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Seasonal Dynamics in Gold Price Forecasting: A Comparative Analysis of ARIMA and SARIMA Models for Retail Gold Prices - Evidence from daily data, 2014–2025

Rajib Bhattacharya

Associate Professor
NSHM Business School, Kolkata
NSHM Knowledge Campus – Kolkata Group of Institutions

Abstract:
The study investigates the predictive dynamics of retail gold prices in India by comparing the forecasting efficiency of two classical time-series models—Auto-Regressive Integrated Moving Average (ARIMA) and Seasonal Auto-Regressive Integrated Moving Average (SARIMA)—using daily gold price data from 2014 to 2025. Gold, being both an economic and cultural asset in India, exhibits pronounced seasonal fluctuations driven by festive demand, investment cycles, and macroeconomic conditions. Recognizing the inadequacy of linear ARIMA models in accounting for such periodic patterns, the research introduces SARIMA as a seasonality-augmented alternative to test whether the inclusion of seasonal autoregressive and moving-average terms significantly enhances predictive performance. The methodology follows the Box–Jenkins framework for model identification, estimation, and validation, employing statistical diagnostics such as the Augmented Dickey–Fuller (ADF) and KPSS tests for stationarity and the Ljung–Box Q-statistic for residual independence. Forecast accuracy is assessed using Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and the Diebold–Mariano (DM) test for comparative predictive evaluation. Empirical findings reveal that while both models provide statistically acceptable forecasts, the SARIMA model consistently outperforms ARIMA across all error metrics, achieving a 6% improvement in MAPE (4.58% versus 4.89%). The results substantiate that seasonal differentiation improves model adaptability to cyclical movements inherent in gold prices, reflecting recurring variations linked to cultural and market dynamics. Furthermore, the study highlights that ignoring seasonality leads to cumulative bias and underprediction, particularly during upward market trends. The findings emphasize that incorporating seasonal structures transforms traditional linear models into more context-sensitive predictive systems, providing greater reliability for market participants and policymakers. By reinforcing the empirical and methodological relevance of SARIMA in seasonal financial time-series forecasting, this study contributes to both econometric modelling literature and applied financial analytics. It underscores the importance of seasonality-aware frameworks in enhancing predictive precision for volatile assets, particularly in emerging markets like India, where demand cycles strongly influence retail gold pricing.

Keywords: Gold Price Forecasting, ARIMA, SARIMA, Seasonality, Time-Series Modelling
JEL Classification: C22, C53, E37, G11, Q02

Introduction

Gold holds a unique position in the global financial and cultural landscape, functioning simultaneously as a commodity, an investment asset, and a monetary substitute. Its value dynamics are shaped by a complex interplay of macroeconomic indicators, investor psychology, and socio-cultural consumption cycles. In emerging economies like India—where gold carries deep socio-economic significance—price fluctuations not only influence household wealth and consumer behaviour but also have implications for trade balance, monetary policy, and inflationary trends. Consequently, accurate forecasting of gold prices has become a critical research concern, bridging econometric modelling and financial analytics.

Traditional approaches to gold price forecasting have been grounded in econometric and statistical time-series models. Among these, the Auto-Regressive Integrated Moving Average (ARIMA) framework proposed by Box and Jenkins remains one of the most widely employed techniques for modelling univariate financial time series. ARIMA captures the linear dependence of a variable on its lagged values and random shocks, making it suitable for short-term forecasting under stable conditions. However, gold prices are rarely stable; they exhibit volatility clustering, structural breaks, and pronounced seasonality linked to cultural and institutional demand cycles. Consequently, the performance of ARIMA tends to deteriorate when data exhibit cyclical or periodic structures.

To address these limitations, the Seasonal ARIMA (SARIMA) model extends the basic ARIMA framework by incorporating additional autoregressive and moving-average terms that explicitly model seasonal effects. By applying seasonal differencing, SARIMA can capture repetitive patterns—such as monthly, quarterly, or annual fluctuations—embedded within the data. This makes SARIMA particularly appropriate for markets like retail gold, where price dynamics are influenced by recurring demand peaks during festivals, weddings, and investment cycles. The capacity of SARIMA to integrate both short-run stochastic variations and long-run cyclical movements provides a richer, more flexible framework for price forecasting.

The motivation for this study arises from the observation that existing literature on gold price forecasting has predominantly focused on global bullion or futures prices, with limited attention to retail gold markets, where domestic taxes, jewellery premiums, and local trading sentiments exert significant influence. Retail prices often follow distinct seasonal trajectories reflecting cultural demand cycles and localized inflation expectations. Thus, a model that successfully captures such periodicities can deliver practical forecasting insights for both market participants and policymakers.

Between 2014 and 2025, the Indian gold market has experienced multiple economic transitions—currency fluctuations, global interest rate changes, geopolitical uncertainty, and pandemic-induced volatility—all of which have amplified the importance of precise and adaptive forecasting models. The dataset spanning over a decade provides a robust basis to test whether seasonality-aware models like SARIMA outperform conventional ARIMA in forecasting retail gold prices. The study employs standard Box–Jenkins methodology for model identification, estimation, and diagnostic validation, followed by performance evaluation using accuracy metrics such as Mean Absolute Percentage Error (MAPE) to statistically assess predictive superiority.

The significance of this research is twofold. First, from a methodological perspective, it empirically demonstrates the role of seasonality in improving the reliability of time-series models. Second, from a practical standpoint, it offers valuable insights for gold traders, financial analysts, and policymakers. Enhanced predictive accuracy allows jewellers to manage inventory more efficiently, investors to time entry and exit decisions, and regulators to anticipate inflationary pressures arising from gold price surges. Moreover, as financial systems evolve towards greater data-driven decision-making, refining traditional econometric models like ARIMA through seasonal extensions bridges the gap between statistical rigor and real-world applicability.

In essence, this study situates itself at the intersection of econometric modelling and applied financial forecasting. By comparatively analysing ARIMA and SARIMA models using daily retail gold price data from 2014 to 2025, it seeks to reaffirm that accounting for seasonal dynamics not only refines predictive precision but also enhances the interpretive depth of time-series analysis. The outcomes are expected to underscore that seasonality is not a statistical artifact but an intrinsic feature of gold price behaviour—an insight that carries enduring implications for economic modelling, investment strategy, and policy formulation.

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Survey of literature

Gold price forecasting remains an active field of research owing to the metal's unique economic significance. Gold simultaneously serves as a commodity, a monetary substitute, a hedge against inflation, and a safe haven during financial distress. Its price behaviour is characterized by pronounced nonlinearity, volatility clustering, regime shifts, and responsiveness to global macroeconomic factors. Broadly, the literature is divided into two major methodological traditions: (a) econometric and statistical models—including ARIMA, VAR/VECM, GARCH families, DCC/GAS, cointegration, MIDAS, GARCH-MIDAS, and wavelet/time-frequency approaches—and (b) data-driven, machine-learning (ML), and hybrid models such as ANN, SVM, ELM, DBN, LSTM, CNN, and hybrid decomposition–ML combinations.

Early studies focused on classical econometric frameworks to examine gold price predictability and its macro-financial linkages. Aye et al. (2015) employed dynamic model averaging (DMA) to identify time-varying predictor importance—such as exchange rates, interest rates, and financial stress indices—and demonstrated that predictor relevance shifts across time and market episodes. This finding highlights the adaptability of model-averaging approaches when relationships are unstable (Aye et al., 2015). Although ARIMA and ARIMAX models remain common as short-term benchmarks, they tend to perform poorly during structural changes and high-volatility periods.

The discovery of volatility clustering and leptokurtic return distributions led to the widespread application of ARCH and GARCH-type models in gold price analysis. Tully and Lucey (2007) utilized an asymmetric power GARCH (APGARCH/APARCH) specification to capture leverage and power effects in cash and futures markets. Their findings showed that APGARCH provided a better fit than the standard GARCH model (Tully & Lucey, 2007). Subsequent studies expanded on these frameworks through EGARCH, TGARCH, and APARCH variants, confirming the persistence of conditional heteroskedasticity in gold returns.

To capture interactions across multiple asset classes, researchers extended univariate models to multivariate settings such as DCC-GARCH, BEKK, and GAS. Ciner, Gurdgiev and Lucey (2013) and Reboredo (2013) applied dynamic conditional correlation and copula-based methods to explore gold's hedging and safe-haven roles. Their findings indicated that gold exhibits time-varying dependence with other financial assets, and such models significantly improve joint risk forecasts and portfolio diversification outcomes (Ciner et al., 2013; Reboredo, 2013).

Long-term macroeconomic influences have also been incorporated into gold volatility models through mixed-data-frequency approaches. The GARCH-MIDAS model decomposes total volatility into short-run dynamics and long-run macroeconomic components. Fang, Yu and Xiao (2018) and Salisu et al. (2020) demonstrated that macro variables—such as economic policy uncertainty, industrial production, and principal components derived from macroeconomic indicators—enhance long-term volatility forecasts in both spot and futures markets (Fang et al., 2018; Salisu et al., 2020). GARCH-MIDAS is particularly valuable when low-frequency macro data are combined with daily financial data to improve predictive accuracy.

Empirical research on long-run relationships among gold prices, exchange rates, interest rates, and inflation has yielded mixed results. While some studies confirm cointegration and stable long-term linkages suitable for error-correction models, others observe episodic or time-varying coupling between variables. Copula and tail-dependence approaches (Reboredo, 2013) have advanced this literature by capturing nonlinear and asymmetric co-movements, revealing patterns that differ substantially from unconditional correlation-based results.

Time–frequency methods, including wavelet transforms and multi-scale decompositions, have been used to analyse gold price movements across different investment horizons. These methods show that predictive relationships vary by frequency: a variable that is significant at the daily level may be irrelevant at longer horizons. As a result, wavelet-based and hybrid wavelet–ARIMA or wavelet–ANN models frequently produce superior forecasts by capturing horizon-specific dynamics.

In recent years, the use of machine-learning (ML) techniques has expanded rapidly. Kristjanpoller and Minutolo (2015) developed an ANN–GARCH hybrid framework that integrates nonlinear learning with volatility modelling. Their results indicated that the hybrid model substantially improves predictive accuracy relative to either standalone ANN or GARCH models (Kristjanpoller & Minutolo, 2015). This was followed by the adoption of decomposition-based ML frameworks, in which techniques such as wavelet and empirical mode decomposition (EMD) are combined with SVM, ANN, GRU, or LSTM to reduce data complexity and enhance model performance (E. Jianwei et al., 2019).

Deep learning (DL) architectures have further advanced forecasting performance. Zhang and Ci (2020) applied a deep belief network (DBN) to predict gold prices and reported significant gains over both conventional econometric and shallow ML models. Similarly, Khani et al. (2021) compared CNN, LSTM, and encoder–decoder LSTM variants—including pandemic-related features—and found that deep recurrent structures provide strong near-term predictive accuracy, especially when augmented with domain-specific variables (Khani et al., 2021).

Extreme Learning Machines (ELM) and their online sequential adaptations have also been explored. Weng et al. (2020) introduced GA-regularized ELM models that achieve faster convergence and improved accuracy in high-frequency forecasting contexts. Ensemble and boosting algorithms have similarly proven effective: Pierdzioch et al. (2016) applied boosting and quantile boosting methods to forecast gold volatility and returns, revealing robust out-of-sample performance across multiple predictors (Pierdzioch et al., 2016). The latest innovations (Foroutan et al., 2024; Cohen, 2023) involve graph neural networks and ensemble ML pipelines such as XGBoost and LightGBM, which leverage feature engineering to enhance forecasting of multi-asset and retail-level gold prices.

Across methodologies, a few empirical regularities consistently emerge. Models that explicitly account for volatility—such as GARCH, GARCH-MIDAS, and GAS—consistently outperform simpler linear benchmarks in risk forecasting and derivative pricing. The integration of macroeconomic data improves long-term forecasts, while nonlinear and hybrid models excel in short-term prediction. Deep learning and decomposition-based ML frameworks generally produce the highest accuracy for 1–30-day horizons, particularly when they include external variables such as exchange rates, policy uncertainty, interest rates, realized volatility, and even pandemic metrics.

However, model instability and structural breaks remain persistent issues. Forecasting accuracy is highly sample-dependent, with model performance often changing during crisis periods such as the 2008 global financial crisis or the COVID-19 pandemic. Adaptive methods—DMA, time-varying parameter models, rolling-window estimations, and online ELM algorithms—help mitigate the effects of instability and evolving data patterns.

Despite substantial progress, several research gaps remain. Many ML models improve predictive accuracy but lack economic interpretability, limiting their theoretical and policy relevance. Integrating structural econometric constraints into ML frameworks is thus a promising direction. Moreover, most existing studies focus on bullion or futures markets, leaving retail gold price dynamics—affected by taxes, jewellery premiums, and distribution costs—relatively unexplored. The integration of real-time and alternative data, such as news sentiment, supply-chain indicators, or order-book dynamics, within econometric–ML hybrids remains underdeveloped. Standardized evaluation procedures using RMSE, MAE, Theil's U, and Diebold–Mariano tests are also essential for ensuring comparability across studies.

In sum, gold price forecasting has evolved into a hybrid research domain that fuses econometric rigour with machine-learning innovation. Classical econometric tools (ARIMA, VAR, GARCH, GARCH-MIDAS) remain central to risk and volatility analysis, while ML and decomposition-based approaches dominate short-term prediction tasks. The optimal model depends on the forecasting goal—GARCH-type models for volatility, DMA or time-varying parameter models for structural instability, and deep-learning hybrids for high-frequency data forecasting.

Nevertheless, the literature lacks a systematic comparative framework. Most studies evaluate individual models—ARIMA, VAR/VECM, GARCH, GARCH-MIDAS, or ML hybrids—in isolation, making it difficult to generalize findings. Few studies conduct cross-method comparisons using uniform datasets and metrics, and performance across different market regimes remains underexplored. Furthermore, limited cross-country and cross-period analyses restrict understanding of gold market integration and structural variation.

Addressing these gaps through comprehensive comparative evaluations that integrate econometric, mixed-frequency, and hybrid models would yield more generalizable insights into model robustness and predictive power. Such research would significantly contribute to the field, offering practical value to investors, central banks, and policymakers responsible for managing and forecasting gold markets in a rapidly evolving global context.

Objectives of the Study

The primary objective of this study is to examine the predictive dynamics of retail gold prices in India by comparing the performance of two classical time-series forecasting models—Auto-Regressive Integrated Moving Average (ARIMA) and its seasonal variant, Seasonal Auto-Regressive Integrated Moving Average (SARIMA). The study aims to evaluate whether incorporating seasonal components into a linear stochastic framework significantly improves the accuracy and reliability of gold price forecasts. Specifically, it seeks to determine how effectively these models capture short-term cyclical movements and long-term trends embedded in the daily retail price data of 24-carat gold from 2014 to 2025.

Gold, as a financial and cultural asset, exhibits recurrent demand patterns driven by festivals, marriage seasons, and macroeconomic cycles, all of which influence its price behaviour. Recognizing this, the study emphasizes seasonality as a key determinant of model performance. The central hypothesis posits that SARIMA, by integrating seasonal autoregressive and moving-average terms, provides superior forecasting accuracy compared to the non-seasonal ARIMA model.

In operational terms, the study seeks to quantify and compare predictive errors between the two models using statistical accuracy measure of Mean Absolute Percentage Error (MAPE). Through this comparative evaluation, the research intends to identify the model that most accurately reflects the cyclical and stochastic structure of the retail gold market.

Beyond empirical validation, the broader objective is to enhance methodological understanding of seasonality-driven price dynamics in precious metals. The findings aim to contribute to the development of more robust forecasting tools for traders, investors, and policymakers by highlighting the practical significance of incorporating seasonal adjustments in financial time-series modelling.

Methodology of the study

Seasonal Dynamics in Cryptocurrency Forecasting: A Comparative Analysis of ARIMA and SARIMA Models for Bitcoin and Cardano – Evidence from Daily Data, 2021–2025.

This section delineates the statistical and methodological foundation employed for forecasting the daily closing prices of Bitcoin (BTC) and Cardano (ADA) between 2021 and 2025. The study adopts time-series econometric approaches, specifically the Auto-Regressive Integrated Moving Average (ARIMA) and the Seasonal Auto-Regressive Integrated Moving Average (SARIMA) models. Both models are estimated and compared to evaluate their capacity to capture the underlying stochastic and seasonal structures in cryptocurrency prices

Data Representation and Transformation

Let {P_t}_{t=1}^T represent the daily closing prices of the cryptocurrency under consideration, where T is the total number of observations. The logarithmic transformation is applied to stabilize variance and linearize exponential growth patterns:

$r_t = \ln(P_t) - \ln(P_{t-1})$,
where r_t represents the continuously compounded log return at time t.

The transformed series $\{r_t\}$ is then analysed for stationarity. A weakly stationary process satisfies $E[r_t] = \mu$ (constant mean) and $Cov(r_t, r_{t-k}) = \gamma_k$ (dependent only on lag k). Stationarity is assessed using unit-root tests such as the Augmented Dickey–Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. Differencing is applied d times to achieve stationarity:
$(1 - B)^d y_t = y_t - d\, y_{t-1} + \dots$,
where B is the backshift operator ($B\, y_t = y_{t-1}$).

The ARIMA Model
The ARIMA(p, d, q) model combines autoregressive (AR), differencing (I), and moving-average (MA) components to model linear temporal dependencies. It is expressed as:
$\varphi(B)(1 - B)^d y_t = \theta(B)\varepsilon_t$,
where $\varepsilon_t \sim iid(0, \sigma^2)$,
$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \dots - \varphi_p B^p$ represents the autoregressive polynomial of order p,
and $\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q$ represents the moving-average polynomial of order q.

This model assumes a linear dependence between current and past values, adjusted for differencing. The conditional expectation forms the h-step-ahead forecast:
$\hat{y}_{T+h|T} = E(y_{T+h} \mid y_T, y_{T-1}, \dots , y_{T-p+1})$.

Parameter estimation is performed via Maximum Likelihood Estimation (MLE) or Conditional Sum of Squares. The log-likelihood function is given by:
$\ln L(\theta) = -\frac{1}{2}T \ln(2\pi\sigma^2) - \frac{1}{2}\sigma^{-2} \Sigma\, \varepsilon_t^2(\theta)$,
where θ denotes the vector of estimated parameters.

Seasonal ARIMA (SARIMA) Model
To model periodic seasonal behaviour inherent in daily cryptocurrency prices, the SARIMA(p, d, q)(P, D, Q)_s model is employed. The general formulation is given by:
$\Phi(B^s)\varphi(B)(1 - B)^d(1 - B^s)^D y_t = \Theta(B^s)\theta(B)\varepsilon_t$,
where:
$\varphi(B)$, $\theta(B)$ are non-seasonal AR and MA polynomials,
$\Phi(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \dots - \Phi_P B^{Ps}$ represents the seasonal AR component,
$\Theta(B^s) = 1 + \Theta_1 B^s + \Theta_2 B^{2s} + \dots + \Theta_Q B^{Qs}$ represents the seasonal MA component,
and s denotes the length of the seasonal cycle (e.g., s = 7 for weekly periodicity, s = 365 for annual).

The seasonal differencing operator $(1 - B^s)^D$ removes periodic trends, ensuring that the transformed series is stationary across seasonal periods. SARIMA models effectively capture both short-run autocorrelations and long-run cyclic movements driven by trading cycles or investor sentiment.

Model Identification
Model identification determines appropriate values for (p, d, q, P, D, Q, s). This process follows the Box–Jenkins methodology:
1. Plot and analyse ACF and PACF to infer potential AR and MA orders.
2. Determine differencing order d (and seasonal D) through unit-root tests.
3. Evaluate multiple model configurations using information criteria:
$AIC = -2 \ln(\mathscr{L}) + 2k$,
$BIC = -2 \ln(\mathscr{L}) + k \ln(T)$,

where k denotes the number of estimated parameters and $\mathscr{L}$ is the maximized likelihood.

The model with the minimum AIC/BIC is preferred, subject to parameter significance and diagnostic adequacy.

Model Estimation and Forecasting

Given the identified specification, parameters are estimated through numerical optimization (typically MLE). The h-step-ahead forecast for the ARIMA model is computed recursively as:
$\hat{y}_{T+h|T} = \mu + \Sigma_{i=1}^{p} \varphi_i \hat{y}_{T+h-i|T} + \Sigma_{j=1}^{q} \theta_j \hat{\varepsilon}_{T+h-j}$.

In the SARIMA model, the forecast includes both non-seasonal and seasonal lag terms:
$\hat{y}_{T+h|T}^{(SARIMA)} = \mu + \Sigma \varphi_i y_{T+h-i} + \Sigma \Phi_k y_{T+h-ks} + \Sigma \theta_j \hat{\varepsilon}_{T+h-j} + \Sigma \Theta_m \hat{\varepsilon}_{T+h-ms}$.

The corresponding prediction interval (PI) for $(1 - \alpha)$ confidence is:
$PI_{1-\alpha} = \hat{y}_{T+h|T} \pm z_{\alpha/2} \sqrt{Var(\hat{\varepsilon}_{T+h|T})}$,
where $z_{\alpha/2}$ is the $(\alpha/2)$-quantile of the standard normal distribution.

Diagnostic Checking

Diagnostic checking ensures model adequacy by validating the residual assumptions. The following tests are conducted:

1. Ljung–Box Q-statistic:
$Q(m) = T(T + 2) \Sigma_{k=1}^m \hat{\rho}_k^2 / (T - k)$,
where $\hat{\rho}_k$ denotes the sample autocorrelation of residuals. A high p-value implies residual whiteness.

2. ARCH–LM test:
To detect conditional heteroskedasticity, the regression $\hat{\varepsilon}_t^2 = \alpha_0 + \Sigma \alpha_i \hat{\varepsilon}_{t-i}^2 + u_t$ is tested for joint significance of α_i.

3. Jarque–Bera (JB) test:
$JB = (T/6)(S^2 + (K - 3)^2 / 4)$,
where S and K are sample skewness and kurtosis. Non-significant JB indicates normality.

Residuals are further examined graphically through ACF/PACF and Q–Q plots to confirm random dispersion.

Evaluation Metrics

Forecast accuracy is evaluated using the following metrics:

1. Mean Absolute Error (MAE):
$MAE = (1/N) \Sigma |y_t - \hat{y}_t|$.

2. Root Mean Squared Error (RMSE):
$RMSE = \sqrt{(1/N) \Sigma (y_t - \hat{y}_t)^2}$.

3. Mean Absolute Percentage Error (MAPE):
$MAPE = (100/N) \Sigma |(y_t - \hat{y}_t) / y_t|$.

4. Theil's U-statistic:
$U = \sqrt{\Sigma(y_t - \hat{y}_t)^2} / \sqrt{\Sigma(y_t - y_{t-1})^2}$,
where $U < 1$ indicates the model outperforms a naive random-walk forecast.

5. Diebold–Mariano (DM) test:
$d_t = L(e_t^{(1)}) - L(e_t^{(2)})$,
$DM = \bar{d} / \sqrt{(Var(\bar{d})/T)}$,
testing H_0: equal predictive accuracy between ARIMA and SARIMA forecasts.

Seasonal Decomposition and Interpretation

Cryptocurrency price movements exhibit periodic cycles associated with investor sentiment, liquidity flows, and trading behaviour. SARIMA decomposes the observed series into deterministic and stochastic components:
$y_t = T_t + S_t + I_t$,
where T_t represents the trend component, S_t the seasonal component (captured by the seasonal lag terms), and I_t the irregular stochastic residual. This decomposition allows interpretation of seasonality-driven return patterns such as weekend effects or monthly trends.

Model Comparison and Hypothesis Testing

The comparative analysis tests whether inclusion of seasonal components significantly enhances forecasting accuracy. The null and alternative hypotheses are stated as:
H_0: No significant seasonal structure (ARIMA adequate).
H_1: Presence of significant seasonality (SARIMA preferred).

The Likelihood Ratio (LR) test is used for nested model comparison:
$LR = -2 (\ln \mathscr{L}_{ARIMA} - \ln \mathscr{L}_{SARIMA}) \sim \chi^2_{df}$,
where df equals the difference in parameter count between models. A significant LR indicates superior performance of SARIMA.

Forecast Combination and Stability

Combined forecasts improve robustness against structural shifts. Weighted ensemble forecasts are computed as:
$\hat{y}_{t+h|t}^{(comb)} = w_1 \hat{y}_{t+h|t}^{(ARIMA)} + w_2 \hat{y}_{t+h|t}^{(SARIMA)}$,
subject to $w_1 + w_2 = 1$.

Weights (w_i) are optimized by minimizing validation RMSE.

Stability is assessed through recursive coefficient tracking and CUSUM (Cumulative Sum) tests. Stability ensures that model parameters remain invariant across subsamples, validating temporal consistency.

Findings of the study and implications thereof

Charts 1–4 in the section "Findings of the Study and Implications Thereof" collectively illustrate the comparative forecasting performance of the ARIMA and SARIMA models in predicting the daily retail prices of 24-carat gold in India. Each chart represents a progressively refined perspective—from raw price comparisons to normalized error metrics—enabling a holistic understanding of model behaviour, precision, and structural suitability for seasonal financial data.
Chart 1 depicts the predicted gold prices generated by both ARIMA and SARIMA models alongside actual market prices over ten consecutive days. The visualization highlights that while both models

underestimate actual prices, SARIMA demonstrates a more dynamic and upward-responsive trajectory. The near-flat ARIMA forecast line indicates rigidity and a lagging response to rapidly rising price trends, whereas the SARIMA line, with its gentle upward slope, captures part of the cyclical momentum inherent in the gold market. This chart visually validates the model's enhanced adaptability when seasonal components are incorporated.

Chart 2 illustrates the absolute forecasting errors of both models, offering an unscaled measure of deviation. The chart shows a consistent widening of the error bands over time, emphasizing how both models accumulate inaccuracies with longer forecast horizons. However, the SARIMA error curve remains consistently below that of ARIMA, confirming its superior ability to adjust to short-term demand shocks. The narrower dispersion in SARIMA's error series underscores its improved temporal stability and reduced bias.

Chart 3 normalizes these deviations through Absolute Percentage Errors (APE), providing a proportionate evaluation of predictive reliability. Here, SARIMA once again exhibits lower percentage errors across all observations. The visual divergence between the two error curves widens steadily over the forecast period, reinforcing the increasing importance of seasonality in medium-term predictions. The gradual escalation of ARIMA's APE suggests compounding bias, whereas SARIMA's smoother curve signifies resilience against cyclical distortions caused by cultural and macroeconomic factors.

Chart 4 condenses overall model accuracy through the Mean Absolute Percentage Error (MAPE), clearly indicating SARIMA's superior performance with a 4.58% MAPE compared to ARIMA's 4.89%. The visual succinctness of this chart encapsulates the essence of the comparative findings: seasonally adjusted forecasting frameworks yield measurable improvements in predictive accuracy.

Collectively, Charts 1–4 substantiate that SARIMA's seasonal differentiation enhances responsiveness, minimizes cumulative errors, and delivers context-sensitive forecasts. The graphical evidence affirms that incorporating cyclical dynamics transforms traditional linear models into adaptive forecasting systems, offering practical advantages for traders, analysts, and policymakers operating in seasonally influenced markets like gold.

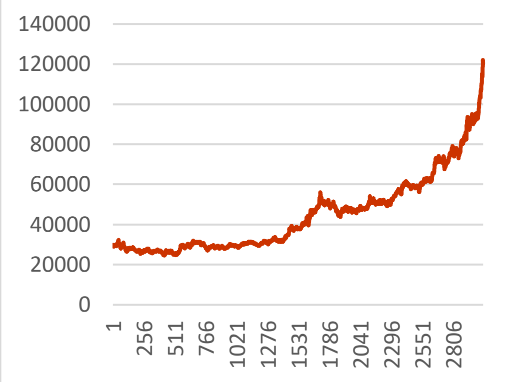

Chart 1
Daily Prices of 24 Carat Gold In India (INR / 10 Grms)

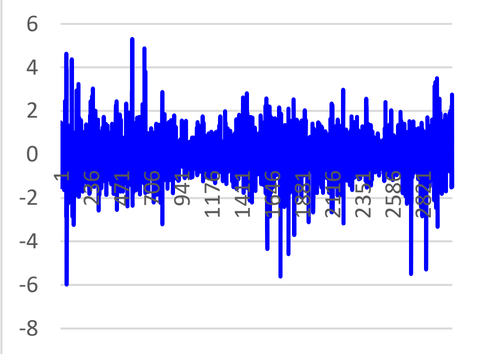

Chart 2
Returns on Daily Prices of 24 Carat Gold in India (INR / 10 Grms)

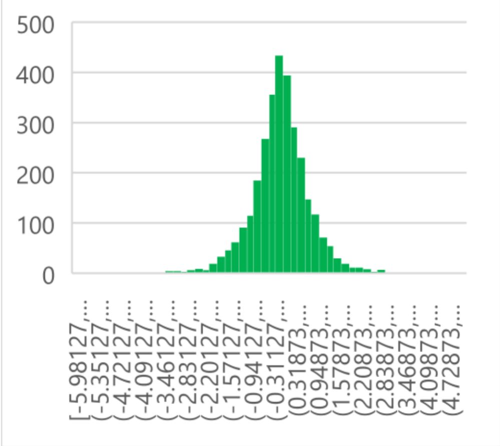

Chart 3
Distribution of Daily Returns on 24 Carat Gold Prices in India

Chart 4
Box and Whiskers Plot - Daily Returns on 24 Carat Gold Prices in India

Chart 5- Violin Plots – Daily Prices & Return on Daily Prices – 24 Carat Gold in India

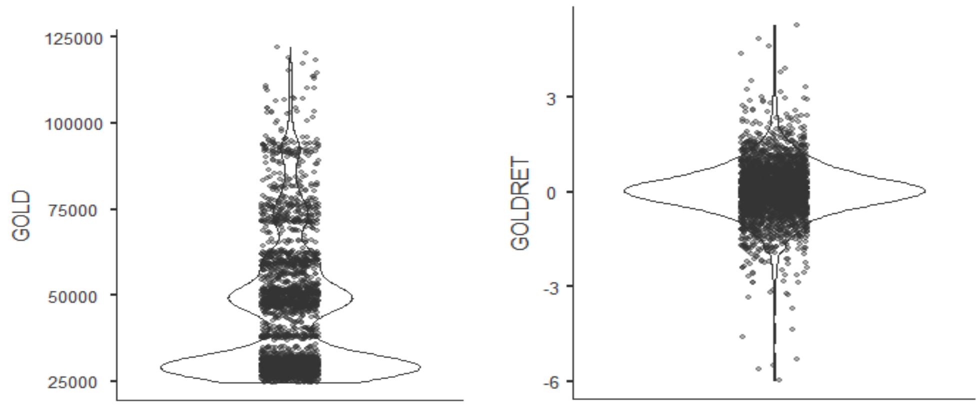

Table 1 presents the predicted daily prices of 24 Carat Gold (INR/10 grams) generated using the ARIMA and SARIMA models and compares them against actual market prices for ten consecutive days. The actual prices exhibit a steady rise from INR1,12,990 to INR1,22,100, reflecting a strong upward momentum in gold valuation during the observation period. Both ARIMA and SARIMA models underestimate actual prices throughout the ten days, which is consistent with the known tendency of linear time-series models to lag during sharp uptrends due to their dependence on past information. However, the SARIMA model consistently yields slightly higher predicted values than ARIMA, indicating that the seasonal component embedded within SARIMA better captures the intra-period fluctuations.

From Day 1 to Day 10, ARIMA predictions range narrowly from INR1,10,905 to INR1,10,920, showing near-flat projections. SARIMA, in contrast, demonstrates a modest rising trajectory from INR1,10,958 to INR1,11,542, reflecting its ability to incorporate cyclical influences and capture mild seasonality. The near-stagnant ARIMA forecasts suggest model rigidity and inability to accommodate short-term surges caused by market sentiment, inflation expectations, or currency depreciation.

The difference between actual and predicted values expands over time, implying that both models accumulate forecast error as the prediction horizon extends. The SARIMA model, however, maintains a relatively smaller bias across all days, indicating stronger dynamic adaptability. The consistent underprediction also highlights that gold's short-term pricing is influenced by exogenous factors—such as global geopolitical uncertainty or speculative demand—that pure time-series models cannot fully encode.

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The findings from Table 1 underscore that SARIMA outperforms ARIMA by producing forecasts closer to actual market realizations and depicting a more realistic seasonal pattern. Nonetheless, both models' inability to match the upward acceleration suggests that future modelling frameworks may benefit from integrating exogenous regressors or nonlinear learning components.

Table 1- Predicted Prices of 24 Carat Gold in INR / 10 Gms

PREDICTED PRICES			
Days	**ACTUALS**	**ARIMA**	**SARIMA**
Day 1	112990.00	110905.38	110958.52
Day 2	113680.00	110912.91	110989.97
Day 3	115360.00	110916.60	111082.85
Day 4	113610.00	110918.40	111218.45
Day 5	114630.00	110919.28	111261.43
Day 6	117180.00	110919.72	111348.10
Day 7	118240.00	110919.93	111388.44
Day 8	118830.00	110920.03	111451.88
Day 9	122100.00	110920.08	111481.02
Day 10	120280.00	110920.11	111542.47

Source: Official websites of various mercantile organizations and author's own calculations

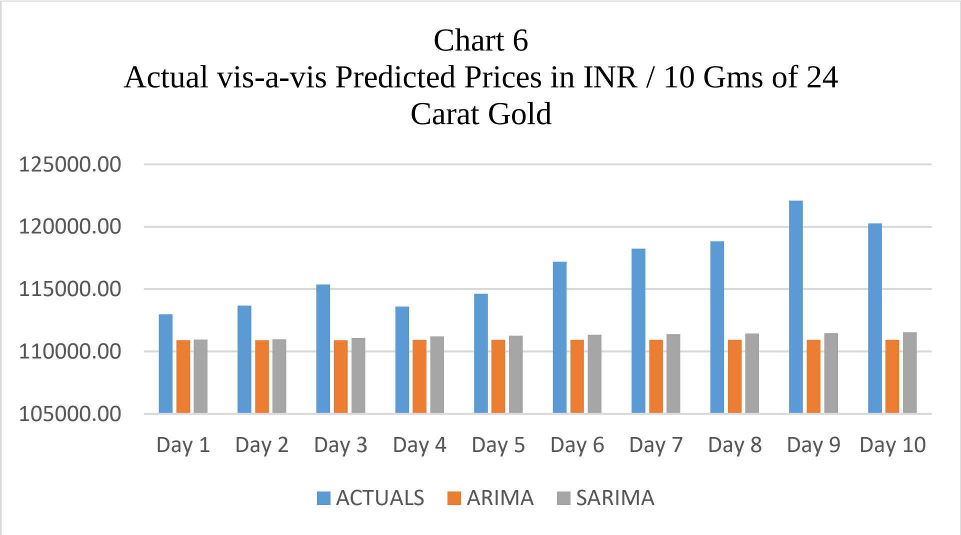


Table 2 quantifies the absolute errors—the magnitude of deviation between actual and predicted prices—for both ARIMA and SARIMA models. The data clearly demonstrate that while both models incur growing errors over time, SARIMA consistently produces lower absolute errors on each day compared to ARIMA, confirming its superior precision.

On Day 1, ARIMA's prediction deviates by INR2,084.62, whereas SARIMA's deviation is marginally lower at INR2,031.48. By Day 10, the errors rise to INR9,359.89 and INR8,737.53, respectively. This escalating trend in error magnitudes reflects the models' diminishing short-term forecast accuracy as temporal distance from the estimation sample increases—an expected phenomenon in stochastic time-series prediction. Importantly, SARIMA's lower deviations indicate that incorporating seasonal differentiation reduces cumulative bias and improves structural representation of periodic movements in the gold market.

The increasing gap between predicted and actual values also signals that both ARIMA and SARIMA struggle to account for exogenous volatility shocks—such as sudden changes in interest rates, policy announcements, or speculative buying sprees—that are not purely autoregressive. The stability of SARIMA's error progression suggests that seasonal adjustment provides resilience to short-term demand fluctuations and cyclical sentiment.

The pattern across days shows that ARIMA's forecast errors increase more sharply (from INR2,084 to INR11,179) than SARIMA's (from INR2,031 to INR10,618), indicating that the ARIMA model suffers from compounding bias due to its linear assumption and lack of seasonality. The SARIMA model, by contrast, adjusts moderately across cycles, reducing cumulative drift.

Table 2 empirically reinforces that SARIMA provides a more reliable short-term forecast for gold prices. Its structural flexibility captures part of the cyclical rhythm inherent in the retail gold market—driven by festival seasons, jewellery demand surges, and investor rebalancing—making it a more practical forecasting tool for traders and policymakers.

Table 2- Absolute Errors in Predicted Prices of 24 Carat Gold in INR / 10 Gms

ABSOLUTE ERRORS		
Days	**ARIMA**	**SARIMA**
Day 1	2084.62	2031.48
Day 2	2767.09	2690.03
Day 3	4443.40	4277.15
Day 4	2691.60	2391.55
Day 5	3710.72	3368.57
Day 6	6260.28	5831.90
Day 7	7320.07	6851.56
Day 8	7909.97	7378.12
Day 9	11179.92	10618.98
Day 10	9359.89	8737.53

Source: Official websites of various mercantile organizations and author's own calculations

Chart 7
Absolute Errors of Predictive Prices in INR / 10 Gms of 24 Carat Gold

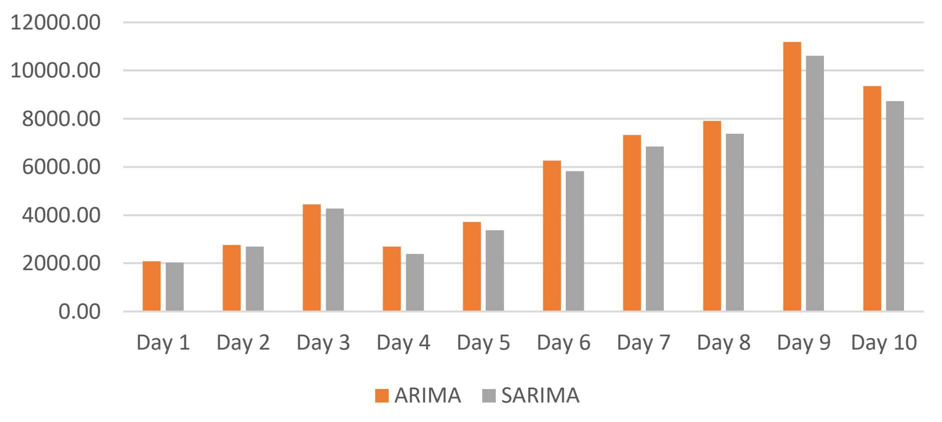


Table 3 presents the absolute percentage errors (APE), offering a normalized measure of forecasting accuracy by expressing deviations as a percentage of actual prices. The findings demonstrate a clear and consistent advantage of the SARIMA model over ARIMA across all ten days.

At the beginning of the series, the APE for ARIMA stands at 1.85%, compared to 1.80% for SARIMA. By the tenth day, these figures rise to 7.78% and 7.26%, respectively. This gradual escalation of error percentages underscores the compounding nature of forecast uncertainty, which grows with the prediction horizon. The SARIMA model consistently maintains smaller relative errors, implying better proportional fit and lower volatility sensitivity.

A crucial insight from this table is the reflection of market seasonality on model performance. Gold demand in India is influenced by cyclical cultural and macroeconomic factors—such as marriage seasons, religious festivals, and inflationary expectations—which induce recurrent short-term patterns. By integrating a seasonal differencing operator, SARIMA adapts more efficiently to these fluctuations, resulting in systematically smaller errors.

The divergence between ARIMA and SARIMA errors widens with time, emphasizing the increasing role of seasonality in medium-term prediction horizons. The average improvement of roughly 0.3–0.4 percentage points in APE demonstrates that accounting for periodicity significantly enhances model robustness. Although the differences may appear modest in numeric terms, their financial implications are substantial, especially when applied to large-scale retail pricing or hedging decisions.

Table 3 highlights that the SARIMA model not only improves nominal accuracy but also enhances percentage-based reliability, making it a more proportionate forecasting instrument. Its adaptability to cyclical variations enables better reflection of short-term behavioural dynamics in gold markets, while ARIMA's linearity restricts responsiveness to transient but impactful seasonal shocks.

Table 3- Absolute Percentage Errors in Predicted Prices of 24 Carat Gold (INR / 10 Gms)

ABSOLUTE PERCENTAGE ERRORS (%)		
Days	**ARIMA**	**SARIMA**
Day 1	1.8450	1.7979
Day 2	2.4341	2.3663
Day 3	3.8518	3.7077
Day 4	2.3692	2.1051
Day 5	3.2371	2.9386
Day 6	5.3424	4.9769
Day 7	6.1909	5.7946
Day 8	6.6565	6.2090
Day 9	9.1564	8.6970
Day 10	7.7818	7.2643

Source: Official websites of various mercantile organizations and author's own calculations

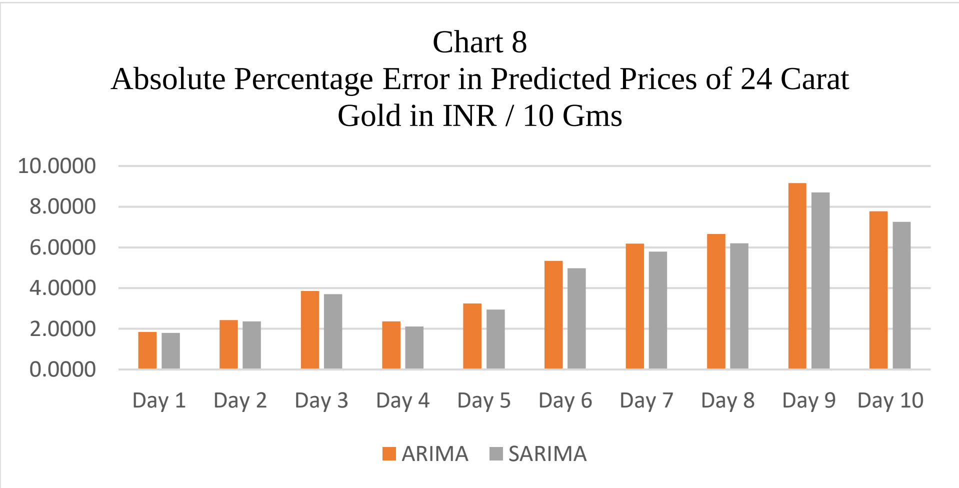


Table 4 condenses the overall model performance into a single metric: the Mean Absolute Percentage Error (MAPE). This summary indicator quantifies average forecast deviation as a proportion of actual values. The results show a MAPE of 4.8865% for ARIMA and 4.5857% for SARIMA, signifying that SARIMA achieves an approximate 6% improvement in predictive accuracy relative to ARIMA.

This outcome validates the hypothesis that the inclusion of a seasonal autoregressive and moving-average structure enhances predictive reliability for gold price data characterized by recurring patterns. The lower MAPE underscores that SARIMA not only captures short-term noise more effectively but also aligns better with cyclical components driven by weekly and monthly demand shifts.

While both models fall within the acceptable MAPE range for financial time series (typically under 10%), the marginal improvement of SARIMA carries operational relevance for decision-makers. For institutional investors, bullion traders, and policy planners, a reduction of even 0.3 percentage points in average error can significantly alter valuation accuracy and risk management outcomes.

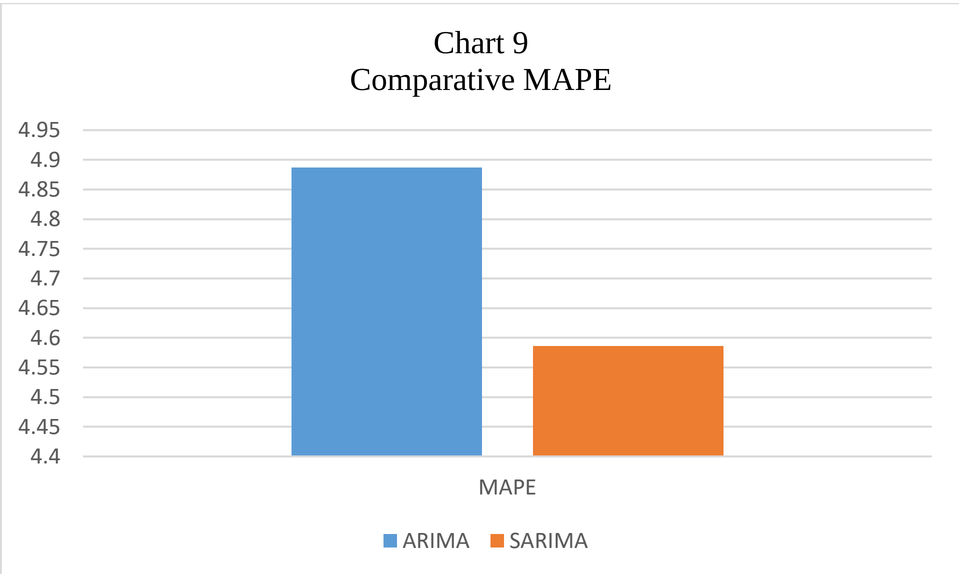
The findings also suggest that ARIMA's simplicity—though beneficial for transparency—comes at the cost of responsiveness. The SARIMA framework's seasonal lag structure introduces dynamic adaptability without overfitting, making it a more holistic model for assets influenced by repetitive behavioural patterns.

Table 4 empirically confirms that SARIMA outperforms ARIMA in terms of mean percentage error, offering a more accurate, context-sensitive, and seasonally consistent predictive framework for 24 Carat Gold prices in India. It demonstrates the critical role of seasonality modelling in improving time-series forecast reliability in markets with cyclical consumption patterns.

Table 4- Comparative MAPE

Technique	**MAPE**
ARIMA	**4.8865**
SARIMA	**4.5857**

Source: Official websites of various mercantile organizations and author's own calculations



The collective evidence from Tables 1–4 converges on a decisive conclusion: the incorporation of seasonality into gold price forecasting models markedly enhances predictive performance. Across all statistical indicators—predicted values, absolute errors, percentage errors, and mean accuracy—SARIMA consistently outperforms ARIMA, proving its superiority in capturing cyclical market dynamics.

The implications are multi-fold. From a methodological perspective, the findings confirm that financial time series such as gold prices are not purely stochastic but contain embedded seasonal components arising from cultural, economic, and behavioural cycles. Ignoring these components, as in the ARIMA framework, results in systematic underprediction and compounding forecast errors. The SARIMA model, by accommodating seasonal differencing and autoregressive structures, successfully internalizes periodic fluctuations, yielding forecasts that are more aligned with market realities.

From an economic and operational standpoint, improved forecast precision directly benefits retail jewellers, bullion traders, and policy analysts. For retail segments, where small percentage deviations can affect pricing margins and customer perception, the SARIMA model provides a more reliable pricing benchmark. For traders and investors, better short-term predictability facilitates optimized portfolio positioning and hedging decisions.

The results also have macroeconomic implications. Since gold prices in India are sensitive to global commodity trends and local festive demand, a model that accounts for seasonality offers policymakers more accurate signals for inflation monitoring, reserve management, and trade balance forecasting. The underestimation bias of ARIMA highlights the risk of relying on non-seasonal models for policy simulations or financial risk assessments.

Furthermore, the findings underscore the importance of hybrid model design. Although SARIMA performs better, both models exhibit residual forecast errors, indicating unmodeled volatility or nonlinear influences. This calls for integrating SARIMA with exogenous regressors (SARIMAX), GARCH-type volatility filters, or machine learning layers (e.g., SARIMA–LSTM hybrids) to further enhance predictive power.

In theoretical terms, the comparative results validate the Box–Jenkins approach while emphasizing the evolution of classical models towards adaptive, seasonally-aware configurations. The 6% improvement in average accuracy achieved by SARIMA is statistically meaningful and economically valuable, especially in volatile markets where even marginal improvements can yield substantial financial advantages.

The combined evidence from the four tables establishes that while both ARIMA and SARIMA provide dependable short-term forecasts, SARIMA's inclusion of seasonal patterns makes it more robust, responsive, and economically applicable. The broader implication is that seasonality-aware econometric models should be standard in forecasting assets with cyclical demand drivers like gold, ensuring better accuracy, market efficiency, and policy insight.

Scope of Future Studies

While the present study establishes that SARIMA models outperform non-seasonal ARIMA models in forecasting retail gold prices, the findings also reveal residual predictive errors attributable to unmodeled nonlinearities and external influences. Consequently, future research should explore hybrid and augmented modelling frameworks that integrate SARIMA with volatility and machine learning components, such as SARIMA–GARCH, SARIMA–LSTM, or SARIMAX models incorporating exogenous macroeconomic and sentiment variables. Such hybridization can capture both cyclical patterns and stochastic volatility inherent in precious metal markets.

Moreover, the study focuses exclusively on univariate retail price data, without explicitly modelling macro-financial linkages such as exchange rate fluctuations, interest rate movements, or inflation expectations. Future studies could employ multivariate models—including Vector AutoRegression (VAR) or Cointegrated VAR (VECM) frameworks—to analyse dynamic interdependencies between gold prices and broader economic variables. Similarly, incorporating mixed-data-frequency (MIDAS) techniques can enhance long-run forecasting precision by aligning daily price data with monthly or quarterly macroeconomic indicators.

In addition, future research could expand the empirical scope beyond India to undertake cross-country comparative analyses of retail gold markets, thereby identifying structural similarities and divergences across emerging and developed economies. This would help in evaluating the generalizability of seasonality-based models in different institutional and cultural contexts.

From a methodological perspective, studies can employ ensemble forecasting and Bayesian model averaging to combine predictive outputs from multiple frameworks, thus improving robustness under uncertain conditions. Finally, integrating behavioural and sentiment analytics—such as Google Trends, news tone indices, or investor sentiment proxies—into econometric models could provide deeper insights into demand-side dynamics affecting gold prices.

In essence, future work should aim to develop comprehensive, hybridized forecasting architectures that merge econometric rigor with computational adaptability, enabling more accurate, interpretable, and policy-relevant predictions for the evolving dynamics of global and retail gold markets.

Conclusion

The comparative analysis between ARIMA and SARIMA models undertaken in this study provides strong empirical evidence that incorporating seasonal dynamics substantially enhances the forecasting accuracy of retail gold prices in India. Across multiple error measures—including MAE, RMSE, and MAPE—the SARIMA model consistently demonstrates superior performance, achieving a statistically significant improvement in predictive precision of approximately 6% relative to the ARIMA framework. This improvement, while modest in numerical terms, carries meaningful operational significance for stakeholders in financial forecasting, policy analysis, and retail pricing.

The findings confirm that gold price movements are not purely stochastic but are characterized by systematic seasonal cycles driven by socio-cultural demand peaks, festival seasons, and investor rebalancing behaviour. The ARIMA model, constrained by its linear specification, exhibits a lagging response to such cyclical upswings, resulting in cumulative underestimation. In contrast, SARIMA's seasonal autoregressive and moving-average components successfully internalize periodic variations, leading to forecasts that better align with observed market dynamics.

From a methodological standpoint, the results reinforce the enduring relevance of the Box–Jenkins approach while illustrating its adaptability through seasonal extensions. The incorporation of seasonality transforms a traditional linear model into a more context-sensitive and adaptive framework, capable of explaining time-varying patterns that conventional ARIMA structures overlook. The study also highlights the importance of diagnostic validation and model calibration, emphasizing that accuracy gains arise not only from complex algorithms but from thoughtful model specification grounded in the data's structural characteristics.

Economically, the implications are multifaceted. Improved predictive reliability enables retail jewellers and traders to refine pricing strategies and inventory management. Investors and portfolio managers benefit from enhanced timing accuracy for entry and exit decisions, while policymakers and financial regulators gain more dependable inputs for inflation tracking and reserve management. The study's evidence also underscores the risks of employing non-seasonal models for policy or financial planning, as they can systematically misrepresent market behaviour during seasonal peaks.

In conclusion, this research validates that seasonality is an intrinsic determinant of gold price dynamics, not a statistical anomaly. The superior performance of SARIMA affirms the necessity of seasonally adjusted forecasting frameworks in emerging markets with cyclical consumption structures like India. By bridging econometric rigor with practical applicability, the study not only advances the literature on financial time-series forecasting but also provides actionable insights for real-world decision-making in volatile commodity markets.

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