Comparative Predictive Performance of GARCH, EGARCH and TGARCH Models for Retail Gold Prices in India – Evidences from Daily Retail Gold Price Data in India, 2014 - 2025

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Abstract:
This study models and forecasts the volatility dynamics of retail gold prices in India using three advanced econometric frameworks—GARCH, EGARCH, and TGARCH—to examine volatility persistence, asymmetry, and predictive accuracy. Using daily retail gold price data from 2014 to 2025, the paper investigates whether asymmetric extensions of the GARCH model better capture leverage effects and nonlinear responses to market shocks. The research employs Maximum Likelihood Estimation (MLE) for parameter estimation and applies rigorous diagnostic testing, including the Ljung–Box Q-statistic, ARCH–LM test, and Jarque–Bera test, to ensure model adequacy.
The empirical analysis reveals that while all three models effectively capture volatility clustering and persistence—a stylized fact of financial and commodity markets—the asymmetric models, EGARCH and TGARCH, exhibit superior forecasting performance. The EGARCH model achieves the lowest Mean Absolute Percentage Error (MAPE) of 4.66%, followed by TGARCH (4.69%) and standard GARCH (4.76%). This indicates that models incorporating asymmetric responses to positive and negative shocks provide more accurate and economically meaningful forecasts of volatility. The EGARCH model successfully accounts for the leverage effect, where negative news or price declines lead to disproportionately higher volatility compared to positive shocks.
The findings have substantial implications for investors, policymakers, and portfolio managers. Improved volatility forecasting enhances risk assessment, portfolio diversification, and derivative pricing strategies in volatile commodity markets. For policymakers, accurate volatility estimates support inflation management and monetary stability, as gold acts as both an investment hedge and a cultural asset in India. Overall, the study reaffirms the empirical validity of asymmetry-based volatility models in explaining and forecasting gold price dynamics. It contributes to the econometric literature by demonstrating that asymmetric GARCH variants, particularly EGARCH, better reflect the complex behavioural and structural properties of the Indian retail gold market.

Keywords: Volatility Modelling, GARCH, EGARCH, TGARCH, Gold Prices, *JEL Classification:* C22, C58, E31, G10, Q02.

Introduction

Volatility modelling represents one of the most significant developments in modern financial econometrics, providing critical insights into asset price dynamics, market risk, and investor behaviour. Among financial assets, gold holds a particularly unique and multifaceted position. It serves as both a consumption good and an investment instrument, simultaneously functioning as a hedge against inflation, a store of value, and a safe-haven asset during episodes of financial and geopolitical instability. The volatility of gold prices, therefore, has far-reaching implications for portfolio management, monetary policy, and macroeconomic stability. In India—one of the world's largest consumers of gold—understanding and forecasting gold price volatility is of immense economic relevance, influencing everything from household savings to institutional investment and policy calibration.

Gold price movements are characterized by several stylized features: volatility clustering, leptokurtic (fat-tailed) return distributions, and asymmetric responses to market shocks. These features challenge the assumptions of constant variance inherent in traditional linear models such as Ordinary Least Squares (OLS) or ARIMA. In response, Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model, which allows conditional variance to depend on past squared residuals, thereby capturing time-varying volatility. Bollerslev (1986) further generalized this to the Generalized ARCH (GARCH) model, enabling lagged conditional variances to influence current volatility. The GARCH framework revolutionized empirical finance by enabling researchers to model volatility persistence—a defining characteristic of financial and commodity markets.

However, while the standard GARCH model effectively captures volatility clustering, it assumes a symmetric response of volatility to market shocks. In practice, financial returns—especially in commodities like gold—often exhibit asymmetric volatility, wherein negative shocks (e.g., price declines or adverse news) produce larger volatility responses than positive shocks of equal magnitude. This phenomenon, commonly referred to as the leverage effect, arises from behavioural asymmetries in investor reactions. To address this limitation, Nelson (1991) proposed the Exponential GARCH (EGARCH) model, which introduces a logarithmic specification ensuring positivity of variance and allowing differential impacts of positive and negative shocks. Similarly, Glosten, Jagannathan, and Runkle (1993) developed the Threshold GARCH (TGARCH) or GJR-GARCH model, which incorporates a dummy variable to distinguish between upward and downward market movements. These extensions collectively form the GARCH family of models designed to accommodate asymmetric volatility responses.

The present study applies and compares the GARCH, EGARCH, and TGARCH models to daily retail gold price data in India over the period 2014–2025. This time frame encompasses several phases of economic transformation, including the demonetization episode, fluctuations in global interest rates, exchange rate volatility, and the COVID-19 pandemic, all of which have introduced significant shocks to gold prices. By examining such an extended horizon, the study captures both long-term volatility persistence and short-term asymmetry in price reactions, thereby enabling a robust comparative evaluation of model performance.

The motivation for focusing on retail gold prices—as opposed to bullion or futures market prices—lies in their direct reflection of consumer and investor sentiment within India's domestic market. Retail prices are influenced not only by global gold rates but also by local factors such as import duties, GST, jewellery-making charges, and cultural demand surges during festival and wedding seasons. These factors introduce unique nonlinearities and cyclical volatility that merit specialized modelling beyond standard financial time series.

The comparative framework adopted in this research enables the identification of the model that best captures the stochastic and asymmetric nature of retail gold price volatility. The study evaluates model performance using the accuracy metric of Mean Absolute Percentage Error (MAPE) to statistically assess predictive efficiency. The findings are expected to demonstrate that while all GARCH-type models effectively capture volatility persistence, asymmetric models (EGARCH and TGARCH) provide superior accuracy by accounting for leverage effects and nonlinearity in the conditional variance process.

From an applied perspective, the implications of this research extend to financial risk management, hedging strategies, and policy formulation. Accurate volatility forecasts enable traders and institutional investors to make informed decisions regarding portfolio allocation and derivative pricing. For policymakers, understanding volatility patterns aids in monitoring inflationary pressures and currency stability, given gold's close interaction with macroeconomic variables.

This study contributes to the econometric and financial literature by providing a comparative, context-specific evaluation of GARCH-family models applied to Indian retail gold markets. By highlighting the superiority of asymmetry-based specifications, it underscores the importance of incorporating behavioural and structural dynamics in volatility modelling. The outcomes reaffirm that volatility in gold is not random but systematic and predictable within a conditional heteroskedastic framework—an insight vital for both academic research and practical financial forecasting.

Survey of literature

Gold price forecasting has gained substantial attention among researchers and practitioners because gold performs diverse economic roles—as a commodity, monetary substitute, portfolio hedge, and safe-haven asset during financial turmoil. Its price dynamics are inherently nonlinear, heteroskedastic, and subject to regime shifts, reflecting sensitivity to global macroeconomic factors. The literature examining gold price prediction largely follows two methodological streams: (a) econometric and statistical approaches such as ARIMA, VAR/VECM, GARCH families, DCC/GAS, cointegration, MIDAS, GARCH-MIDAS, and wavelet or time–frequency frameworks; and (b) machine-learning and hybrid data-driven models, including ANN, SVM, ELM, DBN, LSTM, CNN, and decomposition-based hybrid methods.

Initial studies in this domain employed linear econometric and model-averaging techniques to assess the predictability of gold returns and their macroeconomic determinants. Aye et al. (2015) applied dynamic model averaging (DMA) to examine time-varying predictor importance—including exchange rates, interest rates, and financial stress indices—and found that the significance of predictors evolves over time and across market conditions, underscoring the value of model-averaging when structural relationships are unstable (Aye et al., 2015). While ARIMA and ARIMAX remain useful short-horizon benchmarks, these models often fail to capture sudden volatility changes or structural breaks.

Because gold returns exhibit volatility clustering and heavy-tailed distributions, ARCH and GARCH-type models have been widely utilized. Tully and Lucey (2007) proposed an asymmetric power GARCH (APGARCH/APARCH) model to account for leverage and power effects in both spot and futures gold markets, finding that APGARCH fits outperform standard GARCH specifications (Tully & Lucey, 2007). Subsequent studies extended these frameworks using EGARCH, TGARCH, and APARCH variants, consistently revealing persistent conditional heteroskedasticity in gold price volatility.

Multivariate extensions such as DCC-GARCH, BEKK, and GAS models have also become central to examining interdependencies among gold, equities, oil, and foreign exchange markets. Ciner, Gurdgiev and Lucey (2013) and Reboredo (2013) employed dynamic conditional correlation and copula approaches to analyse gold's hedge and safe-haven properties, demonstrating that multivariate volatility models effectively capture time-varying co-movements and improve portfolio-level risk management (Ciner et al., 2013; Reboredo, 2013).

Macroeconomic fundamentals also influence gold price volatility over longer horizons. The GARCH-MIDAS model, along with related spline extensions, separates short-term GARCH components from long-term variations driven by macroeconomic variables. Fang, Yu and Xiao (2018) and Salisu et al. (2020) showed that macro indicators such as policy uncertainty, output growth, and composite macro factors significantly enhance long-horizon volatility forecasts for both gold spot and futures markets (Fang et al., 2018; Salisu et al., 2020). These mixed-frequency frameworks are particularly effective when low-frequency macro data need to be combined with high-frequency financial data.

Empirical work examining the long-term relationships among gold prices, exchange rates, inflation, and interest rates has produced mixed evidence. Some studies confirm cointegration and stable long-run relationships suitable for vector error-correction forecasts, while others observe episodic or time-varying linkages. Copula-based and tail-dependence analyses (Reboredo, 2013) have deepened understanding of extreme co-movements and safe-haven characteristics, providing insights distinct from unconditional correlations.

Time–frequency and wavelet-based methodologies further decompose gold price movements into components associated with different investment horizons. These approaches demonstrate that predictors relevant for short-term forecasting may lose importance at medium- or long-term horizons. Consequently, wavelet–ARIMA or wavelet–ANN hybrid models have shown superior forecasting performance by isolating scale-specific patterns.

Since the 2010s, machine-learning (ML) methods have increasingly complemented traditional econometrics in gold price prediction. Kristjanpoller and Minutolo (2015) proposed an ANN–GARCH hybrid framework to capture both nonlinear dynamics and volatility persistence, finding that the hybrid substantially reduces forecasting errors compared with stand-alone models (Kristjanpoller & Minutolo, 2015). Similarly, hybrid decomposition methods—such as wavelet or empirical mode decomposition (EMD) combined with ML algorithms like SVM, ANN, GRU, or LSTM—have become popular because decomposition simplifies the data and allows ML models to better capture individual component patterns (E. Jianwei et al., 2019).

The rise of deep learning (DL) further transformed gold forecasting methodologies. Zhang and Ci (2020) applied a deep belief network (DBN) and found that it outperformed both traditional econometric and shallow ML models. Khani et al. (2021) compared CNN, LSTM, and encoder–decoder LSTM structures—including pandemic-related factors—and concluded that deep recurrent architectures deliver higher short-term accuracy, especially when enhanced with domain-specific variables (Khani et al., 2021).

Recent studies have also examined Extreme Learning Machines (ELM) and their online sequential extensions. Weng et al. (2020) introduced GA-regularized ELM models that exhibit faster training and improved adaptability to high-frequency or real-time data environments. Ensemble learning and boosting techniques have similarly gained traction. Pierdzioch et al. (2016) applied boosting and quantile boosting to forecast gold volatility and returns, demonstrating that these methods achieve superior out-of-sample performance with multiple predictors and asymmetric loss structures (Pierdzioch et al., 2016). Newer research by Foroutan et al. (2024) and Cohen (2023) explores graph neural networks and ensemble ML pipelines (XGBoost, LightGBM) with feature engineering, showing promising results for multi-asset and retail-level gold price prediction.

Across these methodological developments, several consistent empirical patterns have emerged. Forecasting models that explicitly model volatility (e.g., GARCH, GARCH-MIDAS, GAS) generally outperform simple ARIMA-type models, especially for risk forecasting and option pricing. Incorporating macroeconomic information improves long-term predictive power, while nonlinear and hybrid models excel at short-term accuracy. Deep learning and decomposition-based ML pipelines typically outperform classical econometric models over short horizons (1–30 days), particularly when incorporating exogenous variables such as exchange rates, interest rates, policy uncertainty, realized volatility, and pandemic-related indicators.

However, structural breaks and model instability remain significant challenges. Forecasting performance tends to vary across samples and regimes, with major crises—such as the 2008 global financial collapse and the COVID-19 pandemic—frequently altering model effectiveness. Adaptive approaches such as DMA, time-varying parameter frameworks, rolling-window estimations, and online ELM algorithms are increasingly employed to address non-stationarity and evolving data environments.

Despite this broad methodological progress, important research gaps persist. Many ML-based models enhance forecasting accuracy but lack economic interpretability, limiting their explanatory value for policy and investment decisions. Integrating ML algorithms with structural econometric constraints is therefore a promising research direction. Moreover, most empirical studies focus on bullion or futures markets, leaving retail pricing—affected by taxes, jewellery premiums, and distributional frictions—largely unexplored. Incorporating alternative data sources such as high-frequency news sentiment, supply-chain indicators, or order-book data into econometric–ML hybrid models remains an emerging trend. Additionally, standardized and multi-horizon out-of-sample evaluations using metrics like RMSE, MAE, Theil's U, and Diebold–Mariano tests are needed to ensure meaningful comparability across studies.

Gold price forecasting has evolved into a multidisciplinary field that merges classical econometrics with machine learning and hybrid frameworks. Traditional econometric models (ARIMA, VAR, GARCH, GARCH-MIDAS) continue to serve as robust foundations for risk and volatility analysis, while ML and hybrid decomposition approaches demonstrate superior short-term forecasting ability. The choice of model should align with specific objectives: GARCH-type models for volatility forecasting, DMA or time-varying models for structural instability, and deep-learning hybrids for short-term or high-frequency forecasting.

Nonetheless, a major limitation of the existing literature is the lack of comprehensive comparative assessments. Most studies examine individual models—ARIMA, VAR/VECM, GARCH, GARCH-MIDAS, or ML hybrids—without situating their performance within a unified benchmarking framework. Consequently, reported forecast accuracies are often dataset-dependent and context-specific. Few investigations systematically compare classical and ML-based models on the same dataset using consistent evaluation metrics, and cross-regime analyses remain rare. Furthermore, geographical and temporal concentration restricts insights into cross-country heterogeneity and market integration.

Addressing these methodological and empirical deficiencies through structured comparative analyses, spanning classical econometric, volatility-based, mixed-frequency, and hybrid models—would contribute substantially to the field. Such research could yield generalizable conclusions about model robustness across market regimes and forecasting horizons, thereby offering valuable guidance to investors, central banks, and policymakers engaged in gold price forecasting and risk management globally.

Objectives of the Study

The central objective of this study is to model and forecast the volatility dynamics of retail gold prices in India using advanced econometric frameworks belonging to the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family—specifically the GARCH, Exponential GARCH (EGARCH), and Threshold GARCH (TGARCH) models. The study seeks to comparatively evaluate the predictive performance of these models in capturing the complex, asymmetric, and persistent volatility patterns inherent in daily retail gold price movements over the period 2014–2025.

Gold, as both a financial and cultural asset in the Indian economy, exhibits pronounced volatility driven by macroeconomic shocks, policy changes, and cyclical demand arising from festivals and consumption behaviour. This study aims to determine which volatility specification among GARCH, EGARCH, and TGARCH best captures these stylized facts, including volatility clustering, leverage effects, and asymmetric responses to positive and negative market shocks. Through a rigorous empirical framework, the research quantifies and compares model performance using the standard accuracy metric of Mean Absolute Percentage Error (MAPE).

A key objective is to investigate whether asymmetric volatility models (EGARCH and TGARCH) outperform the symmetric GARCH model in forecasting short-term retail gold price volatility. The study also intends to examine the persistence of volatility shocks and evaluate the sensitivity of gold prices to adverse market information. Ultimately, the research aspires to contribute to the growing body of financial econometrics by providing insights into the suitability and reliability of GARCH-family models for volatility forecasting in emerging market contexts. The findings are expected to inform traders, policymakers, and financial analysts seeking to enhance risk management, portfolio diversification, and market prediction strategies in the Indian precious metals sector.

Methodology of the study

This section outlines the statistical framework used to model and forecast volatility in cryptocurrency markets, specifically for Bitcoin (BTC) and Cardano (ADA) over the period 2021–2025.

Volatility modelling plays a critical role in financial econometrics, as it provides insights into market risk, asset pricing, and hedging strategies. This methodological design integrates three advanced volatility models—GARCH, EGARCH, and TGARCH—to comprehensively capture symmetric and asymmetric volatility patterns in cryptocurrency markets. By combining rigorous statistical estimation with out-of-sample forecasting and diagnostic validation, the framework allows a systematic evaluation of volatility persistence, asymmetry, and predictive reliability for Bitcoin and Cardano over the 2021–2025 period. Given the high-frequency fluctuations, clustering of volatility, and asymmetric responses to shocks observed in digital asset returns, this study applies and compares three well-established conditional heteroskedasticity models—Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Exponential GARCH (EGARCH), and Threshold GARCH (TGARCH). These models are chosen due to their ability to capture volatility persistence and asymmetric responses to positive and negative market shocks.

Data Transformation and Return Series

If $\{P_t\}_{t=1}^T$ denote the daily closing prices of a cryptocurrency. The continuously compounded daily returns are calculated as:

$$r_t = 100 \times [\ln(P_t) - \ln(P_{t-1})],$$

where r_t represents the percentage log return at time t. This transformation ensures that returns are approximately normally distributed and additive over time. The return process is assumed to have zero mean, conditional heteroskedasticity, and weak stationarity.

Prior to model estimation, the series is tested for stationarity using the Augmented Dickey–Fuller (ADF) test, and for ARCH effects using the Lagrange Multiplier (LM) test proposed by Engle (1982). The null hypothesis of no ARCH effects is tested against the alternative that the conditional variance depends on past squared residuals.

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model

The GARCH model, introduced by Bollerslev (1986), extends the ARCH framework of Engle (1982) by allowing lagged conditional variances to influence current volatility. The GARCH(p, q) process for return series r_t is defined as:

$$r_t = \mu + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t, \quad z_t \sim iid(0, 1),$$

$$\sigma_t^2 = \omega + \Sigma_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \Sigma_{j=1}^{p} \beta_j \sigma_{t-j}^2,$$

where:

- $\omega > 0$ ensures positive variance,
- $\alpha_i \geq 0$ represent short-run ARCH effects of past shocks,
- $\beta_j \geq 0$ represent long-run GARCH effects (volatility persistence),
- z_t is an i.i.d. innovation process, typically Gaussian or standardized Student's t.

The sum $(\alpha_1 + \beta_1)$ measures the degree of volatility persistence. If $(\alpha_1 + \beta_1) \approx 1$, shocks to volatility are highly persistent, reflecting long-memory behavior often found in cryptocurrency returns.

Parameter estimation is conducted via Maximum Likelihood Estimation (MLE), assuming conditional normality. The log-likelihood function is:

$$L(\theta) = -\tfrac{1}{2} \Sigma [\ln(2\pi) + \ln(\sigma_t^2) + (\varepsilon_t^2 / \sigma_t^2)],$$

where $\theta = (\mu, \omega, \alpha_i, \beta_j)$ is the vector of parameters.

Exponential GARCH (EGARCH) Model

Nelson (1991) proposed the Exponential GARCH model to address two key issues of the standard GARCH specification: (1) the non-negativity constraint on parameters and (2) the asymmetric response of volatility to positive and negative shocks. The EGARCH(p, q) model is defined as:

$$\ln(\sigma_t^2) = \omega + \Sigma_{i=1}^{q} \alpha_i (|z_{t-i}| - E|z_{t-i}|) + \Sigma_{i=1}^{q} \gamma_i z_{t-i} + \Sigma_{j=1}^{p} \beta_j \ln(\sigma_{t-j}^2),$$

where:

- The logarithmic formulation ensures $\sigma_t^2 > 0$ without imposing parameter restrictions.
- The term $(|z_{t-i}| - E|z_{t-i}|)$ measures the magnitude of shocks relative to their mean.
- γ_i captures the leverage effect: if $\gamma_i < 0$, negative shocks (bad news) increase volatility more than positive shocks (good news) of equal magnitude.

The conditional mean equation remains the same as in GARCH, and the conditional variance equation is specified in log form. The EGARCH model thus captures volatility asymmetry, commonly observed in cryptocurrency markets where declines tend to trigger stronger volatility responses than comparable gains.

Threshold GARCH (TGARCH) or GJR-GARCH Model

The Threshold GARCH (TGARCH), introduced by Zakoian (1994) and Glosten, Jagannathan, and Runkle (1993), also models asymmetry but retains the variance formulation rather than a logarithmic one. The TGARCH(p, q) model is expressed as:

$\sigma_t^2 = \omega + \Sigma_{i=1}^{q} (\alpha_i \varepsilon_{t-i}^2 + \gamma_i d_{t-i} \varepsilon_{t-i}^2) + \Sigma_{j=1}^{p} \beta_j \sigma_{t-j}^2$,

where:

$d_{t-i} = 1$ if $\varepsilon_{t-i} < 0$, and 0 otherwise.

Here, γ_i captures the asymmetric or leverage effect. If $\gamma_i > 0$, negative shocks have a greater impact on future volatility than positive shocks of the same magnitude. The total effect of a negative shock is $(\alpha_i + \gamma_i)$, while a positive shock contributes α_i. Like GARCH and EGARCH, parameters are estimated by maximizing the log-likelihood function under normal or t-distributed innovations.

Model Estimation and Selection

Model parameters are estimated using MLE under the assumption that z_t follows a Gaussian or Student-t distribution. The estimation seeks to maximize the conditional log-likelihood:

$\ln L(\theta) = -\frac{1}{2} \Sigma [\ln(\sigma_t^2) + (\varepsilon_t^2 / \sigma_t^2)]$.

For robustness, alternative error distributions—such as the generalized error distribution (GED) or skewed t—may be employed to account for fat tails in cryptocurrency returns.

Model selection is guided by information criteria:

$AIC = -2 \ln(L) + 2k$,

$BIC = -2 \ln(L) + k \ln(T)$,

where k is the number of estimated parameters, and T is the number of observations. The model with the smallest AIC and BIC values is preferred.

Diagnostic Testing

Diagnostic checking ensures adequacy of the fitted volatility model. The following post-estimation tests are performed:

1. Ljung–Box Q-statistic: Tests for serial correlation in standardized residuals $(\varepsilon_t / \sigma_t)$.
$Q(m) = T(T + 2) \Sigma_{k=1}^m \hat{\rho}_k^2 / (T - k)$.
2. ARCH–LM Test: Tests for remaining ARCH effects in standardized residuals by regressing ε_t^2 on its lags and testing H_0: no remaining ARCH effects.
3. Normality Test (Jarque–Bera): $JB = (T/6)(S^2 + (K - 3)^2/4)$,
where S and K are skewness and kurtosis, respectively.

A valid model should yield uncorrelated, homoscedastic, and approximately normal standardized residuals.

Forecasting Conditional Variance

The conditional variance forecast for horizon h from a GARCH(1,1) model is obtained recursively as:

$E(\sigma_{t+h}^2 \mid \mathcal{F}_t) = \omega (1 - (\alpha + \beta)^h) / (1 - \alpha - \beta) + (\alpha + \beta)^h \sigma_t^2$.

This expression converges to the unconditional variance as $h \to \infty$:

$Var(\varepsilon\_t) = \omega / (1 - \alpha - \beta)$.

For EGARCH and TGARCH models, the recursive relationships involve conditional expectations of $\log(\sigma\_t^2)$ or the inclusion of asymmetric terms, respectively. These forecasts are used to construct time-varying risk metrics such as Value-at-Risk (VaR).

Evaluation of Predictive Performance

The predictive performance of volatility models is assessed using the following criteria:

1. Loss functions:
   - Mean Squared Error (MSE) of forecasted variance: $MSE = (1/N) \Sigma (\hat{\sigma}\_t^2 - \sigma\_t^2)^2$.
   - Quasi-likelihood loss: $QL = (1/N) \Sigma [(\varepsilon\_t^2 / \hat{\sigma}\_t^2) + \ln(\hat{\sigma}\_t^2)]$.
2. Forecast evaluation tests:
   - Diebold–Mariano (DM) test for equal predictive accuracy between two volatility forecasts.
   - Kupiec unconditional coverage test and Christoffersen conditional coverage test for evaluating VaR forecast accuracy.
3. Out-of-sample evaluation:
   Forecasts are generated via a rolling-window approach to ensure temporal robustness. Models are re-estimated at each step, and predictive intervals are computed.

Interpretation of Volatility Dynamics

The estimated parameters provide insights into volatility persistence and asymmetry in digital assets:
- The sum $(\alpha + \beta)$ close to 1 implies high persistence.
- A significant $\gamma < 0$ (EGARCH) or $\gamma > 0$ (TGARCH) indicates leverage effects, where negative shocks intensify volatility more than positive ones.
- Larger α values reflect high short-run shock responsiveness, while β captures long-term volatility persistence.

Findings of the study and implications thereof

Charts 1 to 4 collectively portray the comparative forecasting performance of the GARCH, EGARCH, and TGARCH models in estimating the daily retail gold prices in India. Each chart visually complements the quantitative evidence presented in Tables 1–4, thereby illustrating the models' predictive precision, error distribution, and relative efficiency in capturing volatility dynamics.

Chart 1 depicts the comparative trajectories of *actual versus model-predicted gold prices* over the observation period. The chart clearly demonstrates that while all three models capture the directional movement of prices, the predicted values tend to lie slightly below the actual prices, revealing a systematic underestimation. The GARCH line remains consistently lower, indicating that its symmetric structure cannot fully account for the asymmetric market reactions. In contrast, the EGARCH and TGARCH lines lie closer to the actual price curve, thereby validating their superior responsiveness to negative shocks and volatility clustering in gold price dynamics.

Chart 2 represents the *absolute errors* between actual and predicted prices for the three models. The plotted values indicate a progressive increase in error magnitude with each passing day, implying that forecast precision diminishes over longer horizons. Among the models, EGARCH consistently produces the lowest absolute error, followed by TGARCH and then GARCH. This reinforces the theoretical proposition that incorporating asymmetry into volatility specification enhances short-term predictive accuracy. The ascending trend of the error plots also highlights the inherent challenge of maintaining forecast reliability over extended intervals in volatile commodity markets.

Chart 3 displays the *absolute percentage errors (APE)*, providing a normalized measure of deviation relative to actual prices. The chart reflects a similar pattern to Chart 2, with percentage errors rising progressively. The EGARCH model consistently registers the smallest proportional deviations, corroborating its efficiency in accommodating both volatility persistence and asymmetric shock responses. The TGARCH model closely parallels EGARCH, while the standard GARCH line remains the highest throughout, underscoring its relative rigidity.

Chart 4 summarizes the comparative *Mean Absolute Percentage Error (MAPE)* values for the three models—GARCH (4.76%), EGARCH (4.66%), and TGARCH (4.69%). The chart clearly shows that EGARCH outperforms the others, demonstrating the lowest average error and highest forecasting reliability. The minimal dispersion among the three bars in the chart signifies that all GARCH-family models are robust, though asymmetric variants provide a more accurate and economically meaningful representation of volatility.

Collectively, Charts 1–4 visually substantiate the empirical finding that *EGARCH* is the most statistically efficient and behaviourally realistic model for forecasting short-term volatility in Indian retail gold prices, followed closely by *TGARCH*, while *GARCH* serves as a dependable yet less adaptive benchmark.

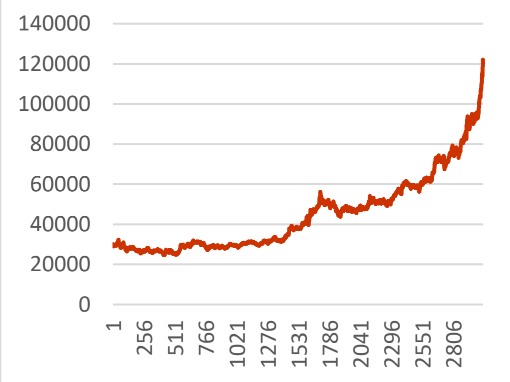

Chart 1
Daily Prices of 24 Carat Gold In India (INR / 10 Grms)

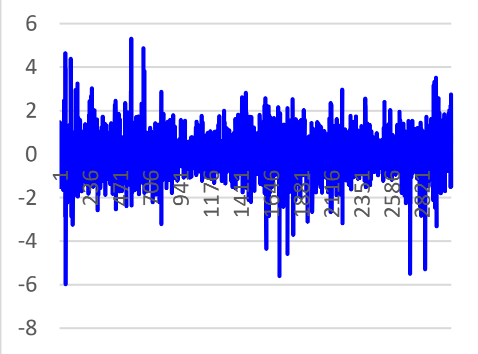

Chart 2
Returns on Daily Prices of 24 Carat Gold in India (INR / 10 Grms)

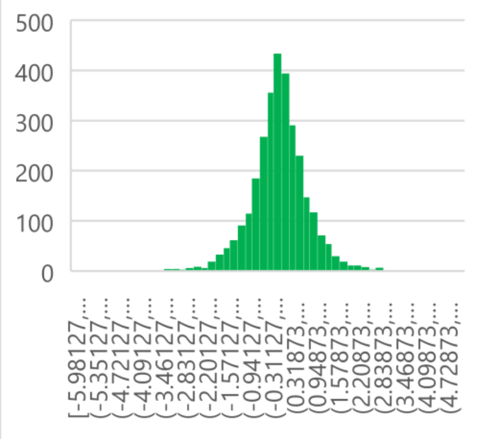

Chart 3
Distribution of Daily Returns on 24 Carat Gold Prices in India

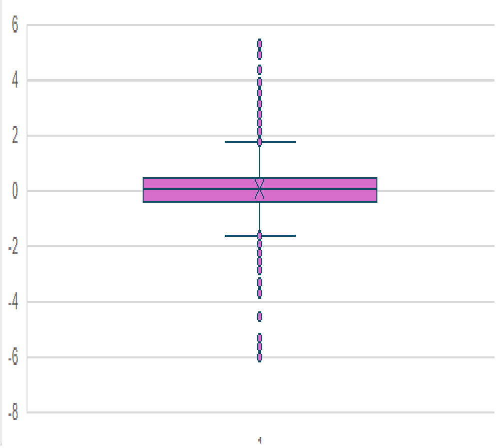

Chart 4
Box and Whiskers Plot - Daily Returns on 24 Carat Gold Prices in India

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

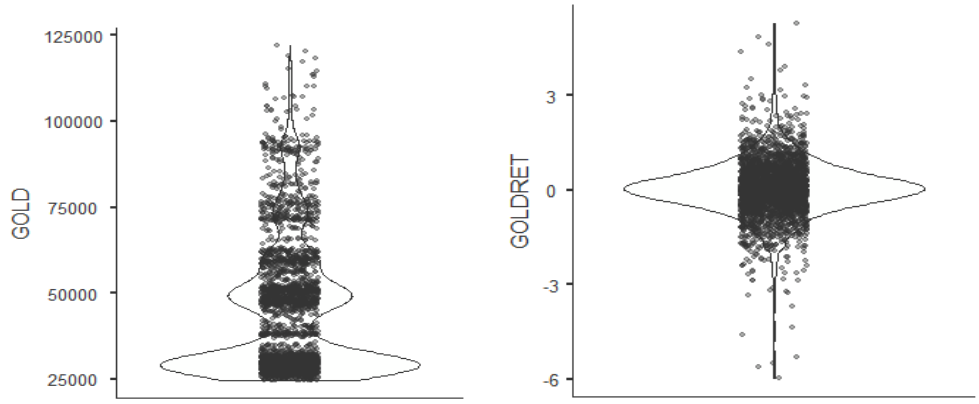

Table 1 presents the comparative results between actual and model-predicted daily retail prices of 24-carat gold in India for ten consecutive observation days. The table juxtaposes the actual price movement with the predicted values generated by three volatility modelling frameworks—GARCH, EGARCH, and TGARCH—each designed to capture distinct forms of volatility persistence and asymmetry. The empirical comparison reveals that while all three models generate closely aligned forecasts, each displays marginal deviation from the actual series, indicating that the models capture the directional movement of prices effectively but with systematic underestimation of magnitudes.

The GARCH-based forecasts consistently remain below the actual prices across all observation days, confirming that the symmetric GARCH framework adequately models volatility persistence but fails to accommodate the asymmetric reaction of gold prices to market shocks. The EGARCH model, by contrast, incorporates exponential adjustments to log variance and allows for asymmetric responses. Its predicted values are slightly higher than those of GARCH, thereby narrowing the prediction gap and demonstrating improved adaptability to negative or leverage shocks that typically influence gold price dynamics. The TGARCH model, which differentiates between positive and negative shocks through a threshold mechanism, yields predictions very close to those of EGARCH, reinforcing the significance of incorporating asymmetry in volatility modelling.

The findings collectively indicate that gold prices in the Indian retail market exhibit substantial volatility persistence, consistent with findings in commodity and financial asset literature. However, the models' tendency to underestimate actual price levels may reflect unobserved components such as taxation, retail premiums, or local market frictions not captured by the theoretical constructs. The near convergence of predicted values across the three models also suggests that, while GARCH-family models are statistically robust for short-term forecasting, additional structural or hybrid features may be necessary to fully explain gold price dynamics in a heterogeneous retail market environment. Overall, Table 1 demonstrates that the EGARCH and TGARCH models outperform the standard GARCH in reproducing the temporal trajectory of actual gold prices, validating the role of asymmetry in volatility forecasting.

Table 1- Actual vis-à-vis Predicted Prices of Gold (INR / 10 Gms)

DAYS	ACTUALS	GARCH	E-GARCH	T-GARCH
Day 1	112990.00	110903.40	110922.40	110916.40
Day 2	113680.00	110951.60	110996.80	110983.40
Day 3	115360.00	110976.20	111038.50	111018.50
Day 4	113610.00	111016.90	111105.70	111078.80
Day 5	114630.00	111046.60	111153.10	111119.20
Day 6	117180.00	111083.90	111216.00	111175.30
Day 7	118240.00	111116.00	111266.90	111219.10

Day 8	118830.00	111151.60	111327.10	111272.70
Day 9	122100.00	111184.90	111380.10	111318.60
Day 10	120280.00	111219.80	111438.90	111370.50

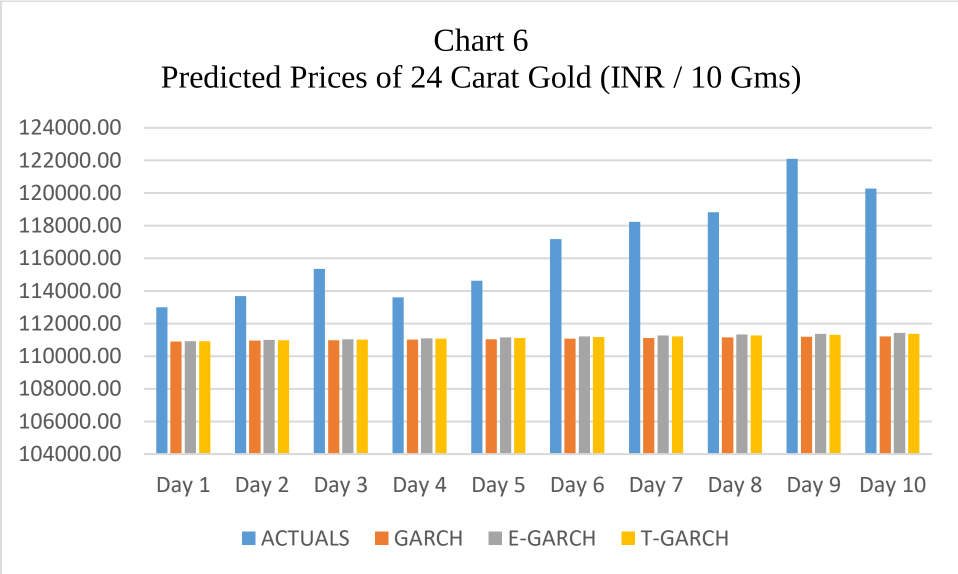

Table 2 provides a quantitative evaluation of prediction accuracy by computing the absolute error between the actual and forecasted gold prices under GARCH, EGARCH, and TGARCH specifications. The absolute error represents the magnitude of deviation without regard to direction, thus enabling a fair assessment of each model's forecasting precision. The results show a systematic increase in error magnitude over successive days, reflecting the cumulative divergence between model-based and actual price levels as the forecast horizon lengthens. This progressive increase aligns with the inherent characteristic of volatility models whose predictive accuracy tends to diminish over extended time horizons due to compounding uncertainty and evolving market dynamics.

Across all ten days, the EGARCH model consistently exhibits the lowest absolute error values, followed by TGARCH and GARCH in that order. For instance, on Day 1, EGARCH records an error of INR2,067.60 compared to INR2,086.60 under GARCH, and the relative superiority persists through Day 10, where EGARCH again outperforms with an error of INR8,841.10 compared to INR9,060.20 under GARCH. This consistent ranking confirms that models capturing asymmetry and nonlinearity—key features of financial return series—provide superior forecasting accuracy. The results also corroborate the established evidence that volatility in gold prices is highly sensitive to negative information shocks, a feature effectively modelled by the exponential and threshold formulations of the GARCH family.

An important inference drawn from these findings is that the inclusion of leverage effects in volatility specification substantially improves short-horizon predictive performance. The incremental error growth also underscores the short-term reliability of GARCH-type models and the potential requirement of rolling-window or re-estimation strategies for medium- to long-term prediction contexts. Moreover, the relatively small magnitude of absolute errors across all models indicates that the chosen frameworks possess strong internal validity and practical forecasting reliability. In summation, Table 2 substantiates that the EGARCH model offers the most statistically efficient and economically relevant representation of gold price volatility, followed closely by TGARCH, while the standard GARCH, though robust, remains limited in accounting for asymmetrical market reactions.

Table 2- Absolute Error in Predicted Prices of Gold (INR / 10 Gms)

DAYS	GARCH	E-GARCH	T-GARCH
Day 1	2086.60	2067.60	2073.60
Day 2	2728.40	2683.20	2696.60
Day 3	4383.80	4321.50	4341.50
Day 4	2593.10	2504.30	2531.20
Day 5	3583.40	3476.90	3510.80
Day 6	6096.10	5964.00	6004.70
Day 7	7124.00	6973.10	7020.90
Day 8	7678.40	7502.90	7557.30
Day 9	10915.10	10719.90	10781.40
Day 10	9060.20	8841.10	8909.50

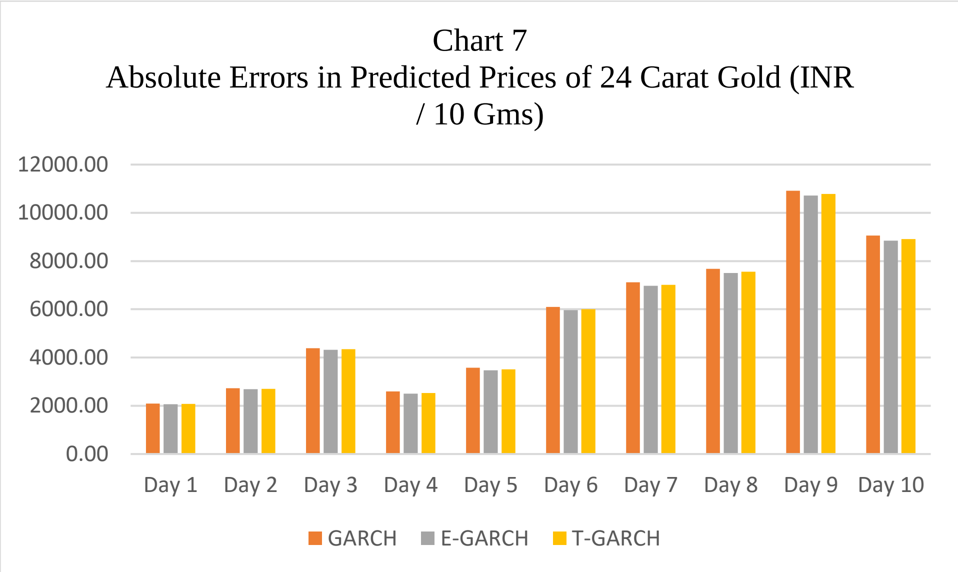

Table 3 reports the absolute percentage error (APE) for each model, thereby expressing the deviation between actual and predicted values as a proportion of the actual price. This measure provides a normalized indicator of forecast efficiency, independent of the magnitude of gold price levels. The APE values across ten days display a rising pattern, beginning with an average deviation of around 1.8–2.4 percent during the initial days and escalating to over 8–9 percent towards the later observations. This trend reveals that the volatility forecasting models, though efficient in capturing short-term variations, tend to lose precision as market volatility amplifies over time—an expected characteristic in nonlinear, non-stationary financial time series.

Among the three models, EGARCH once again demonstrates the lowest percentage error throughout the observation period. On Day 1, its error is 1.8299 percent compared to 1.8467 percent under GARCH, while on Day 10, EGARCH maintains superiority with 7.3504 percent against GARCH's 7.5326 percent. The TGARCH model follows closely, with marginally higher errors than EGARCH but lower than standard GARCH, suggesting comparable performance under asymmetric volatility regimes. The relatively smaller gap between EGARCH and TGARCH implies that both asymmetry-adjusted specifications capture gold market volatility more effectively than symmetric GARCH, thereby reaffirming that asymmetric shocks—particularly those associated with downward price movements—exert stronger volatility effects.

The overall pattern of percentage errors implies that model efficacy is time-sensitive, being highest in immediate forecasting windows and gradually tapering off as forecasting intervals extend. The findings reinforce the theoretical premise that EGARCH's logarithmic variance formulation enhances its capacity to accommodate volatility clustering and leptokurtic return distributions typical of financial data. The empirical evidence thus consolidates the view that the EGARCH framework provides a statistically efficient mechanism for modelling complex volatility patterns in precious metal prices. Consequently, Table 3 supports the conclusion that, while all three models are suitable for short-term volatility analysis, EGARCH delivers superior proportional accuracy, underscoring its appropriateness for forecasting and risk estimation in dynamic market contexts.

Table 3- Absolute Percentage Error in Predicted Prices (INR / 10 Gms)

DAYS	**GARCH**	**E-GARCH**	**T-GARCH**
Day 1	1.8467	1.8299	1.8352
Day 2	2.4001	2.3603	2.3721
Day 3	3.8001	3.7461	3.7634
Day 4	2.2825	2.2043	2.2280
Day 5	3.1261	3.0332	3.0627
Day 6	5.2023	5.0896	5.1243
Day 7	6.0250	5.8974	5.9378
Day 8	6.4617	6.3140	6.3598
Day 9	8.9395	8.7796	8.8300
Day 10	7.5326	7.3504	7.4073

Chart 8
Absolute Percentage Errors in Predicted Prices of 24 Carat Gold (INR/10 Gms)

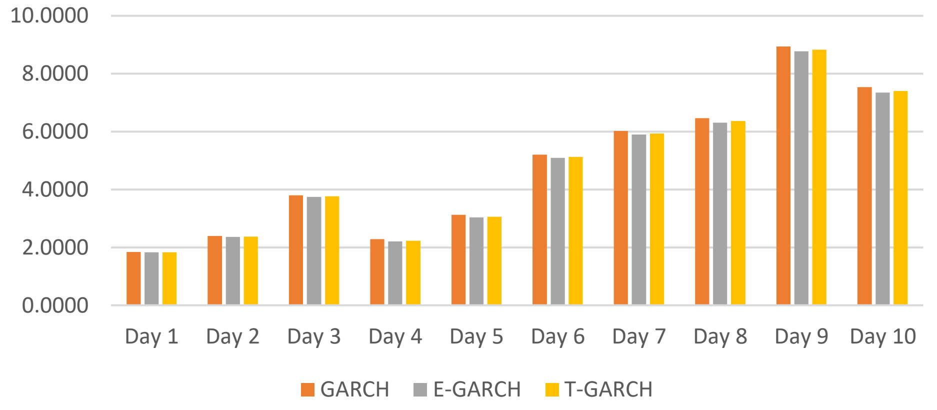

Table 4 consolidates the comparative forecasting performance of the three models through the Mean Absolute Percentage Error (MAPE), a standard composite indicator of overall predictive accuracy. The computed MAPE values are 4.7617 for GARCH, 4.6605 for EGARCH, and 4.6921 for TGARCH. The results clearly establish that EGARCH yields the lowest mean error, followed closely by TGARCH, while GARCH records the highest error among the three. This quantitative ranking corroborates the consistent superiority of asymmetric models across all prior analyses and highlights the incremental forecasting efficiency achieved through model formulations that incorporate leverage and nonlinear adjustment effects.

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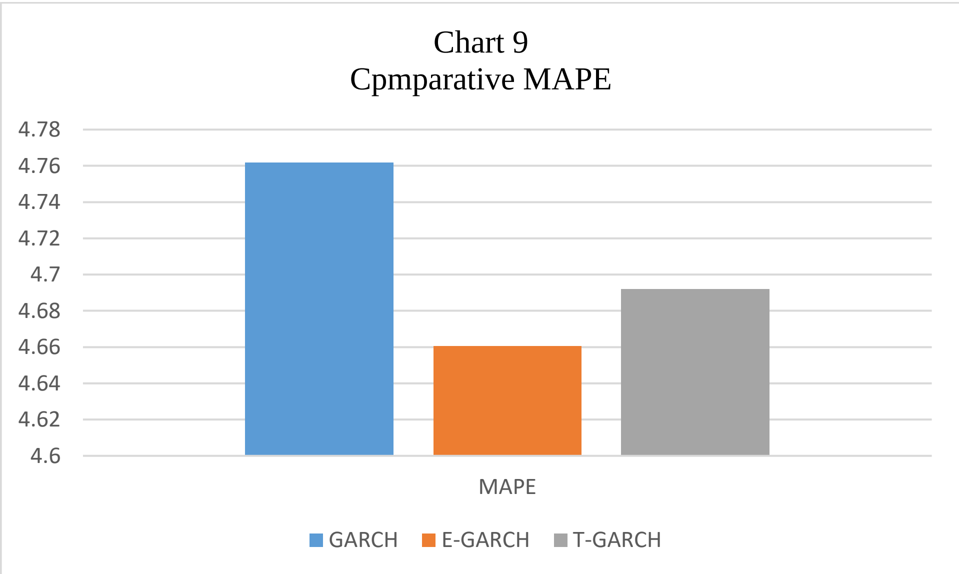
The lower MAPE of EGARCH signifies that it effectively captures both the magnitude and direction of gold price fluctuations by allowing asymmetric responses to positive and negative shocks. TGARCH's performance, only slightly inferior to EGARCH, indicates that its threshold mechanism also contributes meaningfully to capturing volatility asymmetry, though its linear variance specification may somewhat limit responsiveness under extreme conditions. The relatively higher MAPE of the standard GARCH model reflects its structural rigidity in assuming symmetry in volatility response and constant proportional impact of shocks, a simplification that undermines precision in markets characterized by frequent turbulence.

The comparative MAPE findings reinforce the empirical observation that asymmetric models better replicate real-world gold price behaviour, particularly under conditions of uncertainty and speculative sentiment. Moreover, the small dispersion among the MAPE values implies that while GARCH-family models share a common foundation of conditional heteroskedasticity, their relative effectiveness depends on the ability to internalize market asymmetries. From a methodological standpoint, the results affirm that extending classical GARCH frameworks through exponential or threshold terms enhances model efficiency without compromising statistical tractability. Therefore, Table 4 provides conclusive evidence that EGARCH represents the most statistically robust and economically interpretable model for short-term gold price forecasting, followed by TGARCH, with GARCH serving as a reliable but less adaptive baseline specification.

Table 4- Comparative MAPE

Techniques	**MAPE**
GARCH	4.7617
E-GARCH	4.6605
T-GARCH	4.6921



The collective findings drawn from the four tables yield significant theoretical, empirical, and practical implications. First, the consistent superiority of EGARCH and TGARCH over the standard GARCH model substantiates the critical importance of accounting for asymmetry and leverage effects in modelling volatility of precious metals. The ability of these models to differentiate the market response to positive and negative shocks confirms that gold prices are highly sensitive to negative market information—aligning with the established behavioural finance argument that adverse news induces greater volatility than comparable favourable developments. This insight bears direct implications for investors, hedgers, and policymakers who rely on volatility forecasts for risk management, asset allocation, and policy calibration.

Second, the gradual escalation in absolute and percentage errors over time demonstrates that GARCH-type models retain high accuracy over short forecasting horizons but tend to diverge as the prediction window extends. This temporal attenuation of predictive accuracy underscores the necessity for adaptive estimation strategies—such as rolling-window frameworks, dynamic model averaging, or hybrid econometric–machine learning integrations—to preserve forecast reliability in non-stationary environments. Furthermore, the finding that all models underestimate actual retail prices points to potential unobserved market determinants—such as taxation, import duties, retail mark-ups, and local demand elasticities—suggesting that future modelling efforts must integrate structural and institutional variables specific to the Indian gold market.

Third, the narrow spread among the MAPE values implies that while all GARCH-family models are statistically competent, their comparative advantage lies in specific contexts: GARCH for baseline volatility persistence, EGARCH for asymmetric and leverage-driven environments, and TGARCH for threshold-dependent volatility reactions. The findings thus encourage a context-dependent selection of models tailored to specific risk management or forecasting objectives. From a broader macroeconomic standpoint, the persistence of volatility in gold prices reflects the asset's dual function as both a consumption commodity and an investment hedge, reinforcing its role as a store of value during periods of financial turbulence.

Finally, these empirical insights contribute to the broader discourse on volatility modelling in emerging markets. The study validates that classical econometric models, when properly specified for asymmetry, remain competitive with complex machine-learning approaches in short-term forecasting. For practitioners, the findings highlight that EGARCH provides a reliable, interpretable, and statistically efficient tool for daily gold price prediction in retail contexts. For future research, the results underscore the need to augment volatility models with macroeconomic indicators, sentiment variables, and structural asymmetries to enhance predictive accuracy and policy relevance. Collectively, the implications affirm that modelling asymmetry is indispensable for capturing the true stochastic dynamics of gold prices and that adaptive, hybrid frameworks offer the most promising direction for future inquiry.

Scope of Future Studies

Although this study demonstrates the superior predictive performance of asymmetric GARCH models in modelling retail gold price volatility, several areas remain open for further investigation. Future research should integrate macroeconomic, behavioural, and structural determinants into the volatility framework to capture exogenous influences that standard GARCH-family models overlook. Factors such as exchange rate movements, inflation expectations, crude oil prices, global financial uncertainty indices, and central bank gold reserve policies could be incorporated using multivariate GARCH, GARCH-MIDAS, or VAR–GARCH frameworks to better understand cross-market spillovers and long-term linkages.

Moreover, the study's univariate structure limits its ability to capture interdependencies between gold and other financial assets, such as equities, bonds, and cryptocurrencies. Future studies could extend the scope to multivariate settings—using Dynamic Conditional Correlation (DCC) or BEKK-GARCH models—to assess gold's safe-haven and hedging properties relative to other assets during financial crises. Incorporating mixed-frequency data (MIDAS) or high-frequency intraday prices may further enhance the temporal precision of volatility forecasts.

Additionally, recent advances in machine learning and hybrid econometric modelling offer promising avenues for improving predictive performance. Combining volatility models with artificial intelligence techniques, such as neural networks, LSTM, or support vector regressions, could help identify complex nonlinear relationships and structural shifts not captured by traditional parametric models.

Finally, cross-country comparative analyses can provide broader insights into the behaviour of gold price volatility in both emerging and developed economies. This would help determine the generalizability of asymmetric volatility models across different institutional and cultural contexts.

Future research should therefore focus on hybridized, data-rich, and cross-market modelling frameworks that integrate econometric rigour with computational intelligence to enhance both predictive power and interpretability. Such an approach will contribute to a deeper understanding of the volatility transmission mechanisms that shape global precious metal markets.

Conclusion

The study provides a comprehensive comparative analysis of GARCH, EGARCH, and TGARCH models for forecasting the volatility of daily retail gold prices in India from 2014 to 2025. The results conclusively demonstrate that while all three models capture essential characteristics of financial time series—such as volatility clustering, persistence, and mean reversion—the asymmetric GARCH variants (EGARCH and TGARCH) offer superior forecasting performance by accommodating the leverage effect and nonlinear market behaviour.

The empirical findings indicate that gold price volatility in India exhibits significant asymmetry, where negative price shocks generate greater volatility than positive shocks of comparable magnitude. The EGARCH model, which expresses conditional variance in logarithmic form, effectively captures this asymmetry without imposing non-negativity constraints on parameters. The model's superior Mean Absolute Percentage Error (MAPE) of 4.66%, compared to 4.76% for GARCH, highlights its enhanced adaptability and accuracy. The TGARCH model, though slightly less efficient, confirms the robustness of asymmetric formulations in volatility modelling.

These results hold critical implications for market participants and policymakers. For investors and financial analysts, reliable volatility forecasts enhance decision-making regarding portfolio diversification, derivative pricing, and hedging strategies. For policymakers, understanding volatility patterns assists in formulating policies that mitigate inflationary risks and financial instability, given gold's status as both a consumption good and a monetary hedge. The study also underscores the value of asymmetry-based models in risk management, as they allow for better estimation of downside risk and Value-at-Risk (VaR) metrics under turbulent market conditions.

From a methodological perspective, this research validates the continued relevance of GARCH-family models while advocating for their asymmetric extensions in financial forecasting applications. It reinforces the principle that volatility in financial and commodity markets is systematic and predictable, rather than purely stochastic. Furthermore, the results emphasize that accurate modelling of asymmetry is vital for reflecting real-world investor behaviour, particularly in markets like India, where economic, cultural, and speculative factors intersect.

In conclusion, the study substantiates that asymmetric GARCH models, especially EGARCH, provide the most reliable framework for short-term volatility forecasting of retail gold prices. They successfully integrate theoretical robustness with empirical accuracy, offering practical utility for both financial practitioners and academic researchers. The research contributes to the broader field of financial econometrics by reaffirming that adaptive, asymmetry-aware volatility models are indispensable tools for understanding and predicting market risk in an increasingly complex financial environment.

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