

Analysis of Gold Price Movements Through a Financial Forecasting Model Approach

RR ERLINA¹, AYI AHADIAT¹, RIALDI AZHAR², FAJRIN SATRIA DWI KESUMAH¹,
TOTO GUNARTO³

¹Department of Management, University of Lampung, Bandar Lampung, INDONESIA

²Department of Accounting, University of Lampung, Bandar Lampung, INDONESIA

³Department of Economics Development, University of Lampung, Bandar Lampung, INDONESIA

Abstract: - The resilience of gold to situations full of risk has been proven over a long period of time. Forecasting the movement of gold which is in a safe range is done to prove that gold is still stable. The purpose of this study is to obtain the best model, estimate the parameters, and predict the daily gold price change in the last two years. The AR-GARCH(1.1) model is proven to be able to form the best forecasting model so that future gold resistance can be known with a low error rate. This model can be reliably applied to predict gold prices over the next 30 days. This may prompt investors to consider investing in or out of gold.

Key-Words: - Gold Prices, GARCH, Investment, Secure Investment, Financial Forecasting, Risk Investment.

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1 Introduction

Investment is an activity that is invested or financed with the expectation of profit or return in the future. One form of investment is to use gold, [1]. Furthermore, several people are interested in investing in gold, because the price of gold is quite affordable, and investing in gold is also very easy to do and flexible, [2]. Gold is included in the low-risk investment class because price movements tend to follow the inflation rate, usually, gold prices will increase, [3]. In addition, gold is one of the most sought-after investment instruments by the public, [4]. Gold is also even used to store wealth for a long time, [5]. Gold is currently one of the rare commodities and is becoming a raw material that is increasingly difficult to mine, [6]. Investing in gold is also often used as a safe haven or as a hedge against inflation, [7]. Gold prices are volatile and gold price movements are very common, because of the power of supply and demand where when demand is high the price will rise and when supply is high the price will fall indirectly, [8].

In addition, gold prices continue to change from time to time, and the projected future gold price movements can be monitored using forecasting, [9]. By forecasting, it will provide a basis for investors in planning and making decisions to increase profits and prevent losses, [10]. In general, the relationship between return and risk is linear, [11]. These principles are important for investors before making investment deals, [12]. Several methods can be used for forecasting, one of which is the Generalized

Autoregressive Conditional Heteroscedasticity (GARCH) model. In addition, some previous studies have used GARCH's econometric model to estimate variance volatility and calculate the maximum loss percentage from the return of a given portfolio. In Indonesia, [13], found that investors should make investment decisions in equity instruments by monitoring daily volatility movements and trends. In addition, a study conducted by, [14], used the GARCH model to measure conditional variance to forecast daily share prices for one of Indonesia's stock prices.

2 Statistical Model

2.1 Stationary Satisfaction

To satisfy the requirements of the GARCH(p,q) model, the first condition that must be met is that the data set is considered stationary. Statistically, a measurement consists of checking the data record, and if the variation of the dataset is not stable around zero, it is considered non-stationary, [15]. [16], added that tests steady state by computing the autocorrelation function (ACF) and partial autocorrelation (PACF). Non-stationary datasets can be identified by the slow motion of any lag. Furthermore, Dickey and Fuller 1979 introduced the Augmented Dickey-Fuller (ADF) test to mathematically verify the presence of stationarity.

The Augmented Dickey Fuller Test (ADF) is a statistical test for testing the null hypothesis that the

time series is nonstationary and has a root of 1. The ADF test is considered a type of unit root test used to determine the stationarity of time series in econometrics and time series analysis. The "extended" part of the name refers to the fact that the test includes an additional term in the regression equation compared to the original Dickey-Fuller test, making it easier to detect roots of 1. The results of the test can be used to decide whether to differentiate the time series data or apply a transformation to stationary data for further analysis. The hypothesis for the ADF test can be expressed as follows.

$$DF_{\tau} = \frac{\gamma_i}{\hat{s}_{e_{\gamma_1}}} \quad (1)$$

The hypothesis is defined as.

$H_0: DF_{\tau} > 2.57 =$ non-stationary

$H_0: DF_{\tau} < 2.57 =$ stationary

Since most financial data series are non-stationary in both mean and variance, transformation to stationary data must be done by applying differentiation methods, [16].

2.2 Differencing

In 1980, Granger and Joyeux introduced a differentiation method to transform a nonstationary time series data set into a stationary data set to stabilize the mean and volatility. The formula is:

$$a(B) = (1-B)d \quad (2)$$

where B is defined as a backward operator; d is the number of derivatives. a(B) is called an integration filter of order d. The GARCH stable mean and volatility model can be applied if the stationary dataset is satisfied. However, only after confirming that the model introduced in this study was not affected by autoregressive conditional heteroscedasticity (ARCH) effects, [16].

2.2 ARCH-Effect Test

Note that when modelling time series of financial data, the probability of heteroscedasticity is very high, [17]. This means that the estimated parameters of the forecast model can be less accurate. The presence of the ARCH effect is examined by computing the Lagrangian multiplier (LM) test, [18]. If the probability value of the LM test is significant from $(0 < p = 0) > 0$, the variance is estimated as the squared residual of the past data, [16].

2.3 Mean and Variance Model

The average model of the AR (p) is defined to have a delay number p, and the distributed diversification and the dual dips of the number are represented as the latest p and q, respectively. Equations 3 and 4 mathematically express the intended model.

$$XAUUSD_t = \varphi + \sum_{i=1}^p \phi_i XAUUSD_{t-i} + \varepsilon_t \quad (3)$$

$$\sigma_t^2 = \alpha + \sum_{i=1}^q \beta_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \delta_j XAUUSD_{t-j} \quad (4)$$

$XAUUSD_t$ is defined as the mean model of AR(p) and σ_t^2 is a variance model for p and q order. If the mean squared error (MSE) and mean squared error (RMSE) associated with a statistical descriptive model are relatively small, the model is considered to have a good scale for prediction, [17].

3 Result and Discussion

3.1 Analysis of Data Distribution

This research is an observation of the last 2 years with data qualifications that have been considered well. The data used in this study is the daily gold price, where gold is the underlying of various currencies in circulation. Figure 1 shows the distribution of data for more than 700 days, more fully presented in the following graph.



Fig. 1: Data Distribution Graph

After observing the distribution of data from gold, it is highly recommended to check the stationarity of the time series data. Table 1 shows that we performed the first differencing method on 705 data, where it is known that the standard deviation is at a value of 17.86701.

Table 1. Descriptive Data

Name of Variable XAUUSD	
Period(s) of Differencing	1
Mean of Working Series	0.264383
Standard Deviation	17.86701
Number of Observations	705
Observation(s) eliminated by differencing	1

3.2 Stationary Data

Examination of the stationarity of the data continues with the white noise test which is shown in Table 2. At this stage, the initial indication that the data is stationary is because of the distribution of autocorrelation values around 0 which is a factor of confidence in the gold data is stationary.

The next data stationarity check is using indicators from the test ADF. Table 3 provides information that the values of Pr > Q and Pr > LM are significant with p-value < 0.0001. This value indicates that the golden data opportunity for further deeper analysis can continue. More detailed results from the ADF test are shown in Table 3.

Table 2. Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	12.55	6	0.0508	0.044	-0.038	0.024	-0.062	-0.098	0.012
12	20.64	12	0.0560	-0.063	0.022	0.069	-0.022	0.004	0.040
18	30.75	18	0.0307	0.027	-0.012	-0.039	-0.010	-0.036	-0.101
24	38.44	24	0.0313	0.011	-0.042	-0.029	0.077	-0.043	0.006

Table 3. Augmented Dickey-Fuller Unit Root Tests

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-672.600	0.0001	-25.36	<.0001		
	1	-728.467	0.0001	-19.08	<.0001		
Single Mean	0	-672.736	0.0001	-25.35	<.0001	321.34	0.0010
	1	-728.870	0.0001	-19.07	<.0001	181.92	0.0010
Trend	0	-674.501	0.0001	-25.39	<.0001	322.44	0.0010
	1	-733.875	0.0001	-19.12	<.0001	182.84	0.0010

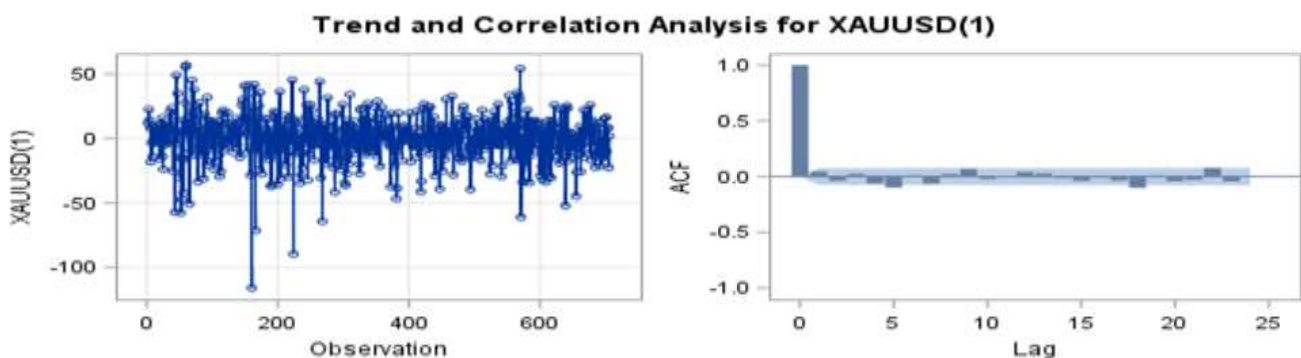


Fig. 2: Observation Graph and ACF After Differencing

Furthermore, Figure 2 confirms that the data mean after differencing has values around zero, indicating the data set is now stationary. Also, from the ACF graph, it can be visually confirmed the rapid decline after lag 1 the data set has been stationary.

3.3 ARCH Effect

The main problem with time series data is heteroscedasticity, which makes the estimation inaccurate. This problem can be solved by appropriate methods, such as the GARCH model. Investigation of whether there is heteroscedasticity or not, in general, can use the ARCH-LM test. This step must be confirmed before determining the best model of GARCH(p,q). Table 4 shows that the hypothesis can be rejected because the Portmanteau test (Q) and LM which is calculated from the squared residual have a very significant p-value (P < 0.0001). This shows that the ARCH effect for the data can be applied to the GARCH(p,q) model in forecasting.

Table 4. Tests for ARCH Disturbances Based on Residuals

Order	Q	Pr > Q	LM	Pr>LM
1	642.3624	<.0001	610.5254	<0.0001
2	1189.1941	<.0001	610.9943	<0.0001
3	1652.3749	<.0001	611.0102	<0.0001
4	2045.5623	<.0001	611.0218	<0.0001
5	2391.0342	<.0001	611.7529	<0.0001
6	2710.7554	<.0001	612.8121	<0.0001
7	3001.0883	<.0001	613.0781	<0.0001
8	3272.3654	<.0001	613.5574	<0.0001
9	3518.8545	<.0001	613.8611	<0.0001
10	3736.3120	<.0001	613.9551	<0.0001
11	3929.6393	<.0001	614.0048	<0.0001
12	4104.8068	<.0001	614.0576	<0.0001

As the probability of the LM test is significant at any order of lag, it confirmed that the differencing data set of gold prices has the variance estimated as the squared residual of the past data, so the study can be carried out for the next steps.

3.4 Estimating the GARCH Model

Finally, based on the results of a series of data analysis, the AR(1)–GARCH(1,1) model can represent the best model. Table 5 shows that the AR(1)–GARCH(1.1) model has an R-square value of 0.96, in other words, 99% of the variables have been explained by the model. Likewise, MSE = 318,73018 provides information that the model has very good forecasting ability. In addition, in Table 5, MAE has a relatively very small statistic, namely 12.9366563, while the forecasting accuracy is very

good as a representation of a very small MAPE value of 0.72095993.

Table 5. Statistical Estimation of GARCH

SSE	225023.507	Observations	706
MSE	318.73018	Uncond Var	323.859706
Log Likelihood	-3008.7904	Total R-Square	0.9699
SBC	6050.3789	AIC	6027.58082
MAE	12.9366563	AICC	6027.66654
MAPE	0.72095993	HQC	6036.39014
		Normality Test	189.4688
		Pr > ChiSq	<.0001

It then requires AR(1)–GARCH(1,1) modeling from Table 6 that the parameter estimation for AR(1) is very significant because the t value is 4.37 and P = 0.001, indicating alignment with zero with a significance of P < 0.05. Thus, based on the results of the AR(1)–GARCH(1,1) analysis, the model estimation can be presented as follows.

Table 6. Parameter Estimates of The AR(1)–GARCH(1,1)

Parameter Estimates					
Variable	DF	Estimate	Std. Error	t Value	Approx Pr> t
Intercept	1	1518	242.7643	6.25	<.0001
AR1	1	-0.9975	0.002815	-354.34	<.0001
ARCH0	1	29.4120	10.5180	2.80	0.0052
ARCH1	1	0.1085	0.0248	4.37	<.0001
GARCH1	1	0.8007	0.0515	15.56	<.0001

Or can be explained by the model of AR(1) as the equation of mean model as:

$$XAUUSD_t = 1518 - 0.9975XAUUSD_{t-1}$$

and the variance model of GARCH(1,1) is as follows.

$$\sigma_t^2 = 29.412 + 0.1085\varepsilon_{t-1}^2 + 0.8007\sigma_{t-1}^2$$

The mean model of AR(1) expresses that the gold prices are affected negatively by its historical data set at lag 1 of 0.9975; while the variance model of GARCH(1,1) examines the gold prices variances are affected by the volatility of its past data at lag 1.

The goal in finding the best model from GARCH, in the end, is to get values that can predict the future based on past data. Forecasting in the financial sector is a future financial forecast for companies, industries, and countries using historical internal accounting and sales data, [19]. Future research into the needs of providers and users of firms and accurate forecasts is essential for disseminating financial knowledge of possible uncertainties, [13].

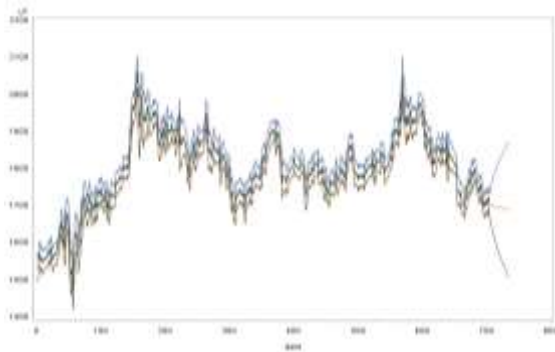


Fig. 3: Graph of Forecasting for XAUUSD Prices

Figure 3 presents a graph of Forecasting for XAUUSD Prices. Specifically, the forecasting results of XAUUSD prices have experienced a not-so-sharp decline for 30 days. The slow decline shows that XAUUSD is a strong instrument, so the movement is not extreme. However, the error range that is also predicted shows a fairly large range. The movement of XAUUSD is very likely to be influenced by external factors, such as macroeconomic conditions both domestically and globally. The projected downtrend of gold prices confirmed the study of, [20], which found that during the economic crisis, almost all sectors have a declining trend.

4 Conclusion

Forecasting is one way to predict how the future will be, besides that it provides an opportunity to take into account the bad risks that will occur, which is then followed by the preparation of a handling strategy. The results of the study show that the AR-GARCH(1.1) model can provide the best model for forecasting with 99% of constructs that can be explained. The opportunity to predict errors is also an advantage of this model.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Rr Erlina, Ayi Ahadiat carried out the concept of the study.

Fajrin Satria Dwi Kesumah collected and run the data analysis.

Fajrin Satria Dwi Kesumah , Rialdi Azhar organized and wrote the article.

Toto Gunarto reviewed the article.

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Conflict of Interest

The authors have no conflict of interest to declare.

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