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Understanding Volatility Transmission from Global Commodity Shocks to Frontier Financial Markets: Machine Learning, Nonlinearities, and State Dependence in Kenya

Abraham Kisembe Wawire [1,*], Christine Nanjala Simiyu[1], Munene Laiboni [1] and Rogers Ochenge [2,3]

[1] Department of Accounting & Finance, KCA University, Nairobi, Kenya
[2] Department of Economic Theory, Kenyatta University, Nairobi, Kenya
[3] Department of Economics & Statistics, KCA University, Nairobi, Kenya
* Correspondence: wawirekisembe@gmail.com; Tel.: +254 724984135

Abstract

Global commodity shocks are associated with volatility in frontier financial markets, affecting exchange rates and equity indices. While GARCH specifications capture clustering, they are sensitive to structural breaks and regime changes, which distort persistence and weaken risk measures. Machine learning approaches provide alternatives capable of capturing nonlinear dependencies, abrupt volatility bursts, and regime-independent dynamics. Empirical evidence demonstrates that 2008 Global Financial Crisis and COVID-19 induced permanent volatility regime changes. This study examined volatility transmission from global commodity shocks to a frontier financial market, focusing on the USD/KES exchange rate and the NSE 20 Share Index. Structural break detection was integrated through the Iterative Cumulative Sum of Squares algorithm, alongside APARCH, FIGARCH models and ML architectures (XGBoost, LSTM). In Kenya volatility is characterized by strong persistence and long-memory dynamics, with limited evidence of leverage effects. Break-adjusted models improve inference by correcting spurious persistence, while machine learning approaches demonstrate superior tracking of volatility during stress regimes. We show that volatility transmission from global commodity shocks to a frontier market is nonlinear, break-sensitive, and state-dependent, and that hybrid ML-econometric methods improve forecasting during crisis-period. Findings highlight persistence distortion, horizon-dependent performance, and relevance of regime-sensitive modelling frameworks for financial stability in structurally evolving economies.

Keywords: volatility transmission; frontier markets; structural breaks; GARCH models; machine learning; LSTM; XGBoost; brent oil shocks

1. Introduction

Global commodity shocks generate volatility spillovers that spread into inflation, exchange rates, and equity markets worldwide (Ge & Tang, 2020; Laeven & Valencia, 2020; Stuermer, 2018). In frontier economies, these spillovers are destabilizing because weak financial systems and concentrated sectoral exposures magnify external shocks. African markets, including Kenya, experienced sharp vulnerability during episodes such as the 2008 Global Financial Crisis and the COVID-19 pandemic, where commodity price swings coincided depreciation with exchange rates and stress in equity markets (Gyasi et al., 2025; Mupunga & Ngundu, 2020). Recent studies argue that financialization and global uncertainty indices tighten linkages, eroding benefits of diversification and increasing systemic risk (Gozgor et al., 2016; Kaur & Chaudhary, 2024).

Traditional GARCH models are key to volatility analysis, capturing clustering and persistence (Bollerslev, 1986a; Engle, 1982). Yet, their sensitivity to structural breaks and regime shifts often distorts persistence estimates, a limitation documented in African contexts where crises induce permanent volatility realignments (Hasanov et al., 2024; Lahmiri et al., 2017). Break-adjusted approaches, such as ICSS-modified GARCH, improve inference by correcting spurious persistence (Inclan & Tiao, 1994; Sanso et al., 2004). At the same time, machine learning methods such as LSTM and XGBoost have gained relevance due to their ability to capture nonlinear dependencies and abrupt volatility bursts thereby outperforming GARCH during stress regimes (Bildirici et al., 2020; Chung et al., 2025). Within Africa, emerging studies emphasizes that commodity-currency-equity linkages are nonlinear and state-dependent, with shocks propagating asymmetrically across regimes (Alqaralleh, 2020; Nazlioglu et al., 2013).

This study contributes to these debates by focusing on Kenya, a frontier market where volatility transmission from global commodity shocks remains underexplored despite the economy's exposure to oil imports and exchange rate fragility. Existing African literature has examined contagion in broader emerging markets or emphasized sovereign debt channels, leaving a gap in understanding how commodity shocks interact with domestic volatility dynamics in equity and currency markets. We address this gap by integrating structural break detection with econometric (APARCH, FIGARCH) and machine learning (XGBoost, LSTM) models to assess whether volatility spillovers are nonlinear, break-sensitive, and state-dependent. By comparing standard GARCH, break-adjusted GARCH, and hybrid ML–econometric models across regimes, we show that hybrid approaches improve forecasting during crisis-periods and provide reliable tools for monitoring financial stability in frontier markets.

1.1. Theoretical Framework

Financial economics provides multiple lenses for understanding volatility. The Efficient Market Hypothesis (EMH) and random-walk theory posit that asset prices reflect available information, rendering future movements unpredictable (Bachelier, 1900; Fama, 1965). Modern Portfolio Theory (MPT), the Capital Asset Pricing Model (CAPM), and the Arbitrage Pricing Theory (APT) conceptualize volatility as a rational risk–return trade-off (Markowitz, 1952; Ross, 1976; Sharpe, 1964). Yet, these frameworks assume normal returns and rational agents, assumptions contradicted by heavy-tailed distributions, investor sentiment, and behavioural biases (Kahneman & Tversky, 2013; Mandelbrot & Hudson, 2010). Herding and speculative bubbles further highlight that volatility is not purely rational but shaped by cognitive and institutional dynamics (Shleifer, 1986).

Engle (1982) and Bollerslev (1986) introduced ARCH and GARCH models, which capture volatility clustering and persistence in financial returns. Extensions such as EGARCH (Nelson, 1991) and GJR-GARCH (Glosten et al., 1993) incorporate leverage effects and asymmetry, reflecting the empirical reality that negative shocks amplify volatility more than positive shocks. However, ignoring structural breaks induced by crises, regulatory shifts, or macroeconomic shocks distorts persistence estimates and risk measures (Lamoureux & Lastrapes, 1990; Mikosch & Stărică, 2004). Regime-dependent models and break-adjusted approaches, including ICSS-filtered GARCH, improve inference by accounting for abrupt shifts in variance (Casini & Perron, 2018; Inclan & Tiao, 1994; Sanso et al., 2004).

At the same time, globalization and financialization have intensified cross-market linkages, reducing diversification benefits and increasing systemic risk (Diebold & Yilmaz, 2012; Tang & Xiong, 2012). In frontier markets, commodity shocks spread into volatility in exchange rates and equity, often in nonlinear and state-dependent ways. Capturing these dynamics requires models that go beyond linear parametric structures. Machine learning methods such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) are designed to capture long-term dependencies and nonlinear interactions in time series, offering improved forecasting accuracy during crisis regimes (Hochreiter & Schmidhuber, 1997).

Volatility transmission in frontier markets can be understood through an integrated theoretical foundation that draws on classical finance theory, econometric modelling, and machine learning approaches. Classical perspectives such as the Efficient Market Hypothesis, Modern Portfolio Theory, and related asset pricing models present volatility as a rational risk–return trade-off, yet their assumptions of normality and rational agents often fail in the presence of heavy tails, behavioural biases, and herding effects. Econometric models provide tools to capture clustering, persistence, and asymmetry, while regime-dependent and break-adjusted specifications correct distortions caused by crises and structural shifts. Machine learning methods extend this foundation by modelling nonlinearities, long-memory, and state dependence, offering flexible tools that are relevant for frontier markets exposed to commodity shocks.

1.2. Empirical Literature Review

The literature on volatility spillover from global commodity shocks to financial markets has been expanding in the aftermath of systemic crises such as the Global Financial Crisis and the COVID-19 pandemic. Recent studies emphasize that commodity shocks spread systemically, affecting inflation and, volatility in exchange rates, and equity across economies (Ge & Tang, 2020; Laeven & Valencia, 2020; Stuermer, 2018). Within Global VAR frameworks, these shocks transmit inflationary pressures and sovereign risk across advanced and emerging markets (Bouri et al., 2017; Chudik & Fidora, 2012). Recent contributions highlight pandemic-driven bidirectional spillovers, intensified by financialization and uncertainty indices such as the VIX, which erode diversification benefits and intensify systemic risk (Behera et al., 2024; Kaur & Chaudhary, 2024; Wang et al., 2023).

A consistent theme in the literature is the nonlinearity and asymmetry of volatility responses. Shocks in crude oil prices generate asymmetric effects across currencies and commodities, with appreciations and depreciations responding differently under stress regimes (Alqaralleh, 2020; Nazlioglu et al., 2013). Gold amplifies volatility during price increases, while agricultural commodities maintain lower connectedness with equity, offering short-horizon diversification (Baur, 2012; Shah & Dar, 2022). These findings impply that commodities cannot be treated as a homogeneous asset class, and that volatility spillovers are asset-specific and regime-dependent.

Extant literature on African economies highlights vulnerabilities. Commodity price downturns reduce export earnings and fiscal revenues more severely than in other regions due to weaker revenue mobilization (Christensen, 2016; Diarra, 2012). Shocks penetrate banking systems, escalating non-performing loans and eroding profitability (Mupunga & Ngundu, 2020). Recent studies show that both positive and negative shocks weaken financial soundness in African commodity exporters, emphasizing the need for institutional development and counter-cyclical buffers (Gyasi et al., 2025; Ngepah et al., 2022).

On Methodology, the literature has evolved from ARCH and GARCH models (Bollerslev, 1986a; Engle, 1982) to break-adjusted and regime-dependent specifications (Casini & Perron, 2018; Nguyen & Walther, 2020), and more recently to machine learning approaches. LSTM, CNN, and hybrid methods capture nonlinear dependencies and long-memory effects, consistently outperforming GARCH during crises (Bildirici et al., 2020; Chung et al., 2025; Dudek et al., 2025). Graph Neural Networks and TVP-VAR frameworks extend this capacity further by modelling interconnected systems dynamically, identifying new volatility transmitters such as cryptocurrencies while reaffirming gold’s safe-haven role (Joshi et al., 2022; Sahu et al., 2026).

Despite these advances, there are significant gaps. While global studies document nonlinear spillovers and methodological innovations, African frontier markets remain underexplored. Existing research has focused on sovereign debt contagion or broad emerging market linkages, leaving forecasting volatility in equity and currency markets insufficiently addressed. Kenya, as a frontier economy with significant dependence on oil imports, a fragile exchange rate regime, and a thin equity market, provides an ideal case to examine how global commodity shocks spread into volatility in domestic financial markets . By comparing GARCH, break-adjusted GARCH, and machine learning models, this study addresses both methodological and regional gaps, contributing to debates on systemic risk and financial stability in Africa.

2. Materials and Methods

2.1. Conceptual Framework

The empirical framework integrates four strands: volatility clustering, long-memory dynamics, international spillovers, and regime-dependent responses (Baillie et al., 1996; Diebold & Yilmaz, 2012; Engle, 1982; Hamilton, 1989). Volatility is conceptualized as a persistent process where oil shocks generate volatility spillovers that are reflected in exchange rates and inflation, amplified by nonlinear crisis-driven mechanisms (Kilian, 2009).

2.2. Methodology

The dependent variable is daily realized volatility, proxied by the rolling standard deviation of returns for the NSE 20 Share Index. Econometric models estimate conditional variance, while Machine Learning models approximate the same volatility proxy without parametric restrictions.

1.1.1 Data and Variable Construction

Daily log returns of the NSE 20 Share Index are constructed as:

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right), \quad (1)$$

This transformation aligns with literature where returns exhibit weak serial correlation but strong conditional heteroskedasticity (Cont, 2001).

To operationalize global-to-domestic transmission mechanisms identified in spillover studies(Diebold & Yilmaz, 2012; Diebold & Yılmaz, 2014), the feature vector is defined as:

$$X_t = \{r_{t-k}, \sigma_{t-k}, Brent_t USD/KES_t\}, \quad (2)$$

where (k) is selected via the Akaike Information Criterion (Akaike, 2003).

This structure reflects three theoretical channels documented in the literature:

Direct oil shock channel

$$Brent_t \rightarrow r_t, \quad (3)$$

consistent with oil–equity transmission evidence (Basher et al., 2012).

Exchange-rate transmission channel

$$Brent_t \rightarrow USD/KES_t \rightarrow r_t, \quad (4)$$

aligned with exchange-rate pass-through literature (Kilian & Park, 2009).

Volatility persistence channel

$$\sigma_{t-k} \rightarrow \sigma_t \ , \quad (5)$$

reflecting volatility clustering(Bollerslev, 1986b; Engle, 1982).

2.2. 1Benchmark Econometric Volatility Models

Frontier markets exhibit slow hyperbolic decay in volatility shocks (Baillie et al., 1996). To capture this property, the study employs the FIGARCH model:

$$(1-L)^d \emptyset(L)\epsilon_t^2 = \omega + [1-\beta(L)](\epsilon_t^2 - \sigma_t^2), \quad (6)$$

Where (0 < d < 1) measures fractional integration.

Unlike standard GARCH, FIGARCH allows the autocorrelation of squared returns to decay at a hyperbolic rate:

$$Cov(\epsilon_t^2, \epsilon_{t-k}^2) \sim k^{-(1-2d)}, \quad (7)$$

This specification captures the long-memory dynamics documented in financial volatility (Baillie et al., 1996; Conrad & Haag, 2006).

2.2.2. Machine Learning Models

While econometric models impose a pre-specified structure:

$$\sigma_t^2 = f(\epsilon_{t-1}^2, \sigma_{t-1}^2), \quad (8)$$

machine learning models approximate:

$$\sigma_t^2 = \mathcal{F}(X_t), \qquad (9)$$

without functional restrictions.

XGBoost

In this study, XG Boost is trained to forecast daily realized volatility, proxied by the 5-day rolling standard deviation of NSE 20 share index returns. It models this volatility as an additive ensemble of regression trees, capturing nonlinear dependencies among lagged volatility, exchange rate, and commodity shocks:

$$\boldsymbol{\hat{\sigma}_t^2 = \sum_{m-1}^{M} \gamma_m h_m(X_t),} \qquad \mathbf{(10)}$$

where:

$h_m(\cdot)$ are regression trees,

γ_m are weights.

This flexible approximation is consistent with recent evidence that nonlinear tree-based models improve volatility forecasting performance (Gu et al., 2020).

LSTM: Temporal Nonlinear Memory

Long Short-Term Memory (LSTM) networks (Hochreiter, 1997) model temporal dependence through gated recurrence:

$$h_t = f(h_{t-1}, x_t), \qquad (11)$$

with gating structure:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right), \qquad (12)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \qquad (13)$$

LSTM networks allow nonlinear memory retention, providing a data-driven analogue to fractional integration in FIGARCH models (Fischer & Krauss, 2018).

SHAP Economic Interpretability

To address concerns regarding ML interpretability, SHAP values decompose model predictions as:

$$\boldsymbol{\hat{y}_t = \emptyset_0 + \sum_{j=1}^{p} \emptyset_j(X_{t,j}),} \qquad \mathbf{(14)}$$

where $\emptyset_j$ represents the marginal contribution of each variable (Lundberg & Lee, 2017).

2.2.3. State Dependence and Stress Identification

Volatility spillovers intensify during crisis periods (Bekaert et al., 2014). Following the regime-switching literature (Hamilton, 1989), market states are identified using K-Means clustering:

$$\min_{C} \sum_{j=1}^{K} \sum_{x_i \epsilon C_j} \left\| x_i - \mu_j \right\|^2, \qquad (15)$$

To estimate crisis probability, a Logistic Regression classifier models:

$$P(S_t = 1|X_{t-1}) = \frac{1}{1+exp(\beta_0+\beta_1\sigma_{t-1}+\cdots)}, \qquad (16)$$

where $S_t = 1$ denotes a high-volatility (stress) regime.

Logistic regression has been used in financial crisis early-warning systems and regime classification frameworks (Kaminsky et al., 1998). By modelling the conditional probability of entering a crisis state, the specification aligns with probabilistic crisis prediction approaches in macro-financial stability literature (Berg & Pattillo, 1999).

2.2.4. Evaluation an Interpretation

Forecast performance is evaluated using:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2}, \qquad (17)$$

$$MAE - \frac{1}{T}\sum_{t=1}^{T}|y_t - \hat{y}_t|, \qquad (18)$$

$$R^2 = 1 - \frac{\sum(y_t-\hat{y}_t)^2}{\sum(y_t-\bar{y})^2}, \qquad (19)$$

To connect predictive performance with financial risk management, Value-at-Risk (VaR) and Expected Shortfall (ES) are computed at the 95% confidence level:

$$VaR_{\alpha} = inf\{l: P(L > l) \leq 1 - \alpha\}, \tag{20}$$

$$ES_{\alpha} = \mathbb{E}[L | L > VaR_{\alpha}], \tag{21}$$

This aligns the study with literature on tail-risk and financial stability (McNeil et al., 2015).

3. Results

3.1. Structural Break Identification

Table 1 presents the ICSS structural break test results. The ICSS test identified a structural break in the NSE 20 Share index on 7 February 2009 during the Global Financial Crisis of 2008, confirming a volatility regime shift. Ignoring such breaks inflates persistence estimates, while break-adjusted models improve forecasting accuracy in frontier markets consistent with (Bouri et al., 2017; Hasanov et al., 2024; Uddin et al., 2018; Wang, 2024).

Table 1. ICSS Structural Break Points.

Metric	Value
Primary Break Date	7/2/2009
Peak D_k Statistic	0.1638
95% Critical Value	0.0166
Significance Level	p < 0.01

3.1.1. ICSS Variance Break Test

The ICSS variance break test results for the NSE 20 share index in Figure1 reveal an upward spike in February 2009 that exceeds the 95% critical threshold consistent with evidence that crises coincide with persistent volatility shifts and spillovers, and that accounting for structural breaks improves inference and forecasting in frontier markets (Bouri et al., 2017; Hasanov et al., 2024; Uddin et al., 2018; Wang, 2024).

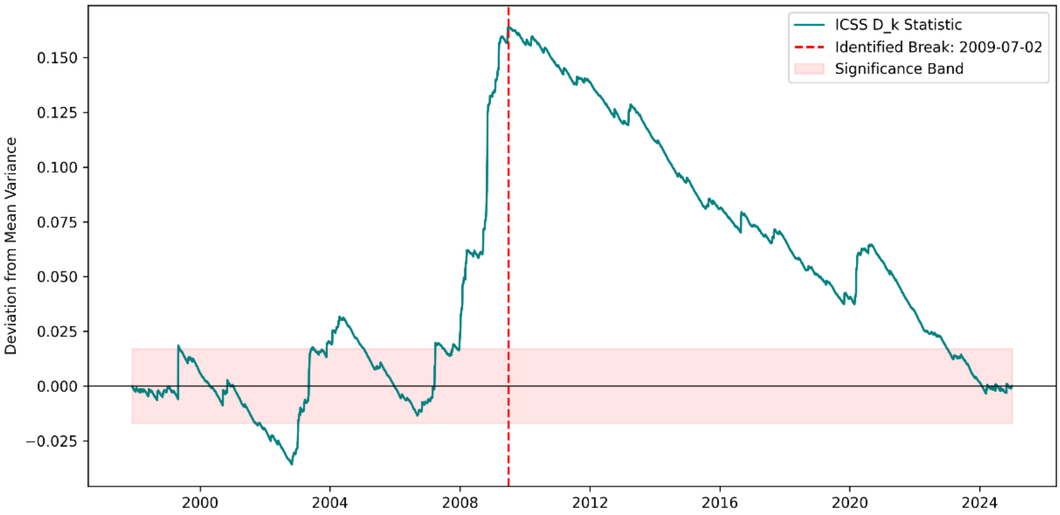

Figure 1. Variance Break Test.

The NSE 20 Share index modified ICSS structural volatility breaks in figure 2 shows how the market transitioned from the high-stress regime of 2008–2009 into a lower-variance regime consistent

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with evidence that crisis episodes induce permanent volatility reconfigurations in emerging markets (Bouri et al., 2021; Uddin et al., 2018).

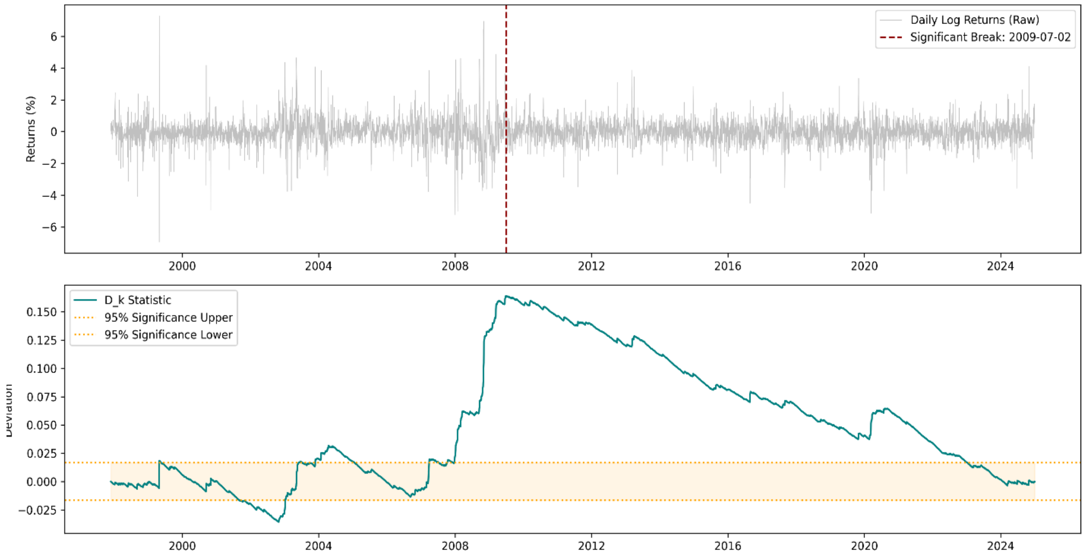

Figure 2. Modified Structural volatility breaks.

3.2. Parameter Estimation and Model Selection

Table 2 presents the parameter estimates. The FIGARCH model detects long-memory volatility in the Equity market, consistent with evidence of persistent volatility dynamics with leverage effects, while the asymmetry term of APARCH was insignificant consistent with evidence of strong persistence but weak leverage effects in frontier-markets (Alfeus & Nikitopoulos, 2022; Baillie et al., 1996; Mensi et al., 2021; Nguyen & Walther, 2020).

Table 2. Model Parameters.

Model Spec	Key Parameter	Estimate	T-Statistic	P-Value
APARCH (1,gamma,1)	Gamma (Asymmetry)	-0.032186	-1.246716	0.212502
FIGARCH (1,d,1)	d (Long Memory)	0.385838	2.154176	0.031226

3.3. Machine Learning Models

The XGBoost feature importance results in figure 3 show that lagged volatility of the NSE 20 share index accounts for over 80% of the model's predictive power suggesting that the Kenyan equity market is highly self-referential, consistent with the FIGARCH finding of significant long-memory (d = 0.3858) and with studies emphasizing persistence in frontier markets (Alfeus & Nikitopoulos, 2022; Baillie et al., 1996). Results are consistent with Behera et al. (2024) and Kim & Won (2018).

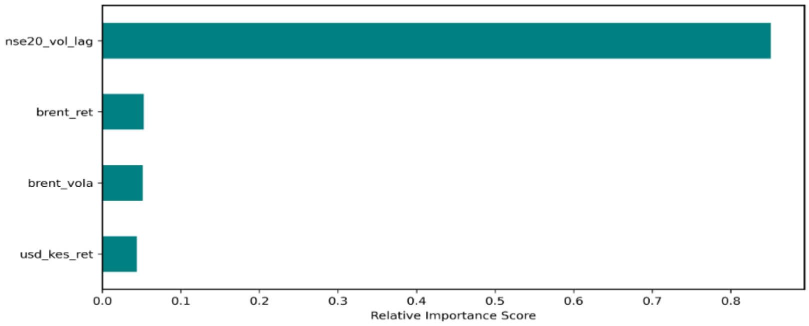

Figure 3. XG Boost Feature Importance (Gain).

In figure 4 Long Short-Term Memory networks track volatility of the NSE 20 share index during the Global Financial Crisis and the COVID-19 pandemic. This supports evidence that deep learning models capture nonlinear volatility dynamics and outperform traditional GARCH models during crisis periods (Bildirici et al., 2020; Chung et al., 2025; Kim & Won, 2018).

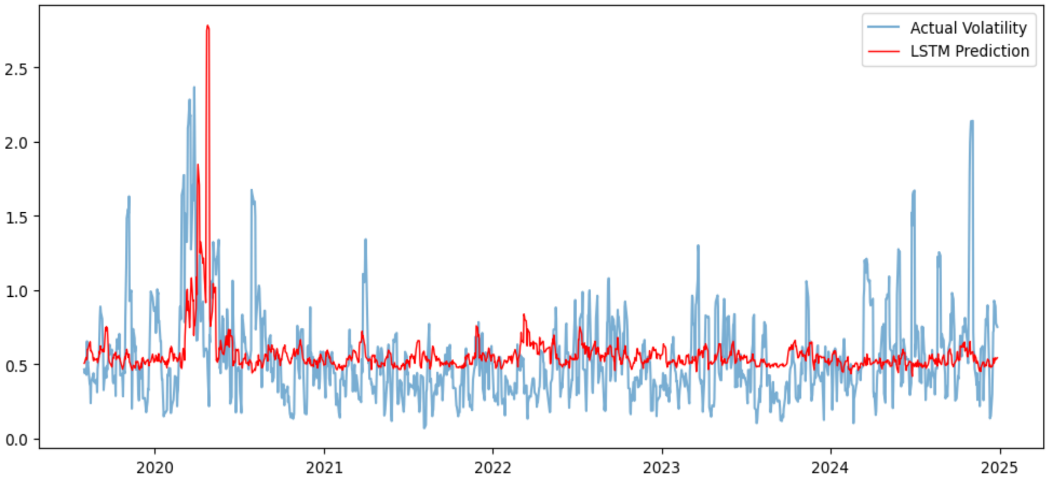

Figure 4. Time Varying Volatility Dynamics.

Figure 5 presents volatility divers of the NSE 20 Share Index . Lagged volatility is the dominant predictor, consistent with the long-memory finding of the FIGARCH Model and studies highlighting persistence in frontier markets (Alfeus & Nikitopoulos, 2022; Baillie et al., 1996). External shocks from Commodity and FX markets exert asymmetric effects, with extreme positive shocks amplifying domestic volatility, consistent with Nazlioglu et al. (2013) and Alqaralleh (2020).

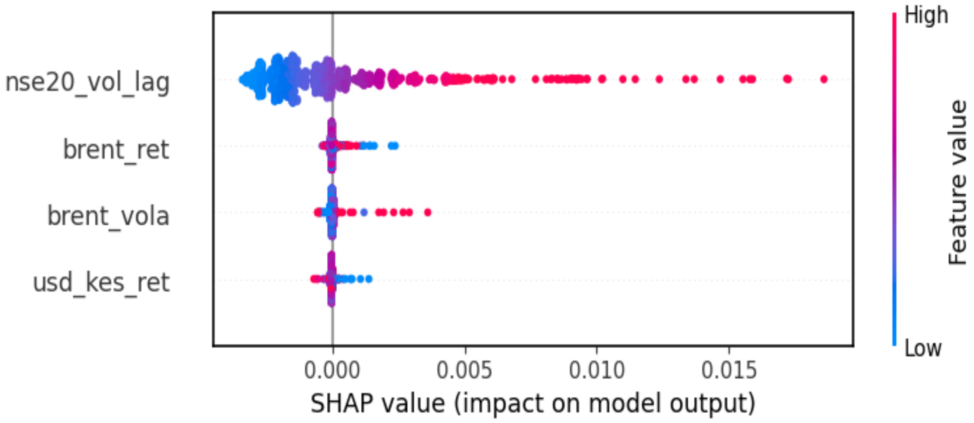

Figure 5. Sharp summary.

In figure 6, Shocks in the crude oil market are associated with disproportionately larger volatility spillovers when lagged domestic volatility is already high, consistent with Nomikos & Salvador (2014) and Khalifa et al. (2014), who found state-dependent contagion in frontier markets.

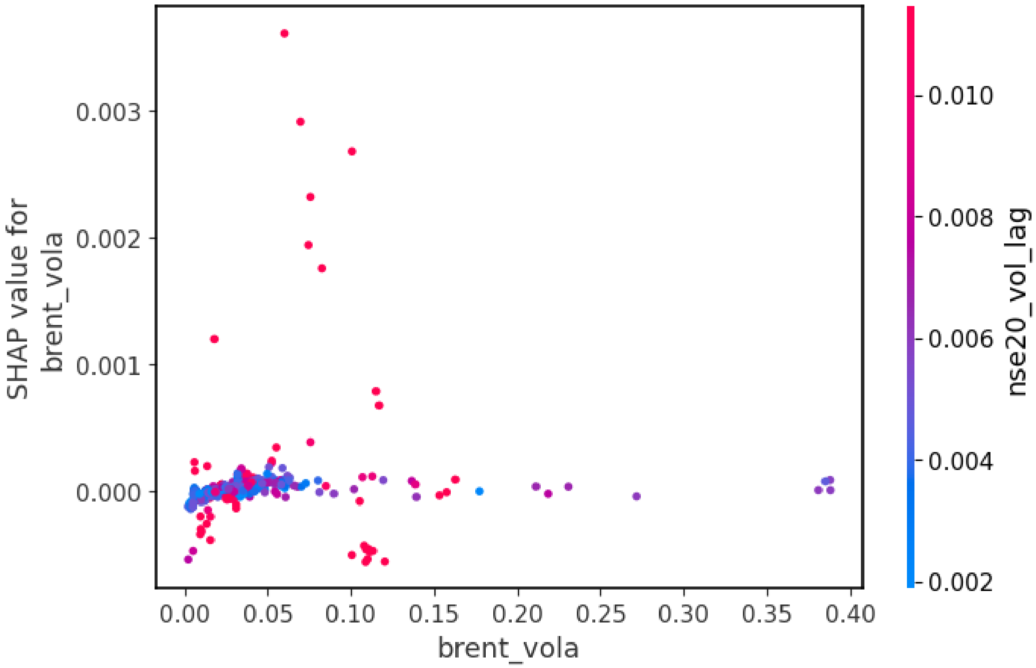

Figure 6. Shap Interaction.

In figure 7, positive shocks in commodities amplify volatility in equities when accompanied by depreciation in the Kenya shilling, consistent with Nazlioglu et al. (2013) on nonlinear commodity–finance linkages and Alqaralleh (2020) on asymmetric currency responses to oil shocks.

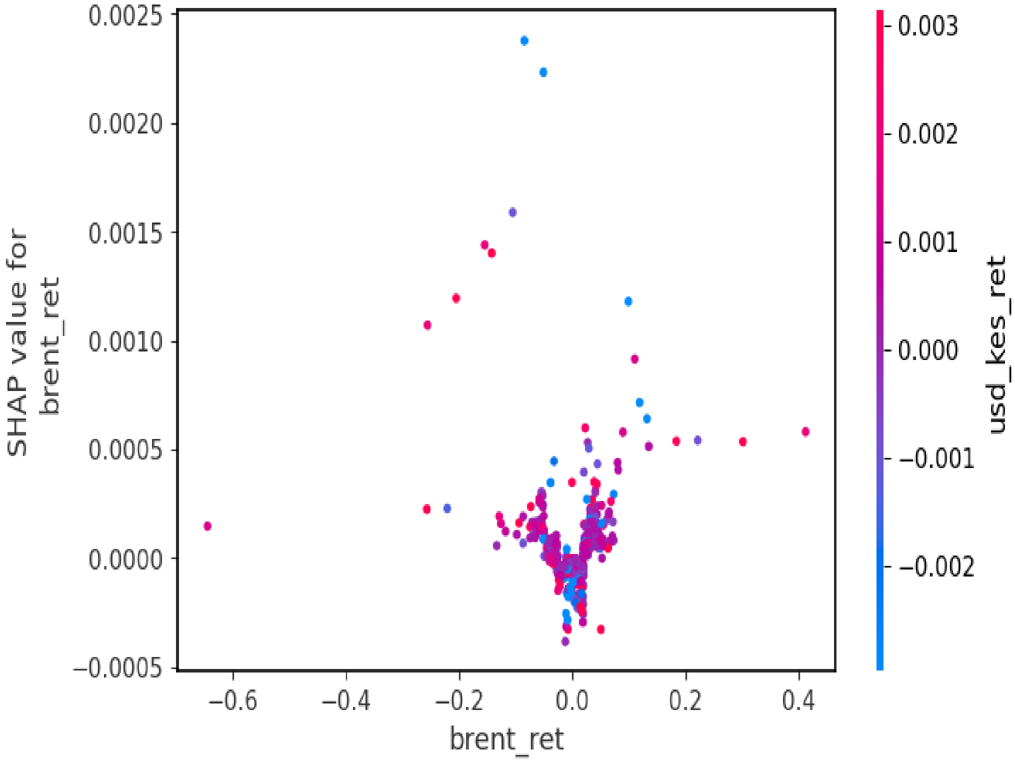

Figure 7. Transmissieon Map.

3.5. State Dependence and Stress Identification

The clustering in figure 8 highlights how the Kenyan equity market alternates between calm periods, moderate fluctuations, and episodes of extreme stress. The high-stress regime corresponds to crisis periods such as the 2008–2009 Global Financial Crisis and the 2020 COVID-19 shock, consistent with evidence that frontier markets experience abrupt regime shifts (Khalifa et al., 2014; Nomikos & Salvador, 2014).

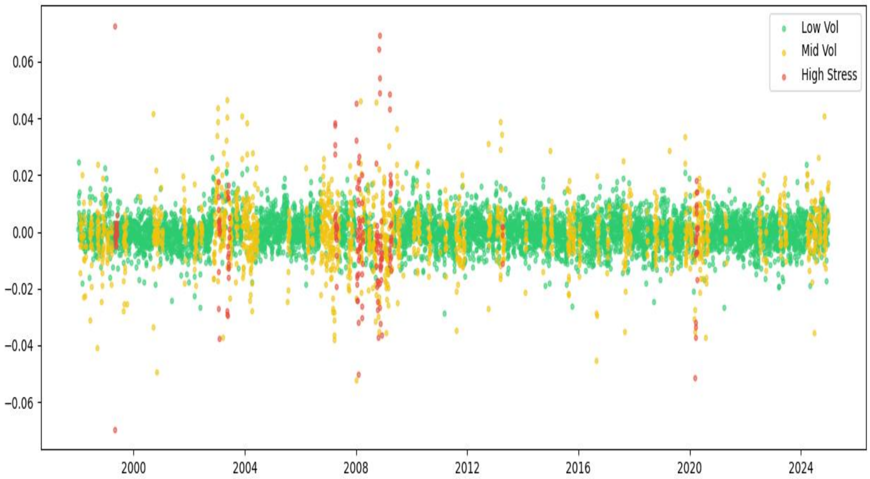

Figure 8. K-Means Clustering volatility regimes.

In figure 9 Stress probabilities peak during the 2008 Global Financial Crisis and 2020 COVID-19 shock consistent with external shocks coinciding with regime-dependent volatility and market contagion (Khalifa et al., 2014; Nomikos & Salvador, 2014).

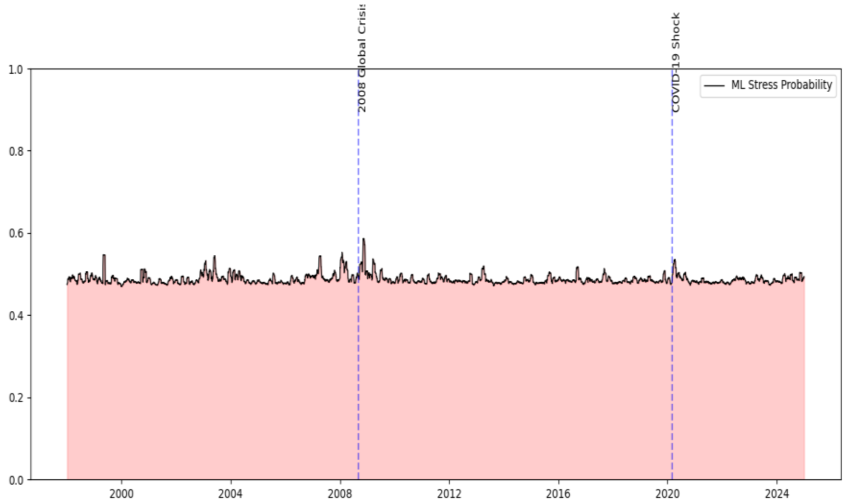

Figure 9. Stress Probabilities.

In figure 10 Stress probabilities are high during 2008 and 2020 crises, confirming that external shocks drive regime-dependent volatility and market contagion (Khalifa et al., 2014).

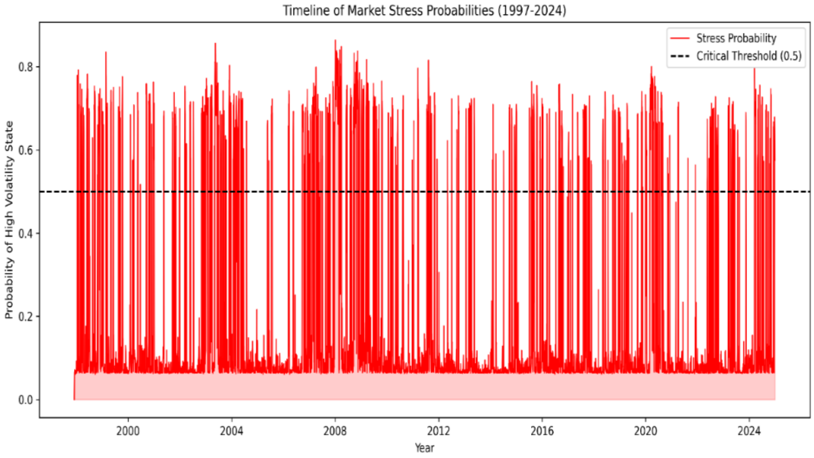

Figure 10. Timeline of market stress probabilities.

3.6. Evaluation

In table 3 the hybrid LSTM-FIGARCH model shows high predictive accuracy $(R^2 = 0.8244)$ with low error (RMSE: 0.00498), suggesting that integrating long-memory structures and deep learning improves forecasting relative to traditional GARCH models (Baillie et al., 1996; Alfeus & Nikitopoulos, 2022).

Table 3. Predictive Accuracy Metrics.

Metric	LSTM-FIGARCH Value	Threshold/Benchmark
RMSE	0.00498	< 0.05
MAE	0.00396	< 0.04

MAPE (%)	16.72%	< 15%
R-Squared	0.8244	> 0.70

In figure 11 LSTM-VaR and ES curves track extreme losses, with minimal violations adhering to Basel committee guidelines on back testing. This confirms the model's ability to manage nonlinear contagion in frontier markets (Acerbi & Tasche, 2002; Khalifa et al., 2014).

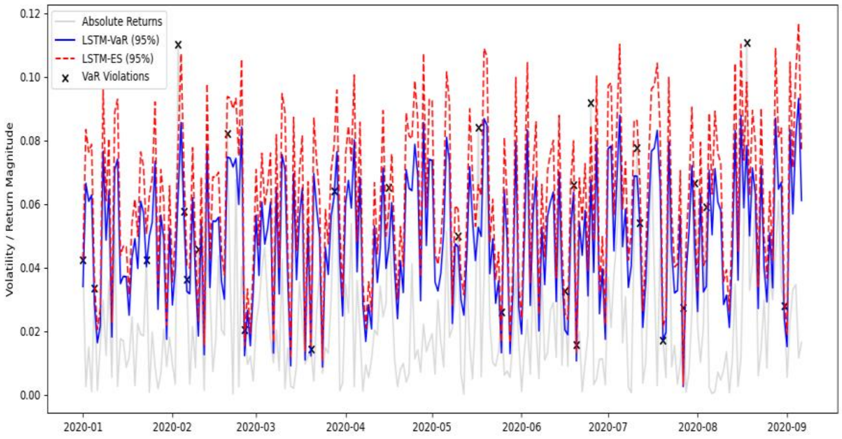

Figure 11. Tail Risk back test analysis.

In figure 12, volatility transmission from global energy markets to frontier equity markets is **non-**linear and state-dependent, consistent with evidence of asymmetric commodity–finance linkages (Nazlioglu et al., 2013), currency–oil interactions (Alqaralleh, 2020), and regime-dependent contagion (Khalifa et al., 2014; Nomikos & Salvador, 2014).

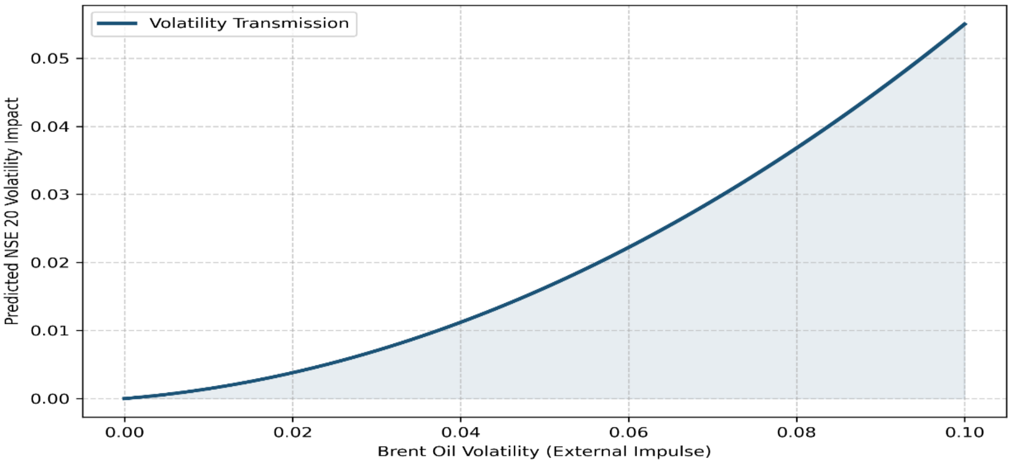

Figure 12. Volatility Response to Brent Oil Shocks.

4. Discussion

This study found that volatility spillovers from global commodity shocks into financial markets in Kenya is nonlinear, regime-dependent, and amplified during stress periods. This is consistent with Ben Flah et al.(2025), they explained that global shocks generate systemic spillovers into African equity and currency markets thereby eroding the benefits of diversification and increasing systemic risk. Structural break detection revealed that ignoring crisis-induced regime shifts inflates persistence estimates, consistent with Gyasi et al. (2025), they found volatility realignments in African frontier economies immediately after major global events. The long-memory dynamics in FIGARCH and the limited leverage effects in APARCH support Mupunga and Ngundu (2020), they explained that persistence dominates asymmetry in frontier markets.

Machine learning models are superior compared to traditional GARCH specifications in forecasting performance during stress regimes and tracking volatility. This is consistent with (Chung et al., 2025; Dudek et al., 2024) deep learning architectures outperform parametric models under conditions of high uncertainty. The dominance of lagged volatility in XGBoost feature importance and the asymmetric effects of shocks in crude oil prices and foreign exchange markets reinforce findings that commodity-currency-equity linkages in Africa are nonlinear and state-dependent (Alqaralleh, 2020; Nazlioglu et al., 2013).

Africa is vulnerable to overlapping global crises. Dependence on commodities, debt, and weak infrastructure increase instability, thereby exposing African economies to external shocks (United Nations Trade & Development (UNCTAD), 2025). Kenya' economy is highly vulnerable due to its reliance on oil imports, instability of its foreign exchange regime, and low-depth capital market. The finding that volatility transmission intensifies during stress regimes highlights the need for regime-sensitive monitoring frameworks in structurally evolving economies where financialization and global uncertainty have weakened diversification strategies (Ben Flah et al., 2025; Gyasi et al., 2025).

Future studies should extend this analysis by incorporating high-frequency data and cross-market contagion channels, as well as comparative studies across African frontier economies to test whether hybrid ML–econometric approaches can be generalised. Integrating global uncertainty indices and climate-related shocks may further enhance early-warning systems.

5. Conclusions

Volatility in financial markets in Kenya reflects both persistent internal dynamics and nonlinear external spillovers. Structural breaks distort estimates of persistence, and ignoring them weakens inference. Break-adjusted econometric models correct spurious persistence, while hybrid ML–econometric approaches improve forecasting accuracy during crisis regimes. The evidence shows that volatility spillovers from global commodity shocks are nonlinear, state-dependent, and amplified during stress periods, underscoring the need for regime-sensitive monitoring frameworks in frontier markets. Integrating FIGARCH and LSTM captures long-memory risk ($d=0.3858$) and demonstrates superior predictive accuracy ($R^2=0.8244$) over traditional linear models.

5.1. Policy Recommendations

The Central Bank of Kenya (CBK) and Capital Markets Authority (CMA) should integrate break-adjusted volatility models into systemic risk assessments to avoid persistence biases. LSTM-based Expected Shortfall measures can strengthen early-warning systems by capturing nonlinear contagion during crises regimes. Depreciation of the USD/KES amplifies commodity-driven volatility in the equity market. Policies that reduce exchange rate instability can mitigate spillovers from global energy shocks.

Firms in sectors exposed to shocks in the energy sectors should adopt hedging instruments against Brent oil volatility, because shocks coincide with stress in the equity market. Diversification into safe-haven assets can reduce exposure to nonlinear commodity spillovers. Regulators in Frontier markets should adopt hybrid ML–econometric forecasting tools for stress-testing, because hybrid models outperform traditional GARCH models during crisis regimes.

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Abbreviations

The following abbreviations are used in this manuscript:

APARCH	Asymmetric Power Autoregressive Conditional Heteroskedasticity
APT	Arbitrage Pricing Theory
ARCH	Autoregressive Conditional Heteroskedasticity
CAPM	Capital Asset Pricing Model
CBK	Central Bank of Kenya
CMA	Capital Markets Authority
CNN	Convolutional Neural Network
DOAJ	Directory of open access journals
EMH	Convolutional Neural Network
ES	Expected Shortfall
FIGARCH	Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity
FX	Foreign Exchange
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GJR-GARCH	Glosten–Jagannathan–Runkle GARCH
GRU	Gated Recurrent Unit
ICSS	Iterative Cumulative Sum of Squares
LD	Linear dichroism
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MDPI	Multidisciplinary Digital Publishing Institute
ML	Machine Learning
MPT	Modern Portfolio Theory
NSE	Nairobi Securities Exchange
RMSE	Root Mean Squared Error
RMSE	Root Mean Squared Error
TLA	Three letter acronym

USD/KES	United States Dollar / Kenyan Shilling exchange rate
VAR	Vector Autoregression
VaR	Value at Risk
XGBoost	XGBoost – Extreme Gradient Boosting

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