

FORECASTING STOCK PRICE USING ARMAX-GARCHX MODEL DURING THE COVID-19 PANDEMIC

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ABSTRACT

The Covid-19 pandemic, which was proclaimed by the World Health Organization (WHO) on March 2020, has impacted stock risk on the capital market. Stock price forecasting can be used to provide future stock projection prices in order to reduce risk. The ARMA GARCH model and its development model can forecast stock prices by incorporating exogenous factors such as the ARMAX GARCH, ARMA GARCHX, and ARMAX GARCHX models. PT Mitra Keluarga Karyasehat Tbk's stock price is analyzed in this study, along with the exogenous factors of total daily positive cases and total daily fatalities cases of Covid-19 from March 16, 2020, to January 31, 2022. The results of several models show that based on MAPE value the ARMAX GARCH model has better accuracy in forecasting stock price.

Keywords: ARMA GARCH, ARMAX GARCHX, forecast

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PRELIMINARY

On December 2019, a new sickness caused by the SARS-Cov-2 virus, was discovered in the Chinese province of Wuhan. As a result of this virus, humans can get Covid-19, a potentially lethal respiratory condition. Because of the virus's rapid spread, the World Health Organization (WHO) proclaimed Covid-19 as a pandemic on March 11, 2020. Upon the discovery of a pandemic, some countries implemented a lockdown or quarantine system. To prevent the virus from spreading, Indonesia imposes quarantine under the Pembatasan Sosial Berskala Besar (PSBB) (Kemenhukam, 2020). The PSBB's adoption had other effects on the economy, one of which was felt in capital markets. Investors are now more aware of the risks associated with their shares due to the uncertain state of the capital market brought on by the epidemic. The study by Zhang et al. (2020), which demonstrates that capital market risk increased in reaction to the pandemic, supports the impact.

The way to decrease risk can be done by forecasting stock. Forecasting stock offers future stock prices so that a decision can be made to reduce risk (Sari et al. 2017). The ARMA model is one of several models that can predict stock prices. George Box and

Gwilym Jenkins created the Autoregressive Moving Average (ARMA) model in 1970 (Emenogu et al., 2019). The ARMA model assumes that historical data is stationary and homoscedastic for predicting stock prices (Box et al., 2013). Stock prices have high volatility and caused heteroscedasticity, so adding the GARCH model proposed by Bollerslev in 1986 is necessary (Endri et al., 2020). Heteroscedasticity is a condition where the residual value at each predictive value varies and is not constant (Cohen et al., 2014). The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model has a more adaptable framework to account for the volatility in financial data (Verbeek, 2004).

Along with the times, model development is always carried out, one of which is by adding exogenous factors, namely the ARMAX model which is a modified model of the ARMA model and the GARCHX model which is a modified model of the GARCH model. Several researchers who have forecasted using the ARMAX model include (Pradana et al., 2022), (Riestiansyah et al., 2022) and (Elvina et al., 2023). The results of their research show that the ARMAX model is more accurate in forecasting than the ARMA model. The ARMAX model followed by the GARCH model also shows more accurate forecasting results than the ARMA model alone, this is based on research from (Arianti et al., 2022). In Apergis and Apergis' research (2020), the GARCHX model used is more accurate than GARCH for predicting Chinese stock returns with the addition of Covid-19 variables such as positive cases and deaths to the model.

The stock forecasting model's accuracy between the ARMA GARCH model and the exogenous factor development model were all compared in this study by the authors. The novelty of this study is that there are several development models with exogenous factors, including ARMAX GARCH, ARMA GARCHX, and ARMAX GARCHX. The exogenous factors used are positive cases and death cases of Covid-19 in Indonesia.

METHODS

This study is quantitative, and the secondary data used spans the dates of March 16, 2020, and January 31, 2021. These data include the daily stock price of PT Mitra Keluarga Karyasehat, the overall daily positive cases of Covid-19 in Indonesia and the overall daily death cases of in Indonesia. The following step were taken in this study

1. Determine the return using daily stock data as shown below.

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Where r_t represents the value return at the time t , P_t represent the value stock price at the time t , dan P_{t-1} represents the value stock price at the time $t - 1$ (Tsay, 2010).

2. Use the Augmented Dickey Fuller (ADF) test to determine the stationarity of the return data.
3. Determine the best ARMA model.
4. Determine the best ARMAX model for combined positive cases and cases of death of Covid-19.
5. Check whether the residuals from the selected ARMA and ARMAX models are heteroscedasticity or homoscedasticity with the ARCH-LM test.
6. Determine the best ARMA-GARCH model.
7. Determine the best model among the ARMA-GARCHX, ARMAX-GARCH, and ARMAX-GARCHX models for exogenous factors is the combination of positive cases and death cases of Covid-19.
8. Forecast the stock price for the model without exogenous factors and with exogenous factors.
9. Calculate the Mean Average Percentage Error (MAPE) for the accuracy of each model as shown below.

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{P_t - \hat{P}_t}{P_t} \right| \times 100\%$$

Where P_t represents the actual value at the time t , \hat{P}_t represents the predicted value at the time t , while n represents the amount of observations (Swamidass, 2000).

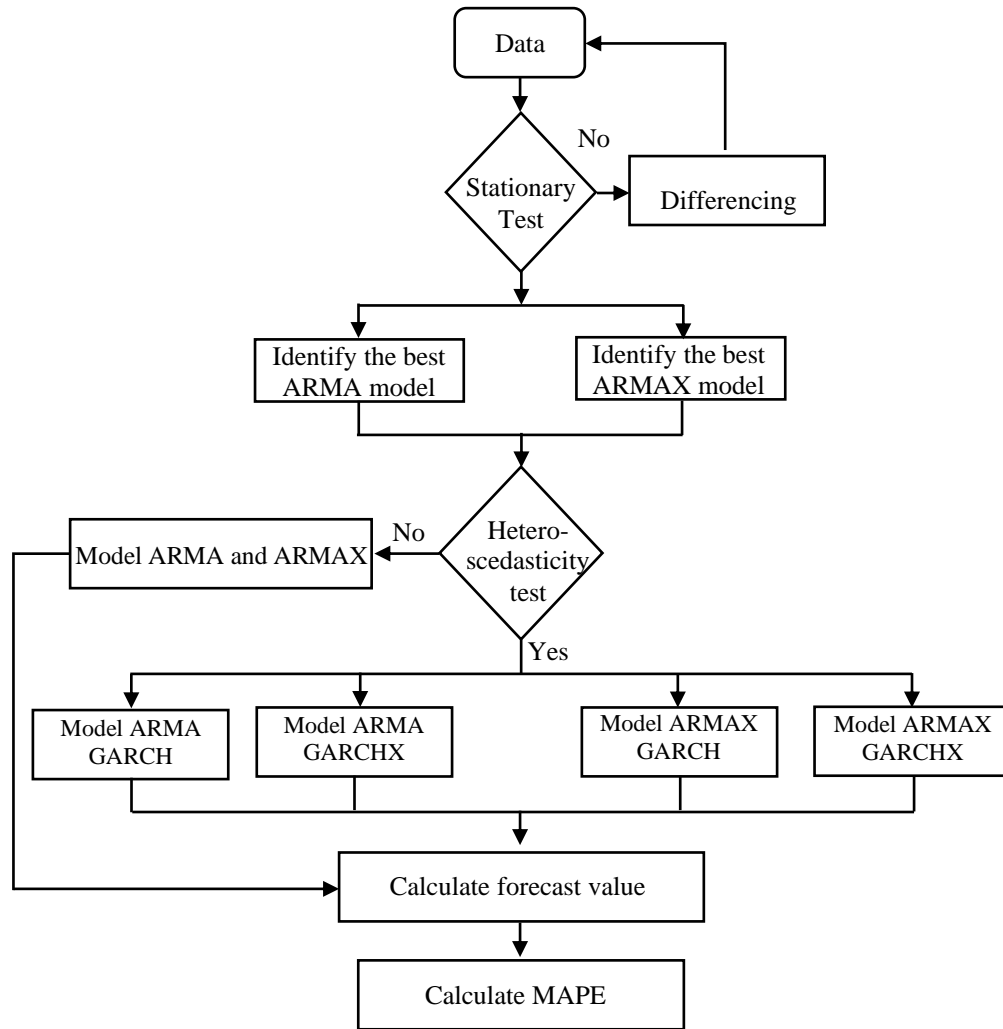


Figure 1. Data Analysis Procedures

Model ARMA

The Autoregressive Moving Average (ARMA) model incorporates the p-order AR and q-order MA models (Montgomery et al., 2008). The ARMA (p,q) model's general form is as follows.

$$y_t = \delta + \sum_{i=1}^p \phi_i y_{t-i} + \varepsilon_t - \sum_{j=1}^q \theta_j \varepsilon_{t-j}$$

Note:

y_t : the observed value at the time t

δ : constant

ϕ_i : the parameter of the AR model

ε_t : the white noise process

θ_j : the parameter of the MA model

Model ARMAX

The Autoregressive Moving Average with Exogenous Variables (ARMAX) model development incorporates exogenous factors into the model equation (Prastyo et al., 2018). (Cryer & Chan 2008). The ARMAX model's general form is as follows

$$y_t = \delta + \sum_{i=1}^p \phi_i y_{t-i} + \varepsilon_t - \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \sum_{k=1}^r \pi_k X_{k,t-1}$$

Note:

- y_t : the observed value at the time t
- δ : constant
- ϕ_i : the parameter of the AR model
- ε_t : the white noise process
- θ_j : the parameter of the MA model
- π_k : exogenous factor parameter
- X_{t-1} : exogenous variable at time $t - 1$

Model GARCH

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is created by combining the conditional variance's p order and the ARCH model's q order model (Cryer & Chan 2008). The following is the GARCH model's basic structure

$$\sigma_t^2 = \mu + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2$$

Note:

- σ_t^2 : the variance at the time t
 - ε_t^2 : the square of the residual at the time t
- With $\mu \geq 0, \beta \geq 0, \alpha \geq 0$.

Model GARCHX

The GARCH model is enhanced by the Generalized Autoregressive Conditional Heteroscedasticity with Exogenous Variable (GARCHX) model, which adds exogenous variables in the model equation (Hwang & Satchell 2005). The GARCHX model's general form is as follows

$$\sigma_t^2 = \mu + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \sum_{k=1}^r \gamma_k X_{k,t-1}^2$$

Note:

σ_t^2 : the variance at the time t

ε_t^2 : the square of the residual at the time t

X_{t-1}^2 : the square of the exogenous variable at the time $t - 1$.

With $\mu \geq 0, \beta \geq 0, \alpha \geq 0, \gamma \geq 0$.

RESULT AND DISCUSSIONS

Stationary

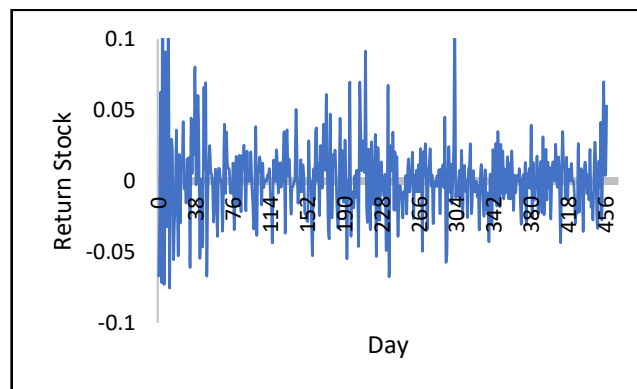


Figure 2. The Plot of MIKA’s Stock Return

Figure 2 shows that the log-return value of MIKA's stock moves around zero and has no up or down trend. It means, stationary in data. Moreover, the Augmented Dickey Fuller (ADF) test is performed to confirm data stationarity. Based on the ADF test, a p-value of 0,01 is obtained so that the $p\text{-value} \leq \alpha = 0,05$, which can be concluded that the data return is stationary.

ARMA Modelling

As shown in Table 1, the best ARMA model can be driven by identifying model orders, estimating parameters, testing autocorrelation, and utilizing the Akaike Information Criterion (AIC) to select the best model.

Table 1. ARMA Model Parameter Estimation

Model	Parameter	Value	p-value	AIC
ARMA(1,2)	δ	0,0007	0,4317	-2014,71
	$\hat{\phi}_1$	-0,6101	0,0024	
	$\hat{\theta}_1$	0,4106	0,0381	
	$\hat{\theta}_2$	-0,1974	0,0001	

Model	Parameter	Value	p-value	AIC
ARMA(2,1)	δ	0,0007	0,4433	-2017,45
	$\hat{\phi}_1$	-0,7375	1,546e-05	
	$\hat{\phi}_2$	-0,2225	1,078e-05	
	$\hat{\theta}_1$	0,5241	0,0019	
ARMA(2,2)	δ	0,0007	0,4785	-2017,66
	$\hat{\phi}_1$	-0,8944	7,772e-07	
	$\hat{\phi}_2$	-0,5424	0,0009	
	$\hat{\theta}_1$	0,7009	0,0004	
	$\hat{\theta}_2$	0,3441	0,0657	

Based on Table 1, the p-value is less than 0,05. So, the ARMA(1,2) and ARMA(2,1) models contain significant parameters. The best model for MIKA's return stock is the ARMA(2,1) model since it has smaller AIC value than the ARMA(1,2) model.

Table 2. Ljung-Box Test Results For The ARMA(2,1) Model

Lag	Test Statistics	χ^2	p-value
1	0,0544	3,8414	0,8156
4	0,6986	9,4877	0,9515
8	8,4032	15,507	0,3951
12	11,623	21,026	0,4764
16	15,449	26,296	0,4885

According to Table 2, the test statistic is smaller than the value χ^2 and the p-value of the Ljung-Box test is more than $\alpha = 0,05$. As a result, there is no autocorrelation in the ARMA(2,1) model's residuals.

ARMAX Modelling

Determining the best ARMAX model with exogenous factors are positive cases and death cases of Covid-19. Determining the ARMAX model can be done similarly to determining the best ARMA model, as in Table 3 below.

Table 3 ARMAX Model Parameter Estimation

Model	Parameter	Value	p-value	AIC
ARMAX(1,2)	δ	-0,0005	0,6264	-2020,31
	$\hat{\phi}_1$	-0,4981	0,0361	
	$\hat{\theta}_1$	0,3381	0,1439	
	$\hat{\theta}_2$	-0,1775	0,0005	
	π_1	0,1471	0,0021	
	π_2	-0,0638	0,0141	
	ARMAX(2,1)	δ	-0,0005	
$\hat{\phi}_1$		-0,6525	0,0017	
$\hat{\phi}_2$		-0,1934	0,0002	
$\hat{\theta}_1$		0,4821	0,0194	
π_1		0,1352	0,0066	
π_2		-0,0527	0,0483	

Model	Parameter	Value	p-value	AIC
ARMAX(2,2)	δ	-0,0005	0,6473	-2020,01
	$\hat{\phi}_1$	-0,8634	2,012e-05	
	$\hat{\phi}_2$	-0,5119	0,0162	
	$\hat{\theta}_1$	0,7031	0,0013	
	$\hat{\theta}_2$	0,3291	0,1597	
	π_1	0,1255	0,0133	
	π_2	-0,0419	0,1169	

Table 3 shows that the ARMAX(2.1) model has significant parameters because the p-value < 0.05 and has the lowest AIC value. The ARMAX(2,1) model with exogenous factors is the best model for MIKA's return stock.

Table 4. Ljung-Box Test Results For The ARMAX(2,1) Model

Lag	Test Statistics	χ^2	p-value
1	0,0363	3,8414	0,849
4	0,9433	9,4877	0,9183
8	9,6718	15,507	0,2888
12	13,396	21,026	0,3409
16	17,71	26,296	0,3412

According to Table 4, the test statistic is smaller than the value χ^2 and the p-value of the Ljung-Box test is more than $\alpha = 0,05$. As a result, there is no autocorrelation in the ARMAX(2,1) model's residuals.

Heteroscedasticity

Before GARCH and GARCHX modelling, it is necessary to know whether the model residuals are heteroscedasticity or homoscedasticity with the ARCH-LM test.

Table 5 Results Of ARCH-LM Tests

Model	p-value
ARMA(2,1)	0,0000
ARMAX(2,1)	0,0000

Based on Table 5, the ARCH-LM test results produced a p-value smaller than the value of $\alpha = 0,05$. It means that the residual data in each ARMA and ARMAX model are known to have heteroscedasticity.

ARMA-GARCH Modelling

Suppose it is known that the data are heteroscedastic. In that case, the ARMA GARCH model can be formed by determining the significant parameters with the smallest AIC value, as shown in Table 6.

Table 6 Parameter Estimation Of The ARMA-GARCH Model

Model	Parameter	Parameter Coefficient	p-value	AIC
ARMA(2,1) GARCH(1,0)	μ	0,0068	0	-4,4804
	$\hat{\phi}_1$	0,9047	0	
	$\hat{\phi}_2$	0,0955	0	
	$\hat{\theta}_1$	-1	0	
	ω	0,0004	0	
	α_1	0,4401	0,00005	
ARMA(2,1) GARCH(1,1)	μ	-0,0003	0,6723	-4,5551
	$\hat{\phi}_1$	0,0571	0,9141	
	$\hat{\phi}_2$	-0,0257	0,7739	
	$\hat{\theta}_1$	-0,2127	0,6855	
	ω	0,00005	0,0466	
	α_1	0,1639	0,0014	
	β_1	0,7663	0	
ARMA(2,1) GARCH(2,0)	μ	-0,0004	0,643	-4,4986
	$\hat{\phi}_1$	-1,0497	0	
	$\hat{\phi}_2$	-0,0107	0,0425	
	$\hat{\theta}_1$	0,9308	0	
	ω	0,0004	0	
	α_1	0,3494	0,0008	
	α_2	0,1578	0,042	

According to Table 6, the ARMA(2,1) GARCH(1,0) and ARMA(2,1) GARCH(2,0) models have a p-value of less than 0,05. It means that the parameter coefficient is significant. The ARMA(2,1) GARCH(2,0) model is the most effective model for MIKA's return stock because it has the minimum AIC value when compared to the ARMA(2,1) GARCH(1,0) model. The resulting ARMA(2,1) GARCH(2,0) model equation is as follows.

Return stock equation:

$$y_t = -1,0497y_{t-1} - 0,0107y_{t-2} + 0,9308\varepsilon_{t-1} + \varepsilon_t$$

With $\varepsilon_t = Z_t\sigma_t$, $Z_t \sim N(0,1)$

Residual variance equation:

$$\sigma_t^2 = 0,0004 + 0,3494\varepsilon_{t-1}^2 + 0,1578\varepsilon_{t-2}^2$$

ARMAX GARCHX Modeling With Covid-19 Exogenous Factors

Determining the best model with exogenous factors is a combination of positive cases and death cases of Covid-19, which can be formed by determining significant parameters with the smallest AIC value in Table 7.

Table 7 Estimation Of Model Parameters With Exogenous Factors

Model	Parameter	Parameter Coefficient	p-value	AIC
ARMAX(2,1) GARCH(1,0)	μ	0,0064	0,00005	-4,4771
	$\hat{\phi}_1$	0,8936	0	
	$\hat{\phi}_2$	0,1062	0	

Model	Parameter	Parameter Coefficient	p-value	AIC		
ARMAX(2,1) GARCH(1,1)	$\hat{\theta}_1$	-1	0,7461	-4,5322		
	π_1	0,0153	0,2469			
	π_2	0,0253	0			
	ω	0,0004	0,0013			
	α_1	0,4182				
	μ	-0,0009	0,4043			
	$\hat{\phi}_1$	-1,0046	0			
	$\hat{\phi}_2$	-0,1384	0,0149			
	$\hat{\theta}_1$	0,8613	0			
	π_1	0,1824	0,0413			
	π_2	-0,133	0			
ARMA(2,1) GARCHX(1,0)	ω	0,00004	0,0812	-4,5460		
	α_1	0,142	0,0071			
	β_1	0,7999	0			
	μ	0,007	0			
	$\hat{\phi}_1$	0,8959	0			
	$\hat{\phi}_2$	0,1042	0			
	$\hat{\theta}_1$	-1	0			
	ω	0,0003	0			
	α_1	0,1467	0,0167			
	γ_1	0,0161	0,0171			
	γ_2	0	0,9999			
ARMA(2,1) GARCHX(1,1)	μ	-0,0003	0,7347	-4,5697		
	$\hat{\phi}_1$	-0,4655	0,6712			
	$\hat{\phi}_2$	-0,1125	0,3882			
	$\hat{\theta}_1$	0,3054	0,7802			
	ω	0,00007	0,1351			
	α_1	0,1281	0,0234			
	β_1	0,7195	0			
	γ_1	0,0012	0,5954			
	γ_2	0,0012	0,3681			
	ARMAX(2,1) GARCHX(1,0)	μ	0,0034		0,0003	-4,552
		$\hat{\phi}_1$	0,8791		0	
$\hat{\phi}_2$		0,1216	0,0431			
$\hat{\theta}_1$		-1	0			
π_1		0,0719	0,3211			
π_2		0,0553	0,4311			
ω		0,0003	0			
α_1		0,1463	0,0305			
γ_1		0,0117	0,0679			
γ_2		0,0042	0,4782			
ARMAX(2,1) GARCHX(1,1)		μ	-0,0007	0,5002	-4,5624	
	$\hat{\phi}_1$	-0,7015	0,3433			
	$\hat{\phi}_2$	-0,1402	0,1025			
	$\hat{\theta}_1$	0,5385	0,4654			
	π_1	0,0459	0,5248			
	π_2	0,0003	0,9931			
	ω	0,00005	0,1345			
	α_1	0,1156	0,0134			
	β_1	0,7734	0			
	γ_1	0,0001	0,9402			
	γ_2	0,0014	0,2565			

Table 7 shows that the ARMAX(2,1) GARCH(1,1) model has significant parameter values with a p-value of less than 0,05. The ARMAX(2,1) GARCH(1,1) model is the best model for MIKA's return stock with exogenous factors are positive cases and death cases of Covid-19. The ARMAX(2,1) GARCH(1,1) model equation that is formed is as follows

Return stock equation:

$$y_t = -1,0046y_{t-1} - 0,1384y_{t-2} + 0,8613\varepsilon_{t-1} + 0,1824X_{1,t-1} - 0,133X_{2,t-1} + \varepsilon_t$$

With $\varepsilon_t = Z_t\sigma_t, Z_t \sim N(0,1)$

Residual variance equation:

$$\sigma_t^2 = 0,142\varepsilon_{t-1}^2 + 0,7999\sigma_{t-1}^2$$

Forecasting Result

The two model equations that were obtained are used to forecast the stock price of MIKA for the 459th to 468th day. In Figure 3, the ARMAX GARCH model with exogenous factors of positive cases and death cases of Covid-19 is closer to the actual value of MIKA's stock.

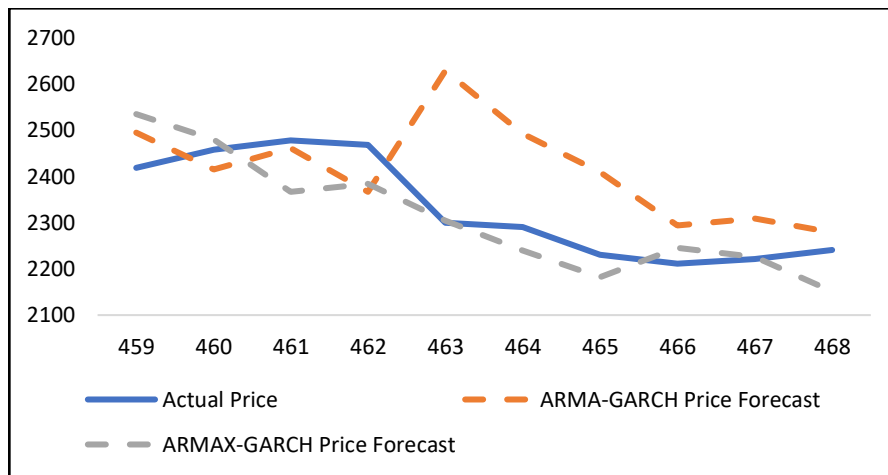


Figure 3 Plot Of Actual And Forecast Prices

The accuracy of the forecasting results from the two models can be evaluated by calculating the value of the Mean Absolute Percentage Error (MAPE). The better model can be used when the MAPE value has the lower number. Table 8 shows the MAPE values for each model.

Table 8 MAPE Value Calculation Results

Model	MAPE
ARMA GARCH	5,01
ARMAX GARCH	2,3447

Table 8 shows that the forecast value of PT Mitra Keluarga Karyasehat Tbk using the ARMAX GARCH model has a lower MAPE value than the ARMA GARCH model. Based on the criteria from (Lewis 1982), if the value is less than 10% then the forecast is very accurate. This means that each model has a very accurate forecast, and Cavanaugh and Neath (2019) reveal that the model with the smallest MAPE value is considered the best model. Thus, stock prices forecasted using the ARMAX GARCH model have a better level of accuracy than the ARMA GARCH model.

The accuracy of the ARMAX GARCH model in forecasting stock prices using information from positive cases and death cases of Covid-19 helps in investment decisions and makes decisions quicker and more precise. This decision can lower investment risk while providing information about stock market trends.

CONCLUSION

The result of this study shows that stock price can be modelled using an exogenous factor are positive cases and death cases of Covid-19, specifically ARMAX(2,1) GARCH(1,1) compared to the ARMA(2,1) GARCH model (2,0).

- The ARMA(2,1) GARCH(2,0) model equation is as follows.

Return stock equation:

$$y_t = -1,0497y_{t-1} - 0,0107y_{t-2} + 0,9308\varepsilon_{t-1} + \varepsilon_t$$

With $\varepsilon_t = Z_t\sigma_t$, $Z_t \sim N(0,1)$

Residual variance equation:

$$\sigma_t^2 = 0,0004 + 0,3494\varepsilon_{t-1}^2 + 0,1578\varepsilon_{t-2}^2$$

- The ARMAX(2,1) GARCH(1,1) model equation is as follows

Return stock equation:

$$y_t = -1,0046y_{t-1} - 0,1384y_{t-2} + 0,8613\varepsilon_{t-1} + 0,1824X_{1,t-1} - 0,133X_{2,t-1} + \varepsilon_t$$

With $\varepsilon_t = Z_t\sigma_t$, $Z_t \sim N(0,1)$

Residual variance equation:

$$\sigma_t^2 = 0,142\varepsilon_{t-1}^2 + 0,7999\sigma_{t-1}^2$$

According to the result, the ARMAX(2,1) GARCH(1,1) model is accurate in forecasting the stock price of PT Mitra Keluarga Karyasehat Tbk based from MAPE value has smaller value than MAPE value ARMA(2,1) GARCH(2,0) model. The accuracy from ARMAX (2,1) GARCH (1,1) can help MIKA's stock investor to make decisions in trading stock, especially in reducing risk.

REFERENCES

- Apergis, N., & Apergis, E. (2020). The Role Of Covid-19 For Chinese Stock Returns: Evidence From A GARCHX Model. *Asia-Pacific Journal of Accounting and Economics*, 29(5), 1175-1183. <https://doi.org/10.1080/16081625.2020.1816185>
- Arianti, R., Sahriman, S., & Talangko, L.P. (2022). Model ARIMA dengan Variabel Eksogen dan GARCH pada Data Kurs Rupiah. *Journal of Statistics Its Application*, 3(1):41–48. <https://doi.org/10.20956/ejsa.vi.11603>
- Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (2013). *Time Series Analysis: Forecasting And Control: Fourth Edition*. New Jersey: John Wiley & Sons, Inc. <https://doi.org/10.1002/9781118619193>
- Cavanaugh, J.E., & Neath, A.A. (2019). The Akaike information criterion: Background, derivation, properties, application, interpretation, and refinements. *WIREs Computational Statistics*, 11(3), 1-11. <https://doi.org/10.1002/wics.1460>
- Cohen, P., West, S.G., & Aiken, L.S. (2014). *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*. New Jersey: Lawrence Erlbaum Associates, Publishers.
- Cryer, J. D., & Chan, K. S. (2008). *Time Series Analysis With Application In R*. New York: Springer.
- Elvina, C., Putra, A.A., Permana, D., & Fitria, D. (2023). Adding Exogenous Variable in Forming ARIMAX Model to Predict Export Load Goods in Tanjung Priok Port. *UNP J Stat Data Sci*, 1(1),31–38. <https://dx.doi.org/10.30811/jim.v7i2.3336>
- Emenogu, N.G., Adenomon, M.O., & Nwaze, N.O. (2019). Modeling and Forecasting Daily Stock Returns of Guaranty Trust Bank Nigeria Plc Using ARMA-GARCH Models, Persistence, Half-Life Volatility and Backtesting. *Science World Journal*, 14(3), 1–22. <https://doi.org/10.20944/preprints201903.0071.v1>
- Endri, E., Abidin, Z., Simanjuntak, T. P., & Nurhayati, I. (2020). Indonesian Stock Market Volatility: GARCH Model. *Montenegrin Journal of Economics*, 16(2), 7-17. <https://doi.org/10.14254/1800-5845/2020.16-2.1>
- Hwang, S., & Satchell, S. E. (2005). GARCH Model With Cross-Sectional Volatility: GARCHX Models. *Applied Financial Economics*, 15(3), 203-216. <https://doi.org/10.1080/0960310042000314214>
- Kemendiknas. (2020). *Peraturan Pemerintah Republik Indonesia Nomor 21 Tahun 2020 tentang Pembatasan Sosial Berskala Besar Dalam Rangka Percepatan Penanganan Corona Virus Disease 2019*. Kementerian Hukum dan Hak Asasi Manusia.
- Lewis, C.D. (1982). *Industrial and Business Forecasting Methods: A Practical Guide to Exponential Smoothing and Curve Fitting*. London: Butterworths Publishing.
- Montgomery, D. C., Jennings, C. L., & Kulahci, M. (2008). *Introduction to Time Series Analysis and Forecasting*. John Wiley & Sons, Inc.
- Pradana, D.A.P., Mahananto, F., & Djunaidy, A. (2022). Sistem Peramalan Menggunakan Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) Untuk Harga Minyak Sawit Indonesia. *Jurnal Teknik ITS*, 11(2), 97-102. <https://doi.org/10.12962/j23373539.v11i2.86373>
- Prastyo, D. D., Handayani, D., Fam, S. F., Rahayu, S. P., Suhartono, & Satyaning Pradnya Paramita, N. L. P. (2018). Risk Evaluation On Leading Companies In Property And Real Estate Subsector At IDX: A Value-At-Risk With ARMAX-GARCHX Approach And Duration Test. *Journal of Physics: Conference Series*, 979(1), 012094. <https://doi.org/10.1088/1742-6596/979/1/012094>
- Riestiansyah, F., Damayanti, D., Reswara, M., & Susetyoko, R. (2022). Perbandingan metode ARIMA dan ARIMAX dalam Memprediksi Jumlah Wisatawan Nusantara di
-

- Pulau Bali. *Jurnal Infomedia: Teknik Informatika Multimedia Jaringan*. 7(2), 58-62.
doi:<http://dx.doi.org/10.30811/jim.v7i2.3336>
- Sari, L.K., Achsani, N.A., & Sartono, B. (2017). Pemodelan Volatilitas Return Saham: Studi Kasus Pasar Saham Asia. *Jurnal Ekonomi dan Pembangunan Indonesia*. 18(1), 35-52.
<https://doi.org/10.21002/jepi.2018.03>
- Swamidass, M. P. (2000). *Encyclopedia Of Production And Manufacturing Management*. New York: Springer.
- Tsay, R. S. (2010). *Analysis Of Financial Time Series*. John Wiley & Sons, Inc.
<https://doi.org/10.1002/9780470644560>
- Verbeek M. (2004). *A Guide to Modern Econometrics(2rd edition)*. West Sussex: John Wiley & Sons Ltd.
- Zhang, D., Hu, M., & Ji, Q. (2020). Financial Markets Under The Global Pandemic of COVID-19. *Finance Research Letters*, 36, 1-6.
<https://doi.org/10.1016/j.frl.2020.101528>
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