

Gold Price Forecast Based on ARIMA and ETS Models

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Abstract: The prediction of gold prices is of paramount importance in the financial sector due to gold's role as a safe-haven asset during periods of global economic uncertainty and market volatility. Accurately forecasting gold prices can help investors, policymakers, and businesses make informed decisions regarding investments, risk management, and hedging strategies. This paper utilizes ARIMA (Auto Regressive Integrated Moving Average) and ETS (Error-Trend-Seasonality) time series models to forecast future gold prices. Both models have been applied extensively in financial forecasting, each with unique strengths in handling different time series characteristics. This study aims to compare the prediction accuracy of these two models using Root Mean Square Error (RMSE) as the evaluation metric. The results show that while both models are effective in capturing the underlying trends in gold prices, the ARIMA model outperforms the ETS model with a lower RMSE of 56.80 compared to 61.51 for the ETS model. This comparative analysis contributes to the field of gold price forecasting by identifying the strengths and limitations of each model and providing insights into their applications in the context of financial time series forecasting.

Keywords: Gold price, Forecasting, ARIMA, ETS, Time series analysis.

1. Introduction

Gold has long been regarded as a valuable asset, particularly during periods of economic volatility. Investors and policymakers rely on accurate forecasts of gold prices to make informed decisions regarding investments, risk management, and economic policies. This study aims to predict future gold prices by applying two prominent time series forecasting models: ARIMA (Auto Regressive Integrated Moving Average) and ETS (Error-Trend-Seasonality) [1].

The selection of these models is driven by their proven ability to forecast time series data across various domains, including financial markets and commodities. ARIMA is widely used for forecasting stationary time series data, while ETS is particularly useful when trend components are present. By comparing the performance of these two models, it becomes possible to identify the most suitable method for predicting gold prices based on historical data.

2. Literature Review

Time series models such as ARIMA (Auto Regressive Integrated Moving Average) and ETS (Error-Trend-Seasonality) are widely used for forecasting financial and commodity markets. ARIMA is particularly effective for stationary data, where differencing is applied to remove trends. It has been successfully used to predict financial variables such as stock prices, inflation, and gold prices [2]. The

model's simplicity and ability to capture short-term fluctuations make it a popular choice, though its performance depends on the data being stationary [3].

ETS models, on the other hand, decompose data into error, trend, and seasonality components, making them suitable for non-stationary data and time series with trend patterns [4]. Studies have shown that ETS models handle long-term trends and error structures more effectively than ARIMA for certain datasets, including commodity prices like gold [5]. For example, Wang et al. compared ARIMA and ETS in gold price forecasting, finding that ETS performed better in capturing the trend component, while ARIMA was more effective for short-term predictions of stationary data [6].

In forecasting gold prices, both ARIMA and ETS have been widely applied, with studies demonstrating their strengths in different contexts. While ARIMA excels in short-term predictions, ETS is preferred for data with multiplicative error patterns and trends. Despite the growing adoption of machine learning methods, ARIMA and ETS remain valuable due to their interpretability and consistent performance with well-structured time series data.

3. Data

This study uses daily gold price data from October 2019 to August 2024, sourced from publicly available financial datasets. In order to enhance the continuity of the data and reduce short-term fluctuations, daily prices are aggregated into monthly averages. The time series is then divided into a training set, covering the period from October 2019 to April 2024, and a test set from May 2024 to August 2024. The gold price trend during the sample period is shown in Figure 1 below.

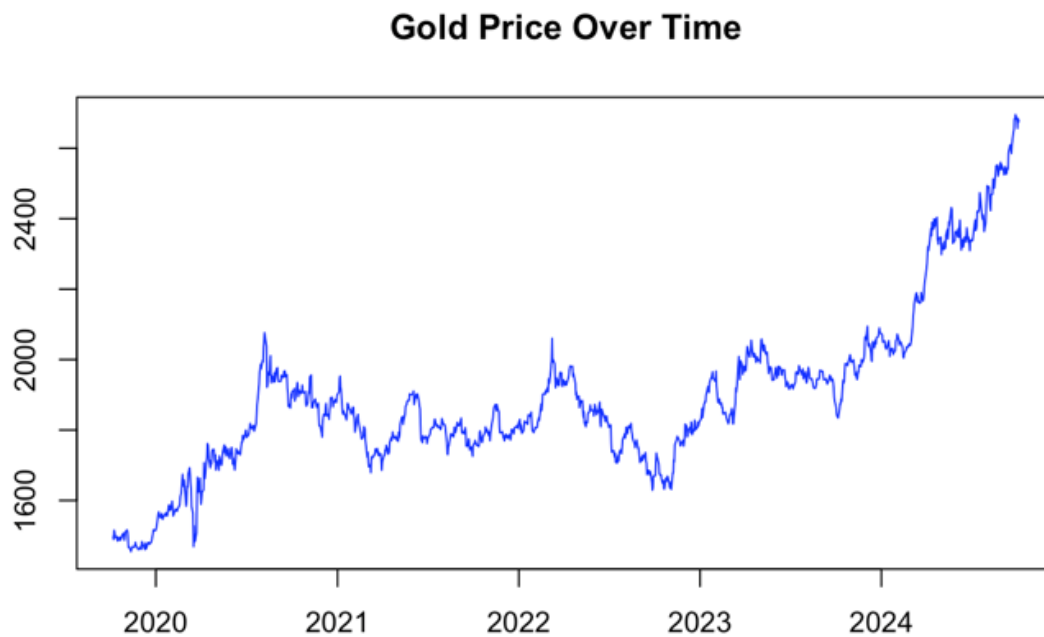


Figure 1: Gold Price

The descriptive statistics for the monthly gold price data are provided in Table 1.

Table 1: Descriptive Statistics

Metric	Mean	Std. Dev	Max	Min	Kurtosis	Skewness
Gold Price	1892	180.12	2695	1455	-0.56	0.27

The data shows significant variation over the sample period, with a positive skewness indicating a right-tailed distribution. The kurtosis value suggests that the distribution has a relatively flat peak compared to a normal distribution.

4. Methodology

This study utilizes two widely recognized time series models, ARIMA (Auto Regressive Integrated Moving Average) and ETS (Error-Trend-Seasonality), to forecast gold prices. Both models have unique strengths that make them effective for analyzing different types of time series data.

4.1. ARIMA

ARIMA is commonly used for forecasting time series data that lack seasonal characteristics. It predicts future values based on three components: autoregression (AR), differencing (I), and moving average (MA) [7].

The autoregressive part (AR) considers the relationship between the current value and its past values. By identifying autocorrelations, ARIMA models how past values influence present ones. For non-stationary data, where the mean or variance changes over time, ARIMA applies differencing (I) to make the data stationary by subtracting the current value from the previous one, eliminating trends and stabilizing the statistical properties of the series. Finally, the moving average (MA) component analyzes past forecast errors to account for the effect of residuals, improving the forecast by smoothing out short-term fluctuations.

The general ARIMA (p,d,q) model is defined as follows in Equation (1).

$$Y_t = c + \sum_{i=1}^p \phi_i Y_{t-i} + \sum_{i=1}^q \theta_i \epsilon_{t-i} + \epsilon_t \quad (1)$$

Where Y_t is the gold price at time t , ϕ_1 to ϕ_p are the autoregressive parameters, θ_1 to θ_q are the moving average parameters, ϵ_t is the error term, and c is a constant. This formulation captures the dynamics of the time series by incorporating both past values and residual errors in forecasting.

4.2. ETS

The ETS model is designed for time series that may include trend and seasonal components, though it can also handle series with no seasonality or trend, such as in the case of gold prices. ETS decomposes a time series into three components: error (E), trend (T), and seasonality (S).

The error component accounts for random fluctuations that cannot be explained by trends or seasonality. The trend component models the long-term direction of the series, while the seasonal component captures recurring patterns over fixed periods. The ETS model is highly flexible, allowing users to specify different forms of each component (additive or multiplicative), depending on the data's characteristics [8].

In this study, the ETS (M, N, N) model is applied, representing a multiplicative error, no trend, and no seasonality. This choice is appropriate for gold prices, where there are no strong seasonal or trend components, but proportional errors may occur as prices fluctuate. The process of applying ETS involves model identification, fitting, forecasting, and performance evaluation. After identifying the structure of the data, the model parameters are estimated using historical data. These parameters are then used to forecast future values, and the model's accuracy is evaluated by comparing the forecasted values to the actual data.

5. Results

Both the ARIMA and ETS models were trained on monthly gold price data from October 2019 to April 2024 and tested on data from May 2024 to August 2024. During the training process, the parameters for each model were determined based on their respective model fitting criteria. The parameter fitting results are shown in Table 2.

Table 2: Parameter Fitting Results

	Parameter 1	Parameter 2	Parameter 3
ARIMA	0	1	1
ETS	M	N	N

Table 2 summarizes the model parameters. For ARIMA, the best fit model was identified as ARIMA (0, 1, 1), where the parameters represent the autoregressive (p), differencing (d), and moving average (q) components, respectively. The ETS model chosen was ETS (M, N, N), indicating multiplicative error, no trend, and no seasonality. Figure 2 compares gold price forecasts from the ARIMA (blue) and ETS (red) models based on data from 2019 to 2024. ARIMA predicts a steeper price rise with more fluctuations, while ETS offers a more stable, conservative forecast. The shaded areas show confidence intervals, with ARIMA having broader uncertainty and ETS showing narrower, more stable predictions. Overall, ARIMA suggests more significant price increases, while ETS expects steadier trends.

ARIMA vs ETS Forecast

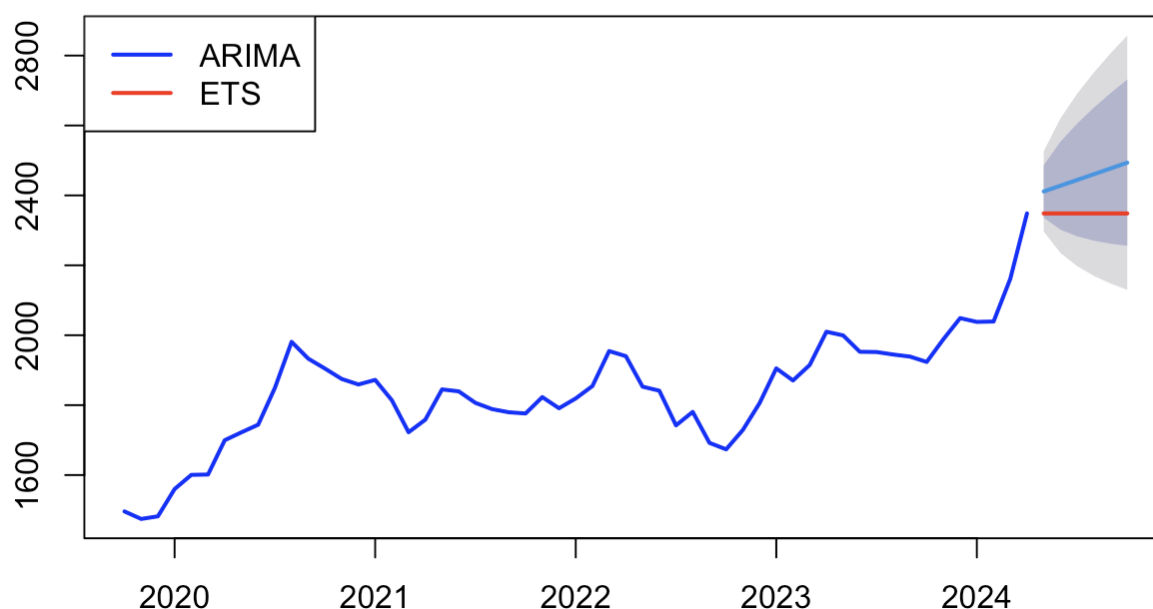


Figure 2: ARIMA and ETS Result

The performance of both models was then compared based on the Root Mean Square Error (RMSE), which evaluates the accuracy of the forecast by measuring the average magnitude of the errors between predicted and actual values [9-10]. Table 3 provides the RMSE results for both models.

Table 3: Comparison Results

Model	Rmse Results
ARIMA	56.80033
ETS	61.51204

As shown in Table 3, the ETS model outperforms the ARIMA model in terms of forecasting accuracy, with a lower RMSE. This indicates that the ARIMA model is better suited for predicting gold prices, which tend to follow non-seasonal trends with consistent short-term fluctuations that are well-captured by the model's moving average component.

6. Conclusion

This study compared the forecasting performance of ARIMA and ETS models for predicting gold prices using historical time series data. The results showed that the ARIMA model provided better accuracy, as evidenced by a lower RMSE compared to the ETS model. This indicates that ARIMA is better suited for forecasting gold prices, which follow non-seasonal trends with consistent short-term fluctuations. ARIMA's ability to capture these patterns through its autoregressive and moving average components contributed to its superior performance.

Although the ARIMA model outperformed ETS in this study, ETS remains useful for time series data with strong trend or seasonal components. Future research could consider incorporating exogenous variables, such as macroeconomic indicators, to improve forecasting accuracy. Moreover, combining ARIMA and ETS with machine learning techniques may offer more robust predictions for gold prices and other financial commodities.

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