ARIMA-GARCH Model Price Forecasting in PT. Unilever Indonesia Tbk

Amanda Defita Pramesti*[1], Wellie Sulistijanti[2]
[1]Institut Teknologi Statistika and Bisnis Muhammadiyah Semarang, Jl. Prof. Dr. Hamka No.KM.1, Central Java, Indonesia
*wellie.sulistijanti@itesa.ac.id

Received: 2023-June-17
Rev. Req: 2023-July-18
Accepted: 2023-August-2

10.54956/eksyar.v10i1.459

How to cite this paper: Pramesti, A.D. & Sulistijanti2, W. (2023). ARIMA-GARCH Model Price Forecasting in PT. Unilever Indonesia Tbk. *EKSYAR : Jurnal Ekonomi Syari'ah & Bisnis Islam (e-Journal)*, *10*(1), 147-156. https://doi.org/10.54956/eksyar.v10i1.459

ABSTRACT: *The purpose of this research is to predict the closing stock price of PT. Unilever Indonesia Tbk using the ARIMA-GARCH method. The data used in this study covers the period from February 20, 2020, to February 17, 2023, consisting of 734 daily observations. The data processing is performed using E-Views software. The closing stock price data of PT. Unilever Indonesia Tbk is non-stationary, thus requiring natural logarithm transformation and differencing. This is followed by model identification, parameter estimation, and diagnostic checking. The best-selected ARIMA model is ARIMA ([3,9],1,0), which accounts for the presence of heteroscedasticity. Subsequently, the GARCH method is applied, including model identification, parameter estimation, and diagnostic checking. The best GARCH model is GARCH (1,1), with the mean equation* σ_t^2 *= 0,000047 + 0,230821* e_{t-1}^2 *+ 0,6819680* σ_{t-1}^2*, which is free from heteroscedasticity effect. The forecast using the ARIMA ([3,9],1,0) GARCH (1,1) model yields a Mean Absolute Percentage Error (MAPE) of 2.423%, indicating a close approximation to the actual data. From the results of this research, the best model for forecasting PT. Unilever Indonesia Tbk for the next period was obtained. Therefore, the findings can assist PT. Unilever Indonesia Tbk and prospective investors in making decisions regarding the sale and purchase of shares in PT. Unilever Indonesia Tbk.*

Tujuan dari penelitian ini untuk memprediksi harga penutupan saham PT.Unilever Indonesia Tbk dengan metode ARIMA-GARCH. Data yang digunakan dalam penelitian ini dari tanggal 20 februari 2020 hingga 17 februari 2023 berupa data harian yang berjumlah 734 hari. Proses Pengolahan data dilakukan dengan software E-Views. Data harga penutupan saham PT. Unilever Indonesia Tbk bersifat tidak stasioner, sehingga perlu dilakukan transformasi logaritma natural dan di differencing. Kemudian dilanjutkan dengan identifikasi model, estimasi parameter dan diagnostic checking. Sehingga diperoleh pemilihan model ARIMA terbaik yaitu ARIMA ([3,9],1,0) yang mengandung efek Heteroscedastisitas. Kemudian dilanjutkan ke metode GARCH dengan melakukan Setelah proses tersebut, dapat melakukan pemilihan model terbaik dengan hasil ARIMA ([3,9],1,0) yang terdapat heteroskedastisitas, sehingga harus melanjutkan ke metode GARCH dengan identifikasi model, estimasi parameter dan diagnostic checking. Model GARCH terbaik yaitu GARCH (1,1), dengan persamaan rata-rata σ_t^2 = 0,000047 + 0,230821ee_{t-1}^2 + 0,681968 σ_{t-1}^2 dan sudah terbebas dari efek Heteroscedasticitas. Peramalan dengan menggunakan model ARIMA ([3,9],1,0) model GARCH(1,1) memiliki mean absolute percantage error (MAPE) sebesar 2,423% dan data ramalannya mendekati data actual. Dari hasil penelitian ini diperoleh model terbaik yang digunakan untuk peramalan PT. Unilever Indonesia Tbk periode selajutnya, sehingga hasil dapat membantu PT. Unilever Indonesia Tbk dan para calon investor untuk mengambil keputusan terhadap penjualan dan pembelian saham di PT. Unilever Indonesia Tbk.

Keywords: *Stock Price, ARIMA Model, GARCH Model.*

I. INTRODUCTION

In 2022, Indonesia experienced pressure due to COVID-19. The economic recovery of Indonesia has shown successful progress. As Indonesia emerged from the severe Delta variant wave from July to August, Indonesia's economic growth increased by 3.7% by the end of 2021. This positive trend continued into the first quarter of 2022, with a 5% economic growth rate, despite the brief and sharp impact of the Omicron variant. One significant factor contributing to the economy in Indonesia is investment. The economy of a country relies on investment to address various economic issues, crises, and challenges. This is due to the fact that investments in specific economic sectors can swiftly transform the different economic challenges that our nation faces. Both private and public investments come with numerous benefits, such as job creation, increased per capita income, reduction of poverty rates, improved living standards, GDP growth, and others (Ilegbinosa et al., 2015).

Investment involves long-term capital allocation to acquire assets or purchase stocks and other securities to generate profits. To enhance the quality of the economy, the growth of the investment sector can be fostered by utilizing instruments in the capital market Shodiqurrosyad, 2014 (Widiyanti & Sari, 2019). The capital market functions as a platform for investors to engage in investment activities. With the capital market playing a crucial role for investors, both individual and corporate investors can channel their surplus funds to be invested, enabling entrepreneurs to obtain additional capital to expand their business networks from investors in the capital market (Malkan et al., 2021). It consists of instruments with a maturity period of over one year, such as common stocks, right issue, bonds, preferred stock, warrants and other financial institutions (V. Putri & Manisha, 2021).

On the other hand, one of the crucial considerations is the stock price. Investors expect a stable stock price with an upward trend over time, but in reality, stock prices tend to fluctuate. The stock price offered by companies each year cannot be guaranteed (Fitrianingsih, 2018). Stocks represent ownership stakes in a company, and investors acquire shares of a company by purchasing its stocks. This means that investors inject capital or funds to finance the company's operations, as stated by The parameter estimations of the GARCH models as follows: Tambunan in (Putra et al., 2013). Koetin in

(Dwimulyani, 2019) stocks are well-printed papers that prove the holder's participation or ownership in the capital of a company, typically a Limited Liability Company (PT). Therefore, it can be said that stocks are a piece of paper that signifies the owner's ownership of the company that issued the security. The ownership percentage is determined by the amount invested in the company (Suastini et al., 2016).

Over the past two years, expressly, after the World Health Organization (WHO) declared that the COVID-19 virus was a dangerous outbreak and classified it as a pandemic, numerous sectors have been impacted due to the pandemic status, including the economy, manufacturing, education, and other sectors. PT. Unilever Indonesia Tbk, as a company operating in the distribution of consumer products in Indonesia, has faced challenges in maintaining its business operations effectively. During this COVID-19 pandemic period, the only option is to continue to grow and innovate (Junaedi et al., 2021). One notable corporation that achieved the first increase in the "Best of the Best Award" category for companies with a market capitalization of USD 1 billion, awarded by Forbes Indonesia magazine, is PT. Unilever Indonesia Tbk. PT. It is a multinational company and one of the largest suppliers of beauty and personal care products. Based on the information disclosed on the Indonesia Stock Exchange (IDX) at the end of 2022, PT. Unilever Indonesia Tbk held 32,424,387,500 shares, accounting for approximately 84.99%.

The stock price and large market capitalization make traders have to be more careful in choosing stocks to trade in a short span of time (Ash-Shidiq & Setiawan, 2020). Therefore it is necessary to use forecasting in the future to assist traders in making buying and selling decisions in markets that tend to be unstable. The closing price movement of PT. Unilever Indonesia Tbk's stock is highly volatile, requiring investors to consider the future stock price movement to profit from their investment transactions (Jonnius, 2017). Predicting future stock prices involves forecasting using historical data, commonly known as forecasting.

Stock price forecasting is one of the most popular research studies to obtain stock price predictions using statistical and computational techniques. Several statistical-based time series techniques and analyses have been developed for stock price prediction, such as Autoregressive Integrated Moving Average (ARIMA), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and multivariate regression (Abreu et al., 2019).

The Autoregressive Integrated Moving Average (ARIMA) model is one of the time series models that can be used to model stock prices, and it is also a commonly used model for various other cases. This can be seen from several studies that have been conducted over the years (D. M. Putri & Aghsilni, 2019).

Several studies have been conducted on fluctuating or heteroscedastic data, including the research conducted (Susanti & Adji, 2020), The best model is ARIMA (7,3,1), and its forecasting results are not far from the actual value of IHSG. In the research by (Laskarjati & Ahmad, 2023), the ARIMA (1,1,1) method was identified as the best model for PT Indofood CBP Sukses Makmur Tbk's stock data, with a Mean Absolute Percentage Error (MAPE) value of 1.064%. In the study (Rezaldi & Sugiman, 2021), ARIMA (0,2,1) was identified as the best model for PT. Telekomunikasi Indonesia's stock data. Putri, Zukhronah, & Pratiwi (2021), cited in (Rakhmawati et al., 2022), The research (Farosanti et al., 2022) proved to be quite successful with the ARIMA (4,2,1) model on the sales data of medical and laboratory equipment at PT, which indicated that an ARIMA model containing heteroscedasticity does not meet the assumptions of the ARIMA model. Heteroscedasticity occurs when the residual variance in time series data is not constant, necessitating a combination of ARIMA and GARCH models. In the study by (Yolanda et al., 2017), the ARIMA (2,1,1)-GARCH(2,2) method was found to be effective in predicting the stock price of BRI, with an R-squared value of 0.99916 or 99.91%. In another study by (Ningsih, 2021), the GARCH (1,1) method was proven to be reliable, as the forecasted data closely approximated the actual data with a Mean Absolute Percentage Error (MAPE) value of 1.273% for the Daily Stock Price of PT BTPN Syariah.

Based on the previous research and the high volatility in the data of the closing stock price of PT. Unilever Indonesia Tbk, it is expected that the forecast using the ARIMA-GARCH method for the period of February 20, 2023, to February 22, 2023, will be conducted.

II. METHOD

The method used to forecast PT. Unilever Indonesia Tbk is a quantitative approach, dengan ARIMA-GARCH. The data processing in this study is performed using E-views 10 software. The analysis involves creating data plots and calculating descriptive statistics of the closing stock prices. Descriptive research is used to describe or depict the collected data as it is, without intending to draw generalizable conclusions Sugiyono, 2009, as cited in (Yunina, 2019). To test for stationary variance in the data of PT Unilever Indonesia, a natural logarithm is used. The data variance is stationary using the natural logarithm, and the average is stationary using the ADF test (Wei, 2006). After the stationary data is obtained, the ARIMA model uses the ACF plot.

The general form of this ARIMA (p,d,q) model is (Octavia et al., 2015):

$$(1-B)(1-\phi_1 B)\,X_t = \mu' + \ (1-\theta_1 B)e_t$$

With:

μ' = mean data

θ_1 = Moving average parameters (MA)

e_t = error value at time t

ϕ_1 = Autoregressive parameters (AR)

After finding the model, parameter testing and diagnostic checking are conducted. The best model is determined based on the lowest AIC value (Agustini et al., 2018). If the residuals of ARIMA are evidence of heteroscedasticity in the model, it proceeds to an ARCH-GARCH model with the order determined from the plot of PACF of squared residuals. The selection of the best GARCH model is based on parameter estimation and significance testing. Generally, the GARCH (p,q) model can be expressed in the following equation (Wijaya & Nugraha, 2020):

$\sigma_t^2 = \sigma_t^2 + \alpha_0 e_{t-1}^2 + \ldots + \alpha_p e_{t-p}^2 + \lambda_1 \sigma_{t-1}^2 + \ldots + \lambda_p \sigma_{t-q}^2$

With:

σ_t^2 = variance of error at time t

α_0 = constant

α_p = ARCH (p) parameter element

λ_p = GARCH (q) parameter element

e_{t-1}^2 = squared residual from the previous periods

σ_{t-q}^2 = squared residual from several previous periods

After obtaining the best GARCH model, it is necessary to perform the Lagrange Multiplier test to detect whether there is still a heteroscedasticity effect in the model (Andreas et al., 2021).

III. RESULT AND DISCUSSION

The research utilizes daily data from February 2020 to February 2023 obtained from the website finance.yahoo.com. The movement of the closing price of PT. Unilever Indonesia Tbk. experienced a very drastic decrease in March, which can be seen in the following graph.

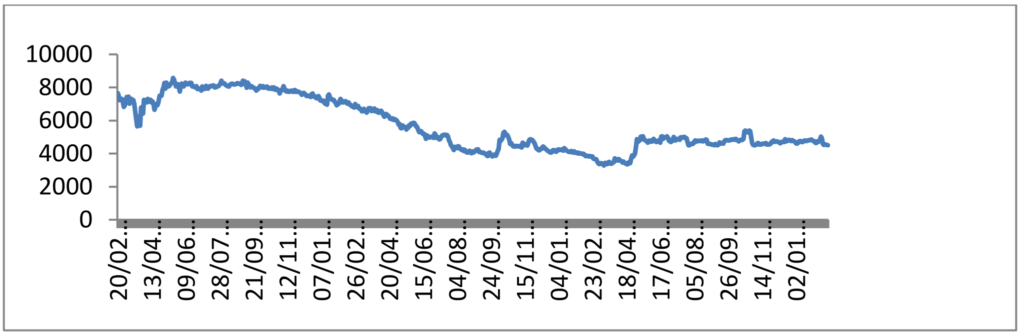

Figure 1. *Closing Stock Price Trend of PT.Unilever Indonesia Tbk*

The descriptive statistical calculations are presented in table 1., the lowest closing price of PT. Unilever Indonesia Tbk stock is 3280, while the highest is 8575, with an average closing price of 5704.

Table 1. Data Descriptive

No	Descriptive Statistics	
1.	Mean	5704
2.	Standart Deviasi	1552
3.	Median	4945
4.	Minimum	3280
5.	Maximum	8575

Stationarity test

The non-stationary data in variance is addressed by transforming the original data into a natural logarithm. To test for stationary mean, the Augmented Dickey-Fuller (ADF) test is used, as shown in the table below:

Table 2. Augmented Dickey-Fuller Test of Closing Price

		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-1.352681	0,6064
Test critical values	1% level	-3.439044	
	5% level	-2.865267	
	10% level	-2.568811	

Based on the results of the table above, it can be concluded that the data is not stationary in terms of the mean because the p-value of 0.6064 is more significant than 5%, indicating a failure to reject the null hypothesis H0. Therefore, differencing needs to be performed, and the result of the ADF test for differencing is as follows.

Table 3. ADF Test of Differenced Data of Closing Price

		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-14.22453	0,0000
Test critical values	1% level	-3.439081	
	5% level	-2.865283	
	10% level	-2.568819	

The probability value in Table 2 shows a value of 0.0000, indicating a rejection of H0. Therefore, the data is stationary in terms of the mean.

Model Identification

Determining the order of AR and MA models can be done using the ACF and PACF correlograms. Significant results occur when the lag falls outside the interval boundaries at lag 3 and 9. Potential ARIMA models formed are ARIMA ([3,9],1,0), ARIMA (0,1,[3,9]), ARIMA ([3,9],1,[3,9]), ARIMA (3,1,0), ARIMA (9,1,0), ARIMA (0,1,3), ARIMA (0,1,9).

Parameter Estimation ARIMA Model

The parameter estimation of the proposed ARIMA models is as follows:

Table 4. Estimation of ARIMA Model Parameters

ARIMA Model	Parameter Estimation	Prob.
ARIMA ([3,9],1,0)	$\emptyset_3$	0,0000
	$\emptyset_9$	0,0043
ARIMA (0,1,[3,9])	θ_3	0,0000
	θ_9	0,0115
ARIMA ([3,9],1,[3,9])	$\emptyset_3$	0,0000
	$\emptyset_9$	0,0043
	θ_3	0,0000
	θ_9	0,0115
ARIMA (3,1,0)	$\emptyset_3$	0,0000
ARIMA (9,1,0)	$\emptyset_9$	0,0036
ARIMA (0,1,3)	θ_3	0,0000
ARIMA (0,1,9)	θ_9	0,0000

Based on Table 3, the model that satisfies the 5% significance level is ARIMA ([3,9],1,0).

Model Identification ARCH-GARCH

After conducting heteroscedasticity testing using the Lagrange Multiplier test, it can be concluded that there is heteroscedasticity in the residuals. Determining the GARCH model can be done using the Q Ljung-Box statistic correlogram. Significant results occur when ACF > 5% is present at lag 3.

Tabel 5. Uji Lagrange Multiplier

Model	Uji LM	Prob.	AIC
ARIMA ([3,9],1,0)	19,0643	0,0000	10,1419
ARIMA (0,1,[3,9])	19,2945	0,0000	10,1252
ARIMA (3,1,0)	18,3881	0,0000	10,1006
ARIMA (0,1,3)	18,9153	0,0000	10,1055

Based on Table 5, it can be concluded that there is a presence of a Heteroscedasticity effect in the residuals of each model, with a probability value of 0.0000 < 0.05. Furthermore, considering the lowest values of AIC and SIC, the ARIMA ([3,9],1,0) model is selected.

Estimation of GARCH Model Parameters

The parameter estimations of the GARCH models are as follows:

Table 6. Estimation of GARCH Model Parameters

GARCH Model	Parameter	Estimation Parameter	Standard Error	Prob.	AIC
GARCH (1,1)	C	0,000047	0,000086	0,0000	-5,032941
	e^2	0,230821	0,032624	0,0000	
	α^2	0,681968	0,040139	0,0000	
GARCH (1,2)	C	0,000061	0,000010	0,0000	-5,039636
	e^2	0,335216	0,044434	0,0000	
	α^2	0,120438	0,069409	0,0827	
	α^2	0,440708	0,058693	0,0000	
GARCH (1,3)	C	0,000062	0,000010	0,0000	-5,037113
	e^2	0,332106	0,051073	0,0000	
	α^2	0,137581	0,100847	0,1725	
	α^2	0,459714	0,062074	0,0000	
	α^2	-0,034884	0,083962	0,6778	
GARCH (2,1)	C	0,000024	0,000055	0,0000	-5,038570
	e^2	0,340603	0,053621	0,0000	
	e^2	-0,193527	0,052673	0,0002	
GARCH (2,2)	C	0,000070	0,000016	0,0000	-5,037182
	e^2	0,330800	0,049725	0,0000	
	e^2	0,037301	0,059925	0,5336	
	α^2	0,037380	0,111803	0,7381	
	α^2	0,475956	0,064178	0,0000	
GARCH (2,3)	C	0,000111	0,000038	0,0035	-5,035205
	e^2	0,338396	0,048498	0,0000	
	e^2	0,231412	0,184725	0,2103	
	α^2	-0,527175	0,585526	0,3679	
	α^2	0,520918	0,073808	0,0000	
	α^2	0,244222	0,292751	0,4042	
GARCH (3,1)	C	0,000026	0,000061	0,0000	-5,035995
	e^2	0,342519	0,054922	0,0000	

	e^2	-0,200793	0,064003	0,0017	
	e^2	0,014847	0,040603	0,7141	
	α^2	0,799309	0,036270	0,0000	
GARCH (3,2)	C	0,000059	0,000014	0,0000	-5,035806
	e^2	0,357944	0,055733	0,0000	
	e^2	0,068967	0,069630	0,3219	
	e^2	-0,101677	0,067958	0,1346	
	α^2	-0,032565	0,135441	0,8100	
	α^2	0,607050	0,126841	0,0000	
GARCH (3,3)	C	0,000061	0,000032	0,0610	-5,033151
	e^2	0,358178	0,055880	0,0000	
	e^2	0,074811	0,163974	0,6482	
	e^2	-0,099650	0,069195	0,1498	
	α^2	-0,051241	0,494121	0,9174	
	α^2	0,605807	0,131308	0,0000	
	α^2	0,009225	0,226245	0,9675	

Based on Table 4, the best probability value obtained is for GARCH (1,1) because the parameters in that model are significant. The equation for the GARCH model is as follows:

$$\sigma_t^2 = \sigma_t^2 + \alpha_0 e_{t-1}^2 + \ldots + \alpha_p e_{t-p}^2 + \lambda_1 \sigma_{t-1}^2 + \ldots + \lambda_p \sigma_{t-q}^2$$

$$\sigma_t^2 = 0{,}000047 + 0{,}230821 e_{t-1}^2 + 0{,}681968 \sigma_{t-1}^2$$

Forecasting

Based on the forecasting results in Table 7, from February 20, 2020, to February 22, 2023, there is no significant increase or decrease observed. The forecasting results yield a Mean Absolute Percentage Error (MAPE) of 2.423%. It can be concluded that the forecasting model is perfect as the MAPE value is < 10%.

Table 7. Forecasting

Period	Actual	Forecast
20 February 2023	4540	4510
21 February 2023	4500	4510

IV. CONCLUSION

The final result obtained in this study is a general overview of the daily data of the closing prices of PT. Unilever Indonesia Tbk shares from 2020 to 2023, consisting of 734 data points. The data experienced a decrease in March 2022 and an increase in May 2022.

Based on the analyzed research results, the best model obtained is the GARCH (1,1) model, yielding the following equation:

$$\sigma_t^2 = \sigma_t^2 + \alpha_0 e_{t-1}^2 + \ldots + \alpha_p e_{t-p}^2 + \lambda_1 \sigma_{t-1}^2 + \ldots + \lambda_p \sigma_{t-q}^2$$

$$\sigma_t^2 = 0{,}000047 + 0{,}230821 e_{t-1}^2 + 0{,}681968 \sigma_{t-1}^2$$

The forecast using the best model, which is ARIMA ([3,9],1,0) GARCH (1,1), resulted in a Mean Absolute Percentage Error (MAPE) of 2.423%, indicating a close approximation between the forecasted data and the actual data.

V. REFERENCES

[1] Abreu, R. J., Souza, R. M., & Oliveira, J. G. (2019). Applying singular spectrum analysis and arimagarch for forecasting eur/usd exchange rate. *Revista de Administracao Mackenzie*, *20*(4). https://doi.org/10.1590/1678-6971/eRAMF190146

[2] Agustini, R., Hajarisman, N., & Sunendiari, S. (2018). Kriteria Pemilihan Model Peramalan Terbaik berdasarkan Kriteria Informasi. *Prosiding Statistika*, *4*(1), 57–64.

[3] Andreas, C., Sediono, S., Ana, E., Suliyanto, S., & Mardianto, M. F. F. (2021). Penerapan Model ARIMAX-GARCH dalam Pemodelan dan Peramalan Volume Transaksi Uang Elektronik di Indonesia. *MUST: Journal of Mathematics Education, Science and Technology*, *6*(2), 241. https://doi.org/10.30651/must.v6i2.11214

[4] Ash-Shidiq, H., & Setiawan, A. B. (2020). Analisis Pengaruh Suku Bunga Sbi, Uang Beredar, Inflasi Dan Nilai Tukar Terhadap Indeks Harga Saham Jakarta Islamic Index (Jii) Periode 2009-2014. *Jurnal Ekonomi Dan Perbankan Syariah*, *3*(2), 25–46. https://doi.org/10.46899/jeps.v3i2.158

[5] Dwimulyani, S. (2019). Analisis Pemecahan Saham (Stock Split): Dampaknya Terhadap Likuiditas Perdagangan Saham Dan Pendapatan Perusahaan Publik Di Indonesia. *Jurnal Informasi, Perpajakan, Akuntansi, Dan Keuangan Publik*, *3*(1), 1–14. https://doi.org/10.25105/jipak.v3i1.4434

[6] Farosanti, L., Mubarok, H., & Indrianto. (2022). Analisa Peramalan Penjualan Alat Kesehatan dan Laboratorium di PT. Tristania Global Indonesia Menggunakan Metode ARIMA. *JIMP: Jurnal Informatika Merdeka Pasuruan*, *7*(2), 14–18.

[7] Fitrianingsih, D. & Y. B. (2018). Pengaruh Current Rasio Dan Debt To Equity Ratio Terhadap Harga Saham Di Perusahaan Food and Beverage Yang Terdaftar Di Bursa Efek Indonesia Periode 2013-2017. *Jurnal Riset Akuntansi Terpadu*, *12*(1), 144–166.

[8] Ilegbinosa, I. A., Micheal, A., & Watson, S. I. (2015). Domestic Investment and Economic Growth in Nigeria From 1970-2013: An Econometric Analysis. *Canadian Social Science*, *11*(116), 70–79. https://doi.org/10.3968/7009

[9] Jonnius. (2017). Peramalan Indeks Harga Saham dengan Pendekatan Exponential Smoothing Model. *Jurnal Penelitian Sosial Keagamaan*, *19*(2), 199–219.

[10] Junaedi, A. A., Winata, R. H., & Mutmainnah. (2021). Pengaruh Return On Asset Dan Return On Equity Terhadap Harga Saham Pada Pt.Unilever Indonesia Tbk Periode 2016-2020 (Sebelum Dan Dimasa Pandemi Covid-19). *Jurnal E-Bis (Ekonomi-Bisnis)*, *5*(2), 326–337. https://doi.org/10.37339/e-bis.v5i2.665

[11] Laskarjati, S. D., & Ahmad, I. S. (2023). Perbandingan Peramalan Harga Saham menggunakan Autoregressive Intergrated Moving Average (ARIMA) dan Fuzzy Time

series Markov Chain (Studi Kasus: Saham PT Indofood CBP Sukses Makmur Tbk). *Jurnal Sains Dan Seni ITS*, *11*(6). https://doi.org/10.12962/j23373520.v11i6.91417

[12] Malkan, Indra Kurniawan, Nurdin, & Noval. (2021). Pengaruh Pengetahuan Tentang Pasar Modal Syariah Terhadap Minat Investasi Saham Di Pasar Modal Syariah. *Jurnal Ilmu Perbankan Dan Keuangan Syariah*, *3*(1), 57–73. https://doi.org/10.24239/jipsya.v3i1.39.57-78

[13] Ningsih, M. (2021). Prediksi Harga Saham Harian PT BTPN Syariah Tbk Menggunakan Model Arima dan Model Garch. *Jurnal Ilmiah Ekonomi Islam*, *7*(03), 1573–1580.

[14] Octavia, T., Yulia, & Lydia. (2015). Peramalan stok barang untuk membantu pengambilan keputusan pembelian barang pada toko bangunan xyz dengan metode arima. *Seminar Nasional Informatika (SEMNASIF)*, *1*(semnasIF), 2–7.

[15] Putra, R. D., Darminto, & Zahroh. (2013). Analisis Pemilihan Investasi Saham Dengan Menggunakan Metode Capital Asset Pricing Model (Capm) Dan Reward To Variability Ratio (Rvar) Sebagai Penentu Pengambilan Keputusan Investasi Saham. *Jurnal Administrasi Bisnis*, *1*(2), 21–30.

[16] Putri, D. M., & Aghsilni. (2019). Estimasi Model Terbaik Untuk Peramalan Harga Saham PT. Polychem Indonesia Tbk Dengan Arima. *Map Journal*, *1*(1), 1–12.

[17] Putri, V., & Manisha, K. (2021). Analisis Minat Penanaman Modal Dalam Negri Dan Penanaman Modal Asing Di Indonesia. *Jurnal Ilmu Manajemen Terapan*, *2*(6), 757–767. https://doi.org/10.31933/jimt.v2i6.640

[18] Rakhmawati, D., Fajarwati, S., Astuti, T., & Arsi, P. (2022). Model ARIMA-GARCH pada Data Kurs JISDOR selama Masa Pandemi COVID-19. *Vygotsky: Jurnal Pendidikan Matematika Dan Pendidikan Matematika*, *4*(2), 129–138.

[19] Rezaldi, D. A., & Sugiman. (2021). Peramalan Metode ARIMA Data Saham PT . Telekomunikasi Indonesia. *Prisma*, *4*, 611–620.

[20] Suastini, N. M., Ida, B. A. P., & Henny, R. (2016). Pengaruh Kepemilikan Manajerial dan Pertumbuhan Perusahaan Terhadap Nilai Perusahaan pada Perusahaan Manufaktur di Bursa Efek Indonesia (Struktur Modal sebagai Variabel Moderasi). *E-Jurnal Ekonomi Dan Bisnis Universitas Udayana*, *5*(1), 143–172.

[21] Susanti, R., & Adji, A. R. (2020). Analisis Peramalan Ihsg Dengan Time Series Modeling Arima. *Jurnal Manajemen Kewirausahaan*, *17*(1), 97. https://doi.org/10.33370/jmk.v17i1.393

[22] Wei, W. (2006). *Time Series Analysis: Univariate and Multivariate Methods, 2nd edition, 2006*.

[23] Widiyanti, M., & Sari, N. (2019). Kajian Pasar Modal Syariah Dalam Mempengaruhi Pertumbuhan Ekonomi di Indonesia. *Ekonomikawan: Jurnal Ilmu Ekonomi Dan Studi Pembangunan*, *19*(1), 21–30. https://doi.org/10.30596/ekonomikawan.v19i1.3236

[24] Wijaya, J. H., & Nugraha, N. M. (2020). Peramalan Kinerja Perusahaan Perbankan Tahun 2017 Yang Terdaftar Di Bursa Efek Indonesia Dengan Metode Arch-Garch. *BISMA: Jurnal Bisnis Dan Manajemen*, *14*(2), 101. https://doi.org/10.19184/bisma.v14i2.17512

[25] Yolanda, N. B., Nainggolan, N., & Komalig, H. A. H. (2017). Penerapan Model ARIMA-GARCH Untuk Memprediksi Harga Saham Bank BRI. *Jurnal MIPA*, *6*(2), 92. https://doi.org/10.35799/jm.6.2.2017.17817

[26] Yunina, F. (2019). Analisis Efektivitas Dan Efisiensi Pelaksanaan Anggaran Belanja Badan Perencanaan Pembangunan Daerah (Bappeda) Aceh Tengah. *Jurnal Akuntansi Muhammadiyah*, *9*(1), 74–81. https://doi.org/10.37598/jam.v9i1.647