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GARCH Model For Forecasting Stock Return Volatility In The Infrastructure, Utilities And Transportation Sectors

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Abstract

The stock market is constantly changing with uncertainties that can pose risks. The rapid dissemination of information and the fast flow of capital will cause fluctuations in stock prices, causing stock price volatility. This study examines the behavior of volatility patterns in the infrastructure, utility, and transportation sectors using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. This study uses monthly data from January 2014 to December 2019. The results show that the volatility of all stocks in this study is influenced by the previous month's error and volatility return. Investors and securities analysts can use these results in making decisions to invest in the infrastructure, utilities, and transportation sectors.

Keywords: Volatility, Stock Returns, GARCH, Forecast, Infrastructure

A. INTRODUCTION

Globalization is the economic sector that has made the role of the capital market more critical for a country (Goryakin, Lobstein, James, & Suhrcke, 2015). Investors from various countries can invest their capital in any country through the capital market (Raneo & Muthia, 2019). In the capital market to measure the stock price index, it is often used as a stock indicator that investors use to sell and buy shares (Sari, Achsani, & Sartono, 2017). The stock market every day experiences price changes (Lin, 2018). Changes in the stock price index can occur because of changes in stock prices on the stock exchange or changes in the stock base's total value (Amini, Buchner, Cai, & Mohamed, 2020; Edmans, Jayaraman, & Schneemeier, 2017). This can lead to a level of risk or volatility.

Stock market volatility is significant for market practitioners and policymakers, especially for developing countries (Lawal, Somoye, Babajide, & Nwanji, 2018; Mohamed Dahir, Mahat, Ab Razak, & Bany-Ariffin, 2018). Stock market volatility has a significant effect on market practitioners and policymakers, especially for developing countries (Lawal, Somoye, Babajide, & Nwanji, 2018; Mohamed Dahir, Mahat, Ab Razak, & Bany-Ariffin, 2018). This is because stock market volatility affects asset prices and risk (Ismail, Audu, & Tumala, 2016). Information flows can help them make decisions. The more information obtained, the smaller the level of risk that is borne (Domínguez & Gámez, 2014). The phenomenon of information asymmetry in fluctuations in financial time series, namely fluctuations caused by bad news is always much more significant than good news (Thampanya, Wu, Nasir, & Liu, 2020).

Infrastructure, utility, and transportation sector stocks are the types of supplies sought after by investors both from within and outside the country. Moreover, the Indonesian government is actively developing this sector to catch up with other countries and accelerate the wheels of the Indonesian economy. Because both infrastructure, utilities, and transportation can boost a country's economy if appropriately managed. In this way, the movement of shares of several companies in this sector is also affected by the impact on the capital market so that which affects the value of shares in the infrastructure, utilities, and transportation sectors in Indonesia.

Figure 1 shows the movement of infrastructure, utility, and transportation stocks from 2014 to 2019, experiencing fluctuating trends. In 2014 share prices increased, then in 2015 decreased due to slowing economic growth and falling oil prices so that stock prices in all sectors of the Jakarta Composite Index (JKSE), including infrastructure stocks, decreased. In 2016 it increased until the following year and experiencing stock price volatility.

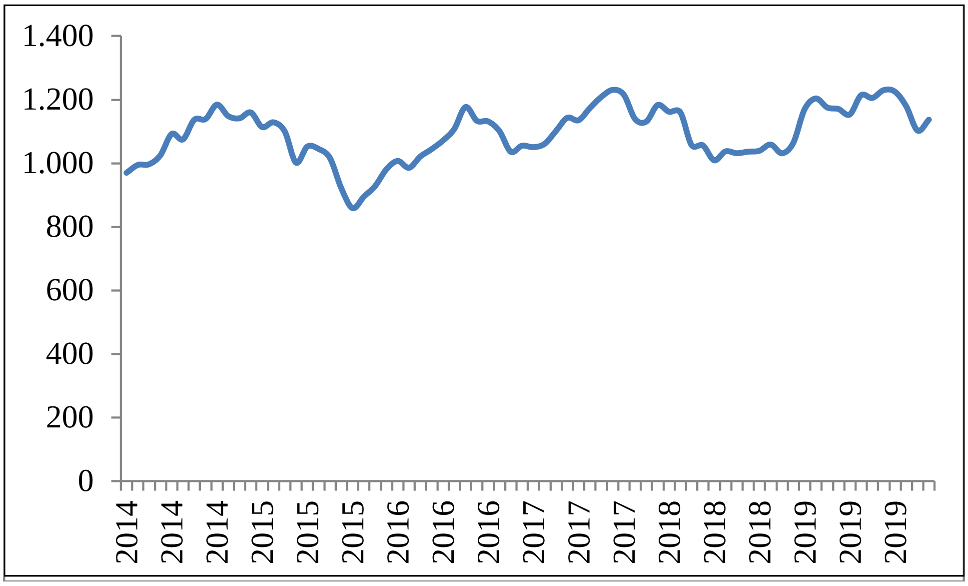


Figure 1. Price Movements of Infrastructure, Utilities, and Transportation Shares

Previous research related to volatility modeling and forecasting has been conducted by Prasad, Bakry, and Varua (2020) on the Australian stock exchange, Sarwar, Tiwari, and Tingqiu (2020) on Asian stock markets, Fang, Lee, and Su (2020), Aliyev, Ajayi, and Gasim (2020), and Herwartz (2017) on the stock exchange in the United States, Raneo and Muthia (2019) on the Indonesian stock exchange market, Ningsih, Sumarjaya, and Sari (2019) on the LQ45 stock index, Lin (2018) on the Shanghai stock index, Sari et al. (2017) on shares of four countries in Asia, Vipul (2016) on stock markets in 16 countries in the world, Birău, Trivedi, and Antonescu (2015) on the stock exchange in India, Chuang, Liu, and Susmel (2012) on Asian stock markets, Alexandrou, Koulakiotis, and Dasilas (2011) on stock exchanges in Europe.

Based on the description that has been stated, the researchers are interested in exploring more about the modeling and forecasting of stock return volatility in the infrastructure, utilities, and transportation sectors in Indonesia which are still rarely done.

The formulation of the problem posed in this study is how to model and predict the volatility of stock returns in the infrastructure, utilities, and transportation sectors in Indonesia. The results of this study are expected to be able to contribute as a reference in assessing financial conditions and as a basis for predicting future stock return conditions.

B. LITERATURE REVIEW

Investment is an investment in the long term with the hope of getting benefits in the future as compensation for delayed consumption, the impact of inflation, and the risks borne. One alternative investment is investing in stocks. Investors urgently need relevant information in making investment decisions in financial assets in the capital market. Investors require an approach in analyzing stock prices in the capital market. An approach to analyzing stock prices in the capital market can help investors make investment decisions using both fundamental and technical methods.

Research related to volatility has been conducted several times by various researchers in the world, including a study conducted by Wang, Ma, Liu, and Yang (2020), which forecasts stock price volatility using the Generalized Autoregressive Conditional Heteroskedasticity-Mixed Data Sampling (GARCH-MIDAS) technique. The sample used in this research is the S&P 500 index using daily stock price data from January 1991 to December 2016. The results show that the effects of asymmetry and extreme volatility in the GARCH-MIDAS model significantly impact stock price volatility.

Fang et al. (2020) researched by testing the stock market's long-term volatility using the Generalized Autoregressive Conditional Heteroskedasticity-Mixed Data Sampling (GARCH-MIDAS) model. The sample used in the study is the S&P 500 index using macroeconomic and financial data from the 1st quarter of 1969 to the 4th quarter of 2018. The results show that the GARCH-MIDAS model has a significant influence in predicting long-term stock market volatility. Raneo and Muthia (2019) tested the application of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model in Volatility forecasting on the Indonesia Stock Exchange using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Threshold ARCH (TARCH), and Exponential GARCH (EGARCH) model. The sample was used, namely the composite stock price index (IHSG) from January 2006 to November 2017. The results of this study indicate that the capital market has a volatility symptom where the GARCH models found are GARCH (1,1), TARCH (1,1), and EGARCH (1,1).

Lin (2018) researched modeling and forecasting the volatility of stock returns on the SSE Composite Index. This study uses the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The results show that stock returns have a positive risk premium where there is a positive correlation between daily returns and the volatility of SSE Composite Index stocks. Sari et al. (2017) researched the modeling of stock return volatility using various asymmetric models of Generalized Autoregressive Conditional Heteroskedasticity (GARCH). The sample used in his research is the stock price index of four countries, including Indonesia (JCI), Singapore (STI), Japan (NKY), and Hong Kong (HSI). The results showed that the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is better at describing stock returns volatility in the four stock markets.

Ismail et al. (2016) researched by testing volatility forecasting on the stock market in Africa using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and Maximal Overlap Discrete Wavelet Transform- Generalized Autoregressive Conditional Heteroskedasticity (MODWT-GARCH). The sample used is the African stock market index from January 2000 to December 2014. The results show that the Maximal Overlap Discrete Wavelet Transform-Generalized Autoregressive Conditional Heteroskedasticity (MODWT-GARCH) model (1,1) is the best model in generating estimated values and accurate return.

Vipul (2016) tested volatility forecasting on the stock market using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) models. The sample used in his study consisted of 16 international stock indices from January 2000 to September 2014. The results show that the Exponentially Weighted Moving Average (EWMA) model is better than the Realized Generalized Autoregressive Conditional Heteroskedasticity (RGARCH) model in the forecasting model. Besides, the Exponentially Weighted Moving Average (EWMA) model is more comfortable to implement than the Realized Generalized Autoregressive Conditional Heteroskedasticity (RGARCH) model.

C. RESEARCH METHODS

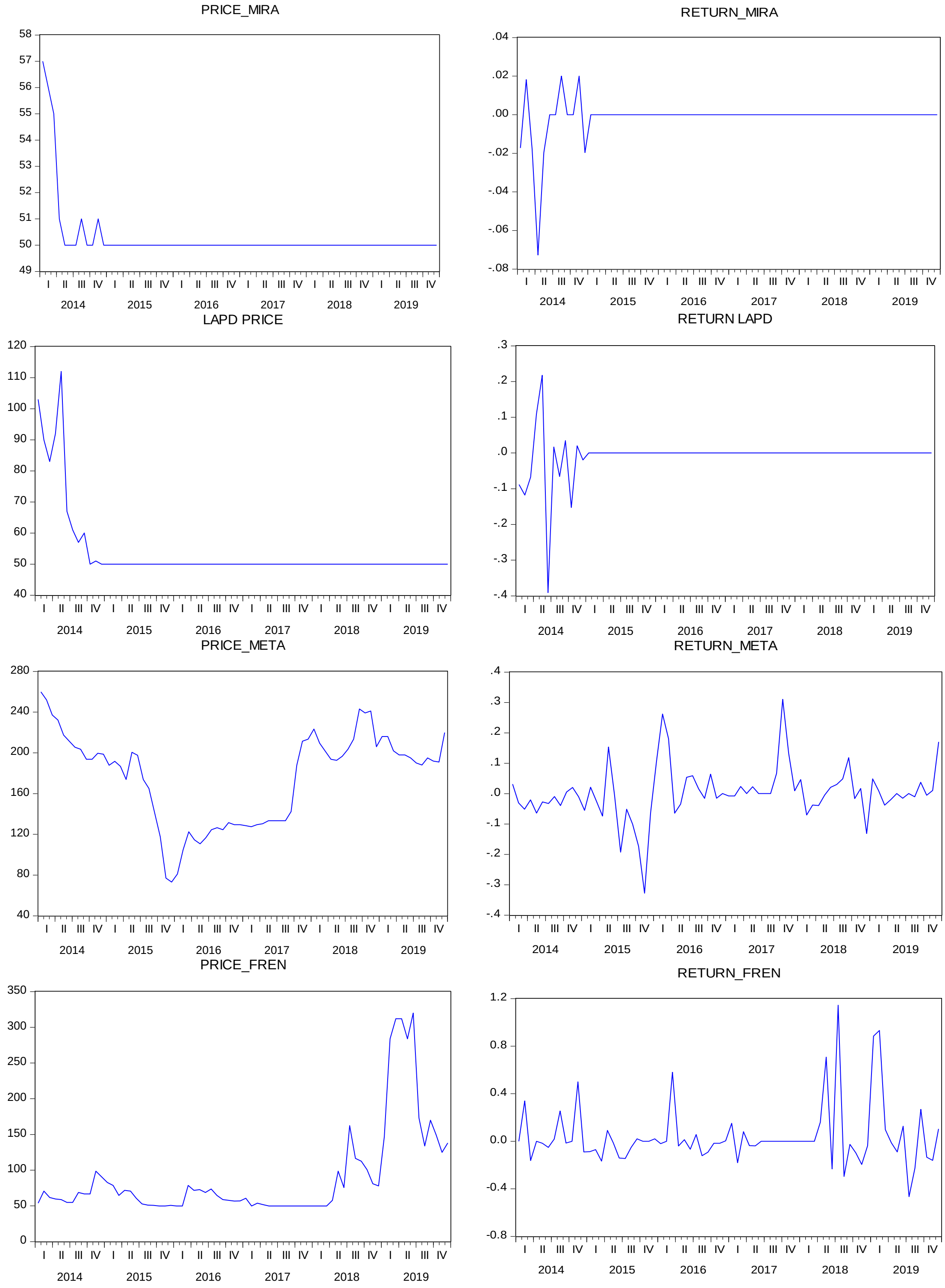
This study uses monthly data from January 2014 to December 2019. The research data is sourced from the Indonesian Stock Exchange. This study uses a stock sample of the utility and transportation infrastructure sector, a service company consisting of 5 sub-sectors, namely energy, toll roads, ports, airports, telecommunications, transportation, and non-building construction. The selection of shares in infrastructure, utility, and transportation sector companies with criteria including publicly listed companies listed as issuers in the period January 2014 to December 2019 and those with heteroscedastic effects. Thus, the company stocks used as research samples are Nusantara Infrastructure Tbk (META), Smartfren Telecom Tbk (FREN), Solusi Tunas Pratama Tbk (SUPR), Garuda Indonesia Tbk (GIAA), Cardig Aero Services Tbk (CASS), Pelayaran Nelly Dwi Putri Tbk (NELY), Trans Power Marine Tbk (TPMA), and Capitol Nusantara Indonesia Tbk (CANI).

This study uses the Autoregressive Conditional Heteroscedasticity-Generalized Autoregressive Conditional Heteroscedasticity (ARCH-GARCH) method to answer the research objectives. The first stage is the model's specification, namely by detecting the ARCH effect of stock data with the autocorrelation test and ARCH test, followed by the appropriate specification of the average equation. The second stage, estimating the parameters and selecting the best variance model by simulating several variance models based on the AIC value. In the third stage, a diagnostic test of variance models with error analysis includes the ARCH test and normality test. The fourth stage is to forecast. By using the GARCH model where h_t = monthly return, $\alpha_1 e^2_{t-1}$ = random error, h_{t-1} = conditional variance.

$$h_t = \delta + \alpha_1 e_{t-1}^2 + \cdots + \beta_1 h_{t-1}$$

D. RESULT AND DISCUSSION

The first step in this research process is to look at each company's stock price movements and stock returns, as can be seen in Figure 2. Each company studied has a high level of volatility. In general, ten stocks' trend shows a massive price change, followed by a more considerable change in return. Likewise, when there is a small change in stock price, followed by a smaller difference in stock returns.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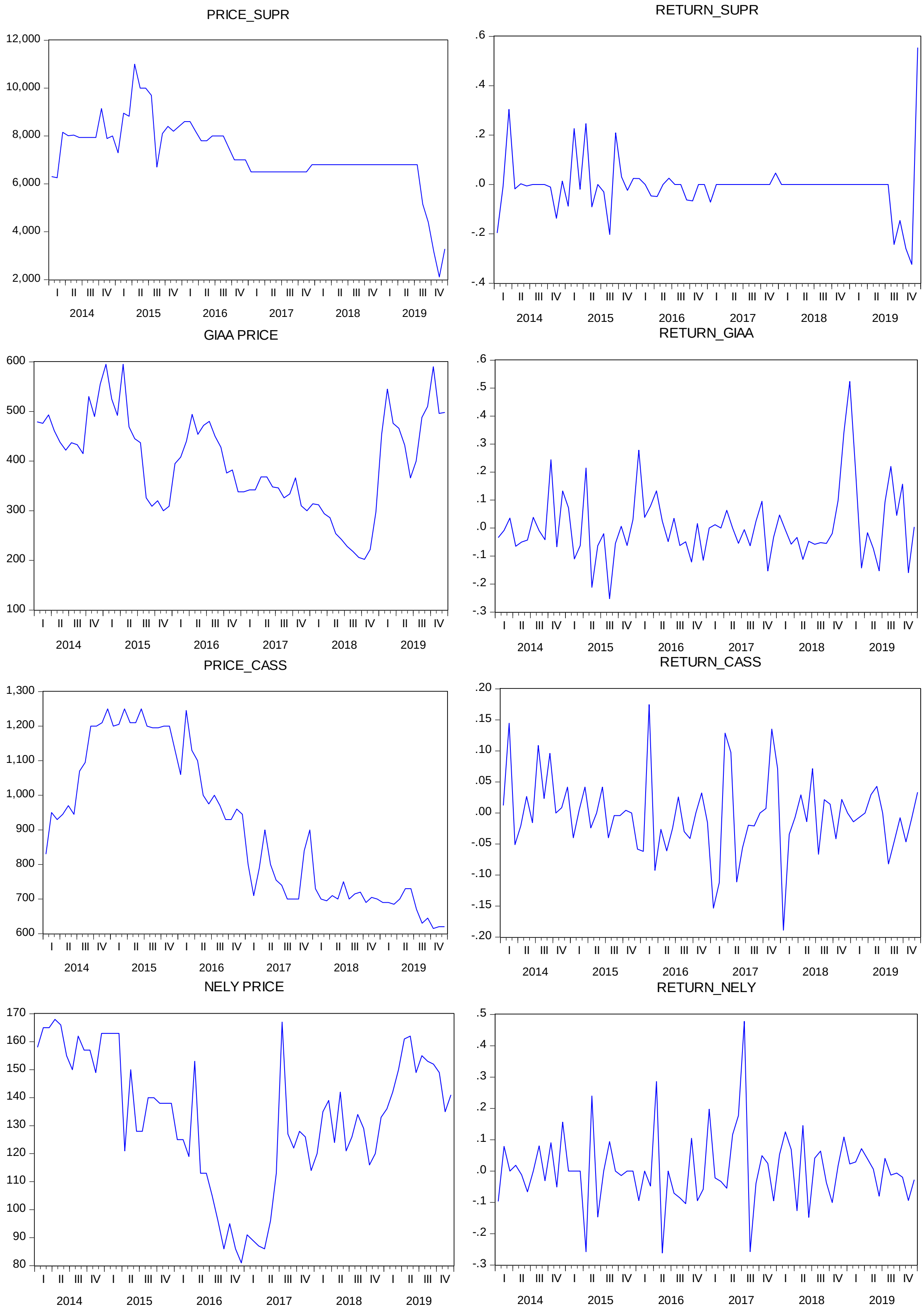
PRICE_SUPR
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GIAA PRICE
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PRICE_CASS
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NELY PRICE
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2014 2015 2016 2017 2018 2019

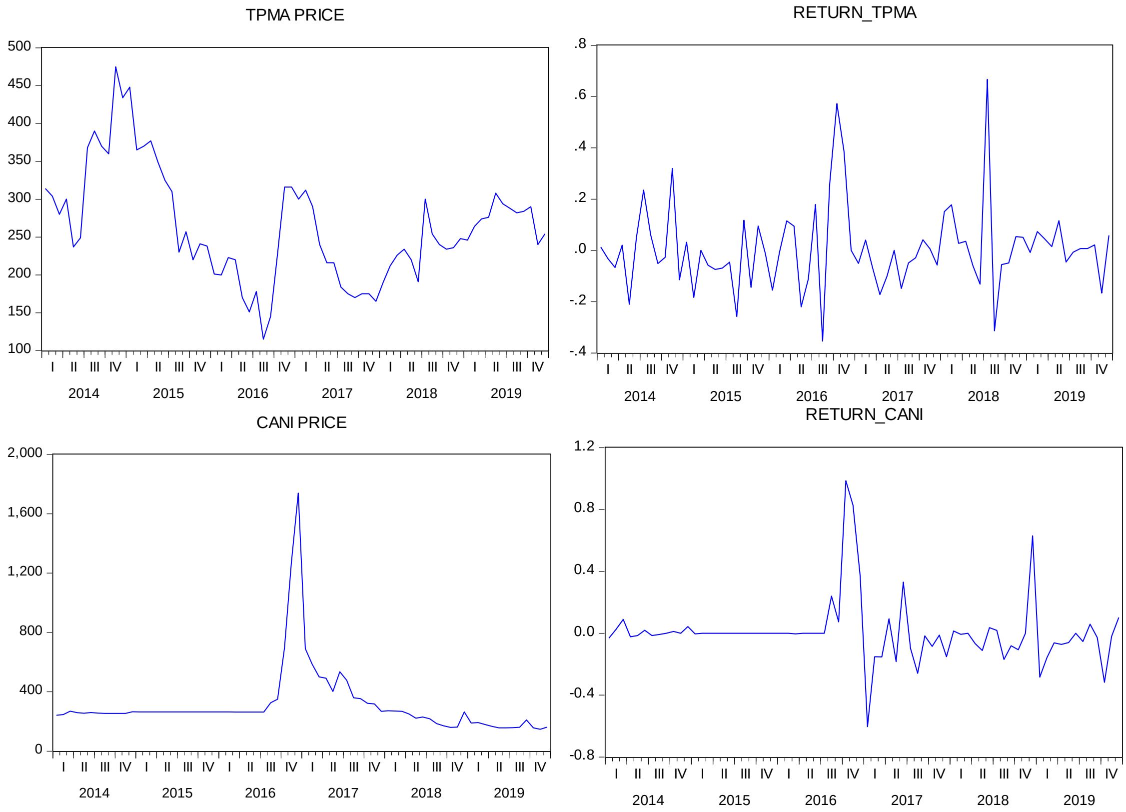

Figure 2. Shares Movement and Stock Return

The second step in the data processing process is to describe the results of descriptive statistics, aiming to provide an overview of the information and characteristics that can be obtained and used because they affect the data analysis to be carried out. Table 1 shows the descriptive statistics of each company analyzed. From the table, the average company return ranges from -0.12% to 4.08%, where the smallest average return at MIRA companies is -0.12%, and the largest is at FREN companies by 4.08%. The most massive return in FREN companies was 114.47%, while the smallest was in CANI companies at -60.34%. Furthermore, companies with a high risk of return are FREN companies of 26.91%, and companies with a low chance of returns are CASS companies.

Table 1. Descritive Statistic

No	Company	Mean	Median	Maximum	Minimum	Standard Deviation
1.	META	0.0022895	-0.002487	0.310343	-0.327587	0.089327
2.	FREN	0.040837	0.00000	1.144736	-0.466049	0.264911
3.	SUPR	-0.005401	0.00000	0.554502	-0.323718	0.115364
4.	GIAA	0.006339	-0.0131015	0.523490	-0.252294	0.124375
5.	CASS	-0.002248	-0.002083	0.174528	-0.188889	-0.062660
6.	NELY	0.005144	0.00000	0.477876	-0.261438	0.116123
7.	TPMA	0.006111	-0.002488	0.666667	-0.353933	0.166252
8.	CANI	0.007718	0.00000	0.985714	-0.603448	0.213407

After descriptive statistics are carried out, the third step in processing the next data is to test the data stationarity. Time series data generally contain unit roots, which cause the data to be non-stationary at the level. Data that have unit roots usually have good results but are unable to describe what happened. One way to avoid this is by ensuring the variables used in the study are stationary. The stationarity test was conducted in this study using the Augmented Dickey-Fuller test. Based on the test, it shows that all the variables studied have a probability that is less than a critical value of 5% so that the data used is stationary.

Table 2. Stationary test results

Company	Augmented Dickey-Fuller	
	t-statistic	Probability
META	-5.121997	0.0001
FREN	-8.364676	0.0000
SUPR	-5.736478	0.0000
GIAA	-6.339170	0.0000
CASS	-8.277100	0.0000
NELY	-11.23092	0.0001
TPMA	-8.744343	0.0000
CANI	-6.180816	0.0000

After ensuring that the data is stationary, the fourth step is to determine the best Integrated Moving Average (ARIMA) Autoregressive Model. Because in the ARIMA method, there is an ARCH effect, the ARIMA model selected error value is used to search for further GARCH models. This study uses the smallest Akaike Info Criterion (AIC) value, and a probability value of less than 5% to determine the best ARIMA (p, d, q), model. AIC can predict models with high probability correctly (Naik, Mohan, & Jha, 2020).

Table 3. Overfitting Model

No	Company	ARIMA Model	AIC	Probability
1.	META	(3,0,3)	-2.045499	0.0000
2.	FREN	(5,0,5)	0.131167	0.0000
3.	SUPR	(0,0,4)	-1.689851	0.0000
4.	GIAA	(1,0,5)	-1.457069	0.0002
5.	CASS	(3,0,3)	-2.745628	0.0000
6.	NELY	(5,0,5)	-1.520583	0.0000
7.	TPMA	(5,0,5)	-0.786778	0.0000
8.	CANI	(0,0,1)	-0.291812	0.0247

After obtaining the ARIMA model, the heteroscedasticity test was carried out using the Autoregressive Conditional Heteroscedasticity-Lagrange Multiplier (ARCH-LM) to see the heteroscedasticity effect. The ARCH-LM test was used to test whether the residue had been standardized by showing additional ARCH (Thampanya et al., 2020). The test results showed that the data contained heteroscedasticity, as evidenced by the probability value of each data is less than 5% so that the data could be continued with the ARCH-GARCH test.

Table 4. ARCH-LM Heteroscedacity Test

Company	Heteroscedasticity
META	0.0200
FREN	0.0438
SUPR	0.0000
GIAA	0.0505
CASS	0.0340
NELY	0.0061
TPMA	0.0378

CANI	0.0499

The next stage uses the ARIMA model using the ARCH-GARCH method to find the GARCH model. Table 5 shows the best GARCH model results for each variable—selection of the best model based on the smallest AIC value and significant coefficient values.

$$\mathrm{META}h_t = 0.000734 + 0.892060\varepsilon_{t-1^2} - 0.447847\varepsilon_{t-2^2} + 0.849754\, h_{t-1} - 0.248899\, h_{t-2}$$

The model above provides information that the level of risk of META stocks is influenced by the amount of return value of the previous two months and the amount of standard deviation of return from the average for the last two months.

$$\mathrm{FREN}h_t = 0.019229 + 0.1332963\varepsilon_{t-1^2}$$

The model above provides information that the risk level of FREN shares is influenced by the amount of the residual return value a month earlier.

$$\mathrm{SUPR}h_t = 0.001799 + 0.544347\varepsilon_{t-1^2} + 0.406040h_{t-1} + 0.360649h_{t-2} + 0.276376h_{t-3}$$

The model above provides information that the risk level of SUPR shares is influenced by the size of the value of the residual return a month earlier and the amount of standard deviation of recovery from the average for the previous three months.

$$\mathrm{GIAA}h_t = 0.00106 + 0.3654153h_{t-1} - 5.39330h_{t-2} - 3.796394h_{t-3} - 1.066909h_{t-4}$$

The model above provides information that the level of risk in GIAA shares is influenced by the amount of standard deviation of return from the average for the previous four months.

$$\mathrm{CASS}h_t = 314.000 + 0.892060\varepsilon_{t-1^2} + 2.016898\, h_{t-1} - 1.025616\, h_{t-2}$$

The model above provides information that the risk level of CASS shares is influenced by the amount of standard deviation of return from its average for the previous two months.

$$\mathrm{NELY}h_t = 0.004953 + 0.630397\varepsilon_{t-1^2}$$

The model above provides information that the level of risk in NELY shares is influenced by the amount of the residual return value a month earlier.

$$\mathrm{TPMA}h_t = 0.009162 + 0.9898\, \varepsilon_{t-1^2}$$

The model above provides information that the level of risk in TPMA shares is influenced by the amount of the residual return value a month earlier.

$$\text{CANIh}_t = 0.000813 + 3.007113\ \varepsilon_{t-1^2}$$

The model above provides information that CANI influences stock risk level by the amount of the value of the residual return a month earlier.

Table 5. Overfitting GARCH Model

Emiten	Model Garch (p,d, q)	C	Arch (t-1)	Arch (t-2)	Garch (t-1)	Garch (t-2)	Garch (t-3)	Garch (t-4)	Prob	AIC
META	(2,0,2)	0.000734	0.892060	-0.447847	0.849754	-0.248899	-	-	0.0235	-2.431213
FREN	(0,0,1)	0.019229	1.332963	-	-	-	-	-	0.0001	-0.107518
SUPR	(3,0,1)	0.001799	0.544347	-	0.406040	-0.360649	0.276376	-	0.0001	-2.249822
GIAA	(4,0,0)	0.00106	-	-	3.654153	-5.39330	3.796394	-1.066909	0.0003	-1.622573
CASS	(2,0,0)	314.000	-	-	2.016898	-1.025616	-	-	0.0007	-2.843471
NELY	(0,0,1)	0.004953	0.630397	-	-	-	-	-	0.0128	-1.687546
TPMA	(0,0,1)	0.009162	0.989844	-	-	-	-	-	0.0004	-0.950775
CANI	(0,0,1)	0.000813	3.007113	-	-	-	-	-	0.0436	-1.0.30727

After finding the GARCH model, then testing the accuracy of the model to catch errors, tested with three test tools, namely the ARCH-LM Test, to test whether the Heteroscedasticity effect remains on the mistake Correlogram Q Statistic test to test the data is autocorrelated or not. The ARCH-LM test results found that the data did not contain heteroscedasticity effects after GARCH modeling was carried out. The Correlogram Q Statistic test results found that the error was random, or the residual value was random. The test results show that the ten variables have no heteroscedasticity effect and do not have autocorrelation problems.

Table 6. Diagnostic Model

Variable	Heteroscedasticity	Autocorrelation
META	0.9419	0.953
FREN	0.4336	0.413
SUPR	0.8321	0.825
GIAA	0.4060	0.387
CASS	0.2221	0.205
NELY	0.7981	0.789
TPMA	0.7066	0.693
CANI	0.5958	0.580

Forecasting results of companies in the infrastructure, utility, and transportation sectors show stock returns for the next three years where META, FREN, SUPR, and CASS have decreased returns for META by -0.89%, FREN of -2.28%, and the SUPR variable of -0.40% and the CAAS variable of -0.76%. In contrast to GIAA, NELY, TPMA, and CANI, which experienced an increase in return, for GIAA of 0.11%, NELY of 0.43%, TPMA of 1.02%, and CANI were predicted to experience the highest growth in return of all the companies studied reaching 7.74%.

This sector is considered to be strong enough to face the impact of pressures from the global economic slowdown. The bright prospects for the infrastructure and construction business will certainly boost the company's performance. The increase in stock returns indicates the potential for investment to be responded to positively by investors. The research results that have been carried out are in line with research conducted by Lin (2018) regarding the modeling and forecasting of stock return volatility on the SSE Composite Index, where returns have a positive risk premium so that there is a relationship between daily returns and stock volatility. Likewise, Sari et al. (2017) tested the return volatility modeling, which shows that the Generalized Autoregressive

Conditional Heteroskedasticity (GARCH) model is better at describing the volatility of stock returns on the stock market.

Table 7. Forecasting Results

Month	META	FREN	SUPR	GIAA	CASS	NELY	TPMA	CANI
1	1,53%	-1,79%	-0,40%	-0,09%	-2,60%	4,29%	-0,76%	-1,08%
2	0,31%	5,78%	-0,40%	0,37%	0,77%	3,29%	2,71%	-33,7%
3	-0,36%	2,99%	-0,40%	3,19%	1,75%	-1,54%	4,45%	-12,6%
4	1,57%	6,44%	-0,40%	-0,86%	-2,75%	2,38%	-3,10%	2,5%
5	0,47%	-1,26%	-0,40%	3,69%	0,55%	1,05%	-1,40%	-4,3%
6	-0,65%	-5,37%	-0,40%	0,00%	1,63%	0,85%	2,18%	10,6%
7	1,47%	10,60%	-0,40%	-0,89%	-2,76%	3,54%	-0,03%	-15,4%
8	0,11%	0,67%	-0,40%	0,81%	0,33%	-0,64%	-2,97%	-3,4%
9	-0,52%	6,95%	-0,40%	-2,74%	1,41%	3,26%	2,97%	16,7%
10	1,39%	0,61%	-0,40%	1,33%	-2,83%	-0,75%	2,21%	13,7%
11	0,16%	-3,92%	-0,40%	2,71%	0,17%	-1,93%	0,00%	16,4%
12	-1,52%	9,32%	-0,40%	-2,02%	1,23%	-4,42%	0,35%	13,2%
13	-3,91%	1,08%	-0,40%	1,54%	-2,89%	3,86%	4,29%	20,9%
14	-2,01%	6,30%	-0,40%	-0,79%	0,10%	3,80%	-1,08%	14,4%
15	-1,45%	1,04%	-0,40%	-2,29%	1,10%	-1,27%	0,46%	11,4%
16	-4,21%	-2,72%	-0,40%	4,16%	-3,05%	-1,93%	2,12%	8,7%
17	-0,56%	8,26%	-0,40%	-0,08%	-0,06%	-2,22%	1,06%	11,6%
18	-0,60%	1,43%	-0,40%	-2,25%	0,92%	2,83%	-0,22%	16,9%
19	-3,05%	5,75%	-0,40%	-0,62%	-3,09%	1,60%	5,15%	10,1%
20	-0,35%	1,39%	-0,40%	0,22%	-0,21%	-2,08%	1,94%	6,5%
21	-0,82%	-6,41%	-0,40%	1,39%	0,79%	0,55%	0,47%	17,3%
22	-3,17%	-13,32%	-0,40%	2,32%	-3,18%	-4,18%	0,36%	18,7%
23	-1,06%	8,52%	-0,40%	0,44%	-0,33%	5,19%	0,73%	21,5%
24	-2,65%	-28,21%	-0,40%	2,68%	0,64%	0,97%	4,98%	15,9%
25	-2,51%	10,33%	-0,40%	5,86%	-3,25%	-2,70%	-3,44%	-32,9%
26	-1,17%	-4,03%	-0,40%	8,57%	-0,45%	1,32%	0,97%	-2,6%
27	-0,10%	-7,64%	-0,40%	3,73%	0,48%	-1,91%	1,15%	10,0%
28	-3,00%	13,30%	-0,40%	-4,35%	-3,31%	4,62%	2,00%	12,2%
29	-1,14%	-21,78%	-0,40%	-8,73%	-0,58%	-0,69%	-2,05%	14,5%
30	0,61%	-16,80%	-0,40%	-13,48%	0,33%	-2,60%	5,21%	15,2%
31	-2,29%	-30,09%	-0,40%	-5,03%	-3,34%	0,92%	1,99%	11,4%
32	-0,95%	-8,69%	-0,40%	6,07%	-0,68%	-2,68%	1,51%	12,6%
33	0,87%	11,93%	-0,40%	2,11%	0,18%	3,75%	0,34%	5,4%
34	-1,98%	-14,90%	-0,40%	0,21%	-3,43%	-0,51%	5,35%	6,4%
35	-0,61%	-17,11%	-0,40%	2,51%	-0,82%	-0,82%	-3,39%	27,8%
36	0,22%	-10,78%	-0,40%	-5,88%	0,03%	0,38%	0,10%	21,9%

E. CONCLUSION

The estimation results for monthly data show that MIRA Shares are affected by errors in the previous two months. LAPD, FREN, NELY, TPMA, CANI stocks are affected by the monthly error. META shares are affected by the last two months' error and the volatility of the return two months earlier. SUPR shares are affected by mistake and return volatility for the previous three months. GIAA shares are influenced by the volatility of return four months earlier. CASS shares are affected by the return volatility for the last two months. Forecasting results indicate that CANI stocks get the highest return of all the variables studied, meaning that CANI stocks have an increase in stock returns for the next three years by 7.74% while META stocks get the lowest forecast value of all the variables studied, which indicates that META stocks decreased by -0.89%. The study recommends using more comprehensive research data and paying attention to the data used. Data processing by adding other model comparisons to determine the best model. The results of these observations can be used by investors and securities analysis to make decisions in investing in the infrastructure, utilities, and transportation sectors.

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