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Akber, Ushna and Muhammad, Nabeel

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2013

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Ushna Akber[1] & Nabeel Muhammad[2]

Lahore University of Management Sciences

1. Ushna Akbar <ushna@lums.edu.pk> is a Teaching Fellow in the Department of Economics at Lahore University of Management Sciences, Lahore, Pakistan.

2. Nabeel Muhammad <nabeel_muhammad1@hotmail.com> is BSc Economics graduate from Lahore University of Management Sciences, Lahore, Pakistan.

Acknowledgements: We would like to thank Dr. Hammad Siddiqui and Dr. Syed Muhammad Hussain of Department of Economics at Lahore University of Management Sciences, and Dr. Gideon Saar of Johnson Graduate School of Management at Cornell University for their valuable feedback and support. Special thanks to Muhammad Awais Zahoor for his research assistance. Both Authors have contributed equally to this paper and are equally responsible for any errors in this paper.

ABSTRACT

In this study, we have attempted to seek evidence for weak-form of market efficiency for KSE 100 Index. Index returns have been studied from 1st January, 1992 to 30th April, 2013. For further analysis, return series has been divided into these groups: 1992-2012, 1992-1994, 1995-1997, 1998-2000, 2001-2003, 2004-2006, 2007-2009, 2010-2012 and 2013. The paper has made use of both Non-Parametric tests (Kolmogrov-Smirnov goodness of fitness test, Runs test and Phillips-Perron test) and Parametric tests (Auto-correlation test, Box-Pierce (Q) statistic test, Ljung and Box (Q) Statistic test, Augmented Dickey-fuller test, Dickey-fuller GLS test, Jarque-Bera test, Kwiatkowski, Phillips, Schmidt and Shin test, Auto-regression and ARIMA model). For further analysis, Runs test has also been run on 20 companies return series for comparison purpose with the results of index return series. In addition, from KSE 30 Index, 20 companies return series based on the free-float of shares have also been analyzed through Runs test to check if increase in numbers of floating shares does increase the randomness in return series or not. To our knowledge, this paper is the first one on KSE 100 Index to study the overall time frame of return series of KSE 100 Index of 22 years with the several random walk and weak-form efficiency tests to ensure the consistency of results; and to compare the results of runs test of index return series with the results of runs test on companies return series from KSE 100 and KSE 30 Indexes. Overall KSE 100 Index has found to be weak-form inefficient, but the last 4 years have shown some signs of efficiency. Companies return series from KSE 30 Index are found to be more random than companies return series from KSE100 Index.

Key words: Efficient Market Hypothesis, Random Walk, Random Walk and Weak-form Efficiency Tests, Free-float of shares, KSE 100 Index and KSE 30 Index.

1. INTRODUCTION

During the last few decades, stock markets have played a major role in the progress of any economy, especially for underdeveloped economies as it is considered to be one of the most crucial leading indicators of an economy. In this paper, we aim to test the weak-form of market efficiency for Karachi Stock Exchange by checking for randomness in return series. We have studied a large index return series of 22 years from 1st January, 1992 to 30th April, 2013 to test the weak-form of market efficiency for KSE 100 Index. For further analysis, data has also been divided into 9 groups: 1992-2012, 1992-1994, 1995-1997, 1998-2000, 2001-2003, 2004-2006, 2007-2009, 2010-2012 and 2013. To our knowledge, no study with such large data has been done to check for weak-form of market efficiency for Karachi Stock Exchange. For comparison purpose, we have used the return series of 20 randomly selected active stocks from KSE 100 Index to apply runs test to check if their results are consistent with the results of runs test for index returns. Moreover, 20 companies return series from KSE-30 Index is also studied to see if the free-floating of shares does increase the chances for prices to follow a random walk or not.

A large amount of research has been carried out on the topic of efficiency of markets. Its need has been felt in both the developed and emerging economies because of the necessary precondition that only efficient markets allow for funds to be allocated to the most efficient and highest-valued projects. Informationally efficient market can enhance the allocative efficiency of investments by effectively channeling the domestic and foreign investments in market (Vives, 1995; Chowdhury, 1995), something which is consistent with the basic aim of any investor. Inefficient stock markets can allow some investors to make abnormal profits at the expense of others, thus stock market efficiency is the basic need of every investor. Hence, to find the best answer, we have studied the overall time frame for KSE-100 Index from 1992 to 2013. KSE-100 Index started in 1991, but we have left 1991 because of very low activity in that year.

Efficient Market Hypothesis (EMH) or Joint Hypothesis Problem states that financial markets are "informationally efficient". In other words, market efficiency asserts that the stock prices reflect all pertinent and accessible information and quickly adjust all the new information (Adam, 2004); while inefficiency of markets suggests that stock prices do not include all the available and concerned information.

The concept of EMH was first developed by Professor Eugene Fama in his Ph.D. thesis in mid 1960s. His idea states that quick and fast incorporation of available information in stock prices does not allow investors to beat the market (Fama, 1965). Hence, it is impossible to make abnormal profits because stocks always trade at their fair value on stock exchanges. This theory has been opposed by many proponents of technical analysis who believe that stock prices are largely based on the behaviors and expectations of investors who seem to believe that past prices influence future prices. Technical analysis is based on the expectations of past prices, past earnings, past volume, track records and other indicators.

Random Walk Hypothesis (RWH) states that stock prices follow a random walk and thus cannot be forecasted. A random walk is a formalization of a pathway that includes a series of random steps. For instance, the trail traced by a molecule of gas, the price of a fluctuating stock and the financial position of a gambler can all be represented as random walk (Pearson, 1905). A random walk in the stock prices can be characterized as price changes being independent of each other. Hence the change in stock prices cannot be forecasted. The Random Walk Model is a non-stationary process. For financial markets data, a random walk having a step size differs according to a normal distribution and is commonly known as the Gaussian random walk model. Therefore, stationarity and normality of data are the two pre-requisites for data having a random walk.

The idea of Random Walk is consistent with the EMH. It is commonly observed that the more random the prices, higher the chances for market to be efficient. The concept of randomness of stock prices was first put forward by Jules Regnault in 1863 and then by Bachelier (1900), in his Ph.D. thesis, "The Theory of Speculation". The same idea was further developed by Kendall (1953) and Cootner (1964). Later on, the idea was further carried on by Fama (1970) in his empirical research that stock prices tend to follow a random walk. Fama (1970, 1991) evaluated both the theoritical and empirical evidence for EMH. He postulated that market can be of three forms in EMH: weak-form efficiency, semi-strong efficiency and strong-form efficiency.

Weak-form efficiency assumes that present security prices reflect all the historical information of past prices, past volume and past returns (Bodie, Kane & Marcus, 2007). Thus, future prices cannot be predicted by looking at past information as it has already been incorporated in current prices. Therefore, technical analysis fails to beat the market (though some forms of fundamental analysis can generate abnormal profits).

Semi-strong form efficiency uses the assumption that stock prices reflect all publically obtainable information of past prices, past volume, past returns, earnings, dividends, P/E ratios, book value ratios, market value ratios, relevant economical and political news and other relevant indicators. Here both the fundamental and technical analyses fail to earn abnormal returns as the publically available information is already incorporated in the stock prices. If market is efficient in semi-strong form, then it is also efficient in the weak-form (Dixon & Holmes, 1992).

Strong-form efficiency assumes that stock prices reflect all public and private information available. This form integrates both the weak and semi-strong forms and hence the investor cannot beat the market based on technical, fundamental or insider information (Brealey, Myers & Marcus, 1999).

Weak-form efficiency can be tested by carrying out simple regression of the form:

$$R_t = \beta_0 + \sum_{i=1}^{p} \beta_i R_{1-i} + e_t$$

where R_t is the rate of return of an index at time *t*. This form entails that $\beta_i = 0$, $i > 0$ and this equation can be run using OLS or GLM with relevant tests (Dwyer & Wallace, 1992).

Free float is also known as float or public float. Free float are the shares that are held by investors and are available for trading unlike restricted shares which are not traded that often. Free float can be understood as:

Free Float = Outstanding Shares - Restricted Shares

It has been observed that the companies with larger free float of shares are less volatile because it takes a large number of trades, shares per trade, or both to raise or lower the stock price. A low volatility means that the stock price would not swing dramatically but would vary at a stable pace over a phase of time. An empirical study by K. Chan, Y.C. Chan and Fong (2004) found out that the substantial decrease in the free float of shares negatively affected the market liquidity in the Hong Kong market.

The remaining paper is divided in these parts: section 2 analyzes the previous studies and findings on weak-form of EMH, section 3 explains the different sets of data for KSE 100 index and companies return series from KSE 100 and KSE 30 Indices, section 4 lays out the research methods and hypotheses used in this paper and section 5 analyzes the tests' results. Finally section 6 presents conclusions and suggestions for future studies.

2. LITERATURE REVIEW

Stock prices following a random walk are closely linked to the theory of EMH. Kendall (1953) was the first one to incorporate random walk in finance literature. He examined 22 British stocks and commodity price series and found out that prices do not follow any cycles and they seem quite random. Fama (1965) found evidence that technical analysis cannot be used to predict the prices in long term. Lo and MacKinley (1999) suggested that there exists autocorrelation in stock prices in short run. Lo, Mamaysky and Wang (2000) suggested that some sophisticated statistical techniques can surely give us some predictive power. It is observed that the more random the prices, the more efficient the market is. Malikiel (2003) also found out the evidence that it is not possible to make abnormal profits in stock prices in long term. Cuthbertson and Nitzsche (2004) identify a random walk with drift (= μ) for some series x_t as:

$$x_t = \mu + x_{t-1} + e_t \qquad\qquad e_t \sim iid\,(0,\ \sigma_e^2)$$

According to Jensen (1978), there has been evidence of strange price behaviors where certain price series are found to be predictable as they appeared to follow a certain path. Hence, it is important to carefully analyze both the concepts of EMH and the procedures and tests.

Michel and Hawawini (1984), Hudson, Dempsey and Keasey (1994) and Nicolaas (1997) found out that prices are hard to predict. They maintained that prices follow a random walk, hence market is efficient. Empirical study by Dickinson and Muragu (1994) supported that Nairobi Stock market is efficient.

Borges (2010) studied the stock markets of UK, France, Spain, Germany, Greece and Portugal for the period of 1993 to 2007. By using runs test and variance ratio test, he observed that only Germany and Spain are the weak-form of efficient markets; otherwise all others are not efficient stock markets.

Magnusson and Wydick (2000) tested the RWH for African countries and amazingly found out greater support for random walk for African Stock markets as compared to other emerging stock markets.

Early studies used serial correlation and runs test to check for random walk and weak-form market efficiency and they discovered that market is weak-form efficient (Cowles, 1960; Osborne, 1959, 1962; Cootner, 1962; Fama and Blume, 1966). Other papers have also used variance ratio test, such as Lo and MacKinlay (1988), and Lee (1992).

Further tests like serial correlation test, Q-test, and variance ratio test have been adopted by many empirical studies (Abeysekera, 2001; Groenwold, Sam & Wu, 2003) while (Alam, Tanweer & Kadapakkam, 1999; Chang & Ting, 2000; Abraham, Seyyed & Alsakran, 2002; Lima & Tabak, 2004) have applied variance ratio test as the main test to check for the weak-form of market efficiency in their studies.

Asma and Keavin (2000) used both parametric tests (Auto-regression, Auto-correlation test, ARIMA model) and non-parametric tests (Kolmogrov-Smirnov normality test and Runs test) and detected that share return series do not follow a random walk, thus rejecting the weak-form of efficiency hypothesis for Dhaka Stock Exchange.

Chen and Hong (2003) used a powerful spectral derivative test to check for EMH in presence of volatility clustering and rejected EMH for both Shanghai and Shenzhen stock markets. However, these markets were seen to become more efficient at later stages.

Dorina & Simina (2007) looked for weak-form of market efficiency in 8 emerging stock markets. Their examination included developing countries of Poland, Slovenia, Hungary, Lithuania, Turkey, Romania, Slovakia, and Czech Republic. They used Q-test, Serial correlation LM test, Runs test and BDS test (applied on residuals generated by ARMA models) and found out that there are linear and non-linear dependencies in most of these stock markets.

In a very remarkable paper, Ball (2009) negatively commented on too much faith in market efficiency and held it responsible as one of the major reasons for the demise of Lehman Brothers and other large financial institutions. Hence market efficiency needs to be studied very carefully for each country because of its imperative for investors. C.C. Lee, J.D. Lee, & C.C. Lee, (2010) examined the stationarity of real stock prices for 32 developed and 26 developing countries from January 1999 to May 2007 and suggested that stock markets are not efficient.

An empirical study by Cox, Brammer and Millington (2004) investigated more than 500 UK companies to check for the relationship between institutional shareholding and socially responsible behavior. Their results showed that there does exist a positive correlation between corporate social performance and long-term institutional investment. They expected a positive relationship between free float and institutional investment and this turned out to be true in results.

For the case of market efficiency in Pakistan, few detailed studies have been done to test the market efficiency and to check for free-float of shares randomness in return series. Husain (1997) concluded that KSE 100 Index does not follow a Random Walk Model. Hussain and Uppal (1999) made use of ARCH and GARCH models to examine the stock market volatility in Pakistan. They found out that volatility have declined drastically after the liberalization of the capital markets. Chakraborty (2006) used variance ratio and serial correlation tests to check for the weak-form efficiency from 1996 to 2000. They rejected the random walk hypothesis.

The Securities Exchange Commissions of Pakistan's installations of circuit breakers has dampened the return volatility, but with a very small magnitude. Weak form efficiency for KSE-100 has been rejected, with returns demonstrating persistence and volatility clustering (Hameed & Ashraf, 2009). Empirical studies found out that KSE 100 index is not a weak-form efficient (M. Irfan, M. Irfan & M. Awais, 2010; M. Irfan, M. Saleem & M. Irfan, 2011). Recently, Rabbani, Kamal and Salim (2013) tested the weak-form efficiency for KSE-100 from 1999 to 2012 by employing four tests (Augmented Dickey-fuller test, Auto-correlation function test, Phillip-perron test and Runs test) to analyze the data. All these tests except the Runs test rejected the EMH. However, they suggested market efficiency for only these two periods (1999-2001 and 2005-2007). They proposed that investors can make abnormal profits in Karachi Stock Market.

However, these studies have proposed their results on the basis of very few tests which can create spurious results. None of them has attempted to analyze the overall time frame of return series to get a clearer picture of Pakistani stock market and none has attempted to compare the index return series with companies return series from KSE-100 and KSE-30 Indices for further analysis on the stock market.

It has been a widespread observation through empirical studies that emerging economies are not weak-form efficient. An empirical study by Ahmad, Daud and Azman-Saini (2010), covering 15 emerging markets for the period 1985 to 2006 suggested that historical information can be used to guess future prices, thus rejecting the weak-form efficient market hypothesis for these markets. Majority of stock prices in emerging markets show a mean reverting process. Another empirical study by Malkiel and Taylor (2007) shows that emerging markets like China (Shanghai and Shenzhen markets) are not efficient, unlike United States. He further pointed out the problems of manipulation but still he asserted that investors can make profits from China's booming economy. A study by Khawja and Mian (2005) found out that in Pakistani Stock Market, brokers can collude to artificially raise prices and attract positive-feedback trades. Manipulation is another big issue in Pakistani Stock Market.

3. DATA

3.1. Index Data:

To test the weak-form of market efficiency for KSE 100, we have used KSE 100 Index daily closing values from 1st January, 1992 to 30th April, 2013 (almost 22 years). Total observations are 5214. Daily market index returns have been calculated by this method:

$$(R_t) = Ln\,(I_t / I_{t-1}),$$

Where, R_t = market return, in period t;
I_t = price index at day t;
I_{t-1}= price index at period t-1 and
Ln = natural log.

For further analysis of market in different periods, the data has been divided into 9 groups of years: (1992-2012), (1992-1994), (1995-1997), (1998-2000), (2001-2003), (2004-2006), (2007-2009) and (2010-2012) and (2013). For instance, (1992-1994) means data from 1st January, 1992 to 31st December, 1994. This is the same for all groups except 2013, which means the return series from 1st January, 2013 to 30th April, 2013.

3.2. Companies Data:

To compare the results of Runs test on index return series, we have calculated daily returns of 20 randomly selected active stocks from KSE 100 Index and companies return series has been used from 1st January, 2005 to 1st December, 2011.

20 other companies have been taken from KSE 30 Index to check whether the companies with more free-float of shares follow a random walk or not.

Top 30 companies participate in KSE 30 Index. The difference between KSE 30 Index and other indices is that other indices represent the total return on the market, while KSE 30 Index only represents the free float of shares rather than paid up capital, and KSE 30 Index is also adjusted for dividends and right shares.

4. METHODOLOGY AND HYPOTHESES

Time series univariate regression analysis has been adopted in this paper. We have used both parametric and non-parametric tests to avoid the bias resulting from non-normal distribution of the data.

Non- Parametric tests include Kolmogrov-Smirnov goodness of fit test, Runs test and Phillips-perron test.

Parametric tests include Autocorrelation coefficient test, Box and Pierce (Q) Statisitc, Ljung and Box (Q) Statistic test, Augmented Dickey-fuller test, Augmented Dickey Fuller GLS test, Kwiatkowski, Phillips, Schmidt and Shin (KPSS) (1992) test, Auto-regression test and Auto-regressive Integrated Moving average model (ARIMA) model.

We would be testing for two hypotheses in this paper.

Hypothesis no.1: To test for the weak-form of the EMH by examining the Random Walk Model in KSE 100 Index, we have these hypotheses:

H_0: KSE 100 Index returns follow random walk, thus weak-form efficient.

H_1: KSE 100 Index returns do not follow random walk, thus weak-form inefficient.

Hypothesis no.2: It has been observed widely that companies with larger free-float of shares are less volatile than companies with few free-float of shares. We aim to check if the free-float of shares of KSE 30 Index increases the randomness or not in the return series of these companies:

$\overline{H_0}$: Free-float of shares does increase the randomness in return series.

$\overline{H_1}$: Free-float of shares does not increase the randomness in return series.

5. TESTS AND ANALYSIS

5.1. Descriptive Statistics:

To check for the normality of data , we have primarily looked at skewness and kurtosis.

Skewness measures the direction and degree of asymmetry. Skewness is defined as:

$$skewness = \frac{\sum_{i=1}^{N}(R_i - \bar{R})^3}{(N-1)s^3}$$

where $R_1, R_2 \ldots R_N$ is log return series and $\bar{R}$ is the mean. For normal distribution, skewness is 0. For the negative values of skewness, data is skewed left; and for the positive values, data is skewed right. Skewed left means that left tail is long relative to right tail and vice versa.

Kurtosis can be described as the distribution of observed data around mean. It measures the heaviness of the tails of a distribution. And for data to be normally distributed, kurtosis value should be of 3 or excess kurtosis value should be of 0 (Blanda & MacGillivray, 1988). Kurtosis is defined as:

$$Kurtosis = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^4}{(N-1)s^4}$$

where $\bar{Y}$ is the mean, s is the standard deviation, and N is the number of data points.

Table 1: Descriptive Statistics for KSE 100 Index return series.

Data	Variable	Obs.	Mean	Std.Dev	Minimum	Maximum	Skewness	Kurtosis
1992-2012	Returns	5090	.00004528	0.0156884	-0.1321329	0.1276223	-0.2546651	8.343427
1992-1994	Returns	707	0.000275	0.0114085	-0.0552722	0.0445279	0.0734457	4.954591
1995-1997	Returns	691	-0.0002322	0.0149703	-0.091453	0.0529832	0.0134106	5.387882
1998-2000	Returns	731	-0.0002011	0.0232289	-0.1321329	0.1276223	-0.2464907	7.378018
2001-2003	Returns	733	0.0014739	0.0153867	-0.0774138	0.0850712	-0.0579424	6.605036
2004-2006	Returns	738	0.0010956	0.0159255	-0.0604175	0.0581842	-0.4753279	4.474391
2007-2009	Returns	738	-0.0000947	0.0160049	-0.0513486	0.0825469	-0.2068831	5.105811
2010-2012	Returns	746	0.0007814	0.0090456	-0.0405779	0.0306944	-0.3041446	5.012562
2013	Returns	82	0.0017166	0.0078137	-0.0320903	0.0197936	-1.23098	7.4911

For distribution to be perfectly normally distributed, skewness and kurtosis value needs to be 0 and 3 respectively. It can be observed from table 1 that many of the return series are negatively skewed with negative values for skewness and kurtosis values are much higher than 3 which indicate the positive excess kurtosis and this kurtosis is called leptokurtic. Negative values of skewness and leptokurtic kurtosis of frequency distribution of KSE 100 Index indicate that all groups of return series are not normal.

The non-normal distribution of log return series deviates from the basic condition of Random Walk Model, thus not weak-form efficient.

5.2. Non-Parametric Tests:

5.2.1. Kolmogorov-Smirnov Goodness of Fit Test:

Kolmogorov-Smirnov goodness of fit test (K-S test) is a non-parametric test that is used to decide if the randomly selected data comes from hypothesized continuous distribution (Chakravarti, Laha & Roy, 1967). K-S test is used to check for normality of data. The advantage of using this test is that it does not make any assumption about the distribution of data as it is based on the empirical cumulative distribution function (ECDF). Given N ordered data points $R_1, R_2, ..., R_N$, and the ECDF is defined as:

$$E_N = n(i)/N$$

where $n(i)$ is the number of points less than $R(i)$; $R(i)$ is the return series for index and the $R(i)$ are ordered from smallest to the largest values. This is a step function that increases by 1/N at the value of each ordered data point (Nist/sematech e-handbook, 2012).

K-S test is a widely used test to check for random walk hypothesis such as Poshakwale (1996), F.M. Zahid, S. Ramzan and S. Ramzan (2012), Elbarghouthi, Yassin, and Qasim (2012) have used it to check for normality in data.

The Kolmogorov-Smirnov test statistic is:

$$D = \max_{1 \le i \le N} \left(F(Y_i) - \frac{i-1}{N}, \frac{i}{N} - F(Y_i) \right)$$

where F is the theoretical cumulative distribution of a continuous distribution (Nist/sematech e-handbook, 2012).

We have used One-sample Kolmogorov-Smirnov test. The Kolmogorov-Smirnov one sample test evaluates the cumulative distribution function for a variable with a uniform or normal distribution and tests whether the distribution is homogeneous (Poshakwale, 1996).

The null hypothesis for this test is that return series are normally distributed and we inspect combined K-S and if the p-value ≤ 0.05, we reject the null of normality at 5% significance level.

Results of Kolmogrov-Smirnov test in table 2 show that for all data sets probability of Z is less than 0.05. So we can reject the null of normality at 5% significance level except for the year 2013. All data sets are not normally distributed except 2013.

Table 2: Results of Kolmogrov-Smirnov test for KSE 100 Index return series.

Data	Combined K-S (Z)	Z-Tailed (P-value)	Results
1992-2012	0.0827	0.000	Not Normal
1992-1994	0.0602	0.012	Not Normal
1995-1997	0.0587	0.017	Not Normal
1998-2000	0.0907	0.000	Not Normal
2001-2003	0.0708	0.001	Not Normal
2004-2006	0.1045	0.000	Not Normal
2007-2009	0.1032	0.000	Not Normal
2010-2012	0.0681	0.002	Not Normal
2013	0.01138	0.239	Normal

5.2.2. Runs Test:

The benefit of the Runs test is that it can be used to check for randomness which may not be perceived by Auto-correlation test. The runs test is a non-parametric test and it is also known as Wald–Wolfowitz test or Geary test. More precisely, it can also be used to check whether the elements of the chain are mutually independent. Each market indices change is designated as a plus (+) sign if it represents an increase or a minus (-) sign if it represents a decrease in index. A run is considered when there is no difference between these two sign changes and if the sign changes differ, then an existing run ends and a new run begins. The null hypothesis is that the observed return series is a random series. The test statistic is defined as (Nist/sematech e-handbook, 2012):

$$Z = \frac{R - \bar{R}}{S_R}$$

where R is the observed number or Runs, $\bar{R}$ is the expected number of runs and S_R is the standard deviation of the number of runs:

Where

R = Total number or runs
$\bar{R} = \frac{2n_1 n_2 + 1}{n_1 + n_2}$

n_1 = Number of Positive Runs
n_2 = Number of Negative runs

$$\sigma = \sqrt{\frac{2\,\text{n}\ln 2\,(2\,\text{n}\ln 2\,-\,\text{n})}{\text{n}^2\,(\text{n}-1)}}$$

$n = \text{n}_1 + \text{n}_2$
z = normal variate

At the 5% significance level, if a test statistic (Z-value) is more than -1.96 and less than +1.96, then the data is random or mutually independent (Sharma & Kennedy, 1977).

The results for Runs test in table 3 show randomness and non-randomness for different groups of data. KSE 100 Index seems like a random market for year 1998-2000 and 2001-2003 and then for 2010-2012 and 2012. Other return series are not random.

Table 3: Results of Runs test for KSE 100 Index return series.

Return Series	Total Observations	Total Number of Runs	Z-Value	Prob (Z)	Results
1992-2012	5090	2244	-8.47	0.000	Non-Random
1992-1994	707	242	-8.46	0.000	Non-Random
1995-1997	691	293	-4.07	0.000	Non-Random
1998-2000	731	347	-1.44	0.150	Random
2001-2003	733	347	-.152	0.130	Random
2004-2006	738	353	-1.25	0.210	Random
2007-2009	738	322	-3.54	0.000	Non-Random
2010-2012	746	362	-0.88	0.380	Random
2013	82	41	-0.22	0.820	Random

To compare the index return series of KSE 100 Index with the companies return series of KSE 100 and KSE 30 Indices, Runs test has also been run on KSE 100 index return series from 2005-2012, as the data for individual company returns was only available for this time period.

Table 4: Result of Runs test for KSE 100 Index return series (2005-2011).

Return Series	Total Observations	Total Number of Runs	Z-Value	Prob (Z)	Result
2005-2011	1726	796	-3.27	0.000	Non-Random

In table 4, return series from year 2005-2012 has a z-value of -3.27, which indicates that this return series is not random.

20 actively traded securities from KSE 100 Index have been randomly selected and we have used maximum volume criterion to signify company as actively traded (Eun & Sabherwal, 2003).

Table 5: Results of Runs test for KSE 100 Index return series (2005-2011).

Individual Companies Return Series, Serial no.	Total Number of Runs	Z-Value	Prob (Z)	Results
1	738	-4.08	0.000	Non- random
2	758	-3.58	0.000	Non- random
3	794	1.73	0.08	Random
4	890	2.87	0.000	Non-Random
5	749	-3.77	0.000	Non- Random
6	860	1.45	0.15	Random
7	649	-0.2	0.84	Random
8	257	-6.35	0.000	Non- random
9	747	-1.43	0.15	Random
10	893	3.30	0.00	Non- Random
11	691	-6.06	0.00	Non- Random
12	744	2.01	0.04	Non-Random
13	795	-1.77	0.08	Random
14	829	-0.07	0.94	Random
15	760	-3.46	0.00	Non-Random
16	831	-0.05	0.96	Random
17	702	-6.02	0.00	Non-Random
18	885	4.59	0.00	Non-Random
19	779	4.54	0.00	Non-Random
20	844	2.14	0.00	Non-Random

The results of runs test in table 5 are showing that out of 20 randomly selected companies, 13 are showing signs of no random behavior in their return series from year 2005-2012, which is consistent with the results of index return series from year 2005-2012. Both series are showing signs of non-randomness in return series. This is not weak-form efficient.

In table 6, 14 out of 20 companies daily return series from KSE 30 Index are random, which is consistent with the general theory and observation that the companies with more free floating stocks tend to have a random walk in their return series as found out in previous empirical study by K. Chan, Y.C. Chan and Fong (2004) on Hong King Stock Market.

Table 6: Result of Runs test for KSE 30 Index return series (2005-2011).

Individual Companies Return Series, Serial no.	Total Number of Runs	Z-Value	Prob (Z)	Results
1	730	-4.87	0.00	Non-Random
2	797	-1.57	0.12	Random
3	827	-0.03	0.98	Random
4	749	-3.77	0.00	Non- Random
5	798	-1.59	0.11	Random
6	773	-2.62	0.01	Non- Random
7	820	-0.64	0.53	Random
8	831	0.18	0.86	Random
9	785	-1.94	0.05	Random
10	691	-6.06	0.00	Non- Random
11	800	-1.28	0.2	Random
12	788	-2.01	0.04	Non-Random
13	756	-2.47	0.01	Non-Random
14	797	-1.72	0.09	Random
15	760	-3.46	0.00	Non- Random
16	807	-0.98	0.32	Random
17	826	-0.42	0.67	Random
18	834	0.17	0.86	Random
19	852	1.16	0.25	Random
20	830	0.08	0.94	Random

We have found out that index return series from 2005-2011 is not random and this is consistent with the majority of non-random return series of 20 companies from KSE 100 Index. 13 out of 20 companies from KSE 100 Index have shown signs of non-randomness while 14 out of 20 companies from KSE 30 Index have shown signs of randomness. The results are consistent with the general theory that the companies with larger free float of shares tend to be less volatile.

5.2.3. Phillips-Perron Test:

The Phillips-Perron (1988) test is a non-parametric test that is used to check whether data has a unit root or not. The advantage of using this test is that it does ask for any level of serial correlation like the Augmented Dickey Fuller test. It is free of parametric errors and it corrects the statistics to accommodate for autocorrelations and heteroskedasticity (Davidson & MacKinnon, 2004). The null hypothesis for this test is that the data has a unit root. If there is a unit root, then it means that the return series is non-stationary. The Phillips-Perron test is based on the following equation:

$$\Delta R_t = \alpha + \beta R_{t-1} + e_t$$

where Δ is the difference operator, R is the index return , α is a constant, β is the slope, ε is the error term and t is the transcript for time.

Results below in table 7 for Phillips-Perron test show that all groups of data have no unit root, which means that all return series are stationary and do not follow random walk.

Table 7: Results of Phillips-Perron test for KSE 100 Index return series.

Return Series	Z (t)	5% Critical Value	P-value	Results
1992-2012	-63.736	-2.86	0.0000	No Unit Root
1992-1994	-18.41	-2.86	0.0000	No Unit Root
1995-1997	-23.038	-2.86	0.0000	No Unit Root
1998-2000	-25.037	-2.86	0.0000	No Unit Root
2001-2003	-25.914	-2.86	0.0000	No Unit Root
2004-2006	-24.797	-2.86	0.0000	No Unit Root
2007-2009	-22.045	-2.86	0.0000	No Unit Root
2010-2012	-26.090	-2.86	0.0000	No Unit Root
2013	-9.777	-2.905	0.0000	No Unit Root

5.3. Parametric Tests:

We have also applied parametric tests to confirm the consistency of results from the non-parametric tests.

5.3.1. Autocorrelation Test:

Autocorrelation test is a consistent measure for testing the dependence or independence for random variables in a series. It is a widely used test to check for randomness. Autocorrelation coefficient measures the correlation degree between the existing stock return and the one which is separated by *k* lags (Campbell, Lo & MacKinlay, 1997).

Many studies have made use of autocorrelation test to check for dependence or independence in series such as Asma et al. (2000), Elbarghouthi et al. (2012) and Nikita & Soekarno (2012). It can be computed as:

$$\rho(k) = \frac{Cov\,(r_t\,,\ r_{t-k}\,)}{\sqrt{Var(r_t)}\,\sqrt{Var\,(r_{t-k})}} = \frac{E[\ (r_t - \mu)(r_{t-k} - \mu)\,]}{E\,[\ (r_t - \mu\,)^2\ ]}$$

where

$\rho\,(k)$ Autocorrelation coefficient of time series.
r_t The return at time t
r_{t-k} The return after k lags.
$Cov\,(\,r_t, r_{t-k}\,)$ The covariance between the two returns.
$Var\,(r_t\,)$, $Var\,(r_{t-k})$ the variance on returns over time period (t, t-k)

Auto-correlation coefficient under the null hypothesis of random walk will not be significantly different from zero.

H_0: $\hat{p}\ = 0$

H_1: $\hat{p}\ \neq 0$

We have also looked at Box-pierce (Q) statistic to look for correlation between return series. Box-Pierce (1970) Q statistic is a portmanteau test that is used to examine the whole set of return series for correlation up to k lags. For instance, return series for 10 lags will examine r_1 to r_{10} all at once. We have used maximum lag as 22. Here is the Box-Pierce formula:

$$Q = n \sum_{k=1}^{h} r_k^2$$

The results in Table 8 show that for return series 1992-2012, autocorrelation coefficients are significant and positive even for higher lags. Furthermore, the coefficients are mostly positive for the sub-periods except for sub-period 2013. This is consistent with empirical findings on stock price movements.

Box-Pierce (Q) statistic tests the null hypothesis that all correlations up to lag 'h' are equal to 0. If Prob>Q is less than 0.05, we can reject the null that all lags are not auto-correlated.

Results of Box-Pierce (Q) statistic in table 8 are showing that there is significant autocorrelation for years 1992-2012, 1992-1994, 1995-1997, 1998-2000 and 2007-2009. No significant autocorrelation is observed for the years 2001-2003, 2004-2006, 2010-2012 and 2013.

Table 8: Results of Autocorrelation and Box-Peirce (Q) Statistic test for KSE 100 Index return series.

Lag	Autocorrelation (1992-2012)	Box-Pierce Q Statistic	Prob>Q	Autocorrelation (1992-1994)	Box-Pierce Q Statistic	Prob>Q	Autocorrelation (1995-1997)	Box-Pierce Q Statistic	Prob>Q
1	0.1261	80.996	0.0000	0.3649	94.556	0.0000	0.1415	13.901	0.0002
2	0.0563	97.17	0.0000	0.1679	114.61	0.0000	0.0646	16.804	0.0002
3	0.0492	109.52	0.0000	0.0763	118.75	0.0000	0.0761	20.84	0.0001
4	0.0208	111.71	0.0000	0.0959	125.31	0.0000	0.0466	22.35	0.0002
5	0.0352	118.02	0.0000	0.1081	133.66	0.0000	0.0269	22.855	0.0004
6	0.0166	119.42	0.0000	0.0142	133.8	0.0000	0.0155	23.023	0.0008
7	0.0212	121.71	0.0000	0.0354	134.7	0.0000	-0.0069	23.057	0.0017
8	0.0336	127.46	0.0000	0.0001	134.7	0.0000	0.0494	24.77	0.0017
9	0.0488	139.59	0.0000	0.0517	136.62	0.0000	-0.0107	24.851	0.0031
10	0.0075	139.88	0.0000	0.0492	138.36	0.0000	-0.0044	24.865	0.0056
11	0.0123	140.65	0.0000	0.0131	138.48	0.0000	0.0101	24.936	0.0093
12	0.0139	141.63	0.0000	0.0093	138.55	0.0000	0.0059	24.96	0.0150
13	0.0134	142.55	0.0000	0.0868	143.99	0.0000	-0.0108	25.043	0.0228
14	0.0106	143.13	0.0000	0.1383	157.82	0.0000	-0.0138	25.178	0.0328
15	0.0168	144.56	0.0000	0.0337	158.65	0.0000	0.0165	25.371	0.0452
16	0.0151	145.72	0.0000	0.0327	159.42	0.0000	-0.0118	25.469	0.0620
17	0.0484	157.69	0.0000	0.0736	163.35	0.0000	0.0435	26.811	0.0609
18	0.0400	165.85	0.0000	0.2039	193.61	0.0000	-0.0113	26.901	0.0809
19	0.0080	166.71	0.0000	0.1657	213.62	0.0000	-0.0546	29.024	0.0656
20	0.0075	166.46	0.0000	0.1382	227.55	0.0000	-0.0008	29.024	0.0873
21	-0.0232	169.2	0.0000	0.0475	229.2	0.0000	-0.0845	34.127	0.0351
22	-0.0196	171.17	0.0000	-0.0740	233.21	0.0000	0.0081	34.2175	0.0471

Lag	Autocorrelation (1998-2000)	Box-Pierce Q Statistic	Prob>Q	Autocorrelation (2001-2003)	Box-Pierce Q Statistic	Prob>Q	Autocorrelation (2004-2006)	Box-Pierce Q Statistic	Prob>Q
1	0.0799	4.6819	0.0305	0.0419	1.2907	0.2559	0.0890	5.8735	0.0154
2	0.0608	7.4018	0.0247	-0.0398	2.4602	0.2923	-0.0052	5.8937	0.0525
3	0.0388	8.5094	0.0366	0.0276	3.0229	0.3881	0.0536	5.0263	0.0455
4	-0.0297	9.1575	0.0573	0.0144	3.1752	0.5290	-0.0094	5.0914	0.0883
5	0.0543	11.335	0.0451	0.0397	4.3391	0.5017	-0.0469	5.7288	0.0833
6	0.0226	11.711	0.0687	0.0095	4.4064	0.6218	-0.0159	9.917	0.1282
7	0.0086	11.765	0.1085	0.0865	9.9597	0.1909	0.0147	10.078	0.1842
8	0.0803	16.547	0.0352	0.0829	15.072	0.0578	-0.0370	11.102	0.1960
9	0.0556	18.843	0.0266	0.0526	17.131	0.0467	0.1312	23.987	0.0043
10	-0.0618	21.683	0.0168	0.0148	17.294	0.0681	0.0570	26.425	0.0032
11	0.0205	21.997	0.0244	0.0527	19.369	0.0548	-0.0395	27.598	0.0037
12	0.0190	22.266	0.0346	-0.0303	20.055	0.0660	0.0217	27.953	0.0056
13	-0.0342	23.138	0.0401	0.0153	20.231	0.0896	0.0432	29.357	0.0058
14	0.0146	23.297	0.0556	-0.0555	22.537	0.0682	-0.0090	29.418	0.0092
15	0.0076	23.339	0.0772	-0.0306	23.24	0.0792	-0.0556	31.757	0.0069
16	-0.0158	23.527	0.1004	0.0411	24.509	0.0790	-0.0407	33.011	0.0074
17	0.0633	26.537	0.0652	0.0212	24.849	0.0981	0.0416	34.324	0.0076
18	-0.0039	26.579	0.0879	0.0268	25.391	0.1145	0.0454	35.888	0.0073
19	-0.0095	26.617	0.01139	-0.0441	26.859	0.1080	0.0274	36.459	0.0093
20	-0.02309	27.047	0.1339	-0.0064	26.89	0.1384	-0.0425	37.83	0.0093
21	-0.0556	29.384	0.1051	-0.0286	27.51	0.1546	0.0581	40.404	0.0066
22	-0.0114	29.482	0.1316	0.0301	28.199	0.1692	-0.0596	43.113	0.0046

Lags	Autocorrelation (2007-2009)	Box-Pierce Q Statistic	Prob>Q	Autocorrelation (2010-2012)	Box-Pierce Q Statistic	Prob>Q	Autocorrelation (2013)	Box-Pierce Q Statistic	Prob>Q
1	0.2234	36.997	0.0000	0.0496	1.84277	0.1746	-0.0981	0.81895	0.3655
2	0.1261	48.796	0.0000	0.0530	3.9516	0.1386	0.0388	0.9483	0.6224
3	0.0623	51.676	0.0000	-0.0144	4.1066	0.2502	-0.0037	0.94947	0.08135
4	0.0782	56.227	0.0000	0.0516	6.1122	0.1909	-0.0179	0.9779	0.9131
5	0.0597	58.881	0.0000	-0.0534	8.263	0.1423	-0.0162	1.0014	0.9624
6	0.0289	59.506	0.0000	0.02233	8.638	0.1950	0.0058	1.0045	0.9854
7	0.0275	60.072	0.0000	-0.0546	10.888	0.1436	-0.0329	1.1036	0.9930
8	-0.0383	61.168	0.0000	0.0248	11.353	0.1825	-0.0765	1.6489	0.9900
9	0.0180	61.412	0.0000	-0.0282	11.956	0.2158	0.0257	1.7114	0.9953
10	0.0545	63.644	0.0000	0.0878	17.806	0.0583	-0.0929	2.5365	0.9903
11	0.0359	64.614	0.0000	-0.0780	22.429	0.0213	-0.0193	2.5728	0.9953
12	0.0242	65.054	0.0000	0.0564	24.845	0.0156	-0.0246	2.6326	0.9976
13	0.0581	67.6	0.0000	-0.0227	25.238	0.0215	-0.0332	2.7423	0.9987
14	0.0195	67.887	0.0000	0.0388	26.385	0.0231	0.0956	3.669	0.9971
15	0.1264	79.949	0.0000	0.0078	26.431	0.0337	-0.0258	3.7373	0.9985
16	0.1059	88.435	0.0000	0.0331	27.27	0.0386	-0.0053	3.7402	0.9993
17	0.0368	89.462	0.0000	0.0387	28.416	0.0403	-0.0974	4.7461	0.9984
18	0.0786	94.148	0.0000	0.0589	31.074	0.0282	-0.1233	6.3819	0.9944
19	0.0517	96.18	0.0000	-0.0269	31.629	0.0344	-0.0159	6.4095	0.9968
20	0.0613	99.035	0.0000	0.0488	33.459	0.0300	-0.0517	6.7068	0.9975
21	-0.0267	99.577	0.0000	-0.0058	33.485	0.0411	0.0442	6.9724	0.9983
22	-0.0440	101.05	0.0000	0.0228	33.887	0.0504	0.0152	6.954	0.9990

5.3.2. Ljung and Box (Q) Statistic Test:

Ljung and Box (1978) is a statistical test to test for autocorrelation in a group of time series. Instead of testing for randomness at each lag like Autocorrelation function test it tests the overall randomness based on the total number of lags. The test statistic (Ljung & Box, 1978):

$$Q = n\,(n+2)\sum_{k=1}^{h}\frac{\hat{p}_k^2}{n-k}$$

where n is the sample size, $\hat{p}_k$ is the sample auto-correlation at lag k and h is the number of lags being tested.

Ljung and Box (Q) statistic tests the null that the data is independently distributed. If p-value is less than 0.05, then we can reject the null of no autocorrelation and return series has autocorrelation at 5% significance level.

Table 9 shows the results of Ljung and Box (Q) statistic test and they indicate that all return series have autocorrelation except 1998-2000, 2001-2003 and 2013.

Table 9: Results of Ljung and Box (Q) Statistic test for KSE 100 Index return series.

Return Series	Q statistic	Prob	Result
1992-2012	203.4126	0.0000	Autocorrelation
1992-1994	253.4550	0.0000	Autocorrelation
1995-1997	57.6131	0.0352	Autocorrelation
1998-2000	48.8482	0.1592	No Autocorrelation
2001-2003	44.5521	0.2861	No Autocorrelation
2004-2006	73.2243	0.0010	Autocorrelation
2007-2010	127.2396	0.000	Autocorrelation
2010-2012	57.7562	0.0342	Autocorrelation
2013	18.0297	0.9984	No Autocorrelation

5.3.3. Augmented Dickey-Fuller Test:

Augmented Dickey-Fuller (Dickey & Fuller, 1981) is an augmented version of Dickey-Fuller test. Augmented Dickey-Fuller test is the most extensively used and popular stationarity test. It was first devised by David Alan Dickey and Wayne Arthur Fuller in 1979 and 1981. ADF tests for unit root in the data. Null hypothesis says that data has a unit root.

The augmented Dickey-Fuller (ADF) statistic is a negative number. More negative the test statistic, stronger the rejection of the hypothesis that there is a unit root in the data. The Null Hypothesis is that data has a unit root and it can be estimated by using the following equation through OLS:

$$\Delta P_t = a_0 + a_1 t + \rho_0 P_{t-1} + \sum_{i=1}^{q}\rho_i\,\Delta P_{it-i} + \in_{it}$$

where P_t is the price at time t, $\Delta P_t = P_t - P_{t-1}$, ρ_i are coefficients to be estimated, q is the number of lagged terms, t is the trend term, a_1 is the estimated coefficient for the trend, a_0 is the constant and $\in_i$ is white noise.

Augmented Dickey-fuller test results in table 10 show that all groups of return series have no unit root. It means that all series are stationary and not behaving according to the random walk model.

Table 10: Results of Augmented Dickey-fuller test for KSE 100 Index return series.

Return Series	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	P-value	Results
1992-2012	-26.432	-3.430	-2.860	-2.570	0.0000	No Unit Root
1992-1994	-9.257	-3.430	-2.860	-2.570	0.0000	No Unit Root
1995-1997	-9.502	-3.430	-2.860	-2.570	0.0000	No Unit Root
1998-2000	-10.113	-3.430	-2.860	-2.570	0.0000	No Unit Root
2001-2003	-10.342	-3.430	-2.860	-2.570	0.0000	No Unit Root
2004-2006	-11.219	-3.430	-2.860	-2.570	0.0000	No Unit Root
2007-2009	-9.438	-3.430	-2.860	-2.570	0.0000	No Unit Root
2010-2012	-10.785	-3.430	-2.860	-2.570	0.0000	No Unit Root
2013	-3.486	-3.544	-2.909	-2.590	0.0084	No Unit Root

5.3.4. Dickey-fuller GLS Test:

Elliott, Rothenberg and Stock proposed an efficient test after modifying the Dickey-Fuller test statistic using a generalized least squares (GLS) rationale (Elliott, Rothenberg and Stock, 1996). According to Elliot et al. (1996), their test has superior power when there exists an unknown trend or mean in data.

In STATA, maximum lag order selection is specified or default value is calculated as provided by Schwert (1989) criterion. For optimal lag order selection, Ng-Perron (1995) sequential test criterion is used. Lag length chosen by Ng-Perron is generally preferred. The null hypothesis is that the data has unit root. Results are quoted using optimal lag selection via Ng-Perron criterion.

DF-GLS test results in table 11 shows that the data has no unit root for all groups of series except 2010-2012 and 2013. All return series are stationary except 2010-2012 and 2013.

Table 11: Results of Dickey-fuller GLS test for KSE 100 Index return series.

Return Series	Test Statistic	Optimal lag length (Ng-Perron seq t)	1% Critical Value	5% Critical Value	10% Critical Value	Result
1992-2012	-10.932	32	-3.480	-2.834	-2.546	No Unit Root
1992-1994	-4.053	19	-3.480	-2.825	-2.541	No Unit Root
1995-1997	-4.209	16	-3.480	-2.832	-2.547	No Unit Root
1998-2000	-7.222	9	-3.480	-2.849	-2.562	No Unit Root
2001-2003	-6.321	13	-3.480	-2.840	-2.554	No Unit Root
2004-2006	-5.924	16	-3.480	-2.833	-2.548	No Unit Root
2007-2009	-3.149	17	-3.480	-2.830	-2.546	No Unit Root
2010-2012	-1.920	19	-3.480	-2.826	-2.541	Unit Root
2013*	-2.479	11	-3.648	-2.739	-2.465	Unit Root

**For 2013, optimal lag length via Ng-Perron criterion was 0, so we have used max lag length via Schwert criterion to quote results.*

5.3.6. Kwiatkowski, Phillips, Schmidt and Shin (KPSS) Test

Kwiatkowski-Phillips-Schmidt-Shin test (KPSS test) is introduced by Kwiatkowski, Phillips, Schmidt and Shin (1992) in their paper, "Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root". The null of the test says that series is stationary around deterministic trend. The KPSS test statistic is the Lagrange Multiplier test which holds the hypothesis that random walk has zero variance (Kwiatkowski, Phillips, Schmidt & Shin, 1992). In KPSS test, the series of observations is sum of three elements: deterministic trend, a random walk, and a stationary error term. The test statistic is defined as:

$$\mathrm{KPSS} = \left(\mathrm{T}^{-2} \sum_{t=1}^{\mathrm{T}} \hat{\mathrm{S}}_{\mathrm{t}}^{\mathrm{t}}\right) / \, \lambda^2$$

where $\hat{S}_t = \sum_{j=1}^{t} \hat{u}_j$, $\hat{u}_t$ is the residual of a regression of of y_t on D_t (deterministic trend), and $\hat{\lambda}^2$ is a consistent estimate of the long-run variance of u_t using $\hat{u}_t$ (Kwiatkowski et al., 1992).

Table 13 summarizes the results of the KPSS test. With the exception of time periods 1992-1994 and 2007-2009, all sub-periods, as well as the overall period was giving statistic values less than the critical values for all lags. Hence, the null was failed to be rejected for these periods, depicting a trend stationarity and no unit roots at 5% and 1% significance levels.

Table 13: Results of KPSS test for stationarity of return series.

Data	Result
1992-2012	Trend stationary (No unit root)
1992-1994	Unit root
1995-1997	Trend stationary (No unit root)
1998-2000	Trend stationary (No unit root)
2001-2003	Trend stationary (No unit root)
2004-2006	Trend stationary (No unit root)
2007-2009	Unit root
2010-2012	Trend stationary (No unit root)
2013	Trend stationary (No unit root)

Critical values for H0: returns is trend stationary
10%: 0.119, 5%: 0.146, 2.5%: 0.176, 1%: 0.216

5.3.6. Auto-regression Test:

We have next applied an autoregressive model with two lags to check if there exists a non-zero significant relation between current return series with first and second lag of return series. An autoregressive model of order p (denoted AR (p)) can be defined as:

$$R_t = c + \beta_0 R_{t-1} + \beta_1 R_{t-2}$$

where R_t is the Index return series, R_{t-1} is the first lag of return series, R_{t-2} is the second lag of the same return series, B_0 is the coefficient of the first lag and B_1 is the coefficient of the second lag. If the coefficient is significantly different from zero, then share return can be predicted from the past information.

To check for the overall significance of first two lags on the current return series, we are going to look at the Prob(F). If Prob(F) is less than 0.05 , then we can reject the null of no significance at 5% significance level. The results of auto regression model of order 2 (AR(2)) in table 13, shows overall significance for first two lags on the current return series at 5% significance level for return series 1992-1994, 199-2012, 1995-1997 and 2007-2009 and no overall significance for return series 1998-2000, 2001-2003,2004-2006, 2010-2012 and 2013.

Moreover, the first lag is also statistically significant for return series 1992-2012, 1992-1994, 1995-1997, 1998-2000, 2004-2006 and 2007-2009, while first lag is of no significance for 2001-2003, 2010-2012 and 2013; though the second lag is not significant for all except 1992-2012 and 2007- 2009.

Therefore, overall analysis postulates that for the return series 2001-2003, 2010-2012 and 2013, the lags of return series do not cause the current return series. Therefore only in these years, market seems weak-form efficient because of the independency of lags.

Table 13: Results of Auto-regression for KSE 100 Index return series.

Return series (1992-2012)	**Coefficients**	**SE**	**T-value**	**Prob (t)**	**F-value**	**Prob (F)**	**Result**
L1	0.1209425	0.0140113	8.63	0.000	45.47	0.0000	Significant
L2	0.0419053	0.0140113	2.93	0.003			
Constant	0.0003804	0.0002182	1.74	0.081			
Return series (1992-1994)							
L1	0.3506628	0.0377135	9.30	0.000	54.70	0.0000	Significant
L2	0.0398573	0.0377492	1.06	0.291			
Constant	0.0001743	0.0004008	0.43	0.664			
Return series (1995-1997)							
L1	0.1348827	0.038149	3.54	0.000	7.72	0.0005	Significant
L2	0.0457024	0.0381509	1.20	0.231			
Constant	-0.0002078	0.0005656	-0.37	0.713			
Return series (1998-2000)							
L1	0.0752352	0.0370697	2.03	0.043	3.42	0.0332	Not Significant
L2	0.0548875	0.0371092	1.48	0.140			
Constant	-0.000147	0.0008584	-0.17	0.864			
Return series (2001-2003)							
L1	0.0434985	0.0370004	1.18	0.240	1.27	0.2810	Not Significant
L2	-0.041661	0.0370009	-1.13	0.261			
Constant	0.0014465	0.0005742	2.52	0.012			

Return series (2004-2006)							
L1	0.0902387	0.0369311	2.44	0.015	3.00	0.0506	Not Significant
L2	-0.0132618	0.0369312	-0.36	0.720			
Constant	0.0010055	0.0005887	1.71	0.088			
Return series (2007-2009)							
L1	0.206075	0.0368365	5.59	0.000	21.84	0.0000	Significant
L2	0.0800258	0.0368332	2.17	0.030			
Constant	-0.0000792	0.0005745	-0.14	0.890			
Return series (2010-2012)							
L1	0.0450894	0.0366822	1.23	0.219	1.81	0.1641	Not Significant
L2	0.0507976	0.0365348	1.39	0.165			
Constant	0.000669	0.0003326	2.01	0.045			
Return series (2013)							
L1	-0.0985165	0.1142888	-0.86	0.391	0.43	0.6512	Not Significant
L2	0.030556	0.1145942	0.27	0.790			
Constant	0.0017428	0.0009317	1.87	0.065			

5.3.7 ARIMA (Auto-Regressive-Integrated-Moving Average) model:

Enders (2004) considers an ARIMA model of the U.S. Wholesale Price Index (WPI) using quarterly data from the first quarter of 1960 to the fourth quarter of 1990. ARIMA models form a vital division of the Box-Jenkins approach to time-series modeling and they are helpful for non-stationary data.

As we know from the theory that ARIMA (0,1,0) supports the random walk model where future price can be determined from the past information.

$$\hat{R}(t) - R\,(t-1) = \mu$$

where $\hat{R}(t)$ is the current return series and $\hat{R}(t-1)$ is the first lag of return series.

We have tried to fit in the relevant ARIMA models. We have used ARIMA instead of ARMA because it also makes use of the integration process. The regression has been run on the return series from 1st January, 1992 to 30th April, 2013 to analyze the entire dataset (5214 observations).

Table 14: Results of ARIMA models for KSE 100 Index return series.

ARIMA (0,1,0)	Coefficient	SE	Z-value	Prob (Z)	AIC	BIC
Constant	1.06e-06	0.0002892	0.00	0.997	**-25463.12**	**-25450.02**
ARIMA (1,0,0)						
AR(L1)	0.1251669	0.0082973	15.09	0.000	**-28442.38**	**-28422.73**
Constant	0.0004682	0.0002511	1.86	0.062		
ARIMA (1,0,1)						
AR(L1)	0.6363774	0.0372153	17.10	0.000	**-28457.3**	**-28431.1**
MA(L1)	-0.5293785	0.0417881	-12.67	0.000		
Constant	0.0004684	0.0002914	1.631	0.108		
ARIMA (2,0,1)						
AR (L1)	0.9667974	0.0385789	25.06	0.000	**-28464.51**	**-28431.76**
AR(L2)	-0.0683735	0.0117752	-5.81	0.000		
MA(L1)	-0.8506271	0.0373949	-22.75	0.000		
Constant	0.0004678	0.0003309	1.41	0.157		
ARIMA (2,0,2)						
AR(L1)	1.078932	0.1821216	5.92	0.000	**-28462.67**	**-28423.37**
AR(L2)	-0.1629264	0.147156	-1.11	0.268		
MA(L1)	-0.9632032	0.1830158	-5.26	0.000		
MA(L2)	0.0870675	0.1337364	0.65	0.515		
Constant	0.0004675	0.0003323	1.41	0.159		

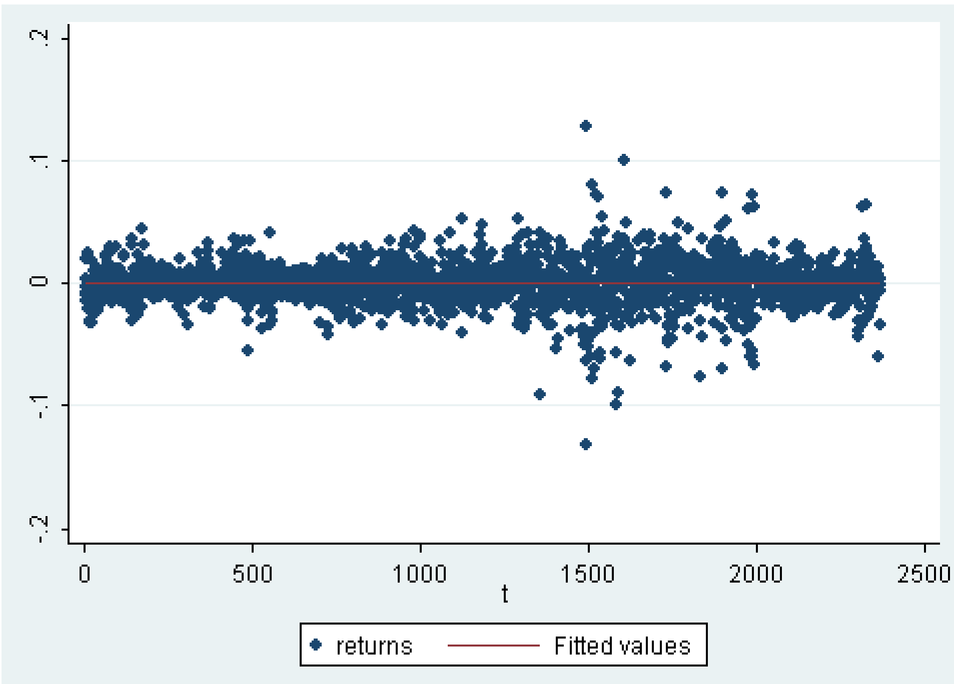
Results of ARIMA modeling in table 14 are showing that ARIMA (0,1,0), which supports the random walk model, is not significant with Prob(Z) of 0.997. In diagnostic checking, the residuals autocorrelations are significant for all models up to 20 lags except for ARIMA (2,0,1). Through AIC and BIC criteria, ARIMA (2,0,1) also has the minimum AIC and BIC values, so our best fitted model is ARIMA (2,0,1).

5.3.8. Building a predictive model:

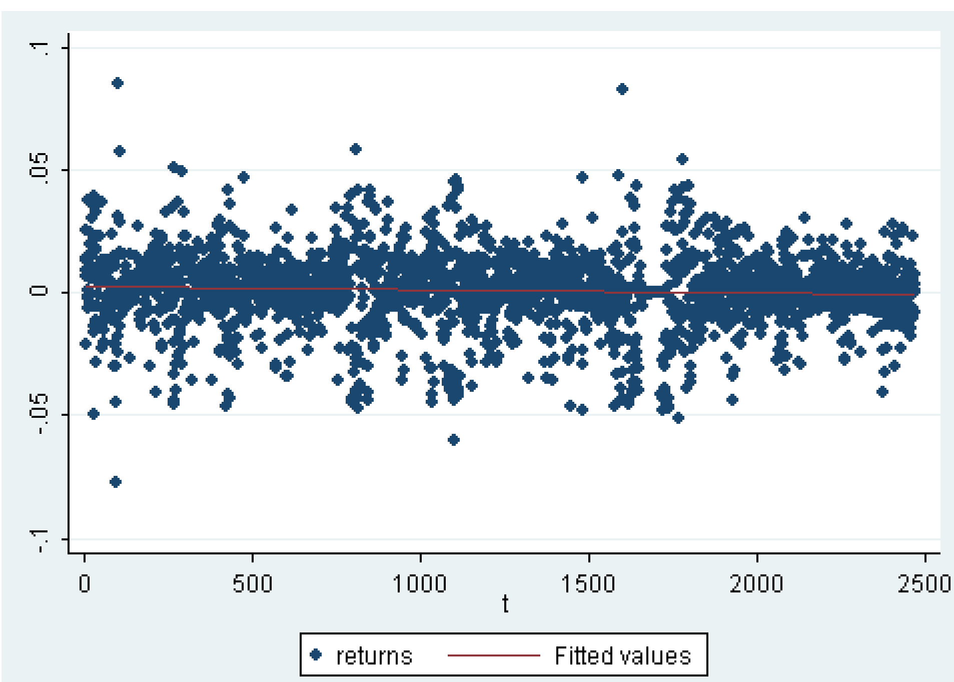
We have attempted to make a predictive model to see if we can predict the future values based on the past values or not. Our best fitted model is ARIMA (2,0,1) because it is with the lowest AIC and BIC values. We have divided the data of return series into two parts to examine if one set of data can be used to predict the future.

Observations have been divided into two groups, 1992-2001(2370 observations) and 2002-2011(2471 observations). We have treated 1992-2001 as the historical data and have used these values to predict the future observations of 2002-2011. We have attempted to look at the pattern in historical and future data by looking at the scatter plot and line of trend.

1992-2001(2370 observations)-Historical data



2002-2011(2471 observations)-Future data



The graphs for historical data and future data show the same patterns for return series providing the evidence that prediction for return series is possible.

6. Conclusion

After analyzing the results of parametric and non-parametric tests, we have considered the overall market performance of KSE 100 Index from 1st January 1992 to 30th April 2013. We can say that the overall market is not weak-form efficient. However, from 2001-2003, the market has shown some signs of weak-form efficiency and over the last four years (2010-2012 and 2013), the results of different tests have showed that the market is moving towards efficiency.

In this paper, we have attempted to test for weak-form efficient market hypothesis in KSE 100 Index by checking for random walk hypothesis. We found that KSE 100 does not follow random walk hypothesis and investors can make abnormal profits by forecasting prices on the basis of historical data. Thus overall market is not weak-form efficient.

For 1998-2000, 2001-2003 and 2004 -2006, results of Runs test and Autocorrelation test provide evidence of randomness and independency in return series, as well as stationarity. For 2010-2012 and 2013, results of Runs test, Autocorrelation test and Dickey-fuller GLS show evidence of randomness, independency and non-stationarity of return series. The KPSS test shows trend stationarity overall, as well as in all sub-periods except 1992-1994 and 2007-2009. Runs tests for actively traded companies showed that companies with a larger free-float tend to display more signs of random walk. Results of Auto-regression show that lags have significant impact on the current return series for years 2001-2003, 2010-2012 and 2013. Thus some of the tests have provided evidence of randomness in the KSE-100 Index from 2001-2003 and from 2010 onwards, hence leading to weak-form of market efficiency.

However, the results in this paper have some limitations too. To our notice, we have not considered the profit making strategies of traders and we have not adjusted for transaction costs (such as brokerage commission, bid-ask spread, and time lag of settlement procedures between different parties). Many of these have significant impact on liquidity considerations, which in turn impact autocorrelations, as suggested by Jegadeesh (1990) and Lehmann (1990).

KSE 100 Index is a backbone of Pakistani stock exchange. Pakistan, as an emerging economy, still has a lot to develop in its stock markets for individual and institutional investors. Inefficiency of KSE 100 Index market can be due to many reasons such as working of the colluding brokerages (Khawaja and Mian, 2005), lack of sophisticated communication and information dissipation technology, lack of market regulations, monopolistic trends and insider information. However recently, Stock Exchange Commission of Pakistan (SECP) has taken significant steps to make our markets more efficient and our investors more responsible. In July, 2012, SECP has directed stock exchanges to introduce certification programs. Since October 15th, 2012, KSE is a free-float Index and recently, KSE has been demutualized.

Future studies can suggest ways as to how KSE 100 Index can become more efficient by adopting certain practices and getting rid of others and the causes behind some tests showing signs of weak-form efficiency in particular groups of years.

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