LONG-TERM MEMORY EFFECT IN STOCK PRICES: AN EMPIRICAL STUDY FROM NAIROBI STOCKS MARKET

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ABSTRACT
This study demonstrated that Nairobi stock market asset return do not behave as any type of white noise processes using the Lo and MacKinlay variance ratio test. This was done by considering the Nairobi All Share Index (NASI) and testing for long memory using Classical Rescaled range analysis, Detrended Fluctuation Analysis and the semi-parametric approach Geweke and Porter-Hudak tests. Data sets consisted of daily return index of NASI for a consecutive period of 8 years, i.e. from when the index was launched in 2008 to 2013 and long memory tests for the returns series. Al three tests suggested presence of long memory, while those of randomness test using variance ratio tests rejected the random walk hypothesis. The test for random walk model has a lot of implication in both theoretical as well empirical researches. Rejection of random walk model implies that the market is inefficient in processing information and one can predict future prices using past prices. Results show evidence of long memory in the Kenyan stock returns, which is inconsistent with weak-form market efficiency, implying that Kenyan stock index consists of impact of news and shocks in recent past. Speculative earnings could be gained via predicting stock prices. These findings will help investors, financial managers and regulators dealing with this market.
Key words: *Hurst exponent, NASI, GPH, long memory, DFA, Variance Ratio Test.*

1. INTRODUCTION

Many financial returns exhibit high autocorrelation at long lags as was first unearthed by Fama and French (1988) and Lo and MacKinlay (1988). The earliest of these studies in long memory were done by Mandelbrot (1971, 1972), Mandelbrot and Wallis (1969) who suggested that in the presence of long memory, arbitrage opportunities may exist as new market information which cannot be absorbed quickly and martingale models of asset prices may not be justified. Using the rescaled-range (R/S) method, Greene and Fielitz (1977) reported evidence of persistence in daily U.S. stock returns series. However, Lo (1991) finds no evidence to support the presence of long memory in the same U.S. stock returns while using the modified rescaled analysis.

The existence of long memory in returns represents a strong possibility of predictability and evidence against weak form of efficiency. This price predictability would give traders a window for above normal profits that would require government efforts to curb the situation. Since this subject is critical both in theory and practice, it has attracted many and extensive research and a lot of literature exist on long memory dynamics with diverse results though in the Kenyan context none of these studies exist. It is with this background that this paper presents an attempt to investigate weak form efficiency of Kenyan stock market taking daily return index of NASI for a consecutive period of 8 years taken for the period 2008-2013 with 1462 observations. The study has employed various methods to examine the efficiency of Kenyan stock. The rest of the paper is divided into five sections as follows; Section one is introduction. The second section reviews some important literature on stock market efficiency. The third section describes data and methodology used. The empirical results are discussed in the fourth section followed by conclusion in the fifth section.

2. LITERATURE REVIEW

An attempt is made in this section to review important studies made on the same area. The phenomenon of long-range dependence has a long history and has remained a topic of active research in the study of economic and financial time series (e.g.,see Lo (1991) and Cutland et al. (1995) and references therein). It is widespread in other areas in the physical and natural sciences (e.g., see Mandelbrot (1982) and Beran(1994) for details) and has been extensively documented in hydrology, meteorology and geophysics (see for example Mandelbrot and Wallis, 1968,1969a,b,c). More recently, long-range dependence has also started to play an important role in the engineering sciences, especially in the analysis and performance modeling of traffic measurements from modern high-speed communications networks (for a recent bibliographical survey of this area, see Willinger et al., 1996).

The existence of long memory in returns and volatility suggests the presence of dependencies among observations. Kasman and Torun (2009) found that Long memory in return and volatility series were related with the high autocorrelation function which decays hyperbolically and finally died out. In contrast, if correlation between distant observations is negligible, the series possesses short memory and exhibits exponential decaying observations.

The existing work on long memory in asset returns derives largely from the pioneering work of Hurst (1951).Greene and Fielitz (1977) and Aydogan and Booth (1988) both test for long memory using the rescaled range statistic of Hurst (1951). Lo (1991), using a modified rescaled range (R/S) statistic, finds no evidence of long memory in a sample of US stock returns. Mills (1993), using the modified R/S statistic and the semi-parametric approach of Geweke and Porter-Hudak (1983), hereafter GPH, finds weak evidence of long memory in a sample of monthly UK stock returns. Lobato and Savin (1997) find no evidence of long memory in daily Standard and Poor 500 returns over the period July 1962- December 1994. Interestingly, Lobato and Savin (1997) find some evidence of long memory in the squared return data, which supports the conclusions of Ding et al. (1993). There has been no comprehensive study of long memory in return in Kenya, which is one of the growing emerging stock markets. Hence, the present paper is devoted to this issue in the Nairobi stocks market.

3. METHODOLOGY

3.1 Variance ratio test

The first attempt is to test for random walk hypothesis of NASI index. We consider a class of variance ratio tests used to test the hypothesis that a given time series or its first difference is a collection of i.i.d observations that follow a martingale difference sequence.

Define the variance ratio of *k*-period return as

$$v(k) = \frac{\mathrm{var}(x_t + x_{t-1} + \ldots + x_{t-k+1})/k}{\mathrm{var}(x_t)}$$

$$= \frac{\mathrm{var}(y_t - y_{t-k})/k}{\mathrm{var}(y_t - y_{t-1})} = 1 + 2\sum_{i=1}^{k-1}\left(\frac{(k-i)}{k}\right)\rho_i \qquad (1)$$

Where ρ_i is the i^th lag autocorrelation coefficient of {xt}. $v(k)$ is a particular linear combination of the first (k−1) autocorrelation coefficients, with linearly declining weights. When the returns are uncorrelated over time the relation $= \mathrm{var}(x_t + x_{t+1} \ldots + x_{t-k+1}) = k\,\mathrm{var}(x_t)$, meaning that V(k)=1 exists.

A test can be constructed by considering a statistic based on the estimator of $v(k)$ such that

$VR(k) = \frac{\sigma^2(k)}{\sigma^2(1)}$ of the one-period return variance and is defined as

$$\sigma^2(1) = (T-1)^{-1}\sum_{t=1}^{T}(X_t - \mu)^2$$

Where $\sigma^2(1)$ is the unbiased estimator

$$= (\mathrm{T}-1)^{-1}\sum_{t=1}^{T}(\mathrm{y}_t - \mathrm{y}_{t-1} - \mu)^2$$

$$= (\mathrm{T}-1)^{-1}\sum_{t=1}^{T}(\mathrm{y}_t - \mathrm{y}_{t-1} - \mu)^2 \quad (2)$$

With $\mu = \mathrm{T}^{-1}\sum_{t=1}^{T} X_t$ being the estimated mean. The estimator of k-period return variance $\sigma^2(\mathrm{k})$ can be estimated by various methods, Lo and MacKinlay (1988) suggested a method of overlapping long horizon return defined as

$$\sigma(\mathrm{k}) = m^{-1}\sum_{t=k}^{T}\left(x_t + x_{t-1} + \ldots + x_{t-k+1} - k\mu\right)^2$$

$$= m^{-1}\sum_{t=k}^{T}\left(y_t + y_{t-k} - k\mu\right)^2 \quad (3)$$

Where $m = k\left(T - k + 1\right)\left(1 - kT^{-1}\right)$. m is chosen such that $\sigma^2(\mathrm{k})$ is an unbiased estimator of the *k*-period return variance when σ_t^2 is constant over time.

3.2 Lo and Mackinlay (1988) variance ratio tests

Lo and MacKinlay (1988) by assuming k if fixed when $T \to \infty$ proposed an asymptotic distribution of VR(x;k).They showed that if X_t is i.i.d under the null hypothesis that $v(k)$=1, the test statistics $M_1(k)$ is given by

$$M_1(k) = \frac{VR(x;k) - 1}{\phi(k)^{1/2}} \quad (4)$$

which follows the standard normal distribution asymptotically. The asymptotic variance, $\phi(k)$, is given by

$$\phi(k) = \frac{2(2k-1)(\mathrm{k}-1)}{3kT} \quad (5)$$

To accommodate x_t exhibiting conditional heteroscedasticity, Lo and MacKinlay (1988) proposed the heteroscedasticity robust test statistic $M_2(k)$ as it is a general consensus among the financial economist that the variance of financial time series data changes over time. Lo and Mackinlay (1988) however states that the variance ratio test will approach unity despite the fact that the data is heteroscedstic. The statistic $M_2(k)$ is given by

$$M_2(k) = \frac{VR(x;k) - 1}{\phi^*(k)^{1/2}} \quad (6)$$

which follows the standard normal distribution asymptotically under null hypothesis
that $v(k)$ = 1, and

$$\phi^*(k) = \sum_{j=1}^{k=1}\left[\frac{2(k-j)}{k}\right]^2 \delta(j) \quad (7)$$

The $M_2(k)$ test is applicable to a time series generated from a martingale difference process .The usual decision rule for the standard normal distribution is applied to both tests.

3.3 The Hurst coefficient, H

The second technique we use is due to the hydrologist H.E Hurst dealing with the data of water heights of the Nile river around 1951. He constructed the Range Statistics, here denominated (R/S) which is now known as the Hurst coefficient or exponent “H ” and he defined a rescaled range “R/S” statistics, which can be described as the span of the partial sums of the gap of a time series to its average divided by its standard error:

$$\left(\frac{R}{S}\right)_t = \frac{1}{\frac{1}{T}\sum_{t=1}^{T}\left(X_j - \bar{X}_T\right)^2}\left(\underset{1<k<T}{Max}\sum_{j=1}^{k}(X_j - \bar{X}_T) - \underset{1<k<T}{Min}\sum_{j=1}^{k}(X_j - \bar{X}_T)\right) \quad (8)$$

It has been proved (Mandelbrot, 1972) that this statistics is asymptotically proportional to T^H where T is the number of observations and the constant H, 0 < H < 1 is precisely the Hurst exponent.
We can thus write;

$$\left(\frac{R}{S}\right)_t = c.T^H \quad (9)$$

Where c is a constant. The Hurst exponent it therefore the estimated slope coefficient obtained by regressing with the OLS technique the logarithm of $\left(\frac{R}{S}\right)_t$ versus the logarithm of the time T. i.e.

$$\ln\left(\frac{R}{S}\right)_t = \ln(c) + H\ln(T) \quad (10)$$

The H obtained has some disadvantages. Its theoretical distribution is unknown (Hosking 1984), it is highly sensitive to the short term dependence (Lo 1991). It is also impossible to have the standard error and the probability law associated with the estimator. To overcome this Lo (1991) developed another test to short range dependence given by

$$\frac{1}{\omega}\left(\underset{1<k<T}{Max}\sum_{j=1}^{k}(X_j - \bar{X}_T) - \underset{1<k<T}{Min}\sum_{j=1}^{k}(X_j - \bar{X}_T)\right)$$

With ω being a non-parametric estimator of the weighted sum of auto covariances at lag *q*. When *q* =0 the modified Lo's statistics is similar to Hurst's. Teverovsky Taqqu and Willinger (1995) showed however that the Lo's estimator might after all eliminate a long term memory which is actually present. In view of this we stick to the H statistic and don't attempt to compute Lo's statistic but use other tests for long memory.The R/S approach was transposed in the field of finance by Mandelbrot (1965, 1972).The value of the exponent H , which lies between 0 and 1, allows to distinguish the time series. When H = 0.5, this can be modeled by the white noise, there is no long term dependence, the financial market might be efficient and is independent; when 0.5 < H < 1 there is a long term memory, the market is inefficient and one can speak of a persistence effect, the time series will show clusters of comparable values. On the other hand, when 0 < H < 0.5, there is a short term memory; one can speak of an anti persistence effect. In general Hurst exponent tells us when there is a long memory process and does not provide the local information needed for forecasting**.**

3.4 Detrended Fluctuation Analysis (DFA)

The Detrended Fluctuation Analysis (DFA) proposed by Peng(1994) is an improvement of classical Fluctuation Analysis (F A) and, according to Grau-Carles (2006), is supposed to deal with power-law correlations in non-stationary time series. This is accomplished by performing linear or higher polynomial order time detrending of the time series in several non-overlapping intervals separately. The method can be summarized as follows:-

1. Calculate cumulative sum series: $Z_t = \sum_{i=1}^{t}(Y_t - \bar{Y})$ for t = 1,2,…,n
2. Divide the whole set into k non-overlapping intervals with m observations in each and perform least squares regression of Z_t on a (linear or higher polynomial order) function of time.
3. Calculate the fitted values from these regressions y_{mt}

4. Compute $Fm = \sqrt{\frac{1}{m.k}\sum_{i=1}^{m.k}\left[y_t - y_{mt}\right]^2}$ for several values of m and k

5. Regress $\log(\text{Fm})$ on $log(m)$ and estimate the slope parameter γ by OLS

The slope parameter γ has similar interpretations as the Hurst parameter, H discussed above. Unfortunately, no asymptotic distribution theory has been derived for the DFA statistics so far (Grau-Carles, 2006). Hence, no explicit hypothesis testing can be performed and the significance relies on subjective assessment.

3.5 Geweke and Porter-Hudak Estimator (GPH Estimator)

Geweke and Porter-Hudak (1983), henceforth GPH, suggested a semi-parametric estimation of the fractional differencing estimator, d, that is based on observations of the slope of the spectral density function of a fractionally integrated series around the angular frequency $\omega = 0$ and does not require complete parameterization of unknown ARMA dynamics. They showed that the spectral density function of a general fractionally integrated model with differencing parameter d is identical to that of a fractional Gaussian noise with Hurst exponent H = d + 0.5 the GPH method can be used to estimate H. The estimator exploits the theory of linear filters to write the process $(1-L)^d Yt = \mu t$ where $\mu_t \sim I(0)$, as

$$SY(\omega) = \left|1-e^{-i\omega}\right|^{-2d} s\mu(\omega), \qquad (11)$$

Where $SY(\omega)$ and $s\mu(\omega)$ are the spectral densities of Y_t and μ_t respectively.

Consider a sample series of Y_t of size T, Taking logarithms of (13) and evaluating at harmonic frequencies $\omega j = 2\pi j / T$, $j = 0,1,...,T-1$ where we have

$$\ln\left(SY(\omega j)\right) = \ln\left(s\mu(0)\right) - d\ln\left(4\sin^2(\omega j/2)\right) + \ln\left[s\mu(\omega j)/s\mu(0)\right]$$

For low-frequency ordinates ωj near 0, say j ≤ n < T , the last term is negligible compared with the other terms. Adding $I(\omega j)$, the periodogram at ordinate j , to both side of (14) yields

$$\ln\left(I(\omega j)\right) = \ln\left(s\mu(0)\right) - d\ln\left(4\sin^2(\omega j/2)\right) + \ln\left[I(\omega j)/SY(\omega j)\right] \qquad (12)$$

This suggest estimating d using a simple linear regression equation

$$\ln\left(s_Y(\omega j)\right) = \beta o + \beta 1\ln\left(4\sin^2(\omega j/2)\right)\varepsilon j \quad j=1,2,\ldots,n \qquad (13)$$

Where ε_j equal $\ln\left[I(\omega j)/s_Y(\omega_j)\right]$ is asymptotically i.i.d. across harmonic frequencies and $n = g(T)$ is an increasing function of T. The theoretical asymptotic variance of εj is known to be equal to $\frac{\pi^2}{6}$ which is often imposed in estimation to raise efficiency. Under some regularity conditions on g(T) ,Geweke and Porter-Hudak (1983) showed that the least-square estimate of $\beta 1$ provides a consistent estimate of d and hypothesis testing concerning the value of d can be based on the t -statistics of the regression coefficient. When d=0, the random process Xt equals to et and therefore, $Xt \sim \left(N\left(0,\delta^2\right), or Xt \sim I(0)\right)$

On the other hand, when d=1, Xt follows a unit root process with a zero mean and infinite variance (Tkacz, 2001). If d is non-integer, the random process Xt becomes fractionally integrated, namely ARFIMA process. Hosking (1981) shows that when 0<d<½ the autocovariance function of the random process declines hyperbolically to zero as a long-memory process. When ½< d<1, the random process takes an infinite variance but still reverts to its trend in the very long run (Tkacz, 2001).Periodogram regression is the only of the presented methods, which has known asymptotic properties.The features of the fractional integration parameter (d) are summarized in table1 below:

Table 1: Memory Features With Respect to the Fractional Integration Parameter Values

D	Variance	Shock Duration	Stationarity
d =0	Finite	Short Memory	Stationary
0< d <0.5	Finite	Long Memory	Stationary
0.5≤ d <1	Infinite	Long Memory -Finite Impact Reflect	Nonstationary
d=1	Infinite	Finite-Not Revert to Its Mean	Nonstationary
d>1	Infinite	Finite-Not Revert to Its Mean	Nonstationary

Source: Tkacz, G. (2001), Estimating the Fractional Order of Integration of Interest Rates Using a Wavelet OLS Estimator, Studies in Nonlinear Dynamics and Econometrics, 5(1): pp. 23.

4. EMPIRICAL RESULTS

4.1 Data

The study utilizes daily close of business return for Nairobi All Share Index (NASI) from January 2008 to 31 December 2013 primarily sourced from NSE. This period is the most recent. The economy during this period has been characterized by various challenges at different point in time e.g the post-election violence of Dec 2008 and the March 2013 elections that pessimists expected it to be chaotic, leading to some fluctuations in the stock prices. This study which uses the data set covering the crisis period and the 'hoped' crisis is, therefore, relevant and instructive for the analysis. The returns are calculated in the usual format by taking the first differences of the natural logarithm of the stocks rates as follows:

$$Y_t = \log P_t - \log P_{t-1}$$

Where Y_t is the present day index and $\log P_t$ is the natural logarithm of the present day's index and $\log P_{t-1}$ is the natural logarithm of the previous day's index. The descriptive statistics of NASI index is reported in table 2 below.

Table 2: Descriptive statistics

Indices	Mean	Median	Std.Dev	Skewness	Ex -Kurtosis	Jarque-Bera
Return	0.0001043	2.7198e-005	0.0040636	0.99327	10.776	7314.06

The average return of the index is positive accompanied with a positively skewness. The index is also leptokurtic suggesting that the distribution has a higher peak around the mean compared to normal distribution. These peaks further suggest that the index is highly concentrated around the mean, due to lower variations within observations. All these together with a large value of Jarque-Bera statistic of 7314.06 leads to rejection of null hypothesis of zero P - value indicates that the return series of NASI index has non-normal distribution. These findings are in accordance with many other previous studies on stock market indices. This does not however disqualify the market efficiency hypothesis but makes it less simple to ascertain.

4.2 Unit root test

There is need to have some regularity in the way the random nature of the time series is generated if at all one has to be sure that the information on the past behavior of an asset's price is of some value in predicting its future. This also implies that any models that claim to explain this behavior must also possess this fundamental regularity. One way of doing this is the concept of stationarity. To this aim, we apply alternatively three standard tests of stationarity: the Augmented Dickey Fuller (ADF), the Phillips Perron (PP) and the Kwiatkowskiet al (1992) (KPSS) test in an attempt to detect presence of unit root. Three tests differ in the null hypothesis. The null hypothesis of the ADF and PP test is that a time series contains unit root while KPSS test has the null hypothesis of stationarity.
Table 3below displays results for ADF, KPSS and PP test.

Table 3: Unit root tests

	ADF			KPSS			PP	
Series	Coeff	t- ratio	P-value	Coeff	t- ratio	P-value	Coeff	P-value
NASI	-0.5423	-7.304	4.9e-01*	0.3830	0.642743	0.084	-815.6195	0.01*

index									

* Represent the rejection of null hypothesis at 5% level of significance.

The null hypothesis for the presence of unit root in ADF and PP test is rejected at 5% confidence interval. KPSS test does not reject the null hypothesis of stationality and thus based on the three tests we conclude that the index is stationary. Further differencing is therefore unjustified.

4.3 The Variance Ratio Test

Table 4 below shows the results of the Lo-MacKinlay,VR(k) test.

Table 4: Variance Ratio Test.

	Number of lags(k)				
	k=2	**k=4**	**k=8**	**k=16**	**k=32**
VR(q)	1.447371	1.993627	2.260978	2.2388889	2.492629
$M_1(k)$	17.105721*	20.307815*	16.299608*	12.064810*	8.947363*
$M_2(k)$	6.0916556*	7.578439*	6.610438*	5.554083*	4.744462*

The variance ratio VR(k) and $M_1(k)$ are calculated for the data set for the cases k = 2, 4, 8 16 and 32. The heteroscedasticity consistent variance ratio tests are also performed by calculating the $M_2(k)$ for each of the cases i.e. k = 2, 4, 8 16 and 32. The variance ratios are reported in the row one, while the $M_1(k)$ and $M_2(k)$ statistics are reported in row two and three. The variance ratio estimates in Table 4 above are more than unity for all the k periods suggesting a persistence behavior. The RWH is rejected under the assumptions of the hypothesis of homoscedasticity and heteroscedaticity in all five sampling intervals at 5% confidence interval .The 95% confidence interval in figure2 below clearly shows the confidence band and that the test statistics $M_1(k)$ and $M_2(k)$ lie outside their respective confidence interval band.

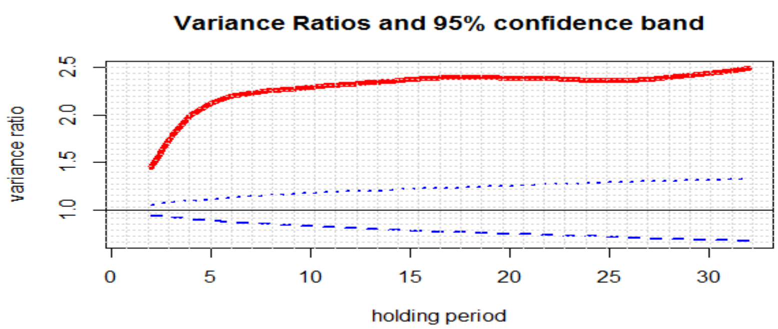

Figure 2: Variance ratios and 95% confidence band

Results in Table 5 below further shows the p- values which supports rejection of RWH both under homoskedastic and heteroskedastic assumption.

Table 5: Confidence interval for a two sided Variance ratio test

Holding period	2.5%	97.5%	Lo McKinley P-value
k=2	-2.001386	1.859152	0
k=4	-1.952516	1.828788	0
k=8	-1.802827	1.817451	0
k=16	-1.659788	1.746088	0
k=32	-1.814930	1.820448	0

Thus the null hypothesis that variance ratio is not statistically different from zero is rejected for the NASI return index.

4.4 Result for tests for long memory

We now turn out attention to investigate the existence of long memory having established that NASI return index does not follow a random walk. Figure 1 below shows the rescaled range analysis for NASI return series together with an estimated Hurst exponent value of 0.679796 which suggesting existence of long memory.

Figure 1: Rescaled range figures for Return series

(logs are to base 2)

Size	RS(avg)	log(Size)	log(RS)
1462	93.241	10.514	6.5429
731	77.097	9.5137	6.2686
365	39.379	8.5118	5.2994
182	24.435	7.5078	4.6109
91	15.470	6.5078	3.9514
45	9.7873	5.4919	3.2909
22	6.2585	4.4594	2.6458
11	3.6271	3.4594	1.8588

Regression results (n = 8)

	coeff	std. error
Intercept	-0.44706	0.14302
Slope	0.67980	0.019413

Estimated Hurst exponent = 0.679796

Results of DFA are displayed as in figure3 below with an estimated H of 0.633.

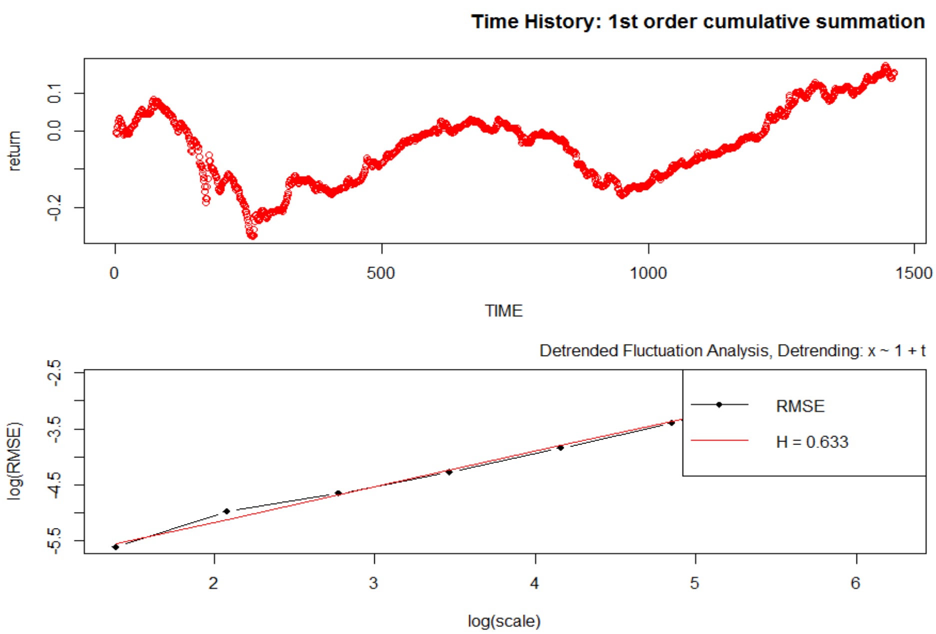

Figure 3: DFA performed on the NASI data

As noted in methodology DFA result interpretation is similar to that of rescaled range. This result in figure 3 differs slightly from those in figure 1 above. Hence the DFA further rejects RWH and suggests long memory property in NASI return. Finally the fractional differencing test GHP is performed on the NASI stock data. The fractional differencing test serves to unearth the fractal structure in a time series based on the spectral analysis of its low frequency dynamics. In applying GHP spectral procedure, the number of low frequency ordinates, ω used in the spectral regression is a matter of choice. While too large value of ω will lead to over estimation of d due to medium or high frequency components a small ω will lead to imprecise estimates due to limited degrees of freedom in estimation. To balance these two considerations, we experiment with a range of μ used for the sample size function $\omega = T^{\mu}$ where T is the number of observations. The results reported are for $\mu = 0.5$. Table 7below contains estimate for the fraction parameter d from the GHP fractional regression.

Table 7: Result for fractional differencing analysis for NASI return series

Series	d	std	Residual std
NASI index	0.09548047	0.1212834	0.1267542

The d estimates are reported together with their standard error and residual standard error. Using Table 1 above to interpret the result we conclude presence of significant memory in NASI return series.

5. CONCLUSION

Using the variance ratio as a test to check the random walk hypothesis, we conclude that the NASI index does not follow a random walk. Therefore, the NASI index can be considered to be a weak-form efficient. Having known this, we went ahead to test the existence of long memory by the use of the classical rescaled range analysis, DFA and GHP and concluded the existence of long memory. The test for random walk model has a lot of implication in both theoretical as well empirical researches. The rejection of random walk model implies that the market is inefficient in processing the information and one can predict the future prices using past prices. A Possible extension is to work with individual stocks instead of indices because one can suspect that some equities might be subject to semi-strong inefficiency.

Generally, the results show the evidence of long memory in the Kenyan stock returns, which is inconsistent with the weak-form market efficiency, implying that the Kenyan stock index (NASI) consists of the impact of news and shocks occurred in the recent past. Hence, speculative earnings could be gained via predicting stock prices. These findings would be helpful to the investors, financial managers, and regulators dealing with the Nairobi stock market. The regulators should understand sources of long-term memory in the market to improve efficiency.

REFERENCES

Aydogan, K. and G.G. Booth. 1988. Are there long cycles in common stock returns? Southern Economic Journal, 55:817-858.

Beran, J. 1994. Statistics for long memory processes, Chapman and Hall, New York.

Cutland, N.J., Kopp, P.E. and Willinger, W. 1995. Stock price returns and the Joseph effect: a fractional version of the Black–Scholes model, p. 327–351. *In*: Bolthausen, E., Dozzi, M., Russo, F. (Eds.)., Seminar on Stochastic Analysis, Random Fields and Applications. Birkhauser, Boston.

Ding, Z., Granger, C.W.J. and Engle, R.F. 1993. A long memory property of stock returns and a new model. Journal of Empirical Finance, 1:83-106.

Fama, E.F. 1970. Efficient capital markets: A review of theory and empirical work, Journal of finance. 25(2).

Geweke, J. and Porter-Hudak, S. 1983 .The estimation and application of long memory time series models, Journal of Time Series Analysis, 4:221-238.

Grau-Carles, P. 2006: Bootstrap testing for detrended fluctuation analysis. Physica A 360: pp. 89–98.

Greene, M, B. Fielitz, Long-term dependence in common stock returns, Journal of Financial Economics 4:339–349.

Hosking, J.R.M. 1984. Modeling persistence in hydrological time series using fractional brownian differencing, Water Resources Research, 20:1898-1908.

Hosking, J.R. 1981. Fractional differencing, Biometrika, 68:165–176.

Hurst, H.E. 1951. Long-term storage capacity of reservoirs, Transactions of the American Society of Civil Engineers 116:770-808.

Kasman, A., S. Kasman and E. Torun. 2009. Dual long memory property in returns and volatility: Evidence from the three countries' stock markets. Emerging Markets Review, 102:122–139.

Kwiatkowski, D., Phillips P., Schmidt P. and Shin Y. 1992. Testing the null hypothesis of stationary against the alternative of a unit root: how sure are we that economic time series have a unit root?, Journal of Econometrics, 54:159-178.

Lobato, I.N. and Savin, N.E. 1997 Real and spurious long memory properties of stock market data, Discussion Paper, Department of Economics, University of Iowa.

Lo, A.W. 1991. Long-term memory in stock market prices. Econometrica 59:1279-1313.

Lo, A.W. and A. MacKinlay. 1988 Stock Market Prices do not Follow Random Walk: Evidence from a simple specification Test, review of Financial Studies. 1(1):41-66.
Mandelbrot, B. 1972. Statistical Methodology for Non Periodic Cycles: From the Covariance to R/S Analysis" Annals of Economic Social Measurement, 1:259-290
Mandelbrot, B.B. 1982. The Fractal Geometry of Nature. W.H. Freeman and Co., San Francisco.
Mandelbrot, B. and J.R. Wallis. 1969. Robustness of the rescaled range R/S in the measurement of non cyclic long-run statistical dependence. Water Resources Research 5:967–988.
McLeod, A.I. and Hipel, K.W. 1978. Preservation of the rescaled adjusted range, Part 1, A reassessment of the Hurst phenomenon. Water Resources Research, 14:491-508.
Mills, T.C. 1993. Is there long-term memory in UK stock returns. Applied Financial Economics. 3:303-6.
Peng, C.-K., Buldyrev, S.V., Havlin, S., Simons, M. and Stanley, H.E.Goldberger, A.L. 1994. Mosaic Organization of DNA sequences. Physical Review E 49:1684-1989.
Pilar Grau-Carles. 2006. Extreme observation in developed and emerging equity markets. Computing in Economics and Finance 2006, 254, Society for Computational Economics.
Taqqu, M.S., Teverovsky, V. and Willinger, W. 1995. Estimators for long-range dependence: An empirical study. Fractals 3(4):785–798. Reprinted In: Evertsz, C.J.G., Peitgen, H.-O., Voss, R.F. (Eds.). Fractal Geometry and Analysis. World Scientific Publishing Co., Singapore.
Tkacz, G. 2001. Estimating the Fractional Order of Integration of Interest Rates Using a Wavelet OLS Estimator", Studies in Nonlinear DynamicsandEconometrics, 5(1).
Willinger, W., Taqqu, M.S. and Erramilli, A. 1996. A bibliographical guide to self-similar traffic and performance modeling for modern high-speed networks, p. 339 –366. *In*: Kelly, F.P., Zachary, S., Ziedins, I. (Eds.). Stochastic Networks: Theory and Applications. Clarendon Press, Oxford.