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Analysis of Asymmetric and Persistence in Stock Return Volatility in the Nairobi Securities Exchange Market Phases

Ogega Haggai Owidi*, Freshia Mugo-Waweru

School of management and Commerce, Strathmore University, Nairobi, Kenya
*Corresponding author: owidoxh@gmail.com

Abstract Volatility persistence of stock returns has a major effect on future volatility of the market under the influence of shocks while asymmetric volatility increases market risk thus, fascinating features of stock market behaviour. This paper examines behaviour of stock return volatility in the Kenyan stock exchange market phases for the NSE20 share index and the 10 sampled stocks over 11 years. The asymmetric effect and volatility persistence were fitted by the Fractionally Integrated Exponential FIEGARCH (1,d,1). The study detected consistent peaks and troughs in the sampled series, obtaining in all cases two bear and three bull phases. The outcome shows persistent bullish phases than the bearish with bear phases much more frequent. Diagnostic tests and estimates shows volatility clustering, that is, shocks to the volatility process persist and react to news arrival asymmetrically with positive news impacting more during bullish and negative news during bearish. The results indicate non-systematic pattern across all stocks though a higher degree of dependence in both the level and volatility in the bull periods is detected. The empirical results would be beneficial to investors and surveillance regime as it provides indication of behaviour of stock market volatility during the market phases. Adopted FIEGARCH models have capability of modelling clusters of volatility and capturing its asymmetry taking into account the characteristic of long memory in the volatility. Findings robustness tested using two bear and three bull cycles. Few studies have examined the behaviour of stock returns volatility during bull and bear stock market phases with the majority of work done on developed markets.

Keywords: *asymmetry, bear, behavior, bull, FIEGARCH, persistence, volatility*

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1. Introduction

Access to investment capital, mainly through well-functioning financial markets, is crucial for economic development. Financial market is where equity and long-term debt securities are exchanged and a platform where governments and business enterprises can raise finances for long term investment [35]. The existence of a well regulated and well organized stock exchange is very much essential for the smooth functioning of the financial markets in any country.

Stock markets experience periods of up and down market phases which infers bull and bear periods [29]. Dukes, Bowlin & MacDonald [10] using the S&P500 index, explained bull and bear market as episodes in which the index is increased and decreased respectively by at least 20% from trough to peak and peak to trough respectively. Stocks returns are noticed to last longer in the bull than in the bear markets, hence it is riskier for investors to hold portfolios when the market is at bull phase [52]. Moreover, Chordia, Roll, & Subrahmanyam [8] affirmed that bull markets are subject to more investments and liquidity whereas bear markets are characterized by higher volatility and liquidity problems.

Maheu, Mccurdy & Song [29] assert that if bull and bear trends do exist, then it is imperative to extract them from the data to examine their properties and consider their use as inputs into investors’ investment decisions. Anecdotally, Batra [4] argue that during a bear market, news is more eagerly expected than in a bull market. Bear markets drool in anticipation of news, assimilate it insatiably, and react more violently than bull markets. Vijayalakshmi & Gaur [49] contend that volatility in the stock return is an important part of stock market with the alternating bull and bear phases. Mittal & Goyal [32] define volatility as the ups and downs in the stock prices and can be a threat in attracting investment in small developing economies like Kenya.

Tripathy & Gil-Alana [48] contend that stock market return volatility exhibits the following common properties; Time varying volatility which is the variation of stock markets volatility with time, Volatility pooling/clustering (It has been found that large shocks are followed by large shocks and small followed by small in either sign), long-term dependence or long memory (slower decay in the autocorrelation of time series) and lastly Leverage effect (volatility is greater after negative news than after positive news of the same magnitude in the stock market). Generally, a rise in stock market volatility is interpreted as an upsurge in risk of stock investment and therefore stimulate the investors to redesign or take decisions regarding their investment portfolios in short and long run [17].

Participants at the NSE are concerned as the market exhibits turbulence with stock prices dropping to new and rising drastically [20]. Consequently, investment decisions as to when to buy, sell or hold is a major challenge to investors in Kenya given the nature of NSE market. Adequate knowledge therefore about the volatility, performance and efficiency of stock returns remains vital and essential information among economists, stock market analysts, investment fund managers, investors and policy makers as asymmetric volatility increases market risk.

Further studies by Ogum, Beer & Nouyrigat [38] established that, NSE is characterized by positive and significant asymmetric volatility signifying that positive shocks upsurge volatility more than negative shocks of similar scale in Kenya. They also established that expected returns can be forecasted and also that persistent volatility is exhibited in Kenya. On the contrary, Nyamongo & Misati [36] study on modelling the time-varying volatility of equities returns in Kenya found out that the effect of news on volatility is not significantly asymmetric but leptokurtic and hence not normally distributed and volatility of stock returns is highly persistent. Olweny & Omondi [39] study on impact of Macro-economic elements on the stock return volatility in the NSE, Kenya on the other hand found out that volatility of stock returns is not highly persistent and the volatility symmetric not significant.

The study results would be beneficial to investors as it provides indication of behavior of stock market volatility during the market phases in the Kenyan stock market. Consequently, they need to study and examine stock market volatility, among many other factors, before making investment decisions. The implications for investors are also significant to the stock exchange administrators and policy makers.

The study aims to contribute to the literature on the volatility behaviour in the Kenyan securities market and fill the literature void by examining the market phases in isolation. The paper investigates whether a bull market responds to news differently than a bear market in understanding of the asymmetric effect and volatility persistence in the NSE and the nature of events that seemingly causes the shifts in volatility.

2. The Theory of Market Phases

Charles Dow theory classified market trends into three phases namely, the Public Participation, Accumulation, and Excess Phases in a bull market and the Panic Phase, Public Participation and Distribution in a bear market [45].

2.1. Bull Market

The Accumulation Phase is where the upward trend begin, which is typically at the bottom of a down trend. It is the point at which the savvy investors enter the market at the best prices when the market is undervalued and at the end of a downtrend when most of the bad news is priced into the market, thus restraining downside risk and offering attractive valuations. The phase is characterized by persistent market pessimism because investors think that things will only get worse. The Public Participation Phase occurs after the positive news starts to be taken on board by the wider population. The Participation Phase is characterized by increasing corporate profits and better economic conditions therefore, more and more Investors buy shares sending prices higher. Negative sentiment starts to drive away as business conditions and marred by earnings growth and strong economic information improve during this phase. This phase generally last longer and the prices moves the most than the Accumulation phase. Lastly, excess phase is where the savvy and informed traders start to diminish their exposure and begin to make some profits. The view is that all is running fantastic and that only good occurrences lie ahead. It is also the time when the final buyers start to enter the market after huge gains have been realized. This is the part of the trend that investors should start examining for signs of upward momentum weakness. The phase is usually seen in a bubble market.

2.2. Bear Market

Panic Phase is the period in which the savvy traders short their positions deliberating that the market is overbought and the knowledgeable buyers are now selling into an overbought market rather than buying in an oversold market. Technical Analysis may be useful here to ascertain this phase as it normally comes after an upward trend and consolidation period. Overall sentiment remains to be optimistic, with anticipations of higher market levels in this phase. The final investors in the market continue buying, particularly those who unexploited the big move but are anticipating for a similar one in the near future. Like the Public Participation in a bull market, this is generally the lengthiest bit of the trend with the greatest price move. During this phase, the business circumstances in the market are worsening and the sentiment is becoming more negative as time goes on. Trend cohorts will often leave the market or take a short position. The market continues to discount the worsening circumstances as selling increases and buying dries up. The final phase of the bear market tends to be packed with market panic and can lead to very large selloffs in a very short period of time. A jerk of negativity enters the market and a stream of selling takes place occasionally at panic levels. The market is shaped up with negative sentiment, comprising weak outlooks on companies, the economy and the general market. Some savvy investors will start contemplating market entry at this point trying to profit on bad news.

2.3. Stylized Facts about Financial Time Series

Studies by Fama [12] and Mandelbrot [31] documented that, financial time series such as, stock returns, exchange rates, and other financial time series data are known to display certain stylized facts which are critical for right model specification, estimation and forecasting. The most popular stylized patterns include:

2.3.1. Volatility Clustering/ Pooling and Persistence

Developed by Mandelbrot (1963), it is where small and large values in the log-returns have a tendency to occur in clusters that is, small movements being followed by small movements and the large changes in stock returns tend to be followed by large changes of either sign. The inference of volatility clustering is that volatility shocks today will impact the anticipation of volatility in some times in the future.

2.3.2. Fat Tails or Non-Normality

Financial time series such as stock returns empirical distribution exhibits fatter or highly non-normal tails also referred to as excess kurtosis hence not normal distributed with fourth moment above 3, meaning that asset returns are normally leptokurtic [12,31].

2.3.3. Leverage Effects and Asymmetry

Downward movement is always followed by higher volatility in financial markets. Stock prices changes tend to be negatively associated with changes in volatility that is; volatility is higher after negative news than after positive news of the same scale [12]. Asymmetry is attributed to leverage effects that is, negative news upsurge predictable volatility in stock markets more than positive news. Black (1976) postulated that when stock price drops, the value of the related firm's stock decreases. As a result, leverage the debt to equity ratio of the firm increases, thus signalling that the firm is more risky. The statistical interpretation of Black's leverage effect infers that negative surprises upsurges predictable volatility in stock markets more than positive surprises. Establishing of the presence of asymmetric volatility is significant in risk management, portfolio selection, valuation of stocks and asset management [40].

2.3.4. Volatility Persistence

Particularly for high-frequency data like daily stock returns, volatility is extremely persistent or possesses long memory if it is characterized by very slow hyperbolic decay in autocorrelations of absolute or squared returns. The persistence in stock return volatility has a major effect on the future volatility of the market under the influence of shocks. Moreover, persistence in volatility can aid in forecasting future volatility which sequentially is beneficial in predicting economic variables. It is also imperative for option traders who want to value options with expirations spreading into the future

2.3.5. Daily Seasonality and Non-trading Periods

Generally, information accrues during the period when financial markets are shut and is immediately revealed in the price when the markets reopen. Therefore, variances are greater following holidays and weekends leading to the observation of daily seasonality in stock returns.

2.3.6. Regular Events

The announcement of significant information is realized to be related with extreme volatility. The behaviour of volatility during the trading day is found to be predictable as volatility is normally higher at the open and close of trading in stock.

2.4. Efficient Market Hypothesis (EMH)

Modelling the capital markets volatility is closely linked to the Efficient Market Hypothesis (EMH), a concept found in conjunction with the rationality of investor behaviour [44]. Fama [11] and more recently Timmermann & Granger [47] highlighted that EMH and the concept of information and the mechanism of reflection a set of information released in the trading price of a security are inseparable. Malkiel [30] clearly describes the random walk hypothesis as the process where the information released is immediately reflected in security prices and the following day's price change will reflect only the tomorrow's information thus independent of today's price change. According to Goudarzi & Ramanarayanan [17], variation of security prices is an indication of market efficiency in stock markets where security price fully reflects all existing information. However, Karolyi [23] asserts that the presence of excessive stock return volatility, or "noise," compromises the worth of equity return as a "signal" about the fair intrinsic value of a company, a concept that is essential to the paradigm of the informational efficiency of markets.

2.5. Nairobi Securities Exchange

Nairobi security market is significant for economic growth as it enables unutilized funds to be invested in productive economic activities [41]. Ogilo [37] establish that stocks experience both the bull and bear market at the NSE with January, February and March when most stocks experience the bear market while August to November majority of stocks experience bull market. The Kenya National Bureau of Statistics (KNBS, 2010) reported that the NSE 20 share index by end of December 2008 recorded a sharp drop to 3531 points and further fell by 7.8% standing at 3247 points in 2009. In 2010, the index increased steadily reaching a high of 4,433 points compared to 2009 but in 2011, the NSE 20 Share Index lost by 26%. Capital Market Authority 2012 reported a gain on NSE 20 index of 29% in 2012, closing at 4,171.87 points as improved macroeconomic conditions and strong foreign investor interest pushed stock prices upwards, the total net equity foreign portfolio inflow during FY 2011/2012 was Kes.11.2 billion, the highest in the history of the NSE. NSE 20 share index closed at 5052.63 points as of 20th October 2013 with all share gaining 43.021% in 2013.

Koutmos [24] while examining time-varying stock price and volatility dynamics of constituent industry sector indices in the Shanghai Stock Exchange demonstrated that good and bad news exert an equal impact on the conditional volatility process and presence of persistence volatility. Oskooe & Shamsavari [40] who conducted similar study in the Iranian stock market also supported the symmetric volatility hypothesis meaning that Iranian returns are volatile and that positive and negative shocks of the same size have the similar effect on the future volatility level. Similarly, they established that the volatility response to a shock tend to persist in the market.

On the contrary, Kang & Yoon [22] employed the FIEGARCH model to capture the asymmetry features and long memory properties in the volatility of Japan, South Korea, Hong Kong and Singapore stock index returns and indicated that the entire sample returns exhibit asymmetries in volatility, and volatility is a long memory process. Further Suleman [46] analysed the volatility on Karachi stock exchange 100 index and in addition, consequence of political news on stock market returns and established that bad news have almost double effect on the volatility than the good news. In Indian stock market, Maheshchandra [27] in his study found out that the volatility persistence property of the BSE market is much stronger than NSE and it could be held that NSE might be having better participation of participating investors than BSE which could result to better informational efficiency in volatility in contrast to BSE.

Boubaker & Makram [7] studied North African stock markets using FIGARCH model and established that the volatility series is a long-memory process. Thus investors in North African stock markets may tend to react slowly and gradually to new information and that their actions do not follow the Martingale process. Kalu & Friday [21] study in Nigeria obtained an evidence of volatility clustering and volatility persistence and also asymmetric volatility effect in Nigeria. Contrary to leverage effect theoretical sign, the positive results suggested that positive news increases volatility more than negative news.

Yaya et al. [52] studied the two phases of the Nigeria financial market using Smooth Threshold Parameter Nonlinear Market model. Stocks returns were realized to stay longer in the upward market (bull) than in the downward market (bear), thus it is riskier for investors to maintain portfolios when the market is at bull phase. Kumar & Maheswaran [25] used iterated cumulative sums of squares (ICSS) to determine regime shifts and then applied in the asymmetric volatility models to study the impact of shocks on volatility persistence and asymmetry. The results showed that the persistence and asymmetry in volatility are reduced considerably when regime shifts are taken into account in the volatility models. Therefore, ignoring sudden changes in volatility will lead to understating or overstating the persistence of volatility which in turn may lead to potential errors by risk managers to come up with the Value-at-Risk (VaR) measure. Batra [4] study showed that in general over the references period the bull phases takes long, the amplitude and volatility of the bull phase is higher. He further established that the gains during bull are greater than the losses during the bear phases of stock market cycles.

2.6. Identifying Market Phases: A Non-parametric Approach

Instead of fitting a fully stipulated statistical data generating process, the approach takes a nonparametric perspective and looks at the original data series in search for the particular characters of the cycle. Explicitly, this procedure examines for periods of generalized upward trend, which will be recognized with the expansions, and periods of a generalized downward trend recognized with the contractions. The key element of the examination is the location of peaks, turning points, and troughs in the series. These turning points establish the different phases of the cycle, which can be consequently analysed. The method was applied by Biscarri & de Gracia [5], Gonzalez et al. [16], Pagan & Sossounov [42] and Woodward & Anderson [51] to the analysis of business cycles and stock market analysis. This approach allows contrast of the actual stock market cycle to parametric benchmarks, and to examine issues associated with predictability of the market.

i. To ensure that spurious phases are not recognized the following three censoring measures are included:
ii. Turns of the beginning/end of the series are eliminated.
iii. Peaks or troughs next to the endpoints of the series are excluded if they are lower/higher than the endpoints.
iv. Phases of less than 4 months are excluded unless the fall/rise surpasses 20% (the traditional rule of thumb for identifying a stock market cumulative movement as bullish or bearish).

2.7. Volatility Behavior Model

The study applied the Fractionally Integrated Exponential GARCH (FIEGARCH) model on the market phases data an extension by Bollerslev & Mikkelsen [6] of FIGARCH model, which captures both the asymmetric shocks and volatility persistence. Bollerslev & Mikkelsen [6] formulated the FIEGARCH model and applied it to daily returns of the U.S. S&P 500 index. They established strong evidence that the conditional variance for the S&P 500 index is described well as a mean-reverting fractionally integrated process. Also, a recent study by Gandhi, Saadi, Ngouhouo, & Dutta [14] found out that the FIEGARCH model provides the optimal fit for daily returns of the Tunisian stock market because it captures high volatility persistence and long memory in the volatility of returns.

The fractionally integrated EGARCH (FIEGARCH) of Bollerslev & Mikkelsen [6] generalize the EGARCH [34]. FIEGARCH models have not only the capability of modelling clusters of volatility (as ARCH and GARCH models do) and capturing its asymmetry (as the EGARCH model does) but they also take into account the characteristic of long memory in the volatility (as the FIGARCH model does). The non-stationary of FIGARCH models (in the weak sense) makes this class of models less attractive for practical applications. Another drawback of the FIGARCH models is that d must be ≥ 0 and the polynomial coefficients in its definition must satisfy some restrictions so the conditional variance will be positive. FIEGARCH models do not have this problem since the variance is defined in terms of the logarithm function, moreover, they are weak stationary whenever the long memory parameter d is smaller than 0.5 [26].

The general specification for the FIEGARCH (m,d,q) model that is estimated is given in equations (1-4). Rt is the stock return for a given market, which has a conditional distribution with mean μt and variance σ_t^2. $\varepsilon_t \sim N(0,\sigma_t^2)$, and υ_t is an i.i.d. sequence with zero mean and unit variance.

$$R_t = \mu_t + \varepsilon_t \tag{1}$$

$$\mu_t = \lambda + \sum_{i=1}^{a} \varphi_i R_{t-i} + \sum_{j=1}^{b} \theta_j \varepsilon_{t-j} \tag{2}$$

$$\varepsilon_t = \sigma_t \upsilon_t \tag{3}$$

$$\varphi(L)(1-L)^d \ln \sigma_t^2 = \alpha + \sum_{i=1}^{q} \left(\beta_i \left| \upsilon_{t-i} \right| + \gamma_i \upsilon_{t-i} \right) \tag{4}$$

where $\varphi(L) = 1 - \varphi_1 L - \varphi_2 L^2 - ... - \varphi_m L^m$.

The φ estimates measure GARCH effects or volatility clustering in the data with positive (negative) values meaning that higher (lower) volatility of stock returns in the past are followed by higher (lower) volatility today. In addition, the β estimates capture the ARCH effects or the impact of past news about volatility on current volatility. Also, asymmetric volatility or leverage of returns is modelled by the γ coefficients with negative values indicating that negative shocks have a bigger impact on volatility than positive shocks of the same scale. For purposes of this study, the coefficient estimate of primary interest is the fractional difference parameter d that models the long run persistence of volatility. Bollerslev & Mikkelsen [6] indicated that, the FIEGARCH specification is stationary if $0 < d < 1$. The existence of volatility persistence is confirmed for significant values of d.

3. Data

The study population consisted of 62 listed companies and the NSE which is an appropriate population as it mirrors the true picture of active companies in the economy. The study used daily time series secondary data for NSE 20 share index and the sampled companies covering a period of 11 years from the NSE registered data vendors of 29,700 observations. The study applied the 80% rule consistent with Cronbach' alpha criterion also used by Ndegwa & Mboya [33]. Actively and continuously traded stocks in the NSE for at least 80% of the study period from 3rd January 2003 to 31st December 2013 were selected. The inactively traded stocks are affected by the problem of thin or infrequent trading. If a company was on suspension from trading during the study period hence had missing data or if the company did share split or reversal, it was also omitted from the study. Furthermore, non-trading day effect account for a significant effect on the return variance and contributes nearly one-fourth as much to the volatility as any trading day. Out of the population of 62 NSE listed companies, 10 stock drawn from all the sectors fitted the sample selection criteria. To obtain bull, bear and turning periods, a nonparametric approach was employed eliminating turns of the beginning/end of the series and also phases of less than 4 months. This approach allows contrast of the actual stock market cycle to parametric benchmarks, and to examine issues associated with predictability of the market.

3.1. Salient Features of Financial Time Series

In order to examine typical features of the time series data, observe extreme values, temporal clustering, and fat-tail (leptokurtosis) in the graph and descriptive statistics are critical. Furthermore, examining the distribution of features of stock returns and/or stock prices is vital to the behaviour of stock prices and returns, accurate model specification, estimation and forecasting. The research begins with a visual inspection of the plot of daily prices and returns on the 10 sampled companies and NSE 20 index as shown in Figure 1. It can be observed that returns continuously oscillate around a mean value that is near to zero. The expected duration of bear markets is only 35% of the total study duration which is consistent with the findings of Yaya et al [52].

NSE experienced 3 bull cycles with 1812 data points while bear phase experienced 2 cycles with 1011 data points over the period of study. Commonly observed bullish periods during the study includes; 2003 to mid-2004, start of 2005 to the mid-2007, start 2009 to mid-2011 and finally start 2012 to end 2013 while bear periods includes mid-2004 to end of 2005, mid-2007 to end 2008 and lastly mid-2011 to end 2011. All the sampled stock prices and the NSE 20 share index tend to experience a similar trend as can be observed in Figure 2. It can also be observed that fluctuations in the series are variable in time and downward trends are much more frequent than upward trends. The fluctuations are both in the positive and negative regions with larger fluctuations tend to cluster together separated by episodes of relative calm. The returns series seems stationary and exhibits dependence over time. Therefore, the current level of volatility tends to be positively associated with its level during the immediately preceding periods.

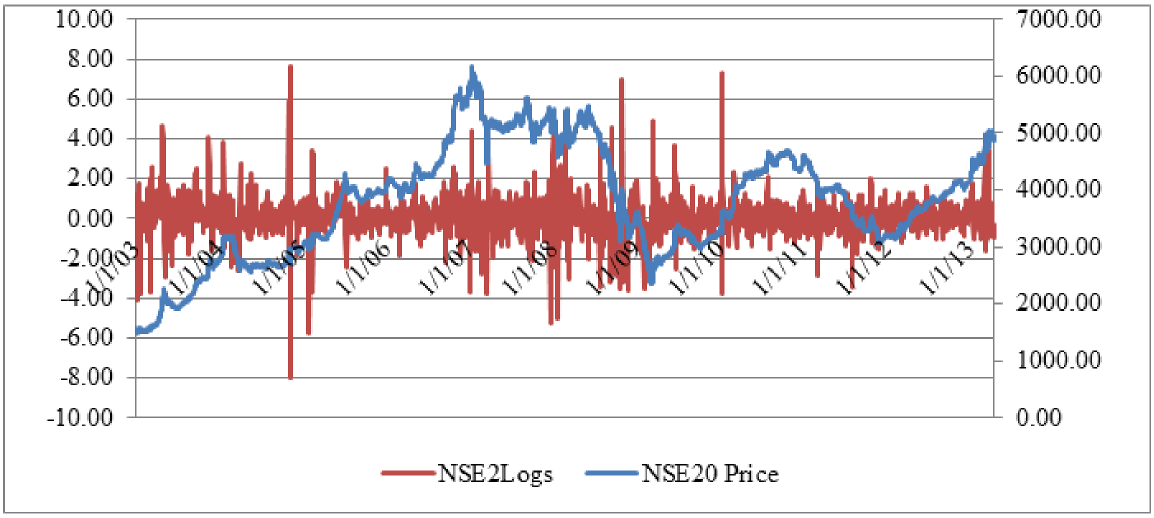

Figure 1. Graph for the observed data series for the NSE20 Share Index and return (2003-2013) (Source: Author's computation)

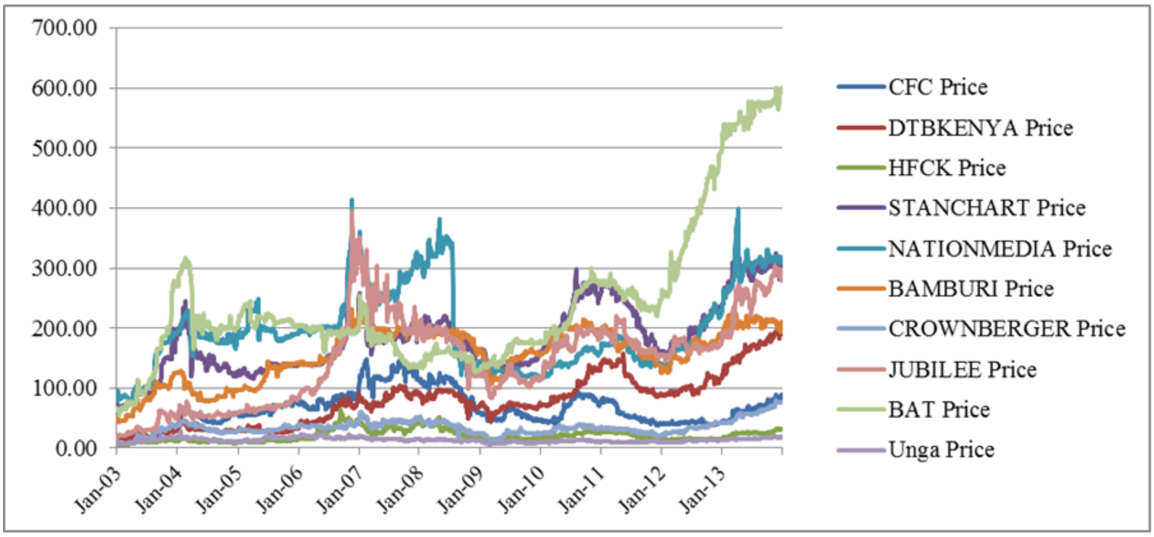

Figure 2. Graph for the 10 sampled Price observed trend over the study duration (2003-2013) (Source: Author's computation)

Table 1. Representation of bull phase statistical analysis

BEARISH	BAMBURI	BAT	CROWN	DTB	HFCK	CFC	JUBILEE	NMG	NSE20	SCB	UNGA
Mean	-0.0815	-0.0643	-0.1624	-0.0538	-0.2052	-0.1007	-0.2089	-0.1920	-0.1349	-0.0805	-0.1566
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.1047	0.0000	0.0000
Max	7.6961	9.1567	40.2224	9.5310	24.2265	27.3041	16.8335	9.4452	6.9477	8.3382	15.4151
Min	-8.8947	-10.536	-65.4433	-10.204	-22.314	-12.361	-31.585	-25.384	-5.2340	-10.536	-10.536
SD	1.8494	2.1015	4.8788	2.5914	3.8573	2.9442	3.2311	2.5586	1.3273	1.8135	3.2223
Skewness	-0.0258	-0.1272	-3.2996	0.2192	0.1897	1.6091	-1.6874	-2.0462	0.6522	-0.4838	0.1912
Kurtosis	8.3918	8.0358	67.3383	5.7755	7.5135	20.4337	21.0137	22.4121	7.6875	10.8362	4.9088
J-Bera	674.77	590.04	97079.64	183.24	476.13	7294.15	7795.32	9134.25	549.45	1446.85	87.95
P	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	-45.4018	-35.813	-90.4595	-29.951	-114.301	-56.097	-116.375	-106.945	-75.154	-44.821	-87.208
ADF	-28.43	-25.33	-13.54	-22.22	-13.26	-21.07	-25.15	-12.55	-14.69	-20.90	-28.06
P	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1% level	-3.4419	-3.4419	-3.4420	-3.4419	-3.4419	-3.4419	-3.4419	-3.4419	-3.4419	-3.4419	-3.4419
Obs	557.00	557.00	557.00	557.00	557.00	557.00	557.00	557.00	557.00	557.00	557.00
KPS	0.3247	0.0731	0.2686	0.0997	0.1302	0.2660	0.0404	0.1817	0.2688	0.1364	0.1397
1% level	0.7390	0.7390	0.7390	0.7390	0.7390	0.7390	0.7390	0.7390	0.7390	0.7390	0.7390

The values are parenthesis statistically significant at 0.10, 0.05 and 0.01 level respectively. This table presents descriptive statistics for the NSE20 index and 10 sampled stocks. This table also presents results of unit root tests Augmented Dickey-Fuller and Kwiatkowski-Phillips-Schmidt-Shin tests.

Table 2. Representation of bear phase statistical analysis

Bullish	BAMBURI	BAT	CROWN	CFC	DTB	HFCK	JUBILEE	NMG	NSE20	SCB	UNGA
Mean	0.0847	0.1592	0.1379	0.1052	0.1681	0.1424	0.1330	0.0736	0.1073	0.1400	0.1047
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0705	0.0000	0.0000
Max	6.2848	8.6540	23.2446	21.3574	10.6018	17.6624	24.4197	7.5349	7.2690	7.4384	45.1985
Min	-8.0043	-8.1678	-22.4944	-23.052	-8.7011	-24.3002	-9.9207	-4.6520	-3.7473	-7.2690	-52.5010
Std. Dev.	1.5627	1.3400	3.5445	2.8502	2.2383	2.4076	2.5313	1.2791	0.8826	1.4916	4.4231
Skewness	-0.5017	0.0550	0.1373	-0.1600	0.1630	-1.3891	2.0840	0.9671	1.7278	-0.0143	-1.3990
Kurtosis	9.5481	13.1553	10.4850	20.1845	7.9319	32.5867	23.1313	10.4518	16.0665	8.8370	69.7943
J-Bera	821.01	1929.60	1049.54	5526.61	457.05	16521.19	7906.92	1108.86	3417.52	637.42	83613.34
P	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	38.0275	71.4809	61.9039	47.2476	75.4705	63.9381	59.7356	33.0242	48.1902	62.8609	47.0004
ADF	-18.2034	-23.764	-16.9154	-18.365	-24.105	-19.6238	-18.4852	-20.820	-10.738	-18.986	-28.7647
Prob.*	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
5% level	-2.8678	-2.8678	-2.8678	-2.8678	-2.8678	-2.8678	-2.8678	-2.8678	-2.8678	-2.8678	-2.8678
Observations	449.00	449.00	449.00	449.00	449.00	449.00	449.00	449.00	449.00	449.00	449.00
KPS	0.1142	0.0957	0.0794	0.2094	0.1885	0.0465	0.0643	0.0736	0.0863	0.2411	0.1127
5% level	0.4630	0.4630	0.4630	0.4630	0.4630	0.4630	0.4630	0.4630	0.4630	0.4630	0.4630

The values are parenthesis statistically significant at 0.10, 0.05 and 0.01 level respectively. This table presents descriptive statistics for the NSE20 index and 10 sampled stocks. This table also presents results of unit root tests Augmented Dickey-Fuller and Kwiatkowski-Phillips-Schmidt-Shin tests.

Table 1 and Table 2 provide descriptive statistics for the sampled and 20 share index stock returns phases. The average mean of the bull (bear) phases daily market return during the period of the study is 0.1233 (-0.311) while the standard deviation is 2.2 (2.76) manifesting a high degree of dispersion from the average return in the market. This fits into the picture on emerging markets like Kenya, that is, higher returns come at cost of higher risk. Generally the bear phase has a large difference between its maximum and minimum returns confirming the high variability of price change during the phase that could be justified might be due to the low liquidity of the stock market, occasioning higher structural volatility.

Positive (negative) skewness signifies that the Kenyan stock returns distribution during bullish (bearish) phases are skewed to the right (left) of the mean and has a long right (left) tail with large positive (negative) returns tend to follow more frequently than large negative (positive) ones. Similarly, the degree of excess or kurtosis, in the Kenya stock returns in the phases is larger than the normal estimate of 3. Consequently, the distribution of Kenya stock returns is peaked and leptokurtic (heavily (thick) tailed and sharply peaked).

It is worth underlining that with respect to the kurtosis and skewness statistics of the Kenyan stock returns, the distribution of stock returns deviates from normal distribution. Besides, results of the estimated Jarque-Bera statistics and corresponding p-value in Table 1 and Table 2, the stock return series is not well estimated by the normal distribution consistent with Olweny & Omondi [39], Kenya stock return time series are characterized by some “stylized fact” such as skewness, fat tails, volatility clustering and high peakness (excess kurtosis).

The null hypothesis of the Augmented Dickey-Fuller test statistic (ADF) is that a time series has unit root while Kwiatkowski-Phillips-Schmidt-Shin test statistic (KPSS) has the null hypothesis of stationary. Huge negative estimates for ADF test for all return series in all the phases strongly reject the null hypothesis of a unit root at the 1% significant level. Moreover, the statistics of the KPSS test signify that return series are stationary. Therefore both the series are stationary and appropriate for subsequent volatility persistency tests in this study. Generally, the non-normality of the series revealed in this study suggests using non-linear model like FIEGARCH.

3.2. Volatility Behavior in the Stock Market Phases

Statistically significant values of δ in almost all the sampled results, confirms negative relationship of the risk-return tradeoff in most stocks in all the phases. Values of ψ are statistically significant at 5% for most stock both during bullish and bearish phase but mostly negative during bearish. It can be concluded that there is propensity for stock returns volatility to upsurge when stock returns fall and to fall when stock returns rise consistent with the findings of Bollerslev & Mikkelsen [6].

Table 3 to Table 6 demonstrates the findings of the application of FIEGARCH (1,d,1) model on the sampled stock returns and NSE 20 share index during the bullish and bearish phases. Given that the probabilities are smaller than the conventional level of significance 5% in both phases, asymmetry term θ in FIEGARCH model is statistically significant. It can be underlined that in the Kenyan stock market participants or investors overreact (underreact) to bad news and underreact (overreact) to good news with positive shocks impacting more during bullish phase (9 out 11 positive θ values during bull 1) and vice versa. Note that the coefficients of asymmetric response of volatility to news, ϒ, are positive and highly significant at the 5% level in all the Kenyan stock and the index considered during the phases. This implies that unexpected positive (negative) returns during bull (bear) phases leads to high volatility than unexpected negative (positive) returns of the same magnitude.

The result implies that the volatility of Kenya stock returns during bullish (bearish) phase is less sensitive to negative (positive) news probably because of market regularity, such as price limit. The degree of asymmetric volatility during bearish phase is high at an average of 0.3120 than the bullish phase at 0.2946 confirming the high volatility during the phase. Bad news is anticipating in a bear market and bad news wobbles market confidence greater than if it has been a bull. A recent study by Jayasuriya, Shambora, & Rossiter [19] establish asymmetric volatility for many mature and emerging markets and propose that asymmetry may be linked to trading costs and trading strategies such as short selling.

Interestingly, the fractional difference parameter is highly significant and lies between a value of zero and one for all stock index returns. Therefore, there is clear evidence of long memory in volatility for the sample of stocks investigated. That is, there is useful information embedded in the past stock return volatility series that can be utilized for future predictions. The findings implies that investors may gain unrealized trading profits by observing past behaviour of return indices.

As a general conclusion little evidence of any systematic pattern in the persistence in the level and in the volatility in bull and bear periods. If any, higher degrees of dependence are detected in both (level and volatility) in some stocks and the index during the bull periods. Comparing the degree of parameter d between the bullish and bearish stock market phases, the volatility is highly persistence during bullish with an average of 0.4451 phase than bearish with an average of 0.3388. The reasons might be related to the reaction of investors and the fact that investors tend to gather lots of information that provides better platform to adopt broader investment strategy.

Consequently, the volatility of all sampled stocks and the index returns seem to be a persistent series which is in conflict with the assumption of the efficient market hypothesis that the stock returns should not exhibit persistence or it would be possible to generate trading profits by observing historical patterns. This result implies that investors in Kenyan stock market do not react to new information until a market trend is distinctly established when news arrives at the market. So the amount of information is accumulated and unexpectedly established in the market, instigating the volatility to persist in stock markets.

Maheu and Mccurdy [29] furthermore argued that, as the bull market persists, investors could become more optimistic about the future and thus wish to invest more in the stock market. This positive feedback indicates that the likelihood of switching out of the bull market decreases with time. In addition, it could be eluded that NSE bearish phase might be having greater participation of competing investors than bullish phase which could lead to better informational efficiency in volatility as investors are optimistic that the downward trade will be over soon. The presence of long memory in volatility, conversely, shows that uncertainty or risk is an imperative determinant of the behavior of daily stock data in the Kenyan stock markets.

Nelson [34] implied that volatility is higher in bear markets and this was rationalized by the tendency for investors to engage in panic selling at such times. Contrary to the findings of Iyiegbuniwe et al. [18] who suggested that for the developing markets, market booms induce higher volatility than market declines and is rationalized by the view that investors believe that booms behave more like speculative bubbles.

A significant implication of these conclusions is that the good shocks and bad shocks have the different effects on stock prices in the Kenyan stock market with good shocks affecting prices during **bullish** phase than negative shocks and vice versa. In this sense, stock prices reflect asymmetrically new information. The potential elucidation for the presence of asymmetric effect can be derived from “inflation advantage”. In inflationary conditions (particularly in developing nations) the long term debts are regard as an advantage to the firm. Therefore, growing debt to assets ratio (leverage) does lead to higher stock volatility (risk) in stock market. Additionally, the lack of “price limit” to control market volatility can be another explanation for the asymmetric effect.

Table 3. Representation of Bull Phase 1 asymmetric and long memory results

	NSE 20	SCB	NMG	DTB	HFCK	BAT	BAMBURI	JUBILEE	UNGA	CROWN	CFC
ω,Ω	2.9266	0.3409	0.2213	2.0340	0.9217	1.8373	1.1583	3.2850	-0.096	-0.0785	-0.055
p	0.0008	0.0515	0.0377	0.0000	0.0000	0.0001	0.0000	0.0000	0.7859	0.4719	0.0000
δ	-0.101	-0.114	-0.250	-0.074	-0.206	-0.193	-0.1209	-0.0370	-0.479	0.6903	-0.130
p	0.1514	0.0237	0.0000	0.2184	0.0000	0.0000	0.0414	0.4864	0.0113	0.0262	0.5211
ψ,Ψ	0.4022	-0.671	0.8657	0.0941	1.8865	0.0723	0.0558	1.0994	0.1169	0.6498	1.0535
p	0.1202	0.0000	0.0000	0.0000	0.0000	0.0000	0.8432	0.0000	0.0000	0.0000	0.0000
ф, Φ	-0.834	0.8484	-0.375	-0.210	0.4786	0.5677	0.4250	-0.6251	0.3268	0.5429	1.0113
p	0.0000	0.0000	0.0012	0.0000	0.0000	0.0000	0.0000	0.0015	0.1164	0.0000	0.0000
Θ, θ	0.3142	0.0856	0.0765	0.1035	0.0206	-0.001	0.0827	0.1093	-0.066	0.0523	0.1450
p	0.0000	0.0381	0.0419	0.1013	0.0756	0.0224	0.0043	0.0079	0.0000	0.0125	0.0347
Γ, ϒ	0.3085	0.5153	0.5997	0.5339	0.0215	0.0005	0.4474	0.2618	0.1686	0.2301	0.1534
p	0.0023	0.0000	0.0000	0.0000	0.0554	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000
D	0.7699	0.4028	0.5212	0.1243	0.7345	0.5053	0.6318	0.3973	0.1140	0.2433	0.4514
p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0749	0.0000	0.0000

Evidence of long memory (d > 0) and asymmetry at the 5% level during Bull phase 1.

Table 4. Representation of Bull Phase 2 asymmetric and long memory results

Column1	NSE20	SCB	NMG	DTB	HFCK	BAMBURI	UNGA	CROWN	CFC
ω,Ω	0.2751	5.7380	1.2651	3.8256	1.7255	0.2397	0.0343	2.5062	0.9144
P	0.2563	0.0000	0.0029	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
δ	-0.1142	0.1076	0.0603	-0.071	17.3510	-0.0893	1.3388	-0.2759	12.2548
p	0.0040	0.0559	0.2151	0.0137	0.0000	0.0003	0.0000	0.0000	0.0000
ψ,Ψ	-0.0975	1.0456	0.1365	1.3605	0.0259	0.0000	0.1441	0.2210	0.5591
p	0.6331	0.0000	0.4408	0.0000	0.0131	0.0000	0.0010	0.0000	0.0000
ф, Φ	0.7146	-0.716	0.3633	0.0757	-0.1477	0.8795	0.7515	-0.1119	-0.9767
p	0.0000	0.0000	0.0131	0.0032	0.0000	0.0000	0.0000	0.0000	0.0000
Θ, θ	0.0723	0.0292	0.0332	0.0008	23.7947	-0.0175	-0.0222	-2.9404	0.1827
p	0.0120	0.1913	0.2815	0.9321	0.0000	0.0798	0.0164	0.0000	0.0000
Γ, ϒ	0.4132	0.5275	0.6215	0.1218	1.5637	0.1849	0.4836	1.9418	0.5967
p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
D	0.3026	0.4922	0.3127	0.5090	0.7710	0.1000	0.4204	0.1078	0.1289
p	0.0014	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Evidence of long memory (d > 0) and asymmetry at the 5% level during Bull phase 2.

Table 5. Representation of Bear phase 1 asymmetric and long memory results

	HFCK	NMG	BAMBURI	CROWNB	NSE20	DTB	JUBILEE	SCB	UNGA	BAT	CFC
ω,Ω	0.3543	1.6145	0.3113	0.0509	1.3161	1.9541	0.5843	0.1949	4.5430	0.0504	0.3740
p	0.1607	0.0000	0.0001	0.0000	0.0013	0.0000	0.0000	0.0000	0.0000	0.0000	0.0888
δ	0.0500	-0.333	-0.0356	-0.0220	-0.168	0.4438	-0.3201	-0.500	0.2805	-0.039	-0.089
p	0.4982	0.0000	0.5600	0.0002	0.0000	0.0659	0.0000	0.0000	0.0000	0.3128	0.4113
ψ,Ψ	-0.484	0.2027	1.3581	-1.0324	1.0146	-0.226	-0.9128	-0.756	1.6295	-0.670	3.2441
p	0.0165	0.0823	0.1140	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1313
ф, Φ	0.8664	-0.713	0.8682	0.9773	-0.977	-0.301	0.8166	-0.086	-0.393	0.1875	0.8236
p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Θ, θ	-0.031	0.5775	-0.0361	0.0272	-0.045	-0.288	-0.2631	-4.246	-0.147	-0.146	-0.001
p	0.5358	0.0000	0.0147	0.0000	0.2684	0.0000	0.0000	0.0000	0.0000	0.0000	0.4831
Γ, ϒ	0.5000	-0.290	0.0152	0.3197	0.5495	0.0480	0.6983	0.3541	0.4494	0.7857	0.0025
p	0.0000	0.0000	0.0206	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1793
D	0.0677	0.1502	0.4559	0.6723	0.4626	0.1424	0.1083	0.0741	0.3748	1.0000	0.2187
p	0.0439	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0109

Evidence of long memory (d > 0) and asymmetry at the 5% level during Bear phase 1.

Table 6. Representation of Bear phase 2 asymmetric and long memory results

Column1	NSE20	HFCK	CFC2	UNGA	CROWN	CFC1
ω,Ω	-0.0807	0.0693	4.1431	0.3406	2.3214	1.2793
p	0.8880	0.0000	0.0000	0.0000	0.0000	0.0000
δ	0.0117	-0.0851	0.1665	0.4556	-0.1923	0.2497
p	0.7319	0.0000	0.0000	0.0000	0.0000	0.0415
ψ,Ψ	0.9870	0.5214	0.5507	-0.9606	-0.4033	-0.2160
p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0974
ф, Φ	-0.9706	-1.0043	-0.7455	0.8617	-0.4134	0.4099
p	0.0000	0.0000	0.0000	0.0000		0.0000
Θ, θ	-0.0020	-0.0877	0.0780	-0.0254	-0.8346	-0.2309
p	0.9369	0.0000	0.0000	0.0499	0.0000	0.0000
Γ, ϒ	0.5935	-0.0358	0.3271	0.3354	5.0314	0.2415
p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
D	0.4878	0.0887	0.1646	0.1374	0.0391	0.2122
p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Evidence of long memory ($d > 0$) and asymmetry at the 5% level during Bear phase 2.

4. Conclusion

Kenya stock exchange has undergone series of bull and bear phases as well as breaks observed in the time plot with bullish market phase taking a longer time to die out than the bearish market phase. For most companies, the stock market spends the vast majority of its time in bull market states than a bear phase that is consistent with findings of Woodward & Anderson [51]. Further, the fluctuations in the series are variable in time and downward trends are much more frequent than upward trends thus a higher volatility. The asymmetry and persistence are regularly observed in the conditional variances of stock returns.

To capture the asymmetry and persistence properties in the volatility of stock index returns, FIEGARCH (1,d,1) model was employed. Approximation of asymmetric coefficient (θ) are mostly positive for bull and mostly negative for bear phase and highly significant for most samples, signifying that all sample returns exhibit asymmetries in volatility, rejecting the symmetric volatility models. Coefficients of ϒ that measures the magnitude of the past errors on the future volatility, implies that unexpected positive returns during bull phase resulted in more volatility than unexpected negative returns of the similar magnitude, also that unexpected negative returns during bear phase resulted in more volatility than unexpected positive returns of the similar magnitude.

Recall that the earlier results indicated that volatility during bull phases tend to exhibit high persistency than that of bear phases relatively low. The study finding alludes that Nairobi stock exchange efficiency is in doubt. The possible explanations of the results might be the fact that the numbers of competing and profit-maximizing participants who analyse the arrival of new information are few. In such a setting, security prices will adjust slowly to the release of all public information so that current prices do not fully reflect all available information and there is useful information are left for future predictions. Also, with a few number of market participants, one group of investors typically has monopolistic access to information that is used to determine equity prices. Relevant information, therefore, will not be cost free and available to everyone at the same time. As a general conclusion little evidence of any systematic pattern in the persistence in the level and in the volatility in bull and bear periods. If any, higher degrees of dependence are detected in both (level and volatility) in some stocks and the index during the bull periods.

The empirical results would be beneficial to investors as it provides indication of behaviour of stock market volatility during the market phases in the Kenyan stock market. Consequently, they need to study and examine stock market volatility, among many other factors, before making investment decisions. The results suggests that, during the bear phase, the conditional volatility tends to upsurge that might be explained by a lot of speculations going on and investors 'buy on rumours.' After the bear phase regime, investors liquidate their stakes in expectations of high returns.

The implications for investors are also significant to the stock exchange administrators and policy makers. The surveillance regime during bearish phase should be stricter to keep excessive volatility under check. With the presence of asymmetric volatility, the policy-makers need to be more pro-active in formulating their economic stimulating measures during periods of negative impacts. This is because, when negative shocks happen, investors would normally have negative sentiment and over-react to the shocks, which can make the already sinking economy even worse. During the time of positive impacts, the economies may face a quick overheating problem due to investors' over-reaction to their optimistic expectation.

Therefore, an appropriate counter-cyclical policy measures have to be undertaken by the government to respond to the adverse impact of negative shocks and to stabilize the macroeconomic environment. The ability to identify breakpoints would provide policy-makers with additional information to identify the causes of the volatility and help to stabilize the economy. Further research can be done to ascertain whether the Nairobi Stock Exchange market efficiency has improved overtime dividing the market into bull and bear phases. The model employed was sensitive to missing data points, share splits and reversals.

Statement of Competing Interests

Authors have no competing interests.

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