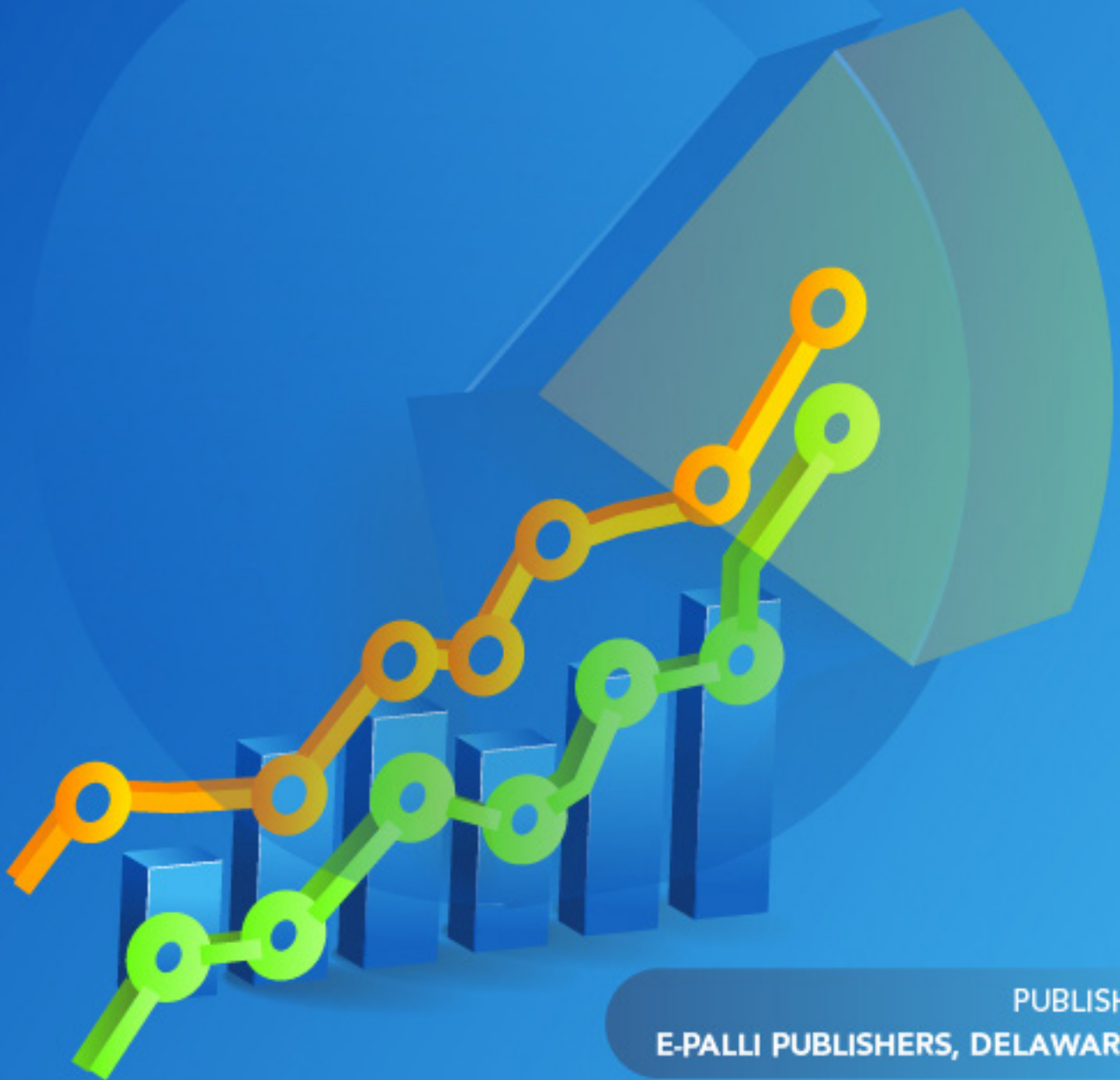




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Modeling and Forecasting the Ghanaian Cedi's Exchange Rate Volatility Against Major Global and Regional Currencies: Evidence from the Bank of Ghana Interbank Market

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ABSTRACT

This study models and forecasts the daily volatility of the Ghanaian cedi (GHS) against eight major and regional trading-partner currencies (the United States dollar, the pound sterling, the euro, the Swiss franc, the Japanese yen, the Chinese yuan, the South African rand, and the Nigerian naira) using symmetric GARCH (1,1) and asymmetric EGARCH (1,1) specifications from the generalized autoregressive conditional heteroskedasticity family. Daily interbank reference rates were taken from the Bank of Ghana's published historical interbank foreign-exchange records for 1 December 2025 to 8 September 2026 (189 dates, 186 usable daily log returns on a common sample). All eight-return series exhibited negative skewness and heavy tails (raw kurtosis between 6.6 and 22.8, against a normal benchmark of 3). Augmented Dickey–Fuller tests did not reject a unit root in the price levels at the 1% level for any currency and did not reject it at the 5% level for five of the eight; the euro, Swiss franc and yen levels rejected at 5% but not at 1%. Log returns were stationary for all eight currencies. The ARCH-LM test rejected the null of no ARCH effects at the 5% level for every series. In the GARCH (1,1) models the ARCH coefficient was significant at 5% for six of the eight currencies (not for the Swiss franc or the yen) and the GARCH coefficient was significant for none. Estimates lay at or on the boundary of the parameter space, with $\alpha + \beta$ equal to one for the dollar, pound, euro, yuan and naira and between 0.31 and 0.80 for the franc, yen and rand, so the fitted GARCH models behave like ARCH (1) processes. The EGARCH (1,1) specification had the lower Akaike Information Criterion (AIC) for all eight currencies, and the leverage parameter was negative and statistically significant for seven of the eight, indicating higher subsequent volatility after cedi-appreciation shocks than after cedi-depreciation shocks of equal size; because the eight series share the cedi leg and the largest shocks are common across pairs, this evidence rests on a small number of episodes. Residual diagnostics showed no significant remaining autocorrelation for the preferred models, with one borderline exception. Forecast accuracy was evaluated out of sample using one-step-ahead variance forecasts for the final 40 trading days, re-estimated on an expanding window and compared with historical-variance, exponentially weighted moving average and random-walk benchmarks. EGARCH (1,1) had the lowest QLIKE loss for seven of the eight currencies and significantly outperformed the historical-variance benchmark for the dollar, yuan, and naira, but historical variance or GARCH (1,1) had lower squared-error loss, and EGARCH (1,1) produced occasional extreme forecasts, so its forecasting advantage is not robust. The short estimation sample is an important limitation: the Bank of Ghana page offers a much longer history (at least for the US dollar), and extending the sample is the main priority for future work.

INTRODUCTION

Ghana operates a managed floating exchange rate regime administered through the Bank of Ghana's (BoG) daily interbank foreign-exchange fixing. Over the past decade the cedi has experienced episodes of sharp depreciation against major international currencies, driven by external shocks (commodity price swings, global monetary tightening), fiscal and debt pressures, and periods of import-driven demand for foreign currency. Ghana's 2023 IMF-supported Extended Credit Facility programme, alongside subsequent debt restructuring, placed renewed emphasis on exchange-rate stability as a precondition for disinflation and macro-fiscal consolidation. Because the cedi's value against the currencies of Ghana's principal trading partners; the United States, the United Kingdom, the Eurozone, China, South Africa, and neighbouring Nigeria has direct consequences for imported inflation, external debt servicing, trade competitiveness, and investor

confidence, an accurate, up-to-date characterization of its short-run volatility dynamics is of practical importance to the central bank, commercial banks active in the interbank market, importers and exporters, and portfolio investors. This study models and forecasts the daily volatility of the cedi against eight currencies chosen to reflect Ghana's principal trade and financial relationships: the US dollar (Ghana's dominant invoicing and reserve currency), the pound sterling and the euro (historical and current European trade and financial links), the Swiss franc and Japanese yen (included, as in comparable exchange-rate volatility studies, as low-volatility 'safe-haven' benchmarks), the Chinese yuan (Ghana's largest single source of imports and a growing bilateral trade and loan-financing partner), the South African rand (a major African financial-market peer), and the Nigerian naira (Ghana's principal ECOWAS trading partner). Using data drawn directly from the Bank of Ghana's

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own published interbank rate records, the study applies both symmetric GARCH (1,1) and asymmetric EGARCH (1,1) specifications to investigate volatility clustering, persistence, and leverage (asymmetric) effects, and evaluates out-of-sample one-step-ahead variance forecasts against simple benchmark models.

LITERATURE REVIEW

The generalized autoregressive conditional heteroskedasticity (GARCH) framework, introduced by Engle (1982) as the autoregressive conditional heteroskedastic (ARCH) model and extended by Bollerslev (1986) to GARCH (p, q), remains the standard tool for modeling the volatility clustering that characterizes most financial and foreign-exchange return series. Nelson (1991) proposed the Exponential GARCH (EGARCH) model to additionally capture the asymmetric response of volatility to positive and negative shocks the so-called leverage effect which the symmetric GARCH specification, by construction, cannot represent because lagged shocks enter the variance equation only in squared form.

Several studies have applied the GARCH family specifically to the Ghana cedi-US dollar exchange rate. Techie Quaicoe, Twenefour, Baah and Nortey (2015), using monthly data, examined a range of ARCH/GARCH-type specifications including ARMA, GARCH, IGARCH, EGARCH and multivariate GARCH for the cedi/dollar exchange rate, confirmed the presence of significant ARCH effects via the Box-Ljung test on squared returns and residuals, and found an ARMA(1,1)-GARCH(1,1) specification to be the most adequate representation of the conditional mean and variance, subsequently using the fitted model to forecast the exchange rate over a 24-month horizon. Yusif, Baidoo and Hanson (2023) applied an EGARCH-in-mean (EGARCH-M) model to monthly cedi exchange-rate data from January 1990 to May 2019 to examine the effect of currency substitution on volatility, finding a significant positive relationship between currency substitution and exchange-rate volatility together with evidence of a genuine leverage effect, in which negative shocks were found to raise volatility by more than positive shocks of equal size. Yussif, Onifade, Ay, Canitez and Bekun (2024) used GARCH and EGARCH specifications, together with a multivariate BEKK-GARCH extension, to examine the relationship between exchange-rate volatility and Ghana's international trade flows, while Ofori, Obeng and Armah (2018) examined the effect of cedi exchange-rate volatility on domestic tax revenue using a GARCH-based volatility measure.

Across this literature, three stylized facts recur: (i) exchange-rate returns in Ghana display significant departures from normality (skewness and excess kurtosis); (ii) conditional variance exhibits strong persistence, often close to or exceeding the covariance-stationarity boundary ($\alpha + \beta \approx 1$); and (iii) asymmetric GARCH-family models, principally EGARCH, are often

found to fit Ghanaian exchange-rate data at least as well as symmetric GARCH, with some studies reporting evidence of a leverage effect. The present study extends this literature in two respects: first, by using the highest-frequency data publicly available from the Bank of Ghana itself (daily, rather than monthly, interbank rates); and second, by examining the cedi against a broader basket of eight currencies — including two currencies, the yuan and the naira, that reflect Ghana's most important and fastest-growing bilateral trade relationships but have received comparatively little attention in the existing cedi-volatility literature.

MATERIAL AND METHODS

Data

Daily interbank foreign-exchange reference rates were obtained directly from the Bank of Ghana's published historical interbank FX rate records (Bank of Ghana, Treasury and the Markets). The mid-rate (the average of the daily buying and selling quotations) was used for each currency pair. Eight currency pairs against the cedi were selected: the US dollar (USDGHS), pound sterling (GBPGHS), euro (EURGHS), Swiss franc (CHFGHS), Japanese yen (JPYGHS), Chinese yuan (CNYGHS), South African rand (ZARGHS), and the Nigerian naira. Because the Bank of Ghana quotes the naira as GHSNGN (naira per cedi), the series was inverted to GHS per naira so that all eight series are expressed in the common direction of cedi units per one unit of foreign currency, consistent with the other seven pairs. The data span 1 December 2025 to 8 September 2026, comprising 189 trading days; one date (1 September 2026) had incomplete quotations for several currencies (the euro, yen, yuan, rand and naira, among others) and was treated as missing. Because the returns on 1 and 2 September 2026 cannot be computed for those series, both were dropped for all eight series so that the sample is common, leaving 186 usable daily log-return observations per series (2 December 2025 to 8 September 2026). This is the extract of the Bank of Ghana records used in this study; it is not the full archive. The Bank of Ghana's historical interbank rate page displays US dollar observations from January 1996, so the short span reflects the extract analysed here and not a limit of the Bank's archive. Mid-rates are published to four decimal places; for the yen (about 0.07 cedi per yen) this rounding makes about 11% of daily returns exactly zero, so yen volatility estimates should be read with this in mind.

Volatility Measurement and Return Computation

Following standard practice in the exchange-rate volatility literature (e.g. Strong, 1992), logarithmic returns are used throughout, computed as

$$r_t = \ln \frac{P_t}{P_{t-1}}$$

where P_t is the mid exchange rate (cedis per unit of foreign currency) on trading day t . Logarithmic returns

are analytically convenient for compounding over sub-periods and are, empirically, more likely to approximate normality than simple percentage changes, though as shown in Section 4.1 the return series examined here nonetheless display material departures from normality.

Testing for ARCH Effects

Before fitting any GARCH-family model, the residuals of a constant-mean equation for each return series were tested for autoregressive conditional heteroskedasticity using the Lagrange Multiplier (LM) test of Engle (1982), which regresses the squared residuals on their own lags and tests the joint significance of the lagged coefficients via the statistic $T \cdot R^2$, distributed asymptotically as $\chi^2(q)$ under the null of no ARCH effects up to lag q . Five lags were used.

GARCH (1,1) and EGARCH (1,1) Specifications

The symmetric GARCH (1,1) model of Bollerslev (1986) specifies the conditional variance as

$$\sigma_t^2 = \omega + \alpha \cdot \varepsilon_{t-1}^2 + \beta \cdot \sigma_{t-1}^2, \quad \omega > 0, \alpha \geq 0, \beta \geq 0$$

where $\varepsilon_t = \sigma_t^{-1} \cdot Z_t$ and Z_t is an independently and identically distributed innovation with mean zero and unit variance. The sum $\alpha + \beta$ measures the persistence of shocks to volatility; values close to or exceeding unity indicate that shocks decay very slowly (or, if $\alpha + \beta > 1$, that the implied unconditional variance process is not covariance-stationary).

Because the symmetric GARCH specification restricts positive and negative shocks of equal magnitude to have an identical effect on future variance, the Exponential GARCH (EGARCH) model of Nelson (1991) is additionally estimated to allow for an asymmetric (leverage) response:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \alpha \cdot [|Z_{t-1}| - E|Z_{t-1}|] + \gamma \cdot Z_{t-1}$$

where,

$$Z_{t-1} = \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

is the standardized residual. A negative and statistically significant γ indicates a genuine leverage effect: because $\gamma \cdot Z_{(t-1)}$ is positive when $Z_{(t-1)}$ is negative and negative when $Z_{(t-1)}$ is positive, a negative shock raises next-period conditional variance by more than a positive shock of equal size.

For each of the eight-currency series, the conditional-mean equation was first screened for residual autocorrelation; where the sample autocorrelation and partial autocorrelation functions of a constant-mean model's residuals indicated remaining structure, a first-order autoregressive, AR (1), mean equation was used instead. Both GARCH (1,1) and EGARCH (1,1) variance equations were then estimated by maximum likelihood under the normal distribution, using the same mean-equation specification for each currency, and the two variance specifications were compared using the Akaike Information Criterion (AIC).

Diagnostics, Model Selection and Forecasting

Model adequacy was assessed using the Ljung–Box Q-statistic applied to the standardized residuals and to the squared standardized residuals (10 lags), testing for any remaining autocorrelation in the conditional mean and conditional variance respectively. The variance specification with the lower AIC was identified for each currency. Forecast accuracy was then evaluated out of sample. The last 40 daily returns (13 July to 8 September 2026) were withheld from initial estimation. For each held-out day t , GARCH (1,1) and EGARCH (1,1) were re-estimated on all returns up to day $t - 1$ (an expanding window) and used to produce a one-step-ahead conditional-variance forecast (analytic at horizon one for both models). Because the true variance is unobserved, the squared deviation of the realised return from the expanding-sample mean was used as the variance proxy. Forecasts were compared with three benchmarks: the expanding-window historical variance; an exponentially weighted moving average (EWMA) with decay factor 0.94 (J.P. Morgan/Reuters, 1996), initialised on the first 30 returns; and a random-walk forecast equal to the previous day's squared deviation. Accuracy was measured by the QLIKE loss, $\ln h + \text{proxy}/h$, which is robust to noise in the variance proxy (Patton, 2011), and by the mean squared error (MSE) of the variance forecast. Differences in loss between pairs of models were tested with the Diebold–Mariano test (Diebold & Mariano, 1995) using the small-sample correction of Harvey, Leybourne and Newbold (1997).

RESULTS AND DISCUSSION

Descriptive Statistics

Table 1 reports descriptive statistics for the eight daily log-return series. All eight currencies exhibit negative skewness, indicating a longer left tail; that is, occasional large negative returns (sharp cedi appreciations against the relevant currency) are somewhat more extreme in the sample than the corresponding positive returns. Every series displays heavy tails: the kurtosis reported in Table 1 is the raw (not excess) measure, for which the normal benchmark is 3, and it ranges from 6.58 for the rand to 22.81 for the dollar (excess kurtosis of 3.58 to 19.81). This confirms leptokurtic, fat-tailed return distributions, a well-documented stylised fact of financial and foreign-exchange return series that motivates the use of conditional heteroskedasticity models. The extreme observations are concentrated: the largest negative return in every series (between about -4.0% and -4.5%) falls on one of two dates, 29 December 2025 (dollar, yen, rand) or 11 June 2026 (pound, euro, franc, yuan, naira), and each series has four or five daily moves larger than 3% in absolute value. Because all eight pairs share the cedi as one leg, these shocks are largely common across the series. Average daily returns are close to zero for all series, with standard deviations that are, in every case, at least an order of magnitude larger than the corresponding mean, indicating, as is typical of short-horizon financial returns,

that daily mean returns are not statistically distinguishable from zero and that volatility, not drift, dominates the day-to-day behaviour of the series.

Table 1: Descriptive Statistics of Daily Log-Return Series (1 Dec 2025 – 8 Sep 2026, $n = 186$)

Currency	Mean	Min.	Max.	Std. Dev.	Skewness	Kurtosis (normal = 3)
US Dollar	0.000014	-0.041385	0.009479	0.006801	-4.2984	22.8063
Pound Sterling	0.000153	-0.044185	0.016126	0.007989	-2.8525	14.4872
Euro	0.000023	-0.043752	0.015400	0.007787	-3.0454	15.5052
Swiss Franc	-0.000002	-0.042963	0.021737	0.008500	-2.1629	11.6292
Japanese Yen	0.000020	-0.042987	0.029068	0.008922	-1.5894	10.7698
Chinese Yuan	0.000295	-0.039970	0.007722	0.006744	-4.1371	22.3582
South African Rand	0.000346	-0.044793	0.032765	0.010118	-1.0812	6.5790
Nigerian Naira	0.000463	-0.040468	0.021118	0.007985	-2.4713	12.4312

Note: All series are computed as $r_t = \ln P_t / P_{(t-1)}$ where P_t is cedis per unit of foreign currency. Kurtosis benchmark for a normal distribution is 3.

Stationarity Test

Table 2 reports Augmented Dickey–Fuller (ADF) unit-root test results for both the price levels and the log-return series (constant included; lag length chosen by AIC). For the price levels, the ADF statistic does not reject the unit-root null at the 1% level for any of the eight currencies. At the 5% level it fails to reject for five currencies (dollar, pound, yuan, rand and naira) but rejects for the euro ($p = 0.0280$), the Swiss franc ($p = 0.0271$) and the yen ($p = 0.0336$). The evidence that exchange-rate levels are non-stationary is therefore clear for five currencies and mixed

for the euro, franc and yen, where the conclusion depends on the significance level. Given the low power of the ADF test in a sample of fewer than 190 observations, and since no level series rejects at 1%, the levels are treated as integrated of order one for modelling purposes, but this is not established for those three currencies. By contrast, the ADF test strongly rejects the unit-root null for every log-return series ($p < 0.0001$ in all eight cases), so the return series are stationary and appropriate for GARCH-family modeling.

Table 2: Augmented Dickey–Fuller Unit-Root Test: Price Levels and Log Returns

Currency	ADF (Level)	p-value	1% Crit.	ADF (Return)	p-value
US Dollar	-2.335	0.1609	-3.466	-8.232	0.0000
Pound Sterling	-2.718	0.0709	-3.466	-8.572	0.0000
Euro	-3.081	0.0280	-3.466	-8.927	0.0000
Swiss Franc	-3.092	0.0271	-3.466	-9.782	0.0000
Japanese Yen	-3.014	0.0336	-3.466	-9.772	0.0000
Chinese Yuan	-1.583	0.4920	-3.466	-8.223	0.0000
South African Rand	-2.391	0.1442	-3.466	-11.769	0.0000
Nigerian Naira	-1.599	0.4839	-3.466	-8.650	0.0000

Heteroscedasticity Test

Before fitting the GARCH-family models, the residuals of a constant-mean equation for each return series were tested for ARCH effects using the Engle (1982) LM test with five lags. Table 3 shows that the null hypothesis of no ARCH effects is rejected at the 5% level for all eight currencies, with the dollar ($LM = 32.95$) and the

yuan ($LM = 33.56$) showing the strongest evidence of conditional heteroskedasticity and the rand the weakest, though still significant ($LM = 11.52$, $p = 0.0419$). This confirms the presence of volatility clustering in every series and justifies the application of the GARCH and EGARCH specifications that follow.

Table 3: ARCH-LM Test for Residual Heteroskedasticity (5 lags)

Currency	ARCH-LM Statistic (5 lags)	p-value
US Dollar	32.9480	0.0000
Pound Sterling	24.3536	0.0002
Euro	25.4277	0.0001
Swiss Franc	24.1503	0.0002
Japanese Yen	14.5470	0.0125
Chinese Yuan	33.5579	0.0000
South African Rand	11.5236	0.0419
Nigerian Naira	28.0342	0.0000

GARCH (1,1) Estimation Results

Table 4 presents the estimated GARCH (1,1) parameters for each currency, together with the mean-equation specification used (a first-order autoregressive mean, AR (1), was used for the dollar and the naira to remove residual autocorrelation; a constant mean was used for the remaining six series). The ARCH coefficient (α) is statistically significant at the 5% level for six of the eight currencies (dollar, pound, euro, yuan, rand and naira), but not for the Swiss franc ($p = 0.0766$) or the yen ($p = 0.2472$). The GARCH coefficient (β) is not statistically significant at the 5% level for any of the eight currencies: it is estimated at exactly zero ($p = 1.0000$) for the dollar, pound, euro, Swiss franc, yen and rand, at 0.0447 ($p = 0.1999$) for the yuan, and at 0.0581 ($p = 0.4405$) for the naira. The fitted GARCH (1,1) models therefore collapse to ARCH (1)-type processes in which all of the measured persistence is carried by α . The persistence parameter $\alpha + \beta$ equals one in the dollar, pound, euro, yuan and naira

models (with $\alpha = 1.0000$ for the dollar, pound and euro, so the variance-stationarity constraint is binding). This is the IGARCH boundary and not evidence of an explosive process. For the Swiss franc (0.800), yen (0.770) and rand (0.307), $\alpha + \beta$ is below one, but because β is zero and α is itself insignificant for the franc and yen, these values should not be read as precisely estimated speeds of mean reversion. Because many estimates lie on the boundary of the parameter space, the usual asymptotic p-values are unreliable and the significance statements above are indicative only. The ARCH-LM test in Table 3 rejects homoskedasticity for the franc and yen even though α is not significant in their GARCH (1,1) fits, which suggests that the short sample carries only weak information about the exact form of the variance dynamics. The boundary estimates and the insignificant β are consistent with the short estimation sample (186 daily observations), which is discussed as a limitation in Section 5.

Table 4: Estimated GARCH (1,1) Models for the Daily Return Series

Model / Parameter	Coefficient	p-value
US Dollar: AR (1)-GARCH (1,1) AIC = 53.077		
ω (omega)	0.01806	0.0005*
α (ARCH)	1.00000	0.0010*
β (GARCH)	0.00000	1.0000
$\alpha + \beta = 1.0000$		
Pound Sterling: Constant-GARCH (1,1) AIC = 361.911		
ω (omega)	0.20844	0.0107*
α (ARCH)	1.00000	0.0326*
β (GARCH)	0.00000	1.0000
$\alpha + \beta = 1.0000$		
Euro: Constant-GARCH (1,1) AIC = 330.869		
ω (omega)	0.16589	0.0000*
α (ARCH)	1.00000	0.0264*
β (GARCH)	0.00000	1.0000
$\alpha + \beta = 1.0000$		

Swiss Franc: Constant-GARCH (1,1) AIC = 407.938		
ω (omega)	0.29236	0.0000*
α (ARCH)	0.80043	0.0766
β (GARCH)	0.00000	1.0000
$\alpha + \beta = 0.8004$		
Japanese Yen: Constant-GARCH (1,1) AIC = 448.992		
ω (omega)	0.39351	0.0395*
α (ARCH)	0.77009	0.2472
β (GARCH)	0.00000	1.0000
$\alpha + \beta = 0.7701$		
Chinese Yuan: Constant-GARCH (1,1) AIC = 165.201		
ω (omega)	0.03875	0.0000*
α (ARCH)	0.95530	0.0042*
β (GARCH)	0.04470	0.1999
$\alpha + \beta = 1.0000$		
South African Rand: Constant-GARCH (1,1) AIC = 517.974		
ω (omega)	0.69944	0.0004*
α (ARCH)	0.30666	0.0012*
β (GARCH)	0.00000	1.0000
$\alpha + \beta = 0.3067$		
Nigerian Naira: AR (1)-GARCH (1,1) AIC = 318.593		
ω (omega)	0.10464	0.0370*
α (ARCH)	0.94187	0.0310*
β (GARCH)	0.05813	0.4405
$\alpha + \beta = 1.0000$		

Note: Coefficients are estimated on returns scaled $\times 100$ for numerical stability; ω is reported on that scale. * denotes significance at the 5% level. Several estimates lie on the boundary of the parameter space ($\alpha = 1$ or $\beta = 0$), where the usual asymptotic p-values are unreliable and should be read as indicative only.

EGARCH (1,1) Estimation Results

Table 5 presents the estimated EGARCH (1,1) parameters. The ARCH coefficient (α) is positive and statistically significant for six of the eight currencies (all except the yen and the rand, where $p > 0.05$). The GARCH coefficient (β) is significant at the 5% level for five of the eight currencies (dollar, Swiss franc, yuan, rand and naira), compared with none in the GARCH (1,1) models, and is estimated at the zero boundary for the pound. More notably, the leverage coefficient (γ) is negative for all eight currencies and statistically significant at the 5% level for seven of the eight (all except the pound sterling, where $p = 0.0601$, marginally short of conventional significance). Because the return series are expressed as cedis per unit of foreign currency, a negative return corresponds to a day on which the cedi strengthened (appreciated) against that currency, while a positive return corresponds to a day on which the cedi weakened (depreciated). A negative and significant γ therefore implies that cedi-appreciation shocks are followed by higher subsequent

conditional volatility than cedi-depreciation shocks of the same magnitude. Prior monthly-frequency studies of the cedi, such as Yusif, Baidoo and Hanson (2023), also report asymmetric volatility responses, but the sampling frequency, sample period and sign convention for ‘negative shocks’ differ, so the results are not directly comparable. Two cautions apply. First, all eight series share the cedi leg, and the largest negative returns fall on only two dates (29 December 2025 and 11 June 2026), so the seven significant leverage estimates are not seven independent pieces of evidence and may be driven by a small number of episodes. Second, one possible explanation, consistent with the managed, interbank-fixing nature of the Ghanaian market, is that sharp cedi appreciations coincide with central-bank or interbank-market corrections that are followed by continued elevated volatility as the market reprices, whereas gradual depreciation is comparatively orderly. This is a conjecture that the present study has not tested.

Table 5: Estimated EGARCH (1,1) Models for the Daily Return Series

Model / Parameter	Coefficient	p-value
US Dollar: AR (1)-EGARCH (1,1) AIC = -19.568		
ω (omega)	-0.80319	0.0033*
α (ARCH)	1.35076	0.0000*
γ (leverage)	-0.67794	0.0000*
β (GARCH)	0.68284	0.0000*
Pound Sterling: Constant-EGARCH (1,1) AIC = 333.538		
ω (omega)	-1.08468	0.0093*
α (ARCH)	0.82118	0.0249*
γ (leverage)	-0.55238	0.0601
β (GARCH)	0.00000	1.0000
Euro: Constant-EGARCH(1,1) AIC = 307.648		
ω (omega)	-0.99962	0.0001*
α (ARCH)	0.85175	0.0477*
γ (leverage)	-0.64838	0.0034*
β (GARCH)	0.11647	0.2411
Swiss Franc: Constant-EGARCH (1,1) AIC = 395.218		
ω (omega)	-0.28340	0.2109
α (ARCH)	0.43159	0.0017*
γ (leverage)	-0.43748	0.0015*
β (GARCH)	0.59088	0.0408*
Japanese Yen: Constant-EGARCH (1,1) AIC = 426.490		
ω (omega)	-0.42667	0.0514
α (ARCH)	0.37438	0.0932
γ (leverage)	-0.59141	0.0000*
β (GARCH)	0.22909	0.2878
Chinese Yuan: Constant-EGARCH (1,1) AIC = 105.496		
ω (omega)	-1.01106	0.0001*
α (ARCH)	1.23343	0.0000*
γ (leverage)	-0.65454	0.0000*
β (GARCH)	0.52320	0.0000*
South African Rand: Constant-EGARCH (1,1) AIC = 505.210		
ω (omega)	-0.09057	0.2516
α (ARCH)	-0.07158	0.7570
γ (leverage)	-0.50126	0.0000*
β (GARCH)	0.49830	0.0005*
Nigerian Naira: AR (1)-EGARCH (1,1) AIC = 292.950		
ω (omega)	-0.39182	0.0582
α (ARCH)	1.18579	0.0000*
γ (leverage)	-0.47388	0.0096*
β (GARCH)	0.67642	0.0000*

Note: γ is the leverage (asymmetry) coefficient; a negative and significant γ indicates that negative return shocks (cedi appreciation) raise subsequent conditional variance by more than positive shocks of equal size. * Denotes significance at the 5% level.

Diagnostic Checking

Table 6 reports Ljung–Box Q-statistic p-values (10 lags) for the standardized residuals and squared standardized residuals of both the GARCH (1,1) and EGARCH (1,1) fitted models. For the EGARCH (1,1) models, no significant remaining autocorrelation is found in either the standardized or squared standardized residuals for seven of the eight currencies (all p-values exceed 0.05); the sole exception is the Swiss franc, whose squared standardized residuals show borderline remaining structure ($p = 0.0452$). With 16 EGARCH tests, one borderline rejection at 5% is not unexpected by chance, but it suggests that a higher-order or alternative asymmetric specification

could be explored for this series. For the GARCH (1,1) models, only the dollar displays statistically significant remaining autocorrelation in the standardized residuals ($p = 0.0258$), even after adopting an AR (1) mean equation; the naira's GARCH standardized residuals show no significant autocorrelation ($p = 0.4952$). The EGARCH (1,1) specification for the dollar passes both diagnostic checks. The diagnostics therefore give modest support to EGARCH (1,1) over GARCH (1,1) for the dollar and are otherwise similar across the two specifications, so the AIC comparison below is the main in-sample basis for preferring EGARCH (1,1).

Table 6: Ljung–Box Q(10) Diagnostic Test p-values on Standardized Residuals

Currency	GARCH Std. Resid.	GARCH Sq. Std. Resid.	EGARCH Std. Resid.	EGARCH Sq. Std. Resid.
US Dollar	0.0258	0.9921	0.1746	0.8222
Pound Sterling	0.4786	0.8031	0.6500	0.6621
Euro	0.3933	0.8307	0.5386	0.3755
Swiss Franc	0.5889	0.1474	0.7423	0.0452
Japanese Yen	0.2618	0.6340	0.3300	0.7200
Chinese Yuan	0.1288	0.9986	0.2221	0.8638
South African Rand	0.8934	0.8643	0.9482	0.9203
Nigerian Naira	0.4952	0.9427	0.7627	0.9240

Model Selection

Table 7 compares the GARCH (1,1) and EGARCH (1,1) specifications by AIC for each currency. The EGARCH (1,1) specification has the lower AIC for all eight currencies, in several cases by a substantial margin (for example, the dollar's AIC falls from 53.08 under GARCH (1,1) to -19.57 under EGARCH (1,1), and the yuan from 165.20 to 105.50). This is consistent with the leverage coefficients in Section 4.5: over this sample, allowing volatility to respond asymmetrically to the direction of

exchange-rate shocks improves in-sample fit relative to the symmetric specification. Two cautions apply. The AIC differences are partly driven by a few extreme appreciation days that are common to all pairs, and the out-of-sample results in Section 4.8 do not uniformly confirm the preference for EGARCH (1,1). The AIC comparison is also not a test of whether the asymmetry term is needed; that is addressed by the significance of γ in Table 5.

Table 7: AIC Comparison: GARCH (1,1) versus EGARCH (1,1)

Currency	GARCH (1,1) AIC	EGARCH (1,1) AIC	Preferred Model
US Dollar	53.077	-19.568	EGARCH (1,1)
Pound Sterling	361.911	333.538	EGARCH (1,1)
Euro	330.869	307.648	EGARCH (1,1)
Swiss Franc	407.938	395.218	EGARCH (1,1)
Japanese Yen	448.992	426.490	EGARCH (1,1)
Chinese Yuan	165.201	105.496	EGARCH (1,1)
South African Rand	517.974	505.210	EGARCH (1,1)
Nigerian Naira	318.593	292.950	EGARCH (1,1)

Out-of-Sample Volatility Forecast Evaluation

Out-of-sample accuracy was assessed with the design described in Section 3.5: the last 40 returns (13 July to 8 September 2026, about 22% of the sample) were held out, and each model was re-estimated daily on an expanding window and used to forecast the next day's conditional variance. Variances in this section are in squared percent because returns were scaled by 100. Table 8 reports average QLIKE loss. EGARCH (1,1) has the lowest QLIKE loss for seven of the eight currencies; the exception is the yen, where the historical-variance benchmark is lowest. GARCH (1,1) also has lower QLIKE loss than the historical-variance benchmark for

the same seven currencies. The random-walk forecast is by far the worst (it forecasts near-zero variance after quiet days), and EWMA is worse than EGARCH (1,1) for every currency. Table 10 shows that the QLIKE advantage of EGARCH (1,1) over historical variance is statistically significant at the 5% level only for the dollar ($p = 0.007$), yuan ($p = 0.002$) and naira ($p = 0.002$), with the euro significant only at 10% ($p = 0.098$). GARCH (1,1) does not significantly beat historical variance for any currency at 5% (naira $p = 0.072$), and EGARCH (1,1) is significantly better than GARCH (1,1) under QLIKE only for the pound ($p = 0.037$) and Swiss franc ($p = 0.034$).

Table 8: Out-of-Sample One-Step-Ahead Variance Forecasts: Mean QLIKE Loss, Last 40 Trading Days (lower is better; best model in bold)

Currency	GARCH (1,1)	EGARCH (1,1)	Hist. variance	EWMA (0.94)	Random walk
US Dollar	0.137	-1.426	0.657	1.767	370.1
Pound Sterling	0.314	0.143	0.774	1.095	10.884
Euro	0.273	0.060	0.769	1.134	38.548
Swiss Franc	0.826	0.525	1.031	1.223	12.903
Japanese Yen	1.563	1.303	1.255	1.487	56.295
Chinese Yuan	-0.258	-1.097	0.702	1.591	66.658
South African Rand	0.926	0.871	1.088	1.177	46.522
Nigerian Naira	-0.292	-0.513	0.578	1.348	136.0

Table 9: Out-of-Sample One-Step-Ahead Variance Forecasts: Mean Squared Error of the Variance Forecast, Last 40 Trading Days (lower is better; best model in bold)

Currency	GARCH (1,1)	EGARCH (1,1)	Hist. variance	EWMA (0.94)	Random walk
US Dollar	4.893	10.439	6.070	6.236	6.230
Pound Sterling	7.725	32.194	6.477	6.680	6.965
Euro	7.529	1413.8	6.351	6.535	6.807
Swiss Franc	8.847	16.849	7.354	7.532	8.623
Japanese Yen	12.126	17.995	8.570	8.754	12.015
Chinese Yuan	7.045	17.228	6.193	6.351	6.351
South African Rand	6.104	6.460	6.698	6.934	8.780
Nigerian Naira	3.689	415.7	5.453	5.619	5.669

The picture is different under squared-error loss (Table 9). Historical variance has the lowest MSE for the pound, euro, franc, yen and yuan, GARCH (1,1) for the dollar, rand and naira, and EGARCH (1,1) for none. The MSE of EGARCH (1,1) is especially large for the euro (1413.8) and the naira (415.7), driven by a few days on which the model forecast variances far above any realised value (maximum EGARCH forecasts of 249 for the euro and 138 for the naira, against maximum realised variance proxies of about 12 and 11). No MSE difference in Table 10 is statistically significant (all $p > 0.3$). Overall,

EGARCH (1,1) improves on the simple benchmarks when losses are judged by QLIKE, which penalises under-prediction heavily, but the advantage is neither uniform nor robust: it is statistically significant for three of eight currencies, it is not confirmed under MSE, and it comes with unstable forecasts after large shocks. With only 40 out-of-sample observations per currency, and with the eight series sharing the same cedi leg, the power of these comparisons is low, so the results are indicative and not conclusive.

Table 10: Diebold–Mariano Tests of Equal Forecast Accuracy (test statistic, with two-sided p-value in parentheses)

Currency	QLIKE: GARCH vs Hist.	QLIKE: EGARCH vs Hist.	QLIKE: EGARCH vs GARCH	MSE: GARCH vs Hist.	MSE: EGARCH vs Hist.	MSE: EGARCH vs GARCH
US Dollar	-0.40 (0.694)	-2.84 (0.007)	-0.97 (0.337)	-0.36 (0.721)	1.02 (0.314)	0.78 (0.441)
Pound Sterling	-1.02 (0.315)	-1.50 (0.141)	-2.17 (0.037)	0.24 (0.812)	1.00 (0.324)	0.84 (0.405)
Euro	-0.99 (0.329)	-1.69 (0.098)	-1.61 (0.115)	0.24 (0.810)	0.99 (0.330)	0.98 (0.331)
Swiss Franc	-0.50 (0.618)	-1.39 (0.172)	-2.19 (0.034)	0.29 (0.770)	0.97 (0.336)	0.60 (0.554)
Japanese Yen	0.57 (0.572)	0.10 (0.920)	-1.45 (0.154)	0.64 (0.525)	1.02 (0.312)	0.45 (0.656)
Chinese Yuan	-1.08 (0.288)	-3.25 (0.002)	-1.04 (0.305)	0.18 (0.858)	1.00 (0.324)	0.71 (0.482)
South African Rand	-0.73 (0.467)	-1.17 (0.249)	-0.67 (0.506)	-0.38 (0.703)	-0.27 (0.790)	0.51 (0.610)
Nigerian Naira	-1.85 (0.072)	-3.30 (0.002)	-1.03 (0.311)	-0.74 (0.466)	1.00 (0.322)	1.00 (0.322)

Note: Statistics use the Harvey–Leybourne–Newbold small-sample correction and are compared with a t distribution with 39 degrees of freedom. A negative statistic means the first-named model has the lower average loss. Hist. = expanding-window historical variance.

CONCLUSION

This study modeled and forecasted the daily volatility of the Ghanaian cedi against eight major and regional trading-partner currencies using daily interbank data from the Bank of Ghana. All eight return series displayed negative skewness and heavy tails, and all eight rejected the null hypothesis of no ARCH effects at the 5% level, supporting the use of GARCH-family models. ADF tests did not reject a unit root in the price levels at the 1% level for any currency and did not reject it at 5% for five of the eight, while the euro, Swiss franc and yen levels rejected at 5% but not at 1%; log returns were stationary throughout. In the GARCH (1,1) models the ARCH coefficient was significant for six of the eight currencies (not the franc or yen), the GARCH coefficient was significant for none, and estimates lay at or near the boundary of the parameter space, with $\alpha + \beta$ equal to one for the dollar, pound, euro, yuan and naira; these fits behave like ARCH (1) models. The EGARCH (1,1) specification was preferred by AIC for all eight currencies and produced negative leverage coefficients, significant at 5% for seven of the eight, consistent with higher volatility after cedi-appreciation shocks than after cedi-depreciation shocks of equal size. Because the eight series share the cedi leg and the largest appreciation moves coincide across pairs, this is better viewed as evidence from a small number of episodes than as seven independent confirmations. Diagnostic tests found no remaining autocorrelation for seven of the eight preferred EGARCH (1,1) models, with borderline structure in the squared standardized residuals of the Swiss franc. In out-of-sample one-step-ahead comparisons over the last 40 trading days, EGARCH (1,1) had the lowest QLIKE loss for seven of the eight currencies and significantly outperformed the historical-

variance benchmark for the dollar, yuan and naira, but historical variance or GARCH (1,1) had lower squared-error loss and EGARCH (1,1) produced occasional extreme forecasts. Its forecasting advantage is therefore suggestive and not established.

Three limitations were observed. First, and most importantly, the estimation sample used for the study spans from 1 December 2025 to 8 September 2026, or 186 usable daily return observations reflecting an extract of Bank of Ghana records and not a limit of the Bank's archive. BoG historical interbank page displays US dollar and all other currency observations from January 1996 and extended sample would need to deal with the 2007 redenomination of the cedi (the 1996 quotations are in old cedis) and with changes in the quotation regime. The short sample contributed to the insignificant GARCH coefficients, the boundary estimates and the near-unit persistence reported in Section 4.4, and to the low power of the out-of-sample comparison, which rests on only 40 observations per currency. Second, the study is univariate, and because every series is a cedi cross-rate the eight series share one currency leg and are not independent, so counts such as seven of eight overstate the independent evidence. Volatility spillovers, for example between the dollar leg and the naira leg of the cedi–naira cross rate, are not modeled. Third, the out-of-sample evaluation uses a squared-return proxy for the unobserved variance, a single one-day horizon and a limited set of benchmarks; longer horizons and richer alternatives (for example, heavy-tailed innovations, GJR-GARCH or realised-volatility measures) were not examined.

Notwithstanding these limitations, the results offer a data-grounded explanation of short-run volatility dynamics in Ghana's interbank foreign-exchange market

and two tentative practical implications. First, the in-sample preference for EGARCH (1,1), the leverage estimates and the QLIKE out-of-sample results suggest that risk-management and value-at-risk calculations for cedi-denominated exposures may benefit from allowing volatility to respond asymmetrically to appreciation and depreciation shocks. The instability of EGARCH (1,1) forecasts after large shocks, however, means that such models should be monitored and compared with simple benchmarks such as the historical variance before being relied upon. Second, the unit-persistence estimates, to the extent they are reliable on a short sample, indicate that volatility shocks to the cedi's cross-rates may decay slowly, which is relevant to banks and corporates managing short-horizon foreign-exchange exposure through the interbank market. The main priority for future work is to re-estimate the models on a longer sample from the Bank of Ghana archive, with out-of-sample evaluation over longer windows and several horizons, and to extend the univariate framework to multivariate specifications linking the naira, dollar and other cross-rates.

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