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Analyzing Structural Breaks and Nonlinear Volatility in Nigerian Quasi-Money using Smooth Transition Autoregressive-GARCH Models

Deebom Zorle Dum[1*] Awogbemi Clement Adeyeye[2*]
Osamo Caleb Kehinde[3]AttahEleojo Vincent[3]
[1]*Mathematics Department, Rivers State University, Port Harcourt, Nigeria*
[2]*Statistics Programme, National Mathematical Centre, Abuja, Nigeria*
[3]*Finance Department, Veritas University, Abuja, Nigeria*

ABSTRACT

This study examines the behavior of Nigeria's quasi-money, focusing on its nonlinear dynamics and volatility from January 1994 to December 2024. By utilizing nonlinear GARCH-type models, specifically the smooth transition autoregressive GARCH models (LSTAR–GARCH and ESTAR–GARCH), and the study indicates notable conditional heteroskedasticity, volatility clustering, and nonlinearity in the series of monetary aggregates. Diagnostic tests such as Chow and BDS highlight the existence of structural breaks and behavior dependent on different regimes, emphasizing the drawbacks of conventional linear models. Among the various models, the LSTAR–GARCH shows better statistical results and is more reactive to abrupt changes in economic or policy conditions. These results stress the essential role of using nonlinear and regime-switching volatility models to analyze quasi-money in developing countries, equipping policymakers with improved methods for forecasting and handling liquidity during structural shifts. The results indicate that those in charge of monetary policy should use nonlinear and regime-switching volatility models, especially the LSTAR–GARCH model, in their analysis to enhance effective prediction of the changes in Nigeria's quasi-money. Moreover, it is advised to frequently check for structural breaks for timely policy updates. Financial analysts, too, should focus on models that can capture both nonlinearity and changing volatility to achieve better forecasts and a clearer understanding of monetary trends.

Keywords: *Structural Breaks, Nonlinear Volatility, Quasi Money, Smooth Transition, Regime Switching*

1. INTRODUCTION

Quasi money otherwise known as near money consists of liquid assets that are not in form of cash, but convertible to cash equivalents with redemption values. Modeling the behavior of monetary aggregates, particularly Nigeria's quasi-money, presents considerable challenges due to issues like structural breaks, nonlinear dynamics, and fluctuating volatility. These factors hinder accurate assessments and predictions of monetary conditions, especially in developing nations where economic instability often arises from frequent changes in policy, external impacts, and governance shifts. Conventional linear time series models typically struggle to capture the behaviors and intricate volatility patterns that are influenced by different regimes, diminishing their effectiveness in policy development and financial analysis. The quest to tackle these challenges is driven by the vital function that quasi-money serves in managing liquidity and ensuring economic stability. For monetary authorities to create effective policies and for researchers to enhance forecasting precision, it is crucial to model the volatility and structural changes accurately. Previous research has highlighted the importance of structural breaks and nonlinear relationships in Nigeria's monetary aggregates. For instance, Mbutor (2014) pointed out how structural breaks influence the stability of these aggregates via monetary policy transmission. Likewise, Olomola and Adejumo (2006) observed that in Nigeria, macroeconomic indicators are sensitive to shifts in oil prices and government actions, resulting in volatility and regime changes that simple linear models cannot properly address.

To effectively depict economic dynamics that depend on regimes, the use of nonlinear time series models, especially smooth transition autoregressive (STAR) models, has been recommended (Van Dijk et al., 2002). In the realm of volatility, Engle (1982) and Bollerslev (1986) laid the groundwork for ARCH and GARCH models, respectively, to manage time-varying volatility. Later studies by Granger and Terasvirta (1993) and Terasvirta (1998) underscored the need to combine nonlinearity with volatility models using STAR-GARCH approaches to better represent complicated phenomena like volatility clustering and asymmetric reactions to disruptions.

Despite these improvements, there is still a lack of studies that effectively integrate structural breaks and nonlinear volatility in Nigeria's quasi-money using smooth transition autoregressive-GARCH models. While research such as Mensi et al. (2014) has shown the existence of fat tails and persistent volatility in emerging markets, and Hamilton (1989) pointed out the deficiencies of linear models in addressing regime changes, extensive implementation and validation of LSTAR-GARCH and ESTAR-GARCH models in Nigeria's monetary framework are sparse. This study aims to bridge this gap by applying Smooth Transition Autoregressive-GARCH models to quasi-money data from Nigeria, covering January 1994 to December 2024. The main focuses of the research include identifying structural breaks, modeling nonlinear volatility, and assessing the effectiveness of LSTAR–GARCH and ESTAR–GARCH models using criteria such as AIC and BIC. The goals are to validate regime-dependent behavior, enhance volatility forecasting, and offer actionable insights for designing monetary policies. By addressing the nonlinear and regime-switching traits present in the data, this study aims to improve the analytical resources available to policymakers and financial analysts, which in turn supports more effective liquidity management and economic stability in Nigeria.

2. LITERATURE REVIEW

Macro and financial time series often show behaviors that depend on different regimes and can have volatility that changes over time. Traditional linear models typically assume that parameters remain the same and that errors are consistent, but numerous key studies indicate these assumptions do not hold true for many macro-financial data sets. In 1982, Engle introduced the ARCH model to account for volatility clustering, meaning past shocks affect the current conditional variance (Deebom, et al. 2021). In 1986, Bollerslev expanded this idea to GARCH, which includes past conditional variances to allow for persistence (Deebom & Essi, 2017). Additionally, Hamilton in 1989 showed that many macroeconomic data sets are better viewed as processes that switch between regimes, where parameters alter significantly across hidden states (Bharat, et al., 2021). Collectively, these insights suggest the need to merge regime-switching or smooth-transition models with conditional heteroskedasticity to address both changes in structure and volatility clustering in monetary aggregates. Research on Nigeria and similar developing nations reveals structural instability in monetary aggregates tied to policy changes, external shocks, and shifts in institutions. Olomola and Adejumo (2006) demonstrate that key macroeconomic indicators in Nigeria, like money supply and exchange rates, react significantly to changes in oil prices and policy decisions, indicating instability in their relationships. Discussions at the national level and documents from central banks, such as Mbutor (2006), stress how changes in monetary policies and financial reforms can create breaks in monetary data. These findings reflect broader trends showing that structural breaks frequently occur in the monetary data of developing countries and must be considered in empirical models; ignoring them can skew conclusions, forecasts, and policy suggestions. When parameter changes occur gradually instead of suddenly, Smooth Transition Autoregressive (STAR) models are often a suitable option. Van Dijk, Teräsvirta, and Franses (2002) review STAR models and suggest they are particularly helpful when regime dependency is gradual or linked to observable transition factors, like policy indicators, deviations from trends, or past returns. Granger and Teräsvirta (1993) provide much of the practical framework for testing and estimating nonlinear economic relationships, showcasing how logistic (LSTAR) and exponential (ESTAR) transition functions capture sudden and gradual regime changes, respectively (Van. et al. 2002). These models are especially pertinent for monetary aggregate data that behave differently during various economic cycles or policy regimes. The ARCH/GARCH literature offers strong methods for modeling and predicting time-varying variance. Following the foundational work by Engle (1982) and Bollerslev (1986), later studies focused on incorporating nonlinearity into the variance processes. Granger and Teräsvirta, along with other researchers, emphasize how smooth transition functions can enhance standard GARCH models, leading to hybrid specifications like STAR–GARCH model (Van. et al., 2002). These hybrids allow the conditional variance to change based on past shocks (α terms), past variances (β terms), and a regime-dependent multiplier G (.), which captures changes in how volatility is generated (Akintunde et al., 2014)). Such combinations are often more effective than linear GARCH when volatility reacts differently during various regimes, such as calm versus crisis periods (Deebom, et al. 2021)).

Many studies confirm the presence of heavy tails, high kurtosis, and volatility clustering in financial and monetary data from emerging markets (Deebom, et al. 2021). Research by Mensi et al. (2014) and others has shown that fat tails and changing volatility in these markets make asymmetric or regime-dependent models more effective than basic symmetric GARCH models. Analyses that look at structural changes along with volatility have revealed that overlooking these regime shifts leads to incorrect variance dynamics and less accurate forecasts. In Nigeria specifically, indications of structural changes, instability driven by oil prices, and shifts in policy suggest that STAR-GARCH models are suitable for analyzing quasi-money returns. To support the use of nonlinear, regime-switching GARCH models, diagnostic tests like Chow tests for parameter instability, BDS and Tsay tests for nonlinear behaviors, as well as ARCH LM tests for conditional volatility, are frequently employed. This study shows that the significant results from the Chow test, the rejection of IID by the BDS test, the Tsay test's dismissal of linearity, and solid results from the ARCH LM test are in line with existing literature, indicating that monetary aggregates in developing countries are both regime-dependent and have heteroskedastic properties. The better performance of LSTAR-GARCH compared to ESTAR-GARCH—reflected in AIC/BIC values—aligns with earlier findings that different transition functions reveal different economic situations: logistic transitions signal abrupt changes (like policy shocks), while exponential transitions indicate gradual adjustments. For those in policymaking, this evidence suggests that variance forecasts, risk evaluations, and simulations should utilize models that account for both regime dependence and changing variance to tailor interventions to current volatility conditions. Collectively, the literature indicates that modeling approaches for monetary aggregates in developing nations, especially Nigeria, must address structural breaks, nonlinearity, and volatility clustering. By applying LSTAR-GARCH and ESTAR-GARCH to Nigeria's quasi-money returns and running a comprehensive set of tests for linearity and heteroskedasticity, this study confirms and builds on previous research: it highlights a notable structural change around midpoint of the series, returns that are non-normal and heavy-tailed, and volatility dynamics that depend on the regime. The finding that LSTAR-GARCH provides slightly better information criteria and eliminates residual ARCH effects strengthens the case for using logistic smooth transitions combined with GARCH dynamics to effectively capture the volatility behavior of Nigeria's quasi-money.

3. METHODOLOGY

The data analyzed in this study were obtained from the Central Bank of Nigeria statistical database and they were 372 monthly data spanning from 2nd January 1994 to 31st December 2024. The Quasi Money series, identified as column QM, which is labeled by year. Initially, the dataset was imported into the analysis python environment, and the date column was formatted as a time index. Instances of missing values in the logarithm-differenced series were eliminated, ensuring the returns and lagged variables were perfectly synchronized for estimation and testing. The process of data transformation and exploratory analysis commenced with the calculation of percentage log-returns from the raw series, using the formula

$$QMR_t = 100 * In * \left(\frac{QM_t}{QM_{t-1}}\right) \qquad (1)$$

Both the original series and the returns series were graphed to examine trends, changes in slope, spikes, and patterns of volatility. The descriptive statistics, including the sample mean, median, sample standard deviation, skewness, and excess kurtosis, were calculated for the returns on the original series. The Jarque–Bera statistic was employed to check for deviations from a normal distribution. To identify any structural changes within the raw quasi-money series, a Chow test was conducted at the midpoint of the sample. The raw series was regressed against a constant and a linear time trend for the complete sample and again for the two subsamples determined by this midpoint. Given the visual evidence of possible shifts in slope and variance, we formally tested for structural stability using the Chow (1960) test. The procedure involves splitting the sample at a hypothesized breakpoint date, identified visually from the time plot (July 2009) and estimating the regression model separately for the two subperiods and for the full sample:

$$Y_t = \alpha + \beta t + \varepsilon_t \qquad (2)$$

Computing the Chow F-statistic:

$$F = \frac{S_c-(S_1+S_2)/_K}{(S_1+S_2)/_{(n_1+n_2-2K)}} \qquad (3)$$

where: S_c= residual sum of squares for the combined sample
S_1, S_2 = residual sums of squares for subsamples 1 and 2
n_1, n_2= number of observations in each subsample
k = number of parameters in the model.

The null hypothesis H_0: no structural change in parameters at the specified break date. The break date producing the maximum F-statistics is considered the most likely structural break point. This finding encourages treating pre- and post-break dynamics separately or considering models that allow regime switching. Prior to estimating the model, a range of diagnostic tests were conducted on the returns. The BDS test (Brock–Dechert–Scheinkman) was performed with embedding dimensions m=2 and m=3 to assess whether the series is independent and identically distributed (IID.). Also, the Tsay test for nonlinearity, applied with a brief lag specification, investigated if linear autoregressive dynamics were adequate or if a nonlinear autoregressive structure existed. Additionally, the ARCH Lagrange-multiplier test (with five lags) evaluated the null hypothesis of no conditional heteroskedasticity; a rejection in this case suggests volatility clustering, which leads to GARCH-type modeling. These initial tests were essential for guiding the model selection process: the presence of strong nonlinearity and ARCH effects supported the choice of STAR–GARCH family models over linear homoskedastic ones. The estimated volatility models integrate a smooth transition mean/variance mechanism and include a GARCH variance component. Two different specifications were estimated for comparison. The LSTAR–GARCH specification employed a logistic transition function, while the ESTAR–GARCH specification used an exponential transition function. The estimated conditional variance equations align with the approach used in this analysis, such as the form for LSTAR–GARCH, which was written and estimated as follows:

$$r_t = \mu + \varepsilon_t, \varepsilon_t = \sigma_t z_t, z_t \sim N(0,1) \qquad (5)$$

Then plug in each conditional variance σ_t^2 model:

LSTAR-GARCH:

$$\sigma_t^2 = \omega + (\alpha * \varepsilon_{t-1}^2 + \beta * \sigma_{t-2}^2) * G(Z_{t-d}) \quad (6)$$

$$where \quad G(Z_{t-d}) = \frac{1}{1 + exp(-\gamma(Z_{t-d} - C)} = (1 + exp(-\gamma(Z_{\{t-d\}} - C))^{-1}$$

ESTAR-GARCH:

$$\sigma_t^2 = \omega + (\alpha * \varepsilon_{t-1}^2 + \beta * \sigma_{t-2}^2) * G(Z_{t-d}) \quad (7)$$

$$where \quad G(Z_{t-d}) = 1 + exp(-\gamma(Z_{t-d} - C)^2)$$

where:
σ_{t-2}^2 = conditional variance at time t
ε_{t-1}^2= lagged squared residual (shock effect)
σ_{t-2}^2 = lagged variance (volatility persistence)
Z_{t-d}= transition variable with delay d

c = threshold value

γ = slope parameter controlling transition speed.

The influence of the regime on the GARCH component is smoothed in distinct ways across the two models. The transition variable Z_{t-d} usually represents either a past value from the series or a modification of earlier returns, while dd indicates the delay used in the transition. To estimate parameters ω, α, β, and γ, the Gaussian log-likelihood was maximized based on the assumption of conditional normality. This was generally executed by numerically minimizing the negative log-likelihood. To evaluate model fit and simplicity, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were employed. The final log-likelihood and the number of estimated parameters were applied in the standard AIC and BIC formula given as:

AIC=2k−2ℓ (8)

BIC=ln(n) k−2ℓ (9)

where k corresponds to the number of parameters, ℓ to the maximized log-likelihood, and nn to the sample size. The model yielding a lower AIC (and correspondingly lower BIC) was chosen as the favored specification for diagnostics and forecasting. A Q-Q plot was generated for the standardized residuals to assess any deviations from normality in the standardized errors; additionally, the Jarque–Bera test can provide a numerical measure of these deviations. The ARCH LM test was reapplied to the standardized residuals to determine if any conditional heteroskedasticity persisted; failing to reject the null hypothesis of no ARCH effects suggests that the GARCH component effectively captured the time-varying volatility. The time series of standardized residuals was examined for any remaining structure, and a lack of systematic patterns further supports the adequacy of the model. For forecasting conditional variance, a recursive approach was used with the fitted parameter vectors and transition function. One-step-ahead forecasts for conditional variance were created by inserting the most recent observed values into the variance recursion, allowing for multi-step forecasts as needed. The point forecasts for σ_{t+h}^2 were presented alongside optional confidence bands that were estimated under the conditional normality assumption, utilizing the predicted variance and an approximation of forecast uncertainty if required. The variances forecasted, as reported in the findings, represent one-step-ahead predictions produced in this manner.

4. RESULTS

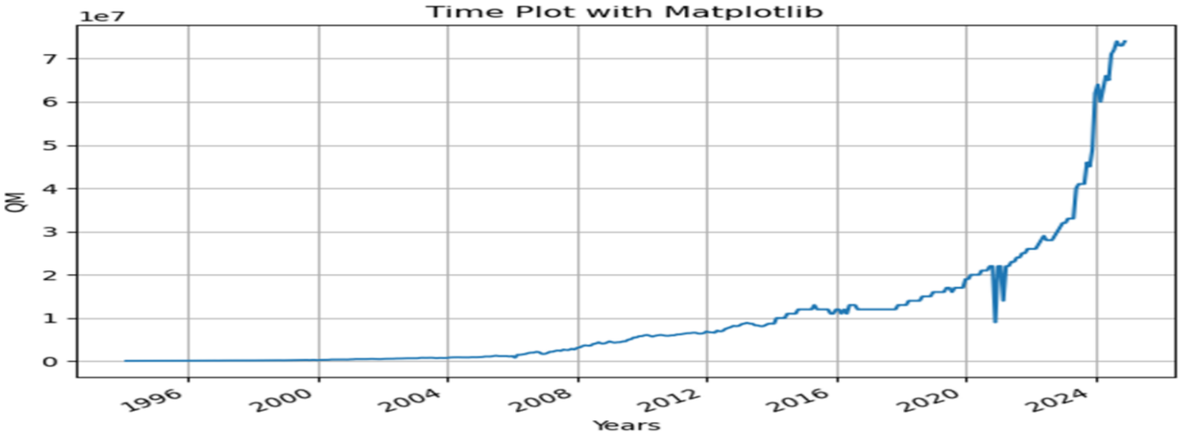

Figure 1: Time Plots of Raw Data on Nigeria Quasi Money Data.

Figure 1: Time graphs ofraw data on Nigeria's Quasi Money. The graph depicting the raw series of quasi-money indicates a general upward trend during the time frame analyzed, signifying consistent growth in Nigeria's quasi-money reserves. However, this growth is not steady; there are distinct changes in the slope, highlighted by phases of rapid increase followed by slower rates. Such variations suggest potential shifts in monetary policy, economic trends, or external factors that may be influencing the economy's liquidity. The sudden changes in both level and slope imply that the underlying dynamics might not be stable, necessitating formal tests for structural breaks.

Structural Break Analysis

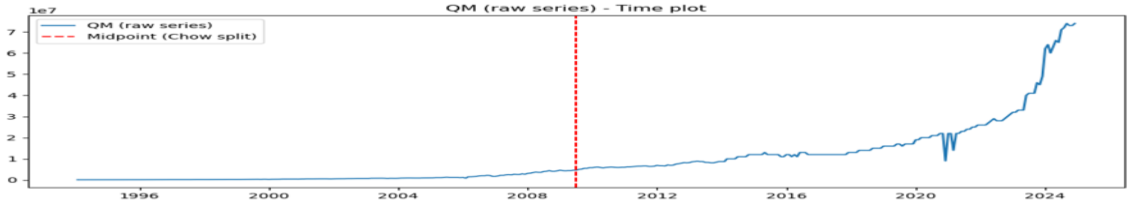

Figure 2: Time Plots of Structural Break Analysis for the Raw Data on Nigeria Quasi Money Data.

Figure 2: Time graphs of Structural Break Analysis for the raw data on Nigeria's Quasi Money. The plot from the structural break analysis points to a significant change occurring around mid-2009, which aligns with the results of the Chow test. Prior to this break, the series shows a relatively constant and moderate growth rate. After this point, there is an evident alteration in the slope and possibly in the series' variance, suggesting a pronounced shift in the dynamics of quasi-money growth. This break may indicate important policy changes, reforms in the banking sector, or macroeconomic occurrences that transformed the relationship between monetary aggregates and economic conditions. The identified break reinforces the necessity to analyze the periods before and after the break separately or to include mechanisms for regime shifts.

Table 1: Chow Test

Chow Test (Midpoint Split)	F -Statistic	p-value
Chow F-statistic	151.279	0.000
Midpoint index: 185	Midpoint date: 2009-07-01	

Table 1 presents the results of the Chow test, which assesses the stability of model parameters over time. The null hypothesis suggests that there are no structural changes in the parameters at the specified split point. The p-value obtained is 0.000, and the F-Statistic stands at 151.279, both of which are significantly below typical significance levels, prompting the rejection of the null hypothesis. This indicates strong evidence of a structural change in the quasi-money series around July 1, 2009, with a midpoint index of 185. This shift indicates that the dynamics of the series underwent a notable transformation after this date, suggesting a change in the data-generating process. Also, descriptive statistics (returns) were investigated, and the results are shown in Table 2

Table 2: Descriptive Statistics (Returns)

Mean	Median	Std Dev	Skewness	Kurtosis	Jarque–Bera	p-value
1.8204	0.1619	9.7143	0.0863	42.9297	28489.5144	0.0000

Table 2 contains descriptive statistics for the returns, detailing their distributional characteristics. The average return is positive at 1.82%, while the standard deviation of 9.71% denotes a high level of volatility. The skewness is nearly zero, reflecting a symmetrical distribution, yet the exceptionally high kurtosis of 42.93 indicates the presence of heavy tails and extreme values relative to normal distribution. The Jarque-Bera test indicates that normality can be rejected with a p-value less than 0.001, which supports the presence of fat-tailed and potentially non-Gaussian characteristics in the quasi-money returns from January 1994 to December 2024.

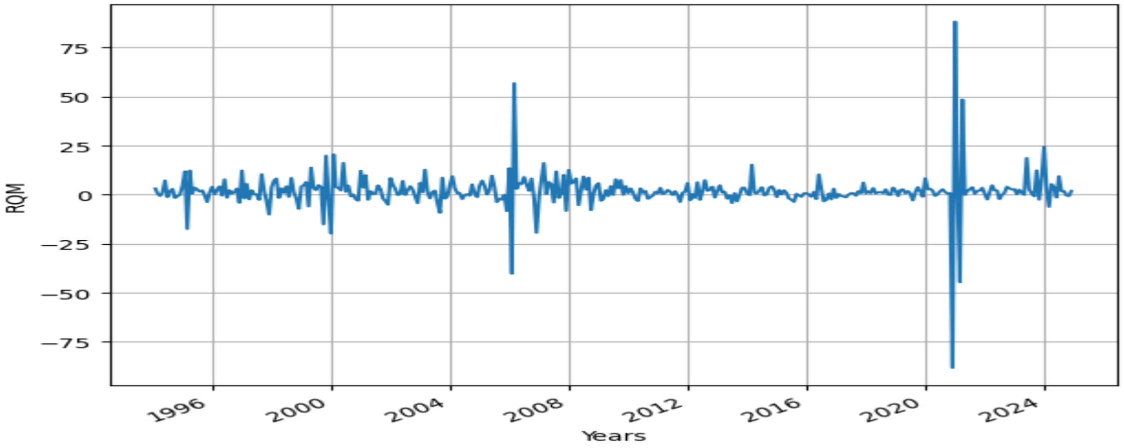

Figure 3: Time Plots of Returns on Nigeria Quasi Money Data.

Figure 3 shows the time series of the returns on Nigeria Quasi Money Data. The series of returns shows significant variation around a mean that is nearly zero, reflecting both increases and decreases in quasi-money. Notable spikes highlight moments of abrupt monetary changes, possibly related to announcements of policies, liquidity shocks, or macroeconomic issues. The pattern, where periods of high volatility follow other high volatility and low changes follow low ones, indicates the persistence of volatility—this is a normal characteristic in financial and monetary time series. The findings visually support the ARCH LM test results, which affirmed the existence of conditional heteroskedasticity, reinforcing the applicability of GARCH-type models for addressing the changing volatility over time.

Nonlinearity & Dependence Tests

Table 3: BDS Test

Embedding Dimension	BDS Statistic	p-value	Conclusion
2	6.294996	3.07e-10	Reject H_0 → dependence present
3	6.805432	1.01e-11	Reject H_0 → strong dependence

Table 3 details the BDS test, which evaluates the null hypothesis that returns are independent and identically distributed (IID). For both examined embedding dimensions (m = 2 and m = 3), the test statistics are (6.295, 6.805), which are very significant with p-values effectively equal to zero, leading us to reject the null hypothesis. This finding suggests that the returns display nonlinearity and dependence structures, justifying the use of nonlinear time series models like LSTAR or ESTAR alongside GARCH.

Table 4: Tsay Nonlinearity and ARCH LM Test

Embedding Dimension	F -Statistic	p-value	Conclusion
Tsay Nonlinearity Test	57.872	0.000	Significant nonlinearity detected
ARCH LM Test (nlags = 5)	126.664	0.000	Strong ARCH effects present in returns

Table 4 summarizes the findings from the Tsay nonlinearity test and the ARCH LM test. The Tsay test yields an estimated F-Statistic of 57.872 and a p-value of 0.000. This result prompts the rejection of the linearity null hypothesis, indicating the existence of nonlinear structures within the quasi-money returns. Similarly, the ARCH LM test investigates the null hypothesis of no conditional heteroskedasticity, producing an estimated F-Statistic of 126.664 at lag 5 and a p-value of 0.000. The very small p-value leads to the rejection of this null hypothesis, confirming the presence of strong ARCH effects. Collectively, these findings suggest that both nonlinearity and time-varying volatility are crucial features of the series, reinforcing the need for nonlinear GARCH-type models.

Table 5:Model Estimation Results

Model Estimation	Parameter	Estimate
LSTAR–GARCH Parameters	ω	39.715
	α	0.258
	β	0.202
	γ	82.599
	c	4.356
ESTAR–GARCH Parameters		
	ω	40.316
	α	0.259
	β	0.192
	γ	5.003
	c	0.0272
Model	AIC	BIC
LSTAR–GARCH	2596.254	2615.835
ESTAR–GARCH	2598.063	2617.644

The LSTAR-GARCH model is represented as:

$$\sigma_t^2 = 39.715 + (0.258 * \varepsilon_{t-1}^2 + 0.202 * \sigma_{t-2}^2) * G(Z_{t-d}) \quad (10)$$

$$where \quad G(Z_{t-d}) = \frac{1}{1 + exp(-82.599(Z_{t-d} - 4.3561)} = (1 + exp(-82.599(Z_{t-d} - 4.3561)^{-1})$$

Similarly, the ESTAR-GARCH model is given as:

$$\sigma_t^2 = 40.316 + (0.259 * \varepsilon_{t-1}^2 + 0.192 * \sigma_{t-2}^2) * G(Z_{t-d}) \quad (11)$$

$$where \quad G(Z_{t-d}) = 1 + exp(-5.003(Z_{t-d} - 0.0272)^2)$$

The results in Table 5 evaluate and compare the performance and parameters of the LSTAR–GARCH and ESTAR–GARCH models. For the LSTAR–GARCH model, the long-run average variance, represented by the parameter ω=39.715, establishes the foundational volatility level. The estimated α value of 0.258 shows how much recent shocks (squared residuals) affect current volatility. Additionally, the β value of 0.202 indicates how much past volatility influences present volatility levels. A notably high γ value of 82.599 suggests a very steep transition between regimes, resembling a threshold switch; this indicates that the model reacts strongly once the transition variable exceeds the threshold. The threshold itself, shown as c = 4.356, is quite high, meaning regime changes occur only with significant fluctuations in the transition variable.

In the ESTAR–GARCH model, the baseline volatility is slightly higher with ω at 40.316. The α estimate of 0.259 is almost the same as that of the LSTAR model, indicating a similar moderate response to recent shocks. The β value of 0.192 suggests slightly less persistence in volatility compared to the LSTAR model. The γ parameter, significantly lower at 5.003, indicates a smoother transition between regimes rather than a sharp change. The threshold value c=0.0272 is very near zero, which suggests that regime switching occurs around the mean, likely happening more often with smaller fluctuations in the transition variable. When assessing model performance using information criteria, the LSTAR–GARCH model achieves a lower AIC (2596.254) and BIC (2615.835) than the ESTAR–GARCH model, which has an AIC of 2598.063 and a BIC of 2617.644. Lower criteria values reflect a better model fit, indicating that the LSTAR–GARCH slightly better captures the underlying volatility process in the data. Nonetheless, the differences are minimal, suggesting both models are suitable, with the LSTAR–GARCH being statistically favored.

4.1 Diagnostics for Best Model

The results from diagnostics and visualizations are used to evaluate the effectiveness, performance, and predictive ability of the chosen nonlinear volatility models (LSTAR–GARCH and ESTAR–GARCH) applied to returns on Nigeria's quasi-money.

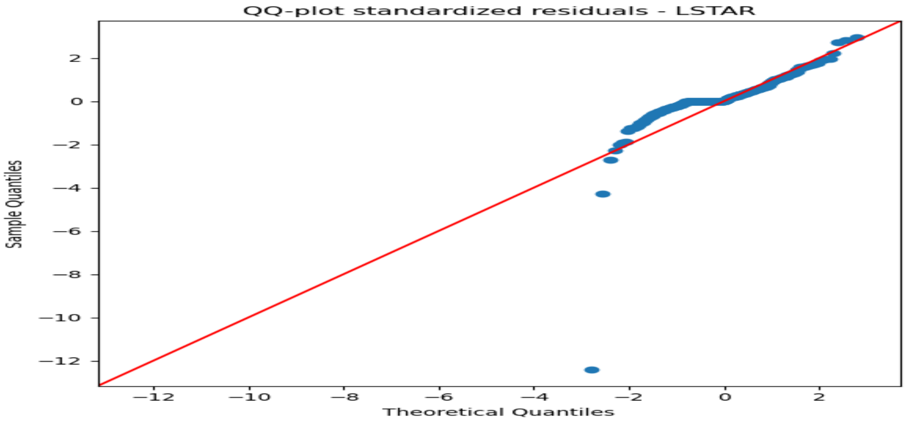

Figure 4: QQ Plot of the Standardized Residuals (Best Model) for ModelingReturnson **Nigeria Quasi Money Data.**

The QQ plot of standardized residuals (Figure 4) for the LSTAR–GARCH model, which performs best according to AIC and BIC, checks if the residuals align with a normal distribution. If the points on the QQ plot are closely aligned with the 45-degree line, it indicates that the standardized residuals are roughly normal, thus validating the model. However, complete normality is rare in financial and monetary data due to the presence of fat tails. If the tails show minor deviations yet the main body is well-aligned, this still indicates that the model is adequate.

Table 6: ARCH LM Test

Test statistics	F -Statistic	p-value	Conclusion
ARCH LM Test (nlags = 5)	0.286842	0.997883	Strong ARCH effects present in returns

The results of the ARCH LM test on the residuals from the top model are displayed in Table 6. The F-statistic recorded is 0.286842, and the p-value is 0.997883, both of which exceed typical significance levels. This signifies that the null hypothesis of no ARCH effects in the residuals cannot be rejected. Essentially, it shows that the GARCH model has effectively captured the time-varying volatility in the return data. This is an important confirmation step—having residuals without ARCH effects verifies that the conditional heteroskedasticity has been well modeled.

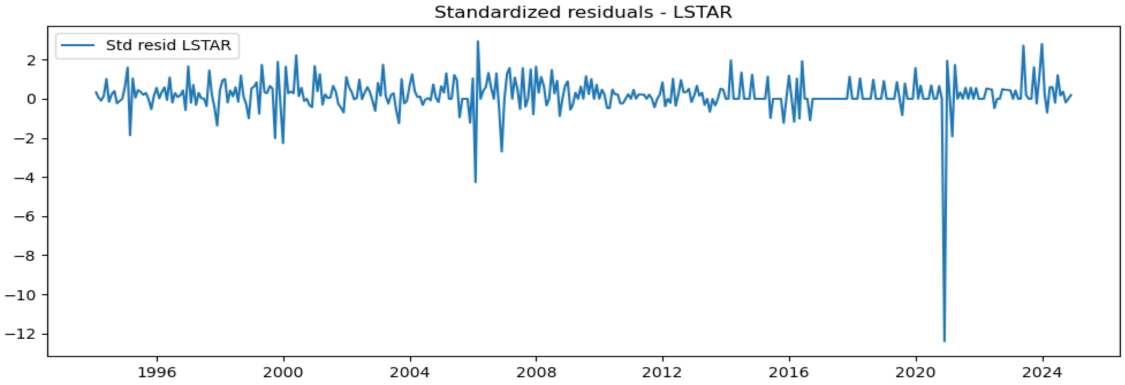

Figure 5: LSTAR-GARCH Standardized Residuals in ModelingReturns on Nigeria Quasi Money Data

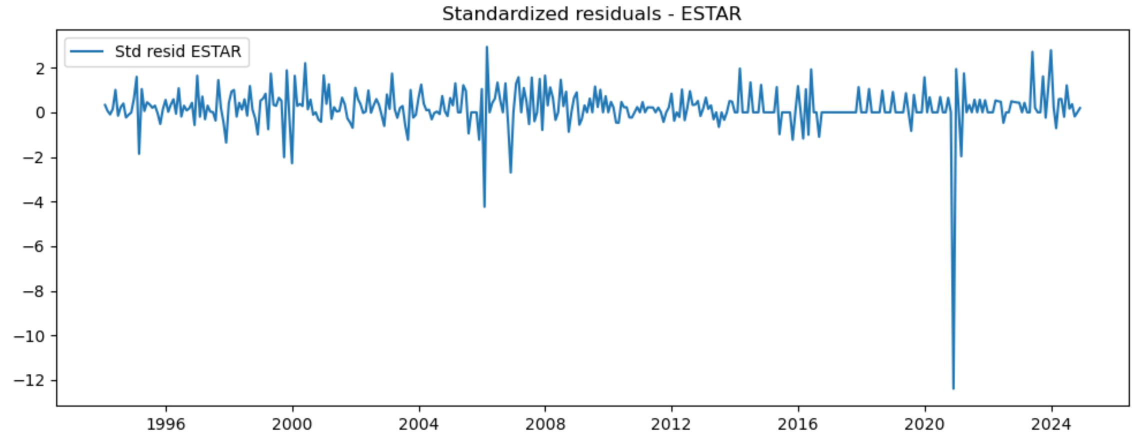

Figure 6: STAR-GARCH Standardized Residuals in ModelingReturns onNigeria Quasi Money Data.

Figures 5 and 6 illustrate the standardized residuals for LSTAR-GARCH and STAR-GARCH models, respectively. These visuals allow a review of whether the residuals show mean reversion, homoscedasticity, and white noise characteristics. A good model that accounts for time-varying volatility should produce residuals that lack noticeable patterns, clusters, or autocorrelation. If both models exhibit relatively stable standardized residuals, it further supports the relevance of the nonlinear GARCH approach.

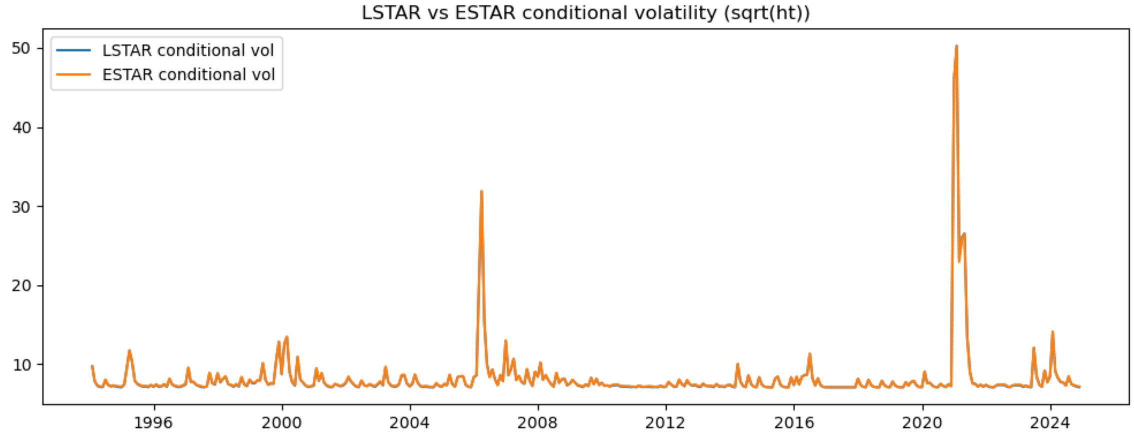

Figure 7: **Volatility Comparison (LSTAR vsESTAR) in Modeling Returns on Nigeria Quasi Money Data.**

Figure 7 compares the conditional volatility patterns estimated by the LSTAR and ESTAR models. This comparison provides insight into how each model reacts to variations in the returns. The LSTAR-GARCH model, with its sharp logistic transition function, might show more abrupt changes in volatility during significant economic events or policy shifts, while the ESTAR-GARCH model, which uses a smoother exponential transition, will indicate more gradual changes. This figure is crucial for understanding how each model portrays the dynamics of Nigeria's quasi-money over time and whether one matches real-world volatility more closely. In the forecasting part, both one-step-ahead and multi-step-ahead forecasts have been made, with confidence intervals shown in Figure 5. The one-step-ahead predicted conditional variances (sigma²) are 39.7152 for the LSTAR model and 40.9595 for the ESTAR model. While these predictions are similar, they suggest that LSTAR anticipates slightly lower volatility in the short term, which aligns with its more abrupt regime-switching nature. The relatively low forecast variance also indicates the stability seen in the latest data set.

4.2 Forecasts

The results of one-step-ahead and multi-step-ahead forecasts plotted with confidence intervals (Figure 8).
Forecasted sigma² (LSTAR): 39.7152
Forecasted sigma² (ESTAR): 40.9595
The values Forecasted sigma² (LSTAR): 39.7152 and Forecasted sigma² (ESTAR): 40.9595 indicate the one-step-ahead estimates of conditional variance (σ^2) generated by the LSTAR-GARCH and ESTAR-GARCH models, respectively. These estimates reflect anticipated fluctuations in Nigeria's quasi-money returns for the upcoming period, based on both current and historical data. A higher σ^2 indicates a forecast of increased volatility (risk or uncertainty) in returns, while a lower figure suggests more stable outcomes. In this analysis, the LSTAR model forecasts slightly less volatility (39.7152) than the ESTAR model (40.9595). Although this difference is minor, it implies that the LSTAR-GARCH model predicts a more stable market in the short term, potentially due to its quicker reaction to changes in market regimes, which allows it to respond better to recent stable conditions. On the other hand, the ESTAR model exhibits a more gradual adjustment and suggests a slightly higher level of volatility, signaling that it may adapt more slowly to recent declines in market variability. Both models' forecasts align with current trends, yet LSTAR's lower variance prediction highlights its agility and slightly better fit, further supported by lower AIC and BIC values in earlier findings.

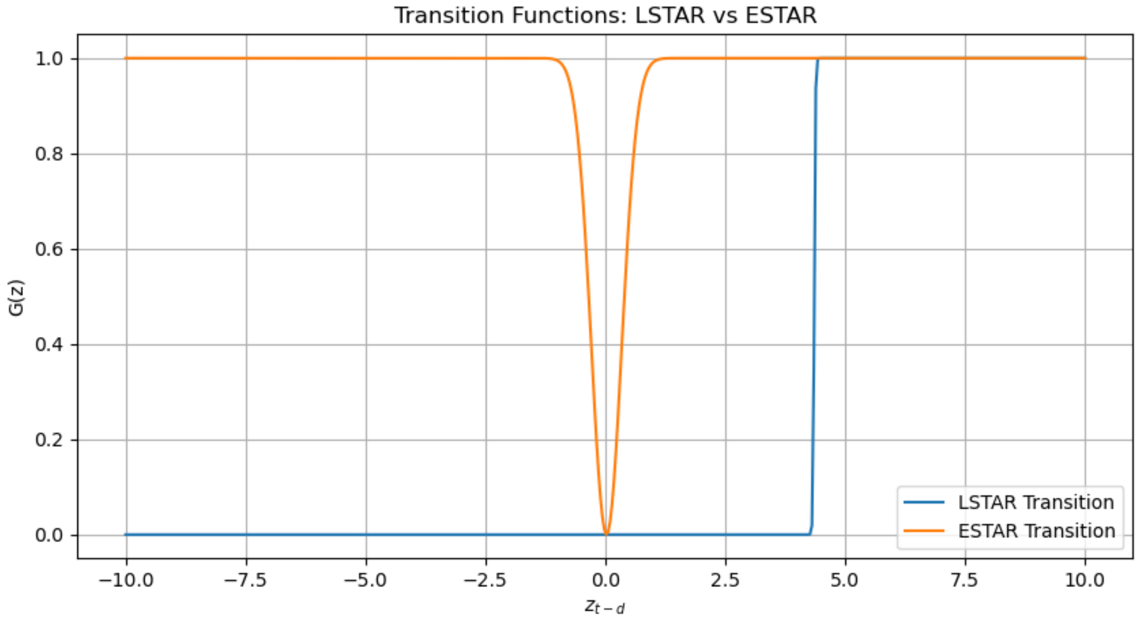

Figure 8: Logistic and Exponential Transition Functions of Varying Values of Gamma (γ) in LSTAR vs ESTAR

Figure 8 shows the logistic and exponential transition functions with different values of γ, which represent the transition speed. This figure helps to illustrate how the regime-switching mechanisms operate. In the case of LSTAR, higher γ values create a transition that resembles a step function, indicating that the model rapidly changes regimes when it surpasses the threshold cc. On the other hand, ESTAR features smoother and symmetric transitions around the threshold. This comparison highlights the differences in nonlinearity between the models, which in turn affects both volatility dynamics and forecasting capabilities.

5 DISCUSSION OF RESULTS.

This research reveals that Nigeria's quasi-money data demonstrates nonlinear relationships and conditional heteroskedasticity, which corresponds with earlier findings in monetary economics and financial time series studies. Numerous investigations have shown that monetary aggregates, particularly in developing nations, experience structural changes and volatility clustering is often influenced by policy alterations, external disruptions, or changes in governance. For instance, Mbutor (2014) explored the transmission of Nigeria's monetary policy, highlighting the significant impact of structural breaks on the stability of monetary aggregates. Similarly, Olomola and Adejumo (2006) discovered that macroeconomic indicators in Nigeria, like the money supply, are extremely responsive to shifts in oil prices and government actions, leading to instability that calls for regime-switching models. Research by van Dijk, Franses, and Paap (2002) also supports the application of nonlinear models, advocating for smooth transition autoregressive (STAR) models for economic data that show regime-dependent behavior. In the realm of volatility modeling, Bollerslev (1986) and Engle (1982) first introduced ARCH and GARCH models to account for time-varying volatility. However, later studies by Granger and Teräsvirta (1998) stressed the importance of integrating nonlinearity into variance modeling through STAR-GARCH combinations. Moreover, this study's findings of non-normality, excessive kurtosis, and volatility clustering align with the results of Mensi et al. (2014), who used GARCH-type models on data from emerging markets and uncovered significant evidence of fat tails and ongoing volatility—important factors that support using models beyond conventional linear or symmetric GARCH.

Additionally, the outcomes of the Chow and BDS tests in this study reinforce Hamilton's (1989) observations, which indicated that standard linear time series models often overlook structural breaks and regime-dependent behaviors in macroeconomic data, especially when responding to shocks or policy changes. The study adds to the expanding literature advocating for nonlinear and regime-switching volatility models when examining monetary aggregates in developing countries. By utilizing LSTAR–GARCH and ESTAR–GARCH models on Nigeria's quasi-money data, the research not only validates earlier findings related to nonlinearity and heteroskedasticity but also improves model selection based on performance indicators such as AIC and BIC. The results from diagnostics and forecasts indicate that the LSTAR–GARCH model outperforms others statistically and shows a greater ability to react to changes in the volatility of Nigeria's quasi-money returns. Analysis of the residuals reveals an absence of remaining ARCH effects, while the forecasting outcomes are both stable and easy to understand. Additionally, the transition functions illustrate that regime changes are handled distinctly in various models, with LSTAR providing a more sudden representation that is sensitive to policy shifts. Together, these diagnostics support the effectiveness of nonlinear GARCH models, especially the LSTAR–GARCH, in capturing the intricate volatility patterns associated with monetary aggregates.

6. CONCLUSION

This research reveals that the data on Nigeria's quasi-money exhibits significant nonlinearity, clustering of volatility, and conditional heteroskedasticity, alongside a notable structural break occurring around mid-2009. The findings indicate that the presence of heavy tails, non-normal distributions, and ongoing volatility suggest that simple linear models fall short in capturing the behavior of monetary aggregates in Nigeria's quasi-money from January 1994 to December 2024. While both LSTAR–GARCH and ESTAR–GARCH models effectively addressed the underlying volatility, the LSTAR–GARCH model slightly outperforms the others according to AIC and BIC metrics andThis shows greater responsiveness to sudden economic or policy changes. The results demonstrate that utilizing regime-switching nonlinear volatility models is more appropriate for examining and forecasting monetary aggregates in settings prone to structural changes and policy influences. Considering structural breaks and notable regime-dependent volatility detected in the series, it is vital for monetary authorities and policymakers to adopt nonlinear and regime-switching models, especially the LSTAR–GARCH framework, in their analysis of liquidity and monetary conditions. These models will aid in predicting times of increased volatility and in implementing prompt monetary policy actions. Furthermore, routine evaluations of structural breaks should be performed to identify early changes in quasi-money dynamics, ensuring that policy measures remain aligned with the current economic reality. Financial analysts and researchers should also focus on models that incorporate both nonlinearity and fluctuating volatility, as they yield more accurate predictions and better illustrate the intricate nature of financial and monetary systems in developing countries.

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