**[VOLATILITY CLUSTERING AND PERSISTENCE IN KENYAN FINANCIAL MARKETS:
A GARCH APPROACH]**

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DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Research Project contains no material previously published or written by another person except where due reference is made in the Research Project itself.

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ABSTRACT

This study aimed to understand volatility in emerging countries, particularly Kenya, by investigating volatility clustering and persistence in the Nairobi Securities Exchange (NSE) utilizing Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. The research emphasized the significance of understanding market volatility patterns, considering their implications for market efficiency, risk management, and investment strategies. Using weekly time series data from the NSE 25 share index spanning January 2016 to December 2023, the study evaluated the effectiveness of various GARCH model specifications, specifically asymmetric EGARCH and TGARCH models, in capturing volatility trends. The findings revealed significant volatility clustering and persistence in the NSE, characterized by periods of high volatility following similar patterns. Notably, the TGARCH model outperformed the EGARCH model in terms of model fit and forecasting accuracy, as evidenced by lower Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values, as well as superior Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics. These results provide insights into the unique volatility dynamics of the NSE and offer actionable recommendations for policymakers and investors to enhance market stability and improve investment decisions. Overall, this research fills existing knowledge gaps related to volatility in the Kenyan financial sector and contributes to the broader literature on emerging markets.

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LIST OF ABBREVIATIONS

AIC	Akaike information criterion
BIC	Bayesian information criterion
EGARCH	exponential generalized autoregressive conditional heteroscedastic
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
MAE	Mean absolute error
NSE	Nairobi Securities Exchange
OGARCH	Orthogonal Generalized Autoregressive Conditional Heteroskedasticity
RMSE	Root mean square error
SARV	stochastic autoregressive volatility
TGARCH	threshold generalized autoregressive conditional heteroskedastic models

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study.

Volatility clustering and persistence in Kenyan financial markets, particularly the Nairobi Securities Exchange (NSE), have sparked academic interest due to their implications on market efficiency, risk management, and investment strategies. Volatility clustering depicts how low and high volatility follow one other. Financial econometrics makes advantage of this trend, which has been researched in a variety of global financial markets. Ali (2019) demonstrated how historical volatility influences future volatility in Sub-Saharan African stock markets. These results are important for portfolio managers and policymakers who need to understand financial markets movements.

The reasons for volatility clustering and its impact on market participants are being contested. Alper, Morales, and Yang (2016) highlight yield curve volatility in Kenya's financial markets since 2012. Kenya's forward-looking monetary policy exemplifies this. Understanding and forecasting market behavior needs rigorous analytical techniques such as the GARCH model. The volatility in these markets implies that external shocks and monetary policy influence market stability.

Although volatility patterns are better recognized, little is known about Kenya's financial markets' local and global effects. To better explain NSE volatility patterns, more complete models must include both local economic drivers and worldwide financial links. The research on how foreign money flows impact market volatility is inexhaustible. Osoro, Simiyu, and Omagwa(2020) discovered that foreign direct investment and equity portfolio inflows reduce stock market capitalizations. This points to a complex link between market stability and foreign investment.

The suggested technique uses GARCH to fill NSE volatility clustering and persistence gaps. This helps investors better understand market volatility, risks, and opportunities. To reduce volatility, the study will assess current monetary policy frameworks and suggest modifications based on empirical evidence. Kenyan financial markets are becoming more international, making this study significant. Finally, resolving persistence and volatility clustering might improve regulatory criteria and investment decisions, therefore supporting financial sector stability and development.

Kenya has distinct political, social, and economic aspects; hence the Nairobi Stock Exchange can employ GARCH models. Political upheaval, macroeconomic policy changes, rapid expansion, and market developments can greatly influence global financial market volatility.

Studies show that GARCH models correctly describe worldwide stock market volatility, hence the NSE should use them. Scholars and researchers may utilize GARCH models to investigate NSE volatility. Kenya's financial system will become more stable, with better risk management and investing approaches.

1.1.1 Factors Affecting GARCH Model

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is often used in financial time series data because of its volatility clustering potential. As a result, much research has been conducted on the subject. The accuracy and utility of GARCH models vary and are not well documented in the literature. A significant flaw in standard GARCH models is their failure to account for asymmetry. According to researchers, Threshold GARCH (TGARCH) and Exponential GARCH (EGARCH) models are more suited to dealing with financial data asymmetries and volatility dynamics.

Important research on new GARCH-type models to enhance existing ones is necessary. The new shock spell models in financial market index research beat GARCH and Orthogonal Generalized Autoregressive Conditional Heteroskedasticity (OGARCH) (Liu, 2010). Recent changes may improve GARCH modeling. Multiplicative GARCH models feature more persistent autocorrelation in squared returns and more kurtosis in returns, which may help address stylized traits that standard GARCH models cannot (Conrad and Kleen, 2016).

GARCH models function via complex estimating and transformation strategies. Nugroho (2019) found the Yeo-Johnson transformation for return series with adaptive random walk. The metropolis estimator may beat GARCH (1,1). Preprocessing and estimation improve GARCH model accuracy.

GARCH models are effective for parameter estimation, filtering, and forecasting, however stochastic autoregressive volatility (SARV) models may provide more accurate predictions (Fleming and Kirby, 2003). This comparison demonstrates the need for several ideas and methodologies for volatility prediction.

Modern technology and sophisticated systems help design GARCH models. Instead of random application, neural network-based methods describe the GARCH (1,1) model (Caldeira et al., 2014). Artificial intelligence and machine learning might improve GARCH models as well.

In simulated and real data sets, locally constant volatility models beat variable coefficient GARCH models in prediction power (Polzehl & Spokoiny, 2006). Comparisons are required to appreciate the advantages and disadvantages of various GARCH model formulations.

Finally, higher-order moment fit, and data temporal frames influenced GARCH model statistics. GARCH(1,1) models with double Gaussian conditional probabilities have limits for fitting statistical moments, highlighting the need for more sophisticated financial time series models (De Clerk & Savelev, 2021).

1.1.1.1 Historical Prices

Stock prices have a significant influence on the development and use of GARCH models. The model indicates that previous volatility may predict future volatility. This problem has been widely discussed in the financial literature. Past prices show market behavior, according to Bollerslev's (1986) GARCH extension and Engle's (1982) ARCH model. Whether previous pricing and volatility predict future volatility is debatable. Some research implies that external shocks and market anomalies may affect prediction (Mandelbrot, 1963; Fama, 1970).

The GARCH model is widely used, but little is known about how historical pricing influences its reliability and accuracy in diverse market conditions. Lower liquidity, higher transaction costs, and regulation changes may have an impact on developing markets such as the NSE (Aggarwal et al., 1999). Given these market characteristics, the efficacy and applicability of the GARCH model using historical prices as the primary variable must be assessed.

The GARCH paradigm for historical price analysis is likewise contested. Conventional methodologies presume that past and future volatility are linearly connected, but not always. Many new models, such Exponential GARCH (EGARCH) and Threshold GARCH (TGARCH), address these concerns. Their unimportance to the NSE impedes market model comparison studies.

1.1.1.2 Political Stability & Regulatory Environment

Control influences the performance of the GARCH model. Transparency, investor protection, and market integrity may aid GARCH in predicting volatility. These hypotheses might also explain consumer behavior. Strong laws and stable markets help to prevent financial crises (Liu 2010). Weak limitations may result in anomalies and unstable markets, jeopardizing the GARCH model's acceptability and accuracy.

Akpan and Moffat (2017) discovered that EGARCH and TGARCH models may be required to control market responses to shocks when traditional GARCH models neglect asymmetric consequences during political instability or legislative change. This stresses the need of adapting GARCH models to shifting political and legal circumstances while maintaining their dependability and consistency across market scenarios.

Interestingly, political stability and government control have differing effects on financial markets. Under conditions of political stability, rules may reduce volatility while increasing market growth. These benefits may be applicable to GARCH models. In politically unstable conditions, extensive regulatory systems may fail to stabilize markets, resulting in unexpected behavior that defies GARCH model assumptions (Huang and Guo 2011). Market predictions and studies that use the GARCH model emphasize political and legal constraints.

Understanding how politics and regulations influence NSE market performance is critical. Politics and legislation influence NSE development. Government stability and regulatory control minimize NSE volatility, which GARCH models forecast more accurately (Fleming & Kirby, 2003). Political unrest or loose rules that disrupt markets may limit even the most powerful GARCH models. These elements must be included in the GARCH model analysis to analyze NSE volatility and mitigate risk.

1.2 Research Problem

The stable financial market allows investors to make informed decisions based on recurring trends and behaviors. Forecasts are more accurate, and investment risk is lower in these markets owing to low volatility and constant asset values. Instead of rapid price volatility, which discourages investment, gradual price modifications based on market value are perfect for the Nairobi Securities Exchange. This culture fosters local and international investor trust, hence increasing Kenya's economy. GARCH and other complex econometric models are simple and may assist in explaining market behavior, guiding better investment and policy responses (Engle, 1982; Bollerslev, 1986).

The NSE has varying market persistence and volatility clustering. This demonstrates that low-volatility periods follow low-volatility periods and high-volatility periods follow high-volatility periods, which causes investors and legislators' concern. Even when employing GARCH models to capture and analyze volatility, Kenyan financial markets are subject to considerable price fluctuations driven by internal factors such as political instability and changes in economic policy, as well as external shocks such as global financial crises. Volatility makes it difficult for stakeholders to forecast price fluctuations and adopt risk management strategies, undermining investor confidence and disrupting the financial system.

Certain levels of market stability and predictability are required to remove targeted NSE volatility. The Kenyan market is unique in sectors such as banking, therefore including regional, economic, political, and social elements may improve GARCH models. Transparency and regulatory measures may help to lessen market volatility. These efforts may increase foreign investment and Kenyan market growth by stabilizing the investment environment. Research and data collection help to develop prediction models and better understand volatility. This technique increases knowledge and establishes the framework for future study on investor confidence and market stability.

Financial market research focuses on volatility clustering and persistence, which have implications for risk management, asset pricing, and financial decision-making. Little research has been conducted on Kenya's financial sector and the Nairobi Securities Exchange. This study uses GARCH to evaluate the NSE volatility clustering and persistence. Few research looks at NSE volatility clustering, persistence and endurance. Rising nations like Kenya are difficult to comprehend because much study has concentrated on developed countries. NSE trading patterns and market microstructure may have distinct effects on volatility patterns than established markets. Chinzara (2011) proposes researching African markets to bridge this gap. NSE sector-specific volatility is also understudied. Understanding how different businesses react to market shocks might help explain market volatility. Although not extensively used on the NSE, GARCH models are widely used in volatility research. To ensure applicability and accuracy, Ndung'u (2018) recommends modifying and testing these models in Kenya. Nobody understands how investing activity causes NSE volatility. Barberis and Thaler (2003) applied behavioral finance to explain market persistence and volatility clustering. More research is needed to better understand how inflation and interest rates influence NSE market volatility. This combination can help explain volatility.

Previous NSE investigations have data constraints such as low frequency and limited time series. Muriithi, Waweru, and Muturi (2016) suggested using high-frequency data with temporal range stretching to assess volatility. The NSE rarely employs multivariate GARCH or regime-switching models. Kivaho et al. (2014) claim that these approaches indicate more complex volatility trends. Finally, the NSE should grow alongside other markets. Patev, Kanaryan, and Lyroudi (2006) argue that comparability studies can disclose NSE volatility trends and features. This paper addresses knowledge gaps in emerging nation financial market volatility for NSE academics, investors, and policymakers.

1.3 Research Objective

The main objective of the study is to evaluate volatility clustering and persistent in Kenyan financial markets in the NSE: a GARCH approach Some of the specific objectives of the study will include.

i. To calibrate a GARCH (p, q) model and obtain their consistency and asymptotic normality properties.
ii. To forecast using GARCH models the NSE data and measure volatility.
iii. To establish which model is best at forecasting volatility of stock returns for NSE.

1.4 Research Hypothesis

H_{01}: There is no significant difference in the consistency and asymptotic normality properties of the calibration of the GARCH (p, q) model.

H_{O2}: There is no significant effect of forecasting using GARCH models on accurately measuring volatility in the NSE data.

H_{03}: There is no significant difference in the ability of different GARCH models to forecast the volatility of stock returns for the NSE.

1.5 Research Questions

i. How can a GARCH (p, q) model be calibrated, and what are its consistency and asymptotic normality properties?
ii. How can GARCH models be used effectively to forecast NSE data and measure volatility?

iii. Which model is the best at forecasting the volatility of stock returns for the NSE?

1.6 Significance of the Study

Many parties gain from understanding persistence and volatility clustering in Kenya's financial markets, particularly the NSE. This research may have an impact on market financial assets. Volatility clustering, which occurs when huge stock price fluctuations coincide with modest changes, can lead to uncertainty. Lowering risk in an investor's portfolio may have an impact on the valuation and returns of other financial assets. Long-term market shocks can have an impact on financial system stability since they are volatile.

Furthermore, investors should evaluate the research findings. Knowing NSE volatility trends allows investors to invest wisely. Volatility and durability trends inform purchase and sell choices, thereby boosting risk management. During moments of excessive volatility, investors can minimize losses by exercising caution. Forecasting market conditions enables financial analysts and portfolio managers to deploy assets.

Market sentiment influences investment decisions in ways that go beyond strategies. Investors' views of NSE volatility may influence market participation, liquidity, and transaction costs. However, models like GARCH can enhance investor confidence and market investment by improving volatility forecasting. Thus, market stability and growth could improve.

Our study benefits market participants and adds to expanding country volatility research. Managing volatility clustering and persistence enhances financial models and processes, which benefits Kenya's financial industry.

A GARCH technique is needed to study volatility clustering and persistence in Kenyan financial markets. Kenya's financial markets' instability deters local and foreign investors, which is a major issue. When periods of high volatility are followed by similar ones, asset prices are unclear. This trait reduces investor trust, making return forecasts tougher.

Political instability, currency rate fluctuations, and economic uncertainty in Kenya cause market inefficiencies. Kenyan investors sometimes disregard the local market in favor of more stable global markets, where information flows more freely, rules are stricter, and risks are fewer.

Kenya's financial markets are also unstable due to fundamental challenges such inadequate financial infrastructure, poor risk management, and low investor financial literacy. This makes the Kenyan market riskier than its more open and liquid overseas rivals. This research analyzes volatility patterns using the GARCH model to understand Kenyan financial markets. Investors and politicians will benefit from this data. Understanding volatility patterns may assist stabilize the market, boost investor confidence, and attract local and foreign investment.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The attention paid to the study of stock market volatility, particularly by applying GARCH models, in financial literature is huge as it has become critically important in risk management, investment strategy formulation and policy making. Several studies have shown that GARCH models capture well and predict the time-varying volatility observed across global financial markets. Different scholars have also tried to improve the basic GARCH model by coming up with other related forms such as TGARCH and EGARCH to overcome issues like non-linearities or asymmetries and leverage effects that are common characteristics of certain markets.

However, few comprehensive research has been conducted on emerging markets like the NSE influenced by factors such as its political, social, and economic realities. The objective of this review is therefore to collate findings from both global and regional research showing where GARCH models are applicable or not in different market conditions besides establishing areas that need future investigations within the context of NSE.

2.2 Theoretical Literature

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models form the foundation for modeling stock market volatility in a theoretical sense within the broader framework of financial econometrics. Bollerslev (1986) introduced the GARCH models, which expanded on Engle's (1982) ARCH model. GARCH models consider volatility clustering, whereby periods with high volatility tend to have high-volatility subsequently and those with low-volatility before have low-volatility subsequently. This is a familiar characteristic in financial time series data.

At the core of the GARCH model is the assumption that the current conditional variance of a time series is a function of past squared observations and past variances. The basic GARCH (1,1) model can be expressed as:

$$y_t = \mu_t + \varepsilon_t \ where \ \varepsilon_t = \delta_t z_t$$

$$\delta_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\delta_{t-1}^2$$

Where y_t is the return series, $\mu_t$is the mean of the returns, ε_t is the error term, z_t is the standard residual, δ_t^2 is the conditional variance and is the β coefficient of lagged conditional variances. ω is a constant term. This formulation captures the persistence in volatility and allows for a dynamic adjustment of the conditional variance over time.

Many extensions of the GARCH model have been developed to accommodate various aspects demonstrated in the financial data. EGARCH (Exponential GARCH) model (which was introduced by Nelson (1991) deals with the leverage effect, implying that negative shocks influence future volatility more than positive shocks. Conversely, TGARCH (Threshold GARCH), which was suggested by Zakoian (1994) captures a similar type of asymmetry by allowing for distinct responses to positive and negative shocks.

In relation to Nairobi Stock Exchange (NSE), using GARCH models offers a theoretical grounding for market volatility understanding and forecasting purposes. Just like any other developing economy around the world, NSE is influenced by unique economic, political, and social factors that produce significant patterns of volatility. It's therefore through this research work where we aim to capture these dynamics using various forms of GARCH as well as provide insights into what steers volatility within NSE. Furthermore, not only does this theoretical approach improve on forecast accuracy, but it also contributes to wider financial econometrics literature denoting usability of GARCH models within an emerging market context.

2.3 Empirical Studies

Empirical research on stock market volatility utilizing GARCH in regional and global markets can provided the NSE with useful approaches and knowledge. The NSE's volatility patterns support the use of GARCH models.

Delays in GARCH models are often debated. The model's persistent volatility may vary with lag time. High lag lengths overfit and add complexity, but short lag lengths may not capture volatility dynamics (Akaike, 1974; Schwarz, 1978). The optimal NSE lag time is debatable, making it a prominent issue for future study since it effects experiment findings.

Error distribution is another important GARCH model element. The GED and Student's t-distributions evolved as a result of financial returns' skewness and fat tails (Bollerslev, 1987; Nelson, 1991), but the normal distribution has remained the standard. Empirical evidence reveals that multiple distributions may be better in different situations, creating debate on which error distribution suits NSE data.

Exogeneous GARCH models are equally troublesome. Economics and market data might assist explain the concept while also complicating it (Engle, 1982; Ding, 1993). Selecting and integrating crucial external inputs into the model is difficult. Inconsistent NSE investigations of outside factors indicate that more investigation is required.

Decision-makers, investors, and financial analysts must consider the methodological problems associated with selecting GARCH model parameters. Errors in model construction may alter investment, risk, and volatility estimations (Engle, 2001; Bollerslev, 2009).

According to Brooks and Persand (2002), macroeconomic uncertainty affects Malaysian stock market volatility. They use a variety of econometric models to show how inflation, interest rates, and currency values influence stock market volatility. Small open economies need macroeconomic stability because economic uncertainty drives stock market volatility. The authors urge that governments eliminate economic uncertainty in order to encourage investment.

Mwita, Odhaimbo, and Ochieng (2013) investigate NSE return volatility using GARCH models. The research is based on daily NSE-20 share index closing values from January 2000 to December 2010. The GARCH, EGARCH, and TGARCH models are used to calculate stock return volatility using return data. The research finds that NSE return volatility is accurately reflected by the EGARCH model. The authors recommend that Kenyan stock market participants replicate volatility in order to make sound decisions.

Muriu (2014) investigates Kenyan stock market volatility and macroeconomic determinants using GARCH. Interest rates, inflation, currency values, and monthly statistics from the Nairobi Securities Exchange (NSE) were analyzed from January 2000 to December 2012. The findings indicate that macroeconomic factors such as inflation and interest rates influence Kenya's stock market volatility. The author emphasizes understanding macroeconomic difficulties and stock market volatility in order to reduce risks and make sound decisions.

Wagala, N potassiuma, Islam, and Mwangi (2012) used ARCH-type models to predict the volatility of the NSE 20 share index. They wanted an ARCH-type model that accurately represented stock and NSE weekly return volatility. This was done using ARCH, GARCH, EGARCH, and TGARCH models on NSE-listed business weekly return data. The model's statistical performance was evaluated for the best match. The research found that NSE weekly return volatility remains constant, implying that previous volatility influences future volatility. EGARCH and TGARCH better captured volatility asymmetry, whereas GARCH outperformed ARCH. Data from many sectors enhanced volatility estimates and expanded market coverage.

Maqsood, Safdar, Shafi, and Lelit employed GARCH models to forecast stock market volatility on the NSE. NSE volatility and the optimal GARCH models were investigated. The study employed NSE index closing data from March 18, 2013, to February 18, 2016, as well as GARCH model parameters. The symmetric and asymmetric models were compared using Schwarz Bayesian Criteria (SBC), RMSE, and the Akaike Information Criteria. The NSE revealed considerable volatility persistence, indicating that volatility shocks have long-term consequences. EGARCH and TGARCH match NSE data better than symmetric models, demonstrating leveraging effects: bad news increases volatility more than positive news (Maqsood, Safdar, Shafi, and Lelit, 2017).

Marobhe and Pastory used GARCH models to anticipate the volatility of the Dar es Salaam Stock Exchange in 2020. Stock return volatility models were investigated, both symmetric (GARCH) and asymmetrical (EGARCH, PGARCH). Marobhe and Pastory (2020) discovered autoregressive conditional heteroskedastic effects in time series, supporting DSE daily closing price index data normality. PGARCH (1,1) predicted stock return volatility more accurately than large-volume GARCH, EGARCH, and PGARCH. These models may be better understood by researching other GARCH models in the literature (Marobhe and Pastory, 2020).

P. Ali (2019) investigated volatility persistence in Sub-Saharan African stock markets, including Kenya, using the GARCH (1,1) model. Research found that stock return shocks had an impact on market volatility. This demonstrates how both local and global issues influence market volatility. Research indicates that volatility promotes trading and risk management in these markets. The findings show that the government should implement market stabilization measures to protect investors from market volatility.

Jason Mattes (2012) studied the African stock market volatility during the Credit Crisis. The research discovered that local and global market connections influence volatility persistence. Financial institutions throughout the world are linked, as seen by the Kenyan market's significant volatility clustering during crisis periods. In the midst of global financial turbulence, the article serves as a reminder to Kenyan authorities and investors of these risk-reducing behaviors. The paper emphasizes the importance of financial infrastructure and crisis management in protecting the market from external shocks.

2.4 Conceptual Framework

To analyze and forecast market volatility, this research is based on an integrated conceptual framework for GARCH modeling of Nairobi Stock exchange. This structure illustrates the connection between significant determinants, use of GARCH models and predicting what will happen in future.

2.4.1 Conceptual Framework Components

1. **Determinants of Stock Market Volatility**:

i. **Economic Indicators**: Macros such as Gross Domestic Product (GDP) growth, inflation rates, interest rates and forex.

ii. **Political Stability**: The role of political happenings, government policies and politics in the country.

iii. **Global Market Trends**: Influence from the world financial markets, commodity prices and international economic status.

iv. **Market Liquidity**: The tradability of assets without causing a disequilibrium in prices.

v. **Regulatory Environment**: Rules guiding financial markets and their effects on market stability.

vi. **Investor Behavior**: Market Sentiments, speculative trading, herding behavior.

vii. **Corporate Performance**: Financial performance of companies quoted at the stock exchange, earnings report, and corporate actions.

viii. **External Shocks**: Natural calamities, pandemics are some examples of crises that could cause market shocks.

2.4.2 Application of GARCH Model:

i. **Model Specifications**: The choice of the suitable GARCH model (such as GARCH (1,1), EGARCH, TGARCH) that will capture the volatility patterns.
ii. **Data Preparation**: Gathering and analyzing stock prices historical data, calculating logarithmic returns, and ensuring data stationarity.
iii. **Model Estimation**: Maximum likelihood estimation is used to fit the model to the time series data.
iv. **Diagnostic Checks**: Testing for autocorrelation, ARCH effects and residual analysis in order to validate the model.
v. **Volatility Forecasting**: Predicting future market volatility using estimates from the fitted model and assessing its accuracy.

2.4.3 Consequences:

i. **Improved Understanding**: Better appreciation of NSE-specific volatility dynamics.
ii. **Investment Plans**: Better risk management and investment choices based on accurate prediction of volatility rates
iii. **Policy Making/Regulation**: Guidelines for policy makers on how to stabilize or improve market efficiency
iv. **Research Contribution**: An addition to literature concerning financial market volatility in developing countries

2.4.4 Framework Explanation

The conceptual framework starts with the factors that contribute to stock market volatility. Analyzing historical stock prices and generating log returns provides data for GARCH modeling.

Choosing a GARCH model that reflects NSE volatility which includes diagnostic testing to verify model acceptance and robustness, as well as model estimate based on past data.

Validating GARCH models can anticipate market volatility. We aim to evaluate volatility, improve investment strategies, influence public policy, and finance university research.

This study seeks to provide an extensive analysis of stock market volatility at Nairobi Securities Exchange with application of GARCH models as tools that will help investors, policymakers and researchers make actionable decisions based on insights derived from it.

2.5 Summary of Literature Review

GARCH literature views stock market volatility as time-varying and diverse across the globe. Bollerslev (1986) and Engle and Bollerslev (1986) are fundamental research in financial econometrics that made GARCH models influential while other variations of EGARCH and TGARCH have provided solutions to non-symmetric volatility effects. Emerging market studies prove that these models apply along with showing how local economic, political, or global issues affect market volatility. Studies shows that there is evidence to support the fact that GARCH models can capture patterns of fluctuations effectively in the NSE but different dynamics within the markets imply need for customized model specifications as well; hence offering better insight to this study on NSE volatility via a more sophisticated GARCH modeling approach. This customization allows for better understanding and management of market risks, which is crucial for investors and policymakers operating in the NSE.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter summarized the research methods that were utilized to conduct this investigation. The target audience, data collection, data analysis, and research design.

3.2. Research Design

The study adopted a quantitative research design to study the impact of volatility clustering on the Kenyan financial markets. The design was ideal as it allowed for use of statistical techniques and econometric models such as the complex GARCH models to better analyze the relationship between volatility clustering and persistence and other variables. The design facilitated the identification of volatility clustering and its impact on the financial market.

The study also conducted correlational research to establish the degree of the relationship between volatility clustering and persistence in Kenya's financial markets, particularly the NSE. The focus was on the lengthy and concentrated volatility in Kenya's financial markets. Through correlational research, the study investigated causal correlations between variables and anticipated the outcomes of research participants on one measure based on their performance on others. Correlational studies examined statistical correlations. This design was deemed appropriate as it allowed the researchers to determine whether variables were positively or negatively associated, as well as the strength of the association (coefficient of correlation). It also enabled hypothesis testing to determine if the relationship was statistically significant.

3.3. Population of the Study

The study employed weekly time series data from the NSE 25 share index between January 2016 and December 2023. Weekly data provided a more accurate picture of market volatility and was therefore ideal for the study. The NSE 25 index captured important industry and price developments and explained stock performance scientifically. The NSE 25 share index assessed Kenyan NSE-listed firms across various economic sectors, analyzing price changes among

Kenyan businesses listed on the NSE. It was considered a stronger predictor of NSE performance compared to the NSE All Share Index, which included all listed stocks, including dormant, less active, and active shares, making it difficult to determine the impact of minor macroeconomic changes.

3.4 Data Collection

Weekly index prices of the NSE 25 index comprised the data that was used. These daily share prices were collected from January 2016 to December 2023. This secondary data, being historical, was collected using a checklist from the Central Bank of Kenya (CBK).

3.5 Data Analysis

The data collected was used to quantify the associations in the study. Stationary series provided the basis for time series analysis. The series stationarity was verified using the Augmented Dickey Fuller (ADF) test. The Jacque-Bera test was used to pre-test data for normality, as the efficient market hypothesis required returns to follow a normal distribution with zero skewness and three kurtosis. To test the accuracy of the strategies, the research first assessed the clustering volatility of multiple models using the GARCH model. The research examined EGARCH and TGARCH models.

3.5.1 Augmented Dickey Fuller Test

The Dickey Fuller test is a unit root test that tests the γ coefficient of the first lag of y. The equation is as shown below:

$$\Delta y_t = \alpha + \beta_t + \gamma y + \delta_1 \Delta_{y_{t-1}} + \delta_2 \Delta_{y_{t-2}} + \cdots + \delta_p \Delta_{y_{t-p}} + \varepsilon_t$$

The constant term α represents the Δ_{y_t}which is not explained by other variables in the model. The term β_t in the model refers to a time-varying component that influences y development. Additionally, the $\Delta_{y_t}$is dependent on its existing level δ_1. $\Delta_{y_{t-1}}$ are lagged differences that demonstrate how previous changes Δ_{y_t} influence its current change. Finally, the error term ε_t

refers to factors that influence y but are not included in the model. It is assumed that it is random and has no mean.

This test tests the null hypothesis that y = 0 time series data has a unit root. The unit root makes time series nonstationary. Null hypothesis rejection occurs if the test statistic falls below the confidence interval threshold.

3.5.2 Jacque-Bera Test

Jacque-Bera examines norms. Goodness of fit tests normal distribution data for skewness and kurtosis. Formula-based statistical testing for Jacque-Bera:

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$$

where n is the number of observations, S is the sample skewness and K is the sample Kurtosis. The test tests the null hypothesis of three kurtosis and zero skewness. Reject the null hypothesis and raise the Jacque-Bera statistic for each deviation to show error terms are not regularly distributed.

3.6 The Models

3.6.1 EGARCH Model

Nelson (1991) created the Exponential Generalized Autoregressive Conditional Heteroscedasticity model for volatility asymmetry. Instead of lagged squared errors, the condition variance's natural logarithm is permitted to fluctuate with time as a function of the lagged error terms. EGARCH(p,q) says:

$$log\ (\sigma_t^2)\ = \omega + \sum_{i=1}^{p} \beta_i log\ (\delta_{t-1}^2)\ + \sum_{j=1}^{q} \left[\gamma_j\ \frac{\varepsilon_{t-j}}{\sigma_{t-j}}\ + \alpha_j \left(\left| \frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right| - E \left| \frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right| \right) \right]$$

The leverage effect is exponentially multiplied by $log\ (\delta_{t-1}^2)$, providing non-negative values. The letters β, γ, and ε denote ARCH, asymmetry, and GARCH effects, respectively. ω is constant.

The parameter y matters while finding asymmetries. Model is symmetric if $\gamma_j = 0$, and positive shocks increase volatility more than negative shocks if $\gamma_j > 0$.

3.6.2 T-GARCH Model

Zakoian (1994) created the TGARCH model to capture positive-negative shock asymmetries. A multiplicative dummy variable is introduced to the variance equation when shocks are negative to test for statistical significance. Unlike EGARCH, influence is linear.

$$\delta_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{q} \gamma_i \varepsilon_{t-i}^2 I(\varepsilon_{t-i} < 0)$$

where if $\varepsilon_{t-i} < 0$, $I(\varepsilon_{t-i} < 0)$ $is\ equal\ to\ 1\ and\ zero\ otherwise$

The word for leverage or asymmetry is γ_i. A large and positive negative shock will have a stronger influence on δ_t^2, if ω > 0, ω > 0, γ = 0, leverage effects are absent.

3.7 Parameter Estimation

Using the student t likelihoods, the maximum likelihood technique was utilized to estimate the GARCH model parameters. The parameters' values are chosen in such a manner that the likelihood of the model-described process producing the observed data is maximized. The optimal model for the data was chosen using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Low AIC and BIC penalize models with additional parameters to balance model complexity and fit quality. Thus, the model with the lowest AIC and BIC will predict NSE volatility best.

$$AIC = \ 2k - 2\ ln\ ln\ (L)$$

$$BIC = ln\ ln\ (n)\ \ k - 2\ ln\ ln\ (L)$$

Where k is the number of parameters in the model, n is the number of observations and L is maximum value of the maximum likelihood function for the model.

Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) was utilized to evaluate the model's forecasting ability. MAE shows the average of absolute errors by calculating the mean of the absolute differences between predicted and actual values, whereas RMSE squares the differences before averaging and then takes the square root, making it more sensitive to larger errors and providing a higher penalty for significant deviations hence shows more defects. Mean absolute error is used for directionless forecasts. Lower MAE and RMSE indicate better model performance.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{n}}$$

$$MAE = \frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)}{n}$$

where $\hat{y}_i$ represents the predicted value for observation i, y_i represents the actual value for observation i and n is the number of observations.

CHAPTER FOUR

DATA ANALYSIS, FINDINGS AND INTERPRETATION

4.1 Data description

Weekly NSE25 share index data was used for this study. The data was obtained from the Central Bank of Kenya website and covered the period between 8th January 2016 and 29th December 2023, comprising a total of 417 observations.

4.2 Data Analysis

The study utilized the return term defined as follows;

$$r_t = \log\left[\frac{P_t}{P_{t-1}}\right]$$

where P_t represented the price of the NSE25 index and r_t represented the return. The descriptive analysis of the data is described in Table 1 below;

Table 1: Summary statistics of NSE 25 Share Index between January 2016 to December 2023.

Variables	Count	Mean	Std.Dev	Min	Max
P_t	418	3612	546.5374	2299	5017
r_t	418	-0.001374	0.03333	0.313100	0.331489

The graphical representation of the share index price shown in Figure 1 below, for the period covered, revealed a long-term downward trend, with the index declining from around KES 4,000 in 2016 to approximately KES 2,500 by the end of 2023. Periods of significant volatility were observed, with sharp peaks and troughs, including an initial rise until 2017, a steep decline around 2020, a brief recovery in 2021, and a consistent drop through 2022 and 2023.

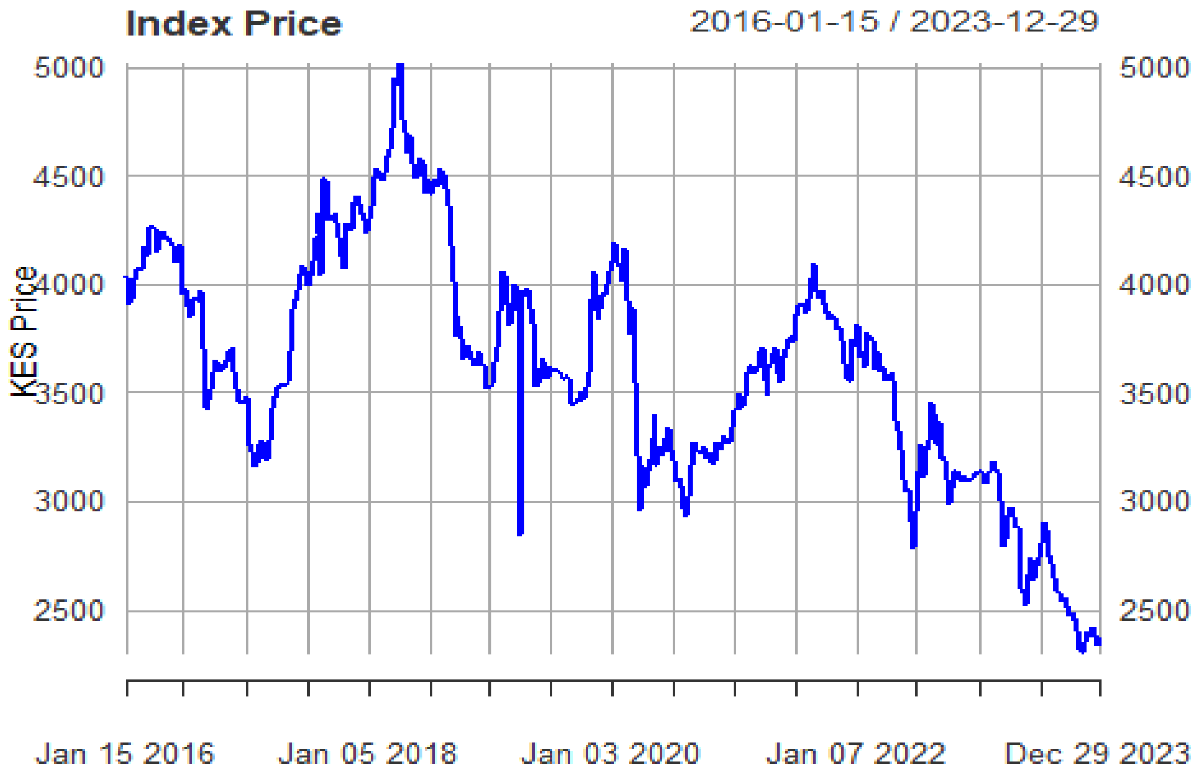

Figure 1: NSE25 Weekly Prices

The graph in Figure 2 illustrates the log returns of the NSE 25 Share Index from 2016 to 2023. The returns fluctuated around zero, with occasional sharp spikes. Returns were relatively stable from 2016 to 2017 but showed a significant negative spike in 2018. After a period of stability in 2019, heightened volatility occurred in 2020, including large negative spikes. From 2021 to 2023, the returns stabilized, with movements closer to zero, reflecting reduced market fluctuations compared to 2020.

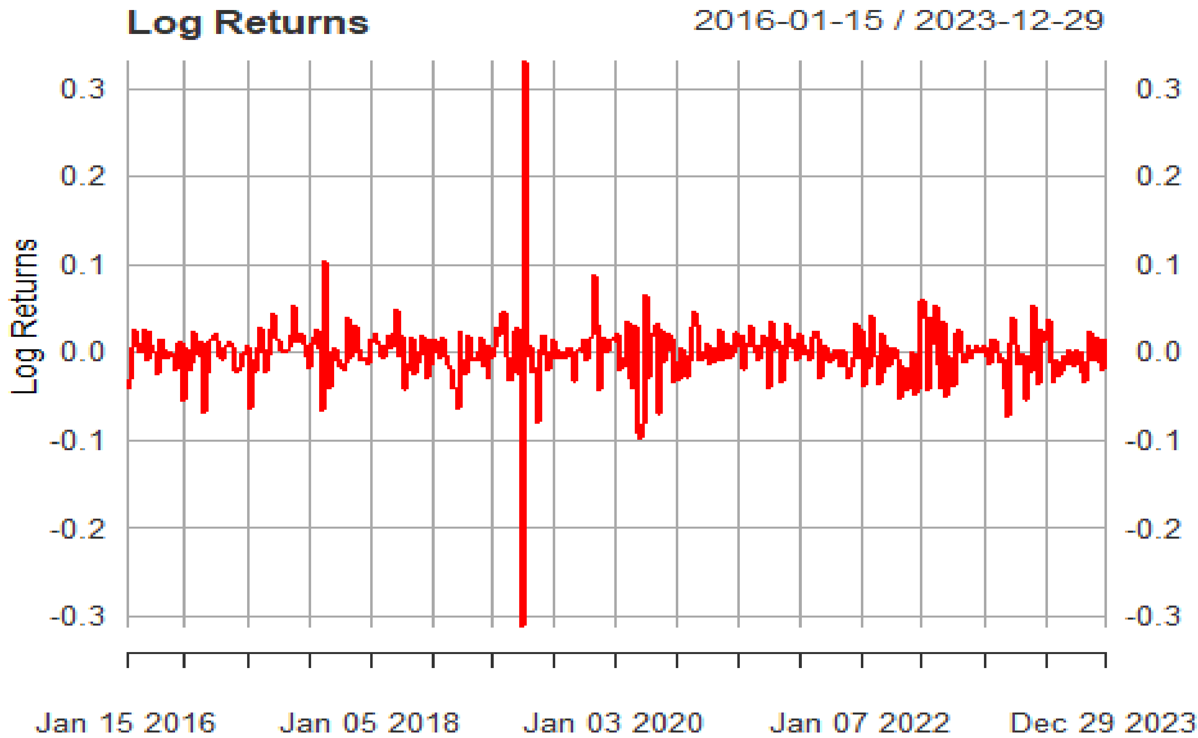

Figure 2: NSE25 Weekly returns

4.2.1 Results of Stationarity test

The null hypothesis when testing for stationarity was that a unit root is present in the time series data which is a characteristic that makes it non-stationary. A p-value of 0.01 indicated that the null hypothesis was rejected at the 1% significance level, confirming the data was stationary**.** The results of the stationarity test are summarized in Table 2 below

Table 2: Augmented-Dickey Fuller Test for Stationarity

		T-Statistics	P-Value
Augmented-Dickey Fuller	Test-Statistic	-7.5331	0.01

4.2.2 Results of Normality test

The Jacque-Bera test of goodness of fit to the normal distribution was used in this study. It tested whether the data had a skewness or kurtosis matching that of a normal distribution. The results for the Jacque-Bera test for the share index weekly returns were shown in Table 3 below. Since the test statistic was far from zero, we rejected the null hypothesis and therefore concluded that the monthly returns were not normally distributed.

Table 3: Jacque-Bera Test for Normality

Variable	Test-Statistic	P-Value
Jacque-Bera	29225	$2.2e^{-16}$

4.3 Empirical Results

4.3.1 Asymmetric GARCH Models

The study focused on two asymmetric GARCH models, namely the EGARCH models and the TGARCH model. The EGARCH model was used on the weekly return of the NSE25 share index to capture the asymmetries in volatility and ensure that the estimates are non-negative. The TGARCH on the other hand was used to test for leverage effect and the relationship between the stock market return and volatility. The summary of the results is as shown below in Table 4

Table 4: Parameter Estimation Results

Parameter\ Model	EGARCH	TGARCH
mu	-0.000814	-0.001995
omega	-5.015474	0.014240
alpha1	-0.318252	0.622398
beta1	0.297815	0.089696
gamma1	0.701927	0.341749
AIC	-1822.185000	-1839.138000
BIC	-1802.032000	-1818.984000
log-likelihood	916.092600	924.568900

The EGARCH model equation is:

$$\log(\sigma_t^2) = -5.015474 + 0.297815 log\ (\delta_{t-1}^2)\ + 0.701927 \frac{\varepsilon_{t-j}}{\sigma_{t-j}} - 0.318252 \left(\left| \frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right| - E \left| \frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right| \right)$$

The TGARCH model equation is:

$$\delta_t^2 = 0.014240 + 0.622398 \varepsilon_{t-i}^2 + 0.089696 \sigma_{t-j}^2 + \ 0.341749 \varepsilon_{t-i}^2 I(\varepsilon_{t-i} < 0)$$

The findings from the EGARCH and TGARCH models provided significant insights into the volatility dynamics of the dataset. The EGARCH model revealed a strong leverage effect denoted by gamma of 0.701927, indicating that negative shocks increase volatility more than positive shocks of the same magnitude. It also showed higher volatility persistence denoted by beta1 of 0.297815, suggesting that the impact of past volatility remained for longer durations. However, the model's fit was slightly less optimal compared to TGARCH, as it had higher AIC (-1822.185) and BIC (-1802.032) values.

Conversely, the TGARCH model demonstrated greater sensitivity to past shocks denoted by an alpha1 of 0.622398, indicating that recent events have a more pronounced effect on current volatility. The TGARCH model had superior model fit statistics, with lower AIC (-1839.138) and BIC (-1818.984) values and a higher log-likelihood (924.5689). These results suggested that while EGARCH captured asymmetries and longer-term volatility persistence effectively, TGARCH offered a better overall fit and captureed immediate shock responses more robustly.

In order to compare the model with the best fit, the study used the AIC and BIC measures. Figure 3 and 4 show a graphical representation of the modelled results.

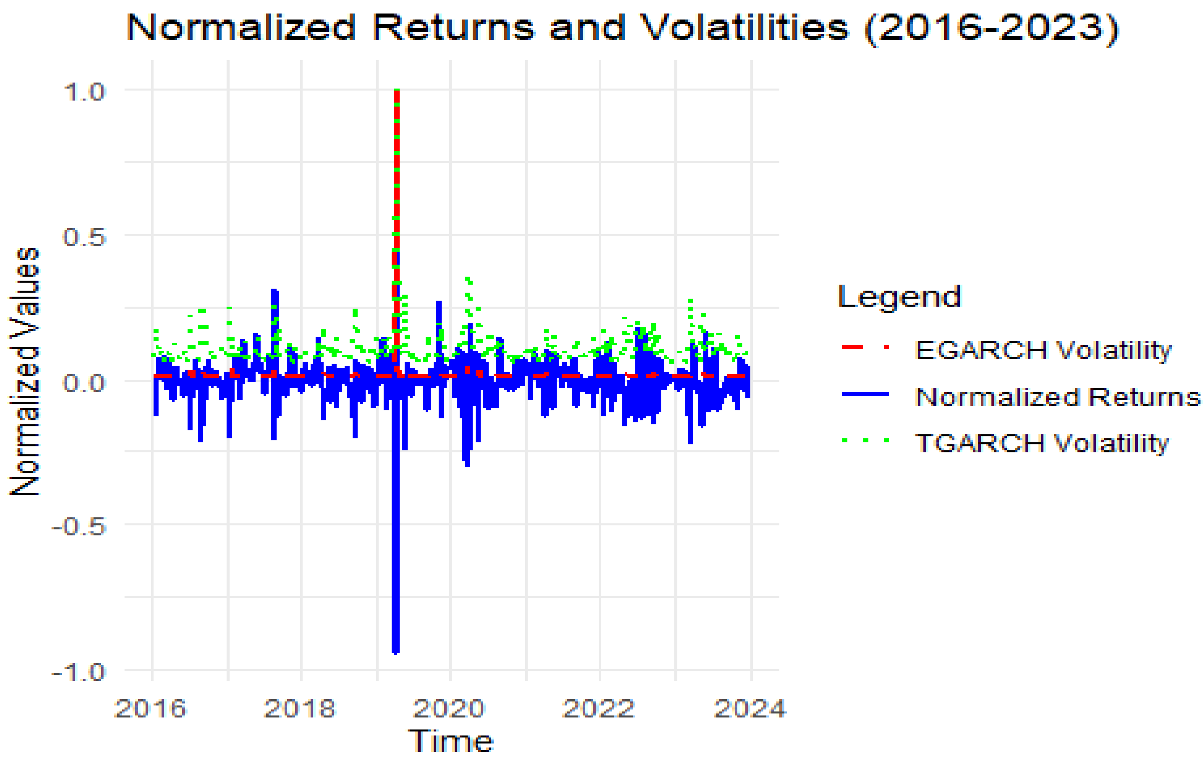

Figure 3: NSE 25 Weekly Returns with EGARCH and TGARCH Volatility

The normalized returns fluctuated around zero, with noticeable sharp spikes that reflected extreme market movements. The significant drop observed in early 2020, corresponding to heightened market stress, can be attributed to the onset of the COVID-19 pandemic, which disrupted global economic activity. Lockdowns, reduced consumer spending, and capital flight from emerging markets, including Kenya, exacerbated uncertainty and led to significant contractions in economic activity. Additionally, the sharp decline in oil prices and policy uncertainty further intensified market stress, contributing to the observed volatility in the NSE 25 index during this period.

The EGARCH model captured a smoother volatility trend, responding strongly to extreme negative returns, such as during 2020, reflecting its ability to model leverage effects. In contrast, the TGARCH model exhibited more pronounced short-term fluctuations and higher volatility spikes, particularly during turbulent periods. Both models effectively captured periods of increased volatility, though TGARCH appeared more sensitive to short-term changes, while EGARCH provided a more stable estimate over time.

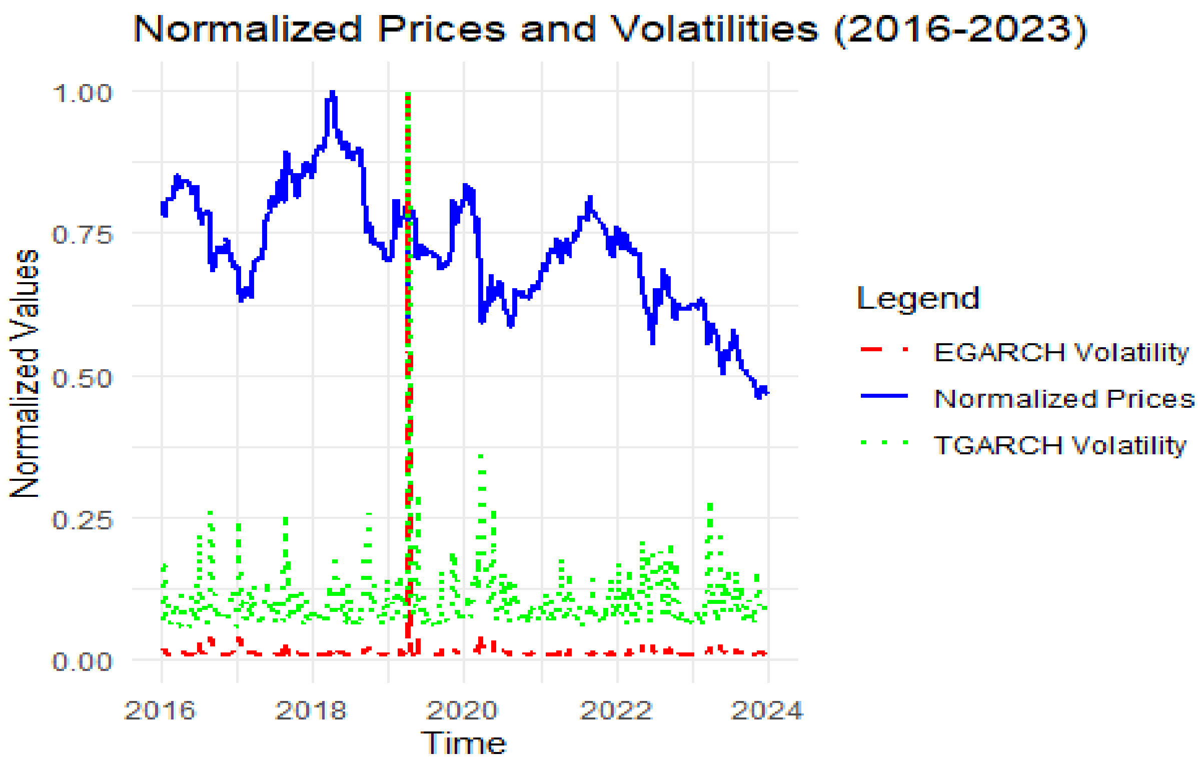

Figure 4: NSE 25 Weekly Volatility Comparison with EGARCH and TGARCH Volatility

The prices showed a long-term downward trend, declining steadily from 2016 to 2023, with notable sharp drops during periods of market distress, particularly in early 2020. EGARCH volatility remained relatively smooth, increasing during periods of significant price declines and remaining stable during less turbulent times. On the other hand, TGARCH volatility reflected greater sensitivity, capturing frequent and pronounced short-term spikes. The TGARCH model was more reactive to sudden shocks, while the EGARCH model better captured the overall trend of volatility associated with price movements.

4.3.2 Forecast Evaluation,

The other objective of the study was to forecast volatility and compare which model is best at forecasting volatility between the EGARCH and TGARCH. In order to identify the best model, the study used the MAE and RMSE measures. The RMSE is the square root of the variance of the residual and it indicates how close the observed data points are to the model's predicted values. The MAE measures the average magnitude of the errors in a set of predictions, without considering their direction.

Table 5: Forecast Evaluation

Model	MAE	RMSE
EGARCH	0.01455597	0.2754746
TGARCH	0.001203603	0.005401607

The lower the value of MAE and RMSE, the better the model is at forecasting. Based on the results in Table 5 above, TGARCH was a better model when it comes to forecasting as it had the lowest MAE and RMSE.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary of Findings

The NSE Share 25 Index showed considerable volatility clustering, with periods of high volatility followed by similar patterns from 2016 to 2023. The study analyzed the volatility at the NSE using the NSE 25 Share Index from 8th January 2016 to 29th December 2023. The weekly returns of the prices were also obtained. Various market efficiency tests such as the Augmented-Dickey Fuller test and Jacque-Bera test were then used to test for stationarity and normal distribution of the share index for the period under observation. The asymmetric GARCH models used in the study were the EGARCH and the TGARCH model. From the empirical results, the NSE 25 Share Index for the period under observation was not normally distributed, the returns were stationary and therefore we can conclude that the returns were mean-reverting in their first differencing form.

Following the results from the parameter estimation of the EGARCH and TGARCH models, the models coefficients were positive and statistically significant which implied volatility clustering and persistence of the market. For the EGARCH model, the results showed that the market reacted differently to positive and negative shocks of the same magnitude whereas for the TGARCH model, the leverage effect were detected which implies that the higher the volatility, the lower the returns. The two asymmetric GARCH models were compared using AIC and BIC to select the model with the best fit and the results showed that the TGARCH model was a better fit compared to the EGARCH model as it had a lower AIC and BIC value.

5.2 Conclusions

This main objective of the study was to understand volatility clustering at the NSE and a number of conclusions can be drawn from the results of the data. First, the stylized facts of the financial time series data such as volatility persistence and leverage effect in addition to volatility clustering were detected. It is necessary to account for stylized facts in order to get reliable future forecasts of volatility. Secondly, for the asymmetric GARCH models the TGARCH model was a better fit at parameter estimation compared to the EGARCH. Lastly, when it comes to forecasting volatility, based on the results we conclude that TGARCH model also outperforms the EGARCH model

Market stress and volatility clustering are seen in Kenya's financial environment in the NSE Share 25 Index between 2016 and 2023. This trend, which demonstrates that high volatility is usually followed by anarchy, is consistent with volatility patterns in other developing African republics and implies that market shocks persist. Local market volatility is largely impacted by external shocks, and Kenya's market is particularly vulnerable to local and international economic difficulties. This increased sensitivity to global swings emphasizes the need of reliable forecasting approaches like as GARCH models, which can anticipate volatility persistence across time.

Kenya's sensitivity to global shocks renders it more susceptible than developed economies, necessitating sophisticated risk management strategies. Thus, volatility clustering in financial markets, particularly in emerging nations, grows. This study emphasizes the need for improved modeling tools to assist investors and regulators in navigating market volatility and protecting against regional and global unpredictability.

5.3 Recommendations

The NSE Share 25 Index's significance to economic shocks and volatility clustering propose several options for Kenyan financial professionals, investors, and regulators. First, improved forecasting techniques, such as GARCH models, are required to capture and anticipate volatility across time. By forecasting future volatility, these models may assist investors in making better decisions and reducing risks during times of financial turbulence.

Policymakers should adopt customized risk management frameworks for Kenya's market. Financial buffers, such as stabilization funds, may help to offset external shocks. Regular financial system stress testing could allow for proactive steps and evaluate resistance to global market movements that might harm Kenya's economy.

Investors must diversify their investments to prevent volatility and reliance on foreign markets. They may be able to mitigate large downturns in Kenya or the rest of Africa by diversifying assets across markets and sectors. This study also underlines the need of combining local and international economic data in risk assessments to better understand and forecast volatility variations.

Finally, due to increased market volatility clustering and vulnerability, Kenya's financial authorities, regional organizations, and international entities should work more closely. This cooperation might develop early warning systems and volatility management best practices to improve resilience to local and international market shocks. These proposals increase Kenya's financial market stability, assisting investors and policymakers in dealing with global economic volatility and reliance.

5.4 Suggestions for further research

Many interesting research topics emerge as a result of volatility clustering and the increasing sensitivity of Kenya's NSE Share 25 Index to economic shocks. Future study should look on the efficiency and adaptability of GARCH models and its variants, such as EGARCH and TGARCH, in Kenyan financial markets. Researchers can see how effectively these models predict volatility patterns during local and worldwide economic disturbances since they include asymmetric shock responses. This will increase understanding of model performance in various market scenarios. Given Kenya's unique economic structure, future research should look at sector-specific volatility dynamics to examine whether some sectors cluster more strongly or react differently to shocks. Sector-based risk management systems benefit from research that identifies sectors that are resilient or vulnerable to external shocks.

The impact of global and macroeconomic data on Kenyan market volatility is intriguing. Researchers could explore how interest rates, inflation, currency rates, and global commodity prices influence volatility. Incorporating micro data, such as daily or hourly price movements, into GARCH models alongside macroeconomic variables can enhance forecast accuracy and provide deeper insights into short-term volatility dynamics. This combined approach improves predictive power and offers a nuanced understanding of volatility patterns.

Investor behavior and volatility could also be investigated in the future. Behavioral finance study on herd behavior, risk aversion, and market sentiment may help Kenyan investors deal with economic shocks and volatility. These findings may aid in the development of more sophisticated volatility control strategies for Kenyan market participants by shedding light on volatility clustering habits.

Finally, legislative and regulatory initiatives aimed at reducing volatility are becoming more important. Financial buffers and stabilization funds might be investigated to see how they impact market resilience. Given Kenya's status as a developing market and sensitivity to global economic shocks, regular financial stress tests may be both practical and useful. Researchers can assist

Kenya's financial markets weather impending economic crises by investigating these issues and giving detailed recommendations to investors and regulators.

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