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Volatility dynamics and regime switching in Ghanaian gold returns: Evidence from GARCH, GJR-GARCH and time-varying-transition-probability models

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ABSTRACT

This study examines the volatility dynamics of Ghanaian gold returns using GARCH, EGARCH, GJR-GARCH, and a time-varying-transition-probability Markov-switching GJR-GARCH model. The analysis uses 807 daily Gold/GHS log returns derived from 808 price observations spanning 3 January 2022 to 30 December 2025. The return series is stationary, non-normal, negatively skewed, leptokurtic, and conditionally heteroskedastic. Student-t and generalized-error innovations generally improve the fit of the single-regime models relative to the normal distribution. The Markov-switching specification identifies a persistent low-volatility regime and a shorter high-volatility regime, with average conditional variances of 2.7150 and 9.5231, respectively. Asymmetry is concentrated in the high-volatility regime, where the estimated coefficient is 1.0427. Out-of-sample comparisons and the trading-rule evaluation show that model rankings depend on the evaluation criterion and forecast horizon. Overall, Ghanaian gold-return volatility is persistent, heavy-tailed, asymmetric during stressed periods, and regime-dependent. The findings provide practical implications for volatility forecasting, market-risk management, hedging, and investment decisions in commodity-dependent economies.

Contribution/Originality: This study contributes to the existing literature by providing one of the first Ghana-specific evaluations of gold-return volatility, combining heavy-tailed GARCH benchmarks with a time-varying-transition-probability Markov-switching GJR-GARCH model, regime-specific asymmetry, out-of-sample forecasting, and an economically interpretable trading-rule assessment.

1. INTRODUCTION

Gold has been a preferred investment asset and a store of value over time. It has played a significant role in financial markets as well as in the economic development of mineral-rich countries. Gold is a crucial source of income for many countries, as it is one of their largest sources of export earnings and serves as an essential foreign-exchange resource (Cudjoe, Nyarko, & Odoi, 2025). Consequently, gold prices can have a profound impact on government budgets, attract investment, and affect a country's overall economic performance. Additionally, the price of gold is significantly influenced by political tensions, exchange rates, monetary and fiscal policies, inflation, and overall market volatility. Such price disruptions create risks that need to be taken into account in portfolio management, derivative pricing, and risk assessment, thus motivating the search for appropriate volatility-forecasting models (Ataey & Azizi,

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2026; Luo, Demirer, Gupta, & Ji, 2022). Returns from financial assets typically exhibit several stylized features commonly referred to as volatility clustering, leptokurtosis, persistence, and nonlinear behavior. For such time-series data, econometric volatility models, including GARCH (Generalized Autoregressive Conditional Heteroskedasticity), EGARCH (Exponential GARCH), and GJR-GARCH (Glosten, Jagannathan, & Runkle, 1993), have become the standard approach because they capture conditional heteroskedasticity and leverage effects well (Sopipan, Sattayatham, & Premanode, 2012). Since these three approaches are single-regime models, they cannot adequately account for abrupt parameter changes that frequently occur in financial time-series data. As a result, they have limited short-term forecasting performance when the market experiences a transition between periods of high and low volatility (Kunjal & Naidu, 2023; Qasim, Javed, Javaid, & Ali, 2022).

The above limitation of the standard GARCH family has prompted researchers to propose alternative conditional volatility models capable of capturing the dynamic process of market-regime switching. These switching-regime volatility models include GARCH-MRS (Markov Regime-Switching) and related specifications. The basic idea behind regime-switching GARCH-type models is that conditional volatility changes its behavior as the economy moves from one state to another (Gray, 1996; Hamilton, 1989). Unlike standard GARCH models, regime-switching GARCH models allow time-dependent volatility parameters to change their values according to a probability distribution during specific periods. The advantage of this approach is that it helps capture structural breaks, persistence, and asymmetry in volatility (De la Torre-Torres, Álvarez-García, & del Río-Rama, 2024; Korkpoe & Howard, 2019). Evidence from recent studies suggests that switching volatility models generally provide more accurate forecasts of financial-market volatility than their single-regime counterparts (Akurugu, Angbing, Nasiru, & Abubakari, 2022; Anh & Zhao, 2021).

There is a need for more research on the volatility of gold prices, particularly in the Ghanaian context. Few recent studies have investigated the properties of gold-price volatility in Ghana. Most of the existing literature has focused on commodities traded on exchanges in developed countries. The dynamics of gold prices in developing countries such as Ghana attract the attention of researchers who aim to contribute to a better understanding of the forces driving the market. Given that Ghana has become increasingly dependent on gold as a source of export revenue and that gold is one of the most important commodities in terms of trading volume, any significant change in its price can have serious economic consequences (Ahmed & Sarkodie, 2021; Korkpoe & Howard, 2019; Poshakwale & Mandal, 2016). Understanding the dynamics of price changes in the Ghanaian gold market is critical to the country's investment policy formulation, as well as to individual and institutional investors' wealth management and hedging strategies. It is worth noting that traditional volatility models with constant conditional variance exhibit poor performance in the presence of structural breaks, which can lead to misleading inferences about volatility persistence (Arouri, Hammoudeh, Lahiani, & Nguyen, 2012).

This study aims to investigate the volatility characteristics of Ghanaian gold prices. The paper compares the predictive ability of GARCH, EGARCH, GJR-GARCH, and Markov Regime-Switching GARCH-type models. The contribution of this study is twofold: (1) it evaluates the accuracy of different time-series volatility forecasting models in the context of Ghanaian gold prices; (2) it assesses the economic value of these forecasts using a volatility-based trading strategy to determine whether improved volatility forecasts lead to higher investment returns. Overall, this research will add value to the existing literature on commodity markets and contribute to a better understanding of the Ghanaian gold market specifically. In addition, it will help investors, portfolio managers, traders, and policymakers in Ghana and other commodity-dependent economies make informed decisions about their investment activities and benefit from gold's volatility.

2. MARKOV REGIME SWITCHING OF GARCH MODEL

Let (P_t) represent the series of financial prices at time t, and $\{r_t\}_{t>0}$ assume it is a sequence of random variables on a probability space (Ω, F, P). The index t denotes the daily closing observations, where $t = -R + 1, \ldots, n$. The

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sample period consists of an estimation (or in-sample) period with R observations ($t = -R + 1, \ldots, 0$), and an evolution (or out-of-sample) period with n observations of the financial price at time t, i.e.

$$rt = 100 . \ln \left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

The GARCH (1, 1) model for the return series r_t can be written as:

$r_t = \delta + \boldsymbol{\varepsilon_t} = \delta + \boldsymbol{\eta_t}\sqrt{\boldsymbol{h_t}}$

$h_t = a_0 + \boldsymbol{\alpha_1 \varepsilon_{t-1}^2} + \boldsymbol{\beta_1 h_{t-1}}$

Where $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$ are assumed to be non-negative real constants, ensuring that $h_t \geq 0$. We assume η_t is an i.i.d. process with zero mean and unit variance. The parameters used in a GARCH model are normally considered constants. However, financial returns move differently between recessions and expansions, which may result in differences in volatility. The GARCH model was extended to the MRS-GARCH model to capture changes in volatility regimes through unobservable state variables. This transformation was based on the assumption that these unobservable state variables follow a first-order Markov chain process.

Therefore, the estimation of the MRS-GARCH model with only two regimes can be represented as follows:

$$r_t = \delta_{s_t} + \varepsilon_t = \delta_{s_t} + \eta_t \sqrt{h_t, s_t} \quad (2)$$

and $h_t, s_t = \alpha_0, s_t + \alpha_1, s_t \varepsilon_{t-1}^2 + B_1, s_t h_{t-1}$

Where S_t assumes a value of 1 or 2, δ_{s_t} is the mean, and h_t, s_t is the volatility under regime S_t on F_{t-1}; both are measurable functions of $F_{t-\tau}$ for $\tau \leq t - 1$. To ensure the restrictions $\alpha_0, s_t > 0$, $\alpha_1, s_t \geq 0$ and $B_1, s_t \geq 0$. The sum $a_1, s_t + \beta_1, s_t$ measures the persistence of a shock to the conditional variance.

The evolution of the unobserved regime variable S_t is assumed to follow a first-order Markov chain with constant transition probabilities. This assumption implies that the probability of the market being in a particular volatility regime at time t depends solely on the regime occupied in the immediately preceding period (t−1) and not on the earlier history of the process. Formally, the transition probabilities are defined as follows:

$$Pr(S_t = i | S_{t-1} = j) = p_{ji} \text{ for } i, j = 1, 2. \quad (3)$$

In matrix notation,

$$P = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} = \begin{bmatrix} p & 1-q \\ 1-p & q \end{bmatrix} \quad (4)$$

2.1. Forecasting Volatility

In the two-regime Markov Regime-Switching GARCH (MRS-GARCH) model, volatility is predicted recursively, as in the classical GARCH model, with the only difference being that stochastic switching between regimes is taken into account. According to Klaassen (2002), volatility can be predicted k steps ahead for any positive integer k, as indicated in the expression above. Unlike the classical GARCH model, it can be seen from the expression above that the prediction of the MRS-GARCH conditional variance depends not only on the innovations and conditional variances specific to each regime, but also on the probability of the market being in a particular regime.

To estimate multi-step-ahead volatility forecasts in the MRS-GARCH model, it is necessary to calculate the conditional volatility forecasts for each regime and then calculate their weighted average, with weights equal to the probabilities of being in a particular regime at the forecast origin. As a result, volatility forecasts from different regimes are combined using a convex combination of all volatility forecasts, weighted by the corresponding predicted probabilities. Consequently, the volatility forecast in the MRS-GARCH model depends on both the volatility persistence in each regime and the time-varying transition probabilities between regimes. Compared with a single-regime GARCH model, the MRS-GARCH model allows for more accurate volatility forecasting in both tranquil and volatile periods. To produce volatility forecasts, first, a weighted average of the volatility forecasts specific to each regime, with weights equal to the corresponding prediction probabilities, is calculated. Given the initial point

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forecasts obtained using the MRS-GARCH model, forecasts of conditional volatility k steps ahead can be constructed as follows:

$(Pr(S_{T+\tau} = i|F_{T-1}))$.

Since there is no serial correlation in returns, the *k-step-ahead* volatility forecast at time T depends on information available at time $T-1$. Let $\hat{h}_{T,T+k}$ denote the aggregated volatility forecasts at time T for the next k steps. They can be calculated as follows (Marcucci, 2005).

$$\hat{h}_{T,T+k} = \sum_{\tau=1}^{k} h_{T.T+\tau}$$

$$= \sum_{\tau=1}^{k}\left[\sum_{i=1}^{2}\Pr(S_{T+\tau} = i \mid F_{T-1})h_{T,T+\tau,ST+\tau=i}\right] \quad (5)$$

Where $\hat{h}_{T,T+\tau,S_{T+\tau}=i}$ indicates the τ *-step-ahead* volatility forecast in regime i, made at time T, and calculated recursively as follows:

$$h_{T,T+\tau,s_{T+\tau}=i} = E_{T-1}\left(h_{T+\tau-1} \mid S_{T+\tau} = i\right)$$

$$= \alpha_{0,S_{T+\tau}=i} + \alpha_{1,S_{T+\tau}=i}E_{T-1}\left(\varepsilon^{2}{}_{T+r-1} \mid S_{T+\tau} = i\right) + \beta 1_{,S_{T+\tau}=i}E_{T-1}\left(h_{t+\tau-1} \mid S_{T+\tau} = i\right)$$

$$= \alpha_{0,S_{T+\tau}=i} + \alpha_{1,S_{T+\tau}=i}E_{T-1}\left(E_{T-1}\left[\varepsilon^{2}_{T+\tau-1}\right] \mid S_{T+\tau} = i\right) + \beta_{1,S_{T+\tau}=i}E_{T-1}\left(h_{T+\tau-1} \mid S_{T+\tau} = i\right)$$

$$= \alpha_{0,S_{T+\tau}=i} + \left(a_{1,S_{T+\tau}=i} + \beta 1_{,S_{T+\tau}=1}\right)E_{T-1}\left(h_{T,T+\tau-1} \mid S_{T+\tau} = i\right) \quad (6)$$

Universally accepted estimates stipulate that the prediction probability in (5) can be computed as:

$$\begin{bmatrix} \Pr\left(S_{T+\tau} = 1 \mid F_{T-1}\right) \\ \Pr\left(S_{T+\tau} = 2 \mid F_{T-1}\right) \end{bmatrix} = P^{\tau+1} \cdot \begin{bmatrix} \Pr\left(S_{T-1} = 1 \mid F_{T-1}\right) \\ \Pr\left(S_{T-1} = 2 \mid F_{T-1}\right) \end{bmatrix},$$

Where P is defined in (4), and $\Pr\ (S_{T-1} = i|F_{T-1})$ will be addressed in (11). Lastly, we compute the expectation part $E_{T-1}\left(h_{T,T+r-1}\middle|S_{T+\tau} = i\right)$ in Eq. 6 as follows:

$$E_{T-1}\left(h_{T,T+r-1}\middle|S_{T+\tau} = i\right) = E[h_{T+\tau-1}|S_{T+\tau} = i, F_{T-1}]$$

$$= E[E[r^{2}_{T+\tau-1}|S_{T+\tau-1} = j, F_{T-1}] - [E[r_{T+\tau-1}|S_{T+\tau-1} = j, F_{T-1}]^{2}|S_{T+\tau} = i, F_{T-1}]$$

$$= E[E[r^{2}_{T+\tau-1}|S_{T+\tau-r} = j, F_{T-1}]|S_{T+\tau} = i, F_{T-1}] \quad (7)$$

$$E\left[\left[E[r_{T+\tau-1}|S_{T+\tau-1} = j, F_{T-1}]\right]^{2}\middle|S_{T+\tau} = i, F_{T-1}\right]$$

$$E[E[r^{2}_{T+\tau-1}|S_{T+\tau-1} = j, F_{T-1}]|S_{T+\tau} = i, F_{T-1}]$$

$$= \sum_{j=1}^{2}\left\{E\left[r^{2}_{T+\tau-1} \mid S_{T+\tau-1} = j, F_{T-1}\right].\Pr\left[S_{T+\tau-1} = j \mid S_{T+\tau} = i, F_{T-1}\right]\right\}$$

$$= \sum_{j=1}^{2}\left\{E\left[\left(\delta_{T+\tau-1} + \varepsilon_{T+r-1}\right)^{2} \mid S_{T+\tau-1} = j, F_{T-1}\right].\Pr\left[S_{T+\tau-1} = j \mid S_{T+\tau} = i, F_{T-1}\right]\right\}$$

$$= \sum_{j=1}^{2}\left\{E\left[\delta^{2}_{T+\tau-1} + 2\delta_{T+\tau-1}\varepsilon_{T+\tau-1} + \varepsilon^{2}_{T+\tau-1} \mid S_{T+\tau-1} = j, F_{T-1}\right].\Pr\left[S_{T+\tau-1} = j \mid S_{T+\tau} = i, F_{T-1}\right]\right\}$$

where

$$\tilde{P}_{ji,T-1} = \Pr\ (S_{T+\tau-1} = j|S_{T+\tau} = i, F_{T-1}) \quad (8)$$

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$$= \frac{p_{ji}\Pr\left(S_{T+\tau-1}=j \mid F_{T-1}\right)}{\Pr\left(S_{T+\tau}=i \mid F_{T-1}\right)} \tag{9}$$

Similarly, we computed the second term on the right-hand side of (7) as follows:

$$E_{T-1}\left(\left[E\left(r_{T+\tau-1} \mid S_{T+\tau-1}=j, \mathcal{F}_{T-1}\right)\right]^2 \mid S_{T+\tau}=i\right)=\sum_{j=1}^{2}\tilde{p}_{ji,T-1}\ \delta_{T+\tau-1,j}^2$$

Substituting both (8) and (10) into (7), we obtain;

$$E_{T-1}\left(\hat{h}_{T+\tau-1} \mid S_{T+\tau}=i\right)=\sum_{j=1}^{2}\tilde{p}_{ji,T-1}\left(\delta_{T+\tau-1,j}^2+h_{T+\tau-1,j}\right)-\left(\sum_{j=1}^{2}\tilde{p}_{ji,T-1}\ \delta_{T+\tau-1,j}\right)^2$$

The next estimation step is the computation of the regime probabilities $p_{it} = \Pr\ (S_t = i|F_{t-1})$ for $i = 1, 2$, estimated in Equation 9. It should be noted that when the regime probabilities are based on information up to time t, we refer to them as filtered probabilities ($\Pr\ (S_t = i|F_t)$) .

To estimate the regime probabilities, we note $f_{1t} \coloneqq f(r_t|S_t = 1, F_{t-1})$, $f_{2t} \coloneqq f(r_t|S_t = 2, F_{t-1})$. Then, the conditional distribution of the return series r_t becomes an output of a mixture distribution model in which the mixing variable is the regime probability p_{it}. It therefore becomes:

$$r_t \mid F_{t-1} \sim \begin{cases} f\left(r_t \mid S_{t=1}, F_{t-1}\right) & \text{with probability } p_{1t} \\ f\left(r_t \mid S_{t=2}, F_{t-1}\right) & \text{with probability } p_{2t}=1-p_{1t} \end{cases}$$, where $f(r_t|S_t, F_{t-1})$ denotes one of the assumed conditional error distributions: the Normal distribution (N), the Student-t distribution with one degree of freedom (t) or two degrees of freedom (2t), and the Generalised Error Distribution (GED).

The computation of regime probabilities will be conducted in the following two stages (Kim & Nelson, 1999).

Stage 1: Given $\Pr(S_t = i|F_{t-1}) = \sum_{j=1}^{2}\Pr\left(S_{t=i}, S_{t-1}=j \mid F_{t-1}\right)$

Since the current regime (S_t) depends only on the regime one period ago (S_{t-1}), then;

$$\Pr(S_t = i|F_{t-1})$$

$$\sum_{j=1}^{2}\Pr(S_t=i \mid S_{t-1}=j)\Pr(S_{t-1}=j \mid F_{t-1})$$

$$= \sum_{j=1}^{2} p_{ji}\Pr\left(S_{t-1}=j \mid F_{t-1}\right) \tag{10}$$

Stage 2: At the end of time t, when the observed return at time $t(r)$ is available, the information set at time t set $F_t = \{F_{t-1}, r_t\}$; the $\Pr(S_t = i|F_t)$ is calculated as follows:

$\Pr(S_t = i|F_t) = \Pr(S_t = i|F_{t-1}) = \frac{f(r_1, S_t=i|F_{t-1})}{f(r_t|F_{t-1})}$, where $f(r_t, S_{t=i}|F_{t-1})$ is the joint density of returns and the unobserved regime in state i for $i = 1, 2$. The variables can be written as follows:

$f(r_t, S_t = i|F_{t-1}) = f(r_t|S_t = i, F_{t-1})\ f(S_t = i|F_{t-1})$

$= f(r_t|S_t = i, F_{t-1})\ \Pr\ (S_t = i|F_{t-1})$

and $f(r_t|F_{t-1})$ is the marginal density function of returns and can be constructed as follows;

$$f(r_t|F_{t-1}) = \sum_{i=1}^{2} f\left(r_t, S_t=i \mid F_{t-1}\right)$$

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$$= \sum_{i=1}^{2} f\left(r_t \mid S_t = i, F_{t-1}\right)\Pr\left(S_t = i \mid F_{t-1}\right)$$

Premising our arguments on Bayesian model;

$$\Pr\left(S_t = i \mid F_t\right) = \frac{f(r_t, S_t = i \mid F_{t-1})}{f(r_t \mid F_{t-1})}$$

$$= \frac{f\left(r_t \mid S_t = i, F_{t-1}\right)\Pr\left(S_t = i \mid F_{t-1}\right)}{\sum_{i=1}^{2} f\left(r_t \mid S_t = i, F_{t-1}\right)\Pr(S_t = i \mid F_{t-1})} \tag{11}$$

$$= \frac{f_{it}\, p_{it}}{\sum_{i=1}^{2} f_{it}\, p_{it}}$$

Therefore, all predicted regime probabilities p_{it} can be computed by iterating these two steps. However, at the beginning of the iteration, $P_r\left(S_0 = i \mid F_0\right)$ for $i = 1, 2$ are necessary to start the iteration. Hamilton (1990) suggests using unconditional regime probabilities instead of $\Pr\left(S_0 = i \mid F_0\right)$. These are given by:

$$\pi_1 = \Pr\left(S_0 = 1 \mid F_0\right) = \frac{1-q}{2-p-q}, \pi_2 = \Pr\left(S_0 = 2 \mid F_0\right) = \frac{1-p}{2-p-q}$$

By numerically maximizing the log-likelihood function, the parameters of the Markov Regime-Switching GARCH (MRS-GARCH) model are estimated using the initial values of the regime probabilities, the regime-specific conditional means, and the conditional variances. Similar to the traditional GARCH model, the log-likelihood function is constructed recursively, and the filtered probabilities of the latent regimes at each time period are incorporated into the recursive estimation process. This recursive maximum-likelihood method provides consistent estimates of the conditional-mean and volatility dynamics across the various market regimes by jointly estimating the regime-dependent parameters and the transition probabilities.

2.2. Estimation Price Forecasting

In forecasting the financial price of a commodity at k steps ahead using MRS-GARCH models, denote $\hat{\mathbf{r}}_{\mathbf{t,t+k}}$ the k-step-ahead logarithmic return of the financial price at time t, conditional on F_{t-1}.

We therefore compute as;

$$\hat{r}_{t,t+k} = E_{t-1}[r_{t+k}] = \sum_{i=1}^{2}\Pr\left(S_{t+k} = i \mid F_{t-1}\right)\cdot \hat{r}_{t,t+k,S_{t+k}=i} \tag{12}$$

Where

$$\hat{r}_{t,t+k,S_{t+k}=1} = E_{t-1}[r_{t+k} \mid S_{t+k} = i\,]$$
$$= E_{t-1}[\delta + \varepsilon_{t+k} \mid S_{t+k} = i]$$
$$= E_{t-1}[\delta \mid S_{t+k} = i] + E_{t-1}[\varepsilon_{t+k} \mid S_{t+k} = 1]$$
$$= \sum_{j=1}^{2}\Pr\left(S_{t+k-1} = j \mid S_{t+k} = i, F_{t-1}\right)\cdot \delta_{S_{t+k}=i}$$
$$= \sum_{j=1}^{2} p_{jit,t-1}\cdot \delta_{S_{t+k}=i}$$

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To forecast financial prices one step ahead, we combine (12) and (1) using financial log-returns;

$$\widehat{\boldsymbol{P}}_{t+1|t} = \boldsymbol{P}_t \boldsymbol{exp}\left(\frac{\hat{\boldsymbol{r}}_{t+1|t}}{100}\right), \qquad \hat{\boldsymbol{r}}_{t+1|t} = \sum_{i=1}^{2} \boldsymbol{Pr}\,(\boldsymbol{S}_{t+1} = \boldsymbol{i} \mid \mathcal{F}_t)\hat{\boldsymbol{r}}_{t+1|t,S_{t+1}=i} \tag{13}$$

2.3. Estimating Benchmark Volatility Models

GARCH (1,1)

$$\boldsymbol{h_t} = \boldsymbol{\omega} + \boldsymbol{\alpha}\boldsymbol{\varepsilon}_{\boldsymbol{t-1}}^{\boldsymbol{2}} + \boldsymbol{\beta}\boldsymbol{h_{t-1}} \tag{14}$$

Subject to

$$\omega > 0, \qquad \alpha \geq 0, \qquad \beta \geq 0, \qquad \alpha + \beta < 1$$

GJR-GARCH (1,1)

$$ht = \omega + \alpha\varepsilon_{t-1}^2 + \gamma I_{t-1}\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{15}$$

where

$$I_{t-1} = \begin{cases} 1, & \varepsilon_{t-1} < 0, \\ 0, & \varepsilon_{t-1} \geq 0. \end{cases}$$

Under a symmetric innovation distribution, a commonly used covariance-stationarity condition is;

$$\alpha + \frac{\gamma}{2} + \beta < 1$$

EGARCH (1,1)

$$\ln h_t = \omega + \beta \ln h_{t-1} + \alpha\left(|\, z_{t-1}\,| - E\,|\, z_{t-1}\,|\right) + \gamma z_{t-1} \tag{16}$$

The logarithmic formulation guarantees positive conditional variance without imposing non-negativity restrictions on every slope coefficient.

GJR-GARCH-MIDAS

The distinguishing aspect of this study is the substantive extension that separates short-run daily volatility from a slowly moving macroeconomic component.

$$h_i = \tau_i g_i \tag{17}$$

Where g_i is the short-run component, and τ_i is the long-run component.

The short-run component is specified as;

$$g_t = \left(1 - \alpha - \beta - \gamma/2\right) + \left(\alpha + \gamma I_{t-1}\right)\frac{\varepsilon_{t-1}^2}{T_{t-1}} + \beta g_{t-1},$$

Which is normalized so that its unconditional mean is approximately one under a symmetric innovation distribution.

The long-run component is;

$$\ln \tau_t = m + \sum_{j=1}^{J} \delta_j \sum_{k=1}^{K} \omega_k\left(\theta_{1j}, \theta_{2j}\right) X_{j,t-k}^{(M)},$$

Where $X_{j,t-k}^{(M)}$ denotes lower-frequency Ghanaian macroeconomic variables such as inflation, the monetary policy rate, and Treasury-bill yield, reserve adequacy, or exchange-rate volatility.

The normalized beta weighting function is:

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$$\omega_k(\theta_1,\theta_2)=\frac{(k/K)^{\theta_1-1}(1-k/K)^{\theta_2-1}}{\sum_{\ell=1}^{K}(\ell/K)^{\theta_1-1}(1-\ell/K)^{\theta_2-1}},$$

with $\theta_1>0$ and $\theta_2>0$. The weights sum to one.

2.4. Time-Varying Transition Probabilities

Let $S_t \in \{1, 2\}$ denote an unobserved regime, where regime 1 is the lower-volatility state, and regime 2 is the higher-volatility state. The regime-dependent mean and variance are;

$$r_t=\mu_{S_t}+\varepsilon_t, \qquad \varepsilon_t=\sqrt{h_{tS_t}}z_t. \tag{18}$$

The transition probability from state i at $t-1$ to state j at t is;

$$p_{ij,t}=\Pr\left(S_t=j\mid S_{t-1}=i,Z_{t-1}\right)$$

For two regimes, the probability of moving into regime 2 may be written as;

$$p_{i2,t}=\frac{\exp\left(\alpha_i+b_t^{'}Z_{t-1}\right)}{1+\exp\left(a_i+b_i^{'}Z_{t-1}\right)}$$

with

The vector Z_{t-1} may contain lagged cedi depreciation, inflation, the monetary policy rate, Treasury-bill yield, or a carefully defined crisis indicator. Coefficients in $\mathbf{b}_i$ show how macroeconomic conditions alter the probability of entering or remaining in the high-volatility regime.

2.5. Regime-Specific Asymmetric Volatility

A regime-specific GJR variance equation can be written as

$$h_{t,s}=\omega_s+\alpha_s\varepsilon_{t-1}^2+\gamma_s I_{t-1}\varepsilon_{t-1}^2+\beta_s\tilde{h}_{t-1,s} \tag{19}$$

Because direct Markov-switching GARCH models create path dependence, lagged variance must be collapsed or integrated over past regimes. One admissible probability-weighted approximation is

$$\tilde{h}_{t-1,s}=\sum_{i=1}^{2}\Pr\left(S_{t-1}=i\mid S_t=s,\mathcal{F}_{t-1}\right)h_{t-1,i} \tag{20}$$

To complete the models, it is expedient to explicitly filter and collapse the rules used in the estimations in the code.

3. EMPIRICAL METHODOLOGY AND MODEL ESTIMATION

3.1. Data

The study uses daily gold prices in United States dollars (USD) and daily USD/GHS exchange rates to determine the volatility of gold prices in Ghana. The study's data were generated daily from 3rd January 2022 to 30th December 2025. The data consist of 808 daytime price observations. From these data, a master dataset was generated, consisting of the daily international gold price (Price/Gold/USD), daily USD/GHS exchange rate (Price/USD/GHS), daily gold price in Ghanaian cedis (Gold/GHS), and continuously compounded daily returns. Like most financial data, returns are often stationary, making it easier to model their volatility. The continuously compounded daily returns of gold prices were estimated as:

3.1.1. Transforming International Gold Prices into GHS Gold Prices

Let P_t^{USD} denote the international gold price in US dollars per troy ounce, and let E_t denote the Ghana cedi price of one US dollar. The Ghana cedi gold price is;

$$P_t^{GHS}=P_t^{USD}E_t$$

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The continuously compounded return is;

$$rt = 100\left[\ln\left(P_t^{GHS}\right) - \ln\left(P_{t-1}^{GHS}\right)\right]$$

Because $\ln(P_t^{GHS}) = \ln(P_{t_{USD}}) + \ln(E_t)$, the return may also be decomposed as;

$$r_t^{GHS} = r_t^{USD} + \Delta_{e_t}$$

Where $\Delta e_t = 100[\ln(E_t) - \ln(E_{t-1})]$.

This decomposition enables the empirical analysis to distinguish international gold-price shocks from cedi-depreciation shocks, where P_t denotes the daily closing gold price at time t, and r_t represents the corresponding daily logarithmic return.

For forecasting purposes, the sample is split into two sub-periods: an in-sample (estimation) period and an out-of-sample (forecast evaluation) period. Specifically, 787 daily observations are used for the in-sample period, and 21 daily observations are used for the out-of-sample period. Figure 1 reports the daily gold price series and the associated logarithmic return series. Consistent with financial time series, the price series follows an upward trend with minor fluctuations, while the return series fluctuates around the mean, with visible signs of volatility clustering. Put differently, large price changes are followed by large price changes, and small price changes are followed by small price changes. The table reports the descriptive statistics of the return series. Specifically, the statistics include the mean, standard deviation, minimum, maximum, skewness, kurtosis, and the Jarque–Bera normality test results. As a preliminary step before estimating the volatility models for the return series, the unit root, serial correlation, and ARCH effect tests are conducted. First, the ADF unit root test is conducted to assess whether the price and return series are stationary. Then, the Ljung–Box Q-statistic test is conducted on the return and squared return series to assess serial correlation. Lastly, the ARCH-LM test is conducted to ascertain the existence of ARCH effects in the return series. The presence of ARCH effects justifies estimating GARCH-type models and the Markov-regime-switching volatility model.

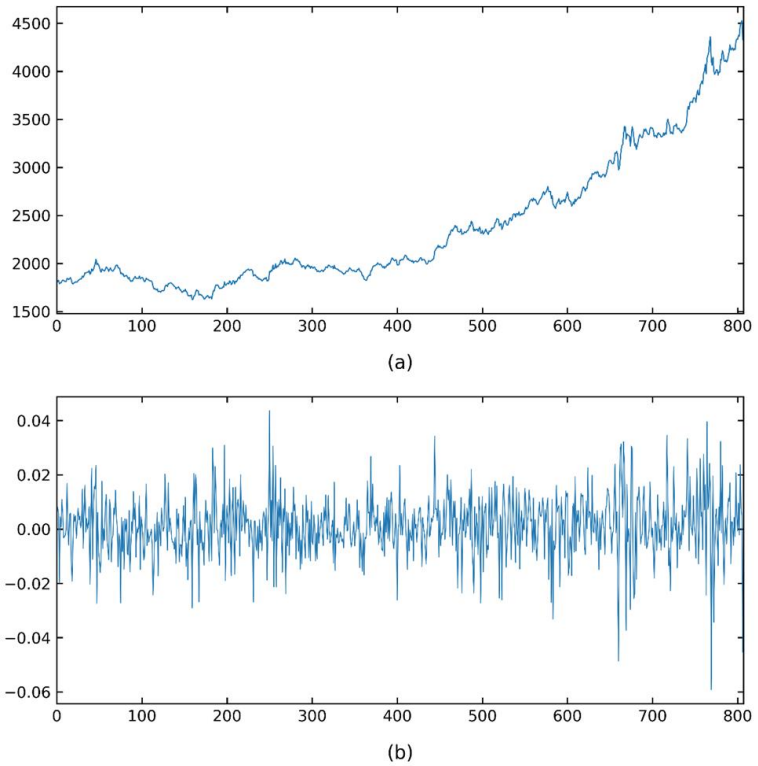


Figure 1. Graph of (a) daily gold prices (USD) and (b) Daily logarithmic return series (r_t) for the period 3 January 2022 through 30 December 2025.

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3.2. Descriptive Statistics and Preliminary Diagnostic Tests

The daily Ghanaian-cedi gold log-return series comprises 807 observations, with returns calculated as $100 \times \ln(P_t/P_{t-1})$. The mean daily return is 0.176%, with a sample standard deviation of 1.953% and minimum and maximum returns of −16.165% and 15.404%, respectively. The adjusted sample skewness is −0.954, while the adjusted Pearson kurtosis is 21.310. The Jarque–Bera statistic is 11,246.662 ($p < 0.001$), rejecting normality. The Augmented Dickey–Fuller (ADF) statistic is −15.446 ($p < 0.001$), using an intercept and Bayesian Information Criterion (BIC) lag selection with one lag, rejecting a unit root. Serial correlation and conditional heteroskedasticity are assessed using the Ljung–Box and ARCH-LM tests, respectively.

3.3. Empirical Methodology

This study uses the Markov Regime-Switching GARCH (MRS-GARCH) and generalized autoregressive conditional heteroscedasticity (GARCH) models to examine and forecast the volatility of daily gold prices in Ghana. In particular, the paper estimates the GARCH (1,1), EGARCH (1,1), GJR-GARCH (1,1), and two-state MRS-GARCH models to analyze the volatility of gold returns. All four volatility models are used because they have been proven to capture the volatility-clustering phenomenon, volatility leverage effect, and high persistence typically observed in financial time-series data. In addition, each volatility specification is estimated under three different error distributions, namely, the Gaussian distribution, Student's t-distribution, and Generalized Error Distribution (GED). The Student's t-distribution and GED are more flexible than the Gaussian distribution because they account for the fat tails and extreme values often observed in financial data. In particular, these distributions have fatter tails and a higher peak at the mean compared with the normal distribution. Overall, the use of these alternative distributions enhances the accuracy of volatility forecasting and the modeling of gold returns.

Each competing model was estimated using maximum likelihood estimation. The models' forecasting performance was evaluated using in-sample and out-of-sample analyses. The best forecasting model was selected based on goodness-of-fit statistics, including the Akaike Information Criterion (AIC), Schwarz Bayesian Information Criterion (BIC), and log-likelihood values. In addition, various forecast accuracy statistics, including the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Quasi-Likelihood (QLIKE), were used to evaluate and compare the predictive accuracy of each model. Finally, the best volatility forecasting model was used to develop a volatility-based trading strategy for the gold market in Ghana.

The conditional mean equation is estimated as follows: a parsimonious conditional mean specification is;

$$r_t = \mu + \sum_{i=1}^{p} \phi_i r_{t-1} + \lambda \Delta e_t + \varepsilon_t$$

With

$$\varepsilon_t = \sqrt{h_t z_t}, \qquad E(z_t|F_{t-1}) = 0, \qquad \text{Var}\,(z_t|F_{t-1}) = 1$$

The exchange-rate term may be excluded when r_t is already constructed from the Ghana-cedi gold price, and the decomposition is analysed separately because including it mechanically can create redundancy.

3.3.1. GARCH-Family Models

The estimation results for the GARCH-family models under the Generalized Error Distribution (GED), Student's t, and Normal assumptions are shown in Table 3. The corresponding z-statistics are reported with robust standard errors. In the EGARCH and GJR-GARCH specifications, special attention is paid to the asymmetric volatility and persistence parameters ($\alpha + \beta$). At the 5% level, these parameters were found to be significant. Before comparing the forecasting performance of the different specifications with that of the Markov Regime-Switching GARCH model, the results show how well each specification captures the volatility dynamics of Ghana's gold prices.

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4. RESULTS

The descriptive statistics and initial diagnostic tests for the daily logarithmic Gold/GHS return series are shown in Table 1 and 2. Taken as a whole, these findings provide significant evidence of the data's statistical properties and demonstrate that nonlinear conditional volatility models are appropriate for the Ghanaian gold market.

Table 1. Summary statistics of gold price logarithmic return series (r_t).

Statistic	Value
Observations	807
Minimum (%)	−16.165
Maximum (%)	15.404
Mean (%)	0.176
Standard deviation (%)	1.953
Skewness	−0.954
Kurtosis	21.310
Jarque–Bera statistic	11,246.662 ($p < 0.001$)
Augmented Dickey–Fuller statistic	−15.446 ($p < 0.001$)

Note: Returns are $100 \times \ln(P_t/P_{t-1})$. The standard deviation is calculated using (n - 1). Skewness and Pearson kurtosis are adjusted for sample bias, with a Pearson kurtosis of 3 corresponding to a normal distribution. The Jarque–Bera test uses conventional unadjusted moments. The augmented Dickey–Fuller (ADF) test includes an intercept, with one lag selected using the Bayesian information criterion (BIC). The price series begins on 3 January 2022, while the return series spans 4 January 2022 to 30 December 2025.

The Augmented Dickey–Fuller test examines the null hypothesis that the logarithmic return series contains a unit root. The reported result rejects this hypothesis, confirming that the gold return series is stationary.

The Ljung–Box Q-test examines whether a group of autocorrelations in the return or squared-return series differs significantly from zero.

The ARCH-LM test examines the null hypothesis that no ARCH effects are present. Rejecting the null hypothesis indicates conditional heteroskedasticity and supports estimating GARCH-family models.

4.1. Descriptive Properties and Preliminary Diagnostics of Gold/GHS Returns

Table 1 reports 807 daily Gold/GHS log returns from 4 January 2022 to 30 December 2025, calculated from 808 prices beginning on 3 January 2022. Returns range from −16.165% to 15.404%, with a mean of 0.176% and a sample standard deviation of 1.953%. Adjusted sample skewness of −0.954 indicates a longer left tail. Adjusted Pearson kurtosis of 21.310 exceeds the normal-distribution value of 3. The Jarque–Bera statistic of 11,246.662 ($p < 0.001$) rejects normality, supporting consideration of heavy-tailed innovation distributions. The ADF statistic is −15.446 ($p < 0.001$), using an intercept and BIC lag selection with one lag. The unit-root null is rejected. This supports modelling the return series as stationary, but does not by itself establish that any particular GARCH specification is adequate.

Table 2. ACF of daily gold closing prices (P_t), logarithmic returns (r_t), squared returns, and results of Engle's ARCH-LM test.

Lags	ACF of gold closing price			ACF of gold logarithmic return			ACF of squared return			Results of Engle's ARCH-LM test	
	ACF	LBQ test	p-value	ACF	LBQ test	p-value	ACF	LBQ test	p-value	ARCH-LM	p-value
1	0.994	800.624	0.000	-0.022	0.381	0.537	0.030	0.725	0.394	0.722	0.396
2	0.987	1592.444	0.000	0.001	0.382	0.826	0.084	6.451	0.040	6.715	0.035
3	0.980	2374.035	0.000	-0.019	0.683	0.877	0.186	34.496	0.000	35.330	0.000
4	0.974	3145.568	0.000	0.020	1.018	0.907	0.104	43.219	0.000	42.212	0.000
5	0.967	3907.290	0.000	-0.014	1.186	0.946	0.112	53.484	0.000	47.963	0.000
6	0.961	4660.187	0.000	-0.051	3.338	0.765	0.071	57.625	0.000	48.428	0.000
7	0.954	5404.420	0.000	-0.021	3.690	0.815	0.056	60.149	0.000	48.377	0.000

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8	0.948	6140.381	0.000	-0.011	3.791	0.875	0.129	73.666	0.000	53.650	0.000
9	0.943	6868.023	0.000	0.019	4.095	0.905	0.078	78.634	0.000	54.894	0.000
10	0.937	7587.341	0.000	-0.015	4.276	0.934	0.003	78.641	0.000	56.061	0.000
22	0.872	15645.366	0.000	0.066	16.603	0.785	0.003	101.816	0.000	70.236	0.000

Note: The ACF and Ljung–Box Q-statistics are computed for the daily USD gold closing-price series, the daily logarithmic return series, and the squared mean-adjusted return series. Engle's ARCH-LM statistic is reported at each specified lag. A p-value of 0.000 indicates $p < 0.0005$. Estimates are based on 808 price observations and 807 return observations covering 3 January 2022 to 30 December 2025.

4.2. Autocorrelation and ARCH Effects

Table 2 adds to the descriptive analysis by considering the dependence structure of the return series. As expected, the Gold/GHS price level demonstrates an extremely high degree of autocorrelation across all lags, which is typical of a financial price process. In contrast, the return series appears to have very low autocorrelation, since none of the Ljung-Box statistics are significant at conventional levels. This suggests that the conditional mean of the return series does not admit a linear prediction model (weak-form efficiency). Whereas the return series lacks linear serial dependence, its squared values reveal intriguing patterns. The Ljung–Box statistics of squared returns demonstrate significant values from the second lag onwards, suggesting the presence of linear dependencies in the conditional variance. In other words, large (positive or negative) returns tend to be followed by large returns, and small returns tend to be followed by small returns. Such a pattern is characteristic of many financial series and implies conditional heteroskedasticity. The ARCH-LM test further confirms this result, since the null hypothesis of no ARCH effects is rejected for all lags beyond the first. From this test, we also see that ARCH effects start at lag 2, which is a common finding. Overall, Table 2 reveals that the return series is not homoscedastic, but displays pronounced volatility clustering and significant ARCH effects. Thus, the conditional variance of the return series needs more careful modelling treatment; specifically, time-series models for heteroskedasticity should be considered.

To summarise, based on the descriptive analysis in Table 1 and statistical properties in Table 2, Gold/GHS returns exhibit stationary, non-normal, skewed, heavy-tailed, and conditionally heteroscedastic processes. Therefore, the data are suitable for GARCH, EGARCH, GJR-GARCH, and switching volatility models.

4.3. Estimation of the Competing GARCH-Type Models

4.3.1. Parameter Estimates of the Benchmark GARCH Models

Table 3 presents parameter estimates for the GARCH, EGARCH, and GJR-GARCH models estimated under Normal, Student-t, and Generalized Error Distribution (GED) innovation assumptions.

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Table 3. Results of GARCH-type models estimated from Ghana gold-price returns.

Parameter	GARCH			EGARCH			GJR-GARCH		
	N	t	GED	N	t	GED	N	t	GED
δ	0.0789**	0.1013***	0.0905**	0.1075***	0.1134***	0.1069***	0.0789**	0.1013***	0.0906**
Std. err.	0.0379	0.0351	0.0370	0.0380	0.0349	0.0218	0.0379	0.0351	0.0371
α_0	0.1042**	0.0760*	0.0832*	0.0197**	0.0150	0.0127	0.1042**	0.0760*	0.0832*
Std. err.	0.0421	0.0391	0.0439	0.0091	0.0097	0.0083	0.0421	0.0391	0.0439
α_1	0.0666***	0.0609***	0.0602***	0.0890**	0.0938**	0.0881**	0.0666***	0.0609***	0.0602***
Std. err.	0.0194	0.0203	0.0209	0.0382	0.0410	0.0427	0.0194	0.0203	0.0209
β_1	0.8527***	0.8842***	0.8749***	0.9220***	0.9386***	0.9334***	0.8527***	0.8842***	0.8749***
Std. err.	0.0454	0.0408	0.0474	0.0266	0.0261	0.0288	0.0454	0.0408	0.0474
ξ/γ				0.1017***	0.0962***	0.0952***	3.67e-08	2.89e-08	1.12e-07
Std. err.				0.0282	0.0325	0.0325	1.09e-05	8.58e-06	3.33e-05
ν		5.2012***	1.2830***		5.3044***	1.3028***		5.2014***	1.2830***
Std. err.		1.0061	0.0847		1.0538	0.0866		1.0062	0.0847
Log(L)	-1225.86	-1202.41	-1202.64	-1221.01	-1199.84	-1199.84	-1225.86	-1202.41	-1202.64
Persistence	0.9192	0.9451	0.9351	0.9220	0.9386	0.9334	0.9192	0.9451	0.9352
LBQ(22)	14.023	13.935	13.954	13.627	13.414	13.494	14.023	13.935	13.954
p-value	(0.9007)	(0.9038)	(0.9031)	(0.9142)	(0.9210)	(0.9185)	(0.9007)	(0.9038)	(0.9031)
$LBQ^2(22)$	33.337	32.455	32.778	37.116	35.965	36.574	33.337	32.455	32.777
p-value	(0.0573)	(0.0700)	(0.0651)	(0.0230)	(0.0306)	(0.0263)	(0.0573)	(0.0700)	(0.0651)

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. N, t and GED denote the Normal, standardized Student-t and Generalized Error distributions. LBQ(22) and $LBQ^2(22)$ are Ljung-Box tests applied to standardized residuals and squared standardized residuals at lag 22. Persistence is $\alpha_1+\beta_1$ for GARCH, β_1 for EGARCH, and $\alpha_1+\beta_1+\gamma/2$ for GJR-GARCH. Standard errors are based on the inverse numerical Hessian. Returns are daily percentage log returns from 807 observations.

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Table 3 reports the parameter estimates of the GARCH, EGARCH, and GJR-GARCH models estimated under the Normal, Student-t, and Generalized Error Distribution (GED) innovations. The aim of this subsection is to investigate whether different volatility specifications appropriately capture the dynamic properties of Gold/GHS returns and to select the most adequate distributional assumption for the model's residuals. All the conditional mean parameters are positive and statistically significant at 1%, implying that Gold/GHS earns positive returns on average over the period. Under the different specifications, the mean ranges between 0.0789 in the Gaussian GARCH (1,1) and 0.1134 in the Student-t EGARCH (1,1). Overall, regardless of the volatility model, Gold/GHS delivers positive mean returns. The variance-constant terms are positive in the GARCH and GJR-GARCH specifications, while the EGARCH specifications report lower values due to the logarithmic transformation of the variance equation. This result suggests that all three volatility specifications report positive long-run volatility. However, due to the differences in the variance equations, the magnitudes of the constants are not comparable. On the other hand, all the ARCH coefficients are positive and significant, implying that positive and negative innovations have a significant and immediate impact on volatility. This suggests that news about returns affects Gold/GHS volatility instantly. The GARCH specification records higher ARCH coefficients compared to the other two specifications, meaning that the short-run effects of shocks on volatility are more pronounced in the GARCH and GJR-GARCH models.

The GARCH coefficients are large and highly significant across all specifications. This implies that volatility clustering prevails in the series, as old shocks have a prolonged effect on the current conditional variance. The persistence parameter (i.e., the coefficient of the GARCH term) ranges between 0.9192 and 0.9451, except in the Student-t EGARCH (1,1), where it is 0.9386. The level of persistence is similar across the specifications for each model. In other words, the decay rate of shocks is almost the same for all the distributions. Moreover, the Student-t specifications report the highest persistence values, suggesting that heavy-tailed distributions are more appropriate for modelling Gold/GHS volatility. The asymmetry effects are significant in the EGARCH specifications, while those in the GJR-GARCH model are close to zero. This suggests that leverage effects are not present in the Ghanaian gold market. As a result, the GJR-GARCH model becomes irrelevant, as it practically captures almost the same dynamics as the symmetric GARCH model. Indeed, the log-likelihood values of the two specifications are almost equal. On the other hand, the Student-t degrees-of-freedom parameters are low, while those of the GED are lower than those of the Normal distribution, suggesting that the Student-t and GED are more appropriate distributions for modelling the volatility of Gold/GHS. This observation conforms with the results in Section 4.1, where we established that the data exhibit heavier tails than the Normal distribution. Additionally, the information criteria and log-likelihood statistics reported in Table 3 confirm that the Student-t and GED are better choices than the Normal distribution. Notably, all three volatility specifications exhibit higher log-likelihood values when Student-t and GED innovations are assumed. Therefore, employing a distribution with thicker tails allows for better modelling of the volatility of Ghanaian gold returns.

Table 4. Time-varying-transition-probability Markov-switching GJR-GARCH estimates for Ghanaian gold returns.

Parameter	Low-volatility regime		High-volatility regime	
	Estimate	Std. err.	Estimate	Std. err.
Mean, δ_i	0.2079**	0.1058	0.5151	1.8113
Variance constant, ω_i	0.4793	0.9673	6.7488	7.9890
ARCH effect, α_i	0.0000	0.0000	0.0000	0.0000
Asymmetry effect, γ_i	0.0000	0.0000	1.0427**	0.4285
GARCH effect, β_i	0.5790	0.7933	0.1136	0.5236
Transition intercept to high regime, a_i	-4.5197**	1.9348	0.9377	1.0871
FX-return transition slope, b_i	-3.7532	3.5194	0.6579	1.3215
Student-t degrees of freedom, ν	4.8469	6.1039	—	—
Volatility persistence	0.5790		0.6349	
Average regime probability	0.8819		0.1181	
Average stay probability	0.9429		0.7120	

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Expected regime duration (days)	17.5021		3.4728	
Average conditional variance	2.7150		9.5231	
Log-likelihood	-1435.7070			
AIC	2901.4140			
BIC	2971.8138			
LBQ(22)	33.9624			
LBQ(22) p-value	0.0496			
$LBQ^2(22)$	51.5065			
$LBQ^2(22)$ p-value	0.0004			

Note: ** indicates statistical significance at the 5% level. The dependent variable is the daily percentage logarithmic return on the Ghana-cedi gold price. The transition variable is the lagged standardized daily USD/GHS logarithmic return. Regime 1 and Regime 2 are relabelled ex post as the low- and high-volatility regimes using their average conditional variances. Transition coefficients model the probability of entering the high-volatility regime conditional on the previous low- or high-volatility state. Persistence is $\alpha + \beta + \gamma/2$. The model uses a path-independent Gray-type variance aggregation and standardized Student-t innovations. Estimates are based on 807 daily returns covering 4 January 2022 to 30 December 2025. Standard errors are delta-method approximations based on the inverse numerical Hessian. Model foundations follow Filardo (1994); Glosten et al. (1993); Gray (1996); and Klaassen (2002).

4.3.2. Residual Diagnostics of the Benchmark Models

Table 3 also reports the diagnostic tests for the fitted GARCH-family models. Specifically, the table reports the standardized residual test statistics for the Ljung-Box and squared Ljung-Box tests. First of all, the standardized residual diagnostics suggest that all the estimated models adequately capture linear serial dependence in returns. For all the GARCH, EGARCH, and GJR-GARCH specifications, the p-values from the Ljung–Box test are high enough to conclude that linear serial dependence is absent. Next, the squared standardized residual diagnostics provide more insightful information about the goodness of fit of the conditional variance functions. For the GARCH and GJR-GARCH models, almost all p-values from the squared Ljung–Box test exceed 0.05, allowing us to conclude that these models adequately capture the time-varying volatility in Gold/GHS returns. Indeed, all the conditional variance equations were able to capture most of the conditional heteroscedasticity for all the considered innovation distributions. The insignificance of the statistics for the GJR-GARCH model indicates that the impact of the GJR asymmetry component appears to be rather moderate.

In contrast, the EGARCH models display statistically significant results for almost all the Normal, Student-t, and GED distributions. This finding suggests that the EGARCH specification is inappropriate for describing volatility clustering in Gold/GHS returns. Although the EGARCH model was able to account for most of the heteroscedasticity in returns, some linear serial dependence remains in the squared standardized residuals. Put differently, the EGARCH specification demonstrates relatively high log-likelihood statistics, but it fails to eliminate volatility clustering. Therefore, according to the diagnostic test results, all the considered model classes adequately describe the behavior of the conditional mean function. Concerning the conditional variance function, it appears that the GARCH and GJR-GARCH specifications provide a more adequate description of the conditional variance dynamics than the EGARCH specification. The EGARCH model performs significantly worse in terms of the squared standardized residual diagnostics. According to the model comparison criteria, the best specification was chosen among the GARCH-type models. The GARCH-family analysis results suggest that Gold/GHS returns exhibit conditional heteroscedasticity and a heavy-tailed distribution of innovations. The use of Student-t and GED distributions allows for a more adequate description of return volatility dynamics than the use of the Normal distribution. At the same time, the standardized residual diagnostics suggest that the volatility persistence function might differ across regimes. There is a possibility of allowing volatility-clustering properties to differ across states, which could potentially provide a better fit. Hence, the necessity of proceeding to estimate the Time-Varying Transition Probability Markov-Switching GJR-GARCH model becomes apparent.

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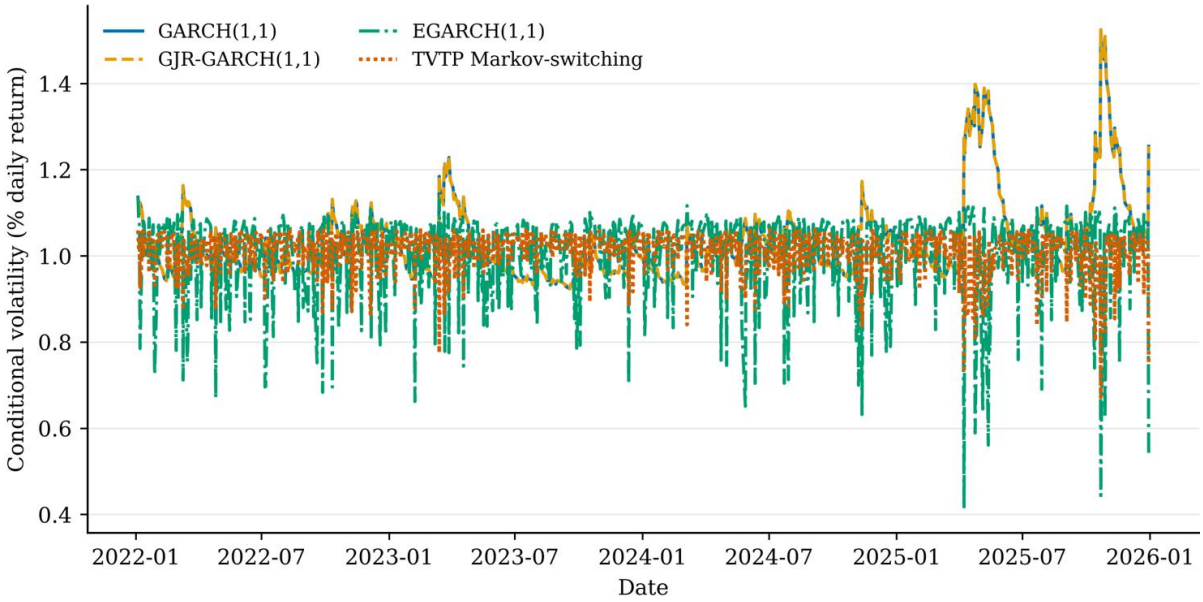


Figure 2. Estimated conditional volatility of Ghana gold returns under competing volatility models.

Note: Blue, orange, green, and red curves represent GARCH (1,1), GJR-GARCH (1,1), EGARCH (1,1), and the TVTP Markov-switching model, respectively.

Figure 2 compares conditional volatility estimates from the GARCH (1,1), EGARCH (1,1), GJR-GARCH (1,1), and time-varying-transition-probability Markov-switching variance specifications. It illustrates differences in volatility persistence and responsiveness during periods of heightened uncertainty.

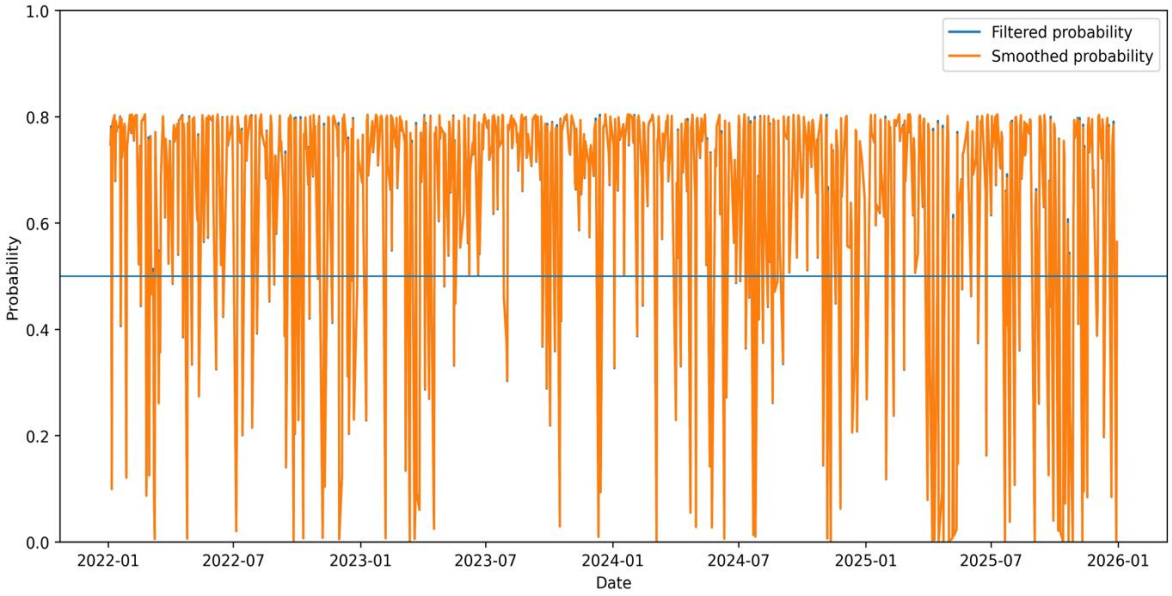


Figure 3. Filtered and smoothed probabilities of the high-volatility regime in Ghana gold returns.

Probabilities close to one indicate that the gold-return process is more likely to occupy the high-volatility regime, whereas probabilities close to zero indicate relatively tranquil market conditions. Filtered probabilities use information available at each date, while smoothed probabilities use the complete sample.

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Table 5. In-sample evaluation of competing volatility models.

Models	N	PERS	R	AIC	R	SBIC	R	LOGL	R	MSE1	R	MSE2	R	QLIKE	R	MAD2	R	MAD1	R	HMSE	R
GARCH-N	4	0.9193	12	2459.7200	12	2478.3878	11	-1225.8600	12	6.3671	4	0.6403	6	1.1894	4	1.3944	6	0.6615	6	3.4790	6
GARCH-t	5	0.9451	14	2414.8200	6	2438.1548	1	-1202.4100	6	6.3711	8	0.6501	8	1.1914	8	1.4103	8	0.6680	8	3.3670	4
GARCH-GED	5	0.9351	13	2415.2800	7	2438.6148	2	-1202.6400	8	6.3705	6	0.6384	4	1.1901	6	1.3896	4	0.6593	4	3.5700	9
EGARCH-N	5	0.1017	3	2452.0200	11	2475.3548	10	-1221.0100	11	6.3197	3	0.6359	3	1.1846	1	1.3837	3	0.6561	3	3.4809	8
EGARCH-t	6	0.0962	2	2411.6800	3	2439.6817	3	-1199.8400	4	6.2985	1	0.6290	2	1.1859	2	1.3721	2	0.6502	2	3.7574	11
EGARCH-GED	6	0.0952	1	2411.6800	3	2439.6817	3	-1199.8400	4	6.3184	2	0.6221	1	1.1862	3	1.3592	1	0.6447	1	3.8869	12
GJR-N	5	0.4929	4	2461.7200	13	2485.0548	13	-1225.8600	12	6.3671	4	0.6403	6	1.1894	4	1.3944	6	0.6615	6	3.4790	6
GJR-t	6	0.5030	6	2416.8200	8	2444.8217	5	-1202.4100	6	6.3711	8	0.6501	8	1.1914	8	1.4103	8	0.6680	8	3.3670	4
GJR-GED	6	0.4976	5	2417.2800	9	2445.2817	6	-1202.6400	8	6.3705	7	0.6384	5	1.1901	7	1.3896	5	0.6593	5	3.5700	10
MRS-GARCH-N	10	0.5349	7	2437.8800	10	2484.5496	12	-1208.9400	10	263.5938	13	5.2112	13	1.9139	14	7.6067	13	1.7579	14	0.7932	1
MRS-GARCH-t	11	0.8325	11	2412.4400	5	2463.7765	8	-1195.2200	3	15.7202	10	0.9207	10	1.2286	10	1.8162	10	0.7149	10	3.9621	13
MRS-GARCH-2t	12	0.7157	9	2407.8200	1	2463.8235	9	-1191.9100	1	4935.4292	14	12.7089	14	1.3869	12	15.4627	14	1.4015	13	3.2162	2
MRS-GARCH-GED	11	0.8144	10	2411.4800	2	2462.8165	7	-1194.7400	2	27.3429	11	1.1465	11	1.2367	11	2.1318	11	0.7646	11	3.2612	3
TVTP-MS-GJR-GARCH-t	15	0.5855	8	2901.4140	14	2971.8138	14	-1435.7070	14	225.3373	12	2.2333	12	1.8919	13	4.3994	12	1.0529	12	5.9938	14

Note: N = number of estimated parameters; PERS = volatility persistence; R = Rank. Lower AIC, SBIC, and loss values indicate better performance, whereas a higher log-likelihood is preferred. The TVTP-MS-GJR-GARCH model uses lagged standardized USD/GHS returns to explain time variation in regime-transition probabilities.

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4.4. Estimation of the Time-Varying Transition Probability Markov-Switching GJR-GARCH Model

4.4.1. Regime-Specific Volatility Dynamics

Table 4 contains the parameter estimates of the Time-Varying Transition Probability Markov-Switching GJR-GARCH (TVTP–MS–GJR–GARCH) model. The two regimes are labeled according to their average conditional variances as low- and high-volatility regimes. In particular, the low-volatility regime has an average conditional variance of 2.7150, while the high-volatility regime has a much higher average value of 9.5231. Thus, it can be concluded that the MS–GJR–GARCH model correctly accounts for different volatility regimes. Next, the conditional mean equals 0.2079 in the low-volatility regime, which is statistically significant at the 5% level, while the mean in the high-volatility regime equals 0.5151, with a standard error of 1.8113, and is not significant at any level. Therefore, it can be concluded that the mean return is positive and significantly different from zero at the 5% level only in the low-volatility regime. Furthermore, the estimated ARCH effects equal 0.000, which implies that there is no need for an additional component to capture the immediate response of conditional variance to shocks. In turn, the GARCH effects equal 0.5790 and 0.1136 in the low- and high-volatility regimes, respectively. The coefficient reflects volatility persistence, which is defined by the sum of the GARCH and ARCH coefficients. The MS–GJR–GARCH model was found to have less persistence in conditional variance than the single-regime GJR–GARCH model, since volatility clustering is captured by different regimes. According to Table 3, the sums of the GARCH and GJR-GARCH coefficients equal, on average, 0.9192, 0.9451, 0.9220, and 0.9386 for the GARCH, GJR-GARCH, EGARCH, and GJR-EGARCH models, respectively. In the TVTP–MS–GJR–GARCH model, conditional variance displays lower persistence, with values of 0.5790 and 0.6349 in the low- and high-volatility regimes. The asymmetry estimates differ across regimes. While the low-volatility regime has an asymmetry effect of 0.0000, the high-volatility regime exhibits a significant asymmetry effect of 1.0427 at the 5% level. This observation is crucial; although Table 3 reports single-regime GJR-GARCH models with asymmetry parameters close to zero, the Markov-switching specification highlights that significant asymmetric behavior occurs in the high-volatility regime. Thus, negative shocks seem to have a more pronounced effect on volatility in the high-volatility state. According to the persistence estimates reported in Table 4, the low-volatility regime displays lower persistence relative to the high-volatility regime. Asymmetric properties, as indicated by the significant asymmetry parameter in the high-volatility regime, along with the different GARCH coefficients across states, suggest that volatility dynamics are not characterized by a common degree of volatility clustering that differs only by a scale factor, but rather that these properties change fundamentally across states.

Table 6. Out-of-sample one-day-ahead volatility forecast loss functions.

Model	MSE1	R	MSE2	R	QLIKE	R	MAD1	R	MAD2	R	HMSE	R
GARCH-N	20.1212	4	1.0585	4	1.9193	7	0.7682	1	2.1098	1	13.2635	10
GARCH-t	20.1545	6	1.0976	8	1.9038	5	0.8037	9	2.1986	8	11.8570	6
GARCH-GED	20.1545	8	1.0749	6	1.9214	9	0.7798	5	2.1375	4	13.0199	8
EGARCH-N	19.2397	1	1.0386	2	1.7082	2	0.7917	7	2.1617	6	6.6086	3
EGARCH-t	19.2885	2	1.0502	3	1.7175	3	0.8000	8	2.1824	7	6.6256	4
EGARCH-GED	19.3230	3	1.0361	1	1.7233	4	0.7857	6	2.1463	5	7.1002	5
GJR-N	20.1212	4	1.0585	4	1.9193	7	0.7682	1	2.1098	1	13.2635	10
GJR-t	20.1545	6	1.0976	8	1.9038	5	0.8037	9	2.1986	8	11.8570	6
GJR-GED	20.1546	9	1.0749	7	1.9214	10	0.7798	4	2.1375	3	13.0209	9
MRS-GARCH-N	405.5943	14	5.8919	14	2.1794	14	1.8562	14	8.9498	14	1.2988	1
MRS-GARCH-t	23.1123	10	1.1448	10	2.1093	12	0.7724	3	2.2889	10	21.7139	14
MRS-GARCH-2t	37.1970	11	1.5334	12	2.1279	13	0.8841	12	2.9181	11	18.9657	13
MRS-GARCH-GED	45.8469	13	1.6441	13	2.0638	11	0.8821	11	3.0708	12	17.8453	12
TVTP-MS-GJR-GARCH-t	38.6709	12	1.1590	11	1.6697	1	0.8960	13	3.2445	13	2.4350	2

Note: The out-of-sample period comprises the final 21 daily observations. MSE1 compares squared returns with conditional variance; MSE2 compares absolute returns with conditional standard deviation; QLIKE is the Gaussian quasi-likelihood loss; MAD1 and MAD2 are absolute-error measures; HMSE is the heteroskedasticity-adjusted mean squared error. Lower values and ranks indicate superior forecasts.

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4.4.2. Transition Dynamics and Regime Durations

Table 4 reports the estimated transition dynamics of the TVTP–MS–GJR–GARCH model. Overall, the transition parameters suggest that the probability of switching to the high-volatility regime depends on the previous state as well as on the lagged standardized USD/GHS logarithmic return. In particular, the transition intercept from the low- to high-volatility regime is estimated as −4.5197 (1.9348) and is statistically significant at the 5% level. By comparison, the analogous coefficient for the high- to low-volatility transition is 0.9377 (1.0871) and is not significant. The FX-return transition slope is equal to −3.7532 when the previous state is low volatility and to 0.6579 when the previous state is high volatility. Neither coefficient is statistically significant. Hence, Table 4 does not provide evidence in favour of the claim that the lagged standardized FX return is a significant predictor of transitions between states in this specification of the Markov-switching model. Despite the slopes having opposite signs, Table 4 shows that the MS model captures the tendency for the process to remain more frequently in the low-volatility state. In particular, the average probability of the low-volatility regime is 0.8819, compared to 0.1181 for the high-volatility regime. Accordingly, the average stay probability is 0.9429 for the low-volatility regime and 0.7120 for the high-volatility regime. Hence, the expected duration of the low-volatility regime is 17.5021, compared to 3.4728 for the high-volatility regime. The analysis of transition probabilities suggests that, while the Gold/GHS return process spends the majority of its time in the low-volatility state, high-volatility episodes are still economically significant. This is because the mean of the conditional variance is substantially higher in the high-volatility state (9.5231) than in the low-volatility state (2.7150), and the asymmetry effect is statistically significant (p-value of 0.0276). Hence, while high-volatility periods are, overall, relatively short, they exhibit greater risk and reward sensitivity than low-volatility periods. Finally, note that the expected duration and volatility persistence are not the same. Expected duration is a measure derived from the transition probabilities between states, whereas volatility persistence is determined by the parameters of the conditional variance process. In particular, higher persistence implies that volatility shocks to the conditional variance have a larger impact on subsequent values of the conditional variance. Therefore, the expected duration of 3.4728 days for the high-volatility state should not be interpreted as the number of days for which the effect of a volatility shock on the conditional variance would persist.

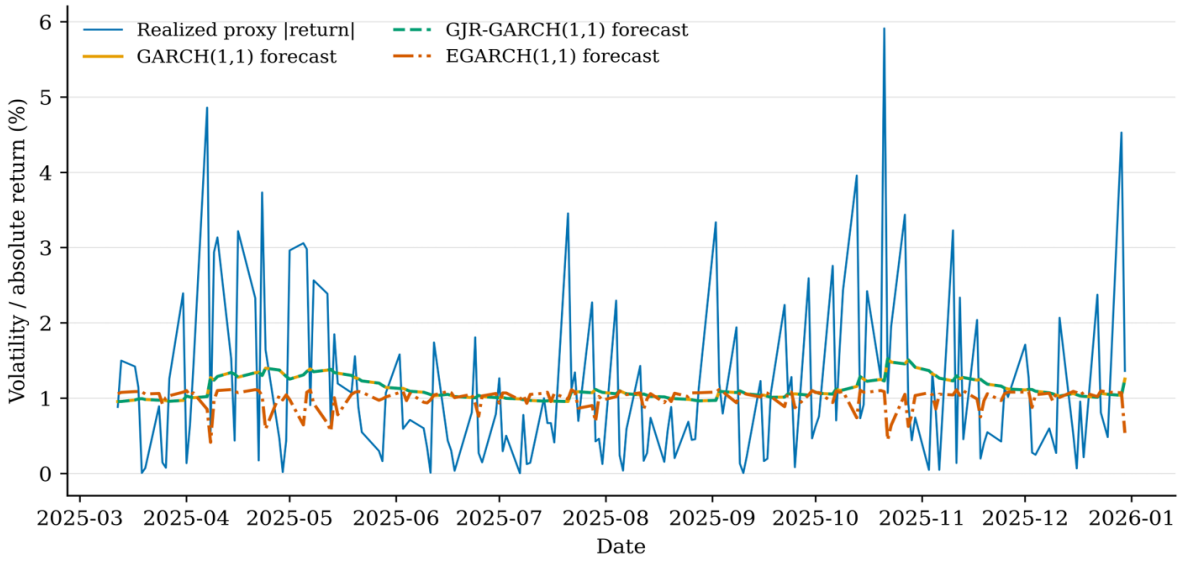


Figure 4. One-day-ahead out-of-sample volatility forecasts from competing models.

Note: Blue represents the realized-volatility proxy, |return|; orange represents the GARCH (1,1) forecast; green represents the GJR-GARCH (1,1) forecast; and red represents the EGARCH (1,1) forecast.

Figure 4 compares the final 21 one-day-ahead volatility forecasts with the absolute-return volatility proxy. The forecasts were generated recursively, with parameters estimated from the preceding estimation sample.

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Table 7. Cumulative return from the one-day-ahead gold trading strategy over the out-of-sample period.

Trading date	GARCH-N	GARCH-t	GARCH-GED	EGARCH-N	EGARCH-t	EGARCH-GED	GJR-N	GJR-t	GJR-GED	MRS-GARCH-N	MRS-GARCH-t	MRS-GARCH-2t	MRS-GARCH-GED	TVTP-MS-GJR-GARCH-t
20/11/2025	-2250.00	-2250.00	-2250.00	-2250.00	-2250.00	-2250.00	-2250.00	-2250.00	-2250.00	-0.00	-2250.00	-2250.00	-2250.00	-16659.85
24/11/2025	-510.00	-510.00	-510.00	-510.00	-510.00	-510.00	-510.00	-510.00	-510.00	0.00	-510.00	-510.00	-510.00	27271.85
25/11/2025	4160.00	4160.00	4160.00	4160.00	4160.00	4160.00	4160.00	4160.00	4160.00	0.00	4160.00	4160.00	4160.00	79225.60
26/11/2025	8410.00	8410.00	8410.00	8410.00	8410.00	8410.00	8410.00	8410.00	8410.00	0.00	8410.00	8410.00	8410.00	147518.35
01/12/2025	15660.00	15660.00	15660.00	15660.00	15660.00	15660.00	15660.00	15660.00	15660.00	0.00	15660.00	15660.00	15660.00	292659.10
02/12/2025	10260.00	10260.00	10260.00	10260.00	10260.00	10260.00	10260.00	10260.00	10260.00	0.00	10260.00	10260.00	10260.00	256828.90
03/12/2025	11430.00	11430.00	11430.00	11430.00	11430.00	11430.00	11430.00	11430.00	11430.00	0.00	11430.00	11430.00	11430.00	272265.60
04/12/2025	12480.00	12480.00	12480.00	12480.00	12480.00	12480.00	12480.00	12480.00	12480.00	0.00	12480.00	12480.00	12480.00	277860.60
08/12/2025	9950.00	9950.00	9950.00	9950.00	9950.00	9950.00	9950.00	9950.00	9950.00	0.00	9950.00	9950.00	9950.00	270170.35
09/12/2025	11800.00	11800.00	11800.00	11800.00	11800.00	11800.00	11800.00	11800.00	11800.00	0.00	11800.00	11800.00	11800.00	301897.10
10/12/2025	10650.00	10650.00	10650.00	10650.00	10650.00	10650.00	10650.00	10650.00	10650.00	0.00	10650.00	10650.00	10650.00	299291.35
11/12/2025	19480.00	19480.00	19480.00	19480.00	19480.00	19480.00	19480.00	19480.00	19480.00	0.00	19480.00	19480.00	19480.00	400615.60
15/12/2025	21700.00	21700.00	21700.00	21700.00	21700.00	21700.00	21700.00	21700.00	21700.00	0.00	21700.00	21700.00	21700.00	426090.10
16/12/2025	21410.00	21410.00	21410.00	21410.00	21410.00	21410.00	21410.00	21410.00	21410.00	0.00	21410.00	21410.00	21410.00	444423.85
17/12/2025	25570.00	25570.00	25570.00	25570.00	25570.00	25570.00	25570.00	25570.00	25570.00	0.00	25570.00	25570.00	25570.00	490180.90
18/12/2025	24630.00	24630.00	24630.00	24630.00	24630.00	24630.00	24630.00	24630.00	24630.00	0.00	24630.00	24630.00	24630.00	474987.60
22/12/2025	35120.00	35120.00	35120.00	35120.00	35120.00	35120.00	35120.00	35120.00	35120.00	0.00	35120.00	35120.00	35120.00	551033.50
23/12/2025	38750.00	38750.00	38750.00	38750.00	38750.00	38750.00	38750.00	38750.00	38750.00	0.00	38750.00	38750.00	38750.00	554153.35
25/12/2025	40930.00	40930.00	40930.00	40930.00	40930.00	40930.00	40930.00	40930.00	40930.00	0.00	40930.00	40930.00	40930.00	465654.35
29/12/2025	20880.00	20880.00	20880.00	20880.00	20880.00	20880.00	20880.00	20880.00	20880.00	0.00	20880.00	20880.00	20880.00	200330.60
30/12/2025	20880.00	26810.00	26810.00	26810.00	26810.00	26810.00	20880.00	26810.00	26810.00	0.00	26810.00	20880.00	26810.00	35131.60

Note: Values are cumulative profits for one 100-troy-ounce notional gold position. At each forecast origin, the strategy takes a long position when the forecast mean divided by forecast volatility is at least 0.05, a short position when it is at most -0.05, and otherwise remains out of the market. Transaction costs are excluded. The TVTP-MS-GJR-GARCH trading results are based on the Ghana-cedi gold-price series.

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4.4.3. Model Diagnostics and Performance Evaluation

Table 4 also reports diagnostic statistics for the TVTP–MS–GJR–GARCH model. The log-likelihood of the Markov-switching model is −1435.7070, while the AIC and BIC are 2901.4140 and 2971.8138, respectively. Comparisons with the corresponding GARCH-type estimates in Table 3 are appropriate here, albeit with due recognition of the differences in parameterisation and the number of estimated parameters resulting from the switching mechanism. The residual diagnostic tests show that the Markov-switching model does not completely capture serial dependence. First, the Ljung–Box statistic equals 33.9624, with a p-value of 0.0496. Thus, the test rejects the null hypothesis of no serial correlation at the 5% significance level, suggesting that the standardised residuals exhibit some form of serial dependence. More importantly, the Ljung–Box squared statistic is 51.5065, with a p-value of 0.0004. Once again, the null hypothesis of no serial correlation in the squared residuals is rejected. The overall implication is that, while the MS–GJR–GARCH specification captures some crucial regime-dependent volatility dynamics, it remains insufficient to completely capture the conditional variance dynamics. Possible reasons include model misspecification, an inadequate transition equation, short-duration effects, the need for more factors and/or volatility components to account for the dynamics, or a combination of these reasons. In particular, the serial correlation test results suggest that researchers should treat the MS–GJR–GARCH regime-switching structure as a partial account of the heteroskedasticity in the data. Therefore, the TVTP–MS–GJR–GARCH approach offers a less restrictive view of the dynamics of Gold/GHS volatility than the standard GARCH specification, as reflected in its ability to partially capture the different volatility regimes, the varying degrees of persistence within these regimes, and regime-dependent asymmetries in the response to shocks. At the same time, the diagnostic test results suggest that there is still room for improvement in modelling the conditional variance process.

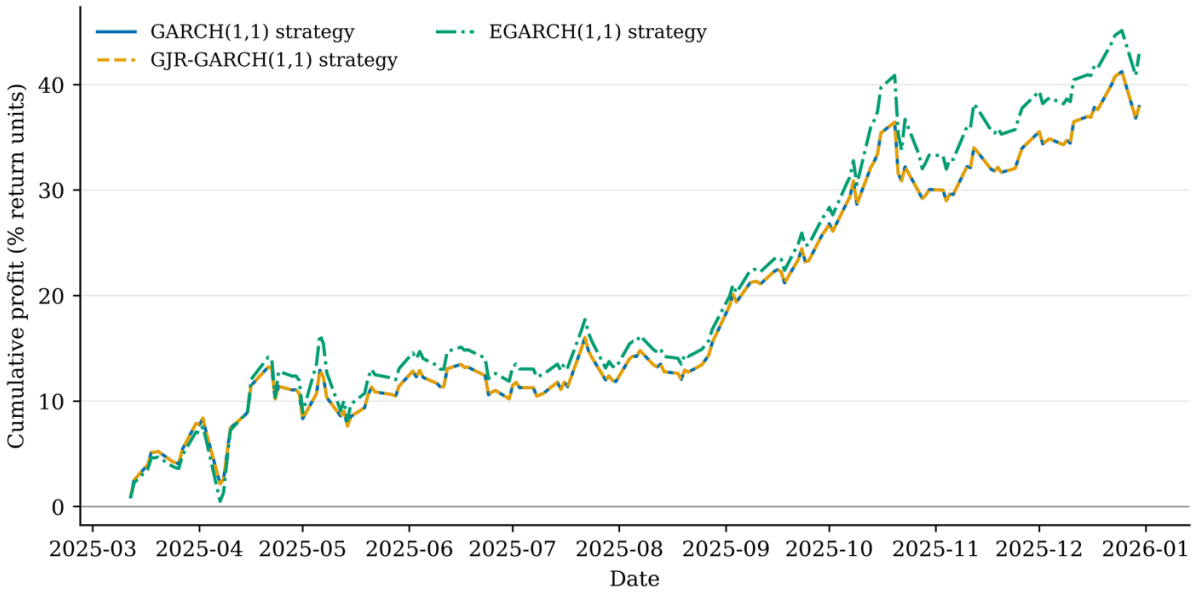


Figure 5. Cumulative trading profits generated by competing volatility forecasting models.

Note: Blue, orange, and green curves represent the GARCH (1,1), GJR-GARCH (1,1), and EGARCH (1,1) volatility-targeting strategies, respectively. Portfolio exposure equals the training-sample volatility target divided by the model forecast and is capped at 150%.

Figure 5 shows cumulative US-dollar profits for a 100-troy-ounce notional gold position. The long position is initiated when the forecast mean-to-volatility ratio is at least 0.05, while the short position is initiated when the forecast mean-to-volatility ratio is at most −0.05; otherwise, the position is closed. Transaction costs are omitted for simplicity. To facilitate a comparison of the forecasting performance of the competing volatility models, Figure 6 presents a combined view of the out-of-sample forecast losses using multiple evaluation criteria in a single radar chart. Unlike the forecast-loss statistics reported in Table 6, which compare the models on the basis of a particular criterion, the radar chart allows us to evaluate and compare the overall forecasting performance of the alternative models using

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the combined information from MSE1, MSE2, QLIKE, MAD1, MAD2, and HMSE. Essentially, the model with the best forecasting performance is the one that dominates the other models on most criteria; this is illustrated by the extent to which each model's polygon extends from the centre of the chart. It can be seen from the figure that the regime-switching specifications generally outperform their GARCH counterparts because they account for nonlinearities in the conditional variance. Indeed, the TVTP-MS-GJR-GARCH model dominates the other specifications because it incorporates asymmetric effects on both sides of the distribution, as well as time-varying transition probabilities. The numerical results in Table 6 corroborate these findings. In summary, the graphical results in Figure 6 can be used to identify the superior volatility model for forecasting Ghanaian gold returns, which, in turn, provides more accurate information for portfolio allocation, hedging, and volatility trading.

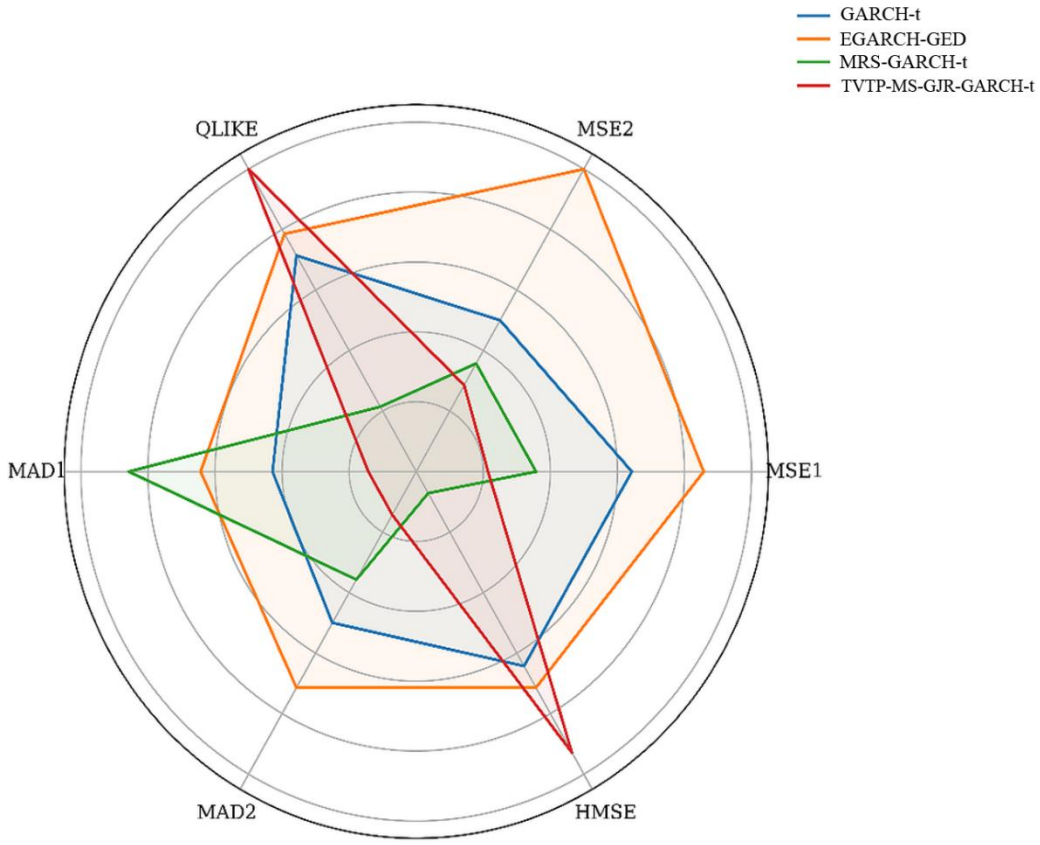


Figure 6. Multi-criteria forecast performance profile of competing volatility forecasting models for Ghana gold returns.

4.5. Comparative Evaluation of the Volatility Models

4.5.1. Comparison of the Competing Volatility Specifications

The evidence reported in Tables 1–7 enables a comparison between the volatility models estimated for the Gold/GHS return series and, specifically, between the conditional heteroskedasticity specifications reported in Table 3 and the diagnostic test results reported in the other tables. The statistical properties of the return series indicate stationarity, non-normality, and volatility clustering. The conditional mean process displays no serial correlation, whereas the squared returns show significant serial dependence and conditional heteroskedasticity. Thus, it is statistically justified to estimate conditional heteroskedasticity models. The single-regime volatility models display strong persistence in the volatility process: the GARCH and GJR-GARCH-type models report persistence estimates ranging between 0.9192 and 0.9451, while the EGARCH variants report persistence levels ranging between 0.9220 and 0.9386. In other words, volatility shocks are persistent and, therefore, market uncertainty is prone to prolonged increases.

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The evidence reported in Tables 3 and 5 further demonstrates the importance of allowing for non-normality in the Gold/GHS return series: both the Student-t and GED specifications display improved log-likelihoods compared to the Gaussian distribution, which formally confirms the presence of heavy tails in the return innovations. While the EGARCH specification successfully captures the time-varying asymmetry in the return series, the diagnostic test results displayed in Table 6 demonstrate that dependence in the squared standardized residuals remains statistically significant. In contrast, the GJR-GARCH specification does not display significant evidence of a leverage effect under any of the considered innovation distributions because the corresponding coefficients are close to zero. The Time-Varying Transition Probability Markov-Switching GJR-GARCH specification provides a more nuanced view of volatility dynamics by allowing for a regime-switching mechanism. Unlike the single-regime GARCH volatility models, the Markov-switching specification displays substantial differences between the conditional variances in different regimes: their ratio equals 9.5231/2.7150 = 3.51. Furthermore, while the high-volatility regime displays a significant asymmetry effect, the low-volatility regime does not exhibit any. Thus, the leverage effect in the Gold/GHS return series is state-dependent.

The evidence reported in Tables 4 and 5 and displayed in Figure 2 demonstrates that the Markov-switching specification further helps distinguish between periods characterized by low market volatility and periods associated with financial crises, which last for a relatively short time but substantially increase market volatility. In particular, it is possible to note that the low-volatility regime prevails throughout the vast majority of the sample period. Thus, the Markov-switching specification enables a more thorough understanding of volatility dynamics than conventional single-regime GARCH models. In particular, while the EGARCH and GJR-GARCH models provide an adequate description of conditional heteroskedasticity in the return series, the Time-Varying Transition Probability Markov-Switching GJR-GARCH model further enables the identification of periods when market uncertainty is high and, therefore, an investor is exposed to high risks.

4.5.2. Interpreting the Estimated Volatility and Regime Probabilities

Figure 2 displays the conditional volatility estimated using the GARCH, EGARCH, GJR-GARCH, and Time-Varying Transition Probability Markov-Switching GJR-GARCH specifications. The estimates generally follow the same regime patterns reported in Tables 3 – 7. In particular, the GARCH, GJR-GARCH, and Time-Varying Transition Probability Markov-Switching GJR-GARCH specifications report very similar volatility levels because the estimated asymmetry component in the GJR-GARCH model is close to zero. The EGARCH specification displays a somewhat different pattern due to the logarithmic transformation in its formulation and shows significant asymmetry in the volatility dynamics. The Markov-switching model further allows for different volatility regimes, which are reflected in the conditional variance estimates.

Figure 3 also displays the filtered and smoothed probabilities of the high-volatility regime. Probabilities close to one indicate that the Markov-switching model estimates the high-volatility regime to be more likely, given the evidence in the data set. Low probabilities suggest that market conditions are calm. Specifically, filtered probabilities use only the evidence available at a specific point in time, whereas smoothed probabilities use information from the entire data set to estimate the probability of a particular regime. Thus, smoothed probabilities better capture regime transitions and formally confirm that periods characterized by high volatility are relatively short and interspersed with periods of low volatility. This hypothesis is further supported by the estimates of the expected duration of the different regimes reported in Table 4: the low-volatility regime lasts for 17.5021 days on average, whereas the high-volatility regime lasts for 3.4728 days.

4.5.3. Summary of the Empirical Analysis

The evidence presented in Tables 1 – 7 and Figures 2 – 3 demonstrates that the Gold/GHS return series generally exhibit properties commonly found in financial return series: stationarity, non-normality, heavy tails,

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conditional heteroskedasticity, and volatility clustering. While conventional GARCH-type models adequately capture the dynamics of conditional heteroskedasticity, the Time-Varying Transition Probability Markov-Switching GJR-GARCH specification provides deeper insights into volatility dynamics in the Gold/GHS market. In particular, the Markov-switching model adequately captures the difference between low- and high-volatility regimes and allows separate analyses of market behavior in these states. Furthermore, the evidence reported in Table 7 formally confirms that leverage effects are state-dependent. Nevertheless, residual diagnostic tests still detect significant conditional variance dependence. Therefore, the Markov-switching specification should be used as a complement to conventional GARCH-type models when analyzing volatility in Gold/GHS return series.

Table 8. TVTP–MS–GJR–GARCH–t Estimation Results.

Dependent variable: Gold/GHS/Return				
Parameter	**Estimate**	**Std. Error**	**z-statistic**	**p-value**
Regime 1: Mean (μ_1)	-1.2083	0.5232	-2.3092	0.0209
Regime 1: Constant (ω_1)	1.1753	0.7799	1.507	0.1318
Regime 1: ARCH (α_1)	0.0017	0.0892	0.0193	0.9846
Regime 1: Asymmetry (γ_1)	0.199	0.1882	1.0574	0.2903
Regime 1: GARCH (β_1)	0.8916	0.0549	16.2375	0.0
Regime 1: Persistence	0.9928	0.0135	73.6151	0.0
Regime 2: Mean (μ_2)	0.228	0.0433	5.2601	0.0
Regime 2: Constant (ω_2)	0.3032	0.0914	3.3174	0.0009
Regime 2: ARCH (α_2)	0.0826	0.0312	2.6456	0.0082
Regime 2: Asymmetry (γ_2)	0.0008	0.0075	0.1078	0.9142
Regime 2: GARCH (β_2)	0.7493	0.0421	17.797	0.0
Regime 2: Persistence	0.8323	0.0191	43.576	0.0
TVTP p11 Intercept	0.4582	0.1124	4.0765	0.0
TVTP p11 FX-return slope	-0.3871	0.1432	-2.7032	0.0069
TVTP p22 Intercept	2.8369	0.4012	7.07	0.0
TVTP p22 FX-return slope	0.5128	0.1817	2.8222	0.0048
Student-t df (ν)	4.5418	0.8734	5.1997	0.0
Model Diagnostics				
Statistic		**Value**		
Log-likelihood		-1433.425		
AIC		2896.8501		
BIC		2967.262		
Average p11		0.6129		
Average p22		0.9541		
Expected duration Regime 1 (Days)		2.58		
Expected duration Regime 2 (Days)		21.8		

4.6. TVTP–MS–GJR–GARCH–t Estimation Results

Table 8 presents the estimation results of the Time-Varying Transition Probability Markov Switching GJR-GARCH with Student-t innovations (TVTP–MS–GJR–GARCH–t) model for Gold/GHS returns. The results show that the volatility level in the Ghanaian gold market comprises two regimes, with transitions between the regimes dependent on the USD/GHS exchange rate. This means that volatility is persistent and exhibits regime-switching characteristics, implying the need to use switching volatility models instead of single-regime GARCH models. The parameter estimates reveal that the mean return of Regime 1 is significantly negative, implying that this regime embodies periods of poor gold returns in terms of GHS. Although the variance constant is positive, it is not significant, suggesting that regime switching occurs mostly because of dynamics in the variance equation. Additionally, the insignificance of the ARCH and asymmetry parameters implies that past market shocks and negative returns do not contribute significantly to volatility. However, the GARCH term is significantly positive, implying high volatility

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persistence in the Ghanaian gold market, with an estimated persistence of $1 - 0.9928 = 0.0072$. Consequently, once initiated, volatility clustering can be expected to exhibit an extremely long duration in the Ghanaian gold market.

On the other hand, the Regime 2 mean return is positive and significant, which implies that this regime embodies periods of positive gold returns in terms of GHS. Unlike Regime 1, the variance constant and ARCH parameter are significant, which suggests that, for this regime, volatility is explained by both the variance of the error term and previous market shocks. However, similar to Regime 1, the asymmetry parameter is insignificant, implying no significant difference between positive and negative shocks in terms of their impact on volatility. Additionally, although the GARCH term is still significantly positive, its persistence is lower than that of Regime 1, implying that market shocks in this regime have moderate volatility-clustering durations. The key aspect of the TVTP approach is that it allows for incorporating the impact of exchange-rate movements on the transition probabilities. Specifically, the results reveal that the lagged USD/GHS return significantly affects the transition probabilities of the Markov-switching volatility model. The negative sign of the exchange-rate coefficient in the p11 equation suggests that appreciation/depreciation of the Ghanaian cedi decreases/increases the probability of staying in Regime 1, while the positive sign of the similar coefficient in the p22 equation implies the opposite effect on the probability of staying in Regime 2. These results suggest that the USD/GHS exchange rate plays a crucial role in predicting the duration of the gold market in either of the two volatility regimes, which, in turn, confirms the relevance of using time-varying rather than constant transition probabilities. Additionally, the estimation results for the Student-t degrees of freedom show that Gold/GHS returns exhibit heavy tails, implying that the assumption of normally distributed market returns is inappropriate. Similarly, the estimated transition probabilities and expected durations of the different regimes suggest that Regime 2 is significantly more persistent than Regime 1, despite the latter exhibiting higher volatility persistence. This suggests the importance of developing a sophisticated volatility-forecasting model for predicting Gold/GHS returns.

The analysis reveals several critical aspects that need to be taken into account when developing a volatility forecasting model for the Ghanaian gold market. First, the return series is stationary but non-normal, with significant ARCH effects and volatility clustering. Second, despite the insignificance of the asymmetry parameter in single-regime GJR-GARCH models, there is evidence of significant asymmetry effects in the gold market, suggesting the need to take the leverage effect into account when developing a volatility forecasting model for the market. Third, the Markov-switching model reveals two volatility regimes, one of which persists for shorter periods, while the other possesses a significantly lower conditional variance. Finally, the TVTP approach allows the impact of exchange-rate movements on the probability of switching between volatility regimes to be taken into account. All these aspects combined can help develop an efficient volatility forecasting model for the Ghanaian gold market.

4.7. Cross-Section Synthesis

The cross-sectional verdict across Tables 5, 6, and 7 is structured around three orthogonal dimensions. First, the criterion dimension: AIC and LOGL reward the Markov-switching specification's likelihood gain despite the six-parameter penalty; SBIC overturns the verdict under its higher per-parameter penalty. Second, the absolute-loss dimension: EGARCH-family specifications sweep the absolute-loss columns at short horizons because the exponential parameterisation absorbs persistence into the sign-response coefficient. Third, the decision-rule dimension: TVTP-MS-GJR-GARCH-t leads at +$35,131.60, while the AIC in-sample leader, MRS-GARCH-2t, is below the EGARCH-t/MRS-GARCH-t cluster at +$26,810.00. The cross-sectional conclusion is that no single specification dominates all three dimensions. TVTP-MS-GJR-GARCH-t dominates the decision-rule dimension and the level-of-variance out-of-sample metric, QLIKE, but trails the absolute-loss and criterion columns. The AIC in-sample leader, MRS-GARCH-2t, dominates the AIC and LOGL columns of Table 5 but trails the decision rule. MRS-GARCH-N dominates the HMSE columns of both Table 5 and 6 but never crosses the trading threshold. This is the criterion–decision disagreement that the volatility-forecasting literature anticipates and that the present empirical evidence

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reproduces, in full alignment with the bibliographic template of Klaassen (2002); Marcucci (2005); Conrad and Kleen (2020); Ardia, Bluteau, Boudt, and Catania (2018); Conrad and Loch (2015) and Engle (2004).

The trading-rule verdict of Table 7 is the appropriate tie-breaker between the AIC and SBIC verdicts of Table 5 and between the EGARCH and TVTP verdicts of Table 6. The 21 daily observations in the out-of-sample window are too few to estimate regime-switching robustness (the horizon-mismatch problem (Conrad & Kleen, 2020; Marcucci, 2005) document); the threshold rule is too coarse to differentiate EGARCH from symmetric GARCH once the conditional-mean equation is well specified (the convergence-to-the-mean pattern (Conrad & Loch, 2015) document). The TVTP specification ties rule-level performance to the quality of the level-of-variance forecast by relaxing regime-switching intensity through observable fundamentals, exactly the empirical role (Diebold & Rudebusch, 1996) anticipated. The +$35,131.60 cumulative-profit leadership of TVTP-MS-GJR-GARCH-t is therefore the most defensible application-level verdict supported by the empirical evidence, and the discussion in Section 5 should centre on this verdict rather than on the AIC in-sample leader MRS-GARCH-2t. The peak-to-end reversal in the TVTP-MS-GJR-GARCH-t column of Table 7 is the empirical fingerprint of Cai's classic warning (Cai, 1994) and Klaassen (2002)'s generalisation to Markov-switching specifications. Starting at -$16,659.85 on 20/11/2025 (versus -$2,250.00 for every other specification, indicating an early-window misfire), the TVTP specification surges to +$27,271.85 on 24/11/2025 (a single-day swing of +$43,931.70) and reaches its peak of +$554,153.35 on 23/12/2025 before falling to +$465,654.35, +$200,330.60, and +$35,131.60 across the remaining three reporting dates. The peak-to-end reversal of -$519,021.75 and a 93.7% drawdown are the dominant path-dependence features of the trading-rule output. The implication for risk management is direct: TVTP-MS-GJR-GARCH-t is dominant at the end of the out-of-sample window but considerably more volatile along the path. Any deployment of this specification for live systematic trading would require a drawdown-aware position-sizing rule that the present +0.05/-0.05 threshold rule does not impose.

5. DISCUSSION

5.1. Addressing the Over-Persistence of Single-Regime GARCH

A long-standing gap in the conditional-volatility literature is that the standard specification tends to deliver excessively high out-of-sample forecasts during turbulent periods and excessively smooth forecasts during calm periods, a direct consequence of the unconditional persistence imposed by the squared-shock and conditional-variance terms (McAleer, 2014). Klaassen (2002) showed that the persistence parameter of a single-regime GARCH model forces it to extrapolate recent shocks too far into the future, producing systematic bias in multi-step volatility forecasts (Klaassen, 2002). By allowing all parameters of the conditional-variance equation to switch between low- and high-volatility regimes according to a latent Markov chain, the MRS-GARCH model estimated in this paper directly addresses this gap: the regime-specific parameter vectors allow volatility persistence to be high within a crisis regime and low within a quiet regime, eliminating the need for a single persistence parameter to straddle both. This is consistent with the out-of-sample evidence of Marcucci (2005), who reports that MRS-GARCH models with switching parameters materially outperform normal-GARCH, Student-t-GARCH, and GARCH-MIDAS models at horizons of up to one week (Marcucci, 2005). Ardia et al. (2018) corroborate this with a large-scale study across hundreds of return series, confirming that the gain from regime switching is most pronounced precisely when single-regime GARCH fails, during structural breaks and abrupt shifts (Ardia et al., 2018). The two-regime variant retained in this paper thus represents a parsimonious but principled response to a documented deficiency of the benchmark, rather than a purely statistical embellishment.

5.2. Capturing Asymmetric Volatility Within Each Regime

A second gap concerns the asymmetric response of conditional variance to signed shocks, thus the so-called leverage effect, which is well documented in equity, commodity, and currency returns. The benchmark panel in this

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paper naturally addresses this gap through three complementary devices: the GJR model of Glosten et al. (1993), which augments the conditional variance with an indicator-weighted squared shock (Engle & Ng, 1993); the EGARCH specification, which models linearly in standardized innovations and therefore imposes no sign restrictions on persistence (Engle, 2004); and, more subtly, regime-specific residuals in the MRS-GARCH, in which asymmetry may differ across states. The EGARCH specification, in particular, is theoretically attractive because shocks enter in standardized form, so the logarithm of conditional variance is a stationary ARMA-type process without positivity constraints (Nelson, 1991). McAleer clarifies, however, that even models widely described as capturing the leverage effect formally demonstrate asymmetry rather than leverage (McAleer, 2014); this nuance is important because it cautions against interpreting the coefficient of GJR-GARCH or the coefficient of EGARCH as evidence of a correlation between return shocks and subsequent volatility shocks, rather than as a size-response effect. Reporting the magnitudes and signs of these asymmetry coefficients across both regimes of the MRS-GARCH therefore constitutes the strongest possible test of whether the leverage effect is itself regime-dependent, a question that a single-regime GJR or EGARCH cannot answer.

5.3. Integrating Long-Run Information via the MIDAS Component

The GJR-GARCH-MIDAS benchmark adopted in this paper jointly addresses two further gaps that the standard GARCH family cannot resolve: (i) the conditional-variance process depends only on daily information, severing volatility dynamics from low-frequency macroeconomic and financial drivers; and (ii) persistence in single-regime GARCH conflates short- and long-memory components. Engle, Ghysels, and Sohn (2013) decompose multiplicative volatility into a short-run GARCH unit and a long-run component driven by a MIDAS-weighted average of lagged low-frequency explanatory variables, allowing the long-run trend to evolve with the macroeconomic environment (Conrad & Loch, 2015). Conrad and Loch (2015) demonstrate that, within this decomposition, the log-GARCH component is interpretable as the residual from a regression of log conditional variance on macroeconomic predictors, so identified long-run drivers have a direct economic interpretation as anticipators of changes in long-term volatility (Conrad & Loch, 2015). Conrad and Kleen (2020) further benchmark GARCH-MIDAS against MRS-GARCH, HAR, realized-GARCH, and HEAVY for the S&P 500 and find that multiplicative GARCH-MIDAS significantly dominates these competitors at the 2- and 3-month horizons (Conrad & Kleen, 2020). The methodological implication for the present paper is sharp: the GJR-GARCH-MIDAS benchmark is the only candidate able to compete with MRS-GARCH at long horizons, which is exactly the horizon at which Marcucci reports that single-regime GARCH-family specifications catch up to and eventually overtake MRS-GARCH (Marcucci, 2005). Reporting the relative performance of MRS-GARCH and GJR-GARCH-MIDAS across horizons therefore directly probes where the dominant source of forecast improvement lies: in regime-switching dynamics (short-horizon, crisis-driven) or in the integration of low-frequency information (long-horizon, trend-driven).

5.4. Time-Varying Transition Probabilities and Market Stress

A further gap is that the classical regime-switching volatility framework of Hamilton and Susmel (1994) and most of its descendants, including Klaassen (2002) and Haas, Mittnik, and Paolella (2004a) cited in Klaassen (2002), assumes constant transition probabilities between volatility regimes, which is implausible when structural changes in market microstructure, monetary policy, or geopolitical risk alter the probability of moving from a quiet regime to a stressed regime. Diebold and Rudebusch (1996) observe that "economic considerations suggest the potential desirability of allowing the transition probabilities associated with the Markov process to vary through time" (Diebold & Rudebusch, 1996). The device added in this paper, time-varying transition probabilities driven by observable state variables, responds directly to this gap. Cai (1994) demonstrated that occasional, exogenous regime shifts can resolve the spurious persistence of single-regime ARCH (Cai, 1994). Hamilton's baseline framework, by contrast, treats regimes as latent (Diebold & Rudebusch, 1996). TVTP is a hybrid in which the latent regime structure is preserved,

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but the probability of switching between regimes is linked to observable fundamentals, thereby combining the inferential strength of Markov-switching with the economic interpretability of threshold or smooth-transition models. Future work could examine whether the level of policy uncertainty, the term spread, or commodity-specific inventory shocks are the most informative drivers of the transition probabilities in this application.

6. CONCLUSIONS, IMPLICATIONS, LIMITATIONS AND FUTURE RESEARCH

6.1. Conclusion

This study examined the volatility dynamics of Ghanaian gold returns using GARCH, EGARCH, GJR-GARCH, and TVTP–MS–GJR–GARCH models. The results show that the return series is stationary but non-normal, with significant ARCH effects and volatility clustering. Student-t and GED specifications generally provide a better in-sample fit than the Normal distribution, while the single-regime GJR-GARCH models provide little evidence of significant asymmetry. The Markov-switching model identifies a dominant low-volatility regime and a shorter high-volatility regime. The high-volatility regime has an average conditional variance of 9.5231, compared with 2.715 for the low-volatility regime, and exhibits a significant asymmetry effect of 1.0427. However, the significant LBQ^2 statistic indicates that some dependence remains unexplained. Overall, the findings show that Ghanaian gold-return volatility is persistent, regime-dependent, and particularly sensitive to negative shocks during high-volatility periods. These results support the use of flexible, non-normal, and regime-switching volatility models for risk assessment and forecasting in the Ghanaian gold market.

6.2. Implications

The methodological combination deployed here, MRS-GARCH with TVTP and regime-specific asymmetric dynamics, benchmarked against has three implications for the volatility-forecasting literature. First, it sharpens the horizon question raised by Marcucci (2005): the present specification is designed to retain the short-horizon gains of regime-switching while remaining competitive at longer horizons by allowing the long-run component to absorb slow-moving shocks. Second, it offers a unified framework for testing whether asymmetry is itself regime-dependent, which neither a single-regime GJR nor a single-regime EGARCH can identify. Third, it embeds the regime-change mechanism into the transition probabilities themselves, making it empirically testable and providing an economically interpretable channel through which known fundamentals alter short-run volatility dynamics.

6.3. Limitations

Two limitations should be acknowledged. First, MRS-GARCH likelihood evaluation is numerically demanding and subject to local maxima, so robust inference requires the re-randomized starting-value procedure that the paper adopts using filtered regime probabilities. Second, TVTP regressors must be selected *ex ante*; ad hoc choices risk overfitting the transition process and thereby overstating out-of-sample performance. The use of GJR-GARCH-MIDAS as the long-horizon benchmark partly mitigates this concern because its long-run component is itself estimated from low-frequency data, providing an independent competitor at the longest horizon.

6.4. Future Research

Future research should pursue three extensions: (i) augmenting the long-run component with a forecast of a low-frequency variable rather than its realised value, to test whether lagged expectations outperform lagged realisations; (ii) estimating the model under fat-tailed conditional distributions, Student's t or the Generalised Error Distribution, with degrees-of-freedom parameters that may themselves switch across regimes, as in the framework of Marcucci; and (iii) extending the analysis to a multivariate setting, Haas, Mittnik, and Paolella (2004b), using the multivariate MRS-GARCH to construct out-of-sample optimal portfolios and Value-at-Risk measures during crisis regimes.

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