Advances in Consumer Research
https://acr-journal.com/
Volume-3 | Issue-10 |Sep: 2026

Original Researcher Article

Forecasting Gold Prices Before and After the COVID-19 Pandemic: An ARIMA Modelling Approach

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ABSTRACT

Gold continues to be an important financial asset because of its ability to preserve value during periods of economic uncertainty and inflation. The post-COVID environment created significant fluctuations in commodity and financial markets, increasing the need for reliable gold price forecasting techniques. This study analyses daily gold prices from 1 April 2021 to 30 March 2026 using the Box-Jenkins ARIMA approach. Stationarity was examined through the Augmented Dickey-Fuller test, which showed that the original series was non-stationary and became stationary after first differencing, indicating an integration order of I (1). Patterns in the autocorrelation and partial autocorrelation functions suggested the estimation of ARIMA(1,1,0), ARIMA(0,1,1), and ARIMA(1,1,1) models. Comparative evaluation based on AIC, SIC, and adjusted R^2 identified ARIMA(1,1,1) as the most suitable model. Both the autoregressive and moving-average coefficients were statistically significant, and diagnostic checking confirmed that the residuals were approximately random. Forecasts produced for 31 March 2026 to 30 September 2026 indicated a moderate upward movement in gold prices during the forecast horizon. Although the model captured the general direction of price changes, the forecasting error measures revealed limitations in obtaining highly accurate point forecasts. The study concludes that ARIMA models are useful for identifying short-term trends in gold prices, but their predictive performance may be improved by incorporating volatility measures and hybrid forecasting techniques in future research..

Keywords: ARIMA model; gold price forecasting; time series analysis; COVID-19; safe-haven asset; Box-Jenkins methodology; unit root test..

INTRODUCTION

Gold has, for centuries, occupied a distinctive position among financial and physical assets, valued not only for its ornamental and cultural significance but also for its function as a store of wealth, a hedge against inflation, and a refuge during periods of economic and financial distress. Unlike most conventional financial assets, gold carries intrinsic value, is not tied to the liabilities of any single issuer, and tends to retain its purchasing power over long horizons. In India, gold holds an especially prominent place in the economy: the country is among the largest global importers and household holders of gold, and demand for the metal is sustained year-round by religious festivals, marriage ceremonies, and its role as a culturally embedded form of savings, in addition to its economic functions as an investment, an inflation hedge, and a component of the Reserve Bank of India's foreign exchange reserves.

The COVID-19 pandemic represented an extraordinary shock to the global economy and financial markets. Lockdowns and containment measures disrupted production, trade, and employment, while extreme uncertainty prompted a marked shift in investor behaviour toward safer asset classes. Gold, consistent with its historical reputation as a safe-haven asset, experienced pronounced price swings during this period, drawing renewed attention from investors, financial analysts, and policymakers to the question of how gold prices behave, and can be forecast, during and after periods of acute economic stress.

Forecasting future gold prices is of direct practical value to investors seeking to manage risk and diversify portfolios, and to policymakers concerned with monetary stability and external sector performance. Among the many available time-series forecasting techniques, the Autoregressive Integrated Moving Average (ARIMA) model, formalised within the Box-Jenkins methodology, remains one of the most widely used and well-established tools for modelling and forecasting univariate financial and economic time series, owing to its capacity to capture autoregressive, integrated, and moving-average dependence structures in historical data using a systematic and replicable model-identification procedure.

This study applies the ARIMA framework to daily gold price data covering the period 1 April 2021 to 30 March 2026, a window that captures the post-pandemic evolution of the gold market, in order to characterise the time-series properties of gold prices and to assess the effectiveness of the ARIMA model in generating short-term price forecasts. The remainder of the paper proceeds as follows. Section 2 reviews the relevant literature on gold price forecasting using ARIMA and related time-series techniques. Section 3 states the research problem and objectives. Section 4 describes the data and methodology. Section 5 presents and discusses the empirical results. Section 6 concludes with a summary of findings and their implications, and Section 7 discusses the limitations of the study and directions for future research.

2. Review of Literature

The theoretical foundation for ARIMA-based time-series forecasting rests on the Box-Jenkins methodology, which established a systematic three-stage procedure of model identification, parameter estimation, and diagnostic checking for autoregressive integrated moving-average processes; this framework remains the standard reference point for applied time-series forecasting across economics and finance.

A substantial body of empirical work has applied the ARIMA model specifically to gold price forecasting. Using data on international gold prices, Yang (2019) demonstrated that an ARIMA specification could effectively capture short-term price trends and generate useful forecasts for investors and enterprises. Guha and Bandyopadhyay (2016) similarly applied the ARIMA methodology to gold price forecasting and found that the model was capable of producing statistically adequate and practically useful forecasts. In the Indian context, Singh (2017) examined the applicability of ARIMA to domestic gold price data and concluded that the model could effectively capture historical price trends, supporting its use by investors and policymakers, while Khaidem, Singh, and Singh (2016) reported comparable evidence that ARIMA-based forecasts of gold prices were reliable enough to assist investment decision-making.

More recent studies have sought to extend or benchmark the ARIMA framework against machine-learning and hybrid approaches. Madhika, Kusrini, and Hidayat (2023) compared ARIMA against Long Short-Term Memory (LSTM) neural networks and found that while ARIMA performed well for linear patterns in gold price data, LSTM offered improved accuracy where nonlinear dependence was present. Similarly, Zhang (2023) demonstrated the versatility of ARIMA across both stock index and gold price series, while Kumar (2024) focused specifically on the model's effectiveness for short-term gold price forecasting. Hybrid specifications have also received growing attention: Juliani (2022) combined ARIMA with a GARCH volatility component to jointly model gold price levels and volatility, finding that the hybrid approach improved forecasting accuracy relative to ARIMA alone, and Pujiarini (2025) reported similar gains from a hybrid ARIMA-LSTM model applied to digital gold price forecasting. Rashidi and Modarres (2025) and Taghipour, Rezaee, and Hajati (2025) extended this line of work further by combining deep-learning architectures with optimisation algorithms, reporting improved predictive performance over standalone statistical models, while Saini (2025) reported comparable gains using a hybrid deep neural network specification.

A parallel strand of literature has examined the macroeconomic determinants of gold prices. Khetan (2024) investigated the relationship between inflation and gold prices in India and the United States, finding that inflation dynamics significantly influence gold price movements and reinforcing gold's traditional role as an inflation hedge. Oltulular (2025) applied the ARIMA model to gold price data in the Turkish context and confirmed the model's ability to capture underlying trends across different economic environments, while Chen (2025) extended similar time-series forecasting techniques to global gold price data.

Taken together, the literature indicates broad support for the use of ARIMA as a baseline, interpretable forecasting tool for gold prices, while also highlighting its principal limitation: as a linear model, ARIMA is less able to capture nonlinear dependence, volatility clustering, and structural breaks of the kind associated with major shocks such as the COVID-19 pandemic. This motivates the continuing use of ARIMA as a transparent benchmark model, evaluated here specifically over a post-pandemic sample period, while acknowledging that hybrid and machine-learning extensions represent a natural direction for further research.

3. Statement of the Problem and Objectives of the Study

Gold has consistently been regarded as one of the safest investment options, particularly during periods of economic uncertainty and financial instability. Gold prices are, however, highly volatile and are shaped by a wide range of factors, including inflation, interest rates, exchange rates, geopolitical events, and investor sentiment. The COVID-19 pandemic created unprecedented disruption in the global economy and financial markets, resulting in significant fluctuations in gold prices and marked shifts in investor behaviour. While a substantial body of research has examined gold price forecasting using statistical and machine-learning models, comparatively limited attention has been paid to the specific behaviour of gold prices in the period following the COVID-19 pandemic, and to a systematic assessment of whether the ARIMA model can capture this behaviour and generate reliable forecasts under the resulting market conditions. Understanding these price dynamics is important for investors, financial analysts, and policymakers seeking to make informed investment and risk-management decisions.

In light of this, the study is guided by the following objectives:

To analyse the behaviour and trend of gold prices during the post COVID-19 period.

To estimate an ARIMA model for forecasting gold prices using time-series analysis.

To forecast short-term gold prices and evaluate the performance of the selected ARIMA model.

4. Data and Research Methodology

4.1 Data Source and Study Period

The study is based on secondary data comprising daily gold price observations collected from reliable and authentic published sources. The sample period extends from 1 April 2021 to 30 March 2026, providing a five-year post-pandemic window for analysis. The study is confined to gold prices alone and does not incorporate other precious metals, financial assets, or macroeconomic variables such as inflation, interest rates, exchange rates, or crude oil prices, in order to maintain a parsimonious univariate time-series framework.

4.2 Research Design and Analytical Framework

The study adopts a descriptive, quantitative research design combined with time-series analysis, following the Box-Jenkins methodology. This approach involves three principal stages: identification of an appropriate model through stationarity testing and correlogram analysis; estimation of candidate model parameters; and diagnostic checking of the fitted model prior to its use for forecasting.

Stationarity of the gold price series was first tested using the Augmented Dickey-Fuller (ADF) test, since stationarity is a precondition for valid ARIMA estimation; where the series was found to be non-stationary, successive differencing was applied until stationarity was achieved, establishing the integration order, d. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the stationary series were then examined to identify candidate orders for the moving-average (q) and autoregressive (p) components, respectively. Multiple candidate ARIMA(p,d,q) specifications were estimated and compared using the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), coefficient significance, and R-squared/adjusted R-squared, with the best-fitting model selected on the principle of parsimony consistent with the standard Box-Jenkins approach. The adequacy of the selected model was then verified through diagnostic checking of the residuals, principally via the residual correlogram and the Durbin-Watson statistic, to confirm that the residuals behaved approximately as white noise. Finally, the validated model was used to generate out-of-sample forecasts, evaluated using standard forecast-accuracy measures including the Theil Inequality Coefficient, Mean Absolute Percentage Error (MAPE), and Bias Proportion.

All estimations reported in this study were carried out in EViews using its Box-Jenkins ARIMA estimation and forecasting routines.

5. Empirical Results and Discussion

5.1 Unit Root Test: Stationarity of the Gold Price Series

The stationarity of the gold price series was first examined using the Augmented Dickey-Fuller (ADF) test at level, with results reported in Table 1.

Table 1: ADF unit root test on the gold price series at level

Test	t-Statistic	Prob.*
ADF test statistic (level)	1.920792	0.9999
1% critical value	-3.435462	—
5% critical value	-2.863685	—
10% critical value	-2.567962	—

Since the ADF test statistic (1.920792) exceeds the critical values at all conventional significance levels and the associated probability (0.9999) is far above 0.05, the null hypothesis of a unit root cannot be rejected. The gold price series is therefore non-stationary at level, implying that its mean and variance change over time and that historical shocks to gold prices have persistent, long-lasting effects. In its original form, the series is unsuitable for direct ARIMA estimation, which requires a stationary input series.

The series was accordingly subjected to first-order differencing, and the ADF test was repeated on the differenced series (FDGOLD), with results reported in Table 2.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FDGOLD(-1)	-1.105336	0.038384	-28.79664	0.0000
D(FDGOLD(-1))	0.188500	0.028209	6.682173	0.0000

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	91.03162	33.38625	2.726620	0.0065

R-squared = 0.482270 | Adj. R-squared = 0.481424 | S.E. of regression = 1164.956 | Akaike info criterion = 16.96119 | Schwarz criterion = 16.97369 | Durbin-Watson stat = 1.970640

Table 2: ADF test on the first-differenced gold price series

The ADF test statistic on the first-differenced series (-28.79664) is far below the 1 per cent critical value, and the associated probability (0.0000) is well under the 0.05 threshold, leading to a decisive rejection of the null hypothesis of a unit root. The gold price series therefore becomes stationary after first differencing, confirming an integration order of d = 1 and establishing that the series is suitable for ARIMA modelling in differenced form.

5.2 Correlogram Analysis: Identification of AR(p) and MA(q) Orders

Having established stationarity at first difference, the correlogram of the differenced series was examined to identify candidate orders for the autoregressive and moving-average components. Both the ACF and the PACF display significant spikes at the initial lags, particularly at lag 2, followed by a gradual decline, indicating the presence of both autoregressive and moving-average dependence in the series. The statistically significant Ljung-Box Q-statistics ($p < 0.05$) confirm that the differenced series retains meaningful temporal dependence suitable for ARIMA modelling. This pattern supports the consideration of low-order specifications, with ARIMA(1,1,1) emerging as a natural candidate, subject to formal confirmation through model comparison and diagnostic testing.

5.3 Estimation of Candidate ARIMA Models

Three candidate specifications, ARIMA(1,1,0), ARIMA(0,1,1), and ARIMA(1,1,1), were estimated on the gold price series. Results are summarised in Tables 3 to 5.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	82.68167	36.32228	2.276335	0.0230
AR(1)	0.069356	0.028590	2.425896	0.0154

AIC = 16.99456 | SIC = 17.00288 | DW = 1.965857 | Inverted AR root = 0.07 | Observations = 1,229

Table 3: ARIMA(1,1,0) model estimation results

In the ARIMA(1,1,0) specification, both the constant (p = 0.0230) and the AR(1) coefficient (0.069356, p = 0.0154) are statistically significant, and the inverted AR root (0.07) lies within the unit circle, confirming model stability.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	82.86314	37.48795	2.210394	0.0273
MA(1)	0.111606	0.028502	3.915670	0.0001

AIC = 16.99085 | SIC = 16.99916 | DW = 2.032739 | Inverted MA root = -0.11 | Observations = 1,230

Table 4: ARIMA(0,1,1) model estimation results

The ARIMA(0,1,1) specification also produces statistically significant coefficients, with a lower AIC and SIC than the ARIMA(1,1,0) model, indicating an improved fit. The inverted MA root (-0.11) lies within the unit circle, satisfying the invertibility condition.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	82.52234	36.41027	2.266458	0.0236
AR(1)	-0.599313	0.091210	-6.570678	0.0000
MA(1)	0.747063	0.076001	9.829587	0.0000

AIC = 16.96747 | SIC = 16.97996 | DW = 2.084347 | Inverted AR root = -0.60 | Inverted MA root = -0.75 | Observations = 1,229

Table 5: ARIMA(1,1,1) model estimation results

In the ARIMA(1,1,1) specification, the constant, the AR(1) coefficient (-0.599313), and the MA(1) coefficient (0.747063) are all statistically significant at the 1 per cent level or better, and both inverted roots lie within the unit circle, confirming that the model is stable and invertible.

5.4 Model Comparison and Selection

The three candidate models were compared using AIC, SIC, coefficient significance, and R-squared/adjusted R-squared, as summarised in Table 6.

Model	AIC	SIC	Significant p-value(s)	R-squared	Adj. R-squared
ARIMA(1,1,0)	16.99456	17.00288	0.0154	0.004773	0.003962
ARIMA(0,1,1)	16.99085	16.99916	0.0001	0.007650	0.006842
ARIMA(1,1,1)	16.96747	16.97996	0.0000, 0.0000	0.032941	0.031363

Table 6: Comparison of candidate ARIMA models

All three candidate models exhibit statistically significant coefficients, but ARIMA(1,1,1) records the lowest AIC (16.96747) and SIC (16.97996), together with the highest R-squared (0.032941) and adjusted R-squared (0.031363) among the three, indicating that it provides the best overall fit to the data. Consistent with the correlogram-based model identification in Section 5.2 and the Box-Jenkins principle of parsimony, ARIMA(1,1,1) was therefore selected as the final forecasting model for gold prices.

5.5 Diagnostic Checking

The adequacy of the selected ARIMA(1,1,1) model was assessed through residual diagnostic checking. The correlogram of the residuals shows that most autocorrelations and partial autocorrelations lie within the confidence bounds, with no substantial systematic pattern remaining, indicating that the model has captured the essential temporal structure of the gold price series. The Durbin-Watson statistic (2.084347) is close to 2, indicating the absence of significant residual autocorrelation. Taken together, these diagnostics suggest that the residuals of the ARIMA(1,1,1) model behave approximately as white noise, confirming that the model is statistically adequate and stable for forecasting purposes.

5.6 Forecasting Gold Prices

Using the validated ARIMA(1,1,1) model, out-of-sample forecasts of gold prices were generated for the period 31 March 2026 to 30 September 2026. The forecast indicates a continuing upward movement in gold prices over the forecast horizon. Forecast accuracy was evaluated using three standard measures: the Theil Inequality Coefficient (0.1756), the Mean Absolute Percentage Error (44.09%), and the Bias Proportion (74.94%). The relatively low Theil coefficient suggests acceptable overall forecasting performance, but the elevated MAPE and, in particular, the high Bias Proportion indicate that the forecasts contain a non-trivial systematic error component and should therefore be interpreted with caution, especially as point estimates rather than directional signals.

On balance, the ARIMA(1,1,1) model succeeds in capturing the broad upward trend and general variability of gold prices over the forecast horizon, making it a useful tool for identifying the likely future direction of the market, but its precision as a source of exact future price levels is limited. This finding is consistent with the well-documented characteristic of linear ARIMA models: they are well suited to capturing autocorrelation-based structure in relatively stable series, but are less able to anticipate the nonlinearities, structural breaks, and volatility clustering associated with major shocks, of the kind that has periodically affected gold markets in the post-pandemic period.

6. Conclusion and Implications

This study set out to examine the behaviour of gold prices in the post-COVID-19 period and to assess the effectiveness of the ARIMA model in forecasting future price movements, using daily data from 1 April 2021 to 30 March 2026. The gold price series was found to be non-stationary at level but stationary after first differencing, establishing an integration order of d = 1. Correlogram-based identification and formal model comparison across three candidate specifications identified ARIMA(1,1,1) as the best-fitting and most parsimonious model, with statistically significant autoregressive and moving-average components and residuals that behaved approximately as white noise, confirming its adequacy for forecasting.

Forecasts generated from the selected model point to a continuing upward trend in gold prices over the six-month forecast horizon, consistent with gold's established role as a safe-haven asset during periods of continuing economic and geopolitical uncertainty. At the same time, the accuracy diagnostics, particularly the elevated Bias Proportion, indicate that the model's point forecasts should be treated with caution and are more reliably interpreted as an indication of directional trend than as precise price targets.

These findings carry several practical implications. For individual and institutional investors, the results reinforce the case for including gold within a diversified portfolio as a hedge against uncertainty, while cautioning against relying on ARIMA-based point forecasts alone for tactical trading decisions. For financial analysts and portfolio managers, the study demonstrates that ARIMA can serve as a transparent, easily interpretable baseline forecasting tool, best used in conjunction with macroeconomic monitoring and, where feasible, more flexible nonlinear or hybrid models. For policymakers and institutions such as the Reserve Bank of India that hold gold as part of foreign exchange reserves, the confirmation of continuing upward price momentum in the post-pandemic period is a relevant input into reserve management and macro-financial stability assessments.

7. Limitations and Scope for Future Research

This study is subject to several limitations that also suggest directions for future research. First, the analysis relies entirely on secondary data, and the accuracy of the results is contingent on the reliability and consistency of the underlying source data. Second, the study is restricted to gold prices alone and does not extend to other precious metals or asset classes such as silver, platinum, equities, or cryptocurrencies, limiting the generalisability of the findings beyond the gold market. Third, the analysis does not explicitly incorporate macroeconomic variables such as inflation, interest rates, exchange rates, or crude oil prices, each of which is known to influence gold prices; incorporating these as exogenous regressors in an ARIMAX or vector autoregressive framework represents a natural extension. Fourth, the ARIMA model is inherently linear and therefore may not fully capture nonlinear dynamics, volatility clustering, or abrupt structural breaks in gold prices; the moderately high forecast bias observed in this study is consistent with this limitation, and future work could compare ARIMA against nonlinear and machine-learning alternatives such as LSTM networks, or hybrid ARIMA-GARCH and ARIMA-LSTM specifications, several of which have shown promising results in the literature reviewed in Section 2. Finally, the forecasting exercise is confined to a six-month horizon; extending the analysis to longer forecast windows and evaluating forecast stability across multiple rolling windows would provide a more robust assessment of the model's long-run predictive reliability...

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