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Evaluating Volatility Dynamics and Testing the Efficiency of the Ghana Stock Exchange

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Abstract: *This study provides an integrated analysis of weak-form market efficiency, volatility dynamics, and macroeconomic shock transmission on the Ghana Stock Exchange (GSE) over a ten-year period from November 2015 to October 2025. The data was obtained from both the Ghana stock exchange and the Bank of Ghana. Using daily closing prices of the GSE Composite Index alongside exchange rate and interest rate data from the Bank of Ghana, the study applies a comprehensive suite of econometric methods. Weak-form efficiency is tested using the ADF, Runs, Variance Ratio, and BDS tests on 2,454 daily return observations. Volatility dynamics are modelled using GARCH(1,1), GJR-GARCH(1,1), and EGARCH(1,1), while macroeconomic shocks are examined through extended GARCH models with exchange rate and interest rate changes as external regressors on 491 weekly observations. Asymmetric effects of shocks are tested through a purpose-built asymmetric variance equation. The GSE is found not to be weak-form efficient: the Runs, Variance Ratio, and BDS tests reject return randomness, confirming significant return dependence, mean reversion, and nonlinear structure. GSE daily returns also exhibit significant time-varying volatility, strong persistence, and a reverse leverage effect, whereby positive shocks raise conditional variance more than negative shocks of equal magnitude. The preferred GJR-GARCH(1,1) model estimates a long-run daily volatility of approximately 0.98% and a half-life of roughly 13 trading days. Exchange rate and interest rate shocks are statistically insignificant in driving GSE conditional variance, and negative shocks produce no asymmetric effects, indicating that GSE volatility asymmetry is endogenous rather than macro-driven. The study contributes the first integrated framework simultaneously testing efficiency, volatility, and shock transmission on the GSE, with insights for investors, regulators, and listed companies.*

Keywords: *Market Efficiency; Volatility Modelling; GARCH; Ghana Stock Exchange; Macroeconomic Shocks; Emerging Markets*

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1. Introduction

Modern financial systems are major drivers of global economic development, and financial markets are central to this because they help allocate funds efficiently within an economy. When financial markets function effectively, funds can be raised easily, which promotes economic growth and stability. The World Bank has established that a well-developed financial market performs its basic functions effectively, thereby improving capital formation, enhancing liquidity, and helping to control inflation. As noted by Ngcobo, Zhou, and Pillay (2025), stock markets help allocate capital in ways that improve overall economic efficiency. Investors with surplus funds supply capital to firms seeking financing, with the expectation of earning returns through dividends or capital gains. Globally, this process has contributed significantly to the growth of large corporations and supported economic development by enabling firms to undertake large-scale investment projects.

Market efficiency and price volatility are two important characteristics that stakeholders need to understand in order to fully appreciate how well a stock market is performing. The concept of market efficiency, as advanced by Fama (1970), defines efficiency as the capacity of prices to instantaneously and accurately absorb available information. How efficiently a market processes and incorporates information into asset prices is therefore a matter of considerable practical and theoretical importance to stakeholders (Fama, 1970; Asiedu et al., 2020). In an efficient market, stakeholders cannot beat the market by exploiting publicly available data, because such information is already embedded in prevailing prices. Market efficiency is conventionally partitioned into distinct levels, each distinguished by the breadth of information that prices are assumed to incorporate, depending on how the market absorbs that information into stock prices. This study focuses specifically on the weak form, the foundational tier of the efficiency spectrum.

Weak-form efficiency concerns the extent to which current prices have already absorbed all the information contained in the historical sequence of prices and returns. Under this condition, successive price changes are treated as probabilistically independent, making it theoretically impossible for investors to exploit historical trading data to anticipate future price movements. Return innovations can be formalised as the deviation between the realised price and the price that was rationally anticipated given all prior available information, with the unexpected component representing new information or shocks entering the market. Traditional return models assume these shocks have an average value of zero and that their variance remains constant over time, implying homoskedastic behaviour in the return series.

Many studies have empirically shown that most financial market stocks exhibit volatility persistence, meaning volatility clustering exists. A related strand of empirical finance research has demonstrated that the variance of financial returns changes over time. This empirical regularity, known as volatility clustering, where turbulent episodes tend to be followed by further turbulence and calm periods by further calm, fundamentally undermines the constant-variance assumption embedded in classical models. This observation led Engle (1982) to develop a model that allows for changing variance. In emerging markets, evolving market structures and imperfect information dissemination, including irregular trading activity, lower liquidity, and slower information diffusion, cause prices to be more volatile and create the potential for deviation from market efficiency (Engle, 1982; Agyarko et al., 2023). African financial markets have increasingly become important for mobilising domestic and foreign investment, and many African economies have established these markets to facilitate capital formation and support economic development. However, comparative analysis of developing and emerging markets identifies limited liquidity, information asymmetry, and higher susceptibility to macroeconomic shocks as recurring challenges.

The GSE is classified as an emerging market that plays an important role in Ghana's economic development. Even though the Ghanaian market is on a growing trajectory, it has experienced major episodes of significant price fluctuation during periods of macroeconomic uncertainty, suggesting the presence of volatility dynamics that require advanced modelling approaches to properly understand stock return behaviour. Existing empirical studies on the GSE have tended to examine either market efficiency or volatility modelling in isolation, often with mixed findings. Asiedu, Mireku-Gyimah, Kamasa, and Otoo (2020), for instance, concentrated exclusively on testing weak-form efficiency without integrating any analysis of market volatility, while Agyarko, Frempong, and Wiah (2023) directed their attention solely toward volatility modelling through GARCH-type specifications. Other researchers have examined how macroeconomic fundamentals, including GDP trajectories and exchange rate dynamics, shape overall stock market performance, but without simultaneously addressing efficiency and volatility within a unified analytical framework. Studying efficiency, volatility, and macroeconomic shocks together within a single framework remains rare in the Ghanaian context, and closing this gap carries tangible significance: a simultaneous understanding of price behaviour and volatility dynamics on the GSE is essential for improving investment decision-making, refining risk management practices, and supporting evidence-based policy interventions in Ghana's financial sector.

1.1 Problem Statement

Efficient financial markets help enable the effective allocation of resources and support economic development. The Efficient Market Hypothesis establishes weak-form efficiency as the condition under which current prices reflect only past information, making it theoretically impossible to use the pattern of previous data to earn returns above the market. Despite this theoretical expectation, the empirical literature on African frontier and emerging markets frequently documents departures from weak-form efficiency, suggesting that historical return data may retain predictive content in several of these markets, with evidence pointing to thin trading, limited liquidity, and structural inefficiencies as the main drivers (Antoniou, Ergul, & Holmes, 1997; Monga, Aggrawal, & Singh, 2023).

The GSE, like many African markets, has displayed characteristics associated with these inefficiencies. Historically, the exchange has shown prolonged low trading activity, irregular price movements, and high volatility, which may indicate weak integration of information into stock prices. Research on emerging markets often highlights that African markets such as the GSE tend to process information slowly, owing to limited market depth and inconsistent investor participation, and this, combined with the volatility clustering commonly observed in African markets, suggests that the GSE may not achieve weak-form efficiency. In recent years, Ghana's macro environment has experienced significant external shocks that have affected price stability and shaped investor confidence. The study period, 2015 to 2025, captures key macroeconomic disruptions, including Ghana's 2022 debt restructuring, the COVID-19 shock, and significant currency depreciation, during which the GSE Composite Index, trading volumes, and market capitalisation moved through periods of relative calm alternating with sharp change.

However, prior Ghanaian research has not sufficiently linked these observable market dynamics to formal tests of efficiency and volatility within a macroeconomic context. GARCH-family models are widely used in volatility research, but limited attention has been paid to how macroeconomic shocks drive stock market volatility in Ghana, and even fewer studies test whether such shocks produce asymmetric effects, leaving an incomplete understanding of how external economic conditions interact with market behaviour.

Consequently, three specific problems emerge from the existing literature. First, the weak-form efficiency of the GSE remains empirically uncertain, as prior studies have produced mixed and methodologically inconsistent findings. Second, the nature and persistence of GSE return volatility are not fully understood within the context of prevailing macroeconomic conditions. Third, the joint and potentially asymmetric effects of macroeconomic shocks, particularly exchange rate and interest rate fluctuations, on stock price formation and volatility have not been systematically assessed within a unified analytical framework.

1.2 Objectives and Hypotheses

The general objective of the study is to test the weak-form efficiency of the GSE, characterise the volatility dynamics of its returns through GARCH-family modelling, and quantify the impact of exchange rate and interest rate shocks on stock market volatility. The specific objectives are to: (i) test the weak-form efficiency of the GSE; (ii) fit the volatility dynamics of GSE returns using GARCH-family models; (iii) investigate the impact of macroeconomic shocks on stock market volatility; and (iv) examine whether macroeconomic shocks exert asymmetric effects on market volatility. Correspondingly, four null hypotheses are tested: H01, the GSE exhibits weak-form efficiency; H02, GSE returns do not exhibit volatility clustering or persistence; H03, macroeconomic shocks do not impact GSE volatility; and H04, macroeconomic shocks do not produce asymmetric effects on GSE volatility.

2. Literature Review

2.1 Theoretical Review

The Efficient Market Hypothesis (EMH), formalised by Fama (1970) building on Bachelier (1900) and Samuelson (1965), distinguishes weak, semi-strong, and strong forms of efficiency according to the information set assumed to be reflected in prices. Weak-form efficiency, the focus of this study, holds that prices fully incorporate all historical price and volume information, so technical analysis of past patterns cannot generate abnormal returns. The Random Walk Theory provides the statistical expression of this idea, modelling price changes as independent, identically distributed increments that cannot be predicted from their own history (Fama, 1965).

Volatility Theory addresses the second pillar of the study. Engle's (1982) Autoregressive Conditional Heteroscedasticity (ARCH) framework, later generalised by Bollerslev (1986) into the GARCH model, allows conditional variance to depend on past squared shocks and past variance, capturing the empirical regularity of volatility clustering. Asymmetric extensions, notably the GJR-GARCH and EGARCH specifications, allow negative and positive shocks of equal magnitude to have differing effects on conditional variance, a phenomenon often described as a leverage effect in developed equity markets. Macroeconomic Volatility Transmission Theory extends this logic to external shocks, positing that exchange rate and interest rate movements can transmit uncertainty into equity markets by altering firms' input costs, competitiveness, and discount rates, thereby raising conditional variance.

2.2 Empirical Review

2.2.1 Weak-Form Efficiency

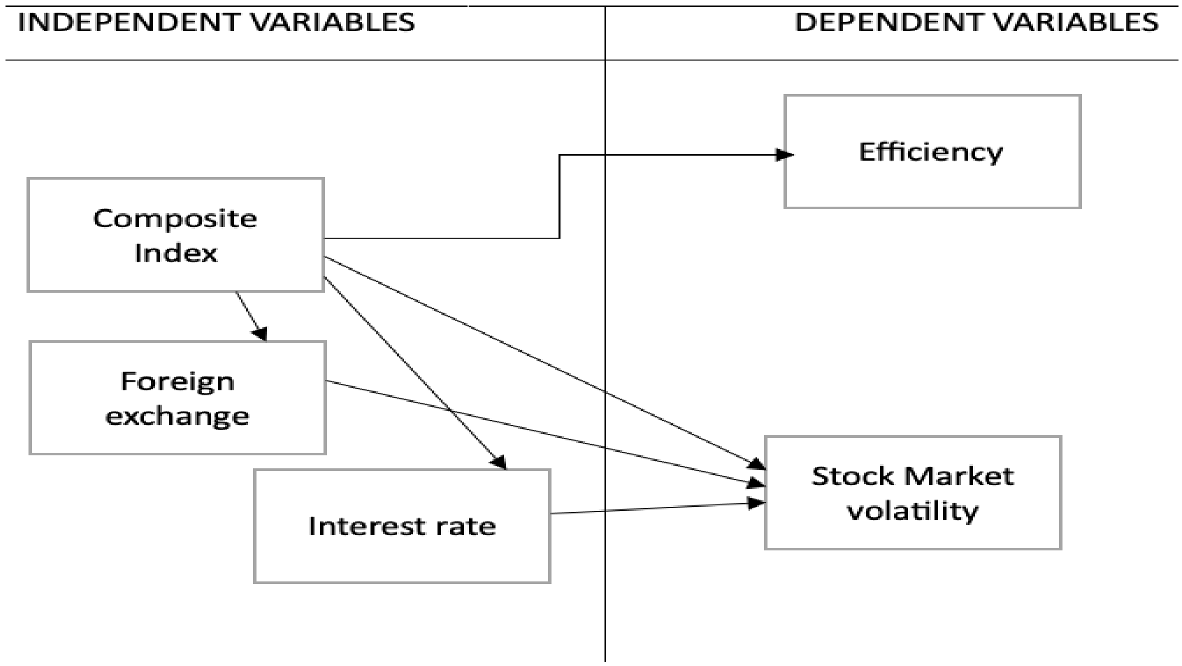
Empirical tests of weak-form efficiency in African and emerging markets typically combine traditional linear procedures, unit root, autocorrelation, runs, and variance ratio tests, with nonlinear techniques such as the BDS test, wavelet-based unit root tests, and long-memory measures including the Hurst exponent and multifractal detrended fluctuation analysis (Afego, 2015). Applying runs and Lo-MacKinlay variance ratio tests to sectoral GSE data, Asiedu, Mireku-Gyimah, Kamasa, and Otoo (2020) found systematic return dependence inconsistent with a pure random walk, a pattern reinforced by multi-test studies elsewhere: Elangovan, Irudayasamy, and Parayitam (2022) for India, Kim (2025) for Thailand during COVID-19, and Boufama and Rogova (2025) across African markets each combined several traditional procedures and reached broadly similar conclusions. Advanced nonlinear approaches tell a consistent story. Kelikume, Olaniyi, and Iyohab (2020) used wavelet unit root tests to capture frequency-based inefficiencies, Dias, Pereira, and Carvalho (2022) applied Wright's rank- and sign-based variance ratio procedures and found evidence of long memory and return persistence, and Lee and Choi (2023) used multifractal DFA and rolling-window techniques to show that efficiency is time-varying rather than fixed. Taken together, the balance of evidence leans toward rejecting weak-form efficiency in African and emerging markets: Afego (2015), Lawal, Somoye, and Babajide (2017), Nguyen and Parsons (2022), and Elangovan et al. (2022) all report violations of the random walk hypothesis, while Ozkan (2021) documents a widespread efficiency breakdown around COVID-19. A smaller strand, however, finds efficiency is conditional rather than absent: Obalade and Muzindutsi (2018) support the Adaptive Market Hypothesis, under which efficiency alternates with market conditions, and Monga, Aggrawal, and Singh (2023) and Scalamonti (2025) report that efficiency improves during periods of high liquidity. For Ghana specifically, Odonkor, Ababio, Darkwah, and Andoh (2022) illustrate a recurring limitation in the literature: studies tend to rely on either traditional or advanced tests rather than combining both, motivating the four-test approach adopted here.

2.2.2 Volatility Modelling and Macroeconomic Shocks

A parallel literature models volatility directly using GARCH-family specifications, which remain competitive even against more complex alternatives: Maingo, Ravele, and Sigauke (2025) find GARCH-type structures hold their own against Generalized Autoregressive Score and hybrid GARCH-XGBoost models, while Boudri and El Bouhadi (2024) and Akgun and Gulay (2025) show that simple ARCH and GARCH specifications can match or outperform deep-learning approaches such as LSTM and CNN. Across African markets, findings consistently point to strong volatility persistence, clustering, and asymmetry. Ben Flah, Samet, El Ammari, and Terzi (2025) document substantial volatility spillovers between commodity and African equity markets using BEKK-GARCH, and Wanjuki, Lumumba, Kimtai, Mbaluka, and Njoroge (2024) find that asymmetric specifications are needed to capture leverage effects in Nairobi, a result echoed by Toong, Goh, and Sim (2023), who show EGARCH outperforms symmetric GARCH in explaining volatility asymmetry. Within Ghana specifically, Prempeh, Frimpong, and Amaning (2022) and Insaidoo, Arthur, Amoako, and Andoh (2021) apply EGARCH to the COVID-19 period and find pronounced volatility clustering and asymmetric shock responses, while Agyarko, Wiah, Frempong, and Odoi (2023) compare GARCH, TGARCH, and EGARCH and identify TGARCH as the best fit for GSE data, a result Ofori-Boateng, Agyapong, Ohemeng, and Annor (2022) extend to commodity-linked stock returns. More recent work pushes toward hybrid and mixed-frequency approaches: Nugroho, Setiawan, and Morimoto (2025) use Realized GARCH with Bayesian estimation, and Nortey, Agbeli, Debrah, Ansah-Narh, and Agyemang (2024) apply GARCH-MIDAS to blend low-frequency macroeconomic data with high-frequency returns, both reporting forecasting gains over standard specifications.

Evidence on macroeconomic transmission into volatility is more mixed. Nortey et al. (2024) identify inflation, exchange rates, and oil prices as significant drivers of volatility using GARCH-MIDAS, and Sheng and Jade (2024) reach similar conclusions for the East African Community, whereas Ali, Nzotta, Akujuobi, and Nwaimo (2020), using a GARCH-X framework across Sub-Saharan Africa, find macroeconomic variables are not always statistically significant in the variance equation. For Ghana specifically, Abdullai, Twumasi, Addo, and Tettey (2023) and Aawaar, Logogye, and Domeher (2023) report that exchange rates and Treasury bill rates are significant volatility drivers, while Mohammed, Mohammed, and Nketiah-Amponsah (2021) show monetary policy rates influence exchange rate volatility, which may transmit indirectly into equity markets. Asymmetric responses to shocks, whether market-level or macroeconomic, are also well documented: Adegboyo and Sarwar (2025) find strong leverage effects across markets, and Ofori-Boateng et al. (2022) and Akurugu, Angbing, Nasiru, and Abubakari (2022) confirm pronounced asymmetry on the GSE, particularly during turbulent regimes. However, none of these studies jointly tests whether negative macroeconomic shocks, specifically, rather than negative return shocks generally, produce disproportionately larger volatility responses using an explicit asymmetric GARCH specification, the question this study addresses directly in Objective 4.

2.3 Conceptual Framework



Source: Developed by author

2.4 Research Gap

Four gaps emerge from this literature. First, efficiency testing on the GSE remains methodologically fragmented, with studies applying either traditional tests or advanced nonlinear techniques rather than combining both (Odonkor et al., 2022). Second, efficiency and volatility are typically studied as separate problems: GSE volatility studies (Prempeh et al., 2022; Agyarko et al., 2023) do not test whether the same return series satisfy weak-form efficiency, leaving it unclear whether documented inefficiencies and volatility patterns are related. Third, evidence on macroeconomic shock transmission into GSE volatility is inconsistent (Nortey et al., 2024; Ali et al., 2020), with limited Ghana-specific evidence directly incorporating exchange rate and interest rate shocks into the variance equation. Fourth, no prior study jointly tests whether negative macroeconomic shocks produce asymmetric volatility responses using EGARCH or GJR-GARCH specifications. This study addresses all four gaps within a single integrated framework applied to the GSE over the 2015-2025 period.

3. Methodology

The study adopts a quantitative, descriptive, and explanatory research design based on secondary time-series data, enabling numerical measurement of returns, volatility modelling, and assessment of macroeconomic relationships using established econometric tools. The study population comprises the GSE Composite Index, a market-capitalisation-weighted index aggregating the daily performance of all 35 ordinary share listings on the exchange, together with corresponding macroeconomic indicators. The study covers 2 November 2015 to 31 October 2025, a ten-year window yielding 2,455 daily observations of index prices and exchange rates and 491 weekly observations of the 364-day Treasury bill rate, obtained from the Ghana Stock Exchange and the Bank of Ghana respectively. A census approach was used, incorporating all available data points within the study period rather than a sample, eliminating sampling bias; 1,040 non-trading days and 154 public holidays were excluded due to missing values.

Data were collected as archival secondary data, cross-checked against GSE Monitor and CEIC Data, compiled in Microsoft Excel, and exported to R Studio for econometric analysis. Stock prices were converted to continuously compounded returns via logarithmic transformation, and macroeconomic variables to logarithmic differences to capture shocks. For the macroeconomic-shock objectives, daily index and exchange rate series were aggregated to weekly frequency to align with the weekly Treasury bill rate. Validity was supported through the use of variables with established precedent in the literature and by triangulating four complementary efficiency tests rather than relying on a single procedure; reliability was supported by sourcing data from official institutions and by diagnostic checks, including the ARCH-LM test, AIC/BIC model selection, and Ljung-Box tests on residuals.

The analytical framework proceeds in four stages, corresponding to the four specific objectives, and is specified formally below.

3.1 Data Transformations

Daily closing prices of the GSE Composite Index were converted to continuously compounded returns:

$$R_t = \ln(P_t / P_{t-1}) \quad (1)$$

where R_t is the return at time t, and P_t, P_{t-1} are the closing prices at t and t-1. Exchange rate data were transformed analogously to log returns:

$$\Delta FX_t = \ln(FX_t / FX_{t-1}) \quad (2)$$

Interest rates, expressed in percentage-point terms, were first-differenced rather than log-transformed:

$$\Delta IR_t = IR_t - IR_{t-1} \quad (3)$$

These transformations stabilise variance and ensure all series are stationary and suitable for the efficiency and volatility tests described below.

3.2 Testing Weak-Form Efficiency

Weak-form efficiency was assessed using four complementary tests, each targeting a distinct dimension of return behaviour: linear dependence, non-linear dependence, and departures from randomness.

The Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979) was used to confirm stationarity of the return series, a precondition for both efficiency testing and GARCH estimation, and is specified as:

$$\Delta R_t = \alpha + \beta R_{t-1} + \Sigma_{i=1}{}^{k}\, \gamma_i \Delta R_{t-i} + \varepsilon_t \quad (4)$$

where α is an intercept, β is the coefficient on the lagged return level, and k is the lag order selected using AIC/SBC. The null hypothesis (β = 0) asserts the presence of a unit root; rejection confirms stationarity.

The Runs Test, a distribution-free procedure, compares the observed number of runs (R) against the number expected under randomness. With n1 and n2 denoting the counts of positive and negative returns:

$$E(R) = (2n1n2)/(n1+n2) + 1 \quad (5)$$

$$Z = (R - E(R)) / \mathrm{sqrt}[\mathrm{Var}(R)] \quad (6)$$

A significant Z-statistic indicates systematic patterning inconsistent with weak-form efficiency.

The Lo-MacKinlay Variance Ratio (VR) test (Lo & MacKinlay, 1988) compares the variance of q-period returns to a scaled multiple of single-period return variance:

$$VR(q) = \mathrm{Var}(\Sigma_{i=0}{}^{\varphi-1}\, R_{t-i}) / (q \cdot \mathrm{Var}(R_t)) \quad (7)$$

$$Z(q) = (VR(q) - 1) / \mathrm{sqrt}[\theta(q)] \quad (8)$$

Under a random walk, VR(q) = 1; rejection of this equality implies return predictability.

The Brock-Dechert-Scheinkman (BDS) test (Brock, Dechert, & Scheinkman, 1987) extends the analysis to non-linear dependence, testing whether returns are independently and identically distributed via the correlation integral $C_m(\varepsilon)$, the proportion of embedded m-dimensional return vectors lying within distance ε of one another:

$$W_m,\varepsilon = (\mathrm{sqrt}(n-m+1) \cdot [C_m(\varepsilon) - C_1(\varepsilon)^m]) / \delta_m,\varepsilon \quad (9)$$

where $C_1(\varepsilon)^m$ is the expected correlation integral under the i.i.d. null and δ_m,ε is its standard deviation under that null. Rejection indicates non-linear structure that linear tests cannot detect.

3.3 Volatility Modelling

Prior to volatility modelling, Engle's (1982) ARCH-LM test was applied to a basic mean equation ($R_t = \mu + \varepsilon_t$) to confirm conditional heteroscedasticity, regressing squared residuals on their own lagged values:

$$\hat{\varepsilon}_t{}^2 = \beta_0 + \beta_1 \hat{\varepsilon}_{t-1}{}^2 + \ldots + \beta_m \hat{\varepsilon}_{t-m}{}^2 + u_t \quad (10)$$

A significant LM = nR^2 statistic confirms ARCH effects and justifies GARCH-family estimation. Three specifications were then fitted, following evidence that GARCH-family models remain highly competitive against more complex alternatives (Boudri & El Bouhadi, 2024).

GARCH(1,1) (Bollerslev, 1986):

$$\sigma_t{}^2 = \omega + \alpha \varepsilon_{t-1}{}^2 + \beta \sigma_{t-1}{}^2 \quad (11)$$

GJR-GARCH(1,1) (Glosten, Jagannathan, & Runkle, 1993), which relaxes the symmetry assumption to capture the leverage effect:

$$\sigma_t{}^2 = \omega + \alpha \varepsilon_{t-1}{}^2 + \gamma I_{t-1} \varepsilon_{t-1}{}^2 + \beta \sigma_{t-1}{}^2 \quad (12)$$

where $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ (negative shock), 0 otherwise, and γ is the asymmetry parameter.

EGARCH(1,1) (Nelson, 1991):

$$\ln(\sigma_t{}^2) = \omega + \beta \ln(\sigma_{t-1}{}^2) + \alpha |\varepsilon_{t-1}/\sigma_{t-1}| + \gamma (\varepsilon_{t-1}/\sigma_{t-1}) \quad (13)$$

In all three specifications, ω is the long-run baseline variance, α is the ARCH (shock) coefficient, β is the GARCH (persistence) coefficient, and, where present, γ is the asymmetry (leverage) coefficient.

3.4 Macroeconomic Shocks and Asymmetric Effects

To align data frequencies with the weekly-quoted interest rate, the daily index and exchange rate series were aggregated to 491 weekly observations using five-day trading means. Equations (11)-(13) were then extended to incorporate exchange rate (ΔFX) and interest rate (ΔIR) shocks directly into the variance equation:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \varphi 1\Delta FX_t + \varphi 2\Delta IR_t \quad (14)$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma I_{t-1}\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \varphi 1\Delta FX_t + \varphi 2\Delta IR_t \quad (15)$$

$$\ln(\sigma_t^2) = \omega + \beta\ln(\sigma_{t-1}^2) + \alpha|\varepsilon_{t-1}/\sigma_{t-1}| + \gamma(\varepsilon_{t-1}/\sigma_{t-1}) + \varphi 1\Delta FX_t + \varphi 2\Delta IR_t \quad (16)$$

where $\varphi 1$ and $\varphi 2$ capture the sensitivity of GSE conditional variance to exchange rate and interest rate shocks respectively (Objective 3). To test whether negative macroeconomic shocks specifically amplify volatility (Objective 4), the GJR-GARCH variance equation was further extended:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma 1\Delta FX_{t-1}^2 I\{\Delta FX_{t-1}<0\} + \gamma 2\Delta IR_{t-1}^2 I\{\Delta IR_{t-1}<0\} + \beta\sigma_{t-1}^2 \quad (17)$$

where $\gamma 1$ and $\gamma 2$ capture the differential impact of negative exchange rate and interest rate shocks respectively, and the indicator functions $I\{\cdot\}$ isolate negative shock periods.

4. Results and Discussion

4.1 Descriptive Statistics

Table 1 presents summary statistics for daily GSE returns alongside the weekly return, exchange rate, and interest rate series used in Objectives 3 and 4.

Table 1: Summary Statistics

Statistic	Daily Returns	Weekly Returns	Forex	Interest Rate
Mean	0.000581	0.002923	0.002148	-0.021678
Median	0.000	-0.000026	0.001196	0.01685
Maximum	0.121111	0.11248	0.139684	10.348
Minimum	-0.11841	-0.056363	-0.364692	-10.1544
Std. Dev.	0.008971	0.01839	0.023805	1.184912
Skewness	0.528713	1.039887	-7.062497	-0.635392
Kurtosis	38.068367	6.955847	122.265474	46.441859
Jarque-Bera	125,860.39	407.81	294,485.28	38,563.20
Probability	0.000	0.000	0.000	0.000
Observations	2,454	490	490	490

Source: Secondary data presented by the author

All four series show mean returns close to zero and pronounced positive excess kurtosis, indicating fat-tailed, leptokurtic distributions typical of financial data. Daily return kurtosis (38.07) is markedly higher than weekly kurtosis (6.96), consistent with the central limit theorem as extreme observations average out under aggregation, while the forex series shows extreme kurtosis (122.27) reflecting the 2022 currency crisis. The Jarque-Bera test rejects normality for all variables at the 1% level, justifying the GARCH-family approach adopted.

4.2 Weak-Form Efficiency (Objective 1)

The ADF test confirmed stationarity of the GSE daily return series (test statistic -12.334, lag order 13, $p < 0.01$), satisfying both the theoretical expectation under weak-form EMH and the precondition for GARCH modelling.

Table 2: Efficiency Test Summary

Test	Statistic	P-Value
ADF (unit root)	-12.334***	< 0.01
Runs Test (Z)	-6.684***	< 0.001
Variance Ratio (q=4 to 44)	M1 = 2.06 to 6.16**	< 0.05 to < 0.01
BDS Test (m=2 to 6)	8.45 to 18.40***	< 0.01

*Note: * significant at 10%; ** significant at 5%; *** significant at 1%. The Variance Ratio statistic is significant at 5% for q = 4 and at 1% for q ≥ 8; it is not significant at q = 2 (p = 0.744, not shown). All other tests reject their respective null hypotheses at the 1% level. Source: Secondary data presented by author*

The Runs Test rejected return randomness at the 1% level ($Z = -6.684$, $p < 0.001$); the observed number of runs (872) was materially lower than the 1,022 expected under randomness, indicating that returns tend to persist in the same direction across consecutive periods. The Lo-MacKinlay Variance Ratio Test found returns statistically indistinguishable from random only at the shortest two-day holding period ($p = 0.744$); from four days onward, the null of a random walk was rejected at the 5% level or better, with Var(q) consistently below one, indicating negative autocorrelation and mean reversion. The BDS test produced statistics of 8.45 to 18.40 across all embedding dimensions and epsilon values tested, far exceeding the 1% critical value of 2.576, confirming significant nonlinear dependence beyond what linear tests alone can detect. Taken together, the four tests provide consistent, robust evidence against weak-form efficiency: H01 is rejected, and the GSE exhibits significant return dependence, mean reversion, and nonlinear structure, indicating that historical price information retains predictive content over future returns.

This finding aligns with the broader African evidence reviewed in Section 2.2 (Afego, 2015; Asiedu et al., 2020; Dias, Pereira, & Carvalho, 2022; Nguyen & Parsons, 2022) and is consistent with the thin-trading, low-liquidity explanation for persistent inefficiency in frontier and emerging markets (Antoniou et al., 1997; Monga et al., 2023).

4.3 Volatility Dynamics (Objective 2)

The ARCH-LM pre-test rejected the null of no ARCH effects (chi-squared = 447.46, df = 12, $p < 0.001$), confirming time-varying variance and justifying GARCH-family estimation.

Table 3: Daily GARCH-Family Model Estimates

Parameter	GARCH(1,1)	GJR-GARCH(1,1)	EGARCH(1,1)
α (ARCH)	0.1334***	0.1638***	0.0474***
β (GARCH)	0.8143***	0.8189***	0.8930***
γ (Asymmetry)	-	-0.0703***	0.2880***
Persistence	0.9477	0.9476	-
Long-run daily volatility	0.978%	0.977%	1.111%
Half-life (trading days)	12.91	12.88	6.12

**** significant at the 1% level. Source: Secondary data presented by author*

All three models produced highly significant ARCH and GARCH coefficients. The GARCH(1,1) model recorded persistence ($\alpha+\beta$) of 0.9477, implying slow dissipation of volatility shocks, a long-run daily volatility of 0.978% ($\omega/(1-\alpha-\beta)$), and a half-life of 12.91 trading days. The GJR-GARCH(1,1) model produced a statistically significant negative asymmetry parameter ($\gamma = -0.0703$, $p < 0.01$), indicating a reverse leverage effect in which positive return shocks raise conditional variance more than negative shocks of equal magnitude, contrary to the pattern typically observed in developed markets. Persistence ($\alpha+\beta+\gamma/2 = 0.9476$), long-run volatility (0.977%), and half-life (12.88 days) were closely comparable to the symmetric model. The EGARCH(1,1) model corroborated the reverse leverage effect with a significant positive gamma (0.2880, $p < 0.01$) and the highest persistence ($\beta = 0.8930$), but a materially shorter half-life of 6.12 days and a slightly higher long-run volatility of 1.111%.

By information criteria, GJR-GARCH(1,1) provides the best fit (lowest AIC of -6.884, highest log-likelihood of 8,451.6) and is selected as the preferred model. However, the Nyblom stability test favours EGARCH(1,1) (joint statistic 2.388, versus 5.726 for GARCH and 5.284 for GJR-GARCH), indicating more stable parameters through the study period, plausibly reflecting structural breaks around Ghana's 2022 macroeconomic crisis. Diagnostic checks (Ljung-Box, ARCH-LM on squared residuals) confirm all three specifications adequately capture volatility dynamics, with no remaining ARCH effects; significant negative sign bias in both asymmetric models corroborates the asymmetric response identified above (Table 5). The 13-day half-life under the preferred model is considerably longer than the two-to-three day half-lives typical of developed markets (Toong, Goh, & Sim, 2023), confirming that GSE volatility shocks are unusually persistent.

Table 4: Model Comparison and Volatility Statistics

Statistic	GARCH(1,1)	GJR-GARCH(1,1)	EGARCH(1,1)
ω (Constant)	0.000005	0.000005	-0.962697
α (ARCH)	0.13342	0.163829	0.047363
β (GARCH)	0.814307	0.818864	0.892996
γ (Asymmetry)	—	-0.070307	0.288007
Persistence	0.9477	0.9476	0.8930
Long-run variance	0.0000956	0.0000954	0.0001234
Long-run volatility (%/day)	0.9778	0.9767	1.1108
Half-life (trading days)	12.91	12.88	6.12
Log-likelihood	8445.415	8451.598	8416.072
AIC	-6.8797	-6.8839	-6.8550
BIC	-6.8703	-6.8721	-6.8432
Nyblom joint statistic	5.726	5.284	2.388
Best model (information criteria)	No	Yes	No
Most stable (Nyblom)	No	No	Yes

Note: GJR-GARCH(1,1) records the lowest AIC and highest log-likelihood (best fit); EGARCH(1,1) records the lowest Nyblom joint statistic (most stable parameters). Source: Secondary data presented by author

Table 5: Combined Diagnostic Test (Appendix C2)

Test	GARCH(1,1)	GJR-GARCH(1,1)	EGARCH(1,1)
Ljung-Box Q, Std. Residuals — Lag 1	11.55 (0.001)	8.377 (0.004)	8.693 (0.003)
Ljung-Box Q, Std. Residuals — Lag 2	15.88 (0.000)	12.101 (0.001)	12.303 (0.000)
Ljung-Box Q, Std. Residuals — Lag 5	27.85 (0.000)	23.000 (0.000)	22.075 (0.000)
Ljung-Box Q, Sq. Residuals — Lag 1	0.468 (0.494)	0.608 (0.436)	1.431 (0.232)
Ljung-Box Q, Sq. Residuals — Lag 5	0.896 (0.883)	1.023 (0.855)	1.724 (0.685)
Ljung-Box Q, Sq. Residuals — Lag 9	2.462 (0.843)	2.456 (0.844)	3.640 (0.650)
ARCH-LM — Lag 3	0.110 (0.740)	0.130 (0.718)	0.121 (0.728)
ARCH-LM — Lag 5	0.602 (0.853)	0.624 (0.847)	0.441 (0.901)
ARCH-LM — Lag 7	1.412 (0.839)	1.514 (0.819)	1.080 (0.900)
Nyblom joint stability	5.726	5.284	2.388
Sign bias	0.555 (0.579)	0.490 (0.624)	0.644 (0.520)
Negative sign bias	1.228 (0.220)	1.771 (0.077)*	1.985 (0.047)**
Positive sign bias	0.451 (0.652)	0.219 (0.826)	0.253 (0.801)
Joint effect	2.382 (0.497)	4.251 (0.236)	5.612 (0.132)

*Note: p-values in parentheses. * significant at 10%; ** significant at 5%. Ljung-Box and ARCH-LM tests on squared residuals show no remaining ARCH effects in any model. Negative sign bias is significant in both asymmetric models, corroborating the asymmetric volatility response. Source: secondary data presented by author*

4.4 Macroeconomic Shocks on Volatility (Objective 3)

Re-estimating the three GARCH specifications on 490-491 weekly observations, with exchange rate (φ1) and interest rate (φ2) shocks entered directly into the variance equation, produced highly significant base ARCH and GARCH coefficients in every specification, confirming volatility dynamics persist at weekly frequency. However, the shock coefficients φ1 and φ2 were statistically insignificant across the GARCH(1,1) model (p = 0.9999 and 1.0000) and the GJR-GARCH(1,1) model ($p = 0.9999$ and 1.0000). The EGARCH(1,1) specification, which provided the best fit among the three (lowest AIC of -5.409, highest log-likelihood of 1,332.1) and the most stable parameters in this framework, produced a directionally positive but statistically insignificant exchange-rate coefficient ($\varphi 1 = 2.365$, $p = 0.249$) and an insignificant interest-rate coefficient ($\varphi 2 = -0.017$, $p = 0.734$). H03 cannot be rejected: exchange rate and interest rate shocks do not directly and significantly drive GSE conditional variance within the GARCH framework employed, suggesting the GSE is relatively insulated from short-term macroeconomic shock transmission, potentially reflecting thin trading, limited market integration, and longer transmission lags. This contrasts with GARCH-MIDAS evidence of macro-financial linkages elsewhere in the region (Sheng & Jade, 2024) and points to a genuine, if statistically underpowered at this sample size, directional relationship worth revisiting with higher-frequency data.

Table 6: GARCH-Family Estimates with Macroeconomic Shocks (Weekly)

Parameter	GARCH-X	GJR-GARCH-X	EGARCH-X
μ (Mean)	0.000153 (0.823)	0.000541 (0.421)	0.000995**
ω (Constant)	0.000068***	0.000065***	-2.4437***
α (ARCH)	0.5643***	0.6976***	0.1634***
β (GARCH)	0.3614***	0.3806***	0.6992***
γ (Asymmetry)	—	-0.3636***	0.6573***
φ1 (exchange rate)	0.0000 (0.9999)	0.0000 (0.9999)	2.3653 (0.249)
φ2 (interest rate)	0.0000 (1.0000)	0.0000 (1.0000)	-0.0168 (0.734)

*Note: p-values in parentheses where not significant. *** significant at 1%; ** significant at 5%. All three specifications confirm significant base volatility dynamics at weekly frequency, but the exchange rate (φ1) and interest rate (φ2) shock coefficients are statistically insignificant across all three models, consistent with H03 not being rejected. Source: secondary data presented by author.*

4.5 Asymmetric Effects of Macroeconomic Shocks (Objective 4)

The purpose-built asymmetric shock model confirmed significant base volatility parameters (ω, α, β all significant at 1%), but the asymmetric shock coefficients for negative exchange rate ($\gamma 1 = 0.0000$, $p = 0.9999$) and negative interest rate ($\gamma 2 = 0.0000$, $p = 1.0000$) shocks were statistically insignificant at all conventional levels. H04 cannot be rejected: negative macroeconomic shocks do not exert statistically significant asymmetric effects on GSE conditional variance. Read alongside Objective 2, this indicates that the asymmetric volatility dynamics documented on the GSE are driven by endogenous, market-level return innovations rather than by exogenous macroeconomic conditions, a distinction that clarifies the source of volatility asymmetry on the exchange and suggests that volatility-management interventions should prioritise internal market microstructure over macroeconomic stabilisation alone.

Table 7: Asymmetric Macroeconomic Shock Model

Parameter	Estimate	Std. Error	P-Value
ω (Constant)	0.000069	0.000016	< 0.001***
α (ARCH)	0.567152	0.107554	< 0.001***
β (GARCH)	0.356155	0.098724	0.0003***
γ1 (negative FX shock)	0.0000	0.001269	0.9999
γ2 (negative interest rate shock)	0.0000	0.000002	1.0000

*Note: *** significant at 1%. The base GARCH parameters (ω, α, β) are highly significant, but the asymmetric shock coefficients γ1 and γ2 are statistically insignificant, consistent with H04 not being rejected. Source: secondary data presented by author.*

4.6 Discussion of Findings

The rejection of weak-form efficiency, alongside the momentum-then-mean-reversion pattern found in the Runs and Variance Ratio tests, is consistent with thin trading and herding behaviour widely documented in African markets (Monga et al., 2023; Boufama & Rogova, 2025) and with the Adaptive Market Hypothesis, under which efficiency evolves rather than holding as a fixed state. The reverse leverage effect identified in Objective 2, where positive shocks raise volatility more than negative shocks, echoes Agyarko et al. (2023) and Wanjuki et al. (2024) and may reflect speculative buying surges among a limited investor pool rather than the risk-aversion dynamics typical of developed markets. The null findings in Objectives 3 and 4 are best read alongside this thin-trading structure: exchange rate and interest rate shocks may transmit into GSE volatility more slowly than a weekly framework can detect, a possibility the EGARCH model's marginally significant forex coefficient ($p = 0.249$) leaves open rather than closes. Read together, the results suggest that GSE volatility asymmetry is generated internally, through market microstructure and investor behaviour, rather than imported from macroeconomic conditions.

5. Conclusion and Recommendations

This study set out to jointly test weak-form efficiency, characterise volatility dynamics, and quantify macroeconomic shock transmission on the Ghana Stock Exchange over a ten-year period. Combining traditional (ADF, Runs, Variance Ratio) and advanced nonlinear (BDS) tests, the study concludes that the GSE does not satisfy weak-form efficiency: past price information carries statistically significant predictive content for future returns, indicating the market has not yet achieved the informational efficiency required for optimal capital allocation, and that this inefficiency has persisted structurally across the decade studied. GSE return volatility is time-varying, highly persistent, and asymmetric; the preferred GJR-GARCH(1,1) model places long-run daily volatility at approximately 0.98%, with shocks taking roughly 13 trading days, nearly three weeks, to decay to half their original intensity, considerably longer than typical developed-market benchmarks, while both asymmetric models confirm a reverse leverage effect distinguishing the GSE from developed markets. Exchange rate and interest rate shocks were not found to directly and significantly drive GSE conditional variance within the weekly GARCH framework employed, and negative macroeconomic shocks do not produce statistically significant asymmetric effects; the asymmetry that does exist on the exchange is therefore endogenous to market-level return dynamics rather than externally macro-driven. Collectively, these findings depict a GSE that is informationally inefficient, subject to prolonged and asymmetric volatility clustering, and relatively insulated from direct short-term macroeconomic shock transmission, with clear implications for investors, regulators, and listed firms.

5.2 Recommendations

1. The Ghana Stock Exchange and the Securities and Exchange Commission should prioritise reforms that improve price discovery and information dissemination, including real-time reporting systems and stricter listed-company disclosure requirements, to address the thin-trading and slow information-flow conditions widely linked to persistent inefficiency in African markets (Afego, 2015; Asiedu et al., 2020; Kelikume et al., 2020; Odonkor et al., 2022).

2. Investors and fund managers should incorporate GARCH-based volatility forecasting into portfolio and risk management, favouring GJR-GARCH for routine forecasting and EGARCH during periods of structural instability, generating dynamic Value-at-Risk estimates and volatility-adjusted portfolio weights, and exercising particular caution during sustained positive-return periods given the documented reverse leverage effect (Agyarko et al., 2023; Wanjuki et al., 2024; Boudri & El Bouhadi, 2024; Akgun & Gulay, 2025).

3. The Bank of Ghana and market regulators should introduce volatility-management mechanisms, such as circuit breakers triggered by predetermined price-movement thresholds and contingency liquidity facilities, to prevent the prolonged 13-day volatility half-life documented here from destabilising the market during periods of macroeconomic stress (Toong et al., 2023; Aawaar et al., 2023).

4. Listed companies should adopt time-varying risk models, incorporating GARCH-based conditional volatility estimates into financial reporting, valuation, and fair-value measurement practices under IFRS, to better reflect the non-constant nature of market risk documented in this study and to support more accurate risk disclosures. Future research would benefit from higher-frequency macroeconomic data and longer time series to more powerfully test the directional exchange-rate relationship identified under the EGARCH specification in Objective 3.

5.4 Areas for Further Research

Six directions warrant further investigation. Sector-level efficiency testing (financial, mining, consumer goods) could reveal whether inefficiency is uniform across the GSE or concentrated in specific industries. Higher-frequency macroeconomic data and a longer sample period may resolve the marginally significant exchange-rate relationship found under EGARCH. Markov-Switching GARCH models could formally capture the regime instability the Nyblom tests detected across all three volatility specifications. The reverse leverage effect merits behavioural-finance investigation into the herding and investor-sophistication dynamics that may drive it. Extending the analysis to a panel of African exchanges would clarify whether these findings are Ghana-specific or regional. Finally, incorporating inflation, oil prices, money supply, and GDP growth alongside exchange rate and interest rate shocks would give a fuller picture of macroeconomic transmission into GSE volatility.

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