Commodity Price Prediction with TAR and MARKOV-SWITCHING Models. Evidence from Gold and Cocoa Markets

Abstract: Accurate forecasting of commodity prices remains a crucial challenge due to inherent market volatility and regime-dependent behaviour. This study examines the predictive performance of two nonlinear time series models, the Threshold Autoregressive (TAR) model and the Markov Switching Model (MSM), in modeling and forecasting the prices of gold and cocoa. These commodities exhibit complex dynamics characterized by abrupt structural breaks and asymmetric responses to economic shocks, features that are inadequately captured by linear models. The TAR model is employed to detect endogenous threshold effects, while the MSM accounts for unobservable regime shifts through a probabilistic framework. Monthly average prices of International Cocoa (US$ /tonne) and International Gold (US$ /fine ounce) spanning the period from January 2003 to December 2022 (a 20-year window) were subjected to unit root testing, transformation, and differencing to ensure stationarity prior to modeling. The models' forecasting accuracy was evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Results indicate that both TAR and MSM significantly improve out-of-sample forecasts by capturing both abrupt and smooth nonlinear transitions. Notably, the gold market showed stronger regime-switching dynamics, while cocoa prices exhibited clearer threshold-based behaviour. MSM model outperforms the TAR model in forecasting gold prices, as it records lower values for both MAE and RMSE, indicating higher predictive accuracy. For Cocoa, TAR slightly outperforms MSM in both MAE and RMSE, though the difference is minimal. Thus, both models perform comparably for Cocoa, with a marginal edge for TAR. Model suitability is observed to be commodity-specific. These findings underscore the utility of regime-sensitive models in commodity price forecasting and offer valuable insights for market participants and policy decision-makers operating in volatile economic environments.

Keywords: Regime-Switching, TAR, Markov-Switching Model, Gold, Cocoa, Forecasting

1 Introduction

Commodity prices play a crucial role in shaping the global economy, influencing inflation, investment decisions, production planning, and international trade. Among the vast array of commodities, gold and cocoa are of particular importance due to their economic significance and market sensitivity.[29] highlighted that, amid uncertain market conditions, efficient commodity price movements are critical to global trade and value-chain resilience, influencing investment strategies across sectors. A panel study of 32

Sub-Saharan countries (1996–2019) shows that fluctuations in global commodity prices, especially oil, gold, and cocoa, positively influence inflation levels and inflation uncertainty in these economies [1].Predicting commodity market behaviour is inherently complex due to the dynamic and volatile nature of financial markets. Baker, 2024 in his work, "Factors influencing Stock market in the United State", stated that Prices are influenced by various interrelated factors, including macroeconomic indicators, investor sentiment, political events, and market microstructure. These complexities create significant challenges in developing accurate and reliable forecasting models. Gold and Cocoa prices often exhibit nonlinear behaviours such as abrupt jumps, threshold effects, and volatility clustering[7] These nonlinearities are influenced by psychological and behavioural factors, making price movements unpredictable with simple linear models. Traditional models like ARIMA and GARCH assume fixed relationships between variables and fail to capture such irregular dynamics. They are unable to model complex relationships in which price changes depend on crossing critical thresholds[21] They cannot adapt to changing market conditions, leading to inaccurate predictions during periods of transition. [5] highlighted that regime shifts, such as those caused by monetary policy changes, are not effectively captured by ARIMA, resulting in poor forecast accuracy during turbulent times.

Commodity prices are affected by irrational investor behaviour, including herding and overreaction, leading to noisy data [12]. This randomness complicates the forecasting because it introduces patterns that lack a clear economic rationale. [6] highlighted that Econometric models such as ARIMA assume that commodity prices follow rational patterns based on past values, ignoring the impact of behavioural biases.

This study adopts a comparative modeling approach to capture the dynamics of gold and cocoa prices using two econometric models. The threshold autoregressive (TAR) model and the Markov switching (MS) model, while the autoregressive Integrated Moving Average (ARIMA) model was used as benchmark model. Each of these models offers distinct strengths. The ARIMA model, a standard linear time series model, serves as a benchmark due to its simplicity and wide usage in short-term forecasting. The TAR model introduces regime-switching behavior based on observable threshold values, thereby allowing different autoregressive processes in different market conditions. On the other hand, the Markov Switching model identifies unobservable (latent) states and allows for stochastic regime changes, making it suitable for capturing persistent shifts in volatility or mean returns.

Recent literature underscores the utility of MS models in commodity markets. For instance, [11] document how financial stress influences commodity price volatility using a Markov-switching VAR framework, while [16] examine regime-switching hedging behavior in gold during inflation periods. Additionally, COVID-19 related research demonstrates that commodity volatility regimes intensified during the pandemic, justifying the need for models capable of detecting latent regime shifts. By applying these models to gold and cocoa price data, this study aims to assess the adequacy and forecasting accuracy of linear versus nonlinear approaches. Furthermore, it examines the extent to which each model can capture the unique characteristics of the two commodities, gold's sensitivity to macroeconomic uncertainty and cocoa's exposure to climatic and geopolitical shocks.

2 Literature Review

Commodity prices play a critical role in the global economy, influencing inflation trends, investment portfolios, monetary policy decisions, and the economic stability of resource-dependent nations [23]. Among these, gold and cocoa represent two distinctly important commodities, gold as a financial hedge and store of value, and cocoa as a vital agricultural export for many developing countries, especially in West Africa. Despite their economic significance, both commodities are highly volatile, with prices subject to abrupt shifts driven by global shocks, weather conditions, supply chain disruptions, investor sentiment, and geopolitical uncertainty [25]; [22]

Given this complexity, conventional linear models such as ARIMA often fall short in accurately forecasting commodity price dynamics, particularly during periods of structural change. In contrast, regime-switching models, including Threshold Autoregressive (TAR) and Markov Switching Models (MSM), have gained prominence for their ability to account for nonlinearities and regime-dependent behaviours in time series data. These models identify hidden states or thresholds that separate distinct periods of volatility, trend, or return behaviour, thereby enhancing predictive accuracy and offering deeper insights into market mechanisms ([24]; [28]). This chapter critically reviews recent empirical and theoretical work on the application of regime-switching models to commodity price prediction, with a focused lens on gold and cocoa markets between 2017 and 2025.

2.1 Regime-Switching in Commodity Market

[14] conducted a comprehensive investigation into the behavior of commodity and financial markets during periods of heightened global uncertainty, specifically during the COVID-19 pandemic. The study used a Markov-Switching Vector Autoregression (MS-VAR) model to analyze the dynamic spillover effects between gold, crude oil, and stock markets under different volatility regimes. Results showed that spillovers were subject to structural shifts, often corresponding to macroeconomic shocks like COVID-19. Gold's hedging power increased in high-volatility states, while crude oil showed strong procyclical behaviour [4] .

[24] explored the dynamic relationships and hedging strategies involving commodity futures by employing a Markov-Switching Vector Autoregressive (MS-VAR) framework. It found that hedging effectiveness varied across regimes, with high-volatility regimes requiring tighter strategies, and MS-VAR hedge ratios outperforming traditional linear models.

[9] investigated how macro-financial stress affects volatility in commodity markets using a Markov-Switching Vector Autoregression (MS-VAR) model. Commodity prices were examined in relation to changes in financial stress regimes, and the results show that high-stress regimes increase sensitivity to global financial conditions and exacerbate volatility spillovers. In order to capture shifting commodity pricing linkages, especially during times of macroeconomic instability like the COVID-19 crisis, the authors stress the necessity of regime-aware forecasting models.

2.2 Markov-Switching Model for Gold

[17] conducted a comparative analysis between Markov Switching models (MSMs) and traditional GARCH models to evaluate their effectiveness in modeling gold price volatility. According to the study, regime-switching models (MSMs) were more adept at identifying abrupt fluctuations in gold prices, which are frequently connected to macroeconomic developments or stress on the financial system. Unlike GARCH models, MSMs are able to differentiate between stable and tumultuous periods. These models demonstrate the value of adaptable modeling approaches in gold price analysis by offering better forecast performance during transitional periods.

[3] explored the time-varying safe-haven properties of gold during the COVID-19 pandemic using a Markov Switching model. The behavior of gold is examined in various financial regimes, with a focus on times of global equity market stress. It distinguishes between the calm and crisis regimes. Regime-switching frameworks aid in capturing changes in gold's function under excessive uncertainty, as the efficiency of gold hedging is contingent upon the current regime. This emphasizes the value of regime-aware models in the analysis of cocoa and gold prices. [11] advanced the traditional Markov Switching model by introducing a Markov-Switching Multifractal (MSM) framework to capture the complex, long-memory volatility structures observed in gold prices. The MSM model, unlike standard regime-switching models, can handle multiscale volatility shifts over time, allowing for more precise modeling of gold market dynamics. The MSM framework effectively captures multifractal scaling behavior, especially during financial instability. This study emphasizes the value of flexible, nonlinear models in commodity price forecasting, particularly for commodities experiencing systemic and idiosyncratic shocks.

[Lü et al.] conclude that Markov Switching GARCH models provide superior performance for gold price volatility forecasting, especially during times of market stress and regime transitions. This supports the application of regime-switching models in financial commodities like gold, where standard linear models or machine learning methods (like SVR) may fail to account for abrupt changes in behavior.

[24] examined how investor sentiment, particularly driven by financial news, can trigger regime shifts in gold price behavior. Using a Threshold Autoregressive (TAR) model augmented with sentiment indicators, the study found that gold markets exhibit nonlinear responses to news—switching between low- and high-volatility regimes based on thresholds in sentiment scores. The TAR framework revealed significant asymmetric dynamics, with negative news having a stronger and longer effect on gold prices than positive news.

[8] applied Threshold Autoregressive (TAR) models to investigate the presence of structural breaks and regime-dependent behavior in various commodity prices, including cocoa. The paper used deterministic (TAR) models to accurately forecast price behaviour during unstable periods, demonstrating the potential for cross-comparing deterministic and stochastic approaches in volatile markets like gold and cocoa.

[19] applied a Nonlinear Autoregressive Distributed Lag (NARDL) model to examine the impact of cocoa production, inflation, and exchange rates on cocoa prices in Nigeria. The findings support the use of regime-switching models like TAR and Markov Switch-

ing, which captured nonlinear behaviour and structural asymmetries in cocoa price movements. This supports the use of nonlinear modeling techniques in commodity forecasting.

[10] evaluated the forecasting performance of Threshold Autoregressive (TAR) models compared to linear ARIMA models across various agricultural commodities, including cocoa, soybeans, and maize. The TAR model outperformed ARIMA in in-sample fit and out-of-sample forecasting, particularly in capturing sudden price shifts. This is due to its ability to accommodate nonlinear threshold effects in agricultural markets. The threshold model identified low and high volatility periods, which linear models struggle to capture. This supports the use of TAR in cocoa modeling, which is exposed to similar volatility drivers.

[25] analyzed the dramatic spike in cocoa prices during early 2024, attributing the surge to severe production disruptions in West Africa, specifically in Ghana and Côte d'Ivoire, which account for over 60 percent of global cocoa output. The study revealed that supply-side disruptions, like weather events and diseases, led to a decrease in cocoa yield, resulting in unprecedented prices, inflation, and high-volatility pricing patterns. It suggests using regime-switching models for forecasting and integrating supply fundamentals in cocoa price dynamics. [27] in their work explained that, The International Food Policy Research Institute (IFPRI) provided a timely analysis of the underlying factors driving the unprecedented cocoa price spikes observed in 2024. The surge in cocoa prices in Ghana and Côte d'Ivoire was caused by weather shocks, the cocoa swollen shoot virus, and underinvestment in farm productivity. These factors disrupted output, shifted supply expectations, and amplified price volatility. The IFPRI analysis provides insights into the regime-like behavior of cocoa markets, supporting the use of regime-switching models for forecasting cocoa price behavior under uncertainty and supply-side stress.

[20] reported on the extreme volatility in the global cocoa market in late 2024, when futures prices more than tripled due to worsening weather conditions, pest infestations, and speculative pressure. The El Niño-related rainfall patterns and black pod disease outbreaks reduced cocoa yields, leading to a panic in the market and a sudden shift in cocoa prices. This qualitative support for regime-switching behavior in cocoa prices highlights the need for Threshold Autoregressive and Markov Switching models to account for state-dependent dynamics. Sachdeva's reporting provides real-world evidence of cocoa's susceptibility to these transitions.

[15] reported on the sudden withdrawal of hedge funds and institutional investors from the cocoa futures market in mid-2024, which significantly reduced market liquidity and contributed to increased price volatility. The cocoa market experienced a significant shift due to high margin costs, extreme price swings, and regulatory concerns. This exodus weakened price discovery, making the market more susceptible to spikes and erratic behavior. The loss of speculative capital made the market more unstable, highlighting the importance of considering behavioral and market-structure factors in price modeling and using regime-aware tools. The study by [2] investigates the volatility and regime behavior of cocoa prices in Nigeria. The researchers aimed to understand how external shocks—particularly weather variability and government policy interventions—create distinct price regimes in the Nigerian cocoa market. The authors used a Threshold Autoregressive (TAR) model to assess the nonlinearity of monthly cocoa price returns. They

found that weather-related shocks and policy interventions trigger regime shifts, which the linear AR model failed to capture. The TAR model improved prediction accuracy by 28%, confirming cocoa prices' influence on threshold-driven dynamics.

[Nunoo et al.] focused on forecasting cocoa returns in West Africa, particularly in Ghana and Côte d'Ivoire, two of the largest cocoa-producing countries globally. The study aimed to capture nonlinear price dynamics, asymmetric responses, and the role of external cycles in cocoa return behavior. Hybrid Threshold Autoregressive–Generalized Autoregressive Conditional Heteroskedasticity (TAR-GARCH) model was employed. With their findings, Cocoa returns switch behavior around a threshold of 1.5 percent monthly return. Threshold statistic was significant at 0.01 level ($F - statistic = 11.64$, $p < 0.01$.) TAR-GARCH outperformed all benchmarks in both in-sample and out-of-sample forecasts. [Nunoo et al.] concluded that cocoa price behavior exhibits distinct threshold effects, and incorporating these with volatility modeling through the hybrid TAR-GARCH framework results in superior forecasting performance. They also found that cocoa markets are highly sensitive to seasonal and political cycles, reinforcing the need for nonlinear, regime-aware forecasting tools.

The literature highlights the growing recognition of nonlinear dynamics in commodity price movements, especially in gold and cocoa markets, leading to the use of models like Threshold Autoregressive and Markov Switching Models.

3 Data and Methodology

The dataset employed in this study comprises monthly average prices of International Cocoa (US$ /tonne) and International Gold (US$ /fine ounce) spanning the period from January 2003 to December 2022 (a 20-year window). These data were sourced from the Economic Data Repository of the Bank of Ghana, a credible institution that regularly publishes macroeconomic and commodity-related statistics. The choice of monthly data over daily observations was deliberate. Monthly frequency helps to smooth out high-frequency noise and short-term volatility, which are prevalent in commodity markets. This enhances the visibility of longer-term trends and structural patterns, critical for identifying regime shifts and threshold effects that the TAR and Markov Switching models aim to detect.

3.1 Method-Specific Details

The study employed Minitab for preliminary statistical analysis and Visual Studio Code (Python) for model implementation. Python libraries such as pandas, numpy, statsmodels, and scikit-learn were used for time series processing and model estimation. The Threshold Autoregressive (TAR) model thresholds were determined using a grid search procedure over the 10th–90th percentiles of the lagged log returns, with the optimal threshold minimizing forecast error. For the Markov Switching Model (MSM), the number of regimes was fixed at two, representing low and high volatility states, following theoretical considerations and prior empirical studies. Model estimation employed Maximum Likelihood Estimation (MLE) for MSM and Ordinary Least Squares (OLS) for each TAR regime.

3.1.1 Log Returns

Before applying the models, the raw price series were transformed into log returns to stabilize the variance and promote stationarity. Log return transformation is a standard approach in financial econometrics, allowing the data to meet the assumptions of many time series models. This transformation is standard in financial econometrics for the reasons stated in the literature. Descriptive statistics and stationarity tests, such as the Augmented Dickey-Fuller (ADF) test, were conducted to assess the statistical properties of the return series. The transformation formula is given by:

$\mathrm{r}_t = \log\left(\frac{P_t}{P_{t-1}}\right)$

where r_t is the log return at time t

P_t is the price at time t.

P_{t-1} the price at the previous time period

3.1.2 Preliminary Testing

Statistical properties of the time series data were assessed to ensure the suitability of nonlinear and regime-switching models. This involved three diagnostic tests, Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS); Tsay's Test and Bai-Perron Multiple Breakpoint Test; for Stationarity, Non-linearity and Structural breaks respectively.

- The ADF and KPSS were used to determine whether the time series data for gold and cocoa returns are stationary or contain unit roots. The ADF test checked the null hypothesis that the series has a unit root while the KPSS test complemented the ADF by testing the null hypothesis that the series is stationary.
- Tsay's Test was used to detect nonlinear dependencies and threshold effects in the autoregressive structure of the time series. Tsay's test evaluated whether the coefficients of a threshold autoregressive model differ significantly across regimes by fitting a piecewise linear model and applying F-statistics.
- Bai-Perron Multiple Breakpoint Test was used to identify multiple structural breaks in the data-generating process that may correspond to economic events, policy changes, or global shocks.

3.2 Model Framework

3.2.1 Threshold Autoregressive (TAR) Model

The Threshold Autoregressive (TAR) model is a nonlinear time series model that allows the dynamics of a time series to switch between regimes depending on the value of a threshold variable. In the context of commodity markets like gold and cocoa, the TAR model helps to capture asymmetric behaviors such as different price dynamics during low and high volatility periods, or under bullish and bearish market conditions. Following [26], a two-regime TAR model of order k with the threshold variable q_t takes the form of

$$y_t = \begin{cases} \delta_0 + \sum_{i=1}^{k_1} \delta_i y_{t-i} + \varepsilon_t, & \text{if } q_{t-d} \le r \\ \theta_0 + \sum_{i=1}^{k_2} \theta_i y_{t-i} + \varepsilon_t, & \text{if } q_{t-d} > r \end{cases}$$

where

- y_t is the dependent variable (i.e., Gold or Cocoa price),
- q_{t-d} is the lagged value of the dependent variable (threshold variable),
- k_1 and k_2 are the lag orders of the autoregressive process,
- δ_i and θ_i are coefficients of lag i in regime 1 and 2 respectively,
- δ_0 and ϑ_0 are the intercepts in regimes 1 and 2,
- ε_t is the error term in each regime, assumed to be white noise,
- r is the threshold value separating each regime,
- $d > 0$ is the delay parameter indicating the lag order of the threshold variable.

The TAR model allowed the behavior of the time series to differ significantly depending on whether the threshold variable crosses a certain critical level. This was useful in capturing real-world phenomena like market panic, sudden corrections, or speculative bubbles, which are not handled well by linear models.

3.2.2 Threshold Estimation Procedure

The parameters of the TAR model (lags, coefficients, threshold) were typically estimated using least squares estimation within each regime, and the threshold was identified through a grid search process

$$R = \{r_1, r_2, r_3, \ldots, r_m\} \subseteq \{q_{t-d}\}$$

A candidate set of threshold values was created by choosing a range of values within the empirical distribution of the threshold variable (usually the middle 70–90% to avoid outliers). For each Threshold $r_i \in R$. TAR Model was estimated splitting the data into two regimes and the coefficients of lags using OLS on their respective regimes. Residual Sum of Squares (RSS) was then computed using the equation;

$$RSS(r_i) = \sum_{t \in r_i} (y_t - \hat{y}_t)^2$$

where

- $RSS(r_i)$ is the residual sum of squares in regime i,
- y_t is the actual value of the dependent variable at time t,
- $\hat{y}_t$ is the predicted value from the model at time t,
- The summation is taken over all time points t that belong to regime r_i,
- A lower $RSS(r_i)$ indicates a better fit of the model within that regime.

The optimal threshold was selected as the one that minimizes the total RSS, ensuring the best fit.

3.2.3 Model Assumptions

- The threshold variable is observable and continuous.
- Error terms are assumed to be independently and identically distributed (i.i.d.) with zero mean and constant variance within each regime.
- The data is stationary within regimes, or made stationary through differencing or transformation.
- Regimes are deterministically defined by the threshold crossing, not stochastically as in Markov Switching models.

In this study, the TAR model was employed to capture regime-dependent autoregressive structures in gold and cocoa prices, enabling better prediction accuracy over models that assume linear behavior.

3.3 Markov-Switching Model (MSN)

A Markov Switching Model (MSM) is an advanced time series modeling technique that accounts for structural changes in data over time. Unlike traditional models with fixed parameters, MSM allows the parameters, such as the mean, variance, or autoregressive coefficients, to switch between different regimes (states). These regime switches are not random but follow a Markov process, where the probability of transitioning to a particular state depends only on the current state, not the full history. This makes MSM especially valuable for modeling data that exhibit abrupt shifts, such as during financial crises, commodity shocks, or changes in policy regimes. Unlike the Threshold

Autoregressive (TAR) model, where regime shifts are determined deterministically by the value of an observable threshold variable, the MSM allows regime transitions to occur probabilistically according to a first-order Markov process. A general Markov Switching Model can be written as:

$$y_t = \mu_{S_t} + \sum_{i=1}^{p} \phi_{i,S_t} y_{t-i} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma^2_{S_t})$$

where

- y_t is the observed time series (e.g., commodity price at time t),
- μ_{S_t} is the regime-dependent intercept,
- ϕ_{i,S_t} are the autoregressive coefficients in regime S_t,
- $S_t \in \{1, 2, \dots, M\}$ is the unobserved state (regime) at time t, governed by a Markov chain,
- $\varepsilon_t \sim \mathcal{N}(0, \sigma^2_{S_t})$ is a normally distributed error term with regime-specific variance.

The transition between regimes is governed by a Markov process with the transition probability matrix:

$$P = \begin{bmatrix} p_{11} & p_{12} & \\ p_{21} & p_{22} & \end{bmatrix}$$

- $p_{ij} = \mathbb{P}(S_t = j \mid S_{t-1} = i)$ is the probability of switching from regime i to regime j.

Regime-specific parameters $(u_1, \theta_1, \delta_1^2) \quad \text{and} \quad (u_2, \theta_2, \delta_2^2)$

The regime is not observed directly but evolves according to a first-order Markov chain, meaning that the probability of transitioning to a particular regime depends only on the regime in the previous time period.

3.3.1 Estimation Approach

Model parameters are estimated via the Expectation-Maximization (EM) algorithm or maximum likelihood estimation (MLE) using techniques such as the Hamilton filter. The process iteratively estimates the regime probabilities and model parameters until convergence.

Regime probabilities

$$\varepsilon_{t|t-1}(i) = P(S_t = i | Y_{1:t-1})$$

Regime-specific likelihood at t

$$f(Y_t | S_t = i)$$

Regime likelihood

$$f(Y_t|S_t = i) = \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(-\frac{(Y_t - \mu_i - \theta_i Y_{t-1})^2}{2\sigma_i^2}\right)$$

Log-Likelihood

$$L = \sum_{t=1}^{T} \log\left(\sum_{i=1}^{2} f(Y_t|S_t = i).\varepsilon_{t|t-1}(i)\right)$$

The MLE was then obtained using Newton-Raphson optimization method

In this study, MSMs were used to capture unobserved structural shifts in gold and cocoa markets, such as transitions between high-volatility and low-volatility regimes which linear models fail to identify.

3.4 Model Evaluation

Evaluating the performance of the TAR and Markov Switching models is essential to determine their statistical adequacy, goodness of fit, and predictive accuracy for commodity price forecasting, specifically for gold and cocoa. The evaluation was performed in both in-sample and out-of-sample contexts using the AIC and BIC, Residual Diagnostics, Forecast Performance

3.4.1 Information Criteria

Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to compare models based on their goodness of fit while penalizing model complexity.

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

Here, L is the maximum value of the likelihood function, and
k is the number of estimated parameters in the model,
n is the sample size
Lower AIC values indicate a better model
BIC imposes a heavier penalty for model complexity than AIC, especially when n is large

Lower AIC and BIC values indicate a better model in terms of the trade-off between fit and parsimony. These criteria are particularly important when comparing models such as TAR and MSM.

3.4.2 Residual Diagnostics

These are used to ensure that the models capture the underlying data dynamics adequately. If the residuals exhibit serial correlation or heteroskedasticity, the model may be mis-specified.

3.3.2.1 Ljung-Box Q Test

Ljung-Box Q Test was used to assess whether the residuals from the models behave as white noise. Residual diagnostics help ensure that the model has adequately captured the structure and dynamics of the underlying data. If residuals exhibit autocorrelation or heteroskdasticity, this suggests that important patterns in the data have been overlooked, implying potential model mis-specification.

- H_0: The residuals are independently distributed (i.e., there is no autocorrelation)
- H_1: The residuals are autocorrelated.

The Ljung-Box test statistic is calculated as;

$$\boxed{Q = n(n+2)\sum_{i=1}^{h}\frac{\hat{p}_k^2}{n-k}}$$

- n is the sample size,
- h is the number of lags tested,
- $\hat{p}_k$ is the sample autocorrelation at lag k.

This statistic follows a chi-squared distribution with h degrees of freedom. If the $p > 0.5$ reject the null hypothesis, suggesting no significant autocorrelation in the residuals, which is desirable and indicates a good model fit. If the $p \leq 0.5$, it suggests that the residuals are autocorrelated, indicating that the model has not fully captured the data's dynamics and may require refinement

3.4.3 Forecast Performance (Out-of-Sample)

The predictive power of each model was assessed using out-of-sample forecast accuracy over a hold-out period

3.3.3.1 Root Mean Squared Error (RMSE):

$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}$

- RMSE measures the square root of the average squared deviations between the actual values Y_t and the predicted values $\hat{Y}_t$
- It penalizes larger errors more severely, making it sensitive to outliers or extreme forecast deviations.
- A lower RMSE indicates better predictive accuracy.

3.3.3.2 Mean Absolute Error (MAE):

$MAE = \frac{1}{n}\sum_{t=1}^{n} |Y_t - \hat{Y}_t|$

- MAE calculates the average absolute difference between actual and predicted values.
- Unlike RMSE, it treats all errors equally regardless of their direction or magnitude.
- MAE is especially useful for interpreting forecast performance in practical units.

3.3.3.3 Diebold-Mariano (DM) Test

The DM test was employed over the same out-of-sample evaluation period to evaluate whether the mean loss differentially is significantly different from zero.

- H_0: the two models have equal predictive accuracy
- H_1: one model significantly outperforms the other

The DM test statistic is given by:

$$DM = \frac{\bar{d}}{\sqrt{\frac{1}{T}\gamma_0 + \frac{2}{T}\sum_{k=1}^{h-1}\gamma_k}}$$

- $\bar{d}$: Mean of the loss differential between two forecasts.
- T : Number of forecasts (sample size).
- γ_k : Autocovariance at lag k of the loss differential.
- h : Forecast horizon.

Under the null hypothesis, the DM statistic asymptotically follows a standard normal distribution, allowing for standard critical value comparison or p-value calculation.

- If the $p > 0.05$: The difference in forecast performance is not statistically significant; both models are considered equally effective.
- If the $p < 0.05$: The difference in forecast performance is statistically significant; one model significantly outperforms the other.

This approach ensures that any observed improvements in forecast accuracy from the hybrid model are not only numerically better but also statistically justifiable.

4 Results And Discussion

Overview This chapter talks about the results obtained from the TAR and MSM model, the model's performance

4.1 Statistical Description

Table 1 shows the descriptive statistics of gold and cocoa prices over the study period. Each commodity has 240 observations. The mean price of gold is approximately $1160.28, with a median of $1237.99, while the mean cocoa price is around $2359.40, with a median of $2414.63. The standard deviation for gold ($462.16) and cocoa ($541.31) indicates a high degree of price volatility, justifying the application of regime switching models such as TAR and MSM. Gold prices range from $329.28 to $1971.07, and cocoa prices range from $1348.60 to $3430.35, showing a broad price dispersion over the period.

Additionally, the interquartile range (IQR) for gold is approximately $697.36 (from $805.51 to $1502.86), and for cocoa, it's $827.77 (from $1955.80 to $2783.57). These wide IQRs reflect considerable variation even within the central 50% of the dataset, further highlighting the presence of non-linear behaviors and structural shifts characteristics well-captured by the hybrid TAR-MSM model used in this study.

Table 1: Summary Statistics

	Count	**Mean**	**Std**	**Min**	**25%**	**50%**	**75%**	**Max**
Gold	**240.0**	**116.3**	**462.1**	**329.3**	**805.5**	**1238.0**	**1502.9**	**1971.1**
Cocoa	**240.0**	**2359.4**	**541.3**	**1348.6**	**1955.8**	**2414.6**	**2783.6**	**3430.4**

4.1.1 Time series decomposition

Figure 1 presents the time series decomposition of gold prices from 2003 to 2022, broken down into trend, seasonality, and residual components. The top panel shows the trend component, which reveals a general upward movement in gold prices, with noticeable increases around 2010–2012 and 2019–2021, reflecting long-term price appreciation and economic cycles. The middle panel displays the seasonal component, which shows consistent, repeating patterns over time. This suggests that gold prices exhibit strong seasonal effects, possibly due to recurring demand cycles, investment behaviors, or macroeconomic factors. The bottom panel shows the residual (irregular) component, capturing short-term shocks and fluctuations not explained by the trend or seasonality. Significant residual spikes around 2008, 2012, and 2020 likely correspond to global financial events, economic crises, or pandemic-related disruptions.

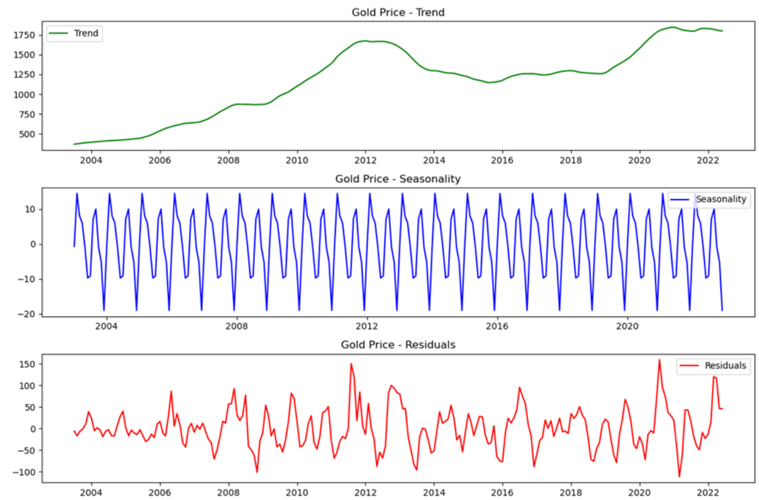

Figure 1: Gold Price Decomposition

Figure 2 displays the time series decomposition of cocoa prices from 2003 to 2022, separating the data into trend, seasonality, and residual components. The top panel illustrates the trend component, which highlights significant fluctuations in cocoa prices. There is a notable upward movement between 2006 and 2016, followed by a decline around 2017, after which prices remained relatively stable. The middle panel captures the seasonal component, showing clear and consistent cyclical patterns over the years. This confirms that cocoa prices are subject to strong seasonal effects, which may be linked to agricultural cycles, export patterns, or climate-related factors. The bottom panel presents the residual component, revealing high-frequency irregularities and unpredictable shocks. Major residual spikes, particularly between 2008–2012 and 2017–2019, suggest periods of external disruptions or volatility beyond trend and seasonality, factors that the hybrid TAR-MSM model is designed to account for. This decomposition underscores the complexity of cocoa price behavior, characterized by long-term shifts, seasonal recurrences, and short-term volatility, supporting the application of nonlinear regime-switching models.

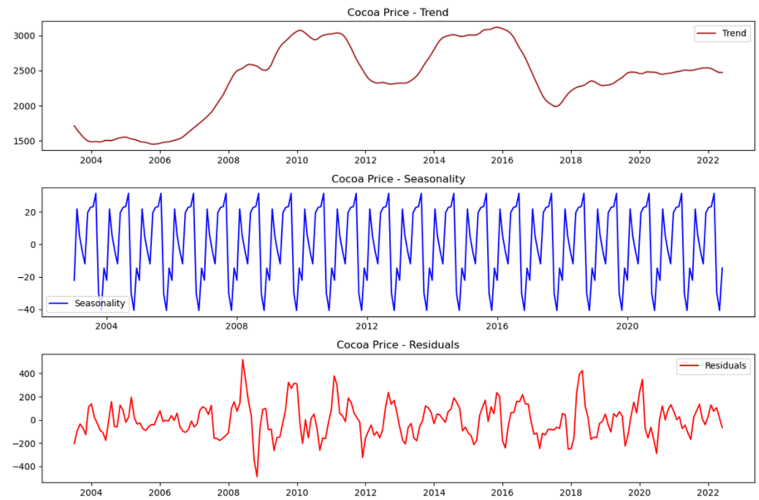

Figure 2: Cocoa Price Decomposition

4.1.2 Test of stationarity

To ensure the suitability of the data for time series modeling, stationarity of the logged series was examined using the Augmented Dickey-Fuller (ADF) test. The ADF test checks for the presence of a unit root, where the null hypothesis indicates whether the series is stationary or not. Initial results revealed that the logged series for both gold and cocoa exhibited non-stationarity, as the test failed to reject the null hypothesis at the 5% significance level. Table 2 and 3 below shows the outcome.

Table 2: ADF Test for Log Gold

Null hypothesis		Data are non-stationary
Alternate hypothesis		Data are stationary
Test Statistic	P - value	Recommendation
- 1.99354	0.289	Test statistic >critical value of - 2.87376
		Significance level = 0.05
		Fail to reject null hypothesis

Table 3: ADF Test for Log Cocoa

Null hypothesis		Data are non-stationary
Alternate hypothesis		Data are stationary
Test Statistic	P - value	Recommendation
- 1.96537	0.302	Test statistic >critical value of - 2.87413
		Significance level = 0.05
		Fail to reject null hypothesis

The three plots; Time Series Plot, Autocorrelation Function (ACF) plot, and Partial Autocorrelation Function (PACF) plot, show that the series fluctuates, suggesting non-stationarity, as the mean level appears to shift over time for both log Gold and log Cocoa. The figures below shows these behaviours;

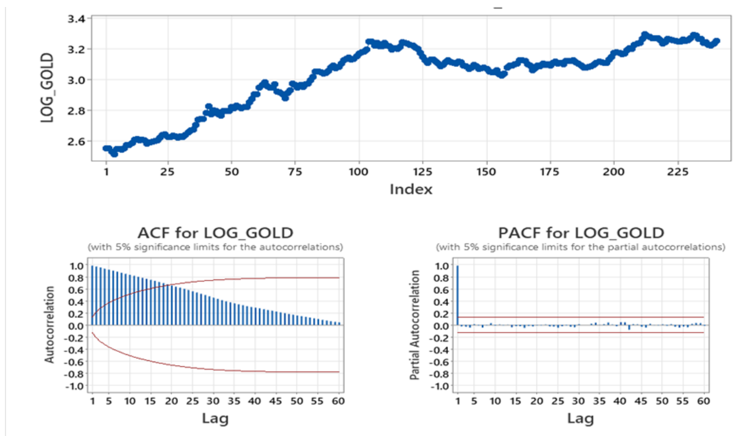

Figure 3: Log Gold Stationarity

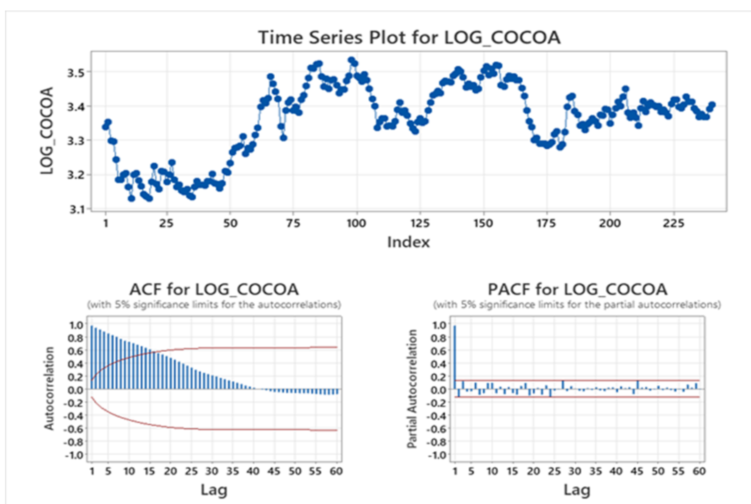

Figure 4: Log Cocoa Stationarity

Both Gold and Cocoa log-price series show non-stationary behaviour, confirmed by ACF and time series plots. The strong lag-1 autocorrelations and gradual decay suggest the need for differencing. Both PACF plots suggest that AR(1) terms may be sufficient to capture short-term dynamics, once stationarity is achieved. Given the observed structural shifts, nonlinear models such as TAR and MSM may better capture regime changes.

The Augmented Dickey-Fuller (ADF) test was again conducted to assess the stationarity of the log return series for both gold and cocoa prices after the differencing. As shown in Table 4, the ADF test statistics for gold (-13.2916) and cocoa (-6.3196) are well below the 0.05 critical value thresholds (-2.8739 and -2.8741, respectively), with p-values of 0.0000.

Table 4: Test of stationarity

Return	ADF	p-value	Critical value(5%)	Conclusion
Gold	-13.2916	0.0000	-2.8739	Stationary
Cocoa	-6.3196	0.0000	-2.8741	Stationary

Figure 5 and 6 presents the ACF and PACF plots of gold and cocoa price log returns to further examine their autocorrelation structure. In both series, there is a strong spike at lag 1 in the ACF and PACF plots, with all subsequent lags falling within the confidence interval.

This pattern suggests that both log return series follow a low-order autoregressive process

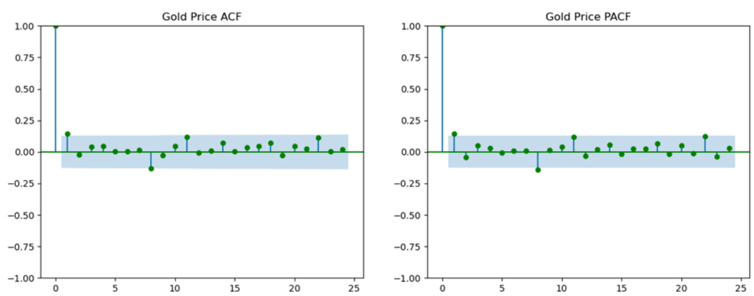

Figure 5: ADF and PACF plot for Gold

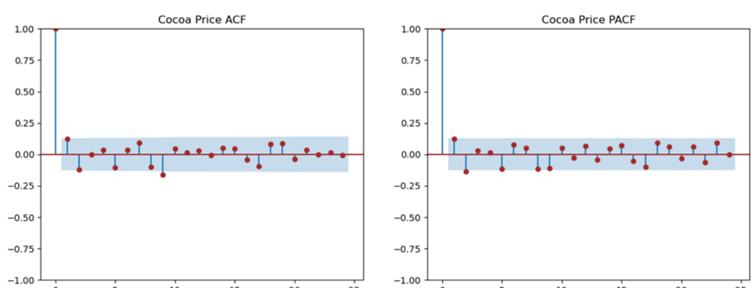

Figure 6: ADF and PACF plot for Cocoa

4.2 TAR Model

4.2.1 Optimal Threshold Value

Table 5 presents the optimal threshold values identified during TAR model training for both gold and cocoa log returns. These thresholds represent the cutoff points used to split the data into two distinct regimes.

- For gold, the threshold value of –0.0056 implies that log return values below this point are classified into Regime 1, while those above it fall into Regime 2.
- Similarly, for cocoa, a threshold of –0.0657 was identified, indicating a more pronounced lower-bound return condition for regime separation.

Table 5: Optimal Threshold Value for TAR Model

Commodity	Optimal Threshold
Gold	- 0.0056
Cocoa	- 0.0657

4.2.2 TAR model for Gold log returns

The Threshold Autoregressive (TAR) model for gold log returns estimated two distinct regime equations based on an optimally selected threshold.

- In Regime 1, the model estimated a strong negative relationship between current and lagged returns, as indicated by the slope of –0.2743. This suggested a pronounced mean-reverting behavior when the market operated below the threshold level.
- In Regime 2, the slope coefficient was –0.0170, indicating a much weaker inverse relationship and suggesting near-random fluctuations or low persistence in return dynamics when above the threshold

Table 6: TAR Model Regime for Gold Log

Regime	Slope Coefficient	Intercept
Regime 1	- 0.2743	- 0.0119
Regime 2	- 0.0170	0.0147

Regime 1 Equation (Gold): $y = -0.2743x - 0.0119$
Regime 2 Equation (Gold): $y = -0.0170x + 0.0147$

4.2.3 TAR model for Cocoa log returns

The TAR model for cocoa log returns estimated distinct dynamics across two regimes based on the threshold defined split.

- In Regime 1, the model estimated a strong positive autoregressive relationship, with a slope of 0.7983, suggesting that during low-return phases, previous returns strongly influenced future returns, indicating momentum-like behaviour.
- In contrast, Regime 2 displayed a weaker positive association, with a slope of 0.1928 and a small negative intercept, implying that during high-return periods, past values had less predictive power, and the series behaved more randomly or diffusely.

Table 7: TAR Model for Cocoa log

Regime	Slope Coefficient	Intercept
Regime 1	0.7983	0.0812
Regime 2	0.1928	- 0.0021

Regime 1 Equation (Cocoa): $y = 0.7983x + 0.0812$
Regime 2 Equation (Cocoa): $y = 0.1928x - 0.0021$

4.2.4 Error Metrics for TAR Model

Table 8 presented the error evaluation metrics, Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) for the TAR models fitted to the log returns of gold and cocoa prices. The TAR model for gold produced the lowest error values across all three metrics, with an MSE of 0.001292, MAE of 0.028499, and RMSE of 0.035948. These values indicated that the model captured gold return dynamics with higher precision and lower residual variance. In comparison, the TAR model for cocoa resulted in higher errors, with an MSE of 0.003230, MAE of 0.043359, and RMSE of 0.056832

Table 8: Error Metrics for TAR

Metric	Gold	Cocoa
MSE	0.001292	0.003230
MAE	0.028499	0.043359
RSME	0.035948	0.056832

Figure 7 compares the TAR model performance for gold and cocoa using three error metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). As observed in the plot, all error values for cocoa are consistently higher than those for gold across all metrics. The steeper slope of the cocoa trend line, particularly from MSE to RMSE, reflects a greater accumulation of forecast error, indicating that the TAR model experienced reduced predictive accuracy for cocoa relative to gold. The green dotted line representing gold remained below the cocoa line throughout, confirming that the TAR model performed better on the gold return series in terms of both magnitude and consistency of error.

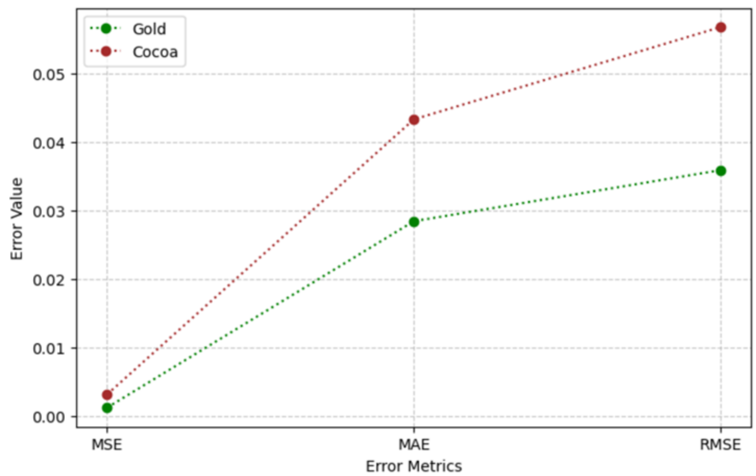

Figure 7: Error Metrics

4.3 Markov-Switching Model (MSM)

4.3.1 MSM for Gold

Table 9 presents the parameter estimates from the Markov Switching Model applied to the gold log return series. The model identified two distinct regimes:

- Regime 0, representing a low-volatility regime, was characterized by a slightly negative mean return (–0.0159) and low variance (0.0005). The coefficient for constant had a marginal significance ($p = 0.061$), while the variance was statistically significant ($p = 0.024$), indicating low but statistically relevant fluctuations.
- Regime 1, identified as a high-volatility regime, showed a statistically significant positive mean return (0.0148, $p = 0.004$) and a larger variance (0.0014), both of which were highly significant ($p < 0.01$). This suggests that the gold market exhibited higher returns alongside greater uncertainty under this regime.

Table 9: MSM for Gold log

Parameter	**Estimate**	**Std. Error**	**z-statistic**	**P-value**	**95% C.I**
Regime 0 (Low Variance)					
Constant	**- 0.0159**	**0.009**	**- 1.871**	**0.061**	**- 0.033, 0.001**
Variance	**0.0005**	**0.000**	**2.265**	**0.024**	**0.00007, 0.001**
Regime 1 (High Variance)					
Constant	**0.0148**	**0.005**	**2.872**	**0.004**	**0.005, 0.025**
Variance	**0.0014**	**0.000**	**6.941**	**0.000**	**0.001, 0.002**

$$y_t = \begin{cases} -0.0159 + \varepsilon_t & \text{in Regime 0} \\ \ \ 0.0148 + \varepsilon_t & \text{in Regime 1} \end{cases} \qquad \text{where } \varepsilon_t \sim \mathcal{N}(0, \sigma^2)$$

with $\underline{\sigma^2 = 0.0005}$ in Regime 0 and $\underline{\sigma^2 = 0.0014}$ in Regime 1.

4.3.2 MSM for Cocoa

Table 10 provides the parameter estimates for the Markov Switching Model fitted to cocoa log returns. The model detected two regimes with distinct statistical behaviors:

- Regime 0, associated with lower volatility, showed a slightly positive mean return of 0.0061, although not statistically significant ($p = 0.233$). However, the variance in this regime (0.0016) was significant ($p < 0.01$), indicating stable but non-trivial fluctuations.

- Regime 1, corresponding to a higher volatility state, had a negative mean return of –0.0047, which was also not statistically significant ($p = 0.567$). The variance was substantially higher at 0.0053, and statistically significant ($p < 0.01$), signaling periods of extreme variability or market stress.

Table 10: MSM for Cocoa

Parameter	**Estimate**	**Std. Error**	**z-statistic**	**P-value**	**95% C.I**
Regime 0 (Low Variance)					
Constant	**0.0061**	**0.005**	**1.192**	**0.233**	**- 0.004, 0.016**
Variance	**0.0016**	**0.000**	**4.133**	**0.000**	**0.001, 0.002**
Regime 1 (High Variance)					
Constant	**- 0.0047**	**0.008**	**- 0.573**	**0.567**	**- 0.021, 0.001**
Variance	**0.0053**	**0.001**	**4.504**	**0.000**	**0.003, 0.008**

$$y_t = \begin{cases} 0.0061 + \varepsilon_t & \text{in Regime 0} \\ \\ -0.0047 + \varepsilon_t & \text{in Regime 1} \end{cases} \qquad \text{where } \varepsilon_t \sim \mathcal{N}(0, \sigma^2)$$

with $\underline{\sigma^2 = 0.0016}$ in Regime 0 and $\underline{\sigma^2 = 0.0053}$ in Regime 1.

Figure 8 displays the smoothed probabilities of being in Regime 1 (low volatility, blue) and Regime 2 (high volatility, red) over time, as estimated by the Markov Switching Model for gold log returns. From the figure, it was evident that the gold market frequently switched between regimes, particularly after 2012. During earlier years (2003–2011), the model assigned a high probability to Regime 2, indicating a persistent high-volatility environment. This was consistent with elevated residual variance seen in the MSM estimates. From 2012 onwards, there was increased alternation between Regime 1 and Regime 2, suggesting greater regime instability or market unpredictability in recent years. Notably, the model frequently assigned probabilities close to 1 for one regime, showing strong confidence in regime classification at many time points.

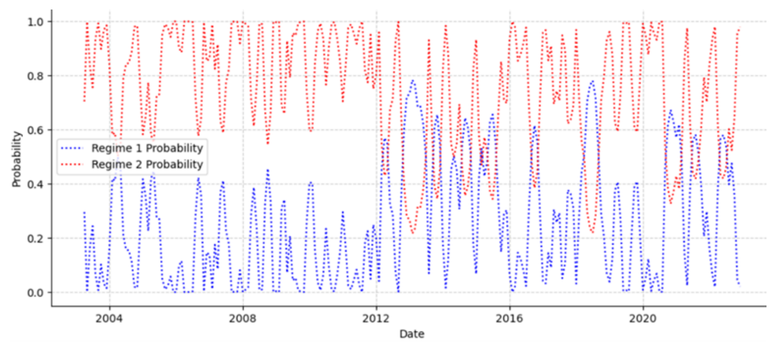

Figure 8: Smoothed Prob by MSM for Gold log

Figure 9 presents the smoothed probabilities of the cocoa market being in either Regime 1 (low volatility, blue line) or Regime 2 (high volatility, red line) over the period from 2003 to 2022. The chart shows that the cocoa market underwent distinct phases dominated by one regime or the other:

- From 2003 to 2006, the market was largely in Regime 2, indicative of a high-volatility state, with probabilities approaching 1.
- Between 2007 and 2011, the regime shifted predominantly to Regime 1, suggesting a more stable market with relatively low volatility.
- From 2012 to 2019, the model captured frequent transitions between regimes, suggesting a period of increased uncertainty or structural instability.
- After 2020, the probabilities strongly favored Regime 1, indicating a return to relative calm in the cocoa market.

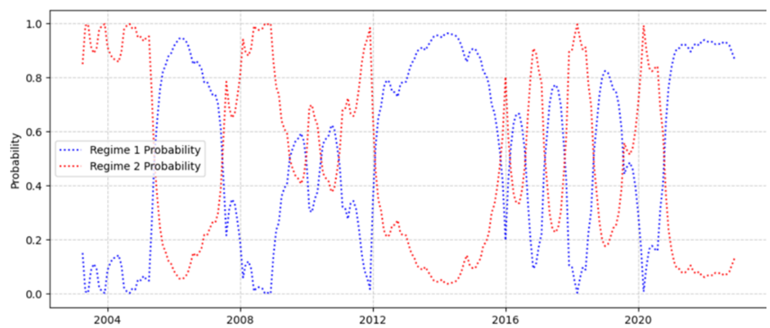

Figure 9: Smoothed Prob by MSM for Cocoa log

In figure 10, the low diagonal values in the gold MSM transition matrix (0.30) indicate short regime persistence, with an average duration of about 1.43 months. This is reflected in the smoothed probability plot, which shows frequent and rapid shifts between regimes rather than long, sustained periods in a single state.

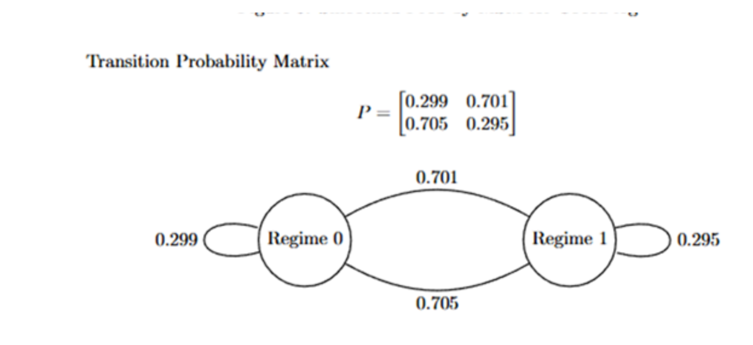

Figure 10: Transition Prob of Gold

The cocoa MSM transition matrix in Fig 11, shows that once in Regime 0, prices remain there about 29.4% of the time and switch to Regime 1 about 70.6% of the time. From Regime 1, there is a 70.3% chance of moving to Regime 0 and only a 29.7% chance of staying. This indicates low persistence in both regimes, with an average duration of roughly 1.42 months, meaning cocoa prices switch frequently between market states. Such rapid transitions suggest that short-term shocks dominate price behaviour, requiring forecasting models that can quickly adapt to changing regimes.

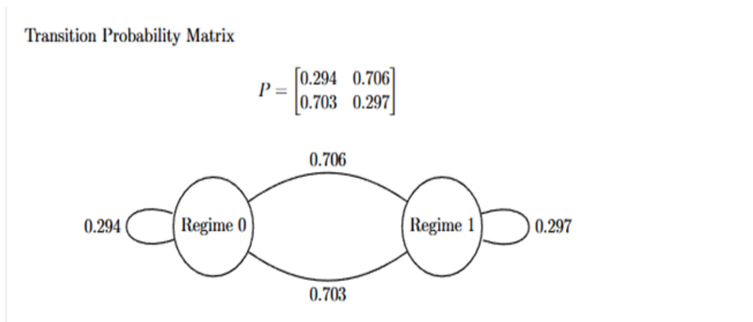

Figure 11: Transition Prob of Cocoa

Table 11 compares the performance of the Markov Switching Models (MSM) fitted to gold and cocoa log return series using key statistical metrics.

The gold MSM model exhibited a higher log-likelihood (446.5271) and more negative AIC (–881.0541) and BIC (–860.2458) values than the cocoa model. This indicated that the MSM model for gold achieved a better overall fit, with lower model complexity penalties and greater explanatory power.

The cocoa MSM model, while still showing strong performance, had comparatively higher AIC and BIC values, suggesting a slightly less optimal model fit.

Table 11: MSM Performance with Gold and Cocoa

Metric	Gold	Cocoa
Log-Likelihood	446.5271	344.8212
AIC	- 881.0541	- 677.6424
BIC	- 860.2458	- 656.8341

4.4 Model Evaluation

Given the presence of structural breaks and regime-dependent behaviour in both markets, nonlinear models, TAR and MSM, were expected to outperform linear benchmarks. Therefore, the evaluation focused not only on how well each model captured the underlying data-generating process but also on how accurately it forecasts future prices. Standard statistical metrics including Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were employed to compare model forecasts and judge predictive superiority.

Table 12: Model Evaluation for TAR and MSM

Model	Gold			Cocoa	
	MAE	RMSE		MAE	RMSE
TAR	0.028499	0.035948	TAR	0.043359	0.056832
MSM	0.024518	0.032875	MSM	0.044474	0.057863

As shown in Table 12 above, the MSM model outperforms the TAR model in forecasting Gold prices, as it records lower values for both MAE and RMSE, indicating higher predictive accuracy. For Cocoa, TAR slightly outperforms MSM in both MAE and RMSE, though the difference is minimal. Thus, both models perform comparably for Cocoa, with a marginal edge for TAR.

Table 13: Diebold-Mariano Test (TARvs MSM, MSE, H = 1)

Series	DM_stat(TAR vrs MSM)	p_value
Gold	7.447594	0.0
Cocoa	0.684849	0.494109

The Diebold–Mariano (DM) test results in Table 13 above compare the one-step-ahead forecast accuracy of the TAR and MSM models using the mean squared error (MSE) loss function. For gold prices, the DM statistic (7.4476) is highly significant (p = 0.0000), indicating a statistically significant difference in predictive performance between the two models. The positive sign of the statistic suggests that MSM forecasts outperform those from the TAR model. In contrast, for cocoa prices, the DM statistic (0.6848) is not statistically significant (p = 0.4941), implying no evidence of a difference in predictive accuracy. This result suggests that, while MSM provides superior forecasts for gold, both models perform comparably in forecasting cocoa prices.

4.4.1 Visual Evaluation of Forecast Accuracy

To complement the quantitative evaluation, Figures 12 and 13 present the actual and predicted price series for Gold and Cocoa, respectively. The plots provide a visual comparison of each model's ability to track market dynamics and highlight periods where forecast deviations occur.

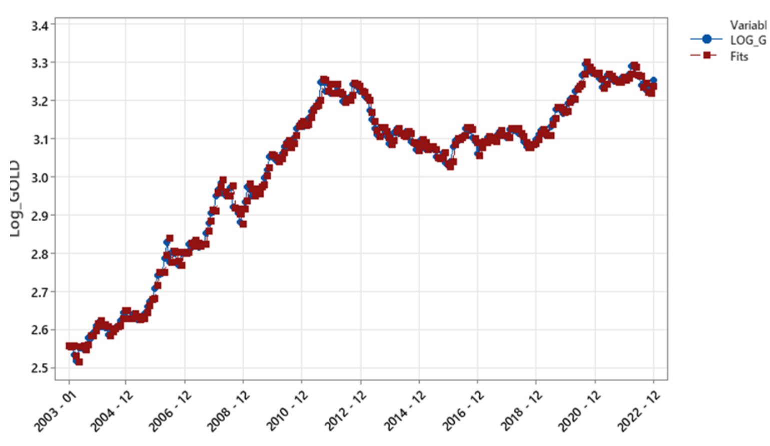

Figure 12: GOLD FORECASTED vrs ACTUAL

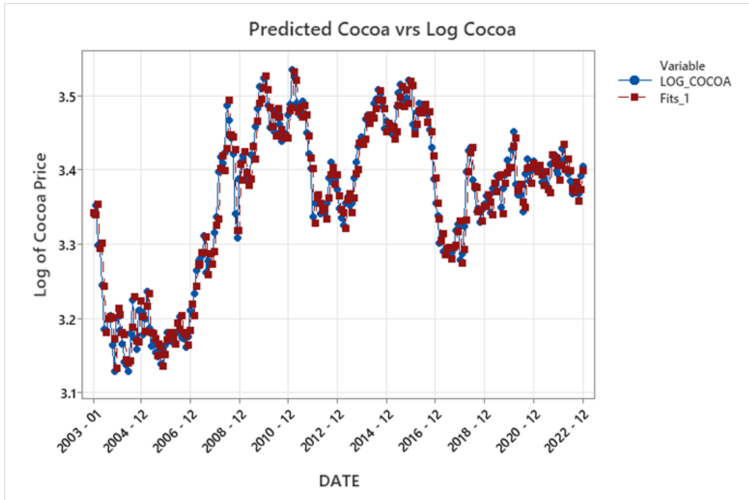

Figure 13: COCOA FORECASTED vrs ACTUAL

5 Conclusion

This study applied Threshold Autoregressive (TAR) and Markov Switching (MSM) models to monthly gold and cocoa prices, revealing that both approaches effectively capture regime changes and nonlinear dynamics, though each excels in different aspects. Gold's price dynamics are heavily influenced by macroeconomic conditions and global sentiment, making MSM's ability to capture smooth probability-driven regime shifts a natural fit. Cocoa prices, by contrast, are often shaped by abrupt supply shocks, such as weather events or political instability in producing countries, making TAR's threshold-based design well-suited to capture these sharp, sudden market shifts. Models were evaluated using forecast accuracy metrics RMSE and MAE, and this reveal that in the gold market, the MSM exhibited better predictive accuracy than the TAR model. For Cocoa, TAR slightly outperforms MSM in both MAE and RMSE, though the difference was minimal. Thus, both models perform comparably for Cocoa, with a marginal edge for TAR. The Diebold-Mariano test confirms MSM's superior performance in several cases, though TAR remains useful for trigger-based insights. Using monthly data provides a clear long-term view but limits detection of rapid intra-month fluctuations. Overall, combining TAR and MSM as a hybrid model would enhance the detection of subtle shifts, respond more rapidly to shocks, and incorporate diverse market signals. Such advancements could improve early warning systems, refined intervention timing, and strengthen resilience strategies in the face of increasing global commodity market volatility.

6 Limitation Of The Study

Despite the insightful findings, this study is subject to some limitations. Firstly, the analysis was based on historical monthly data for gold and cocoa prices, which may not fully capture high-frequency market dynamics. Secondly, while these models (TAR and MSM) are effective in capturing regime shifts, they may not account for other complex features like volatility clustering and long memory as in the case of GARCH or LSTM neural networks. Lastly, this study did not include external variables which may also influence commodity prices.

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