FOREIGN EXCHANGE RATE AND SECTORAL RETURN VOLATILITY AT THE NAIROBI SECURITIES EXCHANGE, KENYA

James Baariu Mungiria.
Postgraduate Student, Department of Accounting & Finance, School of Business, Economics and Tourism, Kenyatta University, Kenya.
Dr. Charity Njoka.
Lecturer, Department of Accounting & Finance, School of Business, Economics and Tourism, Kenyatta University, Kenya.
Dr. Vincent Mutswenje.
Lecturer, Department of Accounting & Finance, School of Business, Economics and Tourism, Kenyatta University, Kenya.

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ABSTRACT

The securities market plays a central role in investment intermediation and risk allocation; however, in emerging economies, this role is constrained by elevated return volatility. At the Nairobi Securities Exchange, heightened volatility was associated with an estimated reduction of KES 1.548 trillion in market capitalisation between April 2018 and December 2023, with the Telecommunications and Technological, Banking, and Manufacturing sectors accounting for over 85 per cent of total trading activity. Although prior studies associate this volatility with macroeconomic fluctuations and oil price shocks, empirical analysis in Kenya has relied mainly on aggregate market indices. This aggregation masks sector-specific risk dynamics and limits the identification of heterogeneous sector vulnerabilities, thereby weakening policy and investment analysis. The absence of a sector-level framework integrating macroeconomic fundamentals has reduced the explanatory depth of existing evidence. This study examined the effects foreign exchange rate on sectoral return volatility at the NSE. Guided by a positivist philosophy and causal research design, the study applied quota sampling across 10 sectors and 47 listed firms using monthly data from 2011 to 2024. The study was grounded on Flow Oriented Exchange Rate model. The findings demonstrate that the foreign exchange rate significantly affect six sectors. They further support sectoral volatility monitoring and sector-specific index development to strengthen risk assessment and market surveillance. The study recommends institutionalised sectoral volatility monitoring. Future research should analyse sectoral return volatility using firm size classifications, asymmetric and regime-switching GARCH models, and unbalanced panel techniques.

Key words: Foreign Exchange Rate, Nairobi Securities Exchange, Sectoral Return Volatility.

INTRODUCTION

Background of the Study

Exchange rate fluctuations have intensified in recent years due to domestic macroeconomic pressures and global shocks (KNBS, 2023). The Trade Weighted Index increased from 121.66 in 2021 to 123.81 in 2022, reflecting depreciation of the Kenyan shilling. In 2022, the shilling depreciated by 7.5 per cent against the United States dollar, while appreciating by 4.3 per cent against the euro and 3.3 per cent against the British pound (CBK, 2023). The United States dollar accounts for more than 60 per cent of Kenya's foreign currency receipts, while the euro and the British pound together account for over 25 per cent through trade, investment, and remittances (CBK, 2024; KNBS, 2023). These movements increase currency risk exposure for listed firms and reinforce volatility dynamics in domestic equity prices (Dao, McGroarty, & Urquhart, 2019). Figure 1 illustrates the movement of the Kenyan shilling against the United States dollar, the sterling pound, and the euro over the period 2010–2024.

Figure 1 Foreign Exchange Rate Trend

Source: CBK (2024)

Figure 1 shows monthly exchange rates for the Kenyan shilling against the US dollar, the British pound, and the euro from 2011 to 2024. The series reveals three broad phases: a sharp depreciation in 2011, a period of relative stability from 2012 to 2019, and a renewed, sustained depreciation from 2020 to 2024. The British pound and the euro remain at higher nominal levels throughout, with pronounced increases in 2023 and early 2024, reflecting intensified exchange rate pressure. These movements alter firm costs, revenues, and foreign-currency balance sheet positions, generating uneven volatility responses across firms that aggregate into observable differences in sectoral return volatility at the NSE.

Over time, the Nairobi Securities Exchange has evolved into the principal platform for trading securities issued by corporate entities and government institutions in Kenya. The exchange operates under the regulatory oversight of the Capital Markets Authority, which is responsible for market supervision, investor protection, and enforcement of compliance standards. As of December 2023, the NSE had 64 listed firms, making it the sole licensed securities exchange in Kenya and a central component of the national financial system (CMA, 2023).

The NSE has implemented several reforms to improve market efficiency, transparency, and liquidity, including the introduction of the Automated Trading System in 2006, rebranding in 2011, self-listing in 2014, and the launch of day trading in 2021. Despite these initiatives, market performance has remained weak. Total market capitalisation declined by 27.5 per cent, from KES 1,986.1 billion in 2022 to KES 1,439.0 billion in 2023 (Economic Survey, 2024). Compared with selected tier-two African markets, the NSE recorded a negative return of 22.3 per cent in the six months to June 2022, outperforming only Egypt (Sterling Capital, 2022). This pattern reflects persistent structural vulnerability and heightened sensitivity to macroeconomic and external shocks.

The NSE plays a central role in Kenya's economic development by facilitating capital mobilisation and supporting financial intermediation in line with Kenya Vision 2030 objectives. At the same time, its high sectoral concentration, exposure to domestic macroeconomic instability, and sensitivity to external energy price movements make it a suitable empirical setting for analysing sectoral return volatility.

Statement of the Problem

The Nairobi Securities Exchange market capitalisation declined from USD 10.2 billion in 2011 to USD 9.2 billion in 2023, while the NSE All Share Index fell by 51.82 per cent between 2018 and 2023, resulting in an estimated investor wealth loss of KES 1.548 trillion (NSE, 2024). The Capital Markets Authority attributes this decline to heightened exposure to external shocks and domestic macroeconomic vulnerabilities, a concern also reflected in Kenya Vision 2030 policy documents. Over the same period, return volatility increased sharply, with NASI volatility rising from 0.58 per cent in 2018 to 1.17 per cent in 2023 (CMA, 2024), indicating a shift toward a more persistent volatility environment. This combination of sustained capital losses, weak returns, and rising volatility signals unresolved structural risks in the Kenyan securities market. Although macroeconomic pressures increasingly influence market performance, sector-specific responses to these macroeconomic conditions remain insufficiently examined within the Kenyan market context.

Despite volatility indicators, risk assessment in the Nairobi securities market predominantly relies on the NSE All Share Index as the principal metric of overall market performance (NSE, 2023). This methodology introduces structural bias, as the telecommunications, banking, and manufacturing sectors dominate the index despite the exchange's classification of firms into 10 sectors. These sectors account for a significant proportion of trading activity and market capitalisation at the NSE (CMA, 2023). Consequently, fluctuations in the overall index primarily mirror the conditions within these sectors, offering limited insight into the behaviour of the remaining sectors. This structural composition constrains the capacity to identify sector-specific vulnerabilities and diminishes the accuracy of assessing how various market segments respond to broader economic changes (Taljaard & Maré, 2019). Furthermore, aggregate indicators are inadequate in capturing sector-level return volatility, as sectors exhibit differential reactions in magnitude and direction to macroeconomic shifts (Balcilar, Demirer, & Hammoudeh, 2021). Relying solely on aggregate indicators, therefore, impairs investor risk pricing, hampers effective portfolio diversification, and constrains regulatory and policy responses to sector-specific sources of market volatility (Bouri, Demirer, Gupta, & Pierdzioch, 2021).

Existing empirical studies establish that exchange rates influence equity market behaviour; however, most studies rely on aggregate market indices or single-sector analyses, which conceals sectoral heterogeneity in volatility responses and limits understanding of how macroeconomic shocks are priced across industries with differing capital structures and cost exposures (Agyemang *et al*., 2021; Eldomiaty *et al*., 2019). Methodologically, prior studies predominantly employ linear regressions, cointegration techniques, ARDL models, or standard GARCH specifications in which volatility is driven solely by past shocks and past variance. These approaches exclude macroeconomic fundamentals from the conditional variance equation, thereby constraining analysis of time-varying risk compensation and weakening empirical testing of theoretical frameworks such as the flow-oriented exchange rate model (Okechukwu, Mbadike, Geoffrey, & Ozurumba, 2019; El-Diftar, 2023), while also failing to model interaction effects through which foreign exchange rates influence conditional volatility dynamics**.**

Within the Kenyan equity market, prior studies have focused mainly on market-wide indices or selected sectors, particularly banking, thereby limiting systematic cross-sector comparisons of risk dynamics (Onyango, 2018; Mugambi & Okech, 2016). Furthermore, Simiyu, Korir, and Laiboni (2020) employ a BEKK MGARCH framework to analyse intra-market volatility transmission via lagged own- and cross-shock spillovers. While this specification advances understanding of sectoral interdependence within the NSE, it models volatility primarily as an internally driven process and does not assess sectoral conditional variation based on macroeconomic fundamentals. Consequently, the sector-specific effects of exchange rates on heterogeneous conditional return volatility at the NSE remain empirically unexamined within a unified modelling framework. Against this background, the present study investigates foreign exchange rate and sectoral return volatility at the NSE, Kenya.

Research Objectives

The research general objective was to investigate effect of foreign exchange rate movements on sectoral return volatility at the Nairobi Securities Exchange, Kenya.

Research Hypotheses

H_{01}: Foreign exchange rate movement does not have a statistically significant effect on sectoral return volatility at the Nairobi Securities Exchange, Kenya.

Theoretical Review

Flow–Oriented Model

Dornbusch and Fischer's Flow-Oriented Model (1980) explains how exchange rate movements influence stock market behaviour through trade balances and corporate earnings. The model suggests that currency depreciation boosts export competitiveness, increases foreign demand, and raises firm revenues, ultimately driving up stock prices. This trade-based transmission mechanism also impacts sectoral return volatility, as exchange rate fluctuations create uncertainty in expected cash flows and firm valuation. In this study, the model is relevant because it links exchange rate dynamics directly to sectoral return volatility. Rai and Garg (2021) argue that this mechanism makes stock markets in open economies especially sensitive to exchange rate moves. Empirical evidence supports this, with studies showing positive stock market responses to depreciation in East Asia (Hưng, 2019), South Asia (Hussain, Bashir, & Rehman, 2023), and Kenya (Kasongwa & Minja, 2022). Samarakoon and Rajapakse (2023) also demonstrate rapid price adjustments in Sri Lanka, while Alqahtani and Klein (2021) confirm stronger effects for export-focused firms.

Consistent with the Flow-Oriented Model, empirical studies confirm that exchange rate shocks are transmitted to stock market returns and volatility through trade-based channels during periods of macroeconomic instability. Elhini and Hammam (2021) find that during the COVID-19 period, exchange rate volatility intensified corporate challenges in the Middle East and North Africa. Cuestas, Huang, and Tang (2018) report similar dynamics in European emerging markets, while Omeje, Chukwu, and Mba (2024) show that exchange rate shocks continue to influence stock returns in African economies. Hussain *et al*. (2023) observe strong effects in South Asia, and Kasongwa and Minja (2022) confirm persistent exchange rate sensitivity in Kenya. However, evidence also points to limitations of the model, as Samarakoon and Rajapakse (2023) argue that investor sentiment can weaken the direct connection between exchange rates and equity prices, especially during crisis periods.

Despite its explanatory value, the Flow-Oriented Model has theoretical limitations. The model emphasises real-sector mechanisms and treats trade balances and firm profitability as the primary drivers of exchange rate movements (Dornbusch & Fischer, 1980). This perspective understates the role of financial integration and external price shocks in modern currency dynamics, particularly in energy-dependent economies (Boubaker, Goodell, Pandey, & Kumari, 2022). Consequently, the model provides only a partial explanation of exchange rate behaviour and requires extension with additional macroeconomic variables to capture broader transmission mechanisms affecting stock market volatility.

The Flow-Oriented Model therefore provides a theoretical foundation for analysing how exchange rate movements influence sectoral return volatility. Its strength lies in linking external trade conditions to firm profitability and stock price dynamics. However, exchange rates also respond to financial flows and commodity price movements, which may alter their impact on equity markets. In this study, the model operates within a broader macroeconomic framework. Integrating this perspective with the GARCH-X framework allows the analysis to capture time-varying volatility and transmission effects between exchange rates, macroeconomic fundamentals, and sectoral return volatility. Building on this theoretical foundation, the research proposes the null hypothesis that the foreign exchange rate has no statistically significant connection with sectoral return volatility.

EMPIRICAL LITERATURE

Ogunsanya and Adamson (2024) employed Driscoll and Kraay standard errors alongside Feasible Generalised Least Squares in their analysis of a Sub-Saharan African panel. They report significant causal relations between exchange rate movements and stock returns, thereby identifying foreign exchange risk as a pivotal regional factor. Evidence from Kenya supports this relationship, as Kima, Olweny, and Okech (2024) investigated macroeconomic effects on stock price volatility at the NSE utilizing monthly data from 2009 to 2021 and an Error Correction Model, reveals that exchange rate movements exert an adverse and statistically significant impact on stock price volatility, confirming the influence of foreign exchange dynamics on market risk.

El-Diftar (2023) examined how fluctuations in exchange rates affect stock market returns in major emerging economies using ordinary least squares, autoregressive distributed lag models, and a GARCH (1,1) specification. The findings demonstrate a positive connection between exchange rates and stock returns in most countries, with little change in volatility when exchange rate variables are included. This research is relevant to the current study as it provides evidence from emerging markets on how exchange rate movements influence stock market behaviour. Nevertheless, the GARCH (1,1) model restricts volatility to past shocks and past variance, without allowing macroeconomic variables to affect the volatility process directly. Additionally, the analysis does not distinguish between short-term return adjustments and long-term volatility transmission mechanisms. The present research addresses these issues by adopting a GARCH-X framework, in which macroeconomic variables are integrated into the conditional variance equation to directly affect volatility. In contrast, the conditional mean equation captures short-term return dynamics. This approach facilitates a clear distinction between immediate market reactions and ongoing risk transmission at the NSE.

Onyango (2018) researched the connection between the foreign exchange and stock markets in Kenya, focusing on the effect of exchange rate volatility on NSE stock prices. The study used monthly data from January 2007 to December 2014 and applied a regression framework to observations from 61 listed firms. The findings indicate a unidirectional relationship in which exchange rate volatility negatively and significantly affect stock prices. These results align with asset pricing theory, which suggests that exchange rate uncertainty affects firm valuation by altering expected cash flows and risk premiums. However, the analysis is conducted at the aggregate firm level. It implicitly assumes that exchange rate effects are homogeneous across firms and relies on a static regression model with constant variance. These assumptions limit the ability to capture sectoral heterogeneity and time-varying volatility dynamics. The present study addresses these limitations by employing a GARCH-X framework over a more extended period and using sectors as the unit of analysis to examine volatility at the NSE.

Kennedy and Nourzad (2016) assessed the impact of exchange rate volatility on stock market volatility in the United States using a GARCH (1,1) model and weekly data from January 1999 to January 2010. The results indicate that increased exchange rate volatility is linked with significantly greater stock return volatility. These results corroborate the Flow-Oriented Model, which proposes that fluctuations in exchange rates influence firms’ competitiveness and cash flows, thereby heightening uncertainty in equity valuation. However, the analysis focused exclusively on the S&P 500 index, which represents large firms and implicitly assumes homogeneous volatility across firms and sectors. Additionally, the GARCH (1,1) model confines volatility to past shocks and variances and does not permit macroeconomic variables to directly enter the volatility process. While the GARCH (1,1) model effectively captures volatility persistence, it falls short of reflecting the direct impact of macroeconomic factors. The current study addresses these limitations by employing a GARCH-X framework to sectoral return volatility at the NSE, enabling macroeconomic fundamentals to directly influence time-varying volatility across various sectors.

RESEARCH METHODOLOGY

This research utilized a positivist research philosophy, which assumes that economic phenomena exist autonomously of the researcher and that objective knowledge is generated through systematic observation and empirical testing. This position aligns with the study’s objective of examining the relationships between foreign exchange rate and sectoral return volatility using time-series econometric techniques.

This study adopted a causal research design to examine the effect of foreign exchange rate on sectoral return volatility. Causal research design focuses on cause-and-effect relations between variables and enables the estimation of directional relationships among the variables under investigation.

The target population comprised sixty-four listed firms classified into thirteen sectors at the NSE. These firms represent companies listed across the Kenyan equity market and reflect the exchange's sectoral composition. The study uses the official Nairobi Securities Exchange listing database to identify firms and sector classifications that form the population frame.

The study employed a purposive sampling design based on data availability and continuity to ensure consistency and statistical validity in time-series modelling (Bluman, 2018). Purposive sampling is a non-probability technique in which elements of the population do not have known selection probabilities; therefore, the findings are interpreted within the context of the selected units of analysis.

This study employs the GARCH-X model, an extension of the standard GARCH specification that integrates exogenous variables directly into the conditional variance equation. This approach enables volatility to respond to both intrinsic market dynamics and external macroeconomic factors (Kazungu & Mboya, 2021; Kumar, Haque, & Sharma, 2017). GARCH-X is preferred to BEKK because the study examines sector-specific volatility responses to macroeconomic fundamentals rather than cross-sector spillovers. Estimation is conducted sector-by-sector using separate univariate GARCH-X models, enabling sector-specific inference. The empirical strategy follows a two-stage approach. The mean and conditional variance models are specified following the formulation proposed by Kalu and Okwuchukwu (2014) and are presented in Equations 3.1 and 3.2.

Equation 3.1

$$\mathrm{R}_{\mathrm{i,t}} = \mu_{\mathrm{i}} + \sum_{\mathrm{k=1}}^{\mathrm{q}} \theta' \mathrm{R}_{\mathrm{i,t-k}} + \varepsilon_{\mathrm{i,t}}$$

Whereby;

$R_{i,t}$ represents the 10x1 vector of monthly log equally-weighted return of the ten sectors at the NSE at time t.

μ_0 is a 10×1 vector of intercept or mean.

θ denotes 10 × 10 matrices of autoregressive coefficients in the mean equation, which accounts for the time dependence in return.

$R_{i,t-k}$ is a 10×1 vector of (k) lagged log returns of the ten sectors

$\varepsilon_{i,t}$ is a 10×1 vector of residuals representing unexpected shocks from the mean equation across the ten sectors. The residual term is assumed to satisfy $\varepsilon_{i,t} \mid \Omega_{t-1} \sim N(0, \sigma_{i,t}^2)$, consistent with standard GARCH modelling assumptions applied in the estimation procedure.

Equation 3.2

$$\sigma_{i,t}^2 = \omega_i + \sum_{p=1}^{P} \alpha_p \sigma_{i,t-p}^2 + \sum_{q=1}^{Q} \beta_q \varepsilon_{i,t-q}^2 + \gamma_1 X_{1,t}$$

Where $\boldsymbol{\sigma_{i,t}^2}$ represents conditional variance or volatility of the sector (i) return (t)

ω_i represents the unconditional variance component and does not vary over time.

$\alpha_p \boldsymbol{\sigma_{i,t-p}^2}$ is the GARCH term capturing the persistence of past volatility.

$\beta_q \varepsilon^2_{i,t-q}$ is the ARCH term capturing the impact of past shocks.

Parameter γ_1 is coefficients that measure the impact of each exogenous variable on the conditional variance of returns.

X_1 is exogenous variables **(**foreign exchange rate**)**

Descriptive Analysis

This study employed monthly time-series data from August 2011 to December 2024, yielding 161 observations per sector. The objective was to establish the relationship between interest rates and sectoral return volatility at the NSE. The analysis covered 10 economic sectors listed on the NSE: Agricultural, Automobiles and Accessories, Banking, Commercial and Services, Construction and Allied, Energy and Petroleum, Insurance, Investment, Manufacturing and Allied, and Telecommunication and Technology.

Sectoral indices were constructed using share price data for listed firms in each sector, obtained from the NSE. Index values were computed using the methodology while sectoral returns were derived as the first differences of the natural logarithms of the sectoral indices. The explanatory variables comprised the trade-weighted index to capture exchange rate movements.

Descriptive Statistics of Foreign Exchange Rate

The statistics provide a statistical summary of the return series and highlight differences in average returns, variability, and distributional behaviour across sectors, as reported in Table 1.

Table 1 Descriptive Statistics of Sectoral Monthly Returns

Sector	Obs	Mean	SD	Min	MAX	Skewness	Kurtosis
Agricultural	161	0.0386	0.2067	-0.6120	0.5902	-0.3057	1.4935
Automobiles & Accessories	161	-0.0433	0.3661	-0.9035	0.9951	0.3225	0.1451
Banking	161	-0.0166	0.2588	-0.6045	0.5214	0.0262	-0.6013
Commercial & Services	161	-0.1506	0.2632	-0.6315	0.5143	0.5500	-0.1439
Construction and Allied	161	-0.0880	0.2862	-0.9076	0.6589	-0.3450	0.5127
Energy & Petroleum	161	-0.1032	0.3303	-1.8849	0.4150	-2.7133	12.1341
Insurance	161	-0.0196	0.2952	-0.5861	0.5953	0.3321	-0.7953
Investment	161	-0.1144	0.2637	-0.5899	0.5328	0.5902	-0.3505
Manufacturing and Allied	161	-0.0118	0.1921	-0.3818	0.5070	0.6213	0.0137
Telecommunication and Technology	161	0.0955	0.3593	-0.6877	0.7736	-0.2682	-0.4307

Source: Study Data (2025)

Table1 presents descriptive statistics for 10 sectors, each comprising 161 observations. The results indicate substantial heterogeneity in average log returns, volatility, and distributional characteristics across sectors. The Telecommunication & Technology and Agricultural sectors record the highest mean log returns at 0.0955 and 0.0386, respectively. These sectors also exhibit relatively high volatility, with variation of 0.3593 and 0.2067, suggesting greater dispersion of returns around the mean. Both sectors exhibit negative skewness, indicating asymmetric distributions with a higher probability of extreme negative returns.

In contrast, the Commercial and Services sector records the lowest mean log return of -0.1506, with a standard deviation of 0.2632, indicating moderate volatility. The positive skewness and negative kurtosis observed in this sector suggest a distribution dominated by moderate fluctuations with limited tail risk. The Energy and Petroleum sector exhibits significant non-normality, as reflected in extreme negative skewness and very high kurtosis. These statistics demonstrate a distribution characterized by thick tails and a significant probability of extreme return values.

Most remaining sectors exhibit mild positive skewness and kurtosis values below 3, indicating relatively symmetric and flatter return distributions than the normal distribution. The descriptive statistics show significant deviations from normality across sectors, supporting the use of conditional heteroskedastic models in subsequent volatility analysis.

Descriptive Statistics of Foreign Exchange Rate

The statistics on foreign exchange rates are displayed in Table 2.

Table 2Descriptive Statistics of Foreign Exchange Rate

Series	Obs	Mean	Std Error	Minimum	Maximum	Skewness	Kurtosis
TWI	161	4.815	0.009	4.667	5.187	1.333	1.484

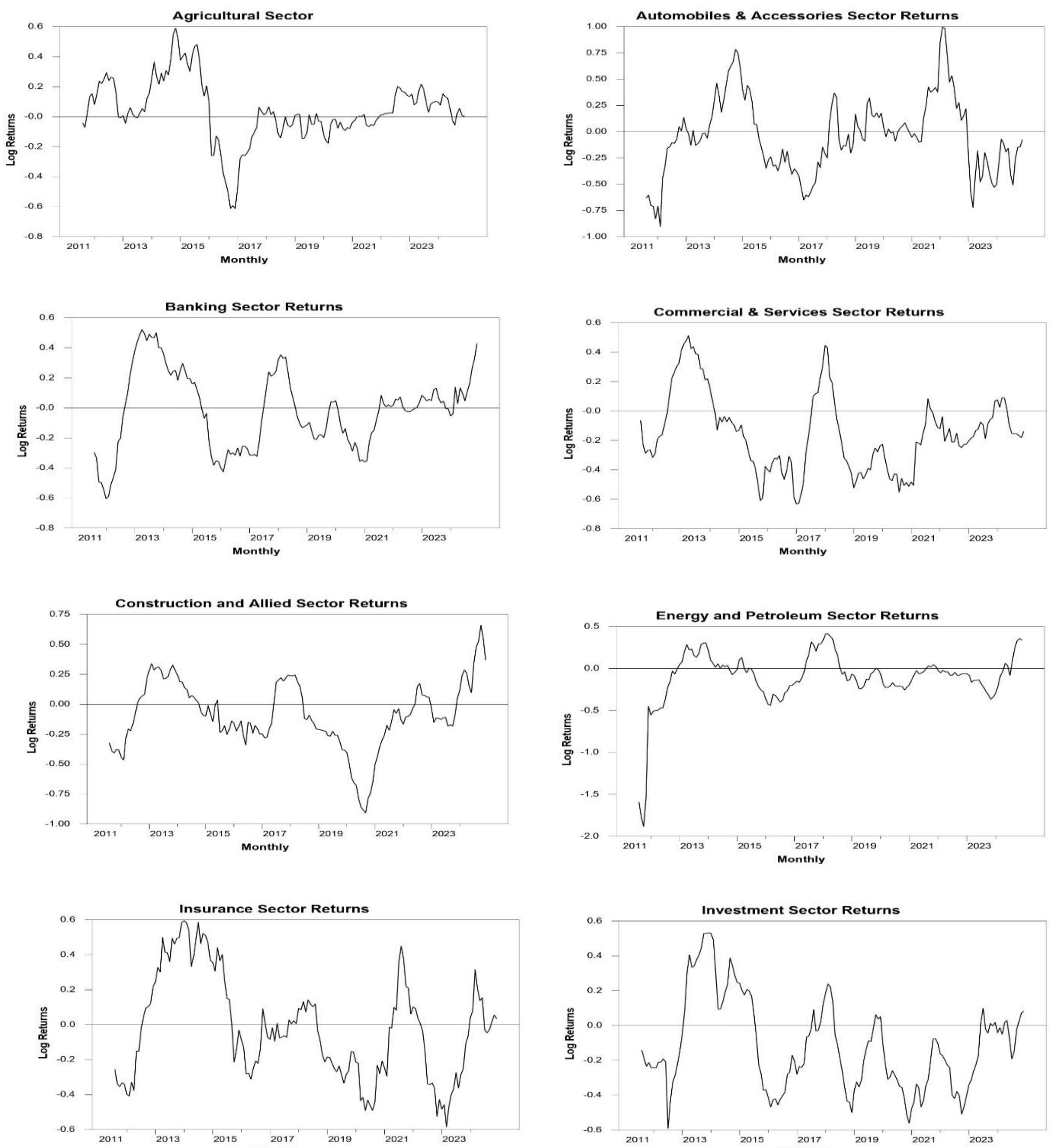
Source: Study Data (2025)

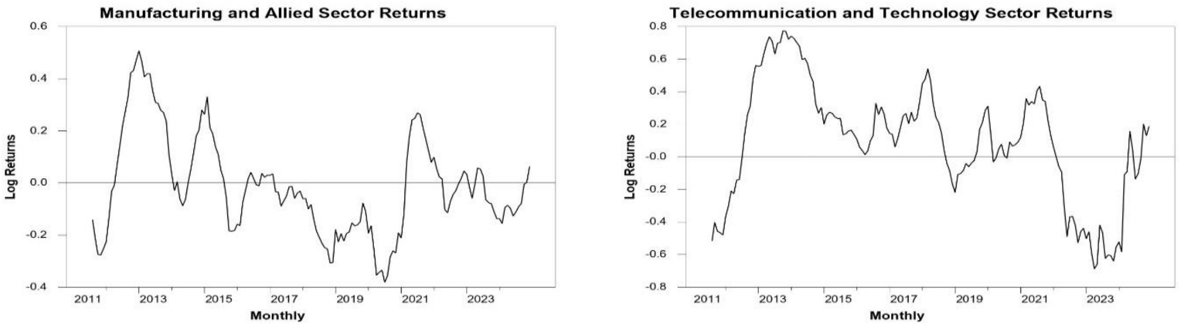
Table 2 reports the descriptive statistics for the Trade Weighted Index which expressed in natural logarithms to stabilise variance, facilitate elasticity-based interpretation, and improve model performance, in line with established macro-financial practice (Okechukwu *et al*., 2019; Onyango, 2018).

The Trade Weighted Index exhibits a stable mean and low dispersion, indicating relatively slow exchange rate changes. However, the positive skewness suggests occasional appreciations, while the low kurtosis indicates a fairly flat distribution. According to the flow-oriented model, exchange rate adjustments influence firm competitiveness and sectoral performance through trade and cost channels (Dornbusch, 1980). Empirical research by Ogunsanya and Adamson (2024) and El-Diftar (2023) supports this view by demonstrating that exchange rate fluctuations are linked to changes in return volatility across markets.

Trend Analysis on Monthly Log Sectoral Return

Trend analyses of monthly log sectoral returns were conducted to examine the general direction and temporal behaviour of market performance over the study period. The analysis utilised time-series plots of monthly log sectoral returns spanning 2011 to 2024 to investigate the temporal evolution of sectoral returns. The plots demonstrate intervals of increased volatility, abrupt adjustments, and relative stability across various sectors amid fluctuating macroeconomic conditions. Examination of these trends facilitates an assessment of whether the return series exhibits behaviour aligned with stationarity, thereby ensuring appropriate model specification. Figure 4.1 exemplifies the time series plots of monthly log sectoral returns for the sectors listed on the NSE.





Source: Study Data (2025)

Figure 1 Trend Analysis on Monthly Index Return

Figure1 depicts the trend behaviour of monthly logarithmic returns across the ten sectors listed on the Nairobi Securities Exchange from 2011 to 2024. The figure shows differences in return movements, volatility levels, and cyclical patterns among the sectors, confirming sector-specific dynamics in return behaviour. The Agricultural sector exhibits moderate volatility during the initial period, subsequently transitioning to sustained, subdued and negative returns. This pattern reflects structural constraints and exposure to external shocks impacting sector performance. The Energy and Petroleum sector experiences an early decline, followed by prolonged periods of low returns and volatility, indicative of weak price adjustments and reduced trading activity within the NSE. The Insurance sector demonstrates a cyclical pattern, with peaks around 2012 and 2016, followed by declines, in alignment with macroeconomic sensitivity (Eldomiaty *et al*., 2019).

The Banking, Commercial and Services, and Investment sectors display cyclical trends with alternating positive and negative returns. The Banking sector demonstrates resilience around 2013 and 2024, alongside mid-period downturns. This behaviour reflects sensitivity to interest rate conditions and monetary policy, which influence credit growth and asset quality (Tuna & Almahadin, 2021). The Investment sector peaks around 2013 and 2015, followed by sharp contractions. These movements reflect heightened macroeconomic uncertainty and align with the time-varying risk–return trade-off, where changes in macroeconomic and uncertainty conditions influence expected returns and volatility (Alemany, Aragó, & Salvador, 2023).

The Automobiles and Accessories, Construction and Allied, Manufacturing and Allied, and Telecommunication and Technology sectors exhibit higher volatility and frequent reversals. These patterns reflect sensitivity to exchange rate movements, cost structures, and demand conditions in an import-dependent economy. The construction and Telecommunication sectors show recovery toward the end of the period, which reflects increased investor activity linked to infrastructure and digital expansion. The Manufacturing and Automobile sectors reflect exchange rate transmission effects on costs and competitiveness (Bouri *et al*., 2021). The Telecommunication sector shows early gains, followed by a decline and partial recovery, which reflects structural and regulatory adjustments in the Kenyan market.

Across all sectors, the return series fluctuate around a relatively stable mean close to zero, with no persistent deterministic trend. This visual pattern indicates mean reversion and provides preliminary evidence of stationarity in the return series. However, graphical analysis alone does not confirm this property, and the next section presents formal unit root tests to establish stationarity.

The return series exhibits stylised features of financial data. Sectoral returns show large fluctuations, which indicate heavy-tailed distributions and non-normality (Bouri *et al.*, 2021). Volatility clusters over time, with persistent high and low phases. Negative shocks generate stronger variability than positive movements, which indicates leverage effects (Habiba, Peilong, Hamid, & Shahzad, 2019). These features confirm time-varying behaviour in sectoral returns at a descriptive level.

Multicollinearity Test

A VIF analysis was performed to evaluate multicollinearity among the explanatory variables in the model. In empirical econometric analysis, VIF values below five are generally considered acceptable, while some studies adopt a more conservative threshold of ten (Gujarati & Porter, 2009; Wooldridge, 2016). A VIF value close to 1 indicates minimal correlation with other predictors, suggesting that the variable provides unique information to the model. Tolerance values, defined as the reciprocals of the VIFs, close to 1 indicate a high degree of independence amongst regressors. Table 3 reports the VIF and tolerance values for foreign exchange rates in the model.

Table 3 Multicollinearity Test (VIF)

Variable	VIF Value	Tolerance (1/VIF)
TWI (DX2)	1.019361	0.9810066

Source: Study Data (2025)

Table 3 presents the VIF and corresponding tolerance values for the key independent variables in the GARCH-X model. These diagnostics were used to assess the extent of multicollinearity among the predictors, which, if present, could distort the statistical reliability of the estimated coefficients and compromise the model's interpretability.

The results suggest that the VIF values was 1.019361 and the tolerance values range fwas 0.9810066. These are well within acceptable limits, indicating no evidence of problematic multicollinearity. In applied econometric analysis, VIF values below 4 and tolerance values above 0.25 are generally considered indicators of low multicollinearity (Ismaeel, Midi, & Sani, 2021).

The empirical values in Table 4.8 are notably below the critical VIF threshold of ten, which would indicate severe multicollinearity. Likewise, none of the tolerance values approaches the critical cut-off of 0.10, suggesting there are no serious collinearity issues.

These findings confirm that the foreign exchange rates is not highly collinear and can therefore be included in the GARCH-X specification without redundancy. This supports the stability and efficiency of the estimated parameters and improves the model's internal validity. The lack of multicollinearity enhances the credibility of conclusions about the effects of foreign exchange rates on sectoral return volatility at the NSE. As a result, no corrective measures, such as removing or transforming variables, are necessary at this stage of analysis.

Optimal Lag Length Determination

This study determined the appropriate lag length for the Vector Autoregression (VAR) model because the lag structure defines the dynamic relationships among the variables and influences the reliability of the estimated results. An incorrect lag specification introduces residual autocorrelation and biased parameter estimates. Information criteria provide a statistical basis for selecting the appropriate lag order. Empirical research frequently applies the Akaike Information Criterion, Schwarz Information Criterion, and Hannan Quinn Criterion because these measures balance model fit with parsimony and limit the risk of over-parameterisation (Liew, 2021; Siddiqui, Ahmed, Naushad, & Khan, 2023). Table 4 presents the optimal lag length determination for the VAR model.

Table 4 Optimal Lag Length Determination

Lags	SBC/BIC	AIC	HQ
0	-6.389764	-6.588612	-6.508406
1	-23.439422*	-25.521842*	-24.744491*
2	-21.615759	-25.360177	-24.107255
3	-19.502221	-24.631621	-23.180143
4	-17.631587	-23.793337	-22.495936
5	-16.035917	-22.771486	-22.086692
6	-13.980812	-20.678659	-21.218013
7	-12.943261	-18.762229	-21.366889
8	-11.527961	-15.26588	-21.138015
9	-11.058397	-10.911011	-21.854878
10	-11.124976	-4.203303	-23.107883

Source: Study Data (2025)

The table presents the outcomes of lag length determination utilising the SBC/BIC, AIC, and HQ criteria. According to the results, all three criteria, BIC (-23.439422), AIC (-25.521842), and HQ (-24.744491), achieve their minimum values at lag 1, thereby indicating that a first-order Vector Autoregressive model constitutes the optimal lag structure. While lag 2 exhibits relatively competitive values, it does not surpass lag 1 across all criteria. Higher-order lags exhibit progressively larger values, suggesting an increase in model complexity without a corresponding increase in explanatory power.

The convergence of AIC, BIC, and HQ enhances the reliability of choosing VAR (1) as the optimal specification, aligning with econometric evidence that concordance among selection criteria offers a robust foundation for lag determination (Liew, 2021; Bruns & Stern, 2018). The designated lag was subsequently used to estimate the residuals for the GARCH-X volatility models, thereby ensuring that the volatility analysis is based on a stable, properly specified time-series framework.

ARCH Effects Test

To evaluate conditional heteroskedasticity in the VAR model residuals, the ARCH test proposed by Hatemi-J and Hacker (2005) was used. This test is appropriate for VAR systems because it accounts for potential non-normality and heteroskedasticity by using a bootstrap method to produce critical values, thereby improving the reliability of statistical inference. The null hypothesis of no ARCH effects was tested against the alternative hypothesis of time-varying variance in the residuals. Table 5 reports the ARCH effects test results for the VAR residuals.

Table 5 ARCH Effects Test Results for VAR Residuals

Sector Residuals	**Test Statistic**	**P value**	**ARCH Effects**
Agricultural	1.4795	0.0000	ARCH effects present
Automobiles and Accessories	0.2193	0.0000	ARCH effects present
Banking	0.0256	0.0000	ARCH effects present
Commercial and Services	0.2175	0.0000	ARCH effects present
Construction and Allied	0.0000	0.0000	ARCH effects present
Energy and Petroleum	6.3700	0.0126	ARCH effects present
Insurance	0.0001	0.0000	ARCH effects present
Investment	4.5968	0.0000	ARCH effects present
Manufacturing and Allied	3.0317	0.0000	ARCH effects present
Telecommunication and Technology	0.0000	0.0000	ARCH effects present

Source: Researcher (2025)

The results shown in Table 5 reveal the presence of Autoregressive Conditional Heteroskedasticity effects in the residuals of the estimated model. The significant test statistic at the first lag indicates that the residuals' variance is time-dependent and affected by past squared innovations. This demonstrates a violation of the homoskedasticity assumption underlying classical linear regression and confirms the existence of volatility clustering in the data.

The presence of ARCH effects at the first lag is economically significant because it indicates that recent shocks have an immediate and lasting impact on current volatility. This provides empirical support for using GARCH-type models, especially the GARCH (1,1) specification, which efficiently captures short-term persistence in conditional variance (Engle, 1982; Bollerslev, 1986). As emphasised by Engle (1982), heteroskedasticity is a fundamental feature of financial time series rather than just a statistical issue. Based on this, adopting the GARCH-X framework is appropriate, as it explicitly models conditional variance, thereby enhancing the accuracy of volatility estimates and ensuring valid statistical inference (Brook, 2008; Gupta, Das, & Gupta, 2022).

Discussions of the Findings

The study examined the relationship between foreign exchange rate fluctuations and sectoral return volatility at the NSE. This objective was tested under the null hypothesis that foreign exchange rate fluctuations are unrelated to sectoral return volatility, and the alternative hypothesis that they are significantly related to it. The findings demonstrate that exchange rate movements significantly influence volatility in certain sectors, while others remain largely unaffected.

Sectors such as Agricultural, Automobiles & Accessories, Energy & Petroleum, Investment, Insurance, and Telecommunication & Technology exhibit statistically significant negative coefficients, indicating that currency appreciation tends to dampen return volatility in these industries. This pattern reflects the structural characteristics of these sectors, which are often export-driven or maintain substantial foreign-denominated earnings and liabilities. When the shilling appreciates, export revenues and foreign income streams contract, trading activity slows, and price fluctuations moderate.

The most pronounced effects are evident in the Agricultural (γ_4 = –0.0645, $p = 0.0000 < 0.05$), Automobiles & Accessories (γ_4 = –0.0661, $p = 0.0001 < 0.05$), and Telecommunication & Technology (γ_4 = –0.0689, $p = 0.0000 < 0.05$) sectors. These sectors rely heavily on export earnings or imported inputs, making their revenues and costs sensitive to exchange rate movements. In agriculture, export commodities such as tea, coffee, and horticultural products respond directly to currency appreciation because a stronger shilling reduces export competitiveness and lowers trading activity. When the Kenyan shilling appreciates, export revenues decline and price fluctuations decrease, which lowers return volatility, a pattern also reported in emerging markets where exchange rate movements influence stock market volatility (Demirer *et al*., 2022). The Automobiles & Accessories sector depends heavily on imported vehicles and components. Currency appreciation lowers input costs and reduces production cost uncertainty, which stabilises sectoral returns (Ogunsanya & Adamson, 2024). The Telecommunication & Technology sector shows a similar response. A stronger shilling reduces the cost of imported equipment and foreign service contracts, which lowers return volatility (El-Diftar, 2023).

Moderate but significant effects are also observed in the Energy & Petroleum ($\gamma_4 = -0.0314$, $p = 0.0247 < 0.05$) and Investment ($\gamma_4 = -0.0459$, $p = 0.0178 < 0.05$) sectors, where foreign-denominated input costs and exposure to international capital flows amplify sensitivity to exchange rate changes. The Insurance sector ($\gamma_4 = -0.0494$, $p = 0.0632 > 0.05$), significant at the 10% level, reflects similar exposure through foreign asset valuations and reinsurance obligations. In contrast, the Banking ($\gamma_4 = -0.0118$, $p = 0.2494 > 0.05$), Commercial & Services ($\gamma_4 = -0.0142$, $p = 0.2478 > 0.05$), Construction & Allied ($\gamma_4 = 0.0019$, $p = 0.8966 > 0.05$), and Manufacturing & Allied ($\gamma_4 = -0.0141$, $p = 0.2793 > 0.05$) sectors exhibit statistically insignificant coefficients. These results suggest that these industries are relatively insulated from exchange rate fluctuations, possibly due to natural hedging, limited foreign currency exposure, or diversified revenue streams that mitigate currency volatility.

CONCLUSIONS AND RECOMMENDATIONS

This study assessed the influence of foreign exchange rate on sectoral return volatility at the NSE within a GARCH-X framework. The results demonstrate that exchange rate fluctuations have a statistically significant and economically meaningful impact on equity market risk. However, the magnitude and direction of these effects vary across different sectors. Currency appreciation correlates with reduced volatility in sectors exposed to external factors, including Agriculture, Automobiles and Accessories, Energy and Petroleum, Insurance, Investment, and Telecommunication and Technology. This suggests enhanced cash flow stability, diminished valuation uncertainty, and decreased earnings risk, consistent with the Flow-Oriented and Stock-Oriented models of exchange rate transmission. Conversely, no significant effects are observed in the Banking, Commercial and Services, Construction and Allied, and Manufacturing and Allied sectors, reflecting the predominance of domestic revenue structures and local currency financing, which supports the notion of differentiated volatility transmission within an emerging equity market context.

Conclusions of the Study

The study concluded that foreign exchange rate movements affect sectoral return volatility differently across industries at the NSE. Currency appreciation is associated with lower volatility in the Agriculture, Automobiles and Accessories, Energy and Petroleum, Investment, Insurance, and Telecommunication and Technology sectors. Similar sector-level responses to exchange rate fluctuations have been reported in African equity markets (Onyango, 2018). Evidence from emerging markets also shows that industries with stronger exposure to international trade respond differently to currency movements (Ogunsanya & Adamson, 2024). Additional studies examining global financial markets also document sector-specific volatility responses to exchange rate movements (El-Diftar, 2023). These findings correspond with the Flow-Oriented Model which explain how exchange rate movements influence firm performance, investor expectations, and capital flows.

Contribution to the Body of Knowledge

This study contributes to finance and economics by refining the theoretical interpretation of macroeconomic transmission mechanisms. The findings support the flow-oriented model by showing that exchange rate volatility exerts stronger effects on export-oriented sectors, particularly Agriculture and Telecommunications. In addition, differences in sectoral volatility responses reinforce the relevance of Modern Portfolio Theory by highlighting the importance of sector-based diversification during periods of macroeconomic uncertainty.

The study makes a methodological contribution by applying a sector-focused volatility modelling framework using a GARCH-X approach. The model captures volatility persistence and allows foreign exchange rate to influence sectoral return volatility directly through the variance equation. This approach addresses a key limitation of conventional GARCH and BEKK models, which rely on past returns and shocks rather than incorporating macroeconomic variables into the volatility process.

The study makes a practical contribution by explaining how monetary policy influences sectoral volatility at the NSE.

Policy Implications and Recommendations

The first policy implication pertains to the combined impact of foreign exchange rate on sectoral volatility. Foreign exchange rate amplify volatility across sectors such as banking, manufacturing, energy, and construction. The study recommends that the CBK and the National Treasury enhance coordination among monetary and fiscal policies.

The second policy implication emphasises the importance of systematic monitoring of sectoral volatility. The study recommends that the CMA establish a Sectoral Volatility Monitoring Framework in collaboration with the NSE. This initiative should be supported by the development and consistent publication of Sectoral Performance and Volatility Indexes to improve transparency and facilitate sector-specific risk assessment.

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