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Research article

Forecasting of Daily Gold Price using ARIMA-GARCH Hybrid Model

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Abstract: Gold is a multifunctional precious metal. Apart from being jewelry, gold is a form of investment. For this reason, the public or investors need to know the estimated daily gold price for transactions for the public or investors who want to invest or also want to sell their gold, so they do not lose. This is the aim of this study. Many forecasting methods can be used to predict the daily gold price, but this study uses the ARIMA-GARCH hybrid model because this model can predict econometric models such as the daily gold price which usually contains high volatility. Daily gold price data was secondary data obtained from the investing.com website. The data was for the period March 12, 2016, to December 31, 2020. The results of this study are obtained for the ARIMA (1,1,1) -GARCH (2,1) hybrid model with a root mean square error (RMSE) forecasting accuracy value is 2.375454, the mean absolute error (MAE) is 1.702908, and the mean absolute percentage error (MAPE) is 0.001168113. From the results of this study, long-term investment is very profitable because there is an upward trend from the model obtained. For short-term investments, the public or investors have to update the research result model because the current gold price is influenced by the gold price only one period ago, so that when trading does not lose.

Keywords: forecasting, daily gold price, investment, hybrid ARIMA-GARCH

JEL Classification: C120, C220

Abstrak: Emas merupakan logam mulia yang multi fungsi. Selain sebagai perhiasan, emas sebagai bentuk investasi. Untuk itu masyarakat atau investor perlu tahu perkiraan harga emas harian untuk bertransaksi bagi masyarakat atau investor yang ingin berinvestasi atau juga ingin menjual emas yang dimiliki supaya tidah mengalami kerugian. Hal ini merupakan tujuan dari penelitian ini. Banyak metode peramalan yang bisa digunakan untuk meramalkan harga emas harian, tetapi penelitian ini menggunakan model hibrida ARIMA-GARCH karena model ini mampu memprediksi model-model ekonometrika seperti harga emas harian yang biasanya mengandung volatilitas yang tinggi. Data harga emas harian merupakan data sekunder yang diperoleh dari website investing.com. Data yang digunakan untuk rentang waktu 12 Maret 2016 sampai dengan 31 Desember 2020. Hasil dari penelitian ini diperoleh untuk model hibrida ARIMA(1,1,1)-GARCH(2,1) dengan nilai akurasi peramalan root mean square error (RMSE) sebesar 2.375454, mean absolute error (MAE) sebesar 1.702908, dan mean absolute percentage error (MAPE) sebesar 0.001168113. Dari hasil penelitian ini, investasi jangka panjang sangat menguntungkan karena ada trend naik dari model yang diperoleh. Untuk investasi jangka pendek, masyarakat atau investor harus melakukan update model hasil penelitian karena harga emas terkini dipengaruhi oleh harga emas hanya satu periode yang lalu, supaya ketika bertransaksi tidak rugi.

Kata Kunci: peramalan, harga emas harian, investasi, hibrida ARIMA-GARCH

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1. INTRODUCTION

Gold is a precious metal that has multiple functions. In general, gold is used as jewelry. Apart from being a piece of jewelry, gold can also, be used as an investment both in the long and short term. Gold is also used as a standard in calculating zakat mal when the assets that want to be zakat is difficult to determine the *Nisab*, namely the requirements for the amount and time to pay zakat, even gold is used as a symbol of many championships as a symbol of first place.

Gold is a material that can be made an investment that is not affected by inflation and it is even said that gold prices always increase from time to time (Iriani & Suprayogi, 2018). Investing in gold during the global crisis that hit the world around 1998 in the safe category was not affected by the crisis (Johari, 2017). Investing in gold is more profitable than buying shares in gold mining companies (three companies) from 2002 to 2012 (Gunawan & Wirawati, 2013). Investing in gold is more profitable than buying shares in the composite stock price index (IHSG) (Kurniawan, 2019). People who invested in gold in the Jombang area were not affected by how much income they had in their household, but what influenced their investment was general knowledge and education. This means that someone willing to invest in gold was influenced by his knowledge of the benefits and benefits of investing in gold. In addition to the knowledge factor, the level of education that affects a person's general knowledge also affects a person's willingness to invest in gold (Rahma & Canggih, 2021). For mothers, gold is not only used as jewelry but also as an investment, which at any time there is a need, can be quickly sold. There are several reasons why gold investment is widely practiced. Investors choose gold as an investment for several reasons, including risk, liquidity, tax-free, and convenience (Lahoti, 2017). The risk here is that the price of gold always goes up, which means that investing in gold if it is sold in the future will give you a big profit. Liquidity means gold is easy to cash or sell. Tax-free means that gold is not subject to tax regardless of the amount, except in Islam, zakat must be issued after exceeding a certain amount in one year. Convenient which means that the price of gold is quite high, if you have a little gold then the price will also remain high.

From the reasons for investing in gold, now many financial institutions such as pawnshops, Shariah Banks, offline gold shops, and online shops such as Shopee, Lazada, Tokopedia, Bukalapak sell gold jewelry that functions as both jewelry and investment. Gold investment in a pawnshop is not only gold pawning but also sells gold with many variants such as international certified gold bullion investment with units of 5 grams, 25 grams, 50 grams, 100 grams, 250 grams, and 1,000 grams with an installment purchase system according to the agreement of the pawnshop and its customers. Gold investment in the Shariah Mandiri bank is in the form of gold pawning and buying gold in installments for a certain period. Purchase the smallest gold weighing 10 grams and the most according to the agreement. Gold investing is in the form of gold bullion or bullion. In BRI Syariah bank, there is also a gold investment in the form of gold ownership through a minimum installment of Rp. 5000, - per day. At the BNI Shariah bank, there is no visible gold investment program. The model of buying gold in small amounts or installments is intended to make it easier for small economic communities to also be able to invest in gold.

For the reasons stated above, many have invested in gold. The problem is when to invest and when to sell back so as not to suffer losses. In response to this, it is necessary to do daily gold price forecasting so that it can be predicted when buying prices are cheap and when selling prices are high and investors make a profit. Many forecasting methods can be used to forecast daily gold prices, but an easy, good and accurate model will be used in this study. A representative statistical forecasting model that can be used in this study is the autoregressive integrated moving average (ARIMA) model. This ARIMA model is relatively easy and uses a lot of data that contains trends and does not contain trends, seasonality, and even data that contains high volatility with advanced analysis.

Investment is the placement of several funds or goods in a business process for profit (Kurniawan, 2019). Gold investment is mostly done because it is more profitable than other investments, as has been discussed in the introduction to this study. Next will be discussed the forecasting models that have been used in predicting quantitative values (numbers), especially predictions about the price of gold.

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Research on gold sales and its estimation using the OLS and semi-average models at PT Aneka Tambang (ANTAM), obtained a model with the smallest mean square error (MSE) (Alkaf et al., 2017). Research on the daily gold price from the NYSE using the proposed model in the form of the development of the neural network method using the Exponential Smoothing method for data transformation which is then proven to improve the results of the gold price prediction by comparing the resulting RMSE values. Research using the artificial neural network (ANN) model to predict the price of gold produces a fairly accurate model (Adem et al., 2017). Forecasting gold prices using a hybrid model between ANN and Genetic Algorithm (GA) with the conclusion that there are two methods used where ANN with pure ANN training and the second ANN with a training model from GA produces fairly good accuracy (Khamis & Yee, 2018). Research on gold price prediction using GA in calculating the fuzzy inference system (FIS) compared to a model that directly calculates FIS is more accurate using GA in calculating FIS than directly calculating with FIS, this is evidenced by the smallest value, namely, the root means square error (RMSE) on FIS calculations with GA (Fathurrachman et al., 2019).

Tripathy (2018) also conducted gold price forecasting using the ARIMA model. The best results in this study were obtained from the ARIMA model (0,1,1). Other researchers also conducted gold price forecasting using the ARIMA model. The results of this study obtained the best ARIMA model, namely ARIMA (7,1,10) . Another research on gold prediction uses the ARIMA-GARCH hybrid model (general autoregressive conditional heteroscedasticity). The data used in this study were daily gold price data from November 26, 2005, to January 18, 2006, as many as 40 data. The results of this study obtained that the best model was ARIMA (1,1,1)-GARCH (0,2) (Yaziz et al., 2013). Research on the performance of the ARIMA-GARCH hybrid model, which is quite good at predicting volatility data, is not only applied to predict gold prices but can also be used to predict world oil prices which also contain high volatility. The results of this study resulted in the best model ARIMA (33,0,14)-GARCH (1,1). This means that the ARIMA-GARCH hybrid model is suitable for predicting data containing high volatility (Dritsaki, 2018). Another field was the volatility of foreign exchange. The performance of the ARIMA model, the ARIMA-ARCH hybrid model, and the ARIMA-GARCH hybrid model was compared to predict the exchange rate. The result of the comparison is that the ARIMA model cannot capture the volatility in the data, the ARIMA-ARCH hybrid model can capture the less-than-optimal volatility of the data, while the ARIMA-GARCH hybrid model can capture the data volatility the best. The best model is the ARIMA (2,1,2)-GARCH (2,2) hybrid (Idris et al., 2021). The several methods used to predict the gold price, the ARIMA model is classified as an easy model when compared to the ANN and its hybrid models. The ARIMA model has a good level of accuracy, so this ARIMA model will be used in this study.

2. RESEARCH METHODS

2.1. Data

This study uses secondary data, namely daily gold price data from 12 March 2016 to 31 December 2020. The data were obtained from the investing.com website which was accessed on 31 December 2020.

2.2. Model

The forecasting method used in this research is the ARIMA-GARCH hybrid model. The initial stage of this research is to prepare daily gold price data, then do a time series plot. The next step is to test the data stationary by using the Dicky Fuller Test (DF-test). If the data is not stationary, differencing is done (Yaziz et al., 2013). Stationary data are performed autocorrelation plot (ACF) and partial autocorrelation plot (PACF) to determine the initial order of the AR (p) autocorrelation model and the initial moving average MA (q) model. If the model is stationary from the beginning, then the model is ARMA (p, q) and if the model is stationary after differencing then the model is ARIMA (p, d, q), d is the order of the differencing. For the ARMA model (p, q) it can be written as ARIMA (p, 0, q) because the data is stationary and there is no differencing, so the differencing value (d = 0) is equal to zero (Wei, 2006).

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The initial model of ARMA (p, q) or ARIMA (p, d, q) is estimated for its parameters using the log-likelihood method and the parameter values are obtained. The next step is to test these parameters with the t-test approached by the Z test to determine whether these parameters are significant or not in the ARMA (p, q) or ARIMA (p, d, q) models. Furthermore, the overfitting model is carried out, namely looking for ARMA (p, q) or ARIMA (p, d, q) models whose orders are around the values of p, d, q whose parameters are all significant (As'ad, 2012).

ARMA (p, q) or ARIMA (p, d, q) models whose parameters are significant are all performed error checking diagnostics. Errors or residues from the ARMA (p, q) or ARIMA (p, d, q) models must be checked to fulfill the ARIMA model's error assumption, namely white noise. The assumption of white noise has two things that must be fulfilled, namely error must be normally distributed and there is no autocorrelation between errors. To check the normality of the remainder, the Shapiro-Wilk test was used, while to test the autocorrelation free between errors, the L Jung-Box test was used (Farida, 2021). ARIMA models (p, d, q) where all the parameters are significant and meet the white noise assumption, the best model is selected based on the value of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The model with the smallest AIC and BIS values is the best. In addition to this, the parsimony principle is used to determine the best model, which is to keep the best model that is simple or the order of p, d, q which is small or low (Wei, 2006).

In econometric cases, such as forecasting the daily gold price, it usually contains an element of volatility. If the best ARIMA model has been obtained but the error does not fulfill the white noise characteristic, then the error may contain heteroscedasticity. For this reason, the autoregressive conditional heteroskedasticity (ARCH) or generalized autoregressive conditional heteroskedasticity (GARCH) test is performed. If the model contains the ARCH or GARCH effect, then the model becomes the ARIMA-GARCH hybrid model. This model is a combination of the ARIMA (p, d, q) and GARCH (p, q) model (Yaziz et al., 2013). In the GARCH (p, q) model, p represents the order as AR (p) in squared error data. The value of q in the GARCH model (p, q), shows the order as MA (q) in the squared error data. Like the ARIMA model, the GARCH model has an initial model identification stage, namely the ACF and PACF plots for the squared error. These ACF and PACF plots are used to determine the GARCH order (p, q), then estimate the GARCH parameters (p, q), and test the parameters using the t-test which is approximated by the Z test. GARCH model (p, q) with all significant parameters is used as a model. To determine the best model, the smallest AIC and BIC values are used as the best model and the parsimony principle, which is the simplest model. The GARCH model error test was carried out, namely the ARCH effect test, white noise with ACF and PACF plots, and normality using the Shapiro-Wilk test. After this test is fulfilled, then forecasting the ARIMA-GARCH hybrid model is carried out (Yaziz et al., 2013).

3. RESULTS AND DISCUSSION

3.1. ARIMA Model Analysis

The analysis of the ARIMA model for the first stage of daily gold price data is plotting the data to get an overview of the data. Briefly, Figure 1 shows a trend of daily gold price data. To ensure this, a statistical test of the data was carried out with the Dicky Fuller test. The results of the Dicky-Fuller test are in Table 1. Table 1 reports the Dicky Fuller test, a test value of 1.4476 is obtained or with a probability value, namely the p-value (0.8122) greater than 0.05, when compared to (5 % = 0.05) it is greater, meaning that it accepts H0 (data is not stationary). Because the data is not stationary, then order one differencing (d=1) is carried out and the data is stationary. Because the data is stationary, then plotting the ACF and PACF data is different. The results of the plot of daily gold price data against time are presented in Table 1 as follows.

Table 1. The result of model estimation

Augmented Dickey-Fuller Test
Dickey-Fuller = -1.4476, Lag order = 10, p-value = 0.8122 Alternative hypothesis: stationary

Source: Authors calculations

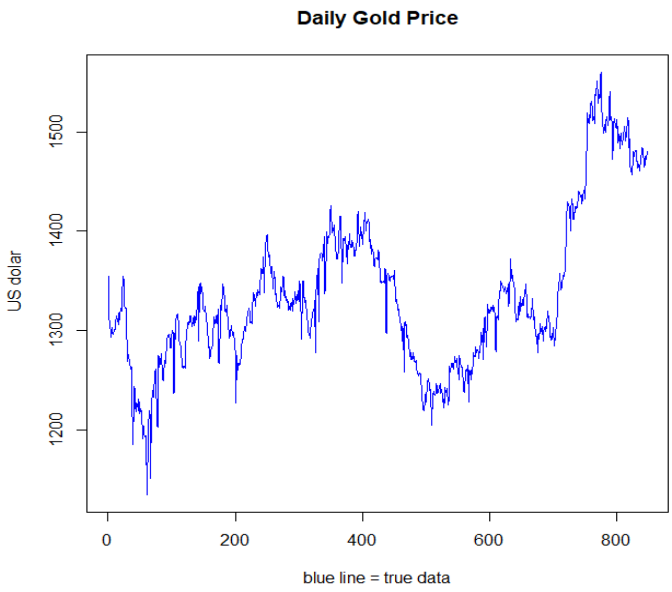
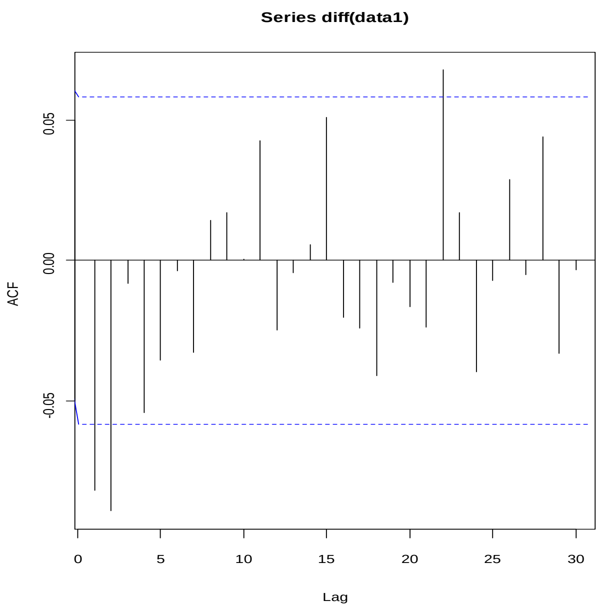


Figure 1. The plot of daily gold price data
Source: Authors calculations



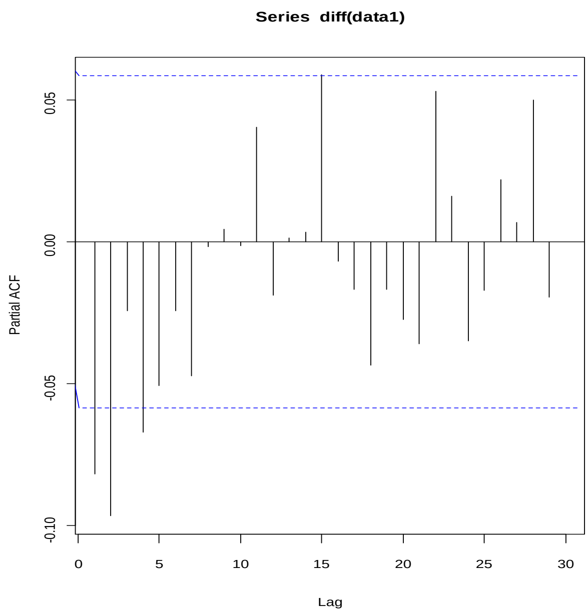


Figure 2. ACF plot of daily gold price data (after differencing)
Source: Authors calculations

Figure 3. PACF plot of daily gold price data (after differencing)
Source: Authors calculations

The ACF plot (Figure 2) lags one and two autocorrelation values exceed the lower limit of 5% (alpha), this means that the initial moving average (MA) model is of order 2 and PACF (Figure 3) has lags 1 and 2 have partial autocorrelation values exceeding the lower limit 5% (alpha), this means that the initial model of autoregressive (AR) is of order 2. The tentative model of ACF (Figure 2) and PACF (Figure 3) is ARIMA (2,1,2). The results of parameter estimation for ARIMA (2,1,2) are presented in Table 2 as follows.

Table 2. ARIMA parameter values (2,1,2)

Call: ARIMA (x = data AR, order = c (2, 1, 2)) Coefficients:				
Parameters	AR1	AR2	MA1	MA2
Coefficients:	0.0222	0.3427	-0.1177	-0.4463
S.E.	0.3940	0.2818	0.3874	0.3098
Sigma^2 estimated as 259.6: log likelihood = -4710.72, AIC = 9429.43				
Test the coefficient of the ARIMA model (2,1,2) z-test of coefficients:				
Parameters	Estimate	Std. Error	z value	Prob.(>|z|)
AR1	0.022187	0.394001	0.0563	0.9551
AR2	0.342688	0.281754	1.2163	0.2239
MA1	-0.117695	0.387429	-0.3038	0.7613
MA2	-0.446284	0.309810	-1.4405	0.1497

Source: Authors calculations

Table 2 reports the parameter estimation value for ar1 is 0.0222, the value of AR2 is 00.3427, the value of MA1 is -0.1177 and the value of ma2 is -0.4463. This ARIMA (2,1,2) model has a minimum AIC value of 9429,43. Furthermore, the estimated value of the ARIMA parameter (2,1,2) was partially statistically tested with the t-test (which was approximated by the Z-test) with the following results (Table 2). Table 2 also reports all parameters (AR1, AR2, MA1, and MA2) are not significant (the value of Prob.(>|z|) is not smaller than 5%) which means this model is not suitable. Then the model is changed to ARIMA (2,1,1).

The results of parameter estimation for ARIMA (2,1,1) are presented in Table 4. Table 4 reports the parameter estimation value for AR1 is 0.6143, the value for AR2 is -0.0302 and the value for MA1 is -0.7139. This ARIMA (2,1,1) model has a minimum AIC value of 9430.42. Furthermore, the estimated value of the ARIMA parameter (2,1,1) was partially statistically tested with the t-test (which was approximated by the Z-test) with the following results (Table 3).

Table 3. ARIMA parameter value (2,1,1)

Call: ARIMA (x = data AR, order = c (2, 1, 1)) Coefficients:				
Parameters	AR1	AR2	MA1	
Coefficients:	0.6143	-0.0302	-0.7139	
S.E.	0.1068	0.0365	0.1031	
Sigma^2 estimated as 259.8: log likelihood = -4711.21, AIC = 9430.42				
Test the coefficient of the ARIMA model (2,1,1) z-test of coefficients:				
Parameters	Estimate	Std. Error	z value	Prob.(>|z|)
AR1	0.614324	0.106806	5.7518	8.831e-09 ***
AR2	-0.030162	0.036526	-0.8258	0.4089
MA1	-0.713929	0.103149	-6.9213	4.475e-12 ***

Note: Significant codes: ***0.001, **0.01, *0.05.
Source: Authors calculations

Table 3 reports the parameter estimation value for AR1 is 0.6143, the value for AR2 is -0.0302 and the value for MA1 is -0.7139. This ARIMA (2,1,1) model has a minimum AIC value of 9430.42. Furthermore, the estimated value of the ARIMA parameter (2,1,1) was partially statistically tested with the t-test (which was approximated by the Z-test). Table 4 also reports that the AR1 parameter is 0.614324 (significant with a p-value of 8.831e-09 < 0.05) and MA1 of -0.030162 which is also significant (there is an asterisk or p-value (4.475e- 12) < 0.05). because ar2 is not significant (p-value (0.4089) > 0.05) then it is eliminated and now the model becomes ARIMA (1,1,1).

The following are the results of the ARIMA model parameter estimation (1,1,1) presented in Table 4. Table 4 reports the parameter estimation value for AR1 is 0.6486, the value for MA1 is -0.7609. This ARIMA (1,1,1) model has a minimum AIC value of 9427.08. Furthermore, the estimated value of the ARIMA parameter (1,1,1) was partially statistically tested with the t-test (which was approximated by the Z-test).

Table 4. ARIMA parameter value (1,1,1)

Call: ARIMA (x = data AR, order = c (1, 1, 1))				
Coefficients:				
Parameters	AR1	MA1		
Coefficients:	0.6486	-0.7609		
S.E.	0.0866	0.0731		
Sigma^2 estimated as 260: log likelihood = -4711.54, AIC = 9427.08				
Test the coefficient of the ARIMA model (2,0,2)				
z-test of coefficients:				
Parameters	Estimate	Std. Error	z value	Prob.(>|z|)
AR1	0.648622	0.086615	7.4885	6.965e-14 ***
MA1	-0.760862	0.073125	-10.4049	< 2.2e-16 ***

Note: Significant codes: ***0.001, **0.01, *0.05.
Source: Authors calculations

Table 5 reports that the parameters AR1 and MA1 are all significant (there is an asterisk or p-value < 0.05). ARIMA (2,1,2), ARIMA (2,1,1) and ARIMA (1,1,1) models will be taken as the best model. Selection of the best model based on the Akaike Information Criteria (AIC) in Table 5. Table 5 also obtained the best ARIMA (1,1,1) model because it has a small AIC value (9429.43 < 9430.42 > 9427.08), namely the ARIMA model (1,1,1) of AIC = 9427.08. In addition to comparing the AIC values, the parsimony principle is also used, namely choosing a simple model that is ARIMA (1,1,1).

Next, we will examine the assumption of white noise from the rest of the ARIMA (1,1,1) model. The first is the autocorrelation-free assumption of residuals. With the Ljung-Box test, the remainder of the ARIMA (1,1,1) model is obtained from Table 5 as follows.

Table 5. Diagnostics test of the remaining data test of the ARIMA model (1,1,1)

Diagnostics	Test	Stat-value	d.f.	Prob.
Autocorrelation test (X^2)	Ljung-Box test	7.4635	12	0.8255
Normality test (W)	Shapiro-Wilk test	0.8875	-	< 2.2e-16
ARCH (X^2) the ARIMA Model (1,1,1)	LM test	68.158	12	7.071e-10

Source: Authors calculations

The Chi-square value with the Ljung-Box test is 7.4635 with a lag of 12, the X^2 value is 7.4635 with a p-value of 0.8255 > 0.05 (alpha) which means the residual is random or there is no autocorrelation. Furthermore, the second residual assumption test is the residual normality test with the Shapiro-Wilk test, the results in Table 6. The statistical value of the W test is 0.88716 with a p-value = 2.2e-16 <0.05 (alpha) meaning that the H_1 acceptance test means that the data is not normally distributed. With the residual test, this model is not white noise, that is, the residual is free of autocorrelation and the residual is not normally distributed. Models with residuals that are not white noise may have a high volatility effect or the residuals of the model are still heteroscedastic, for that reason the ARCH/GARCH effect test will be carried out on the residual data of the ARIMA (1,1,1) model. This test uses the Lagrange Multiplier test or ARCH-LM Test. In the ARIMA (1,1,1) residual data test with the ARCH/GARCH model, the results of the ARCH LM-test are in Table 5. From Table 6 reports the results of the ARCH LM-test for the residual data model 2, the Chi-Squared value = 68,158 with a p-value of 7.071e-10 (P-value < or 7.071e-10 < 0.05), this means that H1 is accepted (the data contains a negative effect). ARCH models). Furthermore, the remainder is modeled with ARCH/GARCH and then added to the ARIMA (1,1,1) model so that it becomes an ARIMA-ARCH/GARCH hybrid model.

3.2. ARCH and GARCH Model Analysis

Before determining the ARCH or GARCH model, a plot of the ARIMA (1,1,1) model residual is performed. The residual plot of the ARIMA (1,1,1) model is presented in Figure 4 as follows. Figure 4 and Table 6 ARCH-LM test reports the residual data test of the ARIMA (1,1,1) model, shows that in Figure 4 there is a volatility cluster, which means there is an ARCH/GARCH effect. Furthermore, ACF and PACF plots were performed to strengthen the heteroscedasticity effect on the residues. The following plots ACF and PACF (figure 6) from ARIMA (1,1,1) residuals are presented in Figure 5 as follows.

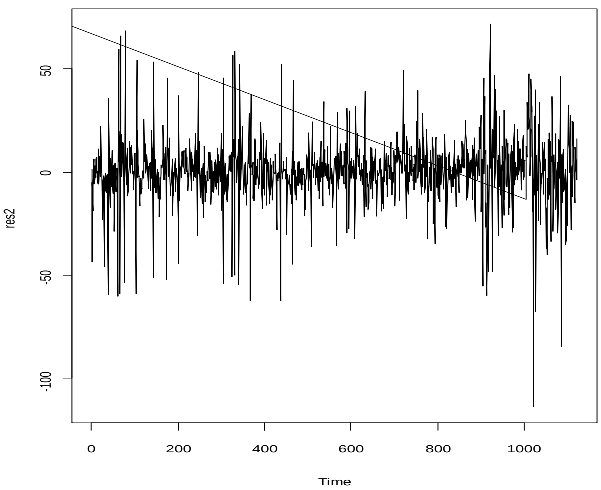


Figure 4. ARIMA Model residual plot (1,1,1)
Source: Authors calculations

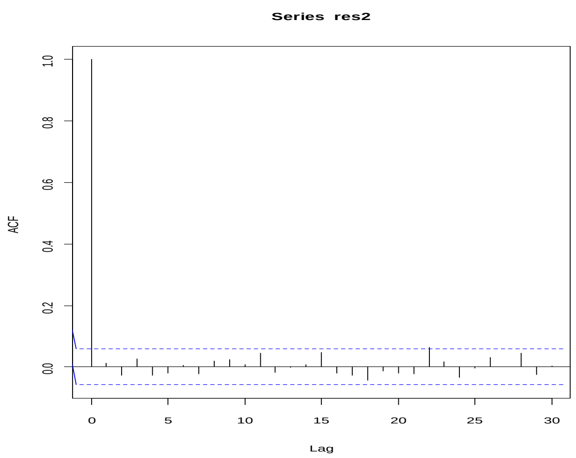


Figure 5. The residual ACF plot of the ARIMA model (1,1,1)
Source: Authors calculations

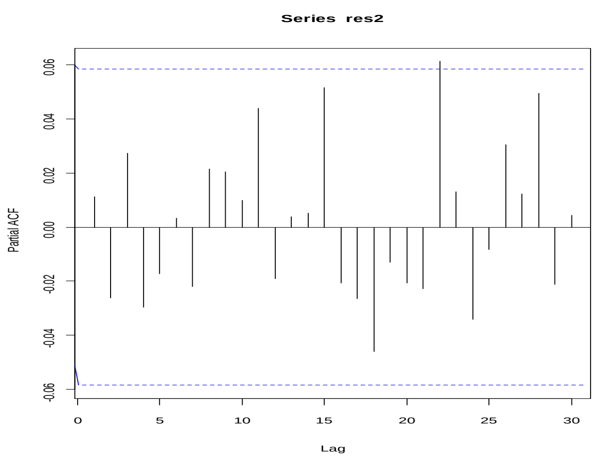


Figure 6. Residual PACF plot of ARIMA model (1,1,1)
Source: Authors calculations

The ACF plot in Figure 5 and the PACF plot in Figure 6 look insignificant (there are no spikes or vertical ACF or PACF lines that exceed the upper and lower boundary lines), this strengthens that the residual contains an ARCH/GARCH effect. Next, calculate the square of the residual and plot and plot ACF and PACF as well. The plots of the three presented in Figures 7, 8, and 9 are as follows.

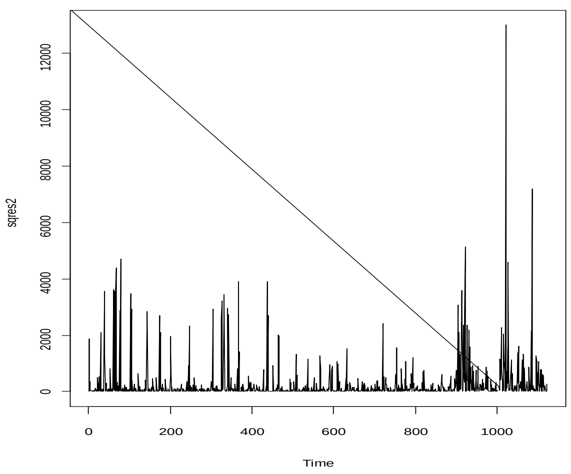


Figure 7. Squared residual plot of the residuals of the ARIMA model (1,1,1)
Source: Authors calculations

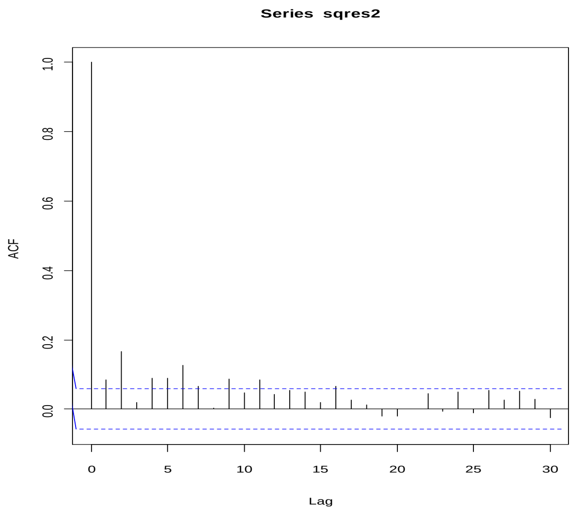


Figure 8. ACF plot of residual squared from residuals of ARIMA model (1,1,1)
Source: Authors calculations

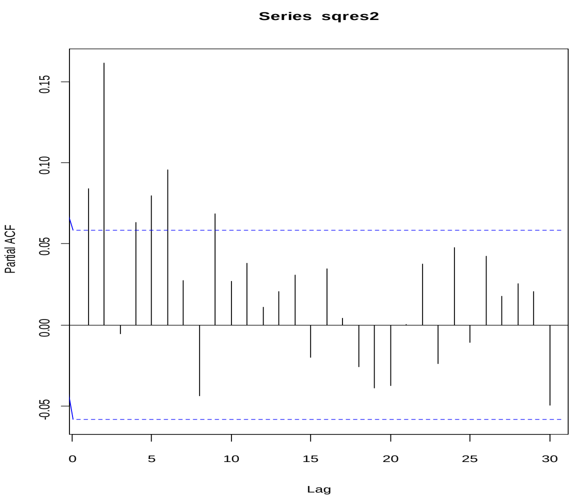


Figure 9. PACF plot of squared residuals from the residuals of the ARIMA model (1,1,1)
Source: Authors calculations

Based on the plots of ACF (figure 8, there is a spike or vertical line that exceeds the upper limit of the blue dotted line in lag 2 which is quite prominent which then dies down) and PACF (figure 9, there is a spike or vertical line that exceeds the upper limit of the line). dotted blue on the 2nd lag which is quite prominent which then dies down), the temporary GARCH model is GARCH (2.2). Estimation of GARCH parameters (2,2) and their significance test are presented in Table 7 as follows.

Table 6 reports the p-value BETA2 (1.00) > 0.05 (alpha=5%) which means it is not significant and is eliminated from the model so that the model becomes GARCH (2,1). Furthermore, the parameter estimation for the GARCH (2,1) model and its significance test is carried out which is presented in Table 6. Table 6 reports the all parameters (OMEGA, ALPHA1, ALPHA 2, and BETA1) except mu, p-value <0.05 (alpha = 5%), which means all parameters are significant. Furthermore, it will be compared with the GARCH model which may be simpler, namely GARCH (1,1), the result of parameter estimates, and their significance tests are presented in Table 7. Table 7 also reports all parameters (OMEGA, ALPHA1, and BETA1) except MU, p-value < 0.05 (alpha=5%), which means all parameters are significant. To obtain the best model from the model with significant parameters, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values will be compared, where the best model is the one with the smallest AIC and BIC.

Table 6. Estimated parameters and significance test

Error Analysis: GARCH (2,2)				
Parameters	Estimate	Std. Error	t-value	Prob.(>|z|)
MU	-5.711e-01	4.063e-01	-1.406	0.1598
OMEGA	6.563e+01	1.223e+01	5.368	7.95e-08 ***
ALPHA1	1.595e-01	3.986e-02	4.003	6.26e-05 ***
ALPHA2	2.112e-01	6.729e-02	3.139	0.0017 **
BETA1	4.177e-01	2.263e-01	1.846	0.0649
BETA2	1.000e-08	1.733e-01	0.000	1.0000

Error Analysis: GARCH (2,1)				
Parameters	Estimate	Std. Error	t-value	Prob.(>|z|)
MU	-0.57109	0.40575	-1.408	0.15928
OMEGA	65.62894	11.33984	5.787	7.15e-09 ***
ALPHA1	0.15954	0.03854	4.140	3.47e-05 ***
ALPHA2	0.21122	0.06450	3.275	0.00106 **
BETA1	0.41774	0.08002	5.221	1.78e-07 ***

Error Analysis: GARCH (1,1)				
Parameters	Estimate	Std. Error	t-value	Prob.(>|z|)
MU	-0.44995	0.41182	-1.093	0.275
OMEGA	37.83806	6.65634	5.685	1.31e-08 ***
ALPHA1	0.21851	0.04095	5.336	9.48e-08 ***
BETA1	0.65282	0.04723	13.823	< 2e-16 ***

Information Criterion Statistics:		
Model	AIC	BIC
GARCH(2,2)	8.231823	8.258664
GARCH(2,1)	8.230042	8.252409
GARCH(1,1)	8.240646	8.258540

Note: Significant codes: ***0.001, **0.01, *0.05.
Source: Authors calculations

The best GARCH model based on Table 7, also reports the GARCH model (2.1) with the smallest AIC value of the three models of 8.230042 and the smallest BIC value of the three models of 8.252409. Furthermore, this model will be used with the best ARIMA model, namely ARIMA (1,1,1), thus forming the ARIMA (1,1,1)-GARCH (2,1) hybrid model. The error of the ARIMA (1,1,1)-GARCH (2,1) hybrid model is checked to meet white noise and does not contain ARCH and GARCH effects anymore. Furthermore, this hybrid model will be used for daily gold price forecasting for the next several periods. Below is a graph of daily gold price data and forecasting results for the ARIMA (1,1,1)-GARCH (2,1) hybrid model as shown in Figure 10. Figure 10 in blue is a daily gold price chart and the red chart is a forecast for the ARIMA (1,1,1)-GARCH (2,1) hybrid model, where the blue and red graph colors appear to coincide so that it looks as if the color is red. just.

Table 7. The accuracy of forecasting of the ARIMA (1,1,1)-GARCH (2,1) hybrid model

Accuracy Model	RMSE	MAE	MAPE
	2.375454	1.702908	0.001168113
Periods three periods of the hybrid model	1	2	3
Forecasting of daily gold price	1891.674	1891.531	1891.196

Source: Authors calculations

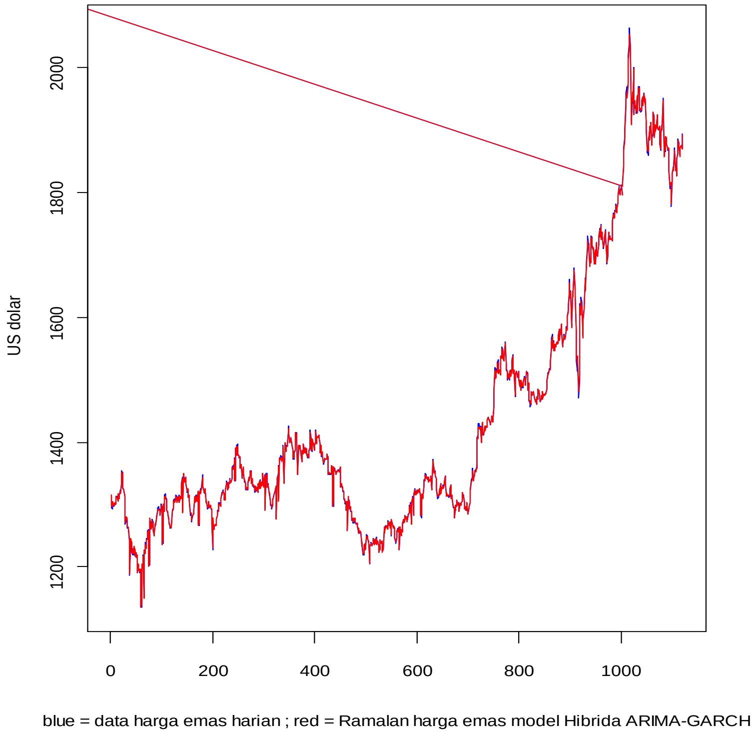


Figure 10. Daily gold price chart and forecast model ARIMA (1,1,1) -GARCH (2,1)
Source: Authors calculations

Forecasting accuracy calculations for the ARIMA(1,1,1)-GARCH(2,1) hybrid forecasting model are presented in the following Table 7. Table 7 reports the RMSE value is 2.375454, the MAE value is 1.702908 and the MAPE value is 0.001168113. The three accuracy values are the smallest values of the three ARIMA(1,1,1)-GARCH(2,2) hybrid models, ARIMA(1,1,1)-GARCH(2,1) hybrid and ARIMA(1,1 hybrid) hybrid models. ,1)-GARCH(1,1). Forecasting results for the next three periods from the ARIMA(1,1,1)-GARCH(2,1) hybrid model are presented also in Table 8. Table 8 reports that there was a decrease for the next three periods, but the decrease was not significant or it could also be said to be a form of data fluctuation. Overall, from the beginning of the data, there was a positive trend, namely an increase from time to time, this is by several previous studies that gold prices always rise for a long period and only fluctuate down in a short time.

3.3. Discussions

The analysis of the ARIMA-GARCH hybrid model is a hybrid forecasting model that is suitable for data containing linear and nonlinear elements. Linear elements are predicted by the ARIMA model and nonlinear elements are predicted by the GARCH model. The nonlinear element in the gold price data is because it contains high volatility, resulting in a conditional heteroscedasticity model. Data from financial markets, such as daily gold price data, often contain high volatility and the GARCH model can be used to model this data.

Overall, the data from the beginning to the end of the daily gold price data used in this study continues to increase. Between the real daily gold price data and the forecast results as shown in Figure 10 above, there is always an increase, this means that the ARIMA-GARCH model forecast results have the same pattern as the actual data. Daily gold prices always rise, this is by the conclusions of previous studies such as Iriani & Suprayogi (2018). This continuous increase in gold prices proves that gold prices continue to rise unaffected by inflation, the pandemic (starting at the end of 2019 until now) which has an impact on significant economic turmoil, according to the results of research from Johari (2017). From the two pieces of evidence above, a statement is made that gold investment in the long term is very profitable because the price of gold in the long term continues to increase.

To get more accurate prediction results, it is necessary to add the latest data so that the ARIMA-GARCH hybrid model undergoes a model update. For short-term daily gold price predictions (in the next few days) it must be observed so that when selling gold with a purchase vulnerability that is not long enough, with prices always fluctuating, they do not experience losses. To get a decision to sell or to buy, do you need an information system for buying or selling decisions so that the analysis is fast and accurate, this all depends on the needs of each party.

4. CONCLUSIONS

Generally, long-term prediction for the price of gold is expected to rise, this can be seen from the data trend in the data stationary-test. In ARIMA modeling, differencing is also carried out because of the trend factor, this strengthens that the gold price in the long term is expected to increase. The prediction of the gold price will increase in the long term according to the research of the researchers written in the introduction in this paper.

Gold price prediction modeling is econometric modeling that contains high volatility (non-constant diversity), this is proven that the best model in research contains elements of autoregressive heteroscedasticity (variance error that is not homogeneous). The best model in this study is ARIMA (1,1,1) -GARCH (2,1). ARIMA (1,1,1) means that the current gold price is reduced by the previous gold price (differencing) and still depends on the differencing result of the previous period (AR 1) and depends on the difference in the average (error) of one period then (MA 1). The model is still combined with the GARCH model (2,1), which means that the current conditional variance depends on lag one from past conditional error and lag two from past conditional variance.

Short-term gold price prediction using the best model in this study, namely ARIMA(1,1,1)-GARCH (2,1) for the next three periods shows no sharp increase, only fluctuates around the value of $ 1891 USA per troy ons. From this research it can be suggested that to get the best model in short-term forecasting with the ARIMA-GARCH model, the model update must be carried out by including the latest data so that the results of forecasting the future period have high accuracy.

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