Market Noise and Its Effects on the Performance of the Nairobi Securities Exchange 20 Share Index in Kenya

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Abstract
In a market, when goods are on offer, sellers use various mechanisms to get the edge over their competitors. Some use professional mechanisms, others go in ways that are not professional, some use visibility, and others use persuasion. At the end of the day, they have to sell their products. The buyers, when making the decisions may be rational or may just react to the loudest/most visible seller.
Purpose: This study dwelt on noise and its effects on the performance of the security markets indices in Kenya, particularly focusing on the Nairobi Securities Exchange (NSE) 20 Share Index. The research covered a 12-year period from January 2004 to December 2015. Anchored on theoretical insights from Dow and Gorton (2006), Milgrom and Stokey (1982), and Homm and Breitung (2011), the study explores the role of noise traders—those who trade based on emotions or reactions or non-supported factors—and their contribution to stock price volatility, deviation from intrinsic value, and investor behavior.
Methodology: Employing a panel data approach, secondary data, in form of stock share prices, was obtained from the Nairobi Securities Exchange, Capital Markets Authority (CMA), Central Ban of Kenya (CBK), and Kenya National Bureau of Statistics (KNBS). Stock returns were computed using Homm and Breitung's rational bubble model to separate actual prices from fundamental prices. The Noise Effect was measured as the deviation between market price and fundamental value, with monthly weighted averages calculated for individual stocks and regressed against the NSE 20 Share Index returns. Descriptive statistics indicated a mean Noise Effect of 0.88 with a standard deviation value of 7.79, while the average index returns showed a mean value of 0.40 and standard deviation of approximately 6.62, indicating moderate but notable volatility linked to noise trading.
Findings: Findings reveal that noise trading Behaviour introduces volatility and temporary inefficiencies in the market, causing stock prices to diverge from their fundamentals. The results support the notion that Behavioural factors, such as investor sentiment and speculative activity, have a measurable impact on market performance, especially during periods of economic uncertainty or market shocks. This research provided invaluable insights into the implications of noise effect on market regulation, investor education, and the design of informed trading strategies within the Kenyan capital markets context.
Conclusion: From the analysis, it can be concluded that bubbles exist in the Nairobi Securities Exchange 20 share index securities. These stocks are indeed demonstrating the features of semi-strong form efficiency.
DOI: 10.7176/RJFA/16-7-03
Publication date: August 31st 2025

1. INTRODUCTION:

When something happens in the financial world, there are reactions. These reactions could be positive or negative, they could be rational or otherwise. (Karungu et al., 2018) (Karungu et al., 2020). There could be an increase in the prices, a drop in the prices, adjustments on the trading volumes and so on. In the stock markets, the major aspects are the stock prices and the trading volumes. Fundamental stock analysis calls for price movements based on the profitability, growth prospects and stability of the organization. Fundamental analysis ensures that a security is not over or undervalued. When noise strikes (and it is loudest when an announcement has been made), rationalism ceases to be followed. Announcements in the securities markets could include dividends, mergers, acquistions, new products, stock splits, bonus issues and so on. This often makes investors irrational; some will have investor sentiment, others do speculative trading, while others depend on media hype which may cause stock price imbalances.

The bubble or the asset values have been deviating since the inception of the markets. In the asset valuation market, the investors are normally depicted to be rational as they gather information that conform with asset price adjustment (Cuthbertson & Nitzsche, 2004). Engsted & Tom, 2014 observes that the prices of the stocks conforms with the bubble approach that encapsulates rational and irrational bubbles. The prices of the stocks rationally replicate the existing information and make it accessibly efficient to those who need it. On the other hand, Eugene Fama pinpoints that irrational bubbles do not support that unpredictability nature of the price declines therefore deemed irrational. Moreover, the rational bubbles are believed to operate on a notion that they will exist again tomorrow since they existed today. Explicitly, the present existence of the bubbles in the asset market depicts that the rational bubbles must be positive– they are perceived to have been rooted since the beginning of the markets.

However, their existence cannot be taken into the account if their price exists on the upper limit. In their study, Engsted and Tom (2014) ascertained that the rational bubbles exist in an efficient dynamic economy where the stock rates does not exceed the growth rate.

The Securities in the NSE that were selected were those that constitute the NSE 20 Share index, being the best components or the representative stocks in the economy. Kakiya et al (2013) observes that the NSE is not semi strong form efficient.

2.0 LITERATURE REVIEW

LeRoy (2004) is an author who dived into the genesis of the rational bubbles in the 1990s. This was the period where the stock market boomed. According to the researcher, a bubble that follows market fundamentals, occurs when investors are conscious when and if they are trading at escalated prices and that, in spite of the bubble, there are no untapped, and/or lucrative trading opportunities. In a rational bubble context, this termed as a situation where expected returns are constant does not necessarily mean that prices would fall in a predictable manner; it may be possible to forecast or foresee the point of the bubble rupture and that its anticipated returns will stay unchanged, but it is hard to anticipate how it will do so (Engsted, 2014). Cuthbertson and Nitzsche (2004) have noted that the specification of the error term's second and higher-order statistical characteristics, (έt+1) distributions is unrestricted by rationality. For example, Auto-Regressive Conditional Heteroskedasticity (ARCH) process is developed when the error term's variance that may be connected to its historical value does not go against the Rational Expectations.

The stock prices will be obtained by the summation of the bubble component which are rational and the fundamental components (Engsted, 2014). An intrinsic or fundamental component is calculated asthe present or current present value of future cash flows values returns expected encapsulating considerations that could influence the security price. According to the researcher, the transversality criteria must be equal to zero in order to eliminate the bubble. Simply, manifolds are essentially "Submanifolds such that, at every point where they intersect, the direct sum of their tangent spaces equals the tangent space of the surrounding (ambient) manifold at that point." according to transversality doctrine.

Contextually, this case implies that the prices only replicate their primary or fundamental value. Therefore, this theory will back up the thought of noise bubbles and its connection with the returns of the Nairobi Securities Exchange indices. Behavioural finance theories helps to comprehend how investors behaviour is influenced by cognitive errors and emotions. Cuthbertson and Nitzsche, (2004), argues that from the ‘smart money and noise traders’ theory,’ the stock market may have an investor whose demand for stocks is willingly increased when the prices of the stock increases. $1 + E_t R_{t+1} = k^*$Where k^* is a constant, $E_t R_{t+1}$ are expected returns over time t+1.

In a scenario or situation where the there are only smart money (fundamental), the prices could only react to events unfolding (James (2012); Cuthbertson & Nitzsche (2004); Komo & Ngugi (2013); Lukanima, (2014)). That is to say, any favourable news will be welcomed by buying the security, raising its price above its value that considers all dynamics, only if these logical investors also happen to be positive analysis traders. Prices are said to be mean reverting when a logical trader sells their equities and the price returns to its fundamental worth after they have identified the aforesaid mispricing, according to Cuthbertson and Nitzsche (2004).

Smart money who are commonly referred to as rational traders, the anticipated equilibrium prices must be constant. According to the available literature, the ability to select appropriate stocks is known as smart money effect (Sapp and Twari, 2004). According to Ross, Randolph, and Jordan (2010), a logical investor considers the variation of the return on their portfolio to be the appropriate indicator of the risk of the portfolio. This is true even when one investment is held in the portfolio, in which case the variation of the returns on that security equals the variance of the returns on the entire portfolio. In an ideal world, all investors would logically modify their stock price predictions in response to new information that is published into the market. Cuthbertson and Nitzsche (2004) alludes that positive returns are positively serially correlated (accompanied by other positive returns) in positive news over the minimum duration, whereas negative returns are not positively serially correlated (followed by other negative news) in negative news over the minimum duration

The returns are negatively serial correlated because rational players return to their arbitrarily assigned standards. This serial association across distinct horizons mean that when the investor buys recent 'winners', they will be buying “champions” in the subsequent timespan, and this is known as the momentum approach. Generally, this strategy can, therefore, be defined as the perception that investors have when they purchase cheap stock with the aim of increasing its price in future.A paper by Pastor Stambaugh and Taylor (2014), it was conducted because, as of 2013, the global mutual funds had total assets under management of about $30 trillion, and half of these were of U.S. mutual funds. Out of the total mutual funds in the United States, fifty-two per cent were in equity, and in these, eighty-one-point six per cent were actively handled. In Pastor et al. (2014), the authors pursued to comprehend why funds that have higher charges and trading expenses trade more than any other non-fund investor. The timeline under this investigation was between the years 1979 and year 2011, and the study contributors find that turnover is high among high fee-charged and small-sized funds and that trading by funds is higher when anticipations are high. This might imply that the securities are typically not correctly priced in situations when, jointly, there is the perception of significant opportunities for profit by funds. From the study, it can be deduced that, indeed, the performance of a fund is dependent on its turnover and other fund's turnover.

Research by Iwarere and Barmish (2014) suggests that the Binomial framework can be formulated by determining the likelihood of price change in securities. The likelihood of getting a return on an investment is a function of time-fluctuating stock price and the amount of money that has been invested. These authors additionally noted that if the total preliminary investment and sum invested are encouraging, then the investor is said to be in a long-standing and if the same sum is negative, then the investor is said to be short, and gains are made if the time fluctuating stock price is low. According to Bloomfield, Hara and Saar (2005), noise traders are not useful in the market because they distort the prices away from their real value, implying that they influence the market's informational efficiency. They argue that the degree of deviation of a market from its fundamentals determines the strength of the white noise; that is, the further the deviation, the stronger the impact of White Noise.

Dow and Gorton (2006) have it that traders who engage in securities for anything other than information are classed as noise traders. These are agents whose theoretic encounter has been thought to hold the key to the solutions to several problems in the current equities market (Dow & Gorton, 2006). Dow and Gorton (2006) also cite Milgrom and Stokey (1982) and Grossman and Stiglitz (1980), who claim that a noise trader does not gamble and noise trading is the reply to postulation. The scholars chose a set of literature, and when they performed a study, they discovered that an agent with more information cannot take advantage of it in trading. Most of these traders are probably, on average, likely to make losses for the amounts that they trade, and these are normally categorized commonly as liquidity traders or noise traders. In the work of Dow and Gorton (2006), the main goal was to examine if noise traders exist, whether they do, and how these traders could manage to operate, given the fact that they were always on the losing end during trade. When investors are offering their CEOs stock-based compensation, the common tendency observed is that the CEO is overdependent on price-based information. (Schneemeier, 2014) suggests that this leads to the following outcomes: the stock prices turn out to be highly volatile and subject to non-basic noise. From their literature, Dow and Gorton (2006) categorize two kinds of traders, that is, the informed trader – the one who trades with regard to some information and the uninformed – the trader who does not possess information but knows that informed traders exist and the price reflects their information.

While equilibrium prices provide full information, no one gains privately from obtaining information (Dow & Gorton, 2006). To get a return on collecting data, well-versed traders come up with the disquiet because if disquiet is nonexistent and the collection of data is expensive, there would be no equilibrium when data is gathered, and the ideal market will fail. Whenever data is expensive, noise is injected into the asset supply and hence, uninformed traders doubt whether prices mirror the data of well-versed traders. For this reason, uneducated buyers will cloud private data with ambiguity (Dow and Gorton, 2006). Such noise or uncertainty causes the informed traders to make trades without passing this information, hence making some profits. Typically, introducing noise into the cumulative supply will produce a balance that is partly disclosing, and this might not be seen since this model does not make any assumptions and if one is to ask what the Noise Effect is replying to in the real sense, it may not be clear.

The writers know that noise trading stems from certain individuals trading without reference to evidence and that it serves as an inducement to stock trading actions by hazard-fearful stockholders. If the noise traders hold sentiments that are not rational, the clever money dealers will choose to exploit and eradicate them. Dow and Gorton (2006) indicate that this is mainly because those smart money buyers or logical traders operate on statistics to complete their trades, and such individuals are wealth optimizers. Illogical traders would ultimately be forced out of move since they continuously produce losses. Nevertheless, occasionally, noise traders prevail; hence, this is not the case every time. The scholars note that if the noise traders continue trading for a little longer, they will survive, while clever money buyers will begin suffering financial negative gains, and this will push the prices further away from the basics.

There is still the issue of how the Noise Effect framework subjects can be utilized to gauge market views that is in explicated by the fundamentals or by the macroeconomic phenomena (James, 2012). Some of the basic variables are based on the financial position, while there are macro variables, such as rates of inflation and interest. It is a known fact that people have their own perceptions regarding everything, and so stock markets respond to these perceptions regardless of whether they are right or wrong. Usually, stock prices can change as quickly as the time it takes for a rumour to spread and change as quickly as the stretch it takes for the market to be informed; when the market gets information on the reality, it can also correct itself in an identical manner. Kadilli (2014) also argues that noise trading ought to escalate in business cycle flows, and this might happen during business series troughs, and this might result in increased stock return expectedness by investor opinions during corporate cycle phases. In fact, in crisis times, investors provide wrong signals as to what information they are interpreting from the free data. Such noise trading is referred to as stockholder sentiment and may well be the source of herd conduct in predicament moments (Kadilli, 2014).

Usually, the origin of market noise is stockholders getting into the marketplace for distinct purposes such as stock liquidation, varying trading activity goals, or when using currencies (James, 2012). According to Sinha and Agnihotri (2014), noise or liquidity traders make decisions that are fueled by factors other than anticipated settlements. The greatest instances of these are investors in institutions who might be trading because of clients' liquidity needs pressure. In their review of the literature, Hiemstra and Jones (1994) establish some of the reasons for the causality relationship between charges and amounts of trading. Possible reasons include new data, non-tax and tax-associated incentives, Noise impacts and stocks traded quantity as a measure of not agreeing.

Miralles-Marcello et al. (2014) focused on the behaviour of the stock market following shocks- the significance of bear and bull marketplaces of the Spanish market. Their study's purpose was to examine the Spanish Stock Market in order to establish if there was an over- or under-reaction of the stock in a very short period after a change in price. These researchers' strategies were used in different ways as follows. First, they applied Average Cumulative Abnormal Returns (ACAR) and Average Cumulative Returns (ACR) to analyze stock behaviour. This approach was consistent with studies by Kithinji, Oluoch, and Mugo (2014) and Kakiya et al. (2013). Second, the scholars focused on evaluation for six days following the shock. This is different from conventional circumstances where investigations were performed a day following the shock of the financial markets. Third, the authors contrasted the market conduct following varying phases and sizes of these marketplaces. This study discovered that in bull marketplaces, following the preliminary overreaction impact, there is a considerable underreaction, which is regarded as typical because of the optimistic context. Nevertheless, they found that both types of strategies yield higher returns after positive shocks compared to negative ones in bear markets.

Several works researched by Bloomfield et al. (2005) and Bloomfield et al. (2006) have investigated the several deeds of noise traders and their implications on stocks achievement and involved a trial to examine the performance of noise traders in the market amongst additional traders and likewise observe how the balance is affected when securities contracts are executed. From this research, it has been appreciated that the noise traders, on average, incur losses due to the fact that they do not do much to contribute to the provision of extensive liquidity. The other reason is that they lose since an effort to gain more profits through the trends is unproductive as they are unable to find the most in security that experiences high volatility.

As stated by Homm and Breitung (2009), whenever a bubble exists, most normal stock trader willing to purchase this stock ought to anticipate that bubble to increase at the rate of the current interest rates. In this instance, it is the government's 91-day treasury bill rate of interest. These scholars additionally indicate that when the bubble feature is positive, the ground for the operation of speculation is set. Typically, a rational stakeholder will be here ready to purchase a highly priced stock with the opinion that via price, they will adequately get bubble compensation. Furthermore, the researchers note that fundamental evaluation is usually overlooked whenever there are positive bubbles. But if as many investors believe this will happen and go ahead and purchase the shares, then the stock values will, in fact, go up and thereby sustain the self-fulfilling prophecy cycle. This, of course, is known as the Noise Effect.

3.0 DATA AND METHODOLOGY

This research work relied on secondary source data collection approaches, and the data collection was done with the help of a data-gathering schedule. The monthly stock prices over the period were collected, and from this, the study was able to identify the various patterns of the investors across the 12 years. Furthermore, the study used panel data, which was consistent with Saunders, Lewis and Thornhill (2009). These authors suggest similar gathering aspects for research that relies on panel data.

3.1 Data Collection Procedure

The secondary data for the article was obtained from the NSE, Central Bank of Kenya (CBK) and Capital Markets Authority in accordance to the study’s objectives except for the financial contagion which in addition to the data vendors from the NSE, was obtained from New York Stock Exchange (NYSE) and London Stock Exchange (LSE). This study employed longitudinal time horizon taking a significant span understudy. The study time horizon underscores other studies that undertook over 10yrs such as (Kakiya et al., 2013), (Olweny et al., 2013), (Owido, Onyuma, & Owuor, 2013) and (Komo & Ngugi, 2013). The study’s data was obtained from fluctuating prices from start of 2004, that is January, to the end of 2015, that is December. These prices were on a monthly basis. This time span has been empirically supported by the available studies as they deem it adequate for analysis. For example, Amata and Muturi (2016) used 13yrs, Kadilli’s (2014), study used 12 years, Hajek’s (2007), took 11 years while Miralles-Marcello *et al* (2014) data collection process spanned 10 years. A data collecting sheet that included daily price fluctuations information, monthly risk-free interest rates as indicated by the Kenyan 91 day Treasury Bills, turnover, the number of outstanding shares, dividends paid in a given year, NSE 20 share index, market capitalization, NSE All Share Index, FTSE NSE 15 Index and FTSE NSE 25 Index was obtained and used as the gauge to gather secondary data. Most of the information regarding the data was obtained from NSE, CMA, CBK and Kenya National Bureau of Statistics (KNBS) similar to Amata and Muturi (2016) case.

3.2 Data Processing and Analysis

Fundamentally, data analysis entails disintegration or breaking down of items into constituents with a study motive. The hypothesis testing was identically tested at a 0.05 significance level. The study adopts a significance level of 0.05 since it is widely used in social sciences (Saunders et al., 2009.) Additionally, since the study observations were more than 30 therefore, z-test was deployed.

Since the researcher's data of interest was the security prices of the firms, on a monthly basis, recorded in the exchange market, the monthly stock returns were assessed from the price movements. Notably, the monthly prices were obtained from the vendors who deal with data at NSE. A point to note is that it is usually stock prices on the last day of trading that was under study that were used in the analysis. SPSS version 25 was used for data analysis and linear time series regression model on Ordinary Least Squares (OLS) standards was assumed for the study. Analysis for each variable was done by feeding all the data for the monthly returns on each model in the given formulas.

From the relationship ith the performance of the NSE indices and its Noise Effect, underscores Cuthbertson and Nitzsche (2004), study that observed that a study is orthogonally property is infringed if the error term ($\acute{\varepsilon}_t$) is autocorrelated. An example is first-order Autoregressive Process. Just like Miralles-Marcello *et al* (2014), study that used a span of 10yrs in analyzing the data, this study's time horizon was for stock prices dated 1st January 2005 to 31st December 2014.

The research endorsed a model used by Homm & Breitung, (2011) which is as follows:

$$R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t} - 1 \ldots\ldots\ldots\ldots \text{(i)}$$

Where

P_t = share price at time t

D_{t+1} =Dividend for time t

R_{t+1} =Return of the shares at time t

When there is risk neutrality, no arbitrage opportunities and constant expected returns, stock price is obtained as:

$$P_t = \frac{E_t[P_{t+1}+D_{t+1}]}{1+R} \ldots\ldots\ldots\ldots \text{(ii)}$$

Where:

R = Return at time t

E_t= Expectation conditional on the information at time t

Fundamental stock price is determined as follows:

$$P_t^f = \sum_{i-1}^{\infty} \frac{1}{(1+R)^i} E_t(D_t + 1) \ldots\ldots\ldots\ldots \text{(iii)}$$

Where P_t^f = Fundamental share price

Bubble component is the difference between the share price at period t and the fundamental share price.

$$B_{t=} P_t - P_t^f \ldots\ldots\ldots\ldots \text{(iV)}$$

4.0 FINDINGS AND DISCUSSIONS

aIn relation to Noise analysis, it was found in fifteen observations an average of 2.93, a standard deviation of 0.29 and a range of 1.22 and is shown in Figure 1.

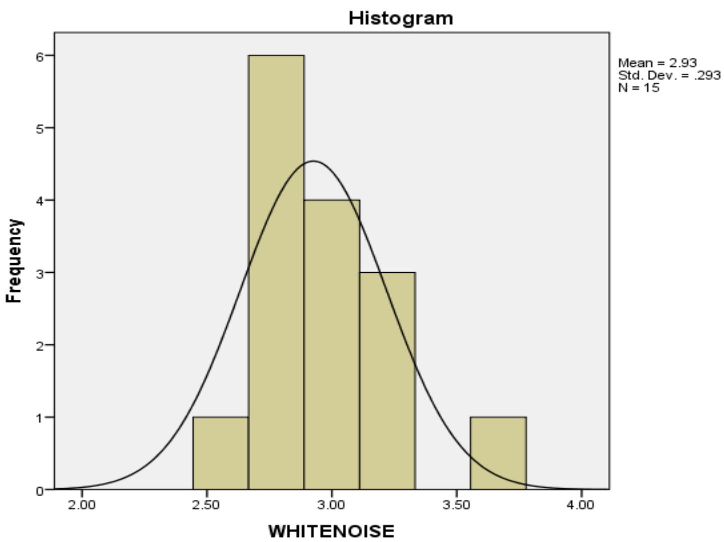

Figure 1: Normality Tests on Noise Effect

The computation of the Noise Analysis, was a twelve-year study which measures the Noise Effect. This was in line with Miralles-Marcelo, Miralles-Quiros, & Miralles-Quiros (2014) proposiotion.This study adopted a 12 year study computation in order to measure the Noise Effect as guided by other empirical studies like Miralles-Marcelo, Miralles-Quiros, & Miralles-Quiros (2014). First, the computations involved recording the monthly share prices for each company from January 2004 to December 2015. Next, the financial statements of respective firms accessed from the CMA Library and websites assisted in obtaining the dividends paid by each company. Homm and Breitung (2011) model was utilized to compute the stock returns at time t. Then, the anticipated conditional of information at time t was recorded. The anticipated or expected conditional information was obtained through determination of riskless return by observing the Kenyan 91-day Treasury bill movements which is taken as a gilt edge security.

To achieve the desired outcome was to determine the primary monthly stock price. The outcome was realized through the equation that encompassed interest rates determined by the 91-day Kenyan Treasury bill, dividends paid by specific stocks for 1 year and the expected conditional of information. From this, the rational bubble was adopted to measure the White Boise Effect. The bubble component is realized when the monthly stock price is subtracted from the month specific intrinsic value (Homm and Breitung, 2011). It is used to test whether the stocks were undervalued or overvalued. These monthly computations for individual stocks were feed in separate or different spread sheet and the monthly weight average was established. As a result, for each stock, 144 observations for the Noise Effect and was run upon the NSE 20 Share Index for 12years. The results are as shown in Figure 2.

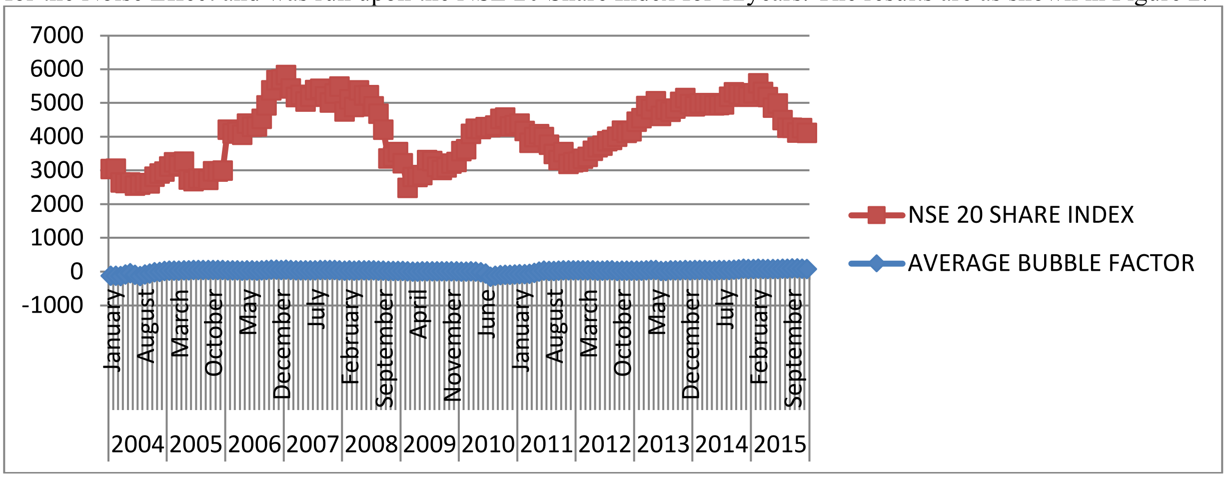

Figure 2: Noise and its Effects on the Performnace of the Nairobi Securities 20 Share Index

As captured in Table 1, the computation outcome for the Noise Effect was; an average value of 0.88 over the period of study with a standard deviation value of 7.786. The average NSE 20 Share Index returns computation mean was 4.0 with a standard deviation of 6.616.

Table 1: Descriptive Statistics Results on Noise and its Effects on the Performance of the NSE 20 Share Index

	Mean	Std. Deviation	N
AVERAGE NSE 20 SHARE RETURNS	.3956	6.616	144
NOISE EFFECT	.8797	7.7866	144

The researcher obtained dividends per share for the firm that was based in Uganda. It's important to note that this was the only foreign firm listed in the NSE. The exchange rates from 31/12 2013 through 2015 were recorded whereby, as at 31st December 2013, 2014 and 2015 one Kenya shilling was exchanging at a rate of 29.2078, 30.60205 and 30.86069 Ugandan shilling respectively.

In addition, the values on Appendix 1, are explained on Table 2. In addition, Table 2 brings out its correlation with the Noise Effect. A total of 144 data sets (the twelve-year span from Jan 2004 to Dec 2015) were included in the research. The rational bubble and NSE 20 share index correlation values were established to be 0.369 with P value of 0. 000.The regression model developed is illustrated below on tables 2 and 3. The model clearly illustrated Noise Effect's influence as measured by the rational bubble on NSE indices Performance. An R square value of 0.136 was established, thus implying that the Noise Effect influenced the NSE 20 share index to a 13.6% extent. It also means a p value of 0.00 that was less than the required threshold value of 0.05. Below is an illustration of the regression model that has been explained in the above write up.

$y = 3985.74 + 6.571\ Noise\ Effect$

Table 2: Model Summary Results on the Noise and Its Effect on the Performance of the NSE 20 Share Index Returns

Model	R	R Square	Adjusted R Square	Std. Error of the Esti	Change Stat					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.369[a]	.136	.130	835.88	.136	22.387	1	142	.000	.094

a. Predictors: (Constant), Noise Effect
b. Dependent Variable: NSE 20 SHARE INDEX

Table 3: Coefficients Results on Noise and Its Effects on the Performance of the NSE 20 Share Index Returns

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3985.738	74.465		53.453	.000	3838.338	4133.139
	NOISE EFFECT	6.571	1.389	.369	4.731	.000	3.826	9.316

a. Dependent Variable: NSE 20 SHARE

From the Table 2 above, the outcome would make the researcher infer that although the correlation is weak and positive, the significance level of 0.05 level depicted a statistically significant impact of Noise Effect. Dow and Gorton (2006), noted that when the information uncertainty is created as a result of the Noise Effect and NSE 20 share index in the same direction, thus causing confusion among the uninformed traders.

The Noise Effect variable had a correlation of (-0.148) and a P value of 0.299 against the NSE 20 Share index performance. This correlation was a weak negative and it can be observed as statistically insignificant at 5% Level of Significance. Noise Effect and NASI have a weakly negative association, as depicted by the correlation of -0.093. At 0.05 significance threshold, the outcomes on the research portrayed a significance of 0.371, which was not statistically significant.

The data indicates that P value of 0.000 and correlation of 0.369 were the values or outcome for computation of the noise effect and the NSE 20 share index. The researcher observes that the performance of NSE and the noise effect (as determined by the rational Noise Effect) were statistically significantly influenced at the significance level of 0.05. In respect to the multiple regression model, the noise effect has a 13.6% impact on the NSE 20 share index, with a R square of 0.136. since the results indicate that noise exists in the NSE 20 share index, this goes against the findings of Kakiya *et al* (2013) who found that the Kenya Securities Market is not semi-strong in terms of efficiency.

The Secondary data analysis revealed that the noise effect had a statistically reliable influence at 0.05 level on the NSE indices performance. As a result, the researcher came to the conclusion that, at the 0.05 level of significance, the null hypothesis—which claimed that the noise effect had no statistically significant impact on the performance of NSE indices was rejected. Statistically, the Noise Effect objective had insignificant influence of all the individual components of NSE and Noise Effect; although the scondary data showed different results. Conversely, the study's findings were significant inspite of the 13.6% extent of Noise Effect influence towards the NSE indices.

5.CONCLUSIONS AND IMPLICATIONS

From the analysis, the results were significant at the 5% criterion. This confirms the existence of rational bubbles that contribute to market noise in the NSE, as supported by the empirical studies reviewed in this research. It is evident that trader behaviour remains largely unpredictable, and even seasoned market experts are unable to fully explain or anticipate their actions. Based on the above, the study would recommend further research that is sector based since this study looked at the entire exchange or specific indices for the analysis. This could have new insights for some industries that are generally affected by regulations or turbulence. This sector-based approach will ensure that the results cancel any smoothing effects that could arise due to looking at the entire exchange in wholesome

ACKNOWLEDGEMENTS

The researcher feels indebted to the Capital Markets Authority and the Nairobi Securities Exchange for the provision of data that was necessary for the analysis. The researcher also acknowledges the Egerton University and JKUAT Repositories for the enablement of the literature review that led to the eventual development of the article.

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Appendix 1: Noise Effect Filled Sheet

Year	Month	AVERAGE BUBBLE FACTOR	NSE 20 SHARE
2004	January	-120.6915729	3157.88
	February	-120.245014	3175.36
	March	-127.7769715	2770.66
	April	-82.50698881	2707.6
	May	-45.08349354	2689.14
	June	-92.54942232	2639.75
	July	-129.0225216	2708.03
	August	-81.69289613	2708.86
	September	-55.03665797	2670.69
	October	-19.14858624	2829.65
	November	-7.689994861	2918.34
	December	15.75373688	2945.58
2005	January	25.62662723	3094.38
	February	28.93049019	3212.81
	March	29.00015843	3126.04
	April	33.9867609	3227.59
	May	37.15462453	2689.14
	June	45.88077719	2639.75
	July	45.71727271	2708.03
	August	47.73208193	2708.86
	September	46.36739744	2670.79
	October	43.01413665	2929.65
	November	45.066779	2918.34
	December	44.99958734	2945.58
2006	January	38.55564105	4171.8
	February	37.23803015	4056.63
	March	36.26529886	4101.64
	April	31.83542546	4025.21
	May	37.84311934	4349.75
	June	35.96991557	4260.49
	July	31.84988193	4271.68
	August	42.63039524	4486.04

Year	Month	AVERAGE BUBBLE FACTOR	NSE 20 SHARE
	September	45.33427813	4879.86
	October	55.81294373	5314.36
	November	56.81615687	5615.2
	December	45.15085292	5645.65
2007	January	56.21704878	5774.27
	February	43.29973614	5387.28
	March	40.04287846	5133.67
	April	40.32680339	5199.44
	May	38.5825046	5001.77
	June	38.11427212	5146.73
	July	41.72231937	5340.08
	August	46.50198748	5371.72
	September	44.96731708	5146.46
	October	43.17627298	4971.04
	November	45.59043732	5234.44
	December	41.60057189	5444.83
2008	January	32.20237385	4712.71
	February	37.27790669	5072.41
	March	32.55738949	4843.17
	April	39.53523108	5336.03
	May	40.83435765	5175.83
	June	41.93410467	5185.56
	July	34.83381317	4868.27
	August	32.66703231	4648.78
	September	25.23999026	4180.4
	October	16.28159212	3341.47
	November	20.64728219	3386.65
	December	21.10730627	3521.18
2009	January	17.16098052	3198.9
	February	5.46131104	2474.75
	March	2.919265673	2805.03
	April	3.085713798	2800.1
	May	4.874734874	2852.57
	June	9.046230435	3294.46
	July	8.882687181	3273.1
	August	7.10210455	3102.68
	September	6.410022861	3005.41
	October	5.966030389	3083.63
	November	9.173943725	3189.55
	December	6.569823165	3247.44
2010	January	2.620050363	3565.28
	February	0.923562604	3629.41
	March	7.137866024	4072.93

Year	Month	AVERAGE BUBBLE FACTOR	NSE 20 SHARE
	April	-1.736442833	4233.24
	May	-19.26917925	4241.81
	June	-54.80275078	4339.28
	July	-154.3128821	4438.58
	August	-123.8921863	4454.49
	September	-101.0733092	4629.8
	October	-94.31822594	4659.56
	November	-92.68827997	4395.17
	December	-88.66982211	4432.6
2011	January	-76.70718625	4464.92
	February	-71.00726136	4240.18
	March	-65.62489836	3887.07
	April	-38.47149115	4029.23
	May	-0.698490534	4078.1
	June	24.88089831	3968.12
	July	19.66308731	3738.46
	August	19.02224771	3465.02
	September	24.43550097	3284.06
	October	34.16690748	3507.34
	November	33.68342254	3155.46
	December	36.34680701	3205.02
2012	January	36.82987638	3224.18
	February	40.61810332	3303.75
	March	38.34081771	3366.89
	April	38.31655459	3546.66
	May	32.01550804	3650.85
	June	30.51847321	3703.94
	July	35.201543	3832.42
	August	33.47253463	3865.76
	September	22.71674977	3972.03
	October	29.60018408	4147.28
	November	32.59321364	4083.52
	December	24.98205108	4133.02
2013	January	27.26175617	4416.6
	February	29.43792019	4518.59
	March	42.65698193	4860.83
	April	43.87379384	4765.23
	May	44.26829882	5006.96
	June	16.15714217	4598.16
	July	16.23220328	4787.56
	August	39.55514017	4697.75
	September	39.3307644	4793.2
	October	42.45804787	4992.88

Year	Month	AVERAGE BUBBLE FACTOR	NSE 20 SHARE
	November	43.53934238	5100.88
	December	41.256806	4926.97
2014	January	47.15802757	4856.15
	February	47.98109301	4933.41
	March	46.49848279	4945.78
	April	40.07240551	4948.97
	May	42.71940961	4881.56
	June	48.52448243	4885.04
	July	49.59408003	4906.09
	August	45.27065353	5139.39
	September	55.87500904	5255.62
	October	62.66898422	5194.89
	November	84.15792296	5156.33
	December	72.56770302	5112.65
2015	January	79.08513902	5212.11
	February	84.67463016	5491.37
	March	80.02751203	5248.16
	April	77.37542345	5091.43
	May	74.11450798	4786.74
	June	79.82334394	4906.07
	July	86.07290214	4404.72
	August	86.4935463	4176.59
	September	90.7322504	4173.52
	October	92.75749397	4025.55
	November	83.21321704	4166.59
	December	75.43678479	4040.75