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The changing market efficiency of the Nairobi securities exchange

Abstract

This paper tests for market efficiency changes of the Nairobi Securities Exchange (NSE) after the year 2000 and determines whether technological advancements have led to an increase in the market efficiency. The data that are used are the NSE 20 share index over the period, January 2001 to January 2015 and the NSE All Share Index (ASI) from its initiation, in February 2008 to January 2015. The data analysis method applied is the variance ratio test. The study finds that the market efficiency of the NSE has increased over the test period which suggests that advancement in technology has contributed to the increase in the market efficiency of the Kenyan market. Therefore, the findings of the study are in line with the Adaptive Market Hypothesis (AMH) for the NSE.

Keywords: adaptive market hypothesis, variance ratio test, Nairobi Securities Exchange.
JEL Classification: G14, G15.

Introduction

In financial markets, the weak form of the efficient market hypothesis (EMH) infers that price returns are serially uncorrelated sequences, that is, prices should follow random walk behavior (Rodriquez, Aguilar-Cornejo, Femat and Alvarez-Ramirez, 2014). However, the authors add that recent developments in evolutionary economic theory (Lo, 2004) have come up with a new version of the EMH, the concept - adaptive market hypothesis (AMH) by proposing that market efficiency is not an all-or-none concept, instead, market efficiency is a characteristic that changes continuously over time and across markets.

The AMH explains the changing degree of market efficiency. Prices generally reflect the information that emerges from specific groups of market participants and environmental conditions. Individuals in financial markets are bounded in their degree of rationality and make choices that are merely satisfactory. A key consequence is that return predictability is time-varying because of changing environmental conditions and changes in the population of market participants. Profit opportunities exist from time to time, declining as they are exploited - at the same time, new arbitrage opportunities arise as conditions change. These changes impact on the degree of market efficiency resulting in a change in return predictability over time. Findings from several studies that carry out efficiency tests in a rolling window are in line with the AMH (Niemczak and Smith, 2013; Lim, Brooks and Kim, 2008; Kim, Shamsuddin and Lim, 2011).

Lo (2005) argues that the battle between proponents of the EMH and champions of behavioral finance has never been more pitched with little consensus as to which side is winning or what the implications are for investment management and consulting. The AMH is a paradigm under which the EMH and market inefficiency can co-exist in an intellectually consistent manner (Lo, 2004). Convergence to equilibrium is, therefore, neither guaranteed, nor likely to occur, and it is, therefore, incorrect to assume that the market must move towards some ideal state of efficiency (Lo, 2005).

The efficiency of stock markets is considered to have increased compared to the level of efficiency many years ago. This has been attributed to the advancement in technology that has enabled information to quickly reflect on the share prices. In a study conducted by Yang, Kwak, Kaizoji and Kim (2008) that analyzed the time series of Standard and Poor's 500 Index (S&P 500), the Korean Composite Stock Price Index (KOSPI) and the Nikkei 225 Stock Average (NIKKEI), it was observed that, before the year 2000, information used to get by slowly, hence, resulting in the markets being less efficient. However, information flow is currently faster and more even because of the rapid development of communication through high speed internet, mobile technologies, and world-wide broadcasting systems. The expectation is of the present stock markets to become more efficient than past markets, confirming the EMH (Yang et al., 2008).

Since the year, 2000, there have been both regulatory and technological developments. Cognizant of the observation by Yang et al. (2008) that, as a result of technology, market efficiency increased significantly from the year 2000 and that by Lim (2009) on using both linear and non-linear tests to determine market efficiency, it is only proper to re-visit the issue for the NSE. Hence, this study seeks an answer to the research question: Has informational efficiency of the NSE improved since the year 2001? The aim of this study is to examine the change in informational efficiency of the NSE over the period of study, testing the AMH that informational efficiency changes continuously over time and across markets (Lo, 2004). The main contribution of this study to litera-

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ture is that the market efficiency of the NSE has increased, since technological advancements were implemented in the NSE.

The remainder of this paper is organized as follows: section 1 presents the literature review. Section 2 presents the methodology. Section 3 describes the data while section 4 discusses the results. Lastly, the final section provides the conclusion.

1. Literature review

A study by Kim et al. (2011) finds strong evidence of time-varying return predictability of the Dow Jones Industrial Average (DJIA) index from 1900 to 2009. Return predictability is found to be driven by changing market conditions consistent with the implication of the AMH. There is evidence that the United States (US) market has become more efficient after 1980 which is probable, as the US market has implemented various measures of market innovation in the 1960s and 1970s, and macroeconomic fundamentals have become much more stable since 1980. The findings of the study align with the AMH, which argues that dynamic market conditions direct the degree of stock market efficiency. Ito and Sugiyama (2009) measure a time-varying structure of market inefficiency of the US stock market and find the degree of market inefficiency varies through time. In addition, the authors find the US stock market becomes the most efficient around the year 2000 in the last half-a-century.

Urquhart and Hudson (2013) empirically investigate the AMH in three of the most established stock markets in the world: the US, United Kingdom (UK) and Japanese markets using very long-run data. Five yearly sub-samples are created using daily data and are, then, subjected to linear and non-linear tests to determine how the independence of stock returns has behaved over time. Results from the linear autocorrelation, runs and variance ratio tests show that each market has evidence of being an adaptive market with returns going through periods of independence and dependence. Interestingly, the results from the non-linear tests show strong dependence for every sub-sample in each market, however, the magnitude of dependence differs quite significantly. The linear dependence of stock returns varies over time, but non-linear dependence is strong throughout. The overall results indicate that the AMH provides a better description of the beha-vior of stock returns than the EMH.

AMH is tested through four well-known calendar anomalies (Monday effect, January effect, Halloween effect and turn-of-the-month effect) in the DJIA index from 1900 to 2013 (Urquhart and McGroarty, 2014). Sub-sample analysis and rolling window analysis are used in the study. Implied investment strategies based on each calendar anomaly are created and determinations of which market conditions are more favorable to the calendar anomaly performance are considered. The findings show that all four calendar anomalies support the AMH with each calendar anomaly's performance varying over time. However, some of the calendar anomalies are only present during certain market conditions. Overall, the study shows that the AMH offers a better explanation of the behavior of calendar anomalies than the EMH.

The martingale hypothesis is tested for 15 European emerging stock markets located in Croatia, the Czech Republic, Estonia, Hungary, Iceland, Latvia, Lithuania, Malta, Poland, Romania, Russia, the Slovak Republic, Slovenia, Turkey and Ukraine (Smith, 2012). Developed stock markets in Greece, Portugal and the UK are also included for comparative purposes. Rolling window variance ratio tests based on returns and signs and with wild bootstrapped *p*-values are used with daily data over the period commencing in February 2000 and ending in December 2009. Changes in efficiency are captured via the fixed-length rolling sub-period window which is also used to identify events which coincide with departure from weak-form efficiency and to rank markets by relative efficiency. Overall, return predictability varies widely. The study finds the most efficient stock markets are Turkish, UK, Hungarian and Polish, while the least efficient are Ukrainian, Maltese and Estonian.

Hiremath and Kumari (2014) explore the AMH in India. The linear test results show that the Indian stock market switched between periods of efficiency and inefficiency, and more importantly, the market has become efficient from the year 2003. The non-linear test results indicate strong presence of non-linear dependence in Indian stock returns throughout the sample period, indicating possible predictability of returns and consequent excess returns. The authors find that the Indian stock market is still evolving and not fully adaptive, however, it is moving towards efficiency. Ghazani and Araghi (2014) examine the existence of the AMH as an evolutionary alternative to the EMH by applying daily returns on the TEPIX index in the Tehran Stock Exchange in Iran. The sample period is from 1999 to 2013. Four different tests (linear and non-linear) are used to study adaptive behavior of returns. The study finds from linear (automatic variance ratio and automatic portmanteau) and non-linear (generalised spectral and McLeod-Li) tests represent the oscillatory manner of returns about dependency and independency which is in line with the AMH.

The weak form of the EMH is tested for eight African stock markets using three finite-sample variance ratio tests (Smith and Dyakova, 2014). Short-horizon predictability is captured via rolling windows and it tracks changes in predictability and is also used to rank markets by relative predictability. The findings show the stock markets experience successive periods when they are predictable and, then, not predictable which is in consistent with the AMH. The degree of predictability varies widely. The least predictable African stock markets and as, a result, more efficient are the Egyptian, South African and Tunisian markets, while the most predictable and a consequence more inefficient are the Kenyan, Zambian and Nigerian markets.

Arouri, Jawadi and Nguyen (2010) demonstrate that there is significant improvement in informational efficiency in emerging markets over recent years. The convergence speed toward efficiency appears to be higher for markets that have noticeably developed in size and liquidity in addition to embarked on comprehensive liberalization programs. Though most of the results are country specific, better market conditions before market openings appear to guarantee the positive impact of such policies on informational efficiency. Furthermore, the authors demonstrate that empirical results show that the weak form efficiency measure fluctuates through time, which is consistent with the gradual changes in emerging markets over the recent decades. Nonetheless, the speed of convergence towards efficiency depends on specific conditions in each market. It is also demonstrated that changes in market efficiency are significantly related to market liberalization policies even when control variables are considered.

The degree of return predictability is measured by Dyakova and Smith (2013) for forty Bulgarian stocks, two Bulgarian stock market indices and thirteen other South East European stock market indices using three finite-sample variance ratio tests. Daily data corrected for infrequent trading are used in a fixed-length rolling window to capture short-horizon predictability and rank Bulgarian stocks and South West European stock market indices by relative predictability. The study finds that the degree of return predictability for both stocks and stock market price indices differs widely. Specifically for the Bulgarian market, the degree of predictability is greater, the less liquid the stock is in the market. In addition, the study finds the degree of predictability is negatively related to capitalization, liquidity and market quality for market indices. Small, new, relatively illiquid and less-developed stock markets are found to be more predictable than large, liquid, developed markets.

2. Methodology

Variance ratio tests originated from the pioneering work of Lo and Mackinlay (1988) which was later modified and extended by Chow and Denning (1993). Karemera, Ojah and Cole (1999) summarized these tests as follows: let S_t denote the log of the equity return series being considered at time t.

The hypothesis of pure random walk is given by the equation:

$$S_t = \mu + S_{t\text{-}1} + u_t, \tag{1}$$

where μ is a drift parameter and u_t is a random error term. The usual stochastic assumption on μ_t is the Gaussian error structure, $E\ (u_t) = 0$ and $E\ (u_t^2) = \sigma_u^2$.

The null hypothesis for the variance ratio test is:

$H_0 = VR\ (q) = 1$ means the markets under the study are weak-form efficient.

$H_a \neq VR\ (q) \neq 1$ means the markets under the study are not weak-form efficient (Patel, Radadia and Dhawan, 2012).

Lo and Mackinlay (1988) developed tests of random walks under alternative assumptions of homoscedasticity and heteroskedasticity on u_t. Key to the test is the fact that, under the random walk hypothesis (RWH) the increments in asset price series are serially uncorrelated and that variance of the increments increase linearly in the sampling intervals. Such that for weekly data, if random walk is the true process generating the stock price series, the variance of the weekly series should be five times the variance of a daily series.

Abedini (2009) state the variance ratio is calculated by dividing the variance of returns estimated from the longer interval by the variance of returns estimated from the shorter interval and then, by normalizing this value to one by dividing it by the ratio of the longer interval to the shorter interval as follows:

$$Var\,(P_t - P_t - q) = {}^{\frac{1}{q}}Var\,(P_t - P_{t\text{-}1}), \tag{2}$$

where q is any positive integer, the variance ratio, VR $_{(q)}$ is determined as follows:

$$VR(q) = \frac{{}^{\frac{1}{q}}Var\left(p_t - p_{t\text{-}1}\right)^2}{Var\left(p_t - p_{t\text{-}1}\right)} = \frac{\sigma^2(q)}{\sigma^2(1)}. \tag{3}$$

For a sample size of $nq + 1$ observation (P_0, P_1,..., P_{nq}), the formulae for computing $\sigma^2(q)$ and $\sigma^2(1)$ are given in the following equations:

$$\sigma^2(q) = \frac{\sum_{t=q}^{nq}\left(p_t - p_{t\text{-}q} - q\mu\right)^2}{h}, \tag{4}$$

where

$$h = q\left(nq + 1 - q\right)(1 - \frac{q}{nq}) \tag{5}$$

and

$$\mu = \frac{1}{nq}\sum_{t=1}^{nq}\left(\mathrm{p}_{\mathrm{t}} - p_{t\text{-}1}\right) = \frac{1}{nq}\left(p_{nq} - p_0\right) \tag{6}$$

and

$$\sigma^2\left(1\right) = \frac{\sum_{t=1}^{nq}\left(p_t - qp_{t\text{-}1} - \mu\right)^2}{(nq-1)}. \tag{7}$$

The variance ratio test techniques test the RWH for two main desirable statistical properties (Karemera et al; 1999). Firstly, Lo and MacKinlay (1988) derived the asymptotic distribution of the variance ratio estimators and formulated an asymptotic standard normal test, $Z(q)$, to indicate the statistical significance of the variance ratios. Secondly, they provided an alternative statistic, Z^* (q) that is robust to heteroscedasticity and non-normal disturbances. Given these attributes and the ease of computation and interpretation, variance ratio tests are appealing, especially for practitioners (Karemera et al, 1999).

The standard normal Z (q) and Z^* (q) test statistics are computed as follows (Abedini, 2009):

$$Z\left(q\right) = \frac{VR\left(q\right) - 1}{[\varnothing\left(q\right)]^{1/2}} \approx N\left(0,1\right), \tag{8}$$

$$Z^*\left(q\right) = \frac{VR\left(q\right) - 1}{[\varnothing^*(q)]^{1/2}} \approx N(0.1), \tag{9}$$

where $\varnothing(q)$ and $\varnothing^*$ (q) are the asymptotic variance of the variance ratio under the assumption of homoscedaticity and the heteroscedasticity respectively:

$$\varnothing\left(q\right) = \frac{2(2q-1)(q-1)}{3q(nq)}, \tag{10}$$

$$\varnothing*\left(q\right) = \sum_{j=1}^{q-1}[\frac{2(q-j)}{q}]^2_{\partial(j)}, \tag{11}$$

where ∂ (j) is the heteroscedasticity - consistent estimator and computed as follows:

$$\partial(j) = \frac{\sum_{t=j+1}^{nq}\left(p_t - p_{t\text{-}1} - \mu\right)^2\left(p_{t\text{-}j} - p_{t\text{-}j\text{-}1} - \mu\right)^2}{\sum_{t=1}^{nq}\left(p_t - p_{t-1\hat{\mu}}\right)^2}. \tag{12}$$

Note that both standard normal Z-statistics and Z^*-statistics are approaching N (0, 1).

Karemera et al. (1999) find that the single variance ratio tests are suitable for testing individual variance ratios for a specific aggregation interval, q. In using these tests, a comparison is made between test statistics, Z(q) and $Z^*(q)$ and the critical values of the standard normal tables. Indeed, the RWH requires that variance ratios for all observation intervals, q's, be simultaneously equal to unity (1.0). Charles and Darné (2009) identify that the central idea in variance ratio tests is founded on the observation that when returns are uncorrelated over time, the variance should be 1.0 which indicates that the returns are serially uncorrelated. Luger (2003) finds the variance methodology exploits the fact that the variance of uncorrelated increments is linear in the sampling interval.

Griffin, Kelly and Nardari (2010) postulate that under the null hypothesis of a random walk with uncorrelated increments, variance ratios should equal one at all lags. Positive serial correlation is indicated when the variance ratios are significantly above one while negative auto-correlation is implied when variance ratios are below one. Since both positive and negative auto-correlation represent departures from a random walk, the absolute value of the variance ratio statistic minus one($|VR - 1|$) is used as a measure of relative efficiency. The authors find this approach to be advantageous because if a market consists of share with both over- and under-reaction to past returns, both would be captured.

Charles and Darné (2009) hypothesize that if the data-generating process of time series is a random walk, the expected value of variance ratio (x; k) should be equal to 1.0 for all horizons k. The variance ratio should be higher (lower) than 1.0, if returns are positively (negatively) correlated. Therefore, a time series is found to be mean reverting if variance ratio (x; k) is significantly lower than unity at long horizons k. This is an indication of negative serial correlation. It is mean averting, i.e. explosive, if variance ratio (x; k) is significantly higher than 1.0 at long horizons. This is an indication of positive serial correlation

Lo and MacKinlay (1989) indicate the simplicity, reliability and flexibility of the variance ratio test make it a valuable tool for inference. The variance ratio test is shown to produce reliable inferences even for moderate sample sizes under the two most commonly advanced null hypotheses: firstly, the random walk with independently and identically distributed Gaussian increments, and, secondly, with uncorrelated but heteroscedastic increments. Moreover, under the specific heteroscedastic null, the test is somewhat more reliable than both the auto-correlation tests, e.g., Dickey-Fuller and Box-Pierce portmanteau tests.

The variance ratio test is known to be more powerful compared to other tests such as the unit root and produces more accurate results. In addition, it is easy to calculate and interpret (Mobarek and Fiorante, 2014). It is very useful to investigate share returns that are not normally distributed (Lo and MacKinlay, 1988) and provides a test statistic that is suitable to heteroskedasticity (Karemera et al., 1999). It is also not susceptible to errors that arise due to spurious autocorrelation that comes about due to non-synchronous trading a feature common in developing countries (Füss, 2005).

3. Data

The data were made available from the NSE and from Bloomberg. The market efficiency of the NSE is analyzed using the NSE 20 share index and the NSE ASI using both daily and weekly data respectively. Each of the indexes is traded on the main investment market segment of the exchange. The currency base denominated is in Kenyan Shillings (KES). The duration of the time series is indicated in Table 1 below.

Table 1. The time period of the time series

Time series	Duration
NSE 20 share index: Daily data	02 January 2001 – 30 January 2015
NSE 20 share index: Weekly data	05 January 2001 – 30 January 2015
NSE ASI: Daily data	25 February 2008 – 30 January 2015
NSE ASI: Weekly data	29 February 2008 – 30 January 2015

The data that were analyzed consisted of index returns that are transformed to natural logs of both the daily or weekly prices of the index.

$$r_t = ln\left(\frac{P_t - P_{t-1}}{P_{t-1}}\right) \times 100. \quad (12)$$

The price returns (r_t) are expressed in percentage terms were calculated as the ending index price minus the beginning index price divided by the beginning index price multiplied by 100.

4. Results

4.1. Descriptive statistics. The skewness of all four time series is positive which indicates the distribution has a right tail. The kurtosis of all four time series is greater than 3, this means the tail of the graph of the density function is leptokurtic. Jarque-Bera statistic is a test of the normal distribution whose results is supported by the kurtosis test and the skewness test. The null hypothesis of normality is rejected if Jarque-Bera > x^2. The 0.05 critical value for the Jarque-Bera test is 5.99. All four time series have Jarque-Bera statistics that are significantly higher than 5.99. Hence, we reject the null hypothesis of a normal distribution and accept the alternative hypothesis of non-normal distribution. Results of the descriptive statistics are reported in Table 2 below.

Table 2. Results of the descriptive statistics

Series (observations)	Mean	Median	Maximum	Minimum	SD	Skewness	Kurtosis	Jarque-Bera Statistic	Probability
NSE 20 Share Index: Daily data	0.003612	0.001321	1.313339	- 1.262414	0.109775	0.547178	19.85817	41869.89	0.000000
NSE 20 Share Index: Weekly data	0.017900	0.011458	1.963580	- 1.274222	0.322315	0.640592	8.699999	1043.853	0.000000
NSE ASI: Daily data	0.006670	0.004268	1.768218	- 0.996621	0.195704	1.091112	16.82577	14195.60	0.000000
NSE ASI: Weekly data	0.031326	0.058297	3.618155	- 2.411904	0.569308	0.113425	9.897935	716.4793	0.000000

4.2. Variance ratio test. Two results are provided in the variance ratio test, the joint tests and individual tests. The joint tests provides the tests of the joint null hypothesis for all test periods while the individual tests apply to the individual test periods, that have been specified.

The NSE 20 share index: daily data have a test period that has a minimum of 100 and a maximum of 3 500 with a step of 100 (i.e.,100 observations). The joint test of the NSE 20 share index: daily data show that the *p*-value is 0.1561 which is greater than 0.05. Therefore, we fail to reject the null hypothesis instead, we accept the null hypothesis. For the individual tests, all the test periods have a probability greater than 0.05, other than the first test period whose probability is 0.0048. Results of the variance ratio test NSE 20 share index – daily data are reported in Table 3 below.

Table 3. Variance ratio test of the NSE 20 share index (daily data)

Joint tests					
		Value	Df.	Probability
Period	Var. ratio	Std. error	*z*-statistic	Probability
100	0.038131	0.341379	-2.817599	0.0048
200	0.057888	0.484608	-1.944072	0.0519
Max |z| (at period 100)*		2.817599	1127	0.1561
Wald (Chi-Square)		34.53883	35	0.4902
Individual tests				

Table 3 (cont.). Variance ratio test of the NSE 20 share index (daily data)

Joint tests				
		Value	Df.	Probability
300	0.080496	0.594266	-1.547293	0.1218
400	0.098861	0.686629	-1.312410	0.1894
500	0.120741	0.767963	-1.144924	0.2522
600	0.140637	0.841472	-1.021262	0.3071
700	0.160014	0.909056	-0.924020	0.3555
800	0.171797	0.971952	-0.852102	0.3942
900	0.181187	1.031019	-0.794179	0.4271
1000	0.199701	1.086880	-0.736327	0.4615
1100	0.213885	1.140007	-0.689570	0.4905
1200	0.220760	1.190766	-0.654402	0.5129
1300	0.220338	1.239448	-0.629040	0.5293
1400	0.222083	1.286289	-0.604776	0.5453
1500	0.220975	1.331484	-0.585080	0.5585
1600	0.246982	1.375193	-0.547572	0.5840
1700	0.243110	1.417556	-0.533940	0.5934
1800	0.259052	1.458689	-0.507955	0.6115
1900	0.247033	1.498693	-0.502416	0.6154
2000	0.252111	1.537657	-0.486382	0.6267
2100	0.257693	1.575658	-0.471109	0.6376
2200	0.246548	1.612763	-0.467181	0.6404
2300	0.246949	1.649034	-0.456662	0.6479
2400	0.218570	1.684524	-0.463888	0.6427
2500	0.205924	1.719282	-0.461865	0.6442
2600	0.188398	1.753351	-0.462886	0.6434
2700	0.173723	1.786770	-0.462442	0.6438
2800	0.176282	1.819575	-0.452698	0.6508
2900	0.137975	1.851800	-0.465507	0.6416
3000	0.107148	1.883473	-0.474045	0.6355
3100	0.075843	1.914623	-0.482684	0.6293
3200	0.067138	1.945273	-0.479553	0.6315
3300	0.052864	1.975448	-0.479454	0.6316
3400	0.034112	2.005169	-0.481699	0.6300
3500	0.008605	2.034456	-0.487302	0.6260

Source: * Probability approximation using studentized maximum modulus with parameter value 35 and infinite degrees of freedom.

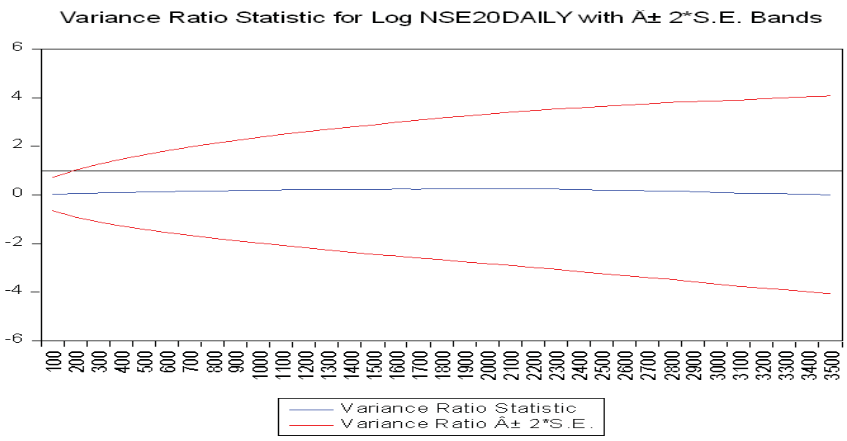

Fig. 1. Graphical illustration of the efficiency of the NSE 20 share index (daily data over the test periods: January, 2001 to January, 2015)

Figure 1 above shows a graph of the level of efficiency of the NSE 20 share index – daily data. It shows the level of efficiency of the NSE 20 share index – daily data has increased as the test periods increased. The NSE 20 share index: weekly data have a test period that has a minimum of 25 and a maximum of 725 with a step of 25. The joint test of the NSE 20 share index: weekly data show that the *p*-value is 0.6401 which is greater than 0.05. Hence, we fail to reject the null hypothesis, instead, we accept the null hypothesis. All the test periods for the individual tests have a probability greater than 0.05, other than the first test period whose probability is 0.0346. Results of the variance ratio test NSE 20 share index – weekly data are reported in Table 4 below.

Table 4.Variance ratio test of the NSE 20 share index (weekly data)

Joint tests				
		Value	df	Probability
Max |z| (at period 25)*		2.112669	236	0.6401
Wald (Chi-Square)		928.1357	29	0.0000
Individual tests				
Period	Var. Ratio	Std. Error	z-statistic	Probability
25	0.229871	0.364529	-2.112669	0.0346
50	0.384185	0.523515	-1.176309	0.2395
75	0.513389	0.644431	-0.755102	0.4502
100	0.643621	0.746006	-0.477716	0.6329
125	0.759463	0.835322	-0.287958	0.7734
150	0.887653	0.915970	-0.122653	0.9024
175	1.017651	0.990072	0.017828	0.9858
200	1.092268	1.059001	0.087127	0.9306
225	1.108636	1.123710	0.096676	0.9230
250	1.200656	1.184891	0.169346	0.8655
275	1.215180	1.243064	0.173105	0.8626
300	1.257951	1.298634	0.198633	0.8426
325	1.244503	1.351922	0.180856	0.8565
350	1.338166	1.403187	0.240998	0.8096
375	1.391763	1.452645	0.269690	0.7874
400	1.347587	1.500473	0.231652	0.8168
425	1.310041	1.546823	0.200437	0.8411
450	1.050601	1.591824	0.031788	0.9746
475	1.185661	1.635588	0.113513	0.9096
500	1.142321	1.678210	0.084805	0.9324
525	0.892326	1.719777	-0.062610	0.9501
550	0.941672	1.760362	-0.033134	0.9736
575	0.866269	1.800033	-0.074294	0.9408
600	0.661600	1.838848	-0.184028	0.8540
625	0.460089	1.876860	-0.287667	0.7736
650	0.320661	1.914118	-0.354910	0.7227
675	0.139242	1.950664	-0.441264	0.6590
700	0.144795	1.986538	-0.430500	0.6668
725	0.100262	2.021775	-0.445024	0.6563

Source:* Probability approximation using studentized maximum modulus with parameter value 29 and infinite degrees of freedom.

The graph of the NSE 20 share index – weekly data are illustrated in Figure 2 below. The level of efficiency of the index increased over the period, but declined at the end of the test period.

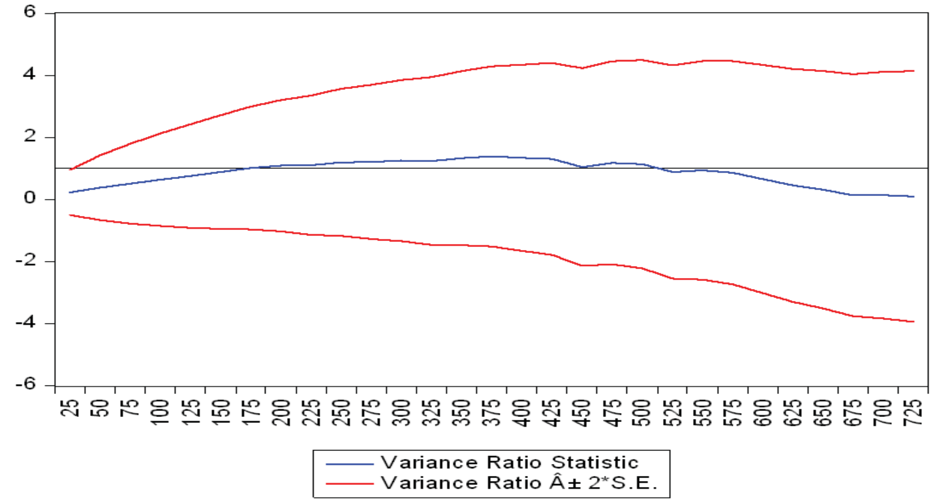

Fig. 2. Graphical illustration of the efficiency of the NSE 20 share index (weekly data over the test periods: January 2001 to January 2015)

The NSE ASI: daily data have a test period that has a minimum of 100 and a maximum of 1700 with a step of 100. The joint test of the NSE ASI: daily data show that the *p*-value is 0.4818 which is greater than 0.05, we fail to reject the null hypothesis; instead, we accept the null hypothesis. For the individual tests, all the test periods have a probability greater than 0.05, other than the first test period which is 0.0379. Therefore, we fail to reject the null hypothesis for all the test periods other than the first one. Results of the variance ratio test NSE ASI – daily data are reported in Table 5 below.

Table 5. Variance ratio test of the NSE ASI (daily data)

Joint tests				
		Value	df	Probability
Max |z| (at period 100)*		2.075586	579	0.4818
Wald (Chi-Square)		4.955891	17	0.9979
Individual tests				
Period	Var. ratio	Std. error	*z*-statistic	Probability
100	0.011447	0.476277	-2.075586	0.0379
200	0.006102	0.676103	-1.470038	0.1416
300	0.005331	0.829093	-1.199706	0.2303
400	0.004753	0.957955	-1.038930	0.2988
500	0.004930	1.071428	-0.928733	0.3530
600	0.004914	1.173985	-0.847614	0.3967
700	0.004962	1.268275	-0.784560	0.4327
800	0.004608	1.356025	-0.734051	0.4629
900	0.005022	1.438432	-0.691711	0.4891
1000	0.004510	1.516367	-0.656497	0.5115
1100	0.003957	1.590487	-0.626250	0.5312
1200	0.003792	1.661304	-0.599654	0.5487
1300	0.002955	1.729223	-0.576586	0.5642
1400	0.002443	1.794574	-0.555874	0.5783
1500	0.001615	1.857627	-0.537452	0.5910
1600	0.000927	1.918609	-0.520728	0.6026
1700	0.000310	1.977711	-0.505478	0.6132

Source:* Probability approximation using studentized maximum modulus with parameter value 17 and infinite degrees of freedom.

The graph of the level of efficiency of NSE ASI – Daily data is illustrated in Figure 3 below. The efficiency increased as the test periods increased.

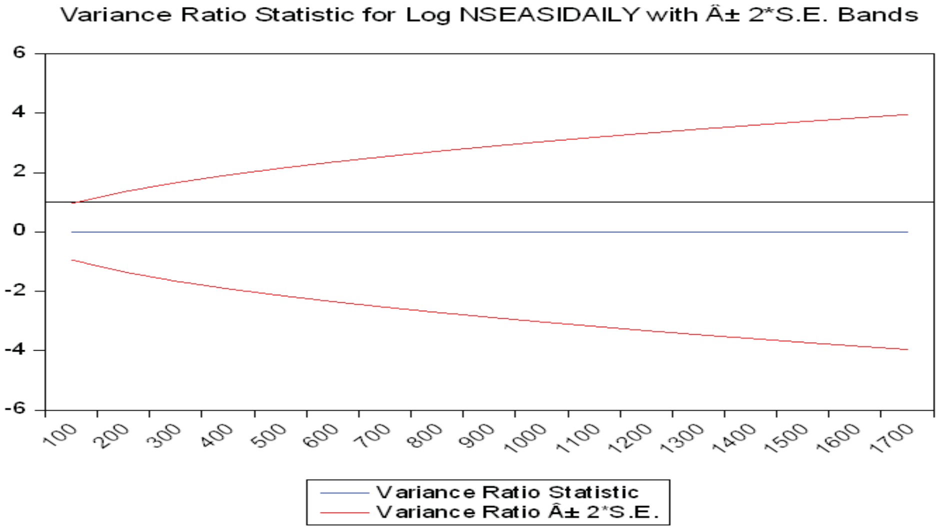

Fig. 3. Graphical illustration of the efficiency of the NSE ASI (daily data over the test periods: February 2008 to January 2015)

The NSE ASI: weekly data have a test period that has a minimum of 25 and a maximum of 350 with a step of 25. The joint test of the NSE ASI: weekly data show that the *p*-value is 0.7713 which is greater than 0.05, we fail to reject the null hypothesis; instead, we accept the null hypothesis. For the individual tests, all test periods have *p*-values that are greater than 0.05, therefore, we fail to reject the null hypothesis for all the test periods. Results of the variance ratio test NSE ASI – weekly data are reported in Table 6 below.

Table 6. Variance Ratio Test of the NSE ASI (weekly data)

Joint tests				
		Value	df	Probability
Max |z| (at period 25)*		1.644742	133	0.7713
Wald (Chi-Square)		18.29661	14	0.1936
Individual tests				
Period	Var. ratio	Std. Error	z-statistic	Probability
25	0.201344	0.485582	-1.644742	0.1000
50	0.318766	0.697363	-0.976871	0.3286
75	0.402133	0.858434	-0.696462	0.4861
100	0.450372	0.993740	-0.553090	0.5802
125	0.521149	1.112715	-0.430344	0.6669
150	0.556304	1.220146	-0.363642	0.7161
175	0.561252	1.318854	-0.332673	0.7394
200	0.678242	1.410674	-0.228088	0.8196
225	0.617204	1.496871	-0.255731	0.7982
250	0.485876	1.578369	-0.325731	0.7446
275	0.356961	1.655860	-0.388341	0.6978
300	0.204900	1.729884	-0.459626	0.6458
325	0.157887	1.800867	-0.467615	0.6401
350	0.055307	1.869157	-0.505411	0.6133

Source: * Probability approximation using studentized maximum modulus with parameter value 14 and infinite degrees of freedom.

The graph of the NSE ASI – weekly data are illustrated in Figure 4 below. It shows the level of efficiency has increased, but slightly declined towards the end of the test period.

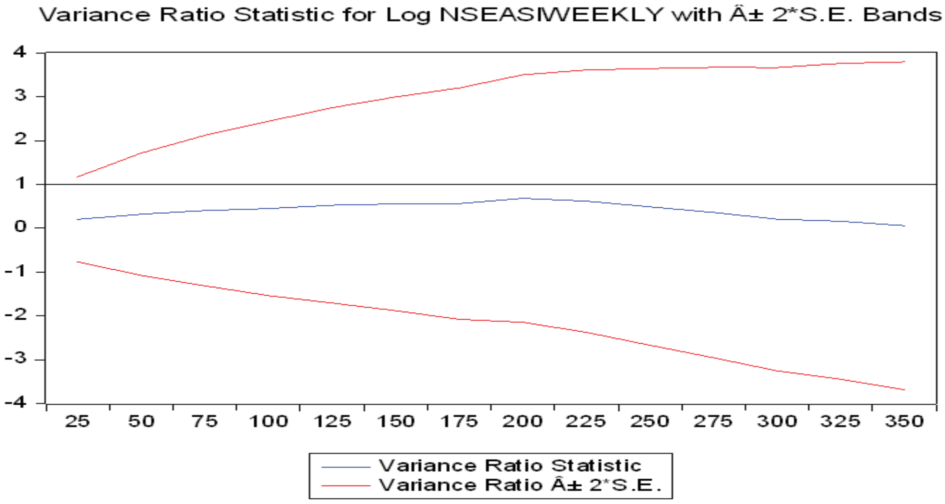

Fig. 4. Graphical illustration of the efficiency of the NSE ASI (weekly data over the test periods: February 2008 to January 2015)

The conclusion of the variance ratio test is that all four time series fail to reject the null hypothesis. Rather, the null hypothesis will be accepted which is the market under study is weak form efficient. In addition, the efficiency of the NSE has increased over the years as illustrated in Figures 1 to 4 above.

Conclusions

The main research objective is to determine whether the informational efficiency of the NSE has improved since the year 2001. Results of the efficiency of the NSE support the AMH. Since the variance ratio test is more powerful than other tests and its results much more precise as stated by Mobarek and Fiorante (2014), we can conclude that the NSE supports the AMH.

The NSE has become more efficient from the year 2001 onwards as illustrated by figures 1 to 4. This increase in market efficiency can be attributed to the improvement in technology that enhances the speedy impounding of information on the share prices mainly due to high speed internet, mobile technologies and world-wide broadcasting systems (Yang et al., 2008). Accordingly, increased automation has enabled market players to be able to process information and trade at a much faster rate as inferred by Tóth and Kertész (2006), this, by reducing the execution time for market orders (Hendershott and Moulton, 2011). This has led to more accurate price discovery than before the year 2 000 (Ciner, 2002). The findings of the research support the AMH which argues that dynamic market conditions direct the degree of stock market efficiency (Kim et al., 2011).

The implication for investors is that return predictability is time varying thus profit opportunities exist in the market, however, since the degree of return predictability seems to decline over time, it means that the possibility of identifying mispriced shares by observing past price changes is decreasing. The implication for policy regulators is that, since they are well informed about the level of efficiency of the NSE, they can improve the flow of information among market participants in order to increase the attractiveness of the NSE to regional and international investment capital, as this will enable the equity market to play a greater role in boosting the country's economic growth (Jamaani and Roca, 2015).

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