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Forecasting gold prices in India: A time series analysis using Box Jenkins methodology

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Abstract

In India, gold holds significant cultural and economic importance. It serves not only as a financial asset but also as a symbol of tradition and social value. This study forecasts gold prices in the Indian market using the Box–Jenkins (BJ) methodology and analyzes monthly data covering the period from 2004 to 2025. Based on the empirical analysis, the ARIMA (1,1,1) model was selected as the best-fitting model. The model demonstrated strong statistical validity and low forecasting errors, indicating a high level of predictive accuracy. The forecast further predicts a steady rise in gold prices from December 2024 to April 2025. This projected increase is consistent with historical trends and seasonal consumer demand. Consumer behavior plays a significant role in influencing gold prices. This is particularly evident in the increased demand during festival and wedding seasons. Gold is also widely preferred as a hedge against inflation and economic uncertainty, which further strengthens demand. In addition, investment patterns are evolving. A growing number of individuals are adopting gold-backed ETFs and digital gold platforms, reflecting the changing investment preferences of Indian households. Macroeconomic factors also significantly influence gold prices, including currency depreciation and global market uncertainties. Collectively, these factors explain the expected upward movement in gold prices in the Indian market.

Keywords: gold price India, autoregressive integrated moving average (ARIMA), time series, forecasting, modelling.

1. Introduction

Gold, commonly known as the "yellow metal," has not only retained its value but also plays a significant and multifaceted role in the Indian economy. Beyond its cultural importance, gold is an essential economic asset in the country. It serves as a store of value, an investment instrument, and a hedge against uncertainty. A key economic aspect of gold in India is its ability to promote financial stability. Many Indian households regard gold as a tangible and secure investment, often passing it down through generations. Families view gold not merely as an ornamental asset but also as a means of preserving wealth. Furthermore, it provides a source of financial security during times of economic instability.

Gold is widely viewed as a favored investment option in India, attracting a diverse range of investors. The introduction of Gold Exchange Traded Funds (ETFs) has greatly enhanced the accessibility of gold investments, allowing individuals to participate in the gold market without needing to hold physical gold. In this context, understanding and predicting gold prices are essential for developing informed investment strategies. Gold prices are influenced by various economic factors, including inflation rates, interest rates, and currency fluctuations. A thorough analysis of these indicators enables investors to anticipate potential changes in market trends, assisting them in strategically adjusting their portfolios. Gold price forecasts act as a guiding tool for investors, helping them navigate the complexities of economic conditions.

This paper is organized as follows. Section 2 offers a thorough review of the literature, emphasizing prior research on forecasting gold prices. Section 3 presents the data utilized in the analysis. In Section 4, the methodology for selecting the appropriate model is detailed. Sections 5 and 6 address the analysis and inferences drawn from the data, while Sections 7 and 8 outline the recommendations and limitations of the study. Finally, Section 9 provides the conclusions.

2. Literature review

The forecasting of gold prices has a significant influence on consumer behavior, particularly in purchase decisions and investment strategies. Consumers often rely on price forecasts to determine the appropriate time to buy or sell gold. This, in turn, affects their spending patterns and their perception of gold as an investment asset. Fluctuations in gold prices directly influence consumer spending behavior. For example, consumers may purchase more gold when they expect prices to rise. Conversely, they may delay purchases if they anticipate a fall in prices (Kakkar and Chitrao, (2020). Price forecasting can also generate a bullwhip effect, in which consumer forecasting behavior influences supply chain dynamics. This effect may help stabilize the supply chain, depending on how consumers respond to price changes. However, this mechanism mainly works when consumer sensitivity to price fluctuations remains moderate (Wang et al., 2014).

Macroeconomic factors, investor fear, and consumer behavior also significantly influence gold price movements. For example, consumer sentiment and global economic stability play a critical role in driving short-term price change (Kumar et al., 2012). Although forecasting can help guide consumer behavior, it is important to recognize the inherent uncertainties and limitations of predictive models. Sudden geopolitical events or unexpected economic changes can cause actual price movements to deviate from forecasted trends. Therefore, consumers and investors need to remain adaptable and well informed while making decisions.

Stabilizing economic conditions and ensuring investor confidence depend on controlling gold prices. Governments and financial organizations recognize that fluctuations in gold prices can significantly impact monetary policy and overall economic stability. Several key factors illustrate this demand for control. Traditionally, gold serves as a store of value and an inflation hedge. Rapid price increases may lead to economic instability, thereby affecting consumer confidence and spending habits (Hall, 2005). Governments can reduce deflation and inflation by regulating gold prices. The erratic nature of gold prices puts investors at risk; therefore, predictive methods (such as Gold Price Prediction using Sentiment Analysis) must be developed. Effective prediction systems can help investors make informed decisions, thereby stabilizing the market (Abdou et al., 2022). Sentiment analysis has been explored as a method to forecast fluctuations in gold prices; however, the results indicate a weak connection with social media sentiment (Abdou et al., 2022). Central banks often maintain gold reserves as part of their asset portfolios, meaning that gold prices influence monetary policy decisions (Shaikh and Vallabh, 2022). Through effective management of gold prices, monetary policy can align more closely with broader economic goals, such as controlling inflation and stabilizing currency values. Conversely, some argue that excessive control over gold prices may lead to market distortions, hindering the natural process of price discovery and potentially resulting in inefficiencies within the financial system.

2.1 Factors influenced the gold market

The gold market represents a distinctive combination of cultural traditions and economic dynamics, making it an important area of study for both policymakers and investors. Consumer demand for gold is largely influenced by its price. Therefore, accurate gold price forecasting is crucial for understanding and anticipating market trends. This is especially relevant in countries where gold serves not only as a store of value but also as a hedge against inflation and economic uncertainty. Previous studies have examined the relationship between gold prices and macroeconomic variables such as real income, interest rates, exchange rates, and fiscal policies. These studies have also considered consumer behavior shaped by cultural and seasonal factors (Kannan and Dhal, 2008). Beyond its cultural significance, gold's investment characteristics also play a crucial role in its demand. It is commonly viewed as a "safe haven" asset. For instance, studies comparing stock and bond returns in the U.S., UK, and Germany to gold returns provide valuable insights. Baur and Lucey (2010) found that gold serves as a safe haven during periods of extreme stock market volatility. This reinforces its role as a stabilizing force in both global and domestic markets. Additionally, it can mitigate negative market shocks by hedging investments in gold. For instance, gold acted as a strong safe haven for most developed markets during the financial crisis in July 2007 (Baur and McDermott, 2010). Such findings highlight gold's capacity to mitigate adverse market shocks and its significance in promoting financial stability.

The Indian gold market is influenced by various factors. Political conditions, inflation, and both international and domestic market conditions significantly affect gold prices. The price of gold in India has shown a substantial increase over the past decade, particularly during the period from 2002 to 2012 (Baber et al., 2013). Traditionally, Indians have shown a strong preference for purchasing and holding physical gold. In contrast, investment in gold ETFs has historically remained relatively limited, as many investors perceive them merely as a paper-based financial instrument rather than a tangible asset. However, over the past year, investment in gold ETFs in India has increased significantly (Vidhyapriya and Mohanasundari, 2014). There is a significant connection between gold prices and several independent factors, including the S&P 500, currency fluctuations, Sensex, crude oil prices, and NIFTY. NIFTY and crude oil prices positively influence gold prices, while the S&P 500, currency fluctuations, and Sensex have a negative impact on gold prices. Specifically, as the BSE Sensex, S&P 500, and the value of the Indian currency increase, gold prices tend to decline. However, crude oil prices and the NIFTY Index exhibit significant beta coefficients, indicating that when NIFTY and crude oil prices rise, the value of gold also increases (Parimi, 2018).

2.2 Studies related to ARIMA model

To build on this foundation, the following section reviews existing literature on gold price forecasting, with a focus on methodologies like ARIMA and their application in the Indian context. This review also highlights the gaps in existing research, particularly regarding the integration of consumer trends and modern investment practices into forecasting models. Several studies and research on gold price prediction remain prominent across literature and the sector.

In one study, Abdullah (2012) employed an ARIMA model to forecast the prices of gold bullion coins. The study found that the ARIMA (2,1,2) model was suitable for monthly data covering the period from 2002 to 2007. The results indicated an upward trend in gold prices. Based on these findings, the study suggested that investors should consider investing in gold bullion coins.

Another group of researchers also adopted the ARIMA model to forecast gold prices using monthly data from 1980 to 2012. However, in this case, the model was found to be unsuitable for predicting gold prices accurately. Therefore, the study further examined the factors affecting gold prices through multiple regression analysis (Deepika et al., 2012).

A study by Ping et al. (2013) forecasts Malaysian gold prices, which are inherently nonstationary. The authors compare the ARIMA and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models. The study concludes that the GARCH model is more effective than ARIMA for predicting gold prices. However, they also note that ARIMA is applicable when the model does not account for variable volatility.

Ye et al. (2014) developed an ARFIMA-GARCH model for forecasting gold prices based on time series theory, using the closing prices of gold in the stock market. The model was designed to capture the dynamic movement of gold prices over time. It also helps in understanding the volatility and long-memory characteristics of the gold price series. This is particularly beneficial for gold sellers and investors, as it provides a deeper understanding of the behavior and underlying attributes of gold price movements.

Kristjanpoller and Minutolo (2015) used an Artificial Neural Network (ANN) together with a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to develop a hybrid ANN-GARCH model for predicting the volatility of both spot and futures gold prices. The authors found that this model showed an improvement over the traditional GARCH model. Specifically, the Mean Absolute Percentage Error (MAPE) was reduced by approximately one-fourth when the ANN-GARCH model was applied.

Sharma (2016) identified notable fluctuations in gold prices during that period. After noting this, the authors attempted to forecast gold prices in India using monthly data from January 1995 to June 2014. They employed the ARIMA model for their forecasting. The authors found that the ARIMA (3,1,3) model was the most appropriate for predicting gold prices in India. They also experimented with various models to determine the most suitable one for prediction. The results indicated that ARIMA (3,1,3) is the most effective model for forecasting gold prices in India.

Guha and Bandyopadhyay (2016) observed that gold has recently gained significant momentum in the Indian economy. Their objective is to provide guidance to investors. To achieve this, they selected a monthly time frame from November 2003 to January 2014. They determined that the ARIMA model (1,1,1) is the most effective for predicting gold prices in India. Additionally, they identified that factors such as political conditions, global events, and inflation have an impact on gold prices.

In a study conducted by Tripathy (2017), gold prices were projected using an ARIMA model over a 25-year period. The researchers determined that the ARIMA (0,1,1) model was suitable for forecasting due to its minimal error proportion. Additionally, the study indicates that the gold price from the previous month has a significant influence on the current gold price.

In a study examining gold price data from July 2013 to June 2018, as reported by the World Gold Council, the authors seek to predict and analyze the daily gold price in USD for the first part of July 2018 using an ARIMA model. Gold has gained significant momentum in the Indian economy recently. Based on the analysis, they determined that ARIMA (3, 1, 2) is the optimal model for predicting the gold price in USD (Yang, 2019).

A group of researchers predicted gold prices using both ARIMA and SVM models. They monitored daily prices over a 41-year period, from January 1979 to December 2019. Their findings indicated that the ARIMA model had a lower error rate, while they utilized SVM for forecasting due to its higher accuracy (Makala and Li, 2021).

Nallamothu et al. (2023) observed that the gold price was impacted by the COVID-19 pandemic. Following this, they attempted to forecast gold prices for 2021. They used daily data from 2018 to 2020 for their study. In their analysis, they found that the ARIMA (0,1,2) model was the most effective for forecasting, based on parameters such as ACF and PACF.

Bunnag (2024) used both the ARIMA and ARIMA-GARCH models to forecast the gold prices. The study uses the daily data from 2021 to 2024. The author recommended that after reaching a certain threshold, policymakers and investors should refrain from making further purchases and instead focus on gradual sales to realize profits.

Another study uses the ARIMA model to forecast the gold prices from 2020 to 2024; they found ARIMA (1,1,2). The chosen model demonstrates greater stability, and according to its results, gold prices will remain stable for a period before rising significantly (Bai, 2024).

Pujiarini and Damayanti (2025) used the hybrid ARIMA-LSTM model to forecast the digital gold prices. The study uses the daily one-year data from 2024. Authors also observe that the hybrid model performs better than standalone models.

Bhattacharya (2025) used SARIMA alongside ARIMA to forecast the gold prices in India. Authors use daily data from 2014 to 2025. The findings show that the seasonal transformation of the traditional model makes it more contextual and also increases the predictive system and reliability for market participants and policymakers.

Zheng (2025) conducted gold price forecasting using a hybrid model based on ARIMA. The findings revealed that the hybrid model outperformed the standard individual models. In the hybrid framework, the author integrated the ARIMA model with the Support Vector Regression (SVR) model, thereby improving the forecasting accuracy by capturing both linear and nonlinear dynamics of gold price movements.

Another study focusing on the Vietnam market was conducted to forecast gold prices. To achieve the study objective, the authors employed the ARIMA model. Based on the empirical analysis, the ARIMA (3,2,1) model was identified as the most appropriate specification for forecasting gold prices in Vietnam. The findings help investors and institutions decrease risk and maximize returns in gold decisions with scientific evidence (Hai and Vu, 2025).

A group of researchers conducted a comparative study on gold prices using Long Short-Term Memory (LSTM), Auto Regressive Integrated Moving Average (ARIMA), and Facebook Prophet from January 2021 to January 2024. ARIMA showed moderate overall performance but achieved the highest directional accuracy of 55.84%, indicating its effectiveness in predicting short-term trend directions despite lower predictive precision. The study emphasizes the importance of selecting forecasting models based on both predictive accuracy and directional performance (Ayub et al., 2026).

Mohammed (2026) also conducted a case study on gold prices for the period from January 1, 2023, to May 25, 2025. The findings revealed that the ARIMA model outperformed the LSTM model in terms of forecasting accuracy. Although the LSTM model employed a multi-layer architecture, the ARIMA model was found to be more stable and suitable for short-term gold price forecasting.

The literature review highlights how gold price demand influences consumer behavior in India. Forecasting gold prices is beneficial not only for consumers and investors but also for policymakers. The methodological review shows that previous studies have widely used ARIMA models for forecasting gold prices.

Researchers have identified temporal discontinuities during the study period. In recent years, several economic events have significantly affected gold prices. This gap and variation in the data motivate the researchers to pursue the present study objectives.

This research intends to use the Box–Jenkins (BJ) approach to determine an appropriate model for predicting gold bullion prices. By applying the BJ methodology, the study will analyze historical data to identify patterns and trends that may improve forecasting accuracy. Furthermore, it will explore the potential impact of these changes on the forecasting performance of the data.

3. Data

This study utilizes secondary monthly data covering the period from January 2004 to November 2024, sourced from Multi Commodity Exchange of India Ltd. (MCX). The collected data were recorded in different quantities. Therefore, before the analysis, the data were standardized to represent quantities per 1000 grams. Subsequently, the price per 10 grams of gold was calculated and used for this study. Figure 1 presents the data spanning from January 2004 to November 2024.

Figure 1. Gold Price (10 gram)

4. Methodology

Based on the study objective, the Box–Jenkins (BJ) methodology was selected. This forecasting method is designed to examine time series data autonomously by focusing on their stochastic or probabilistic characteristics (Box and Jenkins, 1976).

Under this approach, the dependent variable Y_t is explained using its own previous lagged values, along with the current and past values of the residual term, u_t. This residual component is commonly referred to as the "white noise error term." By definition, it represents an uncorrelated random error with a mean of zero and constant variance (Aljandali and Tatahi, 2018).

The researchers have adopted a systematic approach consisting of six phases to predict the future price of gold bullion in India.

- *Step one: Stationarity check of the data:* The Box–Jenkins (BJ) methodology requires the data to be stationary. Therefore, the first step is to verify whether the data are stationary. If the series is found to be non-stationary, it must be transformed to achieve stationarity. This verification can be carried out using two methods. The first involves formal statistical tests, such as the Augmented Dickey–Fuller test and the Phillips–Perron test. The second method involves correlogram analysis, which examines the autocorrelation structure of the series.
- *Step two: Identification:* To determine the appropriate model, the initial step involves examining the autocorrelation and partial autocorrelation within the dataset.
    - *Auto-Correlation Function:* This refers to the correlation of a variable with its own past values over different time periods. In this context, Y_t (the current observation) is correlated with Y_{t+k} (the observation after k periods). The correlation coefficient ranges from -1 to +1. The Autocorrelation Function (ACF) identifies the Moving Average (MA) components.
    - *Partial Auto-Correlation Function:* The PACF measures the conditional correlation between Y_{t+k} and Y_t, after controlling for the effects of intermediate lags. It is defined for positive lags, and its values also range from -1 and +1. This function is used to identify the AutoRegressive (AR) components of the model.

The estimation of the ARIMA model is a crucial step in time series analysis. It consists of three essential components: AutoRegressive (AR) terms, Integrated (I) terms, and Moving Average (MA) terms. The AR component captures the relationship between the current value and its past values. Here, p in AR(p) indicates the number of lagged observations included in the model.

The Integrated component refers to the differencing of the data to achieve stationarity. In this case, d in I(d) represents the order of differencing required. The MA component explains the relationship between the current observation and the past error terms from the moving average process. Here, q in MA(q) denotes the number of past forecast errors included in the model.

- *Step three: Estimation:* The estimation of the ARIMA model is a crucial step in time series analysis. It consists of three essential components: AutoRegressive (AR) terms, Integrated (I) terms, and Moving Average (MA) terms. The AR component captures the relationship between the current value and its past values. Here, p in AR(p) indicates the number of lagged observations included in the model. The Integrated component refers to the differencing of the data to achieve stationarity. In this case, d in I(d) represents the order of differencing required. The MA component explains the relationship between the current observation and the past error terms from the moving average process. Here, q in MA(q) denotes the number of past forecast errors included in the model.

To summarize, the model is expressed as ARIMA (p, d, q), where:

- p: Order of the Auto-Regressive component.
- d: Order of differencing.
- q: Order of the Moving Average component.

After estimating the alternative models, the selection of the most appropriate model was based on six criteria. First, the estimated coefficients should be statistically significant. SIGMASQ (the variance of the error term), AIC (Akaike Information Criterion), SIC (Schwarz Information Criterion), and HQC (Hannan-Quinn Criterion) should be at their minimum values, while the Adj. R^2 (Adjusted R-squared) should be at its maximum value.

- *Step Four: Diagnostics Test:* After selecting the model, the next step is to conduct diagnostic checks. This step mainly involves testing for the absence of autocorrelation and heteroskedasticity, along with checking the stationarity of the residuals.
  - *Absence of Autocorrelation and Heteroskedasticity:* Autocorrelation should be examined using the Ljung–Box Q-statistic. This test helps verify whether the residuals behave as white noise. In other words, the residuals should not exhibit serial correlation. Similarly, the heteroskedasticity test ensures that the model has constant variance over time.
  - *Stationarity check of the Residuals:* Evaluating the stationarity of the residuals is essential to ensure the validity and reliability of the time series model. Stationarity implies that the mean, variance, and autocorrelation structure remain stable over time. If the residuals are found to be non-stationary, the model may be considered invalid, as it suggests that the underlying properties of the model change over time.
- *Step Five: Stability Check:* Similar to the diagnostic assessment, stability checks are essential. They help verify the model's validity, accuracy, and reliability. These measures also indicate how effective the forecasting model remains when new data are incorporated.
  - *Covariance stationarity:* A time series that exhibits covariance stationarity is generally more suitable for modeling and forecasting. This is because its statistical properties, such as mean, variance, and autocovariance, remain stable over time.
  - *Error proportion:* A good forecast should be unbiased, precise, and free from random fluctuations. Measures such as the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are commonly used to assess forecast accuracy (Aljandali and Tatahi, 2018). Since both measures are scale-dependent, they are mainly used as relative indicators to compare different forecasting models for the same time series. Lower values of RMSE and MAE indicate a more accurate model.

The Theil's Inequality Coefficient ranges between 0 and 1. A value closer to 0 indicates better forecasting performance. In general, a value less than 1 suggests that the model performs better than the naïve forecast model (Aljandali and Tatahi, 2018).

The bias proportion measures the difference between the forecast mean and the actual series mean. The variance proportion shows how far the forecast variance differs from the actual series variance. The covariance proportion represents the remaining unsystematic forecasting error. These three proportions together sum to one (Aljandali and Tatahi, 2018).

- *Step Six: Forecasting:* There are two methods of forecasting: static and dynamic.
  - The static approach is generally simpler and uses fixed estimated parameters. It is easier to implement and is more suitable when the data do not exhibit significant changes in patterns over time.
  - The dynamic approach is relatively more complex, especially when it involves time-varying parameters. It is capable of capturing evolving patterns and trends over time. However, it may be more difficult to estimate and interpret.

5. Analysis

5.1 Descriptive statistics

In the descriptive statistics, it can be observed that the mean and median of the data are closely aligned, indicating a relatively symmetric distribution. However, the maximum and minimum values reveal a wide spread, reflecting significant variability in the dataset. In addition, the data exhibit positive skewness and deviate from normality. This is confirmed by the Jarque–Bera test, where the p-value is less than 0.05, leading to the rejection of the null hypothesis of normality. The total number of observations in the dataset is 251.

The study develops a forecasting model based on gold bullion prices in India. The collected data are divided into two phases. The period from January 2004 to January 2024 is used for model estimation, while the remaining data are reserved for further analysis and forecast evaluation.

5.2 Stationarity check of the data

Two stationarity tests have been conducted; one is the augmented dickey fuller test and the other is the Philips perron test.

- Augmented Dickey-Fuller and Phillips–Perron Test:

Hypothesis of the unit root test:

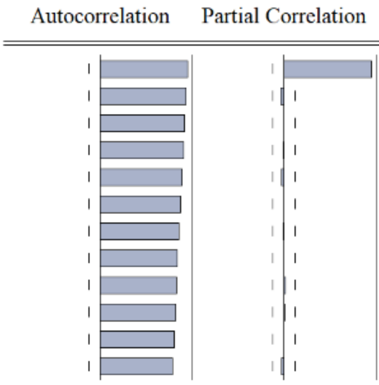
H_0: Gold Price is not stationary and has a unit root.

H_1: Gold Price is stationary and has no unit root.

The data presented in Figure 1 indicate the presence of a trend. Therefore, the authors included a trend component in the unit root test. At the level, the test statistics produced p-values greater than 0.05. Therefore, the researchers were unable to reject the null hypothesis of a unit root. Hence, it can be concluded that the data are non-stationary at level. However, after taking the first difference, all the p-values were found to be less than 0.05. This led to the rejection of the null hypothesis of a unit root. Therefore, the data become stationary at the first difference, indicating that the series is integrated of order one, I(1).

The authors also conducted the Phillips–Perron test. The test results show that the data are non-stationary at level, indicating the presence of a unit root. However, at the first difference, the series becomes stationary. This confirms that the data are integrated of order one, I(1).

- Correlogram: From Figure 2, it can be observed that all the p-values at the level are greater than 0.05. Hence, the researchers failed to reject the null hypothesis, indicating that the data are non-stationary. However, after taking the first difference, the p-values were found to be less than 0.05. This signifies that the data become stationary at the first difference, as the researchers rejected the null hypothesis of a unit root. Therefore, the gold price data exhibit stationarity at the first difference, as depicted in Figure 2.



	AC	PAC	Q-Stat	Prob
1	0.985	0.985	246.65	0.000
2	0.970	-0.034	486.64	0.000
3	0.955	0.005	720.20	0.000
4	0.940	-0.016	947.28	0.000
5	0.924	-0.029	1167.6	0.000
6	0.908	-0.008	1381.3	0.000
7	0.892	-0.008	1588.5	0.000
8	0.876	-0.007	1789.2	0.000
9	0.861	0.019	1983.8	0.000
10	0.847	0.013	2172.8	0.000
11	0.833	-0.003	2356.2	0.000
12	0.818	-0.025	2533.9	0.000

Figure 2. Correlogram at level (Up to 12 lags)

5.3 Identification

To determine the appropriate ARIMA model, researchers must examine the ACF and PACF obtained from the correlogram. Figure 2 reveals that the correlogram at level 1 exhibits an exponential decay in the ACF, while the PACF shows a significant spike at lag 1, suggesting an AR (1) process. Additionally, Figure 2 displays spikes at lag 1 in both the ACF and PACF. This indicates that p=1 (AR process) and q=1 (MA process). Consequently, the selected models are AR (1) and MA (1).

This procedure can be carried out using an alternative statistical method. Researchers determine the standard error of the sample correlation coefficients (Banerjee, 2019), which is:

$$\sqrt{\frac{1}{n}} = \sqrt{\frac{1}{241}} = 0.064$$

After that, the researchers use the confidence interval of the standard normal distribution, ρ~ (0, 1), here in this study researchers use the 5% level of significance. i.e.,

$0 \pm 1.96\ (0.064) = (-0.12544 \text{ to } +0.12544)$

Correlation coefficients lying outside these bounds are statistically significant at the 5% level. On the basis of this, both ACF and PACF correlations at lag 1 are statistically significant (Banerjee, 2019).

5.4 Estimation

In this instance, researchers adhere to the principle of parsimony and select AR (1) and MA (1) based on this criterion. The optimal forecasting model can be determined by comparing the results of the ARIMA (1,1,1), ARIMA (1,1,0), and ARIMA (0,1,1) models. Table 1 represents the model comparison. Based on the first criterion, only the ARIMA (1,1,1) model is found to be statistically significant. In contrast, the ARIMA (1,1,0) and ARIMA (0,1,1) models are statistically insignificant. Since these models fail to satisfy the initial criterion, they are not considered for further evaluation. Accordingly, the subsequent analysis is carried out using Equation (1) based on the ARIMA (1,1,1) specification.

The comparatively low R^2 is understandable in this context (Table 1). As highlighted by Pierce (1979), R^2 is particularly responsive to first differencing. Given that the model is univariate and the data have undergone transformation via differencing to attain stationarity, a significant portion of the variation has been eliminated, resulting in a reduced R^2. Consequently, the limited explanatory power does not inherently suggest inadequate model performance.

Table 1. Model Comparison

d(log_price)	ARIMA (1,1,1)	ARIMA (1,1,0)	ARIMA (0,1,1)
Significant Coefficient	2	0	0
SIGMASQ (Minimum)	0.001360	0.001368	0.004189
Adj. R^2 (Maximum)	0.009378	0.003674	0.004189
AIC (Minimum)	-3.728995	-3.731650	-3.732162
SIC (Minimum)	-3.670985	-3.688142	-3.688654
HQC (Minimum	-3.705621	-3.714119	-3.714632

The estimated equation for the ARIMA (1,1,1) model is:

$$\Delta Yt=0.009596-0.634755\Delta Yt-1+0.709493et-1+et \tag{1}$$

Where:

- ΔY_t is the value of the time series at time t $[\Delta Y_t = Y_t - Y_{t-1}]$,
- c is a constant or intercept term.
- e_{t-1} *is* the error term at the previous time step (lag 1).

5.5 Diagnostics Test

At this stage, the researchers conduct the diagnostic tests of the model. Before proceeding with forecasting, it is essential to satisfy the necessary conditions. These include (i) the absence of autocorrelation and heteroskedasticity and (ii) the stationarity check of the residuals.

- *Absence of autocorrelation:* The absence of autocorrelation is verified using the Ljung–Box Q-statistic test. In this test, all the p-values are greater than 0.05. Therefore, the researchers fail to reject the null hypothesis of no autocorrelation. Hence, the residuals are independent, indicating that no autocorrelation is present in the error terms. This suggests that the ARIMA (1,1,1) model strongly satisfies the assumption that the residuals exhibit white noise characteristics.
- *Absence of heteroskedasticity:* For the heteroskedasticity test, both the p-values associated with the F-statistic and the Chi-square test are greater than 0.05. Therefore, the authors fail to reject the null hypothesis of homoskedasticity. This indicates that there is no evidence of heteroskedasticity in the residuals. In other words, the residuals exhibit constant variance over time, and therefore, no variance-stabilizing transformation is required.
- *Spurious regression check:* The Durbin–Watson statistic exceeds the R^2 value, indicating that the estimated regression is unlikely to be spurious (Bhaumik, 2015).
- *Stationarity check of residuals:* Before performing the Augmented Dickey–Fuller test to check for stationarity, the researchers first store the residuals in a separate series labeled "RESID01" (Aljandali and Tatahi, 2018). Figure 3 is a graphical representation of residuals.

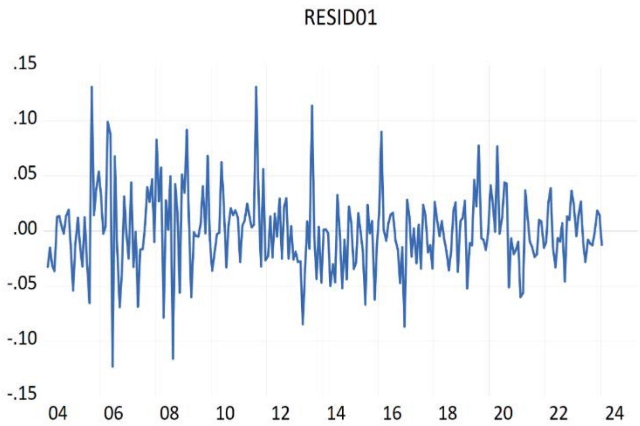


Figure 3. Graphical representation of Residuals

All the observed p-values are below the 0.05 level of significance, leading to the rejection of the null hypothesis (H_0) of a unit root. This indicates that the data are stationary. The residuals behave as white noise, thereby strengthening the validity and reliability of the estimated model (Aljandali and Tatahi, 2018).

5.6 Stability Check

In this study, researchers concentrate on two key aspects to check the stability: the covariance of the stationary component and the error proportion.

- *Covariance of the stationary:* The calculated model exhibits covariance stationarity, as seen by the inverse MA roots being located within the unit circle, as depicted in Figure 4. As shown in the figure inverse MA roots perfectly fit in the unit circle. This confirms that our ARIMA (1,1,1) model meets the stability conditions. The stability of the estimated ARIMA model is critical for producing reliable forecasts that minimize prediction risks.

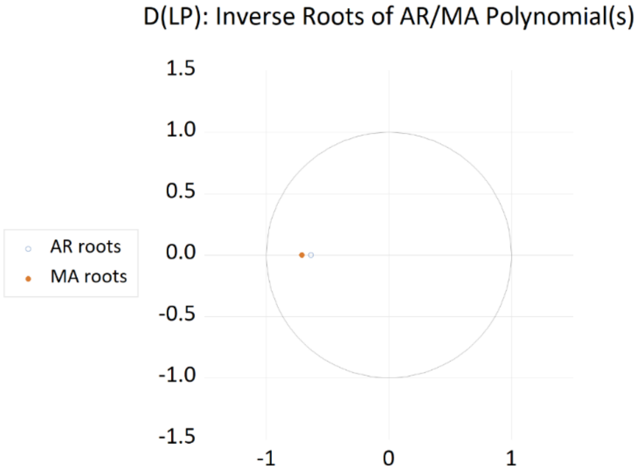


Figure 4. Inverse MA Roots

- *Error proportion:* In Figure 5, the RMSE and MAE values are low, although both measures are scale-dependent. In this context, the MAPE is more useful because it is scale-independent (Aljandali and Tatahi, 2018). A MAPE of 2.74% indicates that, on average, the forecasts generated by this model deviate by approximately 2.74% from the actual observed gold prices. This suggests that the forecasting model demonstrates a high level of predictive accuracy.

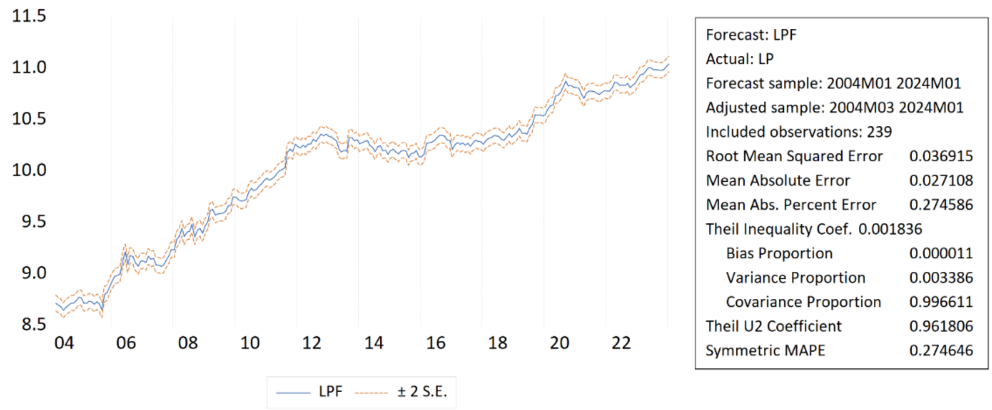


Figure 5. Forecast table on sample data (2004M01 to 2024M01)

The MAPE value observed in this study is relatively low, indicating a high level of forecasting accuracy in predicting monthly gold prices. The Theil's inequality coefficient is calculated as 0.001836, which is substantially lower than 1. This suggests that the fitted model exhibits a high degree of forecasting accuracy and performs better than a naïve benchmark model. The bias proportion is estimated at 0.000011, which indicates a favorable result. This value suggests that the mean of the forecasted series is almost identical to the mean of the actual series, implying that the model is unbiased. As shown in Figure 5, the variance proportion is 0.003386, indicating that the variation in the forecasted series differs only marginally from the variation in the actual series. The covariance proportion, also presented in Figure 5, represents the remaining unsystematic forecasting error. A relatively high covariance proportion, together with low bias and variance proportions, is generally considered desirable, as it implies that most of the forecast error is random rather than systematic. Since both the bias proportion and variance proportion values are satisfactory, the proposed model can be considered effective and reliable for forecasting purposes. A small technical correction: the covariance proportion does not necessarily imply strong temporal dependency. Rather, it mainly captures the unsystematic component of forecast error.

5.7 Forecasting

After evaluating the stability and diagnostic tests, it is concluded that the ARIMA (1,1,1) model is appropriate for forecasting. In order to generate forecasts, researchers have employed two distinct methods: the static method, which is applied to the reserved data, and the dynamic method, which is utilized to predict out of sample.

- *Forecasting with the static method:* In this section, the authors use the reserved data covering the period from January 2023 to August 2023. The data are analyzed using the static forecasting approach based on Equation (1). The results are used to evaluate the model's goodness of fit using RMSE, MAE, MAPE, Theil's inequality coefficient, and the error proportions. In this context, Figure 6 presents a comparison between the actual values and the predicted values.

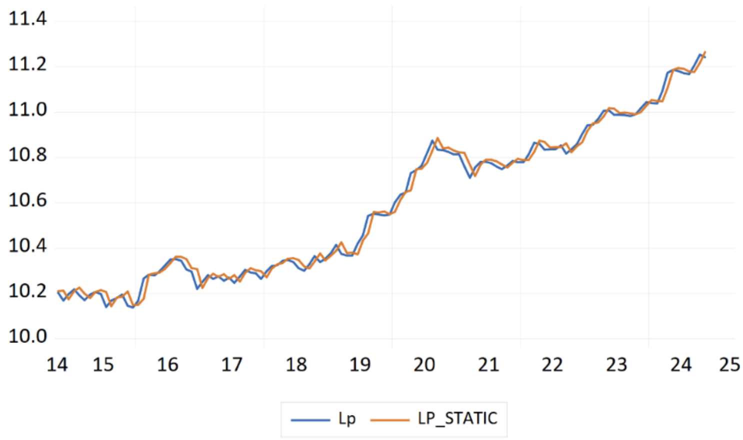


Figure 6. Graphical presentation of the actual and forecasted data

- *Forecasting with the dynamic method:* In this study, the researchers employed the dynamic forecasting method to generate an out-of-sample forecast. The study forecasts gold prices for the period from December 2024 to April 2025. Figure 7 displays the forecast line in blue, while the broken red lines represent the confidence intervals for the forecast period. Table 2 presents the forecasted values for the period from December 2024 to April 2025. This study employed the ARIMA model for short-term forecasting because of its ability to effectively capture temporal dependencies and underlying patterns in the time series data. The predicted values and the actual values are graphically presented in Figure 8. Based on the calculations, the price of gold is expected to increase over the five-month period from December 2024 to April 2025.

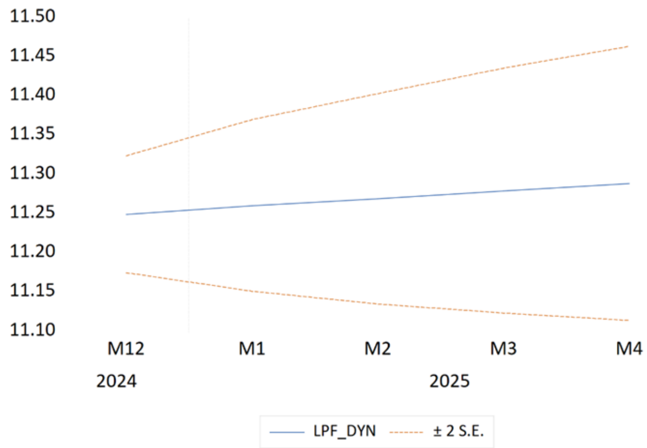


Figure 7. Dynamic Forecast

Table 2. Dynamic forecasted value from September to December 2023

DATE	Dynamic Forecast
2024M12	76877.81606
2025M01	77741.48185
2025M02	78412.60926
2025M03	79218.95123
2025M04	79950.56496

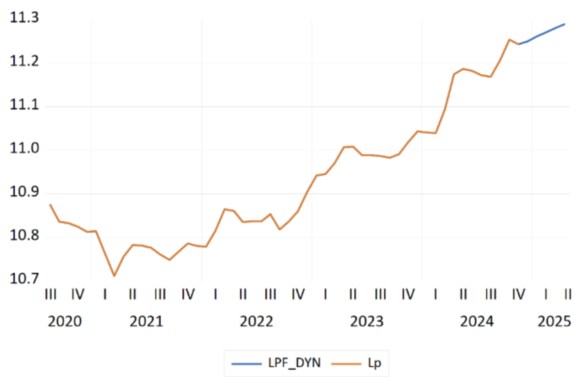


Figure 8. Graphical representation of forecasted value with actual value

6. Inferences

In this study, the authors attempted to forecast gold prices in India. The findings suggested that the ARIMA (1,1,1) model is appropriate for forecasting gold prices. These results are consistent with the findings of Guha and Bandyopadhyay (2016). A large number of previous studies have also employed the ARIMA model to forecast gold prices in India. In the static forecast, the authors found that the difference between the actual values and the forecasted values is relatively low, which indicates a high level of model accuracy. The dynamic forecast represents an out-of-sample prediction. Based on this forecasting approach, the authors found that gold prices are expected to increase during the period from December 2024 to April 2025.

An increase in the price of gold may occur for several reasons. First, gold prices often exhibit seasonal trends driven by cultural, economic, and market-related cycles, especially in countries such as India, where festivals and wedding seasons significantly increase demand (Kakkar and Chitrao, 2023; Rao, 2001; Shankar and Shukla, 2017). Second, inflation and the devaluation of the Indian rupee can also lead to an increase in gold prices (Deepak et al., 2024; Garg, 2021; Singh, 2013). Under such conditions, gold is widely regarded as a hedge against inflation and currency depreciation, which further increases its demand and market price.

Another key consumer trend influencing gold prices is the evolving investment preferences of Indian households. In the current scenario, financial markets do not always provide stable returns to investors (Agarwal, 2024). This may explain why Indian investors are more inclined to invest in gold. Additionally, the increasing adoption of modern investment instruments, such as gold ETFs, reflects a growing preference for diversified investment portfolios (Jayanthi et al., 2013). These factors collectively highlight the interconnection between consumer trends and rising gold prices predicted in this study.

7. Recommendations

The gold price forecasts clearly indicate a rise in prices in the near future. In light of this, the following recommendations are provided for policymakers and financial institutions:

a) The government should introduce government-backed gold savings accounts. Such schemes would allow individuals to gradually build gold reserves through small and regular investments. This can encourage systematic saving and investment, particularly among rural and lower-income households.

b) Policymakers should simplify existing initiatives, such as Sovereign Gold Bonds, by streamlining the application process and increasing public awareness. They may also consider providing tax incentives for investments in digital gold and gold-backed ETFs. This can help bridge the gap between traditional gold buyers and modern investment options while reducing dependence on physical gold. Policymakers should also focus on the younger generation by improving the security and trustworthiness of fintech platforms to facilitate safe digital gold investments.

c) Policies aimed at stabilizing the Indian rupee should be implemented, as currency depreciation significantly influences gold prices. Strengthening foreign exchange reserves and reducing trade deficits can help minimize volatility in gold prices.
d) Market interventions should be introduced during high-demand periods, such as festivals and wedding seasons, to ensure affordability and control excessive price increases. For example, temporary subsidies or discounts on Sovereign Gold Bonds may encourage investment during peak periods. In addition, regulatory measures should ensure fair pricing in the gold jewellery market, especially during culturally significant seasons.
e) Promoting domestic gold mining and refining can reduce dependence on imports. This may be achieved through tax incentives and subsidies for mining and refining companies, thereby lowering production costs and encouraging domestic output.
f) Trade agreements with major gold-exporting countries should be negotiated to ensure a stable supply and fair pricing. In addition, contingency plans should be developed to address global market shocks, such as geopolitical tensions and international price fluctuations, in order to protect the domestic market from sudden disruptions.
g) Advanced analytical tools should be used to predict market behavior and consumer trends more effectively. Furthermore, technologies such as blockchain may be introduced to improve transparency and trust within the gold investment system.

8. Limitations

The implementation of the BJ model for forecasting gold prices provides a systematic and data-driven approach to dealing with the complicated landscape of financial markets. Although its simplicity makes it an effective tool, analysts should be aware of its limitations and the inherent volatility of gold markets. The ARIMA model is primarily designed for short-term forecasting and may fail to detect unexpected changes in the dataset, such as structural breaks. By integrating qualitative observations and external variables into the ARIMA framework, the accuracy of gold price predictions can be enhanced, allowing stakeholders and buyers to make informed decisions in a dynamic economy. If the data demonstrates significant volatility, the ARCH or GARCH model may yield more accurate results.

9. Conclusion

In India, gold holds increasing significance both as a cultural and financial commodity, particularly in terms of price trends that are essential for informed decision-making by consumers, investors, and policymakers. The ARIMA model is frequently employed to analyze these price trends and forecast gold prices. This model aids in identifying patterns and making predictions based on historical data, allowing stakeholders to adjust their strategies as needed. By comprehending these trends, investors can navigate the volatile market more effectively, while consumers can make more informed purchasing decisions.

This study found the ARIMA (1, 1, 1) model appropriate for analyzing and forecasting gold prices. The reliability and stability tests guarantee the capture of short-term trends with minimal error rates and robust statistical validation. The forecasts from December 2024 to April 2025 indicate a steady rise in gold prices, reflecting historical patterns and underlying market dynamics. These projections suggest that investors can expect a consistent upward trajectory in gold prices during this period. Such insights are crucial for making informed decisions in the financial market. Market participants should consider these forecasts when strategizing their investment portfolios, as the anticipated increase in gold prices may offer lucrative opportunities for both short-term trading and long-term investment. Additionally, staying attuned to geopolitical events and economic indicators will further enhance decision-making processes in this volatile landscape.

This study integrates insights into consumer trends, highlighting the crucial role of gold in Indian households. Gold serves as a safeguard against economic instability and a means of transferring wealth across generations. The findings correspond with seasonal and behavioral patterns, such as increased demand during festive and wedding seasons, which affect price movements. Additionally, the paper points out the growing adoption of modern investment vehicles like gold ETFs, reflecting the changing preferences of Indian consumers. This transition illustrates a broader trend toward diversification in investment strategies, as individuals aim to balance traditional assets with contemporary options. Ultimately, grasping these dynamics is essential for stakeholders who seek to navigate the complexities of the Indian gold market effectively.

This enhanced understanding of consumer behavior provides actionable insights for stakeholders. Investors can leverage these forecasts to time their purchases and optimize their portfolios. Policymakers have the ability to create financial inclusion initiatives like gold savings plans or rewards for adopting digital gold.

Although the ARIMA model is well-suited for short-term predictions, its limitations in accounting for external variables or structural breaks present opportunities for future research. Incorporating consumer-centric indicators, such as spending patterns and confidence indices, could further refine forecasting models. Overall, this study bridges the gap between technical forecasting and practical applications in the consumer-driven Indian gold market, empowering stakeholders to make informed, strategic decisions.

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