

ICT and Market Efficiency: A Case Study of the Nairobi Securities Exchange

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Abstract
The efficiency of a capital market is important if savers funds are to be channeled to the highest valued stocks. A recent review of markets in Africa categorized the Nairobi Securities Exchange as one which has no tendency towards weak form efficiency. According to the random walk hypothesis stock market prices evolve in a random pattern and can therefore not be predicted. The weak form hypothesis examines whether or not security prices fully reflect historical returns. The NSE has increasingly used Information and Communication Technology (ICT) in their operation which has improved the integrity of the exchange trading systems and facilitated greater access to the securities market. ICT gives investors and market makers the opportunity to access current information so as to make informed decisions and may help make the market more efficient. In an effort to establish efficiency of this market, we used non-parametric methods to establish the randomness of market returns at the NSE. The distribution of market returns appears normal although slightly negatively skewed and heavy tailed. The Q-Q and P-P plot also shows that the data approximates the normal distribution. The K-S and Runs test confirm that the data is not normally distributed which implies inefficiency in the weak form. This signifies market inefficiency of the weak form.
Keywords: Random Walk, Market Efficiency, Weak form hypothesis, Frequency Tests, Runs test, Autocorrelation test, Kolmogorov-Smirnov test

1.1 Introduction

There are three types of efficient markets hypothesis; the weak, semi-strong and strong form hypothesis (Fama 1970). According to the weak form efficient market hypothesis security prices already reflects all information that can be derived using technical analysis such as past security prices and trading volume. The weak- form of efficient market hypothesis is the lowest and is characteristic of security markets in developing countries. More developed economies have security markets that are either semi-strong or strong form informational efficient. Information and Communication Technology (ICT) is expected to play a big role in making security markets more efficient by driving security prices closer to their true values. The Nairobi Security Exchange (NSE) has increasingly used ICT in their operation which has improved the integrity of the exchange trading systems and facilitated greater access to securities market. If the NSE is weak form informational efficient then security prices should therefore be random.

1.2 Background of the Study

The Nairobi Securities Exchange (NSE) was established in 1954 as a voluntary association of stock brokers registered under the Societies Act. At this time, the business of dealing in shares was confined to the resident European community. At the dawn of independence, stock market activity slumped, due to uncertainty about the future of independent Kenya (NSE 2014). The NSE was privatized in 1988 by the successful sale of a 20% government stake in Kenya Commercial Bank. In July 1994 the NSE set up a computerized delivery and settlement system (DASS). After this the number of stockbrokers increased with the licensing of 8 new brokers. Live trading on the automated trading systems of the NSE was implemented on September 2006. The NSE Automated Trading System (ATS) solution was customized to uphold the spirit of the open outcry rules in an automated environment. In the same breadth, trading hours increased from two to three hours. Other innovations included the removal of the block trades board and introduction of the functionality for the trading of rights in the same manner as equities. Besides trading equities, the ATS is also capable of trading immobilized corporate bonds and treasury (NSE, 2014). In February 2007 NSE upgraded its website to enhance easy and faster access of accurate, factual and timely trading information. The upgraded website is used to boost data vending business. In July 2007 NSE reviewed the index and announced the companies that would constitute the NSE Share Index. The review of the NSE 20-share index was aimed at ensuring it is a true barometer of the market. A Wide Area Network (WAN) platform was implemented in 2007 and this eradicated the need for brokers to send their staff (dealers) to the trading floor to conduct business. Trading is now mainly conducted from the brokers' offices through the WAN. However the Broker Back office did not commence full operations until October 2011. The system has the capability to facilitate internet trading which improved the integrity of the Exchange trading systems and facilitates greater access to the securities market (NSE 2014).

The Nairobi Stock Exchange marked the first day of automated trading in government bonds through the ATS in November 2009. The automated trading in government bonds marked a significant step in the efforts by the NSE and Central Bank of Kenya towards creating depth in the capital markets by providing the necessary liquidity. In December 2009, NSE uploaded all government bonds on the ATS. Also in 2009, NSE launched the Complaints Handling Unit Small Message Service (SMS) system to make it easier for investors and the general public to forward any queries of complaints to NSE. As of March 2012, the NSE became a member of the Financial Information Services Division (FISD) of the Software and Information Industry Association (SIIA). In March 2012 the delayed index values of the FTSE NSE Kenya 15 Index and the FTSE NSE Kenya 25 Index were made available on the NSE website. This initiative gave investors the opportunity to access current information and provides a reliable indication of the Kenyan equity market's performance during trading hours. A total of 60 firms are now listed on the NSE and trade in shares and bonds (NSE, 2014).

Information and Communication Technology (ICT) has made information describing the macro and micro environment of economies readily accessible to stakeholders making them better placed to access and act in markets in accordance with changing dynamics in the environment (Pal and Mittal, 2011). ICT is expected to play a big role in making security markets efficient by driving security prices closer to their true values and therefore erasing trading patterns. This may be because the market is becoming more efficient as information is readily and equally available and buyers are able to value securities fairly. The NSE has increasingly embraced ICT which may be attributed to the comparative lower cost of access to internet via computers and mobile phone technology. This has increased the number of rational buyers in the market none of whom can influence prices in the market making the market more efficient.

1.3 Purpose of the Study

The purpose of the study is to establish if the Nairobi Securities Exchange is weak form efficient post implementation of Information and Communication Technology.

2.1 Literature Review

The Random walk hypothesis states that a security market is efficient if security prices instantaneously and fully reflects all available information. If a security market is efficient then possession of such information cannot allow an investor to continuously make profits in the market because security prices already reflect this information. As such one cannot predict security prices since they are randomly obtained. This includes information that is "privately" held. This is the highest level of informational efficiency and is referred to as the Strong form of efficient market hypothesis. The Semi-strong form hypothesis states that current security prices reflect publicly held information about a firms' prospects such as dividend announcements or the retirement of a director and no investor can continuously beat the market using such information. The weak form market hypothesis posits that current security prices reflect all past information such as past prices and trading volume.

2.2 Testing weak form market efficiency

The weak form efficient market hypothesis implies that prices on traded assets already reflect past information and future prices cannot be predicted by technical analysis techniques. In other words security prices do not follow patterns, thus it is not possible to trade profitably purely on the basis of historical prices and traded volume information. Tests of this hypothesis study how investors may use past information to be able to determine the right time to buy or sell and consistently earn abnormal profits. Research into weak-form market efficiency has particularly observed the cyclical behavior of security prices the days of the week, week of the month, month of the year season of the year and other seasonal effects. They are collectively referred to as the 'calendar anomalies' and question whether some regularities exist in the market returns during the year that would allow investors to predict market returns.

2.3 Tests of Independence

Successive one period security returns should be independent and identically distributed (IID) Al-Loughani and Chapell (1997), since new information comes to the market in a random, independent way, and prices will adjust rapidly to this new information. Tests of independence include Frequency tests, Wald-Wolfowitz Runs test and Autocorrelation tests.

2.4 Frequency Tests

These make use of descriptive statistics of data to test for Normality. Other tests include the Kolmogorov-Smirnov (K-S) Goodness of fit tests or the Chi-square tests and measure the agreement between the distributions of sample data to that of the theoretical distribution.

2.5 Wald-Wolfowitz Runs Test

It tests for serial dependence and observes the runs up and down or the runs above and below the mean. It then compares the actual runs to the expected chi-square run values. A run is defined as a succession of similar events preceded and followed by a different event (Banks et.al, 2001) and occurs when two or more consecutive prices are the same.

2.6 Autocorrelation Tests

This test examines the dependence between numbers in a sequence. It measures the relationship between the values of a random variable at time t and its value in the previous periods. It tests the significance of a positive or negative correlation in returns over a certain period and compares the sample correlation to the expected correlation of zero (Banks et. al, 2001).

2.7 Trading rule tests

A trading rule dictates the price at which a stock should be bought or sold as its price fluctuates. Under this test observation is made if a trader consistently makes abnormal profit using such rules. Dryden (1970) applied a filter rule of the amount of stock price to its average in the NYSE and reported that abnormal returns obtained are usually eroded by transaction costs incurred. However Jensen and Bennington (1970) simply reported no significant abnormal return.

2.8 Cyclical Tests

These tests observe the cyclical behavior in the time series, and investigate the effect of different days, weeks and months of the year on stock behavior. Also collectively referred to as 'Calendar studies' they question whether some regularities exist in the rates of return during the calendar year that would allow investors to predict returns on stocks.

The next section presents the procedure used for analyzing the data and the findings. The study concludes with recommendations for future studies.

3.1 Data and Analysis Methods

The study used the daily NSE 20 share index of the Nairobi Securities Exchange for the period 2nd January 2006 to 18th November 2011. The secondary data was obtained from Synergy Ltd, an authorized data vendor of the NSE for the period of 2006 to 2011. The daily market return R(t) was then calculated using equation 1 (Washer et. al., 2011)

$\mathbf{R_t = Ln\ (PI_t / PI_{t-1}) * 100}$ - (Equation 1)

Where;

PI_t = Closing Price Index on day t

PI_{t-1}= Price Index on day t-1

Ln = Natural Logarithm

The daily market returns obtained are then used in the following empirical analysis using different statistical techniques. Results are classified in the subsequent chapter. Statistical Package for Social Sciences (SPSS) will be used to analyze the data.

3.2 Heuristic Approaches

One of the basic assumptions of the random walk model is that the distribution of the data series should be normal. A density histogram of the daily market return is plotted and a frequency comparison of the normal distribution curve superimposed onto the density histogram to visually ascertain whether the distribution of daily market returns is normal. The density histogram plot is useful in identifying the shape of the distribution. However

it is difficult to tell if the data series fits well since ones perception of the fit depends on the widths of the histogram intervals.

Probability plots are heuristic methods for comparison of an estimate of the true distribution function of the data with the distribution function of a fitted distribution. One such plot is the quantile- quantile (Q-Q) plot and is useful tool for evaluating the distribution fit. A Q-Q plot is a graph of the q_i- quantile of a fitted (model) distribution function $\hat{F}(x)$ versus the q_i- quantile of the sample distribution function $\tilde{F}_n(x)$. If $\hat{F}(x)$ is the same distribution as the true underlying distribution $\tilde{F}_n(x)$, and given a large sample s, then $\hat{F}(x)$ and $\tilde{F}_n(x)$ will be close together thus the Q-Q plot will be approximately linear with an intercept of 0 and a slope of 1. Even if $\hat{F}(x)$ is the correct distribution, there will be departures from linearity for small to moderate sample sizes. (Law, 2007). The Q-Q plot will especially sensitive to differences that exist between the tails of the model distribution function $\hat{F}(x)$ and the tails of the sample distribution function $\tilde{F}_n(x)$.

A probability-probability (P-P) plot is a graph of the model probability $\hat{F}(X_{(i)})$ versus the sample probability $\tilde{F}_n(X_{(i)})$. Corresponding to each abscissa value p are the two probabilities $\hat{F}(p)$ and $\tilde{F}_n(p)$. If $\hat{F}(x)$ and $\tilde{F}_n(x)$ are close together, then the P-P plot will also be approximately linear with an intercept of 0 and a slope of 1. The P-P plot amplifies the differences between the "middles" of the two distribution functions.

3.3 Descriptive Statistics

Heuristic approaches can quite subjective and summary statistics of the distribution parameters are useful for measurement. For a symmetric normal distribution, the mean μ is equal to the median $x_{0.5}$. Thus if the estimates $\bar{X}(n)$ and $\hat{x}_{0.5}(n)$ are "almost equal," it

may be an indication that the underlying distribution may be symmetric. The skewness ν is a measure of the symmetry of a distribution. For the normal distribution, ν=0. If $\nu > 0$, the distribution is skewed to the right while it is skewed to the left if $\nu < 0$

3.4 Kolmogorov Smirnov (K-S) Test

This is a non-parametric procedure for testing the hypothesis that a random sample of data fits a specific distributional form. The K-S Goodness of Fit test compares the continuous cumulative distribution function (cdf), F(x) of the uniform distribution to the empirical cdf, $S_N(x)$ of the sample of N observations. The test statistic D is based on the largest absolute deviation between F(x) and $S_N(x)$ over the range of the random variable. It is based on the test statistic in equation 2 (Banks et al.,2001).

D= max| F(x) – $S_N(x)$|……………………………………………………….(Equation 2)

If the sample statistic D is greater than the critical value, D_α the null hypothesis that the data are a sample from a uniform distribution is rejected. Otherwise it can be concluded that there is no difference detected between the true distribution and the uniform distribution. The hypotheses for this test are:

$\mathbf{H_0}$**:** The daily market returns are drawn from a normal distribution.

$\mathbf{H_1}$**:** The daily market returns are not drawn from a normal distribution.

3.5 Wald-Wolfowitz Runs Test

This approach tests and detects statistical dependencies (randomness) which may not be detected by an auto correlation test. It observes the runs up and down or the runs above or below the mean. It then compares the actual runs to the expected chi-square run values. A run is defined as a succession of similar events preceded and followed by a different event.

Let a be the total number of runs in a truly random sequence, the mean and variance of a series is given by equation 3 and 4 (Banks et al., 2001).

$$\mu_a = \frac{2N-1}{3} \qquad \text{(Equation 3)}$$

$$\sigma_a^2 = \frac{16N-29}{90} \qquad \text{(Equation 4)}$$

The standardized normal test statistic is

$$Z_0 = \frac{a - \left[\frac{2N-1}{3}\right]}{\sqrt{\frac{(16N-29)}{90}}}$$

We also assess the number of runs above and below the mean. The mean and variance for a truly independent sequence is given by equation 5 and 6 (Swed and Eisenhart, 1943)

$$\mu_a = \frac{2n_1\ n_2}{N} + \frac{1}{2} \qquad \text{(Equation 5)}$$

$$\sigma_a^2 = \frac{2n_1 n_2\ (2n_1 n_2 - N)}{N^2(N-1)} \qquad \text{(Equation 6)}$$

The test statistic is

$$Z_0 = \frac{b - \left(\frac{2n_1 n_2}{N}\right) - 1/2}{\left[\frac{2n_1 n_2 (2n_1 n_2 - N)}{N^2(N-1)}\right]^{1/2}}$$

where n_1 and n_2 are the number of individual observations above and below the mean respectively and b the total number of runs.

Further we assess the length of a run. This is the number of events that occur in a run. The expected number of runs, Y of length i in a sequence of N numbers (N>20) can be approximated by Equation 7 (Banks et.al. 2001).

$$E(Y_i) = \frac{Nw_i}{E(I)}$$

where

$$w_i = \left(\frac{n_1}{N}\right)^i \left(\frac{n_2}{N}\right) + \left(\frac{n_1}{N}\right)\left(\frac{n_2}{N}\right)^i$$

The test statistic is.

$$\chi_0^2 = \sum_{i=1}^{L} \frac{[O_i - E(Y_i)]^2}{E(Y_i)}$$

where,

$$E(I) = \frac{n_1}{n_2} + \frac{n_2}{n_1} \qquad \text{(Equation 7)}$$

and

O_i is the observed number of runs of length i

w_i, is the approximate probability that a run has length i.

$E(I)$ the approximate expected length of a run.

The hypotheses are:

H0: The sequence of daily market returns is random.

H1: The sequence of daily market returns is not random.

4.1 Results and Discussion

The distribution of the market returns appears normal although slightly negatively skewed and heavy tailed (Figure 1). It is difficult to tell exactly if the data is well represented by a normal distribution by looking at a histogram. The distribution may also be represented by a Beta, Johnson or Weibull distribution. However the general perception of a straight line is quite clear in the Q-Q plot

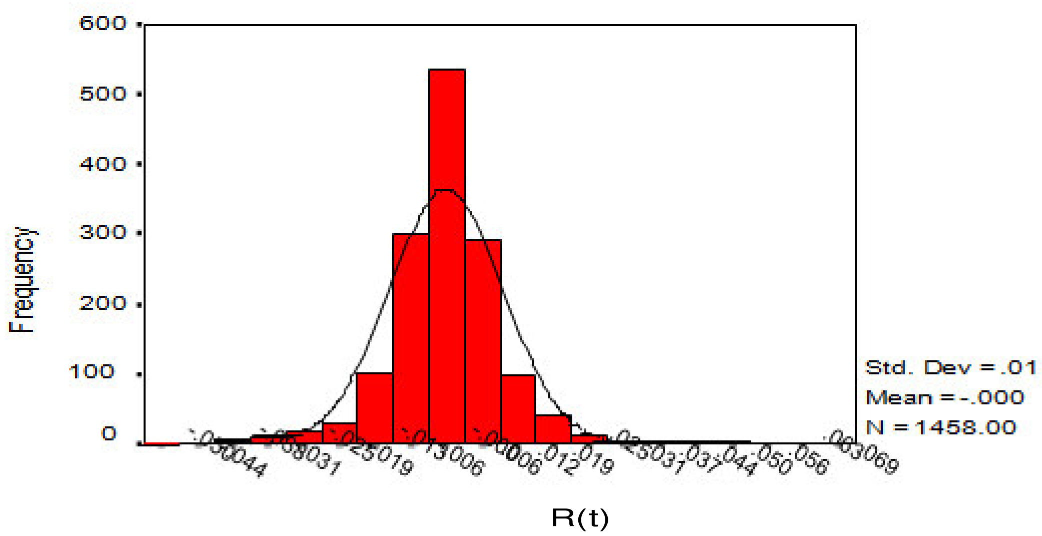

Figure 1: Density histogram plot of 1459 values of daily market returns

The Q-Q plot of market returns (Figure 2) is not quite linear especially in the tails of the plot. However the data points in the middle of the plot are quite linear. Greater discrepancies can be accepted at the extremes as the variances of the extremes are much higher than the variances in the middle of the plot. We may therefore conclude that the data approximates the Normal distribution. On the other hand the p-p plot (Figure 3) shows slight linearity in the tail sections of the distribution showing that the curve quite resembles the normal distribution. For the p-p plot the linearity of the tail section is of
essence.

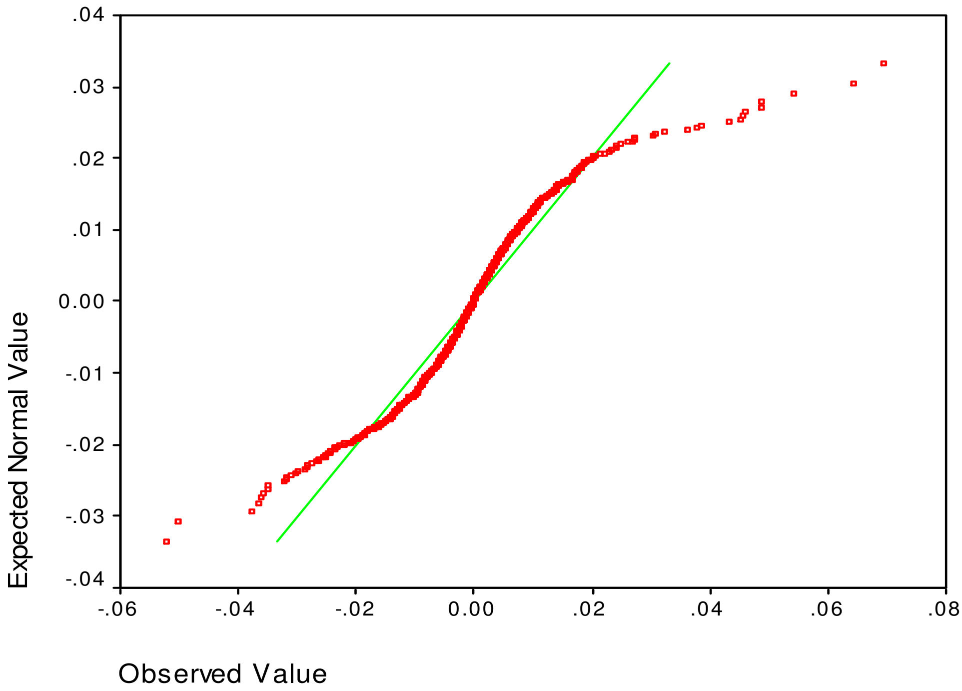

Figure 2: Normal Q-Q plot of the distribution of daily market returns

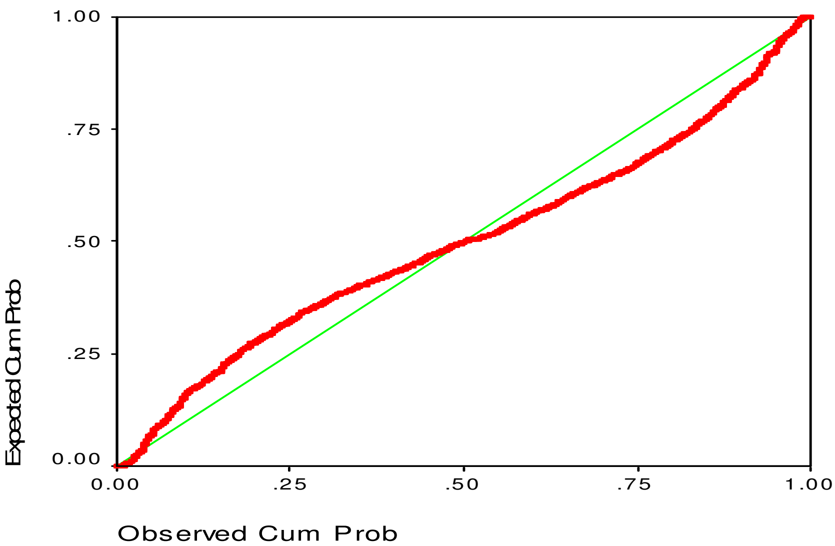

Figure 3: Normal P-P plot of the distribution of daily market returns

The descriptive statistics (Table 1) of the distribution of market returns provide data summaries. The mean does not quite approximate the median. This may indicate that the underlying distribution is not quite symmetric. It is slightly skewed to the right as $\nu > 0$. It may be concluded that the distribution of market returns is not quite normal.

Table 1: Distribution parameters of daily market returns. (N=1459)

Variable	**Mean**	**Median**	**Std. Deviation**	**Minimum**	**Maximum**	**Skewness**
Daily Returns	-0.000120	-0.000150	0.00998629	-0.052340	0.069480	0.535

The K-S test results are shown in **Table 2**. For 1459 market return values the p-value for the daily market return is 0.00. This is the probability that we would be in error if we rejected the null hypothesis. There is enough evidence to reject the claims that the sampled population is normally distributed. So we may conclude that the return data is normally distributed.

Table 2: One-Sample K-S test for Normality of daily market returns
Tests of Normality

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
R(t)	.084	1459	.000	.913	1459	.000

The Runs test results (Table 3), shows the absolute Z- score of 10.292 being much higher than 1.96 (obtained from the standard normal table at the 5% significance level). This indicates non-randomness of the data and therefore the null hypothesis is rejected. The lower than expected runs may indicate markets overreaction to information (Poshakwale , 1996) which suggests an opportunity to make excess returns.

Table 3: Runs Test for the distribution of daily market returns

	R(t)
Test Value Cases < Test Value Cases >= Test Value Total Cases Number of Runs Z Asymp. Sig. (2-tailed)	-.00015 729 730 1459 534 -10.292 .000

4.2 Autocorrelation

Figure 4 and Figure 5 are plots of autocorrelation (ACF) and partial autocorrelation (PACF) functions that help determine whether there are serial dependencies in series across time, in particular, ACF helps to identify and order of Moving Average process q, while PACF is used to settle an order p of the AR part for the corresponding ARMA model.

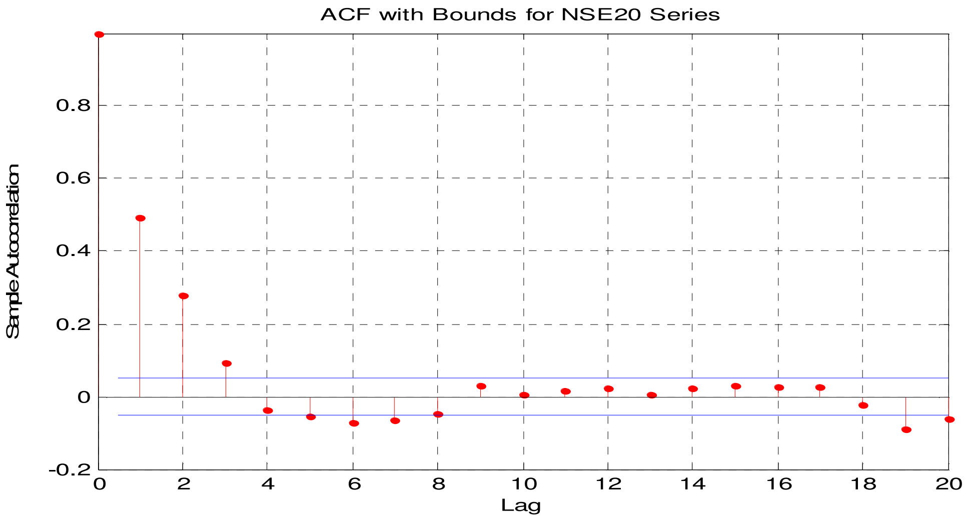

Figure 4: Autocorrelation Function for NSE20 Returns

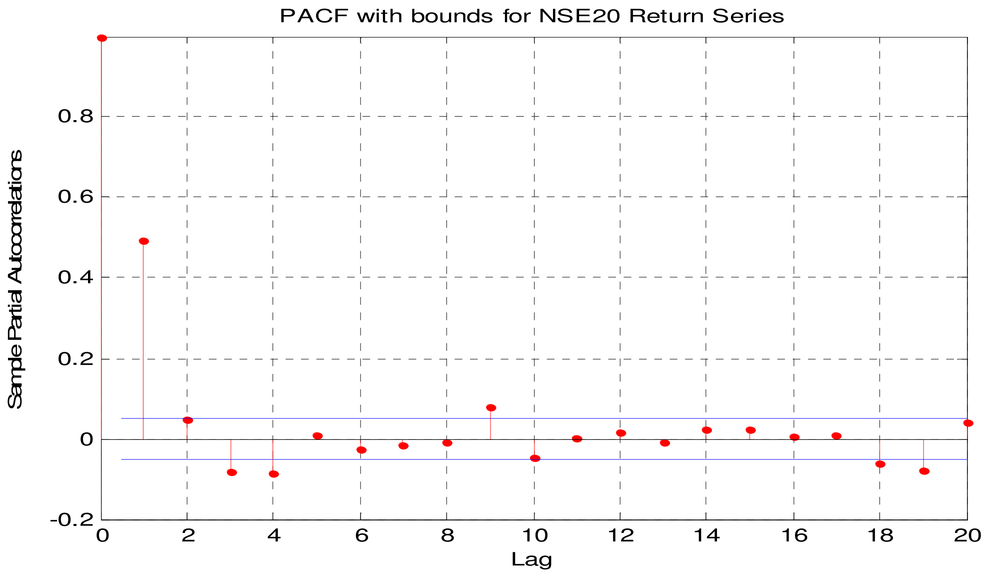

Figure 5: Partial Autocorrelation Function for NSE20 Returns

The ACF and PACF plots show that the time series of the return on the Index is random, but has a rather considerable degree of autocorrelation between adjacent and near-adjacent observations. The first observation being Monday it is highly positively correlated to Friday, Thursday and Wednesday but not correlated to Tuesday.

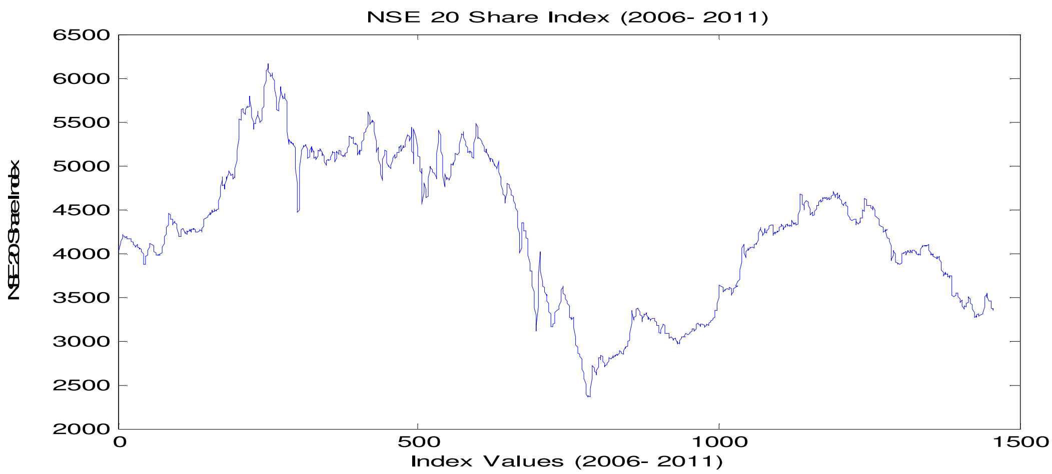

Figure 6: Plot of the NSE 20 Share Index (2006-2011)

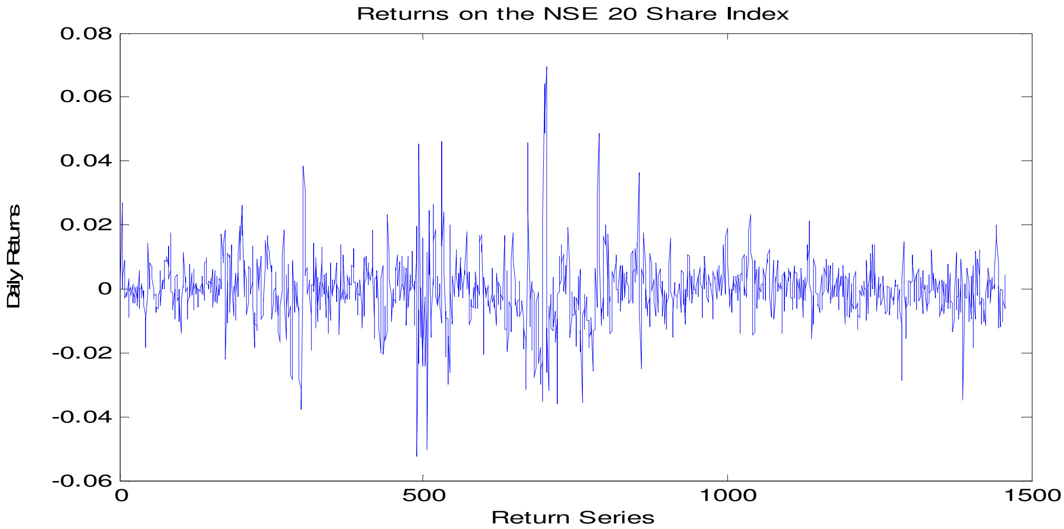

Figure 7: Plot of the Returns on the NSE 20 Share Index (2006-2011)
a period of large volatility in daily returns on the Index are followed by another period of large volatility in daily returns and the period of small volatility in daily returns are followed by another period of small volatility in daily returns. Therefore certain weeks of the month or months of the year have significantly different (higher or lower) returns. This is commonly referred to as the week of the month and the month of the year effect (Alagidede and Panagiotidis, 2008). These are anomalies of the efficient markets hypothesis and contradict the efficient markets hypothesis. From the ACF plot, PACF plot,

5.1 Conclusions and Recommendations
This study has shown that the NSE is still not efficient in the weak form. Using Non-Parametric methods such as the Q-Q and P-P plot, results show that the distribution of returns just approximates the normal curve as they are not quite linear in the middle and tail section respectively. According to the random walk hypothesis, if the distribution is normal then the data is completely random meaning the market is efficient. Data summaries also show that the distribution is slightly skewed to the right. The K-S test for normality rejects the hypothesis that the data is normally distributed and based on the number of runs, the Runs test rejects the randomness assumption at the 5% level of significance. Therefore we may conclude that the market is not efficient in the weak form.

The autocorrelation plot shows significant degree of autocorrelation between adjacent and near adjacent observations which implies non-randomness. Together with the and partial autocorrelation plot they show that Monday returns may be highly correlated to Friday, Thursday and Wednesdays but not Tuesday returns.

In earlier studies the day of the week effect has been generalized to show that stock returns on particular days of the week such as Monday is significantly different from other days of the week. For emerging market such as the NSE, it has been suggested that a possible explanation of this anomaly is that firms and governments release good news during market trading when it is readily absorbed, and store up bad news till the close on Friday when investors cannot react until Monday (Francesco et. al., 2011). In this study we confirm that due to volatility clustering some time periods may be riskier than others and therefore it would not be accurate to generalize that Monday returns are generally lower. Instead we recognize that stock returns on a particular day depends on the previous activity and the notion of a weekly window is rejected. Instead for this period of study one would think of 5 year contiguous return data and using a 3 day window to predict the next days' activity.

For instance if an investor wanted to predict the returns on Monday, then it would be equal to a mean return which will fluctuate depending on the risk of returns of the previous Friday, previous Thursday and previous Wednesday. This is slightly different but more accurate way of predicting stock returns since it takes into account the general economic conditions in the neighborhood of the day being predicted. Since there is no randomness in the data whatever returns realized today will largely depend on the most recent activity in the market.

We conclude that volatility clustering exists in the market and that stock returns does not depend on the day of the week but rather the returns of the previous 3 days of the week. This being a significant pattern in the data it can be concluded that the market is still not weak form efficient. However future work in this area may study an inter-period say yearly data to show if it is different from the overall result. If different it would still indicate volatility clustering. However as long as one is able to consistently predict the daily return, it would point out to the market not being efficient.

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