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The Importance of Gold's Effect on Investment and Predicting the World Gold Price Using the ARIMA and ARIMA-GARCH Model

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Abstract

This paper studies the importance of gold's effect on investment and the fact that gold is often seen as a safe-haven asset during economic uncertainty. When inflation rates rise, investors may turn to gold to preserve their wealth; the government will reserve gold to reduce the exchange rate risk. To provide a comprehensive analysis, the study incorporates forecasting the price of gold using both the Autoregressive Integrated Moving Average (ARIMA) and ARIMA-Generalized Autoregressive Conditional Heteroskedasticity (ARIMA-GARCH) models. The gold price data is daily from 1/01/2021 to 3/01/2024. We perform model comparisons that the ARIMA (2,1,3) and the ARIMA (2,1,3)-GARCH (1,1), which model gives lower mean absolute error (MAE) and root mean squared error (RMSE) values. The results show that the MAE and RMSE predictions of the ARIMA (2,1,3)-GARCH (1,1) model are 80.1371 and 96.8299, better than those of the other model. Therefore, the ARIMA (2,1,3)-GARCH (1,1) model forecast results are better precise. It gives a forecast value for gold prices in the world market at the end of 2024 of 1942.094 USD per troy ounce. Hence, the recommendation for investors and policymakers is that if the price is higher than 1942.094 USD per troy ounce in 2024, investors and policymakers should slow down to buy and wait for it to adjust first, or investors and policymakers with gold should gradually sell to make some profit. Moreover, good portfolio management will reduce the exchange rate risk by including an optimized amount of gold in currency portfolios. However, holding gold is risky; its prices may fluctuate due to factors beyond our control, such as war, uncertainty about world economic growth, and inflation. Therefore, investors and policymakers should consider the abovementioned factors and be careful when hedging in gold.

1. Introduction

Gold is considered one of the most popular financial instruments, making it an important indicator for investors. The price of gold serves as an expectation of investors and reflects the trend of the world's economy. As such, forecasting the price of gold is essential to making informed investment decisions and minimizing risk [1, 2].

The governments utilize gold to control price monetary policies. Gold's ability to smooth inflation fluctuations further emphasizes the significance of accurately predicting its price. Historically, gold prices have proven to be a reliable predictor in numerous countries. Gold remains statistically significant compared to other inflation indicators [3].

The shift away from the Bretton Woods system in 1971, when the United States moved from a gold-backed currency to fiat money, drew considerable attention from scholars and experts to the US financial system. Even though the Bretton Woods system ended, gold has consistently been closely associated with currency throughout history. Despite the system's collapse, gold remains a crucial tangible asset, influencing macroeconomic indicators to manage inflation and exchange rate risks.

However, the effectiveness of gold as a hedge against inflation and as a safeguard for financial stability remains a topic of debate. Studies such as Hautcoeur [4] and Jastram & Leyland [5] show that gold prices remained stable for centuries. Chua and Woodward [6] estimated the long-run relationship between inflation and the cost of gold in Switzerland, USA, Japan, United Kingdom (UK), Canada, and Germany from 1975 to 1980. The finding indicated that gold was a hedge against inflation only in the United States of America.

Other studies, such as Baur and McDermott [7], Narayan et al. [8], and Narayan et al. [9], emphasize that most Countries' gold is considered a profitable investment tool. By using gold as a reserve asset in many central banks, gold would remain an essential element of the global monetary reserves system, and this study finds that the role of gold would be more critical in the present and the future. By establishing a reliable gold price forecasting model, investors can gain profit and mitigate investment risks [10–13].

Furthermore, forecasting the return on gold price for shorter and longer periods can provide valuable information for investors, enabling them to devise effective buying and selling strategies [14–19]. Additionally, accurate forecasting of gold prices can benefit commodity markets and the global economy. Predicting gold prices' volatility more precisely allows market participants to make better-informed decisions regarding their investments in gold [20–23].

It is important to note that gold prices are influenced by the basic principles of supply and demand. Just like any other commodity, the price of gold fluctuates based on the balance between its supply and the demand for it in the market. Therefore, understanding the factors that affect supply and demand in the gold market is crucial for accurate forecasting [24–26].

Researchers and analysts employ various methods and techniques to achieve accurate gold price forecasting, such as statistical models, technical analysis, and fundamental analysis. Statistical models utilize historical price data and mathematical algorithms to identify trends and patterns in gold prices. Based on historical patterns, these models can provide valuable insights into the future direction of gold prices [27–29].

Technical analysis, on the other hand, focuses on studying price charts and indicators to identify potential price movements. This method utilizes various tools and techniques, such as moving averages, trend lines, and oscillators, to forecast future price levels and market trends. Investors can make more informed decisions about buying or selling gold by analyzing chart patterns and market trends. Among the statistical models, Autoregressive Integrated Moving Average (ARIMA) is commonly used for gold price forecasting. ARIMA is a popular time series forecasting method. It analyzes past data to make predictions about future values based on patterns and trends. ARIMA models are suitable and effective in forecasting gold prices by several researchers. ARIMA-Generalized Autoregressive Conditional Heteroskedasticity (ARIMA-GARCH) models go a step further by incorporating the volatility of gold prices into the forecasting process. These models take into account the conditional variance of gold prices, allowing for a more accurate prediction of price movements and volatility. These models are particularly useful in capturing sudden changes in volatility, which is crucial for accurate forecasting in the gold market [30].

Fundamental analysis, meanwhile, involves examining the underlying factors that drive the supply and demand for gold. This includes analyzing economic indicators, geopolitical events, and market sentiment. Understanding the macroeconomic conditions and their impact on gold prices can provide investors with a comprehensive view of the market and enable them to make more accurate forecasts.

In addition to these previous forecasting methods, technological advancements have also contributed to the development of more sophisticated forecasting models. For example, artificial intelligence and machine learning algorithms can process vast amounts of data and identify complex patterns that humans may overlook. By incorporating these cutting-edge technologies into gold price forecasting, analysts can enhance the accuracy and reliability of their predictions [31–33].

Ultimately, accurate gold price forecasting is essential for investors and companies to make informed decisions and mitigate investment risks. It allows them to gauge potential profit opportunities and adjust their strategies accordingly. Additionally, governments use gold as a price-controlling and monetary policy lever, making it vital for them to have accurate forecasts to regulate inflation fluctuations effectively.

Table 1. The reviews of gold price forecasting.

The author	Methodology	Results	Year
Yaziz et al. [34]	The hybrid ARIMA-GARCH	The integration of ARIMA with GARCH offers a promising avenue for surpassing the linear constraints and data limitations inherent in ARIMA models. Thus, this hybridization of ARIMA-GARCH represents an innovative method for modeling and predicting gold prices.	2013
Christina & Umbara [35]	The type-2 neuro-fuzzy modeling and ARIMA model	The type-2 neuro-fuzzy modeling has a smaller error compared to the one obtained using the ARIMA method.	2015
Sopipan [36]	The ARIMA-GARCH models	To suggest the ARIMA-GARCH model predicts value with high accuracy.	2017
Alameer et al. [37]	The NN, PSO–NN, GA–NN, GWO–NN, and ARIMA models	The hybrid WOA–NN model is superior to other models.	2019
Shen et al. [38]	The linear regression model, ARIMA model, and Hidden Markov Models	The Hidden Markov Model is the best predictor.	2020
Nguyen et al. [39]	The ARIMA, SARIMA, RFNN, and LSTM-ARIMA model	The ARIMA, SARIMA, RFNN, and LSTM-ARIMA model predicts value with high accuracy.	2021
Liu [40]	The ARIMA model	The ARIMA model predicts value with high accuracy.	2021
Yin et al. [41]	The ARIMA Model and Boruta Random Forest Algorithm	To suggest the ARIMA model and Boruta Random Forest Algorithm predict value with high accuracy.	2022
Xiang [42]	The ARIMA-GARCH model	The ARIMA-GARCH model can accurately predict short-term price fluctuations in the future.	2022
Lin [43]	The ARIMA model and BP neural network algorithm	Compared to the ARIMA model, the BP neural network has stronger short-term predictive power.	2022
Nanthiya et al. [44]	The ARIMA model	To suggest the ARIMA model predicts value with high accuracy.	2023
Mani and Thoppan [45]	The ARIMA Model and GARCH model	The findings underscore the comparable effectiveness of both ARIMA and GARCH models in capturing and predicting the intricate dynamics of gold price.	2023
Khan [46]	The ARIMA model	Enabling the ARIMA model to effectively forecast future gold price movements with accuracy.	2024

Despite the challenges, this research employs ARIMA and ARIMA-GARCH models to estimate the price of gold, as these methods can predict with satisfactory accuracy. The study compares the two forecasting approaches to determine the most effective method for predicting gold prices.

The novelty between this research and previous studies lies in the fact that while most research on gold price predictions focuses solely on providing predictions for investors, gold is not considered solely as an investment asset based on inflation risk. It is also believed to maintain exchange rate stability during regular or abnormal times, such as during the Israeli-Palestinian War, the War between Russia and Ukraine, or the COVID-19 epidemic. Therefore, this research contributes to the significance of gold in such contexts, along with providing recommendations to policymakers.

The structure of this study is outlined as follows: Introduction, Literature Review, Materials and Methods, Results and Discussion, followed by the Conclusion and Recommendations derived from the findings. Every section plays a distinct role in clarifying the research goals and enhancing the comprehensive grasp of the subject matter.

2. Literature Review

2.1. Overview of Gold Price Forecasting

Gold price forecasting is a complex and multifaceted field that utilizes a range of methods and techniques. It involves analyzing historical data, market trends, and macroeconomic factors to make predictions about future price movements. Accurate forecasting is vital for investors and companies seeking to optimize their investments and make informed decisions. Accurate gold price forecasting helps investors and companies make informed decisions by providing insights into potential profit opportunities and investment risks. Additionally, it assists governments in regulating inflation and implementing effective monetary policies. Therefore, accurate gold price forecasting plays a crucial role in investor decision-making, risk reduction, and profit optimization.

The trend of price changes in precious metals is a key aspect of gold price forecasting. Analysts can gain valuable insights into future price movements by examining the relationship between price changes, reserves, and production rates of precious metals. This approach allows for a more comprehensive understanding of the factors influencing gold prices and can lead to more accurate predictions [32].

In addition to examining the trend of price changes, experts have also explored the use of artificial intelligence and machine learning algorithms in gold price forecasting. These advanced technologies can process large amounts of data and identify intricate patterns that may not be evident to human analysts. By incorporating these algorithms into the forecasting models, analysts can enhance the accuracy and reliability of their predictions.

Furthermore, the use of Neural Phase Networks (NPNs) has shown promise in predicting price changes. NPNs can integrate existing data and make predictions based on the patterns and trends observed. This integration of data from various sources allows for a more comprehensive and holistic approach to gold price forecasting. By considering variables such as the USD index, silver price, interest rate, oil price, and stock market index, the Neural Phase Networks can generate forecasts that take into account a wide range of influencing factors [47, 48].

The analysis of price forecast results using different methods is also an efficient technique in the field of artificial intelligence. By comparing estimation methods, analysts can determine which approach yields the most accurate and reliable predictions. This helps refine forecasting models and enhance their performance.

It is important to emphasize that accurate gold price forecasting is not only beneficial for investors to gain profit and reduce investment risk but also plays a crucial role in government policies.

2.2. ARIMA in Gold Price Forecasting

ARIMA is a popular statistical method used in gold price forecasting. ARIMA models have been widely used in gold price forecasting due to their effectiveness in capturing the trend and dynamic characteristics of the prices. Several researchers have successfully applied ARIMA models to predict gold prices in different periods and regions [49, 50].

The advantage of using ARIMA models for gold price forecasting lies in their ability to capture the trend and dynamic characteristics of prices. This is particularly valuable in the gold market, which is known for its volatility and fluctuations.

One limitation is the assumption of linearity in the models. Gold prices can be influenced by a wide range of factors, including geopolitical events, economic indicators, and market speculation. These non-linear relationships can be difficult to capture using traditional forecasting methods.

Accurate data is crucial for accurate gold price forecasting. Furthermore, it is important to consider external factors that may impact the gold market, such as changes in government policies, interest rates, and inflation rates.

2.3. ARIMA-GARCH in Predicting Gold Prices

ARIMA-GARCH models have also been widely used to predict gold prices. The combination of ARIMA, which stands for Autoregressive Integrated Moving Average, and GARCH, which stands for Generalized Autoregressive Conditional Heteroskedasticity, allows for a more comprehensive analysis of the volatility and time series patterns in gold prices.

ARIMA models capture the linear dependencies in the data, while GARCH models capture the volatility clustering and time-varying volatility. By combining these two models, researchers have been able to achieve better accuracy in forecasting gold prices compared to using either model independently.

The advantage of using ARIMA-GARCH models in forecasting gold prices lies in their ability to handle both the linear patterns and the volatility that exists in the data series. The ARIMA component takes into account the underlying trend and seasonality in the gold prices, while the GARCH component captures the conditional variance and any shocks or fluctuations in the volatility.

Previous studies have shown that the hybrid ARIMA-GARCH model performs well in modeling and predicting daily gold prices. Combining these two models allows for a more comprehensive and accurate data analysis, resulting in improved forecasting precision. Empirical results from a 40-day gold price data series indicate that the ARIMA-GARCH model provides superior results in evaluating and predicting precision compared to linear models. This suggests that the hybrid ARIMA-GARCH model is promising for forecasting gold prices [34, 51].

One of the limitations of the ARIMA model alone is its inability to handle the volatility in the data series. Gold prices are known to exhibit periods of high volatility, and a model that fails to capture this volatility may result in inaccurate forecasts. This is where the GARCH component of the hybrid model comes into play. The GARCH model is designed to handle the conditional variance and volatility clustering in time series data. By incorporating the GARCH component into the hybrid ARIMA-GARCH model, the model can effectively handle the volatility in the gold price data [36].

2.4. Compilation of Gold Price Forecasting Studies

This collection, from Table 1, allowed us to compile research and tools relevant to forecasting gold prices from 2013 to 2024. Details of some of the researches are described. We found several new methods to predict the gold price. However, the most popular and accurate forecasting methods were the ARIMA and ARIMA-GARCH models. Therefore, it is reasonable for this paper to continue using these methods for forecasting. The models are compared to choose the best method and make policy recommendations.

3. Materials and Methods

The research objectives can be divided into studying the importance of gold affecting investment and benefits in the economy, and predicting the price of gold using the ARIMA and ARIMA-GARCH models, while suggesting strategies for investing in gold to policymakers and investors.

3.1. Data Collection for Gold Price

Gold price data spanning from January 1, 2021, to March 1, 2024, sourced from Bloomberg, DataStream, ICE Benchmark Administration, and the World Gold Council, with 826 daily observations, all in US dollars per troy ounce. This timeframe was chosen due to a strong upward trend, starting around $1600 in 2021 and exceeding $2000 by 2024. Prices before 2021 were notably lower, potentially affecting estimation accuracy.

3.2. ARIMA Model

The general form of the ARMA model [52] is represented in Equation 1.

$$X_t = \sum_{j=1}^{p} \phi_j X_{t-j} + \sum_{j=0}^{q} \theta_j \varepsilon_{t-j},\ t \in Z, \quad \begin{cases} \theta_0 = 1, \\ \phi_p \theta_q \neq 0, \end{cases} \tag{1}$$

Where $\{\varepsilon_t\}$ represents a flat noise in zero-mean, real polynomial. $\phi(z) = 1 - \phi_1 z - \cdots - \phi_p z^p$ and $\theta(z) = \theta_0 + \theta_1 z + \cdots + \theta_q z^q$ meet the requirements of stationarity and reversibility, respectively.

The general form of the ARIMA model. In the ARIMA(p, d, q), AR represents autoregressive, p represents the number of autoregressive terms, MA represents average move, q represents the average number of terms of moving, and d represents the difference number. If $Y_t = (1 - B)^d X_t$ is a sequence of $\mathrm{ARMA}\,(p, q)$, it indicates that $\{X_t\}$ is a sequence of $\mathrm{ARMA}\,(p, q)$ and the model is $\phi(B)(1 - B)^d X_t = \theta(B)\varepsilon_t,\ t \in Z$, where B represents the

.

operator, $(1 - B)$ represents finite difference operator, $\{\varepsilon_t\}$ represents a flat noise in zero-mean, and real polynomial $\phi(z) = 1 - \phi_1 z - \cdots - \phi_p z^p$ and $\theta(z) = \theta_0 + \theta_1 z + \cdots + \theta_q z^q$ meet the requirements of stationarity and reversibility, respectively.

The modeling steps of the ARIMA model denoted as $\mathrm{ARIMA}\,(p, d, q)$, involve several stages: Firstly, a stationarity test is conducted on the original time series. If the series fails to meet the stationarity condition, a differencing transformation is applied to achieve stationarity, determining the value of d in the model. Next, the values of p and q are determined using Autocorrelation (ACF) and Partial Autocorrelation (PACF). Here, p represents the number of autoregressive terms, while q signifies the number of lagged forecast errors in the prediction equation. Following this, the unknown parameters of the model are estimated, and their significance is evaluated using criteria such as the Akaike Information Criterion (AIC), Bayesian Information Criteria (BIC), and Hannan-Quinn Criterion (HQ). The model with the smallest statistic value among these measures is selected as the optimal model. Additionally, the diagnostic model's applicability is tested. Finally, the optimal model is utilized to forecast future values of the time series.

3.3. ARCH Model

The ARCH model [53] can be represented in the Equation 2.

$$\{x_t = f(t, x_{t-1}, x_{t-2}, \dots) + \varepsilon_t, \varepsilon_t = \sqrt{h_t} e_t, h_t = w + \sum_{i-1}^{q} \alpha_i \varepsilon_{t-i}^2, e_t \sim IID(0,1), \tag{2}$$

Where α_i is nonnegative and $f(t, x_{t-1}, x_{t-2}, \dots)$ is the deterministic information fitting model of $\{x_t\}$.

3.4. GARCH Model

The GARCH model [54] can be derived from Equation 3.

$$\{x_t = f(t, x_{t-1}, x_{t-2}, \dots) + \varepsilon_t, \varepsilon_t = \sqrt{h_t} e_t, h_t = w + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \gamma_j h_{t-j}, e_t \sim IID(0,1), \tag{3}$$

Where α_i and γ_j are nonnegative and $f(t, x_{t-1}, x_{t-2}, \dots)$ is the deterministic information fitting model of $\{x_t\}$. It is an extension of the ARCH model and claims that h_t has AR $\sum_{j=1}^{p} \gamma_j h_{t-j}$, and the ARCH term is $\sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$. The GARCH model is generally easier to identify and estimate, and the GARCH model can capture the flat period and fluctuation period series.

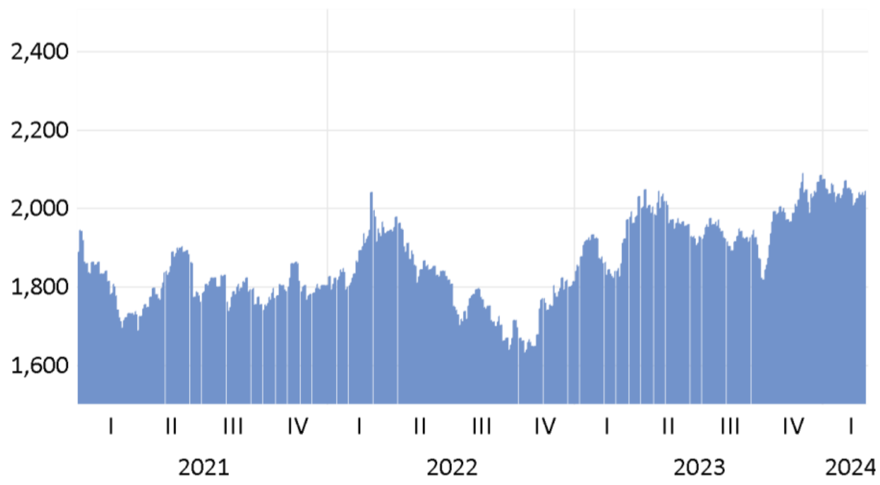


Figure 1. The daily movement of gold prices between 1/01/2021 and 3/01/2024.

Table 2. Descriptive statistics of gold prices.

Data	Gold prices
Mean	1858.598
Median	1841.85
Maximum	2089.7
Minimum	1628.8
Std. Deviation	104.224

3.5. Evaluation Metrics

MAE and RMSE are commonly utilized for assessing the accuracy of recommender systems, including those involving forecasting with the ARIMA model [55]. MAE quantifies the proximity of estimated values to actual observations, while RMSE reflects the sample standard deviation of discrepancies between predicted and actual outputs on the test set. Both metrics are defined in Equation 4.

$$MAE = \frac{\sum_{n=1}^{N} |\grave{r}_n - r_n|}{N} \text{ and } RMSE = \sqrt{\frac{\sum_{n=1}^{N} (\grave{r}_n - r_n)^2}{N}} \quad (4)$$

Where $\grave{r}_n$ means the prediction rating; n means the true rating in the testing data set; N is the number of rating prediction pairs between the testing data and prediction result.

4. Results and Discussion

4.1. Insights into the Importance of Gold

4.1.1. The Relationship Between Gold and Inflation

Gold has demonstrated its ability to maintain value during periods of elevated inflation [56]. When the prices of strategic commodities, such as oil, rise, expectations regarding future inflation also increase. In such situations, investors tend to seek safer assets [57] and avoid currencies [58]. This behavior can be attributed to rational utility maximizers who, under extreme circumstances, become more risk-sensitive and seek alternative investments [59]. If this mechanism holds true, there should be an inverse relationship between the depreciation of local currency and gold prices. Empirical research conducted by Ghosh et al. [60], Beckmann & Czudaj [61], and Bampinas & Panagiotidis [62] supports this mechanism, suggesting that gold serves as a hedge against inflation.

4.1.2. The Potential of Gold to Reduce Exchange Rate Risk

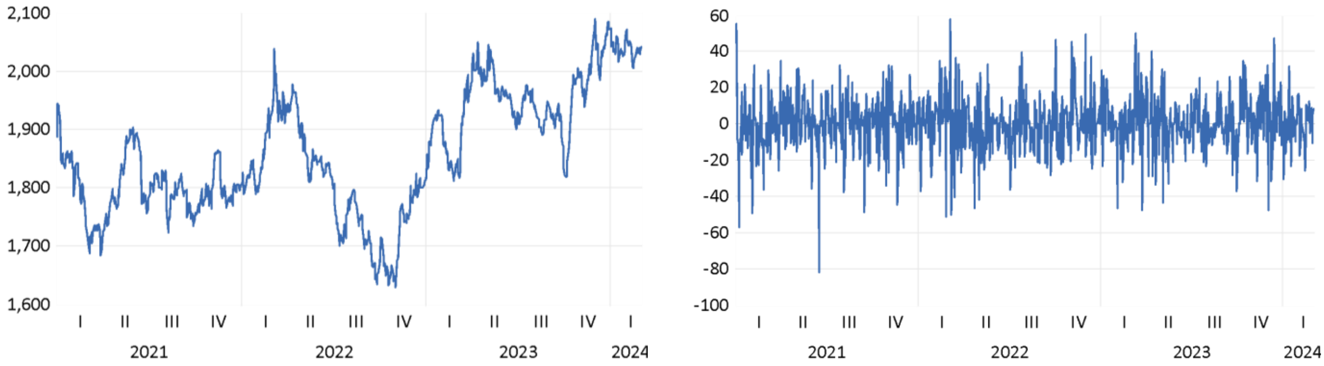
Gold exhibits lower vulnerability to changes in the foreign exchange value of the local currency [63]. In particular, when financial assets denominated in the local currency experience a decline in value due to currency depreciation, the local price of gold will align with its international price. Consequently, owning gold should safeguard investors' purchasing power against exchange rate fluctuations.

4.2. Empirical Analysis and Predictions for Gold Prices

Figure 1 shows the recent movement of gold prices. At the beginning of the fourth quarter of 2023, prices increased and will continue to increase until the first quarter of 2024. In addition, Table 2 shows that the gold price during that period had an average per unit of 1858.598 USD, the highest price was 2089.700 USD, and the lowest price was 1628.800 USD, with a standard deviation of 104.224 USD. Considering the standard deviation, the price of gold moves quite violently. Therefore, this is an attempt to forecast and get a price estimate close to the actual price.

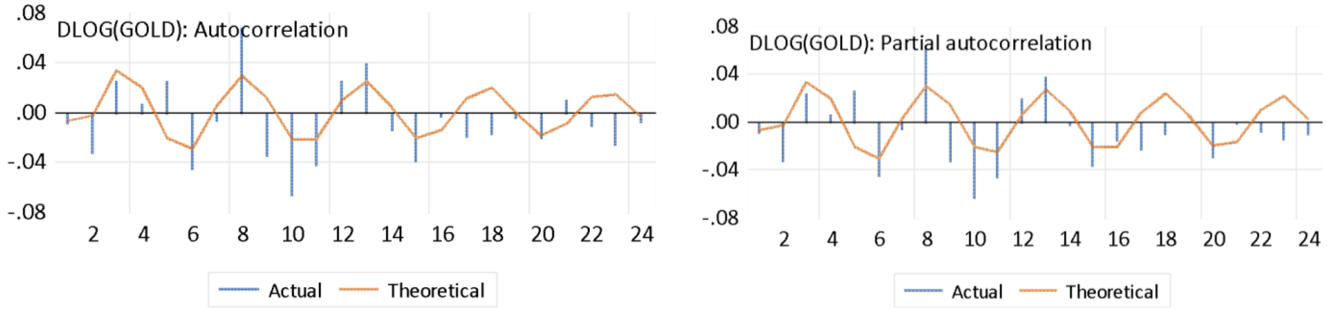
4.2.1. Unit Root Test

In time series analysis, the first step is to determine the integrated order of the variables under investigation. We employ the Augmented Dickey-Fuller (ADF) [64] and PP (Phillips & Perron) [65] tests to examine the order of



(a) **(b)**

Figure 2. Shows the Original Series (a) and First Oder Differenced (b) for gold prices.



(a) **(b)**

Figure 3. Shows the ACF (a) and PACF (b) of the ARIMA(p,1,q) model for gold prices.

Table 3. Unit root test for gold prices.

Variable	ADF test statistic				P-P test statistic			
	Intercept		**Intercept and trend**		**Intercept**		**Intercept and trend**	
	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
Gold prices	-1.854	-29.219*	-2.959	-29.237*	-1.854	-29.219*	-2.926	-29.237*

Note: * indicates significance at the 1% level.

Integration. Our aim is to test the hypothesis concerning the presence of a unit root, with the null hypothesis (H_0) stating that $\alpha = 1$ (unit root exists) and the alternative hypothesis (H_1) stating that $\alpha < 1$ (integrated of order zero, or stationary). Both the ADF and PP tests are based on the null hypothesis of non-stationarity, which indicates the presence of a unit root, while the alternative hypothesis suggests the absence of a unit root, implying that the variable being examined is stationary.

4.2.2. Results of the Unit Root Test

Figure 2 displays the data for gold price variables in both their original and first differenced series. The original series visibly demonstrates non-stationarity, necessitating differentiation. After the first differentiation, the time series becomes stationary. Table 3 presents the results of the stationarity test, which indicate that all variables are stationary in the first difference, denoted as I(1) or integrated of order one. Given these results, we can reject the null hypothesis of the presence of a unit root and accept the alternative hypothesis. Having determined the order of integration, the next step is to verify the existence of integration between variables using the ARIMA (p,1,q) model for estimating and forecasting gold prices.

4.3. ARIMA Model Estimation

The time series of gold prices has transferred to a stationary series after differing at a time, so we need to ensure the values of p and q. Thus, we first observe the difference between ACF and PACF, as shown in Figure 3.

4.3.1. Finding the Value of p Parameter

To determine the optimal value of p (the number of autoregressive terms) after identifying the optimal d value, we analyze the partial autocorrelation function (PACF) plot. The PACF plot correlates the time series with its lags, ignoring the contribution from intermediate lags. This plot reveals the lags not needed in the autoregressive component. In a stationary time series, adding autoregressive terms can capture significant correlations. Using the PACF plot, we set the order of AR terms equal to the lags that exceed a significance threshold.

Table 4. The coefficient of the ARIMA (2,1,3) model.

Variable	Coeff.	Std. er.	Prob.
Constant	9.90E-05	0.000	0.748
AR(1)	0.516	0.035	0.000
AR(2)	-0.928	0.035	0.000
MA(1)	-0.527	0.049	0.000
MA(2)	0.943	0.038	0.000
MA(3)	0.028	0.036	0.438
	Value		
R^2	0.014		
Log-likelihood	2760.322		
AIC	-6.6747		
BIC	-6.6347		
HQ	-6.6593		

Note: AIC, BIC, and HQ denote the Akaike Information Criterion, Bayesian Information Criteria, and Hannan-Quinn Criterion, respectively.

Table 5. The coefficient of the ARIMA (3,1,2) model.

Variable	Coeff.	Std. er.	Prob.
Constant	9.89E-05	0.000	0.748
AR(1)	0.543	0.041	0.000
AR(2)	-0.943	0.036	0.000
AR(3)	0.025	0.035	0.473
MA(1)	-0.557	0.025	0.000
MA(2)	0.960	0.027	0.000
	Value		
R^2	0.013		
Log-likelihood	2760.303		
AIC	-6.6746		
BIC	-6.6346		
HQ	-6.6593		

Note: AIC, BIC, and HQ denote the Akaike Information Criterion, Bayesian Information Criteria, and Hannan-Quinn Criterion, respectively.

4.3.2. Finding the Value of q Parameter

To find the value of q, we can use the ACF plot, which indicates the amount of moving average needed to eliminate autocorrelation from the stationary time series. We can then decide between two choices; the first choice is we select that the value of p is 2 (PACF=-0.038, Prob=0.526), the lags are out of the significance limit, and the value of q is 3 (ACF=0.026, Prob.= 0.607), the lags are out of the significance limit as well, as in Table 4, and the second choice, we select the value of p is 3 (PACF=0.025, Prob=0.607), the lags are out of the significance limit. The value of q is 2 (ACF=-0.038, Prob.=0.526), and the lag values are also beyond the significance threshold, as shown in Table 5. Hence, how do we decide which option provides a better fit? Specifically, the AIC value for the ARIMA (2,1,3) model is -6.6747. The value of the BIC is equal to -6.6347, which is lower than the AIC and the BIC in the ARIMA (3,1,2) model. Moreover, the value of log-likelihood in the ARIMA (2,1,3) model remains higher than that of ARIMA (3,1,2). Finally, we will select the first model most suitable for predicting the gold price.

Based on Table 6, once the model is established, the next step involves assessing its completeness by examining issues such as residual autocorrelation and heteroscedasticity. Regarding residual autocorrelation, the Q-statistic values for lags 1 to 6 were observed to reject the null hypothesis (H_1) at the 1% significance level, indicating the absence of residual autocorrelation. Similarly, when testing for heteroscedasticity using the ARCH test at lag 4 and lag 8, H_1 was rejected at the 1% significance level for both cases, signifying no heteroscedasticity.

Moreover, normality can be tested by evaluating skewness, kurtosis, and Jarque-Bera statistics. Although this model exhibits statistical significance at the 1% level (rejecting H_0), suggesting a non-normal distribution, the flexibility of ARIMA in handling data series surpasses linear constraints, as noted by Khashei et al [66]. In conclusion, considering the overall conditions, this model proves capable of estimating and forecasting gold prices to a reasonable extent.

4.4. ARIMA-GARCH Model Estimation

The ARIMA-GARCH model of the gold prices will be built after we get the optimal ARIMA; next, we must create the GARCH model. Therefore, we will get the conditional mean we choose ARIMA (2,1,3), and the conditional volatility is GARCH (1,1). The reason we can consider

Table 6. The residual diagnostic test for the ARIMA (2,1,3) model.

The ARIMA (2,1,3) model			
Test	**Lags**	**Value**	**Prob.**
Residual Tests for Autocorrelations	1	0.6993	0.403
H_0 = no residual autocorrelation	2	0.8081	0.668
(Q-stat.) (Ljung–Box test)	3	1.3835	0.709
	4	7.2788	0.122
	5	7.2796	0.201
	6	7.2953	0.294
Test	**Lags**	**F-statistic**	**Prob.**
The ARCH test			
H_0 = no Heteroskedasticity			
ARCH	4	1.9517	0.100
ARCH	8	1.2055	0.292
Test	**Lags**	**F-statistic**	**Prob.**
Residual normality test			
H_0=normal distribution			
Skewness	-	-0.1840	0.000
Kurtosis	-	4.9886	0.000
Jarque-Bera	-	140.6073	0.000

Note: AIC, BIC, and HQ denote the Akaike Information Criterion, Bayesian Information Criteria, and Hannan-Quinn Criterion, respectively.

Table 7. The comparison of the goodness of fit between the value of the GARCH(1,1), GARCH(1,2), GARCH(2,1), and GARCH(2,2) model.

Goodness of Fit	**Value of GARCH(1,1)**	**Value of GARCH(1,2)**	**Value of GARCH(2,1)**	**Value of GARCH(2,2)**
R^2	-0.0000	-0.0000	-0.0000	-0.0000
AIC	-6.6825	-6.6802	-6.6802	-6.6733
BIC	-6.6596	-6.6516	-6.6516	-6.6390
HQ	-6.6737	-6.6692	-6.6692	-6.6601

Note: AIC, BIC, and HQ denote the Akaike Information Criterion, Bayesian Information Criteria, and Hannan-Quinn Criterion, respectively.

Table 7 shows the comparison of the value in goodness of fit that we found that the values of AIC, BIC, and HQ of the GARCH(1,1) model are equal to -6.6825, -6.6596 and -6.6737 lower than the other GARCH models. So, the GARCH(1,1) model will be suitable for prediction, and we can build the ARIMA-GARCH model as presented in Table 8.

However, to assess the credibility of conditional volatility, it is imperative to scrutinize the equation's coefficients. Specifically, the parameter α, representing the impact of ε_{t-1}^2 should ideally be small, approximately 0.022, nearing zero. Additionally, the sum of α and γ should equate to 0.908, indicating a value less than 1 (γ is the parameter of h_t).

According to Table 9, it was revealed that residual autocorrelation, examined through the Q-statistic values across lags 1-6, rejected H_1 at the 1% significance level, signifying the absence of residual autocorrelation. Similarly, when testing for heteroscedasticity using the ARCH LM test (ARCH effect) at lag 4 and 8, H_1 was rejected at the 1% significance level for both cases, implying the absence of heteroscedasticity. These results mirror those of the initial model.

Furthermore, normality testing based on skewness, kurtosis, and the Jarque-Bera statistic indicated statistical significance at the 1% level (rejecting H_0), suggesting a non-normal distribution. Nevertheless, the combined capabilities of ARIMA's adaptability and GARCH's effectiveness in managing volatility and risk within the data series have transcended the linear constraints highlighted by Khashei et al. [66]. In summary, this model can reasonably estimate and forecast gold prices. However, before comparing the forecasting accuracy of the first and second models, it's crucial to examine the differences in their predictions, which will be discussed later.

Comparison of predictive accuracy between the ARIMA (2,1,3) and the ARIMA (2,1,3)-GARCH (1,1) are shown in Figure 4, respectively. From the figure, we can see that there is an actual value, prediction value, and standard error. We can see the direction of the prediction ability of each model. From the line in both Figure 4a and 4b, we will see a prediction from the ARIMA (2,1,3)-GARCH (1,1) that is closer to the actual values than the prediction by the ARIMA (2,1,3). However, it is impossible to distinguish clearly from the figures when considering them. Therefore, it will be essential to predict using the

Table 8. The coefficient of the ARIMA (2,1,3)-GARCH (1,1) model.

Variable	**Coeff.**	**Std. er.**	**Prob.**
Conditional Mean			
Constant	4.66E-05	0.000	0.882
AR(1)	1.317	0.247	0.000
AR(2)	-0.563	0.247	0.023
MA(1)	-1.335	0.248	0.000
MA(2)	0.572	0.262	0.029
MA(3)	0.021	0.039	0.591
Conditional Volatility			
Constant (ω)	6.54E-06	6.72E-06	0.330
α	0.022	0.013	0.098
γ	0.886	0.102	0.000
	Value		
α + γ	0.908		
R^2	0.012		
Log-likelihood	2759.866		
AIC	-6.6849		
BIC	-6.6334		
HQ	-6.6652		

Note: AIC, BIC, and HQ denote the Akaike Information Criterion, Bayesian Information Criteria, and Hannan-Quinn Criterion, respectively.

Table 9. The residual diagnostic test for the ARIMA (2,1,3)-GARCH (1,1) model.

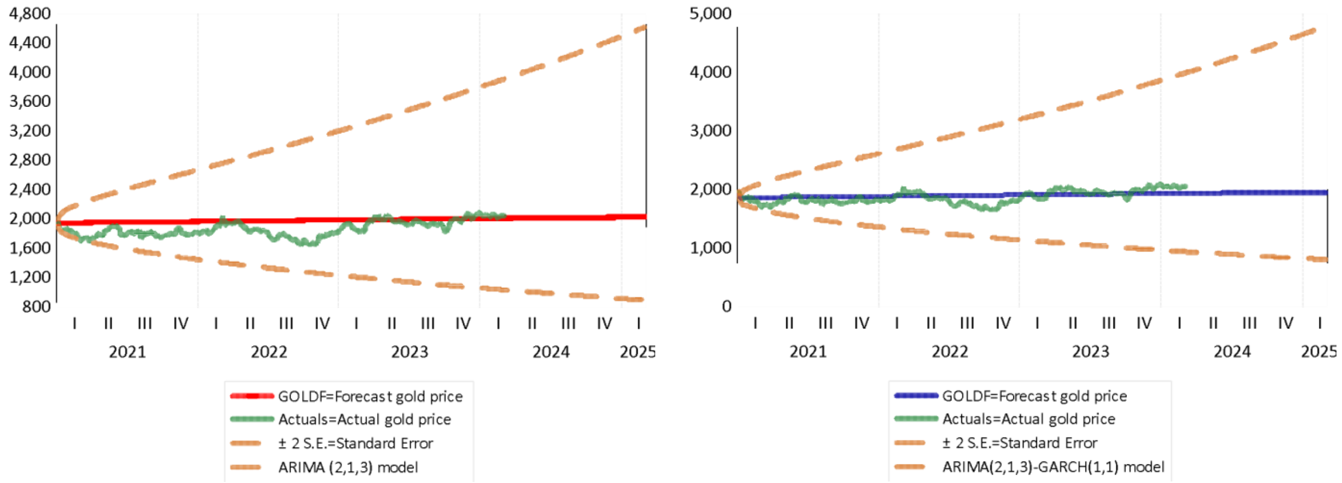
The ARIMA (2,1,3)-GARCH (1,1) model			
Test	**Lags**	**Value**	**Prob.**
Residual Tests for Autocorrelations	1	0.0267	0.870
H_0 = no residual autocorrelation	2	0.2177	0.897
(Q-stat.) (Ljung–Box test)	3	1.3179	0.725
	4	2.1093	0.716
	5	2.4705	0.781
	6	2.5015	0.688
Test	**Lags**	**F-stat.**	**Prob.**
The ARCH test			
H_0 = no Heteroskedasticity			
ARCH LM	4	0.5232	0.718
ARCH LM	8	1.0231	0.416
Test	**Lags**	**F-stat.**	**Prob.**
Residual normality test			
H_0=normal distribution			
Skewness	-	-0.2563	0.000
Kurtosis	-	4.9938	0.000
Jarque-Bera	-	145.3420	0.000

numbers to see which ARIMA (2,1,3) and the ARIMA (2,1,3)-GARCH (1,1) is better for prediction.

We looked at the forecast portion for the In Sample test scheduled from 2/14/2024 to 3/01/2024 and the Out of Sample test from 3/04/2024 to 2/28/2025. It is used to forecast present and future gold price data. We perform model comparisons that the ARIMA (2,1,3) and the ARIMA (2,1,3)-GARCH (1,1), which model gives lower MAE and RMSE values, which indicates better prediction accuracy than the other model. The forecast results can be shown in Table 10 and Table 11. The results show that the MAE and RMSE predictions of the ARIMA (2,1,3)-GARCH (1,1) model are 80.1371 and 96.8299 better than those of the ARIMA (2,1,3) model.

Additionally, when we consider the differentiation between these two models for the In Sample test, we found that the ARIMA (2,1,3)-GARCH (1,1) model is more different from actual values than the ARIMA (2,1,3) model in the first stage, after that, it will be close the actual values later because the gold price is fluctuation in that period. Forecast results are more precise, as shown in Table 11. Thus, in summary, we will choose the ARIMA (2,1,3)-GARCH (1,1) or the second model to forecast recommendations with policymakers and investors next.

Moreover, from the ARIMA (2,1,3)-GARCH (1,1) model, we can predict the gold price at the end of the year 2024 by expecting that it has the price at 1942.094 USD per troy ounce and the price trend will increase. The next step is



(a) **(b)**

Figure 4. Shows forecasts of the daily gold price using the ARIMA (2,1,3) model (a) and the ARIMA (2,1,3)-GARCH (1,1) model (b).

Table 10. The prediction value of the ARIMA (2,1,3) model.

In Sample				Out of Sample					
Date	**Forecast Values**	**Actual Values**	**Differentiation**	**Date**	**Forecast Values**	**Date**	**Forecast Values**	**Date**	**Forecast Values**
2/14/2024	2103.966	2007.200	4.821%	3/04/2024	2106.675	3/21/2024	2109.388	4/09/2024	2112.104
2/15/2024	2104.174	2004.300	4.983%	3/05/2024	2106.884	3/22/2024	2109.597	4/10/2024	2112.313
2/16/2024	2104.382	2014.900	4.441%	3/06/2024	2107.092	3/25/2024	2109.806	4/30/2024	2115.243**
2/19/2024	2104.591	2024.100	3.977%	3/07/2024	2107.301	3/26/2024	2110.015	5/31/2024	2120.065
2/20/2024	2104.799	2025.750	3.902%	3/08/2024	2107.509	3/27/2024	2110.223	6/28/2024	2124.266
2/21/2024	2105.007	2027.500	3.823%	3/11/2024	2107.718	3/28/2024	2110.432	7/31/2024	2129.109
2/22/2024	2105.216	2039.800	3.207%	3/12/2024	2107.927	3/29/2024	2110.641	8/30/2024	2133.539
2/23/2024	2105.424	2034.300	3.496%	3/13/2024	2108.135	4/01/2024	2110.850	9/30/2024	2138.191
2/26/2024	2105.633	2030.700	3.690%	3/14/2024	2108.344	4/02/2024	2111.059	10/31/2024	2142.853
2/27/2024	2105.841	2039.400	3.258%	3/15/2024	2108.553	4/03/2024	2111.268	11/29/2024	2147.525
2/28/2024	2106.050	2029.100	3.792%	3/18/2024	2108.762	4/04/2024	2111.477	12/31/2024	2152.207*
2/29/2024	2106.258	2034.400	3.532%	3/19/2024	2108.970	4/05/2024	2111.686	1/31/2025	2157.113
3/01/2024	2106.467	2042.700	3.122%	3/20/2024	2109.179	4/08/2024	2111.895	2/28/2025	2161.388
MAE	164.7727								
RMSE	184.6769								

Note: Unit in USD per troy ounce, (*) forecast gold price at the end of the year 2024, (**) forecast gold price at the end of the month from 4/30/2024 - 2/28/2025.

to look to 2025; the gold price trend will continue to increase as we consider predicting at the end of February 2025 at 1945.992 USD per troy ounce.

The reason that supports the gold price in 2025 is the strengthening of the de-dollarization policy in developing countries, which encourages developing countries to abandon the US currency in favor of other financial assets, including gold. Investment demand for the haven asset has grown significantly as central banks have built up their gold reserves, and high global inflation has raised concerns, which is also due to the rapid growth of the US government debt. Finally, the rise in geopolitical concerns globally, the hostilities between Ukraine and Russia in Eastern Europe, and the conflict between Israel and Palestine in the Middle East directly influence the current rise in gold quotes.

4.5. Discussion

The first point from the results of the importance of gold is that gold has a relation with inflation that conforms to studies by Bampinas and Panagiotidis [62], which analyzes the long-run hedging ability of two major metal commodities (gold and silver) prices against the consumer price index for the United States and the UK. Using time-invariant and time-varying cointegration methodology, they used a dataset of more than two centuries. They find that gold can hedge expected and core consumer price index (CPI) in the long run. Lucey et al. [67] used a formal test of time variation and time-varying cointegration relationships. The findings show a time-varying relationship in cointegration between gold and inflation in almost all case studies. The next step is to conform to Iqbal's study [68], which shows that gold is a hedge against inflation in the US. Finally, it conforms with

Table 11. The prediction value of the ARIMA (2,1,3)-GARCH (1,1) model.

In Sample				Out of Sample					
Date	**Forecast Values**	**Actual Values**	**Differentiation**	**Date**	**Forecast Values**	**Date**	**Forecast Values**	**Date**	**Forecast Values**
2/14/2024	1921.470	2007.200	-4.271%	3/04/2024	1922.635	3/21/2024	1923.801	4/09/2024	1924.967
2/15/2024	1921.560	2004.300	-4.128%	3/05/2024	1922.725	3/22/2024	1923.890	4/10/2024	1925.057
2/16/2024	1921.649	2014.900	-4.628%	3/06/2024	1922.814	3/25/2024	1923.980	4/30/2024	1926.314**
2/19/2024	1921.739	2024.100	-5.057%	3/07/2024	1922.904	3/26/2024	1924.070	5/31/2024	1928.380
2/20/2024	1921.828	2025.750	-5.130%	3/08/2024	1922.994	3/27/2024	1924.159	6/28/2024	1930.179
2/21/2024	1921.918	2027.500	-5.207%	3/11/2024	1923.083	3/28/2024	1924.249	7/31/2024	1932.250
2/22/2024	1922.008	2039.800	-5.775%	3/12/2024	1923.173	3/29/2024	1924.339	8/30/2024	1934.233
2/23/2024	1922.097	2034.300	-5.516%	3/13/2024	1923.263	4/01/2024	1924.429	9/30/2024	1936.128
2/26/2024	1922.187	2030.700	-5.344%	3/14/2024	1923.352	4/02/2024	1924.518	10/31/2024	1938.205
2/27/2024	1922.276	2039.400	-5.743%	3/15/2024	1923.442	4/03/2024	1924.608	11/29/2024	1940.103
2/28/2024	1922.366	2029.100	-5.260%	3/18/2024	1923.532	4/04/2024	1924.698	12/31/2024	1942.094*
2/29/2024	1922.456	2034.400	-5.503%	3/19/2024	1923.621	4/05/2024	1924.787	1/31/2025	1944.178
3/01/2024	1922.545	2042.700	-5.882%	3/20/2024	1923.711	4/08/2024	1924.877	2/28/2025	1945.992
MAE	96.8299								
RMSE	80.1371								

Note: Unit in USD per troy ounce, (*) forecast gold price at the end of the year 2024, (**) forecast gold price at the end of the month from 4/30/2024 - 2/28/2025.

the study of Xu et al. [69], which found that gold has generally maintained its purchasing power and is a reliable hedge against inflation in the short and long run. The summary indicates that there is cointegration between the gold price and the CPI series, suggesting a typical long-term relationship between gold and CPI. This finding aligns with the belief that gold serves as a hedge against inflation risk, reinforcing the longstanding notion that gold is a resilient commodity that should form the foundation of the global monetary system.

The second point that the result that gold can reduce exchange rate risk conforms to studies from Baur & Lucey [70] and Baur & McDermott [7]. If local currency-denominated gold gains value when the local currency loses against the U.S. dollar (USD), gold can be used as a hedge asset against the U.S. dollar exchange rate risk of international investors.

Moreover, Azimi's study [71] suggests that policymakers prioritize gold's dual role as a hedge and a safe haven against exchange rate volatility across various currencies, particularly those of major emerging economies. These findings serve as valuable insights for investors seeking international diversification through emerging market financial instruments. With growing interest in developing markets amid shifting dynamics in developed countries' equity markets [72]. Understanding the changing dynamics between exchange rates and gold returns during pivotal events like COVID-19 and the Russia-Ukraine conflict becomes crucial for portfolio optimization. The research indicates that including an optimized amount of gold in currency portfolios can mitigate exchange rate risk, particularly during such volatile periods. Additionally, the study underscores that incorporating gold into USD-emerging country currency portfolios leads to greater reduction in portfolio variance compared to portfolios with developed country currencies [71].

For the detail of gold prediction, we know from the result that the best model for predicting gold is the ARIMA-GARCH (2,1,3)-GARCH (1,1), which conforms with studies of Yaziz et al. [34] is the performance of a hybrid of the most potent univariate time series, ARIMA models. GARCH analyzes and forecasts daily gold price data series using the superior volatility model. The Box-Cox formula is applied during the data transformation stage to tackle non-stationarity in variance. The practical outcomes from analyzing a 40-day gold price dataset suggest that the hybrid ARIMA(1,1,1)-GARCH(0,2) model delivers the best results, significantly enhancing estimation and forecasting accuracy.

The following result conforms with Sopipan's [36] study, which involved predicting the volatility of gold prices using ARIMA-GARCH models. All models were evaluated under three distributional assumptions: Normal, Student-t, and GED. It was observed that the logarithmic returns of gold prices exhibited stationarity. The study concluded that the ARIMA(2,0,2) model performed the best in forecasting gold returns. Additionally, there was evidence of serial correlation in the squared returns, indicating conditional heteroskedasticity. Notably, the cumulative returns were higher with the ARIMA(2,0,2)-GARCH-N and ARIMA(2,0,2)-GARCH-GED models compared to the ARIMA(2,0,2)-GARCH-t models.

Finally, this result conforms with Xiang [42], which used the ARIMA-GARCH model to predict the prices of gold and bitcoin from 9/10/2016 to 9/11/2021 and constructed a price prediction model based on the ARIMA-GARCH model, which can accurately predict short-term price fluctuations in the future.

5. Conclusions and Policy Recommendations

Overall, the importance of gold is often seen as a safe-haven asset during economic uncertainty. When inflation rates rise, investors may turn to gold to preserve their wealth; the government will reserve gold to reduce the exchange rate risk. To cover the total study, it must be combined with predicting the price of gold using the ARIMA and ARIMA-GARCH models. From the study results, this research uses two forecasting approaches: ARIMA and ARIMA-GARCH. We chose the best method for the ARIMA (2,1,3)-GARCH (1,1) model because it gives the lowest MAE and RMSE values.

Moreover, we see that ARIMA-GARCH models go a step further by incorporating the volatility of gold prices into the forecasting process. These models consider the conditional variance of gold prices, allowing for a more accurate prediction of price movements and volatility. These models are beneficial in capturing sudden changes in volatility, which is crucial for accurate forecasting in the gold market. Finally, In the results, we get the prediction of gold prices in the world market at the end of 2024 at 1942.094 USD per troy ounce.

Investors and policymakers should slow down to buy and wait for it to adjust if the price is higher than the target price of 1942.094 USD per troy ounce in 2024, or investors and policymakers with gold should gradually sell to make some profit. At this point, gold remains an attractive and safe asset for investors and policymakers, as it gives returns satisfactorily, and the price in 2025 will continue to increase. Moreover, good portfolio management will reduce the exchange rate risk by including an optimized amount of gold in currency portfolios.

Holding gold is risky; its prices may fluctuate due to factors beyond our control, such as war, uncertainty about world economic growth, and inflation. Therefore, investors and policymakers should consider the abovementioned factors and be careful when hedging in gold. Consequently, we should add variables such as demand and supply for gold, inflation, exchange rate, etc., into the prediction to be more precise in the following research.

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References

1. Landajo, M., Presno, M. J., and Fernández González, P. (2021). Stationarity in the Prices of Energy Commodities. A Nonparametric Approach, *Energies*, Vol. 14, No. 11, 3324. doi:10.3390/en14113324.
2. Abebe, T. H. (2020). Modeling Time-Varying Coffee Price Volatility in Ethiopia, *Journal of Applied Economics*, Vol. 23, No. 1, 497–518. doi:10.1080/15140326.2020.1804304.
3. Tkacz, G. (2007). *Gold Prices and Inflation.* Bank of Canada Working Paper.
4. Hautcoeur, P.-C. (2010). Jastram, RW: The Golden Constant, *Journal of Economics*, Vol. 100, No. 2, 189–190. doi:10.1007/s00712-010-0124-5.
5. Jastram, R. (2009). The Golden Constant: The English and American Experience 1560–2007, *The Golden Constant*, Edward Elgar Publishing.
6. Chua, J., and Woodward, R. S. (1982). Gold as an Inflation Hedge: A Comparative Study of Six Major Industrial Countries, *Journal of Business Finance & Accounting*, Vol. 9, No. 2, 191–197. doi:10.1111/j.1468-5957.1982.tb00985.x.
7. Baur, D. G., and McDermott, T. K. (2010). Is Gold a Safe Haven? International Evidence, *Journal of Banking & Finance*, Vol. 34, No. 8, 1886–1898. doi:10.1016/j.jbankfin.2009.12.008.
8. Narayan, P. K., Narayan, S., and Zheng, X. (2010). Gold and Oil Futures Markets: Are Markets Efficient?, *Applied Energy*, Vol. 87, No. 10, 3299–3303. doi:10.1016/j.apenergy.2010.03.020.
9. Narayan, P. K., Narayan, S., and Sharma, S. S. (2013). An Analysis of Commodity Markets: What Gain for Investors?, *Journal of Banking & Finance*, Vol. 37, No. 10, 3878–3889. doi:10.1016/j.jbankfin.2013.07.009.
10. Su, C.-W., Liu, Y., Chang, T., and Umar, M. (2022). Can Gold Hedge the Risk of Fear Sentiments?, *Technological and Economic Development of Economy*, Vol. 29, No. 1, 23–44. doi:10.3846/tede.2022.17302.
11. Kurniawati, Y., and Muhajir, M. (2022). Optimization of Backpropagation Using Harmony Search for Gold Price Forecasting, *Pakistan Journal of Statistics and Operation Research*, 589–599. doi:10.18187/pjsor.v18i3.3915.
12. Markowski, L. (2020). Further Evidence on the Validity of CAPM: The Warsaw Stock Exchange Application, *Journal of Economics and Management*, Vol. 39, 82–104. doi:10.22367/jem.2020.39.05.
13. Hardi, I., Ray, S., Attari, M. U. Q., Ali, N., and Idroes, G. M. (2024). Innovation and Economic Growth in the Top Five Southeast Asian Economies: A Decomposition Analysis, *Ekonomikalia Journal of Economics*, Vol. 2, No. 1, 1–14. doi:10.60084/eje.v2i1.145.
14. Ke, H., Zuominyang, Z., Qiumei, L., and Yin, L. (2023). Predicting Chinese Commodity Futures Price: An EEMD-Hurst-LSTM Hybrid Approach, *IEEE Access*, Vol. 11, 14841–14858. doi:10.1109/ACCESS.2023.3239924.
15. Panagiotou, D. (2021). Revisiting Gold's Safe Haven Status with the Utilization of the Index of Implied Volatility and Values of

Exchange Traded Funds, *Applied Finance Letters*, Vol. 10, 24–39. doi:10.24135/afl.v10i.412.

16. Baboshkin, P., and Uandykova, M. (2021). Multi-source Model of Heterogeneous Data Analysis for Oil Price Forecasting, *International Journal of Energy Economics and Policy*, Vol. 11, No. 2, 384–391. doi:10.32479/ijeep.10853.

17. Samee, N. A., Atteia, G., Alkanhel, R., Alhussan, A. A., and AlEisa, H. N. (2022). Hybrid Feature Reduction Using PCC-Stacked Autoencoders for Gold/Oil Prices Forecasting under COVID-19 Pandemic, *Electronics*, Vol. 11, No. 7, 991. doi:10.3390/electronics11070991.

18. Bidin, J., Syed Abas, S. F., Sharif, N., Che Muhammad Fahimi, C. A. A., and Ku Akil, K. A. (2022). Comparative Study between Holt's Double Exponential Smoothing and Fuzzy Time Series Markov Chain in Gold Price Forecasting, *Journal of Computing Research and Innovation*, Vol. 7, No. 2, 283–293. doi:10.24191/jcrinn.v7i2.320.

19. Antwi, E., Gyamfi, E. N., Kyei, K., Gill, R., and Adam, A. M. (2021). Determinants of Commodity Futures Prices: Decomposition Approach, *Mathematical Problems in Engineering*, Vol. 2021, 1–24. doi:10.1155/2021/6032325.

20. Lu, W., Qiu, T., Shi, W., and Sun, X. (2022). International Gold Price Forecast Based on CEEMDAN and Support Vector Regression with Grey Wolf Algorithm, *Complexity*, Vol. 2022, 1–12. doi:10.1155/2022/1511479.

21. Li, F., Wang, J., Su, L., and Yang, B. (2017). Dynamic VaR Measurement of Gold Market with SV-T-MN Model, *Discrete Dynamics in Nature and Society*, Vol. 2017, 1–9. doi:10.1155/2017/5183914.

22. Sreenu, N., Rao, K. S. S., and D, K. (2021). The Macroeconomic Variables Impact on Commodity Futures Volatility: A Study on Indian Markets, *Cogent Business & Management*, Vol. 8, No. 1. doi:10.1080/23311975.2021.1939929.

23. Antwi, E., Gyamfi, E. N., Kyei, K. A., Gill, R., and Adam, A. M. (2022). Modeling and Forecasting Commodity Futures Prices: Decomposition Approach, *IEEE Access*, Vol. 10, 27484–27503. doi:10.1109/ACCESS.2022.3152694.

24. Asai, M., Gupta, R., and McAleer, M. (2019). The Impact of Jumps and Leverage in Forecasting the Co-Volatility of Oil and Gold Futures, *Energies*, Vol. 12, No. 17, 3379. doi:10.3390/en12173379.

25. Bunnag, T. (2015). The Precious Metals Volatility Comovements and Spillovers, Hedging Strategies in COMEX Market, *Journal of Applied Economic Sciences (JAES)*, Vol. 10, No. 31, 82–103.

26. Bunnag, T. (2016). Volatility Transmission in Crude Oil, Gold, Standard and Poor's 500 and US Dollar Index Futures Using VAR-MGARCH, *International Journal of Energy Economics and Policy*, Vol. 6, No. 1, 39–52.

27. Plakandaras, V., Gogas, P., and Papadimitriou, T. (2018). The Effects of Geopolitical Uncertainty in Forecasting Financial Markets: A Machine Learning Approach, *Algorithms*, Vol. 12, No. 1, 1. doi:10.3390/a12010001.

28. Zhang, J., and Lei, Y. (2022). Deep Reinforcement Learning for Stock Prediction, *Scientific Programming*, Vol. 2022, 1–9. doi:10.1155/2022/5812546.

29. Bunnag, T. (2023). *Guidelines for Econometrics and Application. Emphasis in Tourism and Financial Economics*, RITHA. doi:10.57017/SERITHA.2023.GEA.

30. Tri, H. T., and Nga, V. T. (2019). Factors Affecting the Disparity of Vietnamese Gold Prices and Worldwide Gold Prices, *Journal of Competitiveness*, Vol. 11, No. 3, 160–172. doi:10.7441/joc.2019.03.10.

31. Szczygielski, J. J., Enslin, Z., and Du Toit, E. (2018). An Investigation into the Changing Relationship between the Gold Price and South African Gold Mining Industry Returns, *South African Journal of Business Management*, Vol. 49, No. 1. doi:10.4102/sajbm.v49i1.232.

32. Khamis, A. Bin, and Yee, P. H. (2018). A Hybrid Model of Artificial Neural Network and Genetic Algorithm in Forecasting Gold Price, *European Journal of Engineering Research and Science*, Vol. 3, No. 6, 10. doi:10.24018/ejers.2018.3.6.758.

33. Yuan, F.-C., Lee, C.-H., and Chiu, C. (2020). Using Market Sentiment Analysis and Genetic Algorithm-Based Least Squares Support Vector Regression to Predict Gold Prices, *International Journal of Computational Intelligence Systems*, Vol. 13, No. 1, 234. doi:10.2991/ijcis.d.200214.002.

34. Yaziz, S. R., Azizan, N. A., Zakaria, R., and Ahmad, M. H. (2013). The Performance of Hybrid ARIMA-GARCH Modeling in Forecasting Gold Price, *20th International Congress on Modelling and Simulation, Adelaide*, Citeseer, 1–6.

35. Christina, C., and Umbara, R. F. (2015). Gold Price Prediction Using Type-2 Neuro-Fuzzy Modeling and ARIMA, *2015 3rd International Conference on Information and Communication Technology (ICoICT)*, IEEE, 272–277. doi:10.1109/ICoICT.2015.7231435.

36. Sopipan, N. (2018). Trading Gold Future with ARIMA-GARCH Model, *Thai Journal of Mathematics*, 227–238.

37. Alameer, Z., Elaziz, M. A., Ewees, A. A., Ye, H., and Jianhua, Z. (2019). Forecasting Gold Price Fluctuations Using Improved Multilayer Perceptron Neural Network and Whale Optimization Algorithm, *Resources Policy*, Vol. 61, 250–260. doi:10.1016/j.resourpol.2019.02.014.

38. Shen, L., Shen, K., Yi, C., and Chen, Y. (2020). Regression and Hidden Markov Models for Gold Price Prediction, *2020 IEEE International Conference on Big Data (Big Data)*, IEEE, 5451–5456. doi:10.1109/BigData50022.2020.9378468.

39. Nguyen, V. T., Le, D. T., Huy, P. P., Thao, N. T. H., Chau, D. M., Nho, N. T., Tiep, M. V., Hien, V. T., and Hieu, P. T. (2021). Using Some Machine Learning Methods for Time Series Forecasting regarding Gold Prices, 66–85. doi:10.1007/978-981-16-8062-5_5.

40. Liu, W. (2021). Gold Price Analysis and Prediction Based on Pearson Correlation Analysis, *Proceedings of the 2021 1st International Conference on Control and Intelligent Robotics*, ACM, New York, NY, USA, 358–361. doi:10.1145/3473714.3473777.

41. Yin, Z., Song, Z., and Ziyu, Z. (2022). Research on Investment Strategy Based on ARIMA Model and Boruta Random Forest Algorithm, *2022 International Conference on Data Analytics, Computing and Artificial Intelligence (ICDACAI)*, IEEE, 292–296. doi:10.1109/ICDACAI57211.2022.00064.

42. Xiang, Y. (2022). Comprehensive Trading Strategy of Gold and Bitcoin Based on ARIMA-GARCH Model, J. Xia (Ed.), *Second International Symposium on Computer Technology and Information Science (ISCTIS 2022)*, SPIE, 22. doi:10.1117/12.2653485.

43. Lin, J. (2022). Improved Markowitz Portfolio Investment Model Based on ARIMA Model and BP Neural Network, *2022 IEEE 2nd International Conference on Data Science and Computer Application (ICDSCA)*, IEEE, 504–507. doi:10.1109/ICDSCA56264.2022.9988744.

44. Nanthiya, D., Gopal, S. B., Balakumar, S., Harisankar, M., and Midhun, S. P. (2023). Gold Price Prediction Using ARIMA Model, *2023 2nd International Conference on Vision Towards Emerging Trends in Communication and Networking Technologies (ViTECoN)*, IEEE, 1–6. doi:10.1109/ViTECoN58111.2023.10157017.

45. Mani, A., and Thoppan, J. J. (2023). Comparative Analysis of ARIMA and GARCH Models for Forecasting Spot Gold Prices and Their Volatility: A Time Series Study, *2023 IEEE International Conference on Recent Advances in Systems Science and Engineering (RASSE)*, IEEE, 1–5. doi:10.1109/RASSE60029.2023.10363475.

46. Khan, R. (2024). Fluctuation and Forecasting of Gold Prices in Saudi Arabia's Market, *Kybernetes*. doi:10.1108/K-09-2023-1725.

47. Javid, I., Ghazali, R., Syed, I., Zulqarnain, M., and Husaini, N. A. (2022). Study on the Pakistan Stock Market Using a New Stock Crisis Prediction Method, *PLOS ONE*, Vol. 17, No. 10, e0275022. doi:10.1371/journal.pone.0275022.

48. Mahmoodzada, A., Ahadi, S., and Mahmoodzada, A. B. (2020). Comparison Performance of Artificial Neural Networks and Fuzzy Inference Systems in Forecasting Precious Metals Price Case Study: Gold, Silver, Platinum and Palladium, *Academic Perspective Procedia*, Vol. 3, No. 1, 749–762. doi:10.33793/acperpro.03.01.129.

49. Rubio, L., and Alba, K. (2022). Forecasting Selected Colombian Shares Using a Hybrid ARIMA-SVR Model, *Mathematics*, Vol. 10, No. 13, 2181. doi:10.3390/math10132181.

50. Tripathy, N. (2017). Forecasting Gold Price with Auto Regressive Integrated Moving Average Model, *International Journal of Economics and Financial Issues*, Vol. 7, Nos. 4 SE-Articles, 324–329.

51. Noviandy, T. R., Maulana, A., Idroes, G. M., Suhendra, R., Adam, M., Rusyana, A., and Sofyan, H. (2023). Deep Learning-Based Bitcoin Price Forecasting Using Neural Prophet, *Ekonomikalia Journal of Economics*, Vol. 1, No. 1, 19–25. doi:10.60084/eje.v1i1.51.

52. Box, G. E. P., and Jenkins, G. M. (1976). Time Series Analysis. Forecasting and Control, *Holden-Day Series in Time Series Analysis*.

53. Eagle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of UK inflation, *Econometrica*, Vol. 50, No. 4, 987–1007.

54. Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics*, Vol. 31, No. 3, 307–327. doi:10.1016/0304-4076(86)90063-1.

55. Wang, W., and Lu, Y. (2018). Analysis of the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) in Assessing Rounding Model, *IOP Conference Series: Materials Science and Engineering*, Vol. 324, 012049. doi:10.1088/1757-899X/324/1/012049.

56. Capie, F., Mills, T. C., and Wood, G. (2005). Gold as a Hedge against the Dollar, *Journal of International Financial Markets, Institutions and Money*, Vol. 15, No. 4, 343–352. doi:10.1016/j.intfin.2004.07.002.

57. Neely, C. J., and Weller, P. A. (2013). Lessons from the Evolution of Foreign Exchange Trading Strategies, *Journal of Banking & Finance*, Vol. 37, No. 10, 3783–3798. doi:10.1016/j.jbankfin.2013.05.029.

58. Hammoudeh, S., Sari, R., and Ewing, B. T. (2009). Relationships among Strategic Commodities and with Financial Variables: A New Look, *Contemporary Economic Policy*, Vol. 27, No. 2, 251–264. doi:10.1111/j.1465-7287.2008.00126.x.

59. Sarwar, G. (2017). Examining the Flight-to-Safety with the Implied Volatilities, *Finance Research Letters*, Vol. 20, 118–124. doi:10.1016/j.frl.2016.09.015.

60. Ghosh, D., Levin, E. J., Macmillan, P., and Wright, R. E. (2004). Gold as an Inflation Hedge?, *Studies in Economics and Finance*, Vol. 22, No. 1, 1–25. doi:10.1108/eb043380.

61. Beckmann, J., and Czudaj, R. (2013). Gold as an Inflation Hedge in a Time-Varying Coefficient Framework, *The North American Journal of Economics and Finance*, Vol. 24, 208–222. doi:10.1016/j.najef.2012.10.007.

62. Bampinas, G., and Panagiotidis, T. (2015). Are Gold and Silver a Hedge against Inflation? A Two Century Perspective, *International Review of Financial Analysis*, Vol. 41, 267–276. doi:10.1016/j.irfa.2015.02.007.

63. Wang, K.-M., and Lee, Y.-M. (2016). Hedging Exchange Rate Risk in the Gold Market: A Panel Data Analysis, *Journal of Multinational Financial Management*, Vol. 35, 1–23. doi:10.1016/j.mulfin.2016.02.001.

64. Dickey, D. A., and Fuller, W. A. (1981). Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root, *Econometrica*, Vol. 49, No. 4, 1057. doi:10.2307/1912517.

65. Phillips, P. C. B., and Perron, P. (1988). Testing for a Unit Root in Time Series Regression, *Biometrika*, Vol. 75, No. 2, 335. doi:10.2307/2336182.

66. Khashei, M., and Bijari, M. (2010). An Artificial Neural Network (p, d, q) Model for Timeseries Forecasting, *Expert Systems with Applications*, Vol. 37, No. 1, 479–489. doi:10.1016/j.eswa.2009.05.044.

67. Lucey, B. M., Sharma, S. S., and Vigne, S. A. (2017). Gold and Inflation(s) – a Time-Varying Relationship, *Economic Modelling*, Vol. 67, 88–101. doi:10.1016/j.econmod.2016.10.008.

68. Iqbal, J. (2017). Does Gold Hedge Stock Market, Inflation and Exchange Rate Risks? An Econometric Investigation, *International Review of Economics & Finance*, Vol. 48, 1–17. doi:10.1016/j.iref.2016.11.005.

69. Xu, Y., Su, C.-W., and Ortiz, J. (2021). Is Gold a Useful Hedge against Inflation across Multiple Time Horizons?, *Empirical Economics*, Vol. 60, No. 3, 1175–1189. doi:10.1007/s00181-019-01807-0.

70. Baur, D. G., and Lucey, B. M. (2010). Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold, *Financial Review*, Vol. 45, No. 2, 217–229. doi:10.1111/j.1540-6288.2010.00244.x.

71. Azimli, A. (2024). Is Gold a Safe Haven for the U.S. Dollar during Extreme Conditions?, *International Economics*, Vol. 177, 100478. doi:10.1016/j.inteco.2024.100478.

72. Idroes, G. M., Hardi, I., Hilal, I. S., Utami, R. T., Noviandy, T. R., and Idroes, R. (2024). Economic Growth and Environmental Impact: Assessing the Role of Geothermal Energy in Developing and Developed Countries, *Innovation and Green Development*, Vol. 3, No. 3, 100144. doi:10.1016/j.igd.2024.100144.