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Revisiting the Dynamics of Stock Market Returns Volatility of Listed Companies under the NSE 20 Share Index in Kenya

Daniel Ngigi[1] and Angelica Njuguna[2]
[1]*Department of Econometrics and Statistics, Kenyatta University, Nairobi, Kenya*
[2]*Correspondence: Angelica Njuguna, Department of Econometrics and Statistics, Kenyatta University, P.O. Box 43844-00100 Nairobi, Kenya. E-mail: njuguna.angelica@ku.ac.ke*

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Abstract: This study explored the behavior of stock market returns volatility in the Nairobi Securities Exchange (NSE) for listed companies under the NSE 20 share index in Kenya. The study analyzed stock returns using 2,999 observations from 3 January 2011 to 30 December 2020 and estimated a generalized autoregressive conditional heteroskedasticity, GARCH (1,1) and an exponential generalized autoregressive conditional heteroskedasticity, EGARCH (1,1) models. The study found that the stock returns volatility of companies listed under the NSE 20 share index exhibited both volatility clustering and persistence behavior. However, there was no evidence of the leverage effect on future volatility in returns.

Keywords: stock market returns, volatility clustering, leverage effect volatility, volatility persistence.

1. Introduction

Modeling the volatility of asset returns has become one of the important fields of research in economics and finance since this concept has many applications to both disciplines (Abdalla & Winker, 2012). The areas of applications include Inflation rates, exchange rates, risk management, and asset pricing. The creation of stock markets is an important step in enhancing financial development and economic growth as there is a positive relationship between economic growth and long-term capital (Demirguc & Levine, 1996). Economic literature suggests that stock markets are related to activities in the economy in three ways, namely: current stock prices reflect future economic activities; changes in discount rates affect stock prices and investment; and stock price changes

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could potentially alter wealth affecting consumption and investment, that is, holding all other factors constant, the wealthier people are the more they spend (Steindel & Ludvigson, 1999). Additionally, economies through financial development benefit from allocation efficiency and risk diversification (Park & Lee, 2011).

A stock market is where the government and industries can raise long-term capital where investors can buy and sell securities (Arnold, 2004). Investors earn stock returns from investing in companies by buying in their stocks (Violita, 2019). Stock returns can be positive, negative, low, or high. Investors get returns after trading their stocks over a specified period from which the difference between the selling price of a stock and its buying price, is their returns. Usually, high stock returns attract investors, while low and negative returns discourage them from buying companies' stocks. In general, investors are assumed to be rational in efficient markets (Fama, 1970).

However, since stock returns affect how investors react, investors' sentiments affect the stock market returns making them irrational consequently leading to the mispricing of stocks (Altuwaijri, 2016). Evidence shows that distressed stocks are mispriced during high sentiment periods (Avramov, Chordia, Jostova & Philipov, 2019). Hence, stock returns end up becoming volatile over time. The volatility of stock returns shows the extent of variation of asset returns over time. In an efficient market, volatility is assumed to be systematic (Fama, 1970). Studies have shown that the volatility of financial assets such as stocks displays clustering, asymmetry, and persistent behaviors (Abdalla & Winker, 2012). These characteristics affect investors' response to the stock market because they are indicators of future stock market returns behaviors. For example, stock returns volatility is related to the change in the assets level of companies. Marques, Fuinhas and Marques (2013) found a bidirectional causality between stock returns volatility and asset expansion, as well as between stock market development and economic growth.

When stock returns are highly volatile, investors shy away from trading or acquiring new stock. Cooper, Gulen and Schill (2008) found that there is a negative correlation between activities associated with asset expansion and subsequent abnormal stock returns. This negatively affects companies as they get fewer investments from selling new shares. Nevertheless, this is when risk-takers get high returns if volatility favors them. On the other hand, low stock returns volatility becomes attractive to traders as it implies low risk. Companies have the advantage of attracting investors, and expanding their activities when stock returns volatility is low.

This study revisited the dynamics of the volatility in the stock market returns of listed companies under the NSE 20 share index in Kenya using a more recent period between 3 January 2011 and 30 December 2022 with total observations of 2,999 from daily business transactions. This period for the country was quite eventful where two highly contested presidential elections happened in 2012 and 2017, and occasional droughts experienced in 2014, 2016 and 2017. This was also the period where Covid-19 pandemic occurred worldwide and disrupted almost all economic activities. Incidentally, the returns in the Kenyan stock market displayed volatility during this period which seems to reflect distressed stocks due to uncertainty in the financial market.

The period and observations used in the study were also longer than most empirical studies as far as stock behavior is concerned (e.g. Ombaba, 2015; Herbert, Ugwuanyi & Nwaocha, 2019; Enow, 2023). Increasing the study period and hence the number of observations will help unlock more dynamics of the stock returns volatility that could be missing in previous studies. The study examines whether stock market returns volatility in Kenya continue to exhibit volatility persistence and clustering as observed by some empirical studies (Ombaba, 2015; Kalovwe, Mwaniki & Simwa, 2021). Moreover, the study investigates the presence of leverage effect on volatility in the Kenyan stock market. The literature sent an ambiguous signal as to whether there is evidence of this behavior. The study by Ombaba (2015) concluded the presence of leverage effect in the Kenyan stock market contrary to what Kalovwe et al., (2021) found in their studies.

The remainder of this study is structured as follows. Section 2 provides a look into the Kenyan stock market and describes trends and patterns of daily stock returns volatility from the period 2011 to 2022. Section 3 briefly reviews the literature on stock market returns. Section 4 presents the econometric model and data sources. Section 5 presents the empirical findings of the study. Finally, Section 6 concludes the study and gives policy recommendations.

2. The Kenyan Stock Market

2.1. The Nairobi Securities Exchange

In Kenya, the stock market is called the Nairobi Securities Exchange (NSE). It was established in 1954 and its main functions are to help in stock price discovery and provision of liquidity to corporations through facilitating the issuance of shares of companies in Initial Public Offers (IPOs). Through various policies, the NSE has enhanced trading activities for investors aiming at streamlining its activities, saving time, and giving advice to investors and companies. Such policies include creating share indices such as the Nairobi Securities 20 share index (NSE 20), the Nairobi Securities 25 share index (NSE 25), and the Nairobi All-share index (NASI). Each index comprises various characteristics from which listed companies are classified. The NSE 20 monitors the performance of the 20 best-performing companies in terms of weighted market performance based on the number of shares traded, deals, market capitalization, and turnover for 12 months. The NASI comprises all companies in the stock market and the NSE 25 tracks the best 25 companies in the stock market based on a similar classification as the NSE 20 (NSE, 2022).

Other policies by the NSE include the introduction of an equity settlement cycle from four days after the sale of shares to three days. The Ibuka program was also introduced in 2018 with the objective of companies to grow through various stages of growth. It comprises a panel of advisors and consultants based on the company's growth stages such as the incubation and acceleration programs. Companies have easier access to the market and visibility opportunities through exposure to media, investors analysts, and stakeholders. Companies can get expert advisory, value discovery, and business sustainability (NSE, 2022).

Capital markets connect the financial sector with non-financial sectors, reducing transaction costs, price discovery, provision of liquidity, and risk transfer. As one of the developing economies through the NSE, Kenya has tried to enhance trading activities for investors through the abovementioned policies. However, the Kenyan capital market is still small compared to capital markets in developed economies, despite it being considered relatively more liquid and active than other stock markets in Sub-Saharan Africa. NSE faces challenges in its development such as low liquidity levels, low investors' confidence, lack of competitive pressure, and vulnerability to shocks (Nyasha & Odhiambo, 2014).

Over the years, due to the challenges faced by the market, there has been a stagnation in the yearly total number of companies listed in the stock market from 57 in 1988 to 62 in 2022. The annual change in the number of listings has been low, with 6 new listings in 2014 as the highest number. On the other hand, some companies ended up delisting from the markets, and in 2002, the market saw 8 companies delisting. This trend is illustrated in Figure 1. All the yearly changes in listing show that the listing rate is below the NSE target of 10 listings per year (NSE, 2022). Other problems attributed to low levels of listing are the main factors limiting the supply of shares are the reluctance of small, family-owned businesses to dilute ownership, and the related costs involved in the application for listing, that is, it is costly and tedious to make public offers. Moreover, the perception by companies is that the risks associated with additional disclosure are not adequately compensated for by stock returns (Capital Markets Authority, 2012b).

2.1. Stock Returns Volatility for Companies Listed Under the NSE 20 Share Index

Stock market returns are considered as volatile if they frequently reaching new highs and new lows. Various indices are used to measure stock returns volatility. One such index to measure historical volatility is the beta index. It measures historical volatility, showing how much investors are exposed to systematic risk. A beta value of one (1) shows that investors exposure to a market risk is equal to the broad market risk. A positive beta value of below 1 shows that investors exposure to a market risk is lesser than broader market risk. Finally, a negative magnitude of beta shows that investors are exposed to a market risk that moves opposite to the broader market risk.

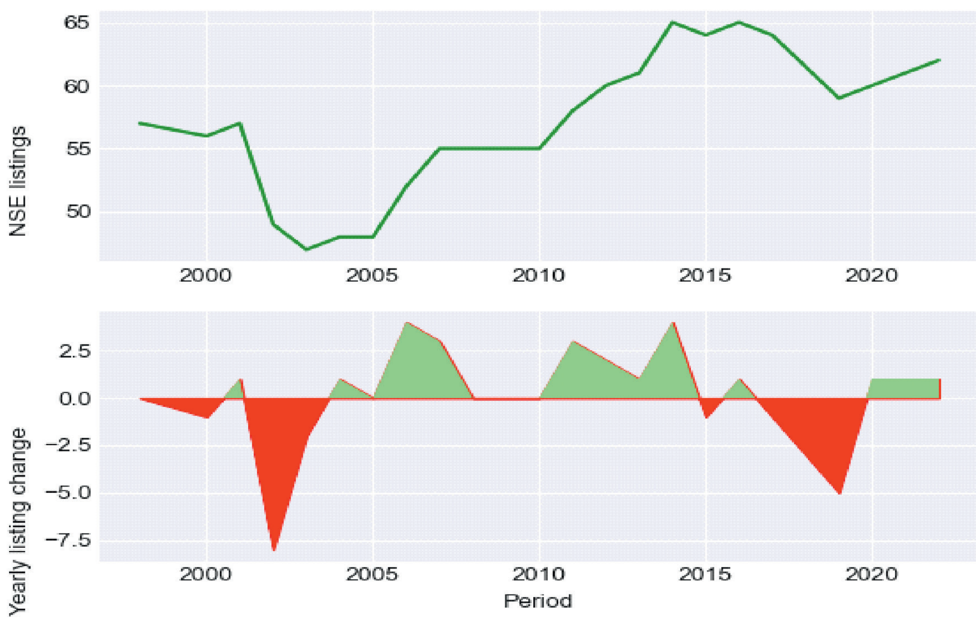

Figure 1: NSE listing and delisting trend from 1998 to 2022

Source of data: World Bank online database (2023).

There is no well-established volatility index in Kenya compared to developed countries. Nonetheless, the beta for NSE 20 can be calculated from historical returns, by taking NSE 20 as the broader market[1]. Table 1 below shows the beta volatility index for NSE 20 individual companies from 2011 to 2022[2]. Companies listed under NSE 20 show that they are not exposed to more than the broader market risk since none of the companies shows a beta greater than 1. However, the Kenya Reinsurance Limited and

STANBIC Bank Limited show that their stock returns risk is moving in the opposite direction of the broader market risk. This shows that most of the NSE 20 companies have not expose investors to more than the broader market risk for the past 12 years.

Table 1: Beta index for NSE 20 Companies, 2011 to 2022

Company	*Beta*	*Company*	*Beta*
1. Absa Bank Kenya PLC	0.0005	11. Kenya Reinsurance Corporation Limited	-7E-06
2. Bamburi Cement PLC	0.0303	12. Kenya Commercial Bank Group PLC	0.0031
3. British American Tobacco Kenya PLC	0.796	13. Kenya Electricity Generating Company Limited	0.0006
4. BRITAM Holding PLC	0.0014	14. Kenya Power and Lighting Company PLC	0.0005
5. Centum Investment Company PLC	0.0046	15. Nation Media Group	0.0275
6. Co-operative Bank of Kenya Limited	0.0002	16. Safaricom Limited	0.0014
7. Diamond Trust Bank	0.0211	17. SCAN Group Limited	0.0041
8. East African Breweries Limited	0.0539	18. Stanbic Bank Kenya Limited	-0.0012
9. Equity Group Holding PLC	0.0034	19. Standard Chartered Bank	0. 00033
10. I&M Holding PLC	0.0023		

Source of data: Wall Street Journal (2023).

The volatility trend for the broader market (NSE 20) shows some volatility clustering and persistence behavior over time. These correspond somehow with the behavior of the total value of all shares traded in the NSE 20. When the total value of traded shares rises or falls gradually, there is less pronounced clustering. However, when the value of total traded shares abruptly rises or falls, the volatility is high and the persistence level falls. Figure 2 above illustrates the NSE 20 stock returns volatility trend from 2011 to 2022.

3. Theoretical and Empirical Literature

3.1. The Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) introduced by Fama (1970), explains how efficient financial markets work. An efficient market has no information asymmetry. Investors therefore cannot overvalue or undervalue stocks. This suggests that an investor cannot outperform the market in the long run since the market value of a stock reflects all relevant information and is available to all rational investors. This further

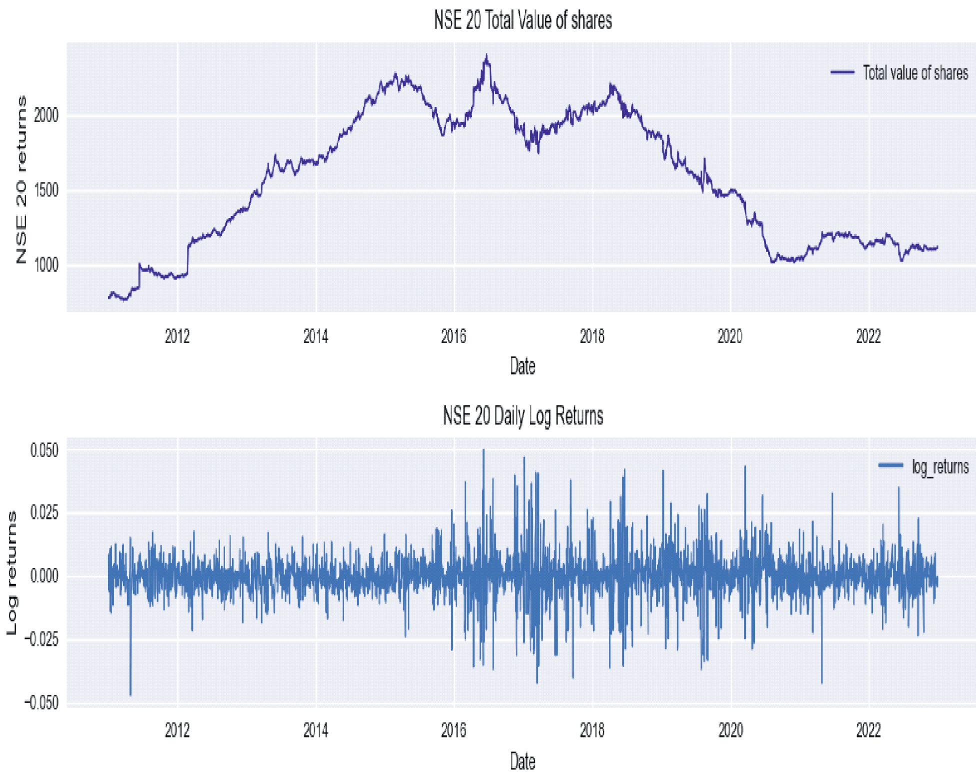

Figure 2: Stock Returns Volatility Trend for NSE 20

Source of data: Wall Street Journal (2023).

implies that there is no possibility of buying an undervalued stock and later selling it at an overvalued price and vice versa.

However, the hypothesis states that the information available differs in three forms: the weak EMH only has full information on past stock prices. The semi-strong EMH has all past information and any new information as it arrives in the market such that prices can adjust quickly factoring in new information. The strong form of EMH assumes that prices reflect public and private information. However, this strong EMH does not give investors an advantage over stock price determination or prediction using technical or fundamental analysis since all private information does not leak to the market. The strong form of EMH hence emphasizes the main hypothesis of the theory that investors cannot outperform the market in the long run.

Malkiel (1973) improved the weak form efficient market hypothesis by Fama (1970) and hypothesized that stock prices follow a random walk behavior. Thus, historical information cannot be used to predict market prices. Malkiel hence stated that since investors act rationally and have equal access to information in the stock market, it can only be through luck for an investor to gain in the stock market. The theory advises investors to invest in a portfolio that resembles the whole market as the best trading strategy. This means, investing in a security whose price movement perfectly reflects the movement of every security in the stock market or a given market index.

3.2. The Behavior of Stock Returns

The asymmetric behavior of stock market volatility in developed and developing countries shows that generalization could be erroneous. This asymmetric behavior could reflect the existence of time-varying risk premiums given that volatility is priced (Bekaetrt & Wu, 2000). Abdalla & Winker (2012) found stock returns volatility is asymmetric in the Cairo and Alexandria and Khartoum Stock exchange markets. In Ghana, the stock market in the presence of the COVID-19 pandemic also showed asymmetric effects (Insaidoo, Arthur, Amoako, & Andoh, 2021). The arrival of news during the COVID-19 pandemic showed strong empirical evidence that similar announcements have different impacts on the volatility of stock returns for developed and emerging markets (Bakry, Kavalmthara, Saverimuttu, Liu & Cyril, 2021). More evidence was found to support this by Muguto and Muzindutsi (2022), who suggested that asymmetric behavior is evident in developed and developing countries. Their findings highlighted that the idea of developed countries being more informed about market behaviors should be questionable.

Persistence in stock returns volatility shows the extent stock returns exhibit similar patterns or trends over time. Some stock returns are more affected by shocks and take longer to revert to the mean (Coffie, 2015), while others have a quicker mean reversion behavior as evident from the Russian stock market (Caporalea, Gil-Alanab &Tripathy, 2019). Stock returns volatility persistence has been observed to have a mixed pattern in developing and developed countries. For example, it was found that persistent behavior and mean reversion in both stocks of the G7 (developed) countries and the BRICS (developing) countries but in different scales (Muguto & Muzindutsi, 2022).

The other characteristic of financial assets is volatility clustering, which shows that periods of high stock returns volatility are followed by periods of high stock returns volatility and periods of low stock returns volatility are followed by periods of low stock returns volatility. This behavior could have more power in explaining the past behaviors of stock returns volatility or more predictive power than the persistence behavior. Volatility clustering could be nonlinear, persistent, and asymmetric across different periods (Ning, Xu & Wirjanto, 2015; Kim & Song, 2020)

4. Method and Data

4.1. The Expected Stock Returns

The study adopted a theoretical framework guided by the efficient market hypothesis (Fama, 1970) and the random walk hypothesis (Malkiel, 1973). If the random walk hypothesis holds, then the weak form of the efficient market hypothesis also holds, but not vice versa (Ko & Lee, 1991). A simple random walk process for stock returns is expressed as:

$$r_t = r_{t-1} + \varepsilon_t, \tag{1}$$

Where r_t is the log returns at time t, r_{t-1} is the log returns at time $t-1$, and ε_t is the error term.

4.2. Model Specification

A stockholder is interested in the rate of stock returns and its variance after buying a stock. Financial assets such as stocks do not have constant variance and an increase in the variance of stock returns means the stock is riskier to hold, and low variance implies lower risk (Enders, 2015). Due to the heteroskedastic behavior, modeling stock returns calls for volatility models that capture several behaviors of series. Engle (1982) introduced a model to overcome the problem brought about by heteroscedasticity called the autoregressive conditional heteroscedasticity (ARCH (p)) model. Since ARCH models are second-level models, it implies that they need a mean equation. The model hence was based on the variance of the error term from a mean model of stock returns expressed in Equation (2). ARCH model had both mean and variance changing simultaneously as an autoregressive process. The mean equation for stock returns is expressed as follows:

$$r_t = \mu + \varepsilon_t,$$

Where μ is the conditional expected log returns (given the information set (I_{t-1}) and ε_t are the log returns innovations.

The log returns at time t are calculated as the difference in the log of closing stock prices as follows:

$$r_t = \Delta\ln(P_t) = \ln(P_t) - \ln(P_{t-1}) \tag{3}$$

Where r_t or $\Delta\ln(P_t)$ is the first difference in the log of stock price, P_t is the stock price at time t, P_{t-1} is the price of stock at time $t-1$, and *ln* is the natural logarithm.

The conditional variance equation for the ARCH(p) model can be expressed as follows:

$$\varepsilon_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \cdots + \alpha_p\varepsilon_{t-p}^2 + v_t, \tag{4}$$

where ε_t^2 is the conditional variance, α_0 is the constant of the ARCH (p) model, $\alpha_1, \alpha_2, \ldots, \alpha_p$ are the coefficients, respectively, of lags of conditional variances $\varepsilon_{t-1}^2, \varepsilon_{t-2}^2, \ldots \varepsilon_{t-p}^2$, p is the lag length, and v_t is an error term which is normally distributed with zero mean and constant variance.

In this study, however, due to the limitations of ARCH(p) models, that is, being extremely general and weak in empirical estimations, the generalized autoregressive conditional heteroskedasticity, GARCH (p,q)) model (Bollerslev, 1986) was used. In the GARCH (p,q) model, the heteroskedastic variance is modeled as an autoregressive part (p) and the moving average part (q). The conditional variance in the GARCH (p, q) model is parameterized as a distributed lag of past innovations squared and conditional variances. According to Brook and Burke (2003), the lag order (1, 1) or GARCH (1, 1) is sufficient to capture all the volatility clustering behavior present in the series. The GARCH (1, 1) for this study is specified as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1\mu_{t-1}^2 + \beta\sigma_{t-1}^2, \tag{5}$$

Where σ_t^2 is the conditional variance, μ_t is the rational value of the expected log returns at time $t-1$, α_0 is the constant term of the model, α_1 is the parameter of the squared residuals at lag 1. The coefficient α_1 captures the volatility clustering behavior of stock returns, that is, the impact of past volatility shocks on current volatility. On the other hand, β is the coefficient of the conditional variance at lag 1 that captures persistence in stocks returns volatility.

The GARCH (p, q) model is limited to capturing stock returns' persistence and volatility clustering behaviors. To capture the effect of news on stock returns volatility, Nelson (1991) introduced the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model. The EGARCH model guarantees that the parameters are positive since it works with the log of variances. There are also no restrictions on the parameters. However, it is necessary to maintain stationarity, *achieved* by having β in equation (6) positive and less than one. Equation (6) below is the EGARCH (1,1) model for conditional variance used in this study.

$$\ln(\sigma^2) = \omega_0 + \alpha\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \beta(\sigma_{t-1}^2) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}}, \tag{6}$$

Where $\ln(\sigma^2)$ is the log of variance of the series, ω_0 is the constant term of the EGARCH model, α is the coefficient of the ARCH effects, β captures the volatility persistence such that if the value is close to one, then volatility persists for a long time. On the other hand, γ is the coefficient that captures the asymmetry behavior which is also referred to as the leverage parameter. The value of γ is expected to be greater than 1 in most empirical situations so that volatility into the future or uncertainty can be increased by a negative shock while a positive shock reduces the effect on future uncertainty (Kalovwe et al., 2021).

The study used maximum likelihood estimation to estimate models in equations (5) and (6).

4.3. Data Sources

The study used secondary data sourced from the Wall Street Journal. It comprised of daily closing prices of 19 of NSE 20 listed companies from 3 January 2011 to 30 December 2020 comprising of 2996 observations. The exclusion of one company was because of the unavailability of consistent data due to a merger between National Industrial Credit (NIC) Bank Group Plc and the Commercial Bank of Africa (CBA) to form NCBA Group Plc in 2019.

4.4. Descriptive statistics

The summary statistics: count, mean, median, standard deviation, skewness, kurtosis, minimum, and maximum values of the stock returns series are presented in Table 2. As expected, the average or mean stock returns is approximately equal to zero.

Table 2: Descriptive statistics of the NSE 20 return series

Statistics	*values*
Count	2996
mean	-0.000004
Standard deviation	0.0086
Skewness	0.0847
Kurtosis	5.2976
Excess kurtosis	2.2976
Minimum	-0.0471
maximum	0.04976

Source: Author's Compilation.

The following tests test the stock returns series to test whether using volatility models is appropriate. ARCH-LM test was the first test to test any evidence of ARCH effects and a check on the distribution properties, that is if the series was normally distributed.

Table 3: ARCH LM test results

ARCH LM statistics	*Prob. Chi-square (5%)*
62.2184	≈0.0000
Shapiro-Wilk Test for Normality	
Test statistics	**P value**
0.9125	≈0.0000

Source: Author's Compilation

From the results in Table 3, the study rejected the null hypothesis for both arch effects and normality. Therefore, ARCH effects are present, but the residual series is not normally distributed.

5. Empirical Results

The first part of the descriptive statistics part presented summary statistics, and in the second part, the residuals were examined for heteroscedasticity (ARCH effects) and normality. From the ARCH-LM test, there is evidence of ARCH effects in the residual series, validating the use of GARCH and EGARCH models. In the test for normality, the residual series showed evidence against normality. In addition, the stock returns had an excess kurtosis, implying that the estimated GARCH model needed to follow a more dispersed distribution. This study therefore used the Student's T distribution only since the skewness of the series was very close to zero. The models are estimated using the maximum likelihood estimation method.

5.1. GARCH (1,1) Estimation Results

The GARCH (1,1) results are presented in Table 4, using the maximum likelihood estimation method. The model was estimated considering that the NSE 20 stock returns had excess kurtosis. The results of the EGARCH (1,1) are presented in Table 5.

Table 4: GARCH (1,1) Model Result Summary

	Coefficient	*Standard error*	*t-value*	*p>|t|*	*95.0% Conf. Int.*
Omega	7.5662e-06	8.627e-06	0.877	0.380	[-9.343e-06,2.447e-05]
Alpha [1]	0.2820	2.359e-02	11.952	6.347e-33**	[0.236, 0.328]
Beta [1]	0.6265	3.173e-02	19.742	9.378e-87**	[0.564, 0.689]

*Note: Significant at the **1% level.*

The GARCH (1,1) results in Table 4 show that the coefficient of the ARCH term (α) and the coefficient of the GARCH term (β) are statistically significant. This means that the lagged conditional variance with a magnitude of 0.2820 and lagged squared disturbance with a magnitude of 0.6265 have a strong explanatory power on the current volatility. The significance of α and β value show the presence of volatility clustering and persistence behaviors, respectively. The sum of the ARCH and the GARCH is 0.9085, which is close to 1. This means that past shocks are quickly absorbed, and the market reverts to its mean. However, the α_0 value is not statistically significant, further supporting the evidence of strong mean reversion behavior of stock returns in the NSE 20.

The empirical results implied that the stock market returns behavior in Kenya continued to exhibit volatility clustering and persistence even at the most recent times which did not contradict the finding by Ombaba (2015) and Kalovwe et al. (2021) using sample with earlier period. In this study, the sample period was characterized by crucial events which ensued distress and volatile stock returns and also reflected the uncertainty of the financial market.

5.2. EGARCH (1,1) Estimation Results

The EGARCH (1,1) model results presented in Table 5 were used to investigate the asymmetric effects or the leverage effects of news on stock returns volatility. The results for ω_0, α, and β coefficients are statistically significant. However, the leverage coefficient, γ, which measures the asymmetric effects is not statistically significant. This means that the contribution of news in the volatility behavior is not statistically significant in the NSE 20, whether they are either good or bad news. The empirical finding of the absence of leverage effect in stock returns in Kenya support the conclusion of Kalovwe et al. (2021).

Table 5: EGARCH (1,1) Model Result Summary

	Coefficient	*Standard error*	*t-value*	*p>|t|*	*95.0% Conf. Int.*
Omega	-0.5359	0.202	-2.650	8.044e-03*	[-0.932, -0.140]
Alpha [1]	0.2935	5.078e-02	5.780	7.458e-09*	[0.194, 0.393]
Gamma [1]	0.0290	2.087e-02	1.392	0.164	[-1.186e-02,6.996e-02]
Beta [1]	0.9423	2.119e-02	44.461	0.000*	[0.901, 0.984]

*Note: Significant at the **1% level.*

For robustness of the asymmetric behavior, the study estimated another model that captures the asymmetric behavior called the threshold GARCH (TGARCH (1,1)) model. The estimated results are presented in *Appendix* A. The coefficient, γ is again found to be statistically insignificant. Both the EGARCH and TGARCH provided no evidence of the presence of the asymmetric behavior of NSE 20 stock returns volatility.

6. Conclusions and Policy Recommendations

This study investigated the behaviors of stock returns volatility in Kenya for companies listed under the NSE 20 share index. The study period covered 12 years from 2011 to 2023. The main focus was to uncover the three most occurring behaviors in financial returns, that is, volatility clustering, persistence, and asymmetric behaviors. The findings were achieved through modeling stock returns volatility using GARCH (1,1) and EGARCH (1,1) models and also using a TGARCH (1,1) model for checking the robustness of the results.

The stock returns in the NSE 20 share index showed that: they exhibit volatility clustering behavior, and that this is persistent over the study period. When persistent behavior is strong that is when the sum of α and β is very close to 1, it can lead to prolonged periods of low or high volatility in stock returns as found in the NSE 20 case. This means that as volatility shocks get into the market during low or high volatility periods, they are absorbed quickly, and the market reverts to average returns.

Another interesting result is the lack of asymmetric effects in the NSE 20 share index. Most stock markets globally are affected differently by good and bad news. However, the NSE 20 shows that positive and negative news does not have statistically significant effects on the volatility of stock returns in Kenya. Similar results were found in China (Lee, Chen & Lui, 2001). This means that their investment decisions are not significantly driven by news or transitory events. In addition, the financial sector has most of the companies under NSE 20. This sector is highly regulated by the Central Bank of Kenya. These results affirm the high number of incidences among institutional investors dominating the stock market who were found to "buy and hold" stocks (Capital Markets Authority, 2012).

The clustering behavior combined with the persistence of the volatility of stock returns as in the NSE 20 can place investors in a better position to invest in the long run. Risk-averse investors prefer this behavior for stock returns because it is less risky than when the stock markets are highly volatile. The periods of the COVID-19 pandemic showed an increase in volatility clustering. In the study period, there were some important events, that directly affected the stock market. It is recommended that investors diversify their portfolios and frequently do market assessments on when volatility levels increase beyond levels that they can take.

Losses on assets because of prolonged high volatility can erode investor wealth posing an even higher risk of solvency for financial institutions. Consequently, market contagion and systemic crises arise. The regulatory authorities therefore need to adopt policies to mitigate such cases through market interventions, and provision of liquidity to avoid incidents such as market clashes.

Lastly, NSE 20's behavior on asymmetric effects could lead to even more persistent trends in the stock market. Persistence implies that the market price of a stock is determined by including upcoming news hence operating as an efficient market (Malkiel, 1973). Investors who rely on news to make investment decisions are disadvantaged and might shy away from investing in the NSE 20. This could have drastic effects on NSE 20 such as low liquidity. An insight into this behavior therefore needs further examination. Future studies can examine how much of the news is factored into the current pricing of NSE 20 stocks.

Notes

1. The companies to be included in the NSE 20 as per the last quarter of 2022 are ABSA Bank (ABSA), Bamburi Cement (Bamburi), British American Tobacco (BAT), Britam Holdings (BRITAM), Centum Investment (Centum), Cooperative Bank (COOP), Diamond Trust Bank (DTB), East African Breweries Limited (EABL), Equity Bank Group (Equity), I&M Bank (IMH), Kenya Reinsurance (KNRE), Kenya Commercial Bank Group (KCB), KENGEN, Kenya Power and Lighting Company (KPLC), NCBA Bank Kenya PLC (NCBA), Nation Media Group (NMG), Safaricom Limited (SAF), Scan Group Limited (SCAN_G), Stanbic Bank (S) and Standard Chartered Bank (NSE, 2022).
2. NCBA Bank Kenya PLC is not included in the list. There is no consistent data due to due merger of two banks (the former Commercial Bank of Africa and National Industrial Credit Bank).

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APPENDIX A: TGARCH (1,1) RESULTS

Volatility Model					
	coef	*std err*	*t*	*P>|t|*	*95.0% Conf. Int.*
omega	0.0101	2.575e-04	39.054	0.000**	[9.553e-03,1.056e-02]
alpha [1]	4.8182e-03	1.425e-05	338.089	0.000**	[4.790e-03,4.846e-03]
gamma [1]	1.9416	8.025	0.242	0.809	[-13.788, 17.671]
beta [1]	0.0150	2.697e-03	5.564	2.638e-08**	[9.720e-03,2.029e-02]

Note: Significant at the **1% level