

Investor Sentiment and Stock Market Volatility: Evidence from the West African Regional Stock Exchange

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Abstract

This study examines the relationship between investor sentiment and stock market volatility in the West African Economic and Monetary Union (WAEMU) using data from the West African Regional Stock Exchange (BRVM). Based on daily data spanning the period 2010–2022, five volatility models are estimated and compared: Generalized Autoregressive Conditional Heteroskedasticity [GARCH(1,1)], Exponential Generalized Autoregressive Conditional Heteroskedasticity [EGARCH(1,1)], Asymmetric Power ARCH [APARCH(1,1)], Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity [FIGARCH(1,d,1)] and the RiskMetrics model. The empirical results indicate a high degree of volatility persistence, pronounced asymmetric effects, and the presence of long-memory dynamics in BRVM stock returns. Among the competing specifications, the EGARCH model with an asymmetric Student's *t* distribution provides the best overall performance in terms of model fit and forecasting accuracy. Furthermore, the inclusion of an investor sentiment index leads to an improvement in volatility forecasts, highlighting the relevance of behavioral factors in explaining market risk dynamics. These findings suggest that investor sentiment plays an important role in volatility dynamics in emerging African stock markets, while also underscoring the need for caution in interpreting sentiment-based measures due to potential methodological limitations.

Keywords: Investor sentiment, Volatility modeling, GARCH Models, Behavioral finance, BRVM

1. Introduction

Financial markets play a central role in modern economies by channeling savings toward productive investment (Demirgüç-Kunt, 2006). Understanding their dynamics, particularly price volatility, therefore represents a major challenge for empirical research. According to Poon (2005), market volatility is a core element of economic and financial analysis, as it reflects uncertainty surrounding future returns and constitutes a key indicator of market risk for investors, regulators, and policymakers alike. While a substantial body of literature has focused on volatility modeling in developed financial markets, emerging and frontier markets remain relatively underexplored, particularly in Sub-Saharan Africa. In this context, the West African Regional Stock Exchange (BRVM), which brings together eight countries of the West African Economic and Monetary Union (WAEMU), provides a particularly relevant case study. As a unique regional stock market worldwide, the BRVM exhibits specific characteristics in terms of liquidity, market depth, information dissemination, and investor behavior. These features may affect volatility dynamics and justify the use of models capable of capturing both shock asymmetry and long-term persistence in financial time series. The financial literature on volatility highlights several well-documented stylized facts, including volatility persistence and the presence of asymmetric effects, whereby negative shocks exert a stronger impact than positive ones. It also documents the existence of long memory in certain return series. Models belonging to the ARCH and GARCH family, introduced respectively by Engle (1982) and Bollerslev (1986), have been widely employed to capture these phenomena. Extensions such as asymmetric GARCH models (Nelson, 1991; Glosten, Jagannathan, and Runkle, 1993) and fractionally integrated models (Baillie and al., 1996) have further improved the empirical representation of volatility. However, these traditional models rely exclusively on historical information, implicitly assuming that volatility depends solely on past shocks and persistence, thereby overlooking the psychological dimension of financial markets. In contrast, behavioral finance emphasizes the role of investor sentiment defined as optimism or pessimism not fully justified by economic fundamentals in influencing asset prices and volatility dynamics (Gebka, 2013; Lutz, 2015). Investor sentiment, often proxied by variables related to trading volume or market activity, is likely to affect asset price volatility, particularly in markets characterized by imperfect information and limited institutional participation. Recent studies

(Huang and Li, 2021; Zhang and al., 2021) show that incorporating sentiment measures can improve the predictive performance of volatility models, while simultaneously raising important methodological issues regarding their measurement and interpretation.

The main objective of this paper is to provide new empirical insights into the volatility dynamics of BRVM stock indices through a structured comparative approach based on different volatility models. More specifically, the study aims to: (i) compare the performance of standard GARCH-type models with that of models incorporating asymmetric effects; (ii) assess the relevance of long-memory models in capturing volatility persistence in the BRVM; and (iii) examine the relationship between investor sentiment and volatility. This analysis follows an exploratory and comparative perspective and does not claim to establish a strict causal relationship between investor sentiment and volatility. The contribution of this paper is threefold. First, it provides an original empirical contribution by analyzing a regional African stock market that has received limited attention in the literature, using advanced volatility modeling techniques. Second, it offers a rigorous and progressive methodological comparison of alternative volatility models, allowing an evaluation of their relative performance in terms of estimation and forecasting. Third, the paper contributes to the investor sentiment literature in the context of African financial markets, by highlighting the precautions required when incorporating sentiment measures into volatility models applied to emerging and frontier markets. To the best of our knowledge, this study is among the first to jointly examine asymmetric effects, long-memory dynamics, and the role of investor sentiment in volatility, while explicitly discussing the associated methodological limitations, in the context of a regional African stock market.

The remainder of the paper is organized as follows. Section 2 reviews the literature on financial volatility, asymmetric models, long memory, and investor sentiment. Section 3 describes the data and variables used in the analysis. Section 4 presents the econometric methodology and the models employed. Section 5 reports and discusses the empirical results. Section 6 provides an in-depth discussion of the economic implications and limitations of the study. Finally, Section 7 concludes and suggests avenues for future research.

2. Literature Review on Volatility and Investor Sentiment

Early studies on asymmetric volatility behavior primarily focused on calendar anomalies (French, 1980; Jaffe and Westerfield, 1985; Hsieh, 1989), without explicitly incorporating behavioral factors. Lamoureux and Lastrapes (1990) extended the GARCH framework by introducing trading volume as a proxy for market activity and investor behavior. Subsequent studies (Chen and al., 2001; Giot and Laurent, 2003) proposed non-Gaussian distributions, such as the Student's t and skewed Student's t distributions, to better capture the leptokurtic nature of financial returns. Asymmetric volatility models, including the EGARCH model developed by Nelson (1991) and the APARCH model proposed by Ding and al. (1993), allow for the modeling of leverage effects, whereby negative shocks increase volatility more strongly than positive shocks of the same magnitude. In parallel, Baillie et al. (1996) introduced the FIGARCH model, which incorporates fractional integration in the conditional variance in order to capture long-memory behavior in financial time series. These modeling approaches aim to explain time-varying volatility dynamics across different market contexts. However, several authors (Baker and Wurgler, 2007; Huang and al., 2014; Gouider and al., 2015) argue that incorporating psychologically driven variables can significantly improve the forecasting performance of volatility models. They emphasize the importance of investor sentiment in explaining volatility dynamics, particularly in markets characterized by informational frictions. Empirical studies [Zivot and Wang, (2003); Robinson and al, (2018)] also document the existence of long-memory properties in financial time series, characterized by a slow decay of the autocorrelation function while maintaining stationarity. This phenomenon has attracted growing attention in financial market analysis. According to de Melo Mendes and Kolev. (2008), the presence of long memory in conditional variance may obscure the true dependence structure of financial data. Building on the seminal work of Mandelbrot (1971), Greene and Fielitz (1977) suggest that perfect arbitrage is difficult to achieve when asset returns exhibit long-term dependence, whereas traditional models tend to focus primarily on short-term dynamics. To address this issue, Baillie and al. (1996) proposed the FIGARCH (Fractionally Integrated GARCH) model, which introduces a fractional differencing operator in the conditional variance to more accurately model long-memory behavior in financial volatility. In the context of emerging markets such as the BRVM, where informational efficiency may be limited, this combined framework integrating asymmetric volatility models, long-memory dynamics, and investor sentiment provides a relevant basis for empirically examining the persistence and asymmetry of volatility, while testing for the presence of long-memory effects without presuming a strict causal relationship.

3. Data Sources and Study Variables

This study uses daily data from the West African Regional Stock Exchange (BRVM) covering the period from January 4, 2010 to February 26, 2022, yielding a total of 2,791 observations. The data are obtained from Investing.com and the Official Quotation Bulletin (*Bulletin Officiel à la Cote*).

3.1 Overview of the Stock Market

The BRVM is a common stock exchange shared by the eight member countries of the West African Economic and Monetary Union (WAEMU) and currently lists 46 companies. The market is characterized by two main indices: the BRVM 10, which includes the ten most liquid firms, and the BRVM Composite, which tracks the performance of all listed companies. In addition to the main indices, this study also considers sectoral indices in order to examine potential differences in volatility dynamics across sectors. For operational and data availability reasons, the analysis focuses on the three sectoral indices with the largest number of listed firms: the financial sector (15 firms), the distribution sector (7 firms), and the industrial sector (7 firms).

3.2 Variables and Justification

This subsection first presents the variables used to construct the investor sentiment indicator, followed by a justification of their relevance based on the existing literature.

3.2.1 Variables

The selected variables include trading volume, the price-to-earnings ratio (P/E ratio), the inflation rate, the number of shares traded, the average market return, the market liquidity ratio, the market trend ratio, and the market satisfaction ratio. These variables are intended to capture different dimensions of market activity, valuation, liquidity, and investor behavior.

3.2.2 Justification of Variables

- **Trading volume:** According to Wen and al. (2015), trading volume reflects market flows resulting from supply and demand forces and thus serves as a relevant indicator of investor sentiment and market activity.
- **Price-to-earnings ratio (P/E ratio):** This ratio is widely used to assess stock valuation. Campbell and Shiller (2001) argue that the P/E ratio reliably anticipates stock price movements, as it captures deviations between market prices and fundamental values.
- **Inflation rate:** Numerous studies (Nelson, 1976; Fama and Schwert, 1977) document a negative relationship between stock returns and inflation.
- **Number of shares traded per day:** This variable reflects both market vitality and investor confidence (Baker and Wurgler, 2007).
- **Average market return:** This variable corresponds to the average return of dividend-paying listed stocks over the sample period.
- **Average market liquidity ratio:** Defined as the ratio of the daily value of transactions to total market capitalization (transaction value divided by market capitalization), this indicator captures the overall liquidity conditions of the market.
- **Average market trend ratio:** This ratio represents the average relationship between the volume of sell orders and buy orders, reflecting prevailing market pressure.
- **Average market satisfaction ratio:** Defined as the ratio of the number of shares traded to the volume of buy orders, this indicator aims to capture the degree to which market demand is effectively executed.

Macroeconomic variables such as inflation and the P/E ratio are available at lower frequencies. Following common practice in the literature, these variables are converted to daily frequency using a stepwise interpolation procedure where the latest available value is carried forward until the next observation.

4. Econometric Methodology

This section presents the econometric methodology adopted to analyze volatility dynamics in the BRVM. It is structured into three subsections. The first describes the construction of the investor sentiment index. The second introduces, in a progressive manner, the volatility models employed. The third presents the methods used to evaluate model performance in both estimation and forecasting.

4.1 Construction of the Investor Sentiment Index

The empirical literature proposes several approaches to measuring investor sentiment, including survey-based indicators, market-based proxies, and trading activity variables. In emerging and frontier markets, where survey data are often unavailable, market-based indicators are commonly used as indirect approximations of investor sentiment. According to Naik and Paddhi (2016), indirect market-related indicators offer the advantage of reflecting the general mood of the economy, while being readily available and easily generalizable. In this study, investor sentiment is proxied using trading volume, in line with previous contributions (Baker and Wurgler, 2007; Huang and al., 2014), which consider volume as a useful indicator of investor optimism or pessimism. The sentiment index is constructed from an auxiliary

regression in which trading volume is explained by a set of macro-financial control variables and the interest rate, in order to isolate its behavioral component. Formally, the relationship is specified as follows:

$$Volume_t = \alpha + \beta_1 X_t + \beta_2 Rate_t + \varepsilon_t \quad (1)$$

Where X_t , denotes the vector of explanatory variables described in the data section, and $Rate_t$ represents the average inflation rate in the WAEMU area. The estimated residual $\hat{\varepsilon}_t$, which captures the unexplained component of trading volume, is interpreted as a proxy for investor sentiment and is referred to as the Investor Sentiment Index (ISI). To further examine the relationship between investor sentiment, stock returns, and changes in market conditions, a dummy

variable V_t is constructed as follow:
$$V_t = \begin{cases} 1 & \text{if } ISI_t > \frac{1}{5} \sum_{i=1}^5 ISI_{t-i} \\ 0 & \text{Otherwise} \end{cases}$$

This indicator captures periods in which current sentiment exceeds its recent average, reflecting relative shifts in market sentiment.

4.2 Volatility Models

To model the volatility dynamics of stock returns on the BRVM, a progressive comparative approach is adopted, ranging from standard models to more advanced specifications incorporating asymmetry and long-memory effects.

4.2.1 Benchmark Model: GARCH(1,1)

The GARCH(1,1) model proposed by Bollerslev (1986) serves as the benchmark specification and captures volatility persistence commonly observed in financial time series. The conditional variance is specified as:

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

Where σ_t^2 denotes the conditional variance and ε_t the return innovation.

4.2.2 Asymmetric GARCH Models

Standard GARCH models do not allow for asymmetric responses to shocks. To account for the fact that negative shocks may exert a stronger impact on volatility than positive shocks, two asymmetric specifications are considered.

- **EGARCH**

The EGARCH model (Nelson, 1991) specifies the conditional variance in logarithmic form, ensuring positivity and allowing for a direct test of leverage effects in the BRVM.

- **APARCH**

The APARCH model generalizes previous specifications by jointly allowing for asymmetry and a flexible functional form of the conditional variance. Its specification is clearly distinguished from that of the FIGARCH model to avoid conceptual ambiguity.

4.2.3 Long-Memory Models

Volatility persistence may exceed what standard GARCH models can capture. To address this feature, fractionally integrated models are employed.

- **FIGARCH**

The FIGARCH model (Baillie and al., 1996) allows for a hyperbolic decay of past shocks, capturing long-memory behavior in volatility dynamics.

4.3 Incorporating Investor Sentiment into GARCH Specifications

To assess the influence of investor sentiment on volatility dynamics, the GARCH-type models are augmented with the investor sentiment index (ISI), which is introduced as an explanatory variable in both the mean and conditional variance equations. This extension aims to examine whether sentiment contributes to explaining volatility variations beyond purely autoregressive effects.

- GARCH (1.1) with ISI
- Mean

$$r_t = \mu_0 + \mu_1 ISI_t + \varepsilon_t, \quad (3)$$

where $\varepsilon_t = \sigma_t z_t$, and $z_t \sim iid(0,1)$

a) Variance

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma ISI_t \quad (4)$$

where $\omega > 0$ and $\alpha, \beta \geq 0$

where the parameter γ measures the sensitivity of conditional volatility to investor sentiment. A positive value would indicate that strengthening sentiment (extreme optimism or pessimism) increases stock market volatility. Analogous extensions are specified for the EGARCH, APARCH, and FIGARCH models, with parameters capturing asymmetric effects, nonlinear responses, and long-memory dynamics. Model estimation is conducted using the R software, following the methodological framework proposed by Tsay and Chen (2018).

4.4 Hurst Exponent Test

Depending on the persistence of shocks, a time series may exhibit short memory, long memory, or infinite memory. The Hurst exponent is estimated to test for the presence of long-term dependence. A value significantly greater than 0.5 indicates long-memory behavior, thereby justifying the use of FIGARCH models. The modified R/S test proposed by Lo (1991) is employed, which corrects for short-term autocorrelation using a HAC-type variance estimator. Rejection of the null hypothesis provides evidence in favor of long-memory dynamics.

4.5 Model Performance Evaluation

Model performance is assessed both in-sample and out-of-sample. In-sample fit is evaluated using the log-likelihood, the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and residual diagnostic tests. Out-of-sample forecasting performance is analyzed using several loss functions, with realized volatility serving as a proxy for unobserved volatility. This dual evaluation strategy allows for a robust comparison of the competing models.

5. Empirical Results and Discussion

This section presents the empirical results obtained from estimating various volatility models applied to BRVM stock indices. It is organized into three subsections. The first examines the statistical properties of the data. The second analyzes the estimation results of the volatility models. The third evaluates forecasting performance.

5.1 Statistical Properties of the Data

Table 1 reports the descriptive statistics of stock returns for $V=0$ and $V=1$ across the BRDI¹, BRFI², BRVM 10, and BRVM Composite indices. Standard deviations reflect substantial volatility, ranging from 0.321 for the BRVM Composite to 2.032 for the BRFI, while mean returns vary between -0.029 (BRDI) and 0.075 (BRFI).

5.1.1 Descriptive Statistics

The results in Table 1 indicate that return distributions are asymmetric, exhibiting either negative or positive skewness depending on the index considered.

Table 1. Descriptive statistics of the returns of the various indices.

Indices	V_t	mean	Max	Min	Stand dev	Skewness	Kurtosis	Jarque-Bera stat.
Brvm10	0	-0.017	21.909	-20.454	1.098	-0.043	89.547	48564.45*** (0,000)
	1	0.005	17.675	-18.567	0.333	-0.432	77.425	45765.53*** (0,000)
Brvm C	0	0.021	10.561	-9.654	0.321	0.248	33.564	35675.52*** (0,000)
	1	0.024	14.324	-7.880	1.675	0.256	30.564	37895.55*** (0,000)
BRDI	0	-0.029	13.342	-10.675	1.321	-0.769	45.342	47435.43*** (0,000)
	1	0.034	12.453	-12.651	1.324	-0.426	37.536	56786.65*** (0,000)
BRFI	0	-0.017	21.909	20.454	0.098	-0.346	32.320	45102.35*** (0,000)
	1	0.075	17.675	-18.567	2.032	-0.213	30.213	38128.21*** (0,000)

Notes: here (***) indicates significance at 1%, (**) indicates significance at 5%, (*) indicates significance at 10%.

Moreover, all return series display pronounced leptokurtosis, with kurtosis values far exceeding the Gaussian benchmark of 3, ranging from 30.56 for the BRVM Composite to 89.55 for the BRVM 10. The Jarque–Bera statistics strongly reject the null hypothesis of normality at the 1% level. Consistent with Alberg et al. (2008) and Huang et al. (2020), these distributional features suggest nonlinear dynamics and the potential presence of ARCH effects, which motivates formal testing.

¹BRDI, here represents the BRVM sector index which records companies in the distribution sector.

² BRFI here represents the BRVM sector index that records companies in the financial sector

5.1.2 ARCH Effects Tests

Table 2 presents the results of ARCH effect tests using the McLeod and Li (1983) Ljung–Box approach and Engle's (1982) ARCH–LM test. For all BRVM indices, both tests reject the null hypothesis of homoscedasticity at conventional significance levels..

Table 2. ARCH test according to Macleod and Lagrange multiplier test

ARCH effect test returns	Ljung-Box method according to McLeod and Li (1983)	Lagrange multiplier method according to Engle (1982)
BRVM 10	$Q^2(m)=244.63$; $m=1$ p-value= 2.2 e-16	F-stat =21.18; $m=1$ p-value= 2.2 e-16
BRVM Composite	$Q^2(m)= 212.77$; $m=5$ p-value = 2.2 e-16	F-stat = 15.75; $m=5$ P-value = 2.2 e-16
BRFI	$Q^2(m)=209.49$; $m=2$ p-value = 2.2 e-16	F-stat=18.34; $m=2$ p-value = 2.2 e-16
BRDI	$Q^2(m)=211.04$; $m=2$ p-value = 2.2 e-16	F-stat=12.24; $m=2$ p-value = 2.2 e-16

Note: null hypothesis H_0 : if $\alpha_1 = \alpha_2 = \dots = 0$, absence of heteroscedasticity. Here, (m) represents the optimal lag in terms of day of the week for both indices. F-stat is the associated Fisher statistic.

These findings confirm the existence of conditional heteroscedasticity and justify the use of GARCH-type models

5.1.3 Unit Root and Stationarity Tests

Prior to model estimation, several unit root tests were conducted to assess the stationarity of return series.

Table 3. Unit root or stationarity tests on BRVM data

	Stat.ERS	Stat.ADF	Stat.pp	Stat.KPSS
BRVM10	-22.616 **(-1.94)	-26.126**(2.56)	-28.108**(2.56)	0.063**(0.463)
BRVMC	-8.321**(-1.94)	-13.524**(2.56)	-27.134**(2.56)	0.137**(0.463)
BRFI	-24.478**(-1.94)	-28.342**(2.56)	-33.276**(2.56)	0.234**(0.463)
BRIN	-14.302**(-1.94)	-16.509**(2.56)	-19.475**(2.56)	0.034**(0.463)
BRDI	-17.905**(-1.94)	-19.321**(2.56)	-24.904**(2.56)	0.123**(0.463)

Notes: Stat. ADF is the augmented Dickey-Fuller statistic compared to the critical value of -2.56 at the 5% significance level. Asterisks indicate significant values. Stat. ERS is the Elliott-Rothenberg-Stock statistic compared to the critical value of -1.94 at the 5% significance level.

As reported in Table 3, the ADF, Phillips–Perron, ERS, and KPSS tests unanimously indicate that all return series are stationary in levels.

Combined with the evidence of conditional heteroscedasticity, these results validate the econometric framework adopted.

Returns are computed as logarithmic differences of index prices:

$$R_t = 100(\ln P_t - \ln P_{t-1}), \text{ with } P_t, \text{ the price at time } t \quad (13)$$

Figure 1. Daily changes in the main BRVM indices from 2010 to 2022

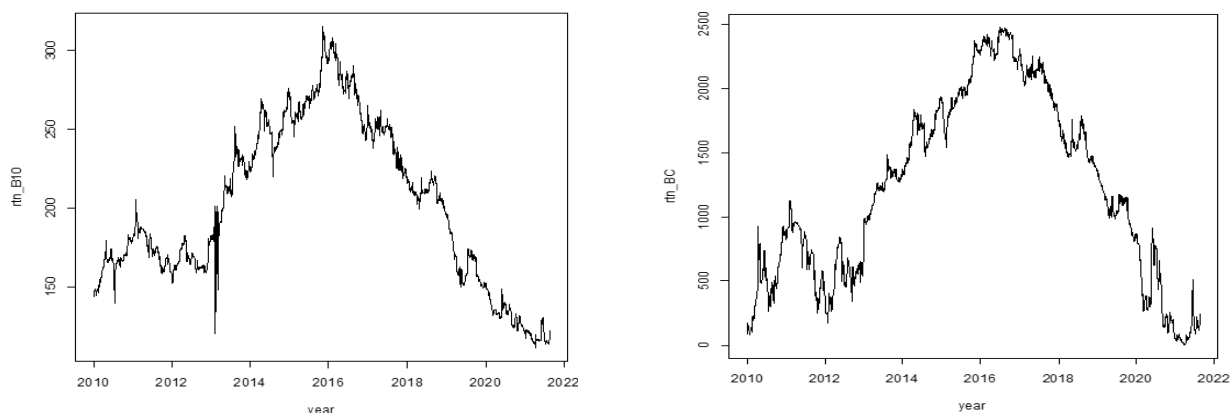
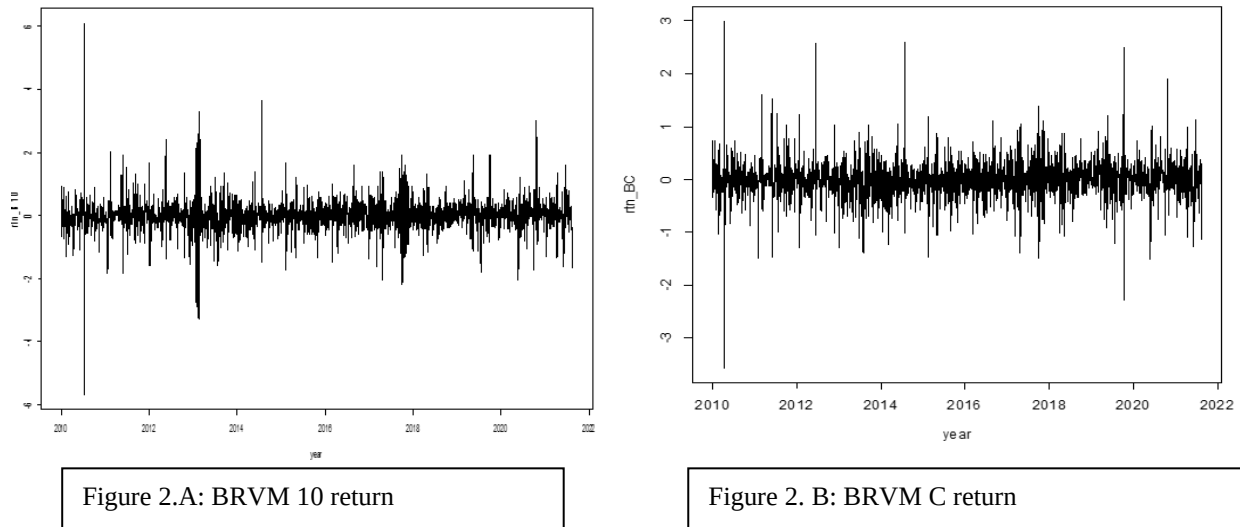


Figure 1.A: Evolution of the BRVM C Index

Figure 1 B: BRVM10 index performance

Figure 2. Daily changes in BRVM returns from January 2010 to February 2022



The sample consists of daily observations from 2010 to 2022, yielding 2,790 observations, of which 2,500 are used for estimation and 290 for out-of-sample forecasting. Graphical analysis (Figures 1–3), together with ARCH and Ljung–Box tests, reveals significant volatility clustering and serial dependence in squared returns, further supporting the GARCH modeling strategy.

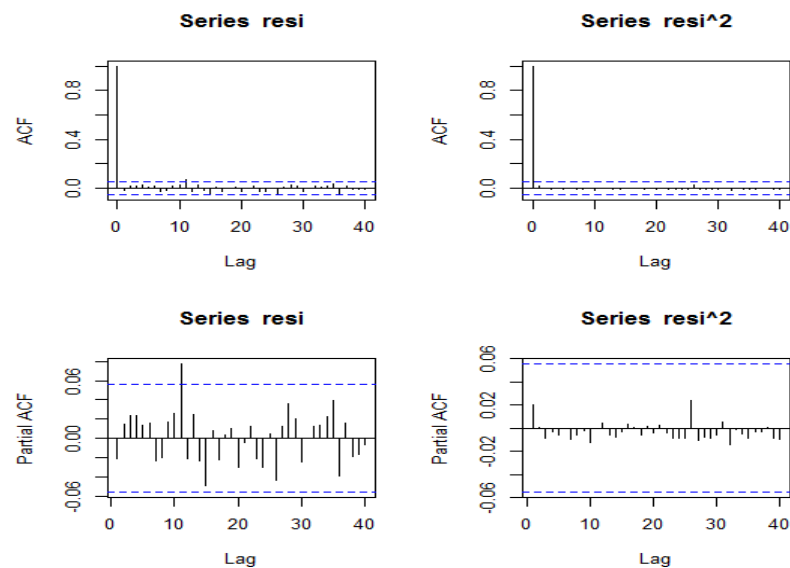


Figure 3. ACF and PACF of residuals from the BRVM yield series

Source: author based on daily BRVM index data via R software

5.2 Hurst Exponent Results

The Hurst exponent estimated using the R/S method over the 2010–2022 period yields $H=0.64$. The modified R/S statistic of 1.581 is significant at the 10% level based on Lo (1991) critical values. This result provides evidence of long-memory behavior in BRVM returns, thereby justifying the use of FIGARCH models.

5.3 Estimation and Forecasting Results without Investor Sentiment

Tables 4-7 report the estimation results of the GARCH, EGARCH, FIGARCH, APARCH, and Risk Metrics models under normal, Student's t , and skewed Student's t distributions. Diagnostic tests confirm the absence of residual autocorrelation and remaining ARCH effects, indicating well-specified models. Information criteria (AIC, BIC) and log-likelihood values show that EGARCH, FIGARCH, APARCH, and Risk Metrics outperform the standard GARCH model. Models estimated under Student and skewed Student distributions consistently provide a superior fit compared

to the Gaussian assumption. EGARCH and APARCH models, in particular, capture asymmetry and leverage effects effectively, reflecting high volatility persistence and nonlinear shock responses.

Table 4. Results of BRVM 10 index estimates without investor sentiment with different distribution functions

<i>DISTRIBUTIONS</i>												
BRVM10	Normal				t-Student				t-Student asym érique (Skewed t)			
	FIGARCH	EGARCH	RiskMetr	APARCH	FIGARCH	EGARCH	RiskMetr	APARCH	FIGARCH	EGARCH	RiskMetrics	APARCH
μ	0.046** (0.031)	0.030** (0.029)	0.022** (0.029)	0.099** (0.029)	0.022** (0.019)	0.014** (0.018)	0.013*** (0.001)	0.011** (0.018)	0.036** (0.024)	0.033** (0.025)	0.063** (0.027)	0.025** (0.025)
ω	0.008*** (0.000)	0.074** (0.029)	0.652* (0.094)	0.485* (0.090)	0.002*** (0.001)	0.089* (0.088)	0.478 (0.158)	0.388 (0.113)	0.423 (0.149)	-0.086* (0.087)	0.005*** (0.001)	0.381 (0.112)
α	0.000*** (0.000)	-0.135** (0.031)	0.44** (0.025)	0.109** (0.024)	0.000*** (0.001)	-0.071* (0.057)	0.295 (0.137)	0.423 (0.117)	0.175 (0.143)	-0.064* (0.057)	0.001*** (0.000)	0.410 (0.113)
β	0.999*** (0.000)	0.525* (0.085)	0.294* (0.087)	0.467* (0.089)	0.999*** (0.000)	0.684* (0.072)	0.403* (0.095)	0.478* (0.093)	0.445 (0.102)	0.687* (0.072)	0.999*** (0.000)	0.485* (0.094)
γ	-0.123** (0.023)	0.255** (0.046)	-0.200* (0.061)	1.000*** (0.000)	-0.234** (0.034)	0.542 (0.101)	0.457* (0.034)	0.235 (0.105)	-0.544*** (0.000)	0.536 (0.101)	-0.006*** (0.000)	0.225 (0.107)
d-fgarch	0.432*				0.321**				0.564*			
δ	-	-	-	1.126 (0.239)	-	-	-	1.302 (0.366)	-	-	-	1.288 (0.351)
$\mathcal{G}$	-	-	-	-	2.421 (0.152)	2.613 (0.235)	2.599 (0.235)	2.582 (0.228)	2.586 (0.231)	2.613 (0.233)	2.504 (0.118)	2.586 (0.226)
Log-Lik	-1882.8	-1792.78	-1797.4	-1791.10	-1567.52	-1531.06	-1533.2	-1532.06	-1535.85	-1530.58	-1563.39	-1531.2
AIC	3.053	2.906	2.909	2.919	2.545	2.487	2.490	2.490	2.494	2.488	2.541	2.491
BIC	3.069	2.929	2.066	2.904	2.565	2.512	2.515	2.519	2.418	2.517	2.570	2.524
Q (1)	10.84** (0.006)	1.760 (0.679)	1.612 (0.712)	1.876 (0.648)	20.7*** (0.000)	2.246* (0.056)	2.544 (0.496)	2.505 (0.504)	2.888 (0.523)	2.158 (0.581)	31.01*** (0.000)	2.444 (0.517)
Q ² (1)	233.6*** (0.000)	0.274 (0.999)	0.390 (0.999)	2.875 (0.782)	260.8*** (0.000)	0.478 (0.999)	0.386 (0.999)	0.409 (0.999)	0.304 (0.999)	0.477 (0.999)	164.1*** (0.000)	0.000 (0.999)

Note: The Q (1) and Q2 (1) which are the Box-Pierce statistics at lag 1 of the standardised and squared standardised residuals,

Table 5: Results of composite index estimates without investor sentiment using different distribution functions.

<i>DISTRIBUTION</i>												
BRVM C	Normal				t-Student				t-Student asym érique (Skewed t)			
	FIGARCH	EGARCH	RiskMetr	APARCH	RiskMetr	EGARCH	FIGARCH	APARC	RiskM	EGARCH	FIGARCH	APARCH
μ	0.036** (0.022)	0.049** (0.017)	0.039** (0.024)	0.039** (0.022)	0.029** (0.014)	0.026** (0.014)	0.026** (0.014)	0.026** (0.014)	0.044** (0.019)	0.039** (0.020)	0.038** (0.020)	0.038** (0.020)
ω	0.287** (0.041)	-0.129** (0.040)	0.280** (0.041)	0.188** (0.044)	0.018** (0.071)	-0.035** (0.078)	0.218** (0.085)	0.212** (0.077)	0.176 (0.069)	-0.039* (0.074)	0.207* (0.083)	0.205* (0.079)
α	0.171** (0.033)	0.012** (0.030)	0.187** (0.043)	0.109** (0.037)	0.415** (0.149)	-0.058** (0.054)	0.323 (0.132)	0.424 (0.141)	0.398 (0.143)	-0.048 (0.053)	0.319 (0.130)	0.416 (0.144)
β	0.432* (0.068)	0.542* (0.076)	0.444* (0.068)	0.412* (0.072)	0.583* (0.086)	0.740* (0.075)	0.538* (0.095)	0.550 (0.102)	0.599* (0.088)	0.750* (0.074)	0.553* (0.098)	0.567 (0.103)
γ	-0.234 (0.454)	0.370** (0.043)	-0.039** (0.052)	-0.073** (0.059)	-	0.598 (0.113)	-0.263 (0.093)	0.149* (0.092)	-	0.585 (0.109)	-0.229 (0.085)	0.137 (0.103)

d-Figarch	0.453*						0.324**				0.234**	
δ				3.500				1.847				1.029**
				(0.777)				(0.536)				(0.035)
ϑ					2.546	2.560	2.537	2.554	2.549	2.571	2.543	2.542
					(0.217)	(0.218)	(0.217)	(0.212)	(0.215)	(0.218)	(0.216)	(0.215)
Log-Lik	-1491.47	-1493.608	-1490.98	-1485.56	-1238.99	-1234.72	-1237.58	-1237.55	-1238.5	-1234.177	-1237.241	-1237.19
AIC	2.419	2.424	2.423	2.413	2.012	2.007	2.012	2.013	2.013	2.004	2.013	2.014
BIC	2.436	2.445	2.452	2.438	2.033	2.032	2.037	2.042	2.038	2.034	2.042	2.048
Q (5)	3.000	3.447	2.582	2.449	2.869	3.492	3.177	3.258	2.888	3.435	3.146	3.243
	(0.407)	(0.331)	(0.733)	(0.516)	(0.431)	(0.324)	(0.375)	(0.361)	(0.427)	(0.333)	(0.381)	(0.364)
Q ² (5)	1.300	1.024	0.945	0.602	0.709	0.885	0.921	0.965	0.731	0.863	0.923	0.978
	(0.970)	(0.985)	(0.871)	(0.997)	(0.995)	(0.999)	(0.989)	(0.987)	(0.994)	(0.999)	(0.989)	(0.987)

Note: The Q (1) and Q2 (1) which are the Box-Pierce statistics at lag 1 of the standardised and squared standardised residuals,

Out-of-sample forecasting results confirm that EGARCH, FIGARCH, and Risk Metrics models deliver superior predictive accuracy, whereas APARCH exhibits relatively weaker performance. The significant parameters (ω , γ , δ , ϕ , β) indicate high volatility persistence and asymmetry of shocks. The asymmetry coefficient γ , which is often negative, reveals a leverage effect, i.e., an inverse relationship between returns and volatility. This persistence may reflect a climate of uncertainty or repeated mispricing by investors.

Table 6. Main BRVM10 forecast results using the four GARCH models

BRVM10	FIGARCH		EGARCH		RiskMetrics		APARCH	
	Dist-std	Dist-sstd	Dist-std	Dist-sstd	Dist-std	Dist-sstd	Dist-std	Dist-sstd
MSE	0.657	0.588	0.3045		0.909		0.487	0.4034
MAE	0.455	0.364	0.345		0.878		0.466	0.274
MedSE	0.304	0.252	0.245		0.955		0.354	0.300
AMAPE	0.984	0.983	0.568		0.974		0.906	0.349

Note: Dist-std is the Student's distribution and Dist-sstd is the asymmetric Student's distribution.

Table 7. Main BRVM C forecast results using the four GARCH models

BRVMC	FIGARCH-std	EGARCH-std	RiskMetrics-std	APARCH-std
MSE	0.116	0.116	0.104	0.400
MAE	0.495	0.502	0.423	0.704
MedSE	0.116	0.100	0.194	0.156
AMAPE	0.349	0.321	0.306	0.679

Note: Dist-std is the Student distribution and Dist-sstd is the asymmetric Student distribution.

Unlike the APARCH model, whose predictive performance remains limited, the Risk Metrics, EGARCH, and FIGARCH models offer high-quality forecasts. The loss functions, considered to be the main decision criteria, have similar values and are minimised by these three models. Finally, Student's and asymmetric Student's distributions prove to be the most effective for forecasting the conditional variance of BRVM indices. Hence, our results are consistent with the main conclusions of financial theory, which generally reject the normal distribution hypothesis in the analysis of financial series.

5.4 Estimation and Forecasting Results with Investor Sentiment

Incorporating the investor sentiment index significantly improves model performance. As shown in Table 8, sentiment-related coefficients are positive and statistically significant at the 5% level across most specifications, suggesting that investor sentiment contributes additional explanatory power to both the mean and conditional variance of BRVM returns.

Table 8. Main results of index estimation using GARCH models with investor sentiment

DISTRIBUTIONS												
	Normale				t-Student			t-Student asym érique (Skewed t)				
	GARCH	EGARCH	FIGARCH	APARCH	FIGARCH	EGARCH	RiskMetrics	APARCH	FIGARCH	EGARCH	RiskMetrics	APARCH
BRVM C												
Cst (M)	-0.023** (0.019)	-0.011** (0.000)	-0.013** (0.000)	-0.021** (0.005)	-0.029** (0.014)	-0.026** (0.014)	-0.026** (0.014)	-0.016** (0.014)	-0.124** (0.019)	-0.035** (0.020)	-0.038*** (0.000)	-0.038** (0.020)
V(M)	0.018** (0.031)	0.028** (0.000)	0.212** (0.021)	0.018** (0.144)	0.018** (0.071)	-0.035** (0.078)	0.118** (0.001)	0.432** (0.057)	0.166 (0.069)	-0.029* (0.074)	0.207*** (0.001)	0.205* (0.079)
Cst (V)	-0.002** (0.009)	-0.027** (0.016)	-0.243** (0.032)	-0.209** (0.007)	-0.115** (0.049)	-0.058** (0.054)		-0.224 (0.141)	-0.298 (0.443)	-0.048** (0.033)		-0.416*** (0.001)
V(V)	0.523* (0.029)	0.783* (0.006)	0.213* (0.000)	0.462* (0.002)	0.483* (0.056)	0.140* (0.005)	0.128* (0.065)	0.450 (0.102)	0.569* (0.088)	0.350* (0.064)	0.553*** (0.000)	0.127 (0.103)
γ		-0.923** (0.000)	-0.016** (0.033)	-0.073** (0.059)	-	-0.138** (0.013)	-0.263* (0.093)	-0.149* (0.062)		-0.095*** (0.009)	-0.229*** (0.000)	-0.137*** (0.000)
d-FIGARCH			0.213**		0.119**				0.222***			
δ	-	-	-	2.111 (0.054)	-	-	-	2.147 (0.036)	-	-	-	1.029** (0.005)
θ	-	-	-	-	2.546 (0.217)	2.560 (0.018)	2.537 (0.017)	2.554 (0.012)	2.549 (0.115)	2.571 (0.018)	2.513 (0.016)	2.142 (0.015)
Log-Lik	-1071.08	-1098.58	-1024.12	-1035.64	-1022.99	-1034.71	-1037.59	-1037.58	-1020.34	-1030.17	-1037.21	-1037.19
AIC	1.199	1.112	1.143	1.146	1.012	1.001	1.012	1.013	1.013	1.008	1.000	1.014
BIC	1.261	1.127	2.321	2.238	1.033	1.012	1.037	1.042	1.038	1.004	1.001	1.048
Q (5)	2.872 (0.041)	2.345 (0.013)	2.532 (0.033)	2.558 (0.022)	2.769 (0.031)	3.492 (0.024)	3.177 (0.075)	2.158 (0.061)	2.888 (0.027)	2.435 (0.003)	2.146 (0.081)	2.243 (0.064)
Q ² (5)	1.060 (0.170)	1.002 (0.220)	0.782 (0.174)	0.670 (0.777)	0.709 (0.195)	0.885 (0.999)	0.921 (0.989)	0.965 (0.987)	0.731 (0.994)	0.863 (0.999)	0.923 (0.989)	0.978 (0.987)
Q (10)	2.100 (0.021)	3.043 (0.013)	2.198 (0.032)	1.098 (0.031)	2.343 (0.071)	3.947 (0.065)	2.743 (0.043)	3.748 (0.091)	1.215 (0.043)	3.543 (0.080)	4.210 (0.012)	2.309 (0.032)

Note: Models augmented with sentiment display lower AIC and BIC values and higher log-likelihoods than their traditional counterparts. Moreover, Student and skewed Student distributions clearly outperform the normal distribution, reinforcing the relevance of heavy-tailed and asymmetric innovations in modeling BRVM volatility.

5.5 Individual Model Performance

Across all specifications, EGARCH models exhibit robust parameter significance with or without sentiment effects. FIGARCH estimates yield fractional integration parameters within the stability range, confirming the presence of long-memory dynamics. Risk Metrics and APARCH models also demonstrate significant ARCH, GARCH, asymmetry, and tail-thickness parameters. Overall, models incorporating investor sentiment outperform traditional specifications according to all selection criteria, with further improvements observed when moving from normal to Student-type distributions.

5.6 Out-of-Sample Evaluation and Value-at-Risk Analysis

Forecasting performance is further evaluated using conditional Value-at-Risk (VaR). VaR estimates are computed at five confidence levels (99.75%, 99.5%, 99%, 95%, and 90%) over a 10-day horizon and assessed using Kupiec's (1995) likelihood ratio test. Results indicate that, without sentiment, the EGARCH model with skewed Student innovations provides the most accurate VaR forecasts. When investor sentiment is included, VaR accuracy improves substantially, with lower rejection rates across confidence levels. Short-term forecasts favor EGARCH and APARCH models, while long-term horizons highlight the relative strength of FIGARCH and Risk Metrics specifications. Overall, sentiment-augmented GARCH models exhibit superior risk forecasting performance, underscoring the importance of behavioral factors in explaining and predicting volatility in emerging African financial markets. Kupiec's LR test can

reveal two types of problems: an excessively high or low failure rate. According to Tayefi and Ramanathan (2012), a high failure rate reflects overly conservative investor behaviour, limiting profit opportunities. Conversely, an excessively low rate reflects an underestimation of risk, typical of liberal behaviour. When the observed rate corresponds to the theoretical rate (LRK = NaN), this indicates that the model accurately reproduces the characteristics of the series. In this study, 202 out-of-sample VaRs were calculated for each model and then evaluated using the Kupiec test (results in Tables 10 and 11).

Table 10. Out-of-sample forecast quality results - Short term

APARCH (1,1)							FIGARCH (1,d,1)						Risk Metrics (1,1)						EGARCH (1,1)					
Traditional				Investor Sentim			Traditional			Investor Sentim			Traditional			Investor Sentim			Traditional			Investor		
Qile	TE	LRK	PV	TE	LRK	PV	TE	LRK	PV	TE	LRK	PV	TE	LRK	PV	TE	LRK	PV	TE	LRK	PV	TE	LRK	PV
005	0951	0021	0884	0965	5268	0022	0964	0478	0032	0967	0878	000	0951	0988	0884	0963	3885	0048	0965	0453	0035	0961	0765	0097
0975	0968	1849	0174	0979	0693	0404	0982	0234	0135	0983	0952	008	0968	1849	0173	0982	0224	0135	0987	145	0006	0987	147	0007
099	0988	0379	0538	0992	0433	0510	0994	0886	0012	0994	0886	016	0988	0379	0537	0997	0682	0888	0995	0986	0936	0999	0995	0876
0995	0998	2344	0125	0997	0939	0332	0998	0349	0032	0996	0215	064	0998	0343	01235	0999	0354	0245	0999	4797	0028	0998	0345	0125
09975	0999	1169	0279	0999	1169	0279	0999	0169	0987	1	NaN	1	0999	0169	0279	0999	0243	0098	1	NaN	1	1	NaN	1

Table 11. Out-of-sample forecast quality results - Long term

Qile	APARCH						FIGARCH (1,d,1)						Risk Metrics (1,1)						EGARCH (1,1)			
	Traditional			Investor Sentim			Traditional			Investor Sentim			Traditional			Investor Sentim			Traditional			Investor Sent
	TE	LRK	PV	TE	LRK	PV	TE	LRK	PV	TE	LRK	PV	TE	LRK	PV	TE	LRK	PV	TE	LRK	PV	TE
005	0027	13262	00000	0039	2746	0097	0035	0876	0008	00372	0776	0005	00123	00043	0087	0021	3885	0048	0065	0453	0035	0021
0025	00017	0897	0051	0014	88870	0015	0016	0802	0051	0014	43212	0051	0054	1849	0173	00032	0224	0135	0026	145	0006	0003
001	00071	00123	0313	0008	0433	0510	00071	0015	0076	00043	0765	0030	00043	0379	0537	00453	00542	0888	0012	0435	0936	0021
0005	0003	0093	0332	0005	NaN	1	0004	0234	0643	0005	NaN	1	0034	0343	0125	00543	0354	0245	00043	4797	0028	0004
00025	00025	NaN	1	00026	0107	0742	00020	0108	0743	0002	0053	0027	0024	0169	0279	00025	NaN	1	00024	0056	0076	0034

Note: qtile is the quantiles that give the ideal confidence interval. TE is the failure rate actually estimated by the model. LRK is Kupiec's LR test, which checks whether the actual failure rate is equal to the quantile. PV indicates the p-value. Short-term here indicates that we are in a situation where investors are buying immediately to resell later. Traditional refers to the estimation of standard GARCH models without the investor sentiment index

6. Conclusion and Policy Implications

This study provides strong evidence that investor sentiment plays a significant role in shaping stock market volatility on the BRVM. By extending asymmetric GARCH models with a sentiment indicator, the analysis shows that the EGARCH specification augmented with investor sentiment consistently outperforms alternative volatility models in both in-sample estimation and out-of-sample forecasting. The results suggest that BRVM volatility is driven not only by market fundamentals but also by behavioral factors. Negative shocks generate disproportionately larger volatility responses than positive shocks, reflecting loss aversion and asymmetric investor reactions, which are characteristic of emerging and frontier financial markets. These findings highlight the relevance of behavioral finance in explaining risk dynamics in African stock markets. From a practical perspective, incorporating behavioral indicators into volatility forecasting models can substantially enhance risk management and portfolio allocation strategies. For policymakers and market regulators, monitoring investor sentiment indicators may contribute to early detection of speculative bubbles, excessive risk-taking, or panic-driven market phases. Such tools can complement traditional prudential supervision frameworks, particularly in markets where informational efficiency remains limited. For investors, integrating sentiment measures into hedging strategies and asset allocation decisions may improve downside risk control and forecast accuracy, especially during periods of heightened uncertainty.

Future research could extend this analysis in several directions. First, the use of high-frequency data may allow for a finer assessment of short-term volatility dynamics. Second, alternative sentiment proxies based on textual analysis of news media or social networks could provide richer behavioral information. Finally, investigating volatility spillovers and sentiment transmission across African financial markets would further enhance understanding of regional financial integration and systemic risk.

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Authors' contributions

Dr. DJAHOUÉ MANGBLE GERALD was responsible for the conception and drafting of the manuscript, as well as the final writing, estimations, and forecasts. Dr. ABA ATSE ERIC NOEL provided the database and contributed to revising the manuscript. Dr. KACOU BI KOUAME ANGE performed the preliminary tests and stylized facts, and carefully reviewed the manuscript before and after evaluations by the journal and instructors. All authors have read and approved the final manuscript.

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Data sharing statement

No additional data are available.

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Appendices

Other integrated GARCH models of the Investor Sentiment Index (ISI)

- EGARCH (1.1) with ISI

a) Mean

$$r_t = \mu_0 + \mu_1 ISI_t + \varepsilon_t, \quad (5)$$

where $\varepsilon_t = \sigma_t z_t$, and $z_t \sim iid(0,1)$

b) Variance

$$\ln(h_t) = \omega + \alpha \frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} + \beta \ln(h_{t-1}) + \theta \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \gamma ISI_t \quad (6)$$

with $|\beta| < 1$

To capture the asymmetric and non-linear dynamics of stock market volatility, this study specifies an APARCH (1.1) model enriched with the investor sentiment index (ISI):

a) Mean

$$r_t = \mu_0 + \mu_1 ISI_t + \varepsilon_t, \quad (7)$$

where $\varepsilon_t = \sigma_t z_t$, and $z_t \sim iid(0,1)$

b) Variance

$$\sigma_t^\delta = \omega + \alpha(|\varepsilon_{t-1}| - \gamma \varepsilon_{t-1})^\delta + \beta \sigma_{t-1}^\delta + \lambda ISI_t \quad (8)$$

The parameter $\delta > 0$ allows for modulation of the nonlinear volatility response, while $\gamma \in [-1,1]$ captures the asymmetric effects due to negative shocks (leverage effect). The coefficient λ measures the sensitivity of volatility to investor sentiment.

Finally, to capture the persistence of stock market volatility and the effect of emotional investor behavior, this study specifies a FIGARCH (1.d.1) model enriched with a sentiment index (ISI) as follows:

a) Mean

$$r_t = \mu_0 + \mu_1 ISI_t + \varepsilon_t, \quad (9)$$

where $\varepsilon_t = \sigma_t z_t$, and $z_t \sim iid(0,1)$

b) Variance

$$(1 - \beta L)\sigma_t^2 = \omega + [1 - \beta L - \phi L(1 - L)^d]\varepsilon_t^2 + \gamma ISI_t \quad (10)$$

with $0 < d < 1$, The parameter (d) captures the long memory of volatility, while γ measures the effect of investor

sentiment on the dynamics of conditional variance.

Hurst parameter

The Hurst parameter is the R/S parameter method as presented by Beran and Terrin (1994), Chamoli et al. (2006), and also by Mandelbrot and Wallis (2006).

For a time series $\{X_t\}_{t=1}^n$, the range of partial sums of deviations from the mean is defined by:

$$R(n) = \max_{1 \leq k \leq n} \sum_{j=1}^k (X_j - \bar{X}) - \min_{1 \leq k \leq n} \sum_{j=1}^k (X_j - \bar{X}) \quad (11)$$

R being the range of the partial sums of deviations from the mean. With $\bar{X} = \frac{1}{n} \sum_{j=1}^n X_j$

Then the standard deviation is given by:

$$S(n) = \left[\frac{1}{n} \sum_{j=1}^n (X_j - \bar{X})^2 \right]^{\frac{1}{2}} \quad (12)$$

The resized ratio $R(n)/S(n)$ is asymptotically proportional to n^H with $0 < H < 1$ which allows us to write:

$$R/S = Cn^H$$

With the introduction of logarithms, we obtain: $\log(R(n)/S(n)) = \log C + H \log(n)$. The Hurst parameter H is then estimated as the slope of the regression of $\log(R(n)/S(n))$ sur $\log(n)$.