FABA
Finance, Accounting and Business Analysis
ISSN: 2603-5324

Finance, Accounting and Business Analysis
Volume 8 Issue 1, 2026
http://faba.bg/
ISSN 2603-5324
DOI: https://doi.org/10.37075/FABA.2026.1.07
Check for updates

Effects of Investor Sentiment and Geopolitical Risk on Stock Return Volatility in East African Frontier Markets: Evidence from a GARCH-X Framework

Arnold Gideon Irangi[1*] Paul-Francois Muzindutsi[2] Hilary Tinotenda Muguto[3] Malibongwe Cyprian Nyati[4]

School of Commerce, University of KwaZulu-Natal, Durban, South Africa[1]
School of Commerce, University of KwaZulu-Natal, Durban, South Africa[2]
School of Commerce, University of KwaZulu-Natal, Durban, South Africa[3]
Faculty of Economics and Finance Tshwane, University of Technology Pretoria, South Africa[4]
* Corresponding author

Info Articles

History Article:
Submitted 27 December 2025
Revised 16 February 2026
Accepted 19 April 2026

Keywords:
investor sentiment; Geopolitical risk; GARCH; modelling; East African markets

JEL: G1; G2; G4; G32.

Abstract

Purpose: In an environment of rising global uncertainty and increasing sensitivity to behavioural and geopolitical shocks, this study examines the effects of investor sentiment and geopolitical risk on stock return volatility in East African frontier markets.
Design/Methodology/Approach: Daily stock index returns data for Nairobi, Dar es Salaam, Uganda, and Rwanda from 2014 to 2025 are analysed using ARMA-GARCH and extended ARMA-GARCH-X models. Investor sentiment is constructed using principal component analysis (PCA) of market-based proxies of international indicators, and geopolitical risk is measured using the Caldara-Iacoviello index. Investor sentiment and geopolitical risk are incorporated into both the mean and variance equations within a GARCH-X framework to assess their effects on return dynamics and time-varying volatility.
Findings: Volatility exhibits strong persistence, clustering, and heavy tails across East African frontier markets. Investor sentiment exerts a consistent influence on volatility, while geopolitical risk plays a weaker and more episodic role. Asymmetric volatility responses are evident in most markets, and the limited predictability of returns in the mean equation remains broadly consistent with weak-form efficiency, although the overall results better support an adaptive market interpretation.
Practical implications: The sensitivity of volatility to sentiment and geopolitical risk highlights the importance of incorporating behavioural and external risk indicators into risk management and portfolio allocation decisions in frontier markets.
Originality/Value: This study contributes to the limited literature on East African frontier markets by providing direct evidence on the role of investor sentiment and geopolitical risk in explaining volatility, extending beyond traditional volatility modelling frameworks to offer novel perspectives.
Paper Type: Research Paper

* Address Correspondence:
Email address 223146781@stu.ukzn.ac.za[1]
MuzindutsiP@ukzn.ac.za[2]
mugutoh@ukzn.ac.za[3]
NyatiMC@tut.ac.za[4]

INTRODUCTION

Stock return volatility is a critical determinant of risk transmission capital allocation and market stability particularly in periods of heightened uncertainty (Kuttu 2018; Muguto and Muzindutsi 2022). Episodes of elevated volatility erode market liquidity accelerate price dislocations and trigger rapid shifts in investor behaviour as capital moves towards perceived safe assets often amplifying systemic fragility (Gkillas et al. 2018). In such conditions understanding the underlying drivers of volatility becomes not only analytically important but essential for effective risk management and policy intervention. Yet despite its importance empirical research remains disproportionately concentrated on developed and emerging markets where institutional depth and informational efficiency differ markedly from frontier markets. This leaves a critical gap in understanding volatility dynamics in frontier market environments characterised by structural constraints limited liquidity and pronounced informational frictions (Muguto 2022).

In this context the limitations of existing volatility research become pronounced in East African stock markets. While these markets play an important role in capital mobilisation and economic development they are constrained by low liquidity shallow market depth and institutional inefficiencies that intensify their sensitivity to shocks (Obalade and Muzindutsi 2020). Such conditions amplify the influence of non-fundamental factors allowing behavioural responses and external disturbances to exert a disproportionate effect on price dynamics. Despite these prior studies examining volatility in African markets remain narrow in scope frequently excluding smaller or less developed exchanges such as the Rwanda Stock Exchange and largely overlooking the combined roles of investor sentiment and geopolitical risk (Yunvirusaba et al. 2019; Kengere 2023). As a result, existing evidence offers only a partial and fragmented account of how volatility is formed and transmitted in these structurally constrained market environments.

Building on these limitations external forces such as investor sentiment - the collective mood and expectations of market participants - and geopolitical risk - the uncertainty arising from political instability conflict and policy tensions - become central to understanding volatility in these markets. At the international level these factors are increasingly recognised as key drivers of asset price dynamics particularly during volatile periods (Ferreira et al. 2023; Kunjal 2023; He 2023). By shaping risk perceptions and influencing capital flows they introduce additional volatility beyond what fundamentals alone can explain. However, the evidence is largely derived from developed markets and specific asset classes limiting its relevance to frontier markets where structural constraints amplify such shocks. Crucially to the author's knowledge no study jointly examines the effects of investor sentiment and geopolitical risk on stock return volatility in East African frontier markets leaving an unresolved gap in the literature.

Against this background this study investigates the effects of investor sentiment and geopolitical risk on stock return volatility in East African frontier markets explicitly addressing the tension between volatility as a reflection of underlying fundamentals and volatility driven by behavioural and geopolitical forces in structurally constrained environments. The analysis employs GARCH-type models (GARCH GJR-GARCH EGARCH) selected using the Akaike Information Criterion (AIC) to capture volatility persistence clustering and asymmetry while incorporating behavioural and geopolitical variables into both the mean and conditional variance frameworks (Akaike 1978; Burnham and Anderson, 2002; Brooks 2019; Enders 2012). This approach allows for a structured evaluation of whether observed volatility dynamics are consistent with standard market efficiency assumptions or reflect amplified responses to sentiment and external shocks in markets characterised by limited liquidity and institutional inefficiencies.

This study makes two interrelated contributions. First it provides evidence on the joint influence of investor sentiment and geopolitical risk on stock return volatility in under-researched East African frontier markets including previously overlooked exchanges demonstrating that observed volatility may not fully reflect underlying fundamentals but is instead shaped by behavioural and external shocks. This has direct implications for investors and fund managers who rely on volatility as a proxy for risk raising questions about the reliability of standard risk measures in these environments. Second the study extends conventional volatility modelling by incorporating behavioural and geopolitical variables into the mean and conditional variance framework offering a more appropriate representation of volatility dynamics in frontier markets and providing evidence that challenges the assumptions of the efficient market hypothesis while supporting the relevance of adaptive market behaviour in these contexts.

LITERATURE REVIEW

Theoretical and conceptual background

The Efficient Market Hypothesis (EMH) provides the benchmark framework for understanding stock price behaviour positing that asset prices fully reflect available information and that volatility arises from the rational assimilation of new information (Fama 1970; Statman 2024). Under this framework stock return volatility reflects fundamental risk with price movements driven by economic news rather than behavioural distortions or external shocks. However, this assumption is restrictive in frontier markets such as East Africa where thin trading limited information flows and institutional constraints weaken the efficiency of price adjustment. In such settings geopolitical risk introduces exogenous shocks that disrupt information processing while investor sentiment influences how these shocks are interpreted and incorporated into prices (Biau 2018; Kamazima and Omurwa 2018; Atenya 2019). Empirical evidence from African markets documents deviations from weak-form efficiency suggesting that volatility is not solely driven by fundamentals (Muguto et al. 2019; Musembi 2020; Njuguna et al. 2024). This creates a tension between the predictions of EMH and observed market behaviour.

Behavioural finance extends this framework by relaxing the assumption of fully rational investors and recognising that psychological biases influence decision-making under uncertainty (Kahneman and Tversky 2013; Statman 2024). In markets characterised by informational frictions investor sentiment can dominate price formation leading to overreaction underreaction and persistent volatility clustering. Geopolitical risk further amplifies these dynamics by increasing uncertainty and altering risk perceptions often triggering disproportionate market responses relative to fundamentals. Prospect theory explains this asymmetry as investors exhibit loss aversion and respond more strongly to negative shocks contributing to leverage effects in volatility dynamics (Kahneman and Tversky 2013). From this perspective stock return volatility reflects both the arrival of new information and its behavioural interpretation particularly during periods of elevated geopolitical uncertainty.

The Adaptive Market Hypothesis (AMH) integrates these perspectives by proposing that market efficiency evolves over time in response to changing market conditions participant behaviour and external shocks (Lo and Zhang 2024). Rather than assuming constant efficiency AMH implies that the influence of fundamentals investor sentiment and geopolitical risk on volatility is time-varying and context-dependent. This is particularly relevant in frontier markets where structural constraints and limited liquidity amplify the effects of external disturbances. Within this framework volatility persistence clustering and asymmetry can be interpreted as outcomes of adaptive behaviour in response to shifting economic and geopolitical conditions (Obalade and Muzindutsi 2019). This provides a unified theoretical basis for modelling volatility using GARCH-type approaches in which the conditional variance captures the dynamic interaction among information behavioural responses and external shocks. Accordingly, stock return volatility in East African markets reflects an evolving interplay between fundamentals sentiment and geopolitical risk rather than a single underlying mechanism.

Empirical review and hypothesis development

Empirical research on stock market volatility in East Africa has largely focused on market interdependencies and spillover effects with limited attention to the underlying drivers of volatility. Evidence documents both bidirectional and unidirectional volatility transmission across regional exchanges indicating the presence of cross-market linkages (Mensi et al. 2014; Muguto et al. 2019; Yunvirusaba et al. 2019; Marobhe and Pastory 2020). However, structural integration remains weak, suggesting that volatility is not fully explained by regional interactions and may instead reflect market-specific conditions (Rosengren 2019). These studies attribute volatility dynamics primarily to information transmission and market linkages without accounting for behavioural and geopolitical factors.

Empirical studies examining investor sentiment show that behavioural factors influence market outcomes particularly in environments characterised by informational frictions. For instance, early evidence demonstrates that sentiment-driven trading leads to mispricing and predictable return patterns (Brown and Cliff 2005; Baker and Wurgler 2006). More recent evidence from the Nairobi Securities Exchange confirms that sentiment significantly influences stock returns indicating that investor behaviour shapes price dynamics beyond fundamentals (Musembi et al. 2020). However, (Musembi et al. 2020) focuses on individual markets and does not account for the interaction between sentiment and broader sources of uncertainty particularly in frontier markets.

For instance, GPR has been identified as a key driver of financial market volatility. Foundational work shows that geopolitical risk affects asset prices and macro-financial conditions through uncertainty shocks (Caldara and Iacoviello 2022). Subsequent studies provide evidence that geopolitical risk influences volatility, capital flows, and risk premia, particularly in emerging and institutionally weak markets (Balcilar et al. 2016; Bouri et al. 2019). More recent evidence shows that global shocks can induce structural changes in market relationships and generate asymmetric volatility responses with realised events causing immediate spikes and anticipated risks sustaining prolonged uncertainty (Njuguna et al. 2024; Eissa and Al Refai 2024). Despite this the preceding studies are largely conducted outside the East African context and do not incorporate sentiment and GPR transmission channels. As a result, the interaction between GPR and investor sentiment on volatility in returns remains largely unexplored in frontier markets.

Although GARCH-type models are widely used to capture volatility persistence clustering and asymmetry their application in East African markets has primarily emphasised forecasting performance rather than the structural drivers of volatility (Enders 2012; Brooks 2019; Marobhe and Pastory 2020). These models are typically specified without incorporating behavioural or geopolitical variables treating market

interdependencies sentiment and external shocks as separate influences rather than interconnected mechanisms. This gap motivates a joint analysis of investor sentiment and geopolitical risk as drivers of stock return volatility. Accordingly, the study tests the following hypotheses:
H1: Investor sentiment has a significant effect on stock return volatility in East African frontier markets.
H2: Geopolitical risk has a significant effect on stock return volatility in East African frontier markets.
H3: The inclusion of investor sentiment and GPR improves the explanatory power of volatility models.

METHODS

Data and sampling

This study investigated stock return volatility across East African markets using daily closing index data from January 2014 to March 2025. Daily all-share index prices were obtained from Bloomberg and Trading Economics for the region's four exchanges: the Nairobi All-Share Index (NSEASI) Rwanda All-Share Index (ALSIRW) Uganda All-Share Index and the Dar es Salaam Stock Exchange Index (DSEI). Bloomberg's exclusion of non-trading days such as weekends and public holidays ensured that returns were calculated only for active trading sessions thereby improving consistency and comparability across markets. Daily log returns were computed to ensure continuous compounding and facilitate time-series analysis (Brooks 2019). Returns are defined as:

$$R_t = \ln\left(P_t/P_{t-1}\right) \tag{1}$$

To capture time-varying volatility dynamics a 200-day rolling window approach was employed consistent with (Zhang 2021; Muguto 2022). This approach allowed for the identification of structural shifts persistence and volatility clustering over time all necessary for accurately capturing volatility dynamics in structurally evolving markets. However, the structural characteristics of East African markets including thin trading and occasional extended market closures due to institutional or political factors may distort volatility estimates and yield biased or spurious volatility patterns from irregular price adjustments. To address this the analysis was restricted to synchronised trading periods across all four markets where observations were available concurrently and robustness checks were conducted to ensure that the results were not driven by data gaps.

GPR was proxied using the global Geopolitical Risk (GPR) index developed by Caldara and Iacoviello (2022) as consistent country-specific measures were not available for East African frontier markets. The global index has been widely applied in emerging market research to capture broad geopolitical uncertainty and cross-border spillover effects (Gkillas et al. 2018; He 2023). Given the objective of maintaining parsimony within a GARCH-X framework and considering the thin trading structures characteristic of frontier markets the aggregate GPR index was employed rather than decomposing it into realised "acts" and potential "threats." This avoids over-parameterisation while retaining the ability to capture time-varying geopolitical uncertainty relevant to volatility dynamics. Accordingly, the index is interpreted as a measure of overall geopolitical risk intensity.

Investor sentiment lacks a single definitive proxy particularly in frontier market contexts where survey-based measures are limited and subject to biases such as prestige bias (Baker and Wurgler 2007; Muguto et al. 2019). As a result, market-based proxies have been widely adopted as they provide more objective and high-frequency measures of investor behaviour (Baker and Stein 2004; Finter et al. 2012). These proxies - defined as observable market indicators that reflect investor attitudes expectations and risk perceptions - are individually noisy and may not fully capture sentiment. Consequently, they are often combined into composite indices through techniques such as principal component analysis to capture the multidimensional nature of sentiment and reduce idiosyncratic noise (Muguto et al. 2019). Therefore, the global investor sentiment was constructed using seven variables: the VIX MOVE index, gold prices, oil prices, the U.S. Dollar Index (DXY), Citi Economic Surprise Index (CESI), and the Global Financial Conditions Index (GFCI), all obtained from Bloomberg. These variables capture different dimensions of market sentiment including volatility expectations safe-haven demand macroeconomic uncertainty and financial conditions (Kilian and Park 2009; Baur and Lucey 2010; Brogaard and Detzel 2015; Smales 2017; Adrian et al. 2019; Anderson et al. 2020).To construct a composite sentiment measure and reduce dimensionality principal component analysis (PCA) was applied to the selected global financial proxies. The variables were first standardised to ensure comparability. PCA was then implemented using the covariance matrix and orthogonalization was achieved through the standard eigenvalue decomposition ensuring that the extracted components are uncorrelated. No rotation was applied as the objective was dimensionality reduction rather than factor interpretability. The Global Sentiment Index was constructed from the first principal component which captures the largest proportion of the data's total variance and serves as a summary measure of common sentiment dynamics.

$$Global\ Sent_t = W_1 VIX_{t-1} + W_2 MOVE_{t-1} + W_3 GOLD_{t-1} + W_4 OIL_{t-1} + W_5 DXY_{t-1} + + W_6 CESI_{t-1} + W_7 GFCI_{t-1} \quad (2)$$

Lagged values were used to account for delayed market responses (Rohilla et al. 2023). To capture region-specific sentiment dynamics a Local Sentiment Index was constructed using three proxies: (i) Total Revenue Index to Dividends (TRID) (ii) market volatility (Vol) and (iii) local currency exchange rates (UGX TZS KES RWF) against the U.S. dollar. These variables capture valuation sentiment market uncertainty and cross-border capital flows. High TRID values indicate optimism while increased volatility and currency depreciation reflect heightened uncertainty and risk (Campbell et al. 2001; Calvo and Reinhart 2002; Baker and Wurgler 2006; Coulibaly and Kempf 2010).

The Local Sentiment Index is defined as:

$$Sentiment\ index_t = W_1 TRID_{t-1} + W_2 Vol_{t-1} + W_3 Spot_{t-1} \quad (3)$$

Both indices were standardised to ensure comparability across variables and time.

Analysing the nature of stock market return volatility

The symmetric and asymmetric generalized autoregressive conditional heteroskedasticity (GARCH) models are employed to determine the nature of volatility amongst East African stock markets. These models have an advantage over Engle (1982) ARCH model which has limitations such as requiring numerous parameters and often violating non-negativity constraints only considers past squared residuals and overlooks past volatility. In contrast the GARCH models incorporate past squared residuals and past conditional variance providing a precise framework. Bollerslev (1986) demonstrated that a simple GARCH model with one lag is adequate making it the preferred choice for volatility modelling. The present analysis includes the estimation of three GARCH models namely: the standard symmetric GARCH (1,1) the asymmetric Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) and the exponential GARCH (EGARCH) following (Glosten et al.1993;Nelson 1991). These models effectively capture volatility persistence mean reversion and asymmetry (leverage effects). The mean equation for the models is determined as ARMA (p,q) to handle autocorrelation (Tsay 2005; Brooks 2019).

$$r_t = \mu + \sum_{i=1}^{p} \alpha_i r_{t-i} + \sum_{i=1}^{q} \nu_i \varepsilon_{t-q} + \varepsilon_t \quad (4)$$

Where r_t is the daily index returns from each of the bourses μ is the mean return/ intercept term ϕ_1 is the coefficient for the first lag of return r_{t-1} is the first lagged return and ε_t is the error term shock at time t. This framework captures key features of financial time series including volatility clustering persistence and mean reversion. In addition, extensions of the standard GARCH model enable the modelling of asymmetry in which negative and positive shocks have different impacts on volatility. The GARCH (1,1) specification is generally sufficient to capture volatility dynamics in financial data as higher-order models rarely provide significant additional explanatory power (Brooks 2019). Accordingly, the conditional variance equations are specified sequentially using the GARCH (1,1) GJR-GARCH (1,1) and EGARCH (1,1) models. These models progressively allow for symmetric threshold and exponential asymmetry respectively which are essential for capturing the asymmetric and nonlinear nature of volatility in financial markets. Their respective equations are presented below:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 o_{t-1}^2 \quad (5)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma . I_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (6)$$

$$\log(\sigma_t^2) = \omega + \beta . \log(\sigma_{t-1}^2) + \alpha . \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \gamma . \left[\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right] \quad (7)$$

Where σ_t^2 denotes the conditional variance $\alpha_1 \varepsilon_{t-1}^2$ captures the impact of past shocks and $\beta_1 \sigma_{t-1}^2$ reflects volatility persistence. Larger shocks lead to higher subsequent volatility, a phenomenon known as volatility clustering (Brooks 2019). The GARCH (1,1) model is widely regarded as sufficient to capture these dynamics in financial time series (Bollerslev et al. 1994) with model selection guided by the Akaike information criterion (AIC). However standard GARCH models do not capture leverage effects which are addressed by GJR-GARCH through the inclusion of an asymmetry term allowing negative shocks to have a greater impact on volatility (Tsay 2005; Muguto 2022). The EGARCH model further extends this by modelling the logarithm of variance capturing both the magnitude and direction of shocks without imposing non-negativity constraints (Brooks 2019). Accordingly, this study employs univariate GARCH-family models to analyse within-market volatility dynamics.

Analysing the influence of GPR and investor sentiment on volatility

Having established the baseline properties of volatility the next step extends the framework to examine whether volatility dynamics in East African frontier markets are driven purely by past information or are influenced by behavioural and geopolitical factors. This step directly addresses the central tension of the study namely whether observed volatility reflects fundamental information as implied by standard models or is shaped by investor sentiment and geopolitical risk. To this end investor sentiment and changes in geopolitical risk are incorporated into both the mean and variance equations within a GARCH-X framework. The mean and respective variance equations are specified as follows:

$$r_t = \mu + \alpha r_{t-1} + \nu\varepsilon_{t-1} + \varphi_1 Sentiment_t + \varphi_2 GPR_t + \varepsilon_t \quad (8)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 o_{t-1}^2 + \varphi_1 Sentiment_t + \varphi_2 GPR_t \quad (9)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \gamma . I_{t-1}\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \varphi_1 Sentiment_t + \varphi_2 GPR_t \quad (10)$$

$$\log(\sigma_t^2) = \omega + \beta.\log(\sigma_{t-1}^2) + \alpha.\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \gamma.\left[\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}}\right] + \varphi_1 Sentiment_t + \varphi_2 GPR_t \quad (11)$$

The operationalisation remains consistent: GARCH (1,1) captures volatility persistence while GJR-GARCH and EGARCH account for asymmetry and leverage effects with mean reversion assessed using the half-life measure. Differences in volatility behaviour following the inclusion of investor sentiment and geopolitical risk reflect the influence of non-fundamental factors. Although pairwise correlations between sentiment and GPR are low potential simultaneity cannot be ruled out (He 2023; Rohilla et al. 2023); accordingly, sentiment indices were constructed using orthogonalized principal components and lagged proxies. Given the reduced-form GARCH-X specification results are interpreted as conditional associations rather than causal effects (Enders 2012; Brooks 2019).

RESULTS AND DISCUSSIONS

This section presents the results of the symmetrical (GARCH 1,1) model and the asymmetrical GJR-GARCH and E-GARCH models of Bollerslev (1986), Glosten et al. (1993), and Nelson (1991), respectively. GARCH models effectively capture features of financial data such as leverage effects volatility clustering volatility persistence mean reversion and asymmetry (Brooks 2019).

Preliminary test results

Preliminary diagnostics confirm that East African stock returns satisfy the conditions for ARMA–GARCH modelling. Normality is rejected across all series as indicated by Shapiro–Wilk and Jarque–Bera statistics (Table 1), reflecting excess kurtosis and heavy tails, particularly in NSE and USE. This is consistent with frequent extreme price movements and standard financial return behaviour supporting the use of general conditional heteroskedastic models (Bollerslev 1986; Brooks 2019). ARCH-LM statistics are significant across all markets, confirming volatility clustering, while Ljung–Box statistics indicate serial dependence, especially in NSE and RSE, justifying the inclusion of ARMA terms in the mean equation (Tsay 2005; Brooks 2019).

Unit root tests reinforce this specification. ADF and Phillips–Perron statistics confirm that the return series are stationary at levels. In contrast both local and global sentiment indices are non-stationary in levels but become stationary after first differencing. The GPR index is stationary at levels. This integration structure supports modeling returns in levels while incorporating appropriately transformed exogenous variables to avoid spurious regression (Alabi et al.2020; Muguto and Muzindutsi 2022; Chowdhury 2023).

Table 1. Diagnostic tests

Variable	Returns RSE	NSE	DSE	USE	Ls-RSE	Ls-NSE	Ls-DSE	Ls-USE	GIS	GPR
Shapiro-Wilk (W)	0.1470***	0.0540***	0.2090***	0.0650***	0.9210***	0.9770***	0.9800***	0.8900***	0.9440***	0.8860***
Jarque-Bera (χ²)	262993.7640***	165002272.5620***	5588754.8640***	40140235.9350***	278.9746***	44.0835***	41.4567***	408.0702***	156.2090***	8796.6980***
ADF I(0)	-48.7510***	-60.0750***	-52.3350***	-60.6330***	-2.6340	-2.5590	-3.2448	-2.2842	-1.7970	-16.4940***
ADF I(1)	NA	NA	NA	NA	-52.2805***	-31.5598***	-43.6857***	-38.5660***	-63.1210***	NA
PP I(0)	NA	NA	NA	NA	-2.4304	-2.5284	-3.2867	-2.2935	NA	-182.8628***
PP I(1)	NA	NA	NA	NA	-93.1902***	-40.4570***	-68.0987***	-54.7100***	-173.8279***	NA
KPSS I(0)	0.0230	0.6360	0.5810	0.2560	3.8120	1.3780	0.5219	4.2950	NA	NA
KPSS I(1)	NA	NA	NA	NA	0.0773	0.0549	0.0796	0.0268	0.0024	NA
ARCH LM (χ²)	177.4800***	61.7050***	38.0840***	43.5800***	30844.5044***	30737.5071***	28613.7558***	30815.6754***	180.0713***	199.4443***
Ljung-Box (χ²)	108.9490***	63.0160***	10.5700	19.0750**	30909.3463***	30765.1743***	28648.4203***	30828.5210***	655.6622***	760.6222***
Integration	I(0)	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)

Source: Author's estimate (2026)
Notes: *** ** denote significance at 1% and 5% levels respectively. Returns are analysed in levels (standard for GARCH models). LS-local sentiment GIS-global sentiment and GPR-geopolitical risk

Model estimation results

To examine whether volatility in East African frontier markets is driven by fundamental dynamics or influenced by behavioural and geopolitical forces, it is first necessary to establish whether investor sentiment and geopolitical risk capture distinct sources of variation. Otherwise, any observed effects may reflect overlapping information, thereby obscuring their individual contributions to volatility dynamics. Table 2 presents the covariance and correlation structure between local investor sentiment global investor sentiment and GPR across markets. The results show consistently negligible correlations with coefficients close to zero and statistically insignificant (high p-values), indicating that these variables represent independent dimensions of market behaviour rather than overlapping signals. This finding is important for addressing the study's central objective. If investor sentiment and GPR were highly correlated their inclusion in the volatility framework would introduce multicollinearity obscuring their individual effects. Instead, their statistical independence supports their joint inclusion in the GARCH-X models allowing the analysis to disentangle the relative contribution of behavioural sentiment and exogenous geopolitical shocks to volatility dynamics. In this context investor sentiment captures endogenous behavioural responses while GPR reflects external uncertainty shocks enabling a clearer evaluation of whether volatility reflects underlying fundamentals or is shaped by non-fundamental influences.

These results are consistent with prior evidence that investor sentiment and geopolitical risk affect financial markets through distinct transmission channels, particularly in environments characterized by informational frictions and structural constraints (Smales 2017; Gkillas et al. 2018; He 2023). Evidence further highlights the importance of sentiment in explaining deviations from price-based fundamentals (Muguto and Muzindutsi 2022). Their independence therefore provides a robust empirical foundation for testing the study's hypotheses and directly examining the extent to which volatility in East African markets is driven by behavioural and geopolitical factors in line with the adaptive market perspective (Brooks 2019; Lo and Zhang 2024).

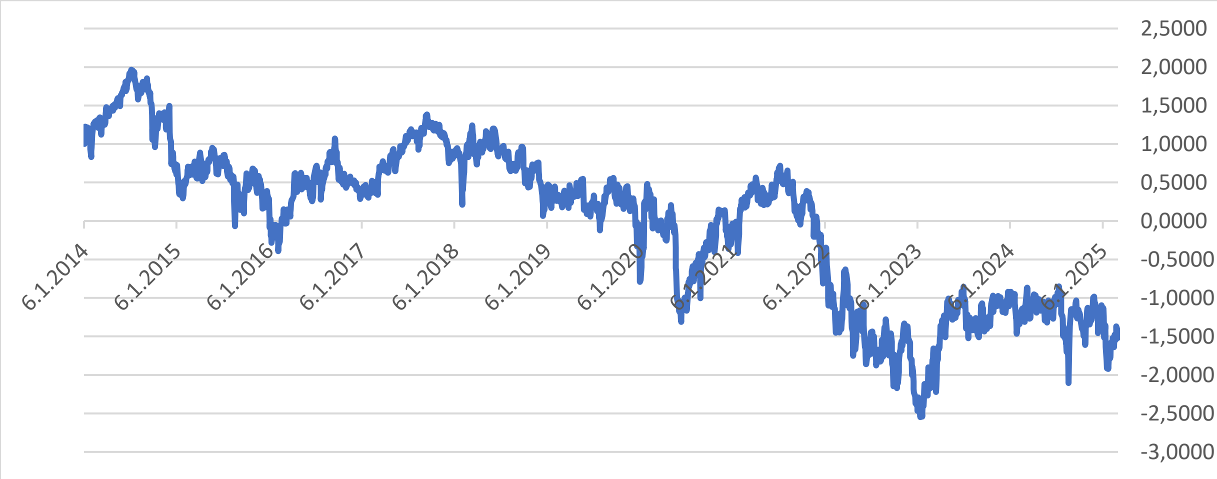
Table 2. Exogenous variables covariance output

Market	Pair	Covariance	Correlation	p-value
RSE	Ls–GIS	0.0788	0.0009	0.9634
	Ls–GPR	-0.0628	-0.0007	0.9713
	GIS–GPR	0.0068	0.0034	0.8633
NSE	Ls–GIS	0.0036	0.0002	0.9906
	Ls–GPR	0.0119	0.0008	0.9692
	GIS–GPR	0.0068	0.0034	0.8633
DSE	Ls–GIS	-0.1960	-0.0017	0.9321
	Ls–GPR	0.3762	0.0031	0.8720
	GIS–GPR	0.0068	0.0034	0.8633
USE	Ls–GIS	0.0652	0.0003	0.9876
	Ls–GPR	-0.0600	-0.0003	0.9887
	GIS–GPR	0.0068	0.0034	0.8633

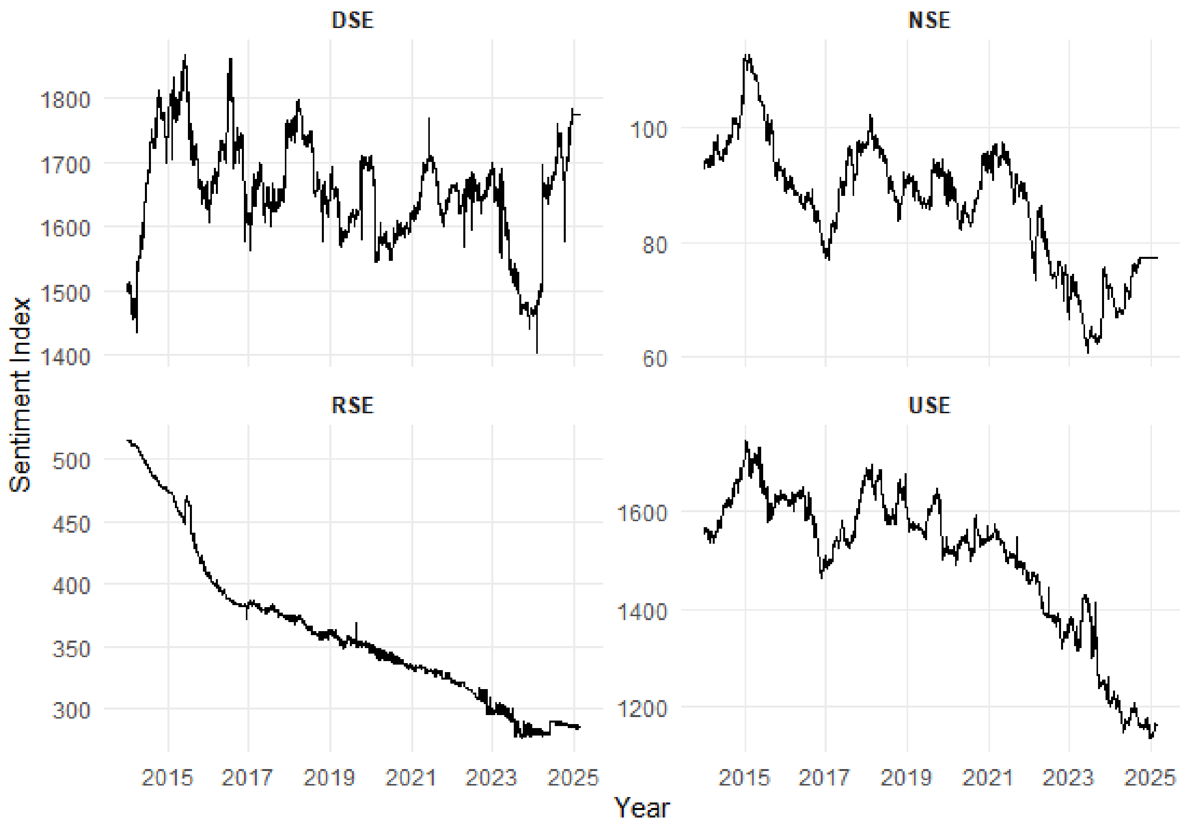
Source: author's estimate (2026), where Ls-local sentiment index GIS-global investor sentiment and GPR-geopolitical risk

PCA results reveal a dominant latent factor (PC1) that explains approximately 45–55% of the variance in local sentiment proxies suggesting shared behavioural dynamics across East African markets. In the NSE PC1 loads positively on TRID and exchange rate strength and negatively on volatility reflecting a "risk-on" sentiment regime characterised by optimism improving returns and lower uncertainty. Similar factor structures are observed in the DSE RSE and USE with only minor variations in volatility loadings suggesting a consistent behavioural pattern across markets. This reinforces the suitability of PCA in frontier market contexts where thin trading and market frictions may distort individual indicators (Campbell et al. 2001; Calvo and Reinhart 2002; De Bondt and Thaler 1985).

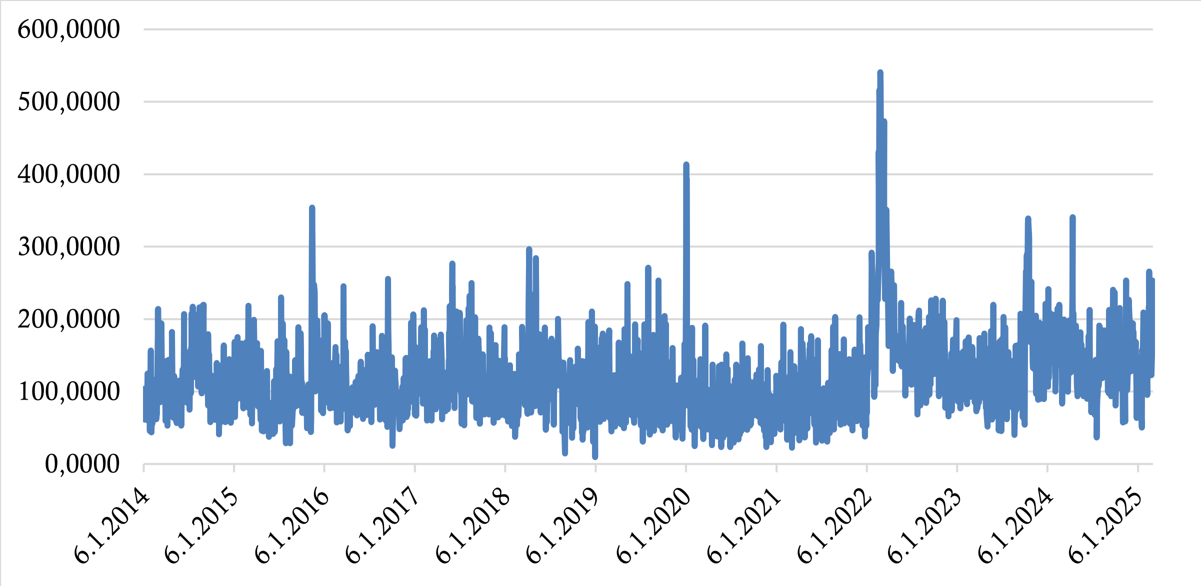
At the global level PCA identifies a dominant "risk-off" factor explaining 32.7% of the variance with positive loadings on MOVE gold USD and VIX and a negative loading on the Global Financial Conditions Index. This reflects defensive market positioning under heightened uncertainty (Rahman and Shamsuddin 2019; Smales 2021). The resulting Global Sentiment Index captures cross-asset responses to global risk providing a high-frequency proxy for external shocks. The use of orthogonalized components and lagged specifications further ensures that the index isolates behavioural responses rather than macroeconomic drift (Brogaard and Detzel 2015; Rohilla et al. 2023). Figures 1 and 2 illustrate the evolution of local and global sentiment dynamics and GPR over time.



Source: Author's estimate (2026)
Figure 1. Global investor sentiment index over-time.



Source: Author's estimate (2026)
Figure 2. Local sentiment index over-time.



Source: Author's estimate (2026)
Figure Грешка! В документа няма текст със зададения стил.**.** Daily change in GPR over time

Return series are filtered using ARMA (p,q) models selected by AIC which imposes a less restrictive penalty on model complexity and is better suited to noisy frontier-market data where BIC may induce underfitting (Enders 2012; Brooks 2019). Mean specifications vary across markets with most following MA-dominated processes ARMA (0,1) for the NSE DSE and USE and ARMA (13) for the RSE indicating that returns are driven more by short-term shock adjustments than persistent autoregressive effects consistent with thin trading and delayed price discovery. Baseline estimates (Table 3 panel A) show sGARCH (1,1) as the best fit with GJR-GARCH second suggesting volatility is largely symmetric and internally driven with limited evidence of asymmetry.

This pattern shifts once investor sentiment and GPR are introduced. Augmented results (Table 3 panel b) select EGARCH(1,1)-X across all markets revealing that volatility becomes asymmetric and nonlinear under behavioural and external shocks. Small AIC differences between competing models suggest sensitivity to distributional assumptions rather than structural form. The contrast between baseline and augmented models highlights that asymmetry is not inherent but emerges from the interaction of market structure, investor sentiment, and GPR. Financially, this implies that risk is conditional: adverse or uncertainty-driven shocks amplify volatility disproportionately compared to positive shocks.

Table 3. Model selection based on AIC

Panel A. Unaugmented specifications

Market	ARMA(p,q)	sGARCH	EGARCH	GJR-GARCH	Selected model	Second best
NSE	(0,1)	**–6.7608**	–6.7438	–6.7606	sGARCH	GJR-GARCH
DSE	(0,1)	**–6.7921**	–6.7869	–6.7914	sGARCH	GJR-GARCH
RSE	(1,3)	**–12.1091**	–10.3572	4.0081	sGARCH	EGARCH
USE	(0,1)	**–6.5970**	–6.5726	–6.5967	sGARCH	GJR-GARCH

Panel B. Augmented specifications

Market	Selected model	ARMA (p,q)	Distribution	AIC, best	Second best model	AIC, second best
RSE	EGARCH(1,1)-X	(0,1)	GED	**–15.70**	sGARCH(1,1)-X	–5.95
NSE	EGARCH(1,1)-X	(1,1)	GED	**–6.87**	sGARCH(1,1)-X	–6.83
DSE	EGARCH(1,1)-X	(0,1)	Student-t	**–6.70**	sGARCH(1,1)-X	–6.61
USE	EGARCH(1,1)-X	(0,1)	Student-t	**–6.70**	GJR-GARCH(1,1)-X	–6.65

Source: Author's estimates (2026)
Notes: Lower AIC values indicate better model fit. Bold values denote the selected model.

Results from Unaugmented GARCH models

Table 4 presents the baseline volatility estimates before investor sentiment and geopolitical risk are introduced. The purpose of this specification is to establish whether volatility in East African stock markets can be explained by past shocks and past volatility alone, thereby providing the benchmark against which Hypothesis 3 is later evaluated. The results show that volatility in all four markets is clustered, persistent, and heavy-tailed, consistent with the ARCH-GARCH framework of (Engle 1982; Bollerslev 1986). Significant ARCH effects indicate that current volatility reacts strongly to recent shocks, confirming time-varying conditional variance. This remains broadly compatible with weak-form efficiency, since return predictability is limited, although slow volatility adjustment weakens a strict semi-strong efficiency interpretation in frontier markets characterised by informational frictions and structural constraints (Fama 1970; Biau 2018).

Persistence differs markedly across markets. The DSE shows near-unit persistence and an exceptionally long half-life, implying very slow dissipation of shocks and prolonged uncertainty. This is more consistent with the Adaptive Market Hypothesis than with strong or semi-strong efficiency, since adjustment appears constrained by market depth, liquidity, and information-processing capacity (Lo 2004). By contrast, the NSE and USE display lower persistence and shorter half-lives, indicating faster volatility reversion and closer alignment with weak-form efficiency, though not with strong-form efficiency. The RSE occupies an intermediate position, with meaningful but less extreme persistence, consistent with partial adjustment under structural constraints (Calvo and Reinhart 2002; Marobhe and Pastory 2020).

The mean equations reinforce this interpretation. ARMA(0,1) is selected for the NSE, DSE, and USE, while the RSE follows ARMA(1,3), indicating that return dynamics are driven more by short-run shock adjustment than by sustained autoregressive dependence. This broadly supports weak-form efficiency, although the more complex RSE structure suggests delayed adjustment and market microstructure frictions rather than frictionless price discovery (Fama 1970). The shape parameters further confirm heavy-tailed innovations, validating the use of Student-t errors and indicating that extreme returns occur more frequently than under normality, as is common in frontier markets exposed to episodic shocks and abrupt repricing (Yunvirusaba et al. 2019; Kengere 2023).

Table 4. Unaugmented GARCH results

Parameter	NSE	DSE	RSE	USE
Selected Model	GARCH(1,1) with t-dist.	GARCH(1,1) with t-dist.	GARCH(1,1) with t-dist.	GARCH(1,1) with t-dist.
Mean Equation	ARMA(0,1)	ARMA(0,1)	ARMA(1,3)	ARMA(0,1)
		Conditional Mean Equation		
M	0.0002	0.0001	-0.0000	-0.0000
AR(1)	—	—	-0.4361***	—
MA(1)	0.2328***	-0.0289	—	0.0713***
MA(2)	—	—	0.4125***	—
MA(3)	—	—	0.0460***	—
		Conditional Variance Equation		
Ω	0.0000***	0.0001***	0.0000***	0.0001***
α_1 (ARCH)	0.5171***	0.9990***	0.6937***	0.6808***
β_1 (GARCH)	0.2909**	0.0000	0.0752	0.0000
δ (Leverage)	—	—	—	—
Shape (ν)	3.4186***	2.3218***	2.1076***	2.5702***
		Volatility Dynamics		
Persistence	0.8080	0.9990	0.7689	0.6808
Half-Life (days)	3.25	691.00	2.65	1.80

Source: Author's estimate (2026)
Notes: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$ Half-life (HL)=

Taken together, the baseline models show that past shocks and past variance explain an important share of volatility dynamics, but the strength and duration of these effects vary across markets. The DSE appears least efficient in adjustment terms, the NSE and USE adjust more quickly, and the RSE shows moderate persistence. These results establish that volatility dynamics are heterogeneous across East African markets and provide the benchmark for testing H3. However, because the unaugmented models capture only historical volatility dynamics and not behavioural or geopolitical influences, they cannot yet confirm whether model performance improves once investor sentiment and GPR are included. Hypothesis 3 is therefore assessed in the next section by comparing these baseline results with the augmented GARCH-X estimates.

Results of Augmented GARCH models

The augmented results show that investor sentiment and GPR affect East African markets primarily through the risk channel rather than through systematic return predictability. The inclusion of these variables in the mean equation is motivated by their potential to influence expected returns through behavioural demand liquidity shifts and capital flow dynamics as documented in behavioural and international finance literature (Baker and Wurgler 2006; Bouri et al. 2019). However, the limited and inconsistent significance of local and global sentiment and GPR in the mean equation indicates that expected returns remain largely unpredictable consistent with weak-form efficiency (Fama 1970). Where significance is observed, particularly for sentiment variables, the effects are small and short-lived, suggesting temporary deviations driven by trading pressure rather than persistent return predictability. In contrast their significance in the variance equation alters the volatility structure indicating that these factors influence how risk evolves rather than how returns are generated. This distinction is consistent with financial econometric theory which holds that volatility responds more strongly to uncertainty shocks than mean returns (Engle 1982; Bollerslev 1986; Caldara and Iacoviello 2022). Empirical evidence (Balcilar et al. 2016; Bouri et al. 2019 from emerging markets supports this mechanism showing that sentiment and GPR shape volatility dynamics and risk premia without generating systematic arbitrage opportunities. Economically, this implies that these variables operate as risk shifters affecting uncertainty and required returns rather than expected returns directly.

This pattern becomes clearer when examined across markets. In the NSE the significance of GIS in the mean equation indicates sensitivity to external risk conditions. This is consistent with relatively higher integration and exposure to foreign capital flows (Biau 2018) who notes that the NSE is more integrated with global markets than its counterparts. Whereas the weak negative role of local sentiment suggests a short-term correction following sentiment-driven mispricing. In the DSE, both local and global sentiment enter the mean equation significantly, indicating that returns are jointly influenced by domestic behavioural dynamics and external conditions, reflecting partial integration combined with local trading frictions. In the USE the significance of local sentiment alongside its negative sign indicates a reactive market where behavioural trading induces short-term reversals rather than persistent trends. In contrast, the RSE shows no statistically significant effects in the mean equation, indicating weak transmission of both behavioural and external signals into expected returns, consistent with limited liquidity and lower trading intensity (Kamuhanda 2020). Across all markets GPR does not exhibit consistent significance in the mean equation reinforcing the conclusion that it does not directly drive return predictability but operates indirectly through volatility and risk channels.

Building on this the dominance of asymmetric volatility dynamics indicates that risk responses are not neutral. Negative information increases volatility more than positive information reflecting loss aversion and asymmetric belief updating (Brown and Cliff 2005; Baker and Wurgler 2006; Kamuhanda and Tversky 2013). This pattern departs from a strict interpretation of the EMH which assumes symmetric and unbiased information processing. Subsequently aligning with evidence by (Bouri et al. 2019; Eissa and Al Refai 2024) from emerging and frontier markets showing that sentiment and informational frictions generate asymmetric volatility responses. However, this effect is not uniform across markets. While asymmetry is strong and statistically significant in the DSE NSE and USE it is not statistically significant in the RSE indicating that leverage effects are not a dominant driver of volatility in that market. This weakens a purely behavioural interpretation for the RSE and suggests that its volatility dynamics are more influenced by structural factors than by asymmetric responses to news. From a pricing perspective these results imply that downside risk is systematically higher than upside risk in most markets with implications for portfolio allocation and hedging though this asymmetry is market dependent.

These dynamics are further clarified through persistence and half-life measures which provide a direct inference of risk duration. Persistence captures how strongly volatility shocks propagate while half-life measures the time required for these shocks to dissipate. These metrics translate directly into risk horizons. Markets such as the NSE exhibit higher persistence and longer half-life indicating sustained exposure to risk and slower adjustment to shocks. In contrast the USE and DSE show shorter half-lives indicating rapid but transitory volatility responses which may reflect shallow trading and limited shock propagation rather than efficient price discovery (Mbanga et al. 2019; Rohilla et al. 2023). The RSE exhibits moderate persistence consistent with partial adjustment and structural constraints typical of smaller frontier markets (Biau 2018). Empirical evidence links these persistence patterns to liquidity conditions and information diffusion, in which financially constrained markets exhibit prolonged volatility due to slower shock absorption (Mensi et al. 2018; Marobhe and Pastory 2020). Consistent with (Calvo and Reinhart 2002) high persistence reflects structural inefficiencies rather than adaptive efficiency.

The cross-market heterogeneity observed in the results reflects underlying structural differences in liquidity market depth and information-processing capacity. The NSE with greater participation and liquidity exhibits more stable and internally driven volatility dynamics. The DSE and USE show stronger sensitivity to sentiment variables indicating that volatility is more responsive to behavioural and external shocks in thinner markets. The RSE, while less responsive in the mean equation and lacking significant asymmetry, still exhibits volatility persistence, suggesting that its dynamics are driven more by structural constraints than by behavioural amplification. This is consistent with empirical findings showing that liquidity conditions and institutional quality are key determinants of volatility behaviour in frontier markets (Marobhe and Pastory 2020; Kengere 2023). Volatility in this context is therefore not purely stochastic but conditioned by market structure.

The inclusion of exogenous variables clarifies the transmission mechanisms underlying these dynamics. Global sentiment captures shifts in international risk appetite and influences capital flows and trading intensity in emerging markets (Baker and Wurgler 2006; Bouri et al. 2019). GPR introduces external uncertainty that affects investment decisions and required returns (Caldara and Iacoviello 2022; Balcilar et al. 2016). Local sentiment reflects domestic behavioural responses that amplify or dampen volatility depending on market depth and investor composition. Evidence shows that these factors interact with geopolitical shocks often transmitted through behavioural channels leading to amplified volatility responses in frontier markets (He 2023; Eissa and Al Refai 2024). The empirical results support this interaction as sentiment variables exhibit stronger and more consistent effects than GPR indicating that behavioural transmission is the dominant channel.

Taken together these findings are not consistent with a purely EMH-based interpretation of volatility. Instead, they support a hybrid framework. The weak and inconsistent roles of sentiment and GPR in the mean equation align with the EMH's view of return unpredictability. However, their strong influence on volatility asymmetry and persistence supports behavioural finance and the AMH where efficiency evolves with market conditions institutional structures and investor behaviour (Lo and Zhang 2024). This aligns with evidence that volatility dynamics in emerging markets are state-dependent and shaped by both behavioural and structural factors (Balcilar et al. 2016; Bouri et al. 2019). The observed heterogeneity across markets reflects differences in adaptation rather than deviations from a single equilibrium.

Table 5. Augmented results

Variable	DSE (t-dist)	NSE (GED)	RSE (GED)	USE (t-dist)
Mean Equation				
μ	-0.0008***	0.0001***	0.0000	-0.0003
AR(1)	—	0.2713***	—	—
MA(1)	-0.1307***	-0.0195***	0.0001	0.0995***
GIS	-0.0002***	0.0004***	0.0000	0.0004***
GPR	0.0000***	0.0000	0.0000	0.0000
LS	0.0001***	-0.0001***	0.0000	-0.0002**
Variance Equation				
ω	-3.0288*	-1.9704***	-2.8524	-4.4418**
α_1	0.0852**	-0.0402	0.1404	-0.0735*
β_1	0.6474***	0.7998***	0.7060	0.5151**
γ_1 (Asymmetry)	0.5591***	0.4315***	0.2001	0.4207***
GIS (variance)	-0.0990	0.0275	0.0988	0.0477
GPR (variance)	-0.0008	0.0004	-0.0044	0.0002
LS (variance)	-0.0673*	0.0078	-0.3016	-0.0626*
Persistence (β_1)	0.6474	0.7998	0.7060	0.5151
Half-life (days)	1.5900	3.1000	1.9900	1.0400
Distribution	Student-t	GED	GED	Student-t
AIC	-6.6980	-6.8690	-15.6570	-6.6970
N	2267	2383	2415	2413

Source author’s estimate (2026)
Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

These empirical findings herein provide differentiated support for the study hypotheses by separating return dynamics from risk dynamics. H1 is only partially supported as investor sentiment does not generate consistent predictability in the mean equation, indicating that expected returns largely conform to weak-form efficiency (Fama 1970), although isolated significance in some markets reflects short-term behavioural effects rather than persistent pricing inefficiencies. H2 is also partially supported, as geopolitical risk does not exert a systematic influence on expected returns but does contribute to volatility, confirming that its primary role is shaping uncertainty rather than return formation. In contrast, H3 is strongly supported as the inclusion of local, global, and geopolitical sentiment in the variance equation materially alters volatility dynamics, improves model fit, and reveals asymmetric and persistent risk structures across markets. Taken together, the results show that these variables operate predominantly through the risk channel rather than the return channel. Thus, reinforcing the conclusion that volatility, rather than expected returns, is the primary mechanism through which behavioural and external factors affect East African financial markets.

CONCLUSIONS AND RECOMMENDATIONS

This study examined whether volatility in East African frontier stock markets is explained only by past shocks and past volatility or whether investor sentiment and geopolitical risk add explanatory power. The results show that volatility is clustered, persistent, and heavy-tailed across all markets, but the pattern is heterogeneous. The DSE exhibits the strongest persistence and slowest adjustment to shocks, the NSE and USE adjust more quickly, and the RSE shows moderate persistence consistent with a smaller and more constrained market. These differences indicate that volatility is shaped by market-specific conditions rather than a uniform regional process.

The augmented models show that investor sentiment and geopolitical risk matter mainly through the risk channel rather than through systematic return predictability. Their effects in the mean equation are limited and inconsistent, which remains broadly consistent with weak-form efficiency. In contrast, their inclusion in the variance equation changes the volatility structure, improves model fit, and supports the augmented EGARCH-X specification. This shows that historical price dynamics alone do not fully explain volatility in East African markets.

Investor sentiment is the more consistent driver of volatility, while geopolitical risk plays a weaker and more episodic role. Asymmetric volatility responses are evident in the DSE, NSE, and USE, where negative shocks increase volatility more than positive shocks of similar magnitude, but this pattern is not statistically strong in the RSE. Overall, the findings do not support a strict strong-form or semi-strong efficiency interpretation. Instead, they are more consistent with the Adaptive Market Hypothesis, under which market efficiency varies across markets and conditions.

The practical implication is that volatility forecasting and risk management in East African frontier markets should incorporate behavioural and external risk indicators, especially investor sentiment, rather than relying only on historical returns. For policymakers, the results highlight the importance of improving liquidity, transparency, and institutional quality to reduce volatility persistence and strengthen market resilience. The main limitations are the short sample and data constraints, especially for the RSE, and the reduced-form nature of the GARCH-X framework, which identifies conditional associations rather than causal effects. Future research can extend this analysis using longer samples, alternative sentiment and geopolitical proxies, and regime-dependent or structurally identified models.

Acknowledgments
Not applicable.
Funding
This research received no external funding.
Data Available Statement
The raw data supporting the conclusions of this article will be made available by the authors on request.
Conflict of interest
The authors declare no conflicts of interest.
AI Tools Statement
AI-based language editing tools were used to improve grammar and clarity. All intellectual content, interpretation, and conclusions are solely the responsibility of the authors.
Author contribution
• Conceptualization: Arnold Gideon Irangi, Paul-Francois Muzindutsi
• Methodology: Arnold Gideon Irangi, Paul-Francois Muzindutsi, Hilary Tinotenda Muguto, Malibongwe Cyprian Nyati
• Software: Arnold Gideon Irangi, Paul-Francois Muzindutsi, Hilary Tinotenda Muguto, Malibongwe Cyprian Nyati
• Validation: Paul-Francois Muzindutsi, Hilary Tinotenda Muguto, Malibongwe Cyprian Nyati
• Formal analysis: Arnold Gideon Irangi
• Investigation: Arnold Gideon Irangi
• Resources: Paul-Francois Muzindutsi, Hilary Tinotenda Muguto, Malibongwe Cyprian Nyati
• Data curation: Arnold Gideon Irangi
• Writing – original draft: Arnold Gideon Irangi
• Writing – review & editing: Paul-Francois Muzindutsi, Hilary Tinotenda Muguto, Malibongwe Cyprian

Nyati
• Visualization: Arnold Gideon Irangi, Paul-Francois Muzindutsi, Hilary Tinotenda Muguto, Malibongwe Cyprian Nyati
• Supervision: Paul-Francois Muzindutsi, Hilary Tinotenda Muguto, Malibongwe Cyprian Nyati
• Project administration: Arnold Gideon Irangi, Paul-Francois Muzindutsi, Hilary Tinotenda Muguto, Malibongwe Cyprian Nyati
• Funding acquisition: Paul-Francois Muzindutsi
All authors have read and agreed to the published version of the manuscript.

REFERENCES

Adrian, T., N. Boyarchenko, and D. Giannone. 2019. Vulnerable growth. *American Economic Review*, 109(4): 1263–1289. https://doi.org/10.1257/aer.20161923.

Akaike, H. 1978. A Bayesian analysis of the minimum AIC procedure. *Annals of the Institute of Statistical Mathematics*, 30(1): 9–14. https://doi.org/10.1007/BF02480194.

Alabi, O. O., K. Ayinde, O. E. Babalola, H. A. Bello, and E. C. Okon. 2020. Effects of multicollinearity on type I errors of heteroskedasticity tests. *Open Journal of Statistics*, 10(4): 664–677. https://doi.org/10.4236/ojs.2020.104041.

Anderson, H. M., F. Vahid, and K. Nam. 2020. Asymmetric nonlinear smooth transition GARCH models. *Journal of Financial Econometrics*, 18(1): 120–150. https://doi.org/10.1007/978-1-4615-5129-4_10.

Atenya, M. K. 2019. The status quo of East African stock markets: Integration and volatility. *African Journal of Business Management*, 13(5): 176–187. https://doi.org/10.5897/AJBM2019.8742.

Baker, M., and J. C. Stein. 2004. Market liquidity as a sentiment indicator. *Journal of Financial Markets*, 7(3): 271–299. https://doi.org/10.1016/j.finmar.2003.11.005.

Baker, M., and J. Wurgler. 2006. Investor sentiment and the cross-section of stock returns. *Journal of Finance*, 61(4): 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x.

Baker, M., and J. Wurgler. 2007. Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2): 129–152. https://doi.org/10.1257/jep.21.2.129.

Balcilar, M., R. Gupta, and C. Pierdzioch. 2016. Uncertainty and gold price: Evidence from a quantile-on-quantile regression. *Resources Policy*, 49: 74–80. https://doi.org/10.1016/j.resourpol.2016.04.004.

Baur, D. G., and B. M. Lucey. 2010. Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review*, 45(2): 217–229. https://doi.org/10.1111/j.1540-6288.2010.00244.x.

Biau, C. 2018. *Common Capital Market Infrastructure for East Africa: Options for the Way Forward*. Milken Institute. https://milkeninstitute.org/sites/default/files/reports-pdf/FINAL-Capital-Market-Infrastructure-in-East-Africa.pdf.

Bollerslev, T. 1986. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3): 307–327. https://doi.org/10.1016/0304-4076(86)90063-1.

Bollerslev, T., R. F. Engle, and D. B. Nelson. 1994. ARCH models. In R. F. Engle, and D. L. McFadden, eds. *Handbook of Econometrics*. Vol. 4. Amsterdam: Elsevier, 2959–3038. https://doi.org/10.1016/S1573-4412(05)80018-2.

Bouri, E., R. Demirer, R. Gupta, and H. Marfatia. 2019. Geopolitical risks and movements in Islamic bond and equity markets: A note. *Defence and Peace Economics*, 30(3): 367–379. https://doi.org/10.1080/10242694.2018.1424613.

Brogaard, J., and A. Detzel. 2015. The asset-pricing implications of government economic policy uncertainty. *Management Science*, 61(1): 3–18. https://doi.org/10.1287/mnsc.2014.2044.

Brooks, C. 2019. *Introductory Econometrics for Finance*. 4th ed. Cambridge: Cambridge University Press. https://doi.org/10.1017/9781108524872.

Brown, G. W., and M. T. Cliff. 2005. Investor sentiment and asset valuation. *Journal of Business*, 78(2): 405–440. https://doi.org/10.1086/427633.

Burnham, K. P., and D. R. Anderson. 2002. *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach*. 2nd ed. New York: Springer.

Caldara, D., and M. Iacoviello. 2022. Measuring geopolitical risk. *American Economic Review*, 112(4): 1194–1225. https://doi.org/10.1257/aer.20191823.

Calvo, G. A., and C. M. Reinhart. 2002. Fear of floating. *Quarterly Journal of Economics*, 117(2): 379–408. https://doi.org/10.1162/003355302753650274.

Campbell, J. Y., M. Lettau, B. G. Malkiel, and Y. Xu. 2001. Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *Journal of Finance*, 56(1): 1–43. https://doi.org/10.1111/0022-1082.00318.

Chowdhury, S. S. H. 2023. Spillover of sentiments between the GCC stock markets. *Global Business Review*, 24(6): 1434–1453. https://doi.org/10.1177/0972150920935595.

Coulibaly, D., and H. Kempf. 2010. Does inflation targeting decrease exchange rate pass-through in emerging countries? *Documents de Travail du Centre d'Economie de la Sorbonne*, No. 2010.49. Université Paris 1 Panthéon-Sorbonne. https://doi.org/10.2139/ssrn.1706025.

De Bondt, W. F. M., and R. Thaler. 1985. Does the stock market overreact? *Journal of Finance*, 40(3): 793–805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x.

Eissa, M. A., and H. Al Refai. 2024. Context-dependent responses to geopolitical risk in Middle Eastern and African stock markets: An asymmetric volatility spillover study. *International Review of Economics and Finance*, 94: 103402. https://doi.org/10.1016/j.iref.2024.103402.

Enders, W. 2012. *Applied Econometric Time Series*. 3rd ed. Hoboken, NJ: Wiley.

Engle, R. F. 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50(4): 987–1007. https://doi.org/10.2307/1912773.

Fama, E. F. 1970. Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, 25(2): 383–417. https://doi.org/10.2307/2325486.

Ferreira, J. J., S. Gomes, J. M. Lopes, and J. Z. Zhang. 2023. Ticking time bombs: The MENA and SSA regions' geopolitical risks. *Resources Policy*, 85: 103938. https://doi.org/10.1016/j.resourpol.2023.103938.

Finter, P., A. Niessen-Ruenzi, and S. Ruenzi. 2012. The impact of investor sentiment on the German stock market. *Zeitschrift für Betriebswirtschaft*, 82: 133–163. https://doi.org/10.1007/s11573-011-0536-x.

Gkillas, K., R. Gupta, and M. E. Wohar. 2018. Volatility jumps: The role of geopolitical risks. *Finance Research Letters*, 27: 247–258. https://doi.org/10.1016/j.frl.2018.03.014.

Glosten, L. R., R. Jagannathan, and D. E. Runkle. 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance*, 48(5): 1779–1801. https://doi.org/10.1111/j.1540-6261.1993.tb05128.x.

He, Z. 2023. Geopolitical risks and investor sentiment: Mechanistic insights from machine learning. *North American Journal of Economics and Finance*, 67: 101947. https://doi.org/10.1016/j.najef.2023.101947.

Kahneman, D., and A. Tversky. 1979. Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2): 263–291. https://doi.org/10.2307/1914185.

Kamuhanda, R. 2020. *Determinants of Capital Market Performance in Uganda: A Case Study of Uganda Securities Exchange*. Unpublished Master's Thesis, Makerere University. https://makir.mak.ac.ug/items/f106e482-07a6-4a40-b09a-14fad7eecf8e.

Kamazima, B. K., and J. K. Omurwa. 2018. The determinants of emerging financial markets development: A case study of the Dar es Salaam Stock Exchange, Tanzania. *European Journal of Business and Management*, 10(17): 92–108. https://doi.org/10.7176/EJBM/10-17-10.

Kengere, H. A. 2023. Volatility persistence in East African stock markets. *European Journal of Economic and Financial Research*, 7(1): 223–250. https://doi.org/10.46827/ejefr.v7i1.1454.

Kilian, L., and C. Park. 2009. The impact of oil price shocks on the U.S. stock market. *International Economic Review*, 50(4): 1267–1287. https://doi.org/10.1111/j.1468-2354.2009.00568.x.

Kunjal, D. 2023. Does geopolitical risk matter for ETF flows in emerging markets? *Finance, Accounting and Business Analysis*, 5(2): 102–112. https://faba.bg/index.php/faba/article/view/169.

Kuttu, S. 2018. Asymmetric mean reversion and volatility in African real exchange rates. *Journal of Economics and Finance*, 42(3): 575–590. https://doi.org/10.1007/s12197-017-9412-z.

Lo, A. W. 2004. The adaptive markets hypothesis. *Journal of Portfolio Management*, 30(5): 15–29. https://doi.org/10.3905/jpm.2004.442611.

Lo, A. W., and R. Zhang. 2024. *The Adaptive Markets Hypothesis: An Evolutionary Approach to Understanding Financial System Dynamics*. Oxford: Oxford University Press. https://doi.org/10.1093/oso/9780199681143.001.0001.

Marobhe, M., and D. Pastory. 2020. Modeling stock market volatility using GARCH models: Evidence from the Dar es Salaam Stock Exchange. *Review of Integrative Business and Economics Research*, 9(2): 138–150.

Mbanga, C., A. F. Darrat, and J. C. Park. 2019. Investor sentiment and aggregate stock returns: The role of investor attention. *Review of Quantitative Finance and Accounting*, 53(2): 397–428. https://doi.org/10.1007/s11156-018-0753-2.

Mensi, W., F. Z. Boubaker, K. H. Al-Yahyaee, and S. H. Kang. 2018. Dynamic volatility spillovers and connectedness between global, regional, and GIPSI stock markets. *Finance Research Letters*, 25: 230–238. https://doi.org/10.1016/j.frl.2017.10.032.

Muguto, L. 2022. *Analysis of Stock Return Volatility and Its Response to Investor Sentiment: An Examination of Emerging and Developed Markets*. Unpublished Doctoral Dissertation, University of KwaZulu-Natal. https://researchspace.ukzn.ac.za/.

Muguto, H. T., L. Rupande, and P.-F. Muzindutsi. 2019. Investor sentiment and foreign financial flows: Evidence from South Africa. *Zbornik Radova Ekonomski Fakultet u Rijeka*, 37(2): 473–498. https://doi.org/10.18045/zbefri.2019.2.473.

Muguto, L., and P.-F. Muzindutsi. 2022. A comparative analysis of the nature of stock return volatility in BRICS and G7 markets. *Journal of Risk and Financial Management*, 15(2): 85. https://doi.org/10.3390/jrfm15020085.

Musembi, M. M., R. Mugo, and D. Ochieng. 2020. Symmetric and asymmetric effects of investor sentiment on equity market performance in Kenya. *International Journal of Management and Commerce Innovations*, 8(1): 438–447. https://www.researchpublish.com/upload/book/paperpdf-1598703691.pdf.

Nelson, D. B. 1991. Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*, 59(2): 347–370. https://doi.org/10.2307/2938260.

Obalade, A. A., and P.-F. Muzindutsi. 2019. The adaptive market hypothesis and the day-of-the-week effect in African stock markets: The Markov switching model. *Comparative Economic Research: Central and Eastern Europe*, 22(3): 145–162. https://doi.org/10.2478/cer-2019-0028.

Rahman, M. L., and A. Shamsuddin. 2019. Investor sentiment and the price-earnings ratio in the G7 stock markets. *Pacific-Basin Finance Journal*, 55: 46–62. https://doi.org/10.1016/j.pacfin.2019.03.003.

Rohilla, A., A. K. Singh, N. Tripathi, and V. Bhandari. 2023. Does investor sentiment affect volatility in the Indian stock market: An ARDL approach. *International Journal of Banking Risk and Insurance*, 11(1): 12. https://doi.org/10.48001/jbmis.1101004.

Rosengren, E. S. 2019. Perspectives on the U.S. economic outlook. Speech, Federal Reserve Bank of Boston, 17 December. https://www.bostonfed.org/home/news-and-events/speeches/2019/perspectives-on-the-us-economic-outlook.aspx.

Salisu, A. A., A. E. Ogbonna, L. Lasisi, and A. Olaniran. 2022. Geopolitical risk and stock market volatility in emerging markets: A GARCH-MIDAS approach. *North American Journal of Economics and Finance*, 62: 101755. https://doi.org/10.1016/j.najef.2022.101755.

Smales, L. A. 2017. The importance of fear: Investor sentiment and stock market returns. *Applied Economics*, 49(34): 3395–3421. https://doi.org/10.1080/00036846.2016.1259752.

Smales, L. A. 2021. Geopolitical risk and volatility spillovers in oil and stock markets. *Quarterly Review of Economics and Finance*, 80: 358–366. https://doi.org/10.1016/j.qref.2021.03.008.

Statman, M. 2024. Harry Markowitz's two intellectual children: Mean-variance and behavioral portfolio theories. *Journal of Portfolio Management*, 50(8). https://doi.org/10.3905/jpm.2024.50.8.024.

Tsay, R. S. 2005. *Analysis of Financial Time Series*. 2nd ed. Hoboken, NJ: Wiley. https://doi.org/10.1002/0471746193.

Yunvirusaba, N., J. Aduda, and A. Kube. 2019. Volatility spillovers between East African stock markets. *International Journal of Economics and Finance*, 11(10): 32–41. https://doi.org/10.5539/ijef.v11n10p32.

Zhang, M. Z. 2021. *Stock Returns and Inflation Redux: An Explanation from Monetary Policy in Advanced and Emerging Markets*. International Monetary Fund. https://doi.org/10.5089/9781513586755.001.