effect)

Statistic test:

$$LM = nR^2 \tag{14}$$

If $LM > x_{(a,k)}^2$ or $p\text{-}value < 0{,}05$ then H_0 rejected which idicated there is heteroscedasticity effect.

2.10 Parameter Estimation of the GARCH Model.

According to Enders (2004), parameter estimation for the GARCH model uses Maximum Likelihood Estimation (MLE) if the residuals are normally distributed with an average of 0 and a variance σ_t^2. The Log Likelihood function is given in equation (18).

$$\ln L = \sum_{t=1}^{n}\left(-\frac{1}{2}\ln(2\pi) - \frac{1}{2}\ln\sigma_t^2 - \frac{1}{2}\frac{a_t^2}{\sigma_t^2}\right), \tag{15}$$

2.11 Value at Risk

VaR is a risk assessment concept developed by J.P Morgan in 1994. VaR can be calculated by equation (21).

$$VaR = -M(\hat{Z}_t + z_\alpha \hat{\sigma}_t), \tag{16}$$

2.12 Backtesting on Value at Risk

According to Sukono, et al. (2015), after getting the VaR results, Bactesting is carried out which is a method to see the performance of the estimated VaR. The loss function used to test the performance of the VaR risk measure proposed by Lopez in 1998 is given in equation (21).

$$C_t = \begin{cases} 1 + (r_t - VaR)^2, & r_t > VaR \\ 0 \quad , & r_t \leq VaR \end{cases} \tag{17}$$

the test statistic used to test the performance of the VaR risk measure is the Quadratic Probability Score (QPS) which can be calculated by a formula based on equation (22).

$$QPS = \frac{2}{n}\sum_{t=1}^{n}(C_t - p)^2 \tag{18}$$

2.13 Selection of the Best Model

According to Wei (2006), the best model selection can be done using Akaike's Information Criterion (AIC) and Schwartz's Bayesian Criterion (SBC) models.

$$AIC = -2\ln L + 2n \tag{19}$$

$$SBC = -2\ln L + n\ln(n) \tag{20}$$

3. Materials and Methods

The data used in this study is daily closing price data for Bank BCA (BBCA) and Bank Mandiri (BMRI) shares starting from January 2, 2017 – November 30, 2021. Descriptive statistics are given in Table 1. This daily closing price then calculated for daily return, which going to be use for this paper. After attaining daily return, then modeling could be done.

4. Results and Discussion

4.1 Estimating the ARIMA Model

After knowing that the data is stationary, it is possible to estimate the provisional model, it is obtained the following provisional model estimates: ARIMA (1,0,1), ARIMA (1,0,3), ARIMA (3,0,1) for BBCA shares and ARIMA (2,0,2), ARIMA (2,0,9), ARIMA (9,0,2) for BMRI shares.

4.2 Estimating the GARCH Model

Before estimating the GARCH model, a Lagrange Multiplier test was performed to determine whether there was a heteroscedasticity effect or not. Based on calculations using Eviews 10 software, it is known that each model has a heteroscedasticity effect. After estimating the model parameters, the ARIMA-GARCH model for each company is obtained as follows: ARIMA (3,0,1) – GARCH (2,0) for BBCA and ARIMA (2,0,9) – GARCH (3, 0) for BMRI. Then the heteroscedasticity effect was checked again and it was found that the model did not have a heteroscedasticity effect. Therefore the ARIMA – GARCH model for BBCA is as follows:

$$Z_t = 0{,}0530Z_{t-3} + a_t + 0{,}1071\alpha_{t-1} \quad (21)$$

$$\sigma_t^2 = 0{,}0001 + 0{,}1455\alpha_{t-1}^2 + 0.2521\alpha_{t-2}^2 \quad (22)$$

Next, for ARIMA – GARCH model for BMRI is as follows:

$$Z_t = -0{,}0606Z_{t-9} + a_t + 0{,}1007a_{t-2} \quad (23)$$

$$\sigma_t^2 = 0{,}0002 + 0{,}1438\alpha_{t-1}^2 + 0{,}1327\alpha_{t-2}^2 + 0{,}1875\alpha_{t-3}^2 \quad (24)$$

4.3 Value at Risk and Backtesting

After obtaining the ARIMA – GARCH model, then VaR assessment and backtesting are carried out to measure the performance of the estimated VaR. The calculation results are given in Table 1.

Tabel 2. VaR dan QPS

Saham	*VaR*	*QPS*
BBCA	0,0298	0,0675
BMRI	0,0336	0,0965

5. Conclussion

From the result we can see that BBCA has better performance than BMRI because of the lower VaR value, beside that QPS for BBCA also lower which indicated that the acuracy of VaR model is better predicted. From the result we can conclude that ESG Risk rating doesn't bring significant difference to stock performance.

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