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SERIAL DEPENDENCE IN THE DHAKA STOCK EXCHANGE RETURNS: AN EMPIRICAL STUDY

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ABSTRACT

This study reviews the econometric specification of the null hypothesis that stock returns are serially independent against the alternative that they are not. Tests used in this study are the well-known runs test and the variance ratio test. The fact that stock returns are serially dependent has important practical and theoretical consequences for financial economists and also for the market participants. Firstly, if returns are serially dependent, their variance will depend on the time interval used to estimate returns. Secondly, when asset returns are serially dependent, they become predictable, at least partially. Together, these consequences imply that active fund management can "beat the market". Test results obtained in this study suggest significant linear dependence between weekly lagged price changes (returns) of the Dhaka Stock Exchange.

Introduction

This study aims at examining the serial dependence structure of stock returns of the Dhaka Stock Exchange (hereafter, *DSE*). It also scrutinizes the least restrictive version of the random walk hypothesis that return increments are serially uncorrelated.[1] Serial dependence means that observations of a series are correlated with their prior values. Such dependence in a time series has two variations. One is known as mean reversion. This occurs when returns or asset prices tend to revert to the long run equilibrium or mean value. In other words, when above or below equilibrium returns tend to go back to their mean level, they are termed as mean reverting. The second variation of serial dependence is asset returns, known as trend or *mean aversion*. In a trending situation, returns are more likely to go away from their mean levels. In other words, above equilibrium positive returns will be followed by positive returns and/or below equilibrium negative returns will be followed by negative returns.[2]

Stylized facts about serial dependence in speculative asset prices can be summarized as follows:

(a) Asset returns show positive autocorrelation over short horizons, e.g., 1-12 months and negative correlation over longer periods, e.g., 13-24 months (Poterba and Summers, 1988; Campbell *et al*, 1997).

(b) Patterns of serial dependence mentioned in (a) are similar in different markets irrespective of the market specific risk (Huang, 1996; Chow *et al*, 1996).

Nonsynchronous trading is perhaps the most widely recognized source of serial dependence in portfolio returns (Scholes and Williams, 1977; Lo and MacKinlay, 1988, 1990; and Kadlec and Patterson, 1999). It refers to the phenomenon that all securities do not trade with the same frequency. Some securities trade almost every day whereas others do not. New information will be first impounded in security prices that are traded frequently followed by those not traded frequently. Therefore, prices of infrequently traded stocks reflect information of an earlier time. Stale prices for infrequently traded stocks can in turn artificially induce positive dependence in returns of a portfolio consisting mostly of these stocks.

Feedback traders in the market may also cause serial dependence in asset returns (Cutler *et al*, 1990; Shleifer and Summers, 1990; Sentana and Wadhwani, 1992).[3] The term feedback trading depends entirely on the speed with which traders incorporate new and relevant news into demand.[4] In the case of positive feedback trading, traders buy after price increases; and in the case of negative feedback trading traders sell after price increases. If traders react differently to price increases than to price decreases, the effect of such reactions on the index returns may be asymmetric. In a simple model of feedback trading and return autocorrelation, Sentana and Wadhwani (1992) show that positive feedback trading results in negative return autocorrelation while negative feedback trading results in positive return autocorrelation.

The serial dependence in asset returns has the following theoretical consequences:

(a) Firstly, if returns are serially dependent, their variance will depend on the time interval used to estimate returns. Instead of varying proportionately, variance will grow at a higher rate when asset returns are positively correlated and at lower rate when they are negatively correlated. For an autocorrelated process, variance will decay at a rate different from the usual rate of T^{-1}.

(b) Secondly, when asset returns are serially dependent, they become predictable, at least partially.

From the viewpoint of investment strategy, that is, from the practitioner's viewpoint serial correlations in asset returns have the following consequences:

(a) A positive serial correlation in asset returns would be exploited by a strategy of buying after periods with positive returns and selling after periods with negative returns.

(b) On the other hand, a negative serial correlation would suggest a strategy of buying after periods with negative returns and selling after periods with positive returns.

This study is structured as follows. In the following section, a brief description of the relevant literature is included. Next, tests used to identify serial dependence in the *DSE* composite return index, that is, the runs test and the variance ratio tests, are briefly discussed. Data used in this study and their statistical properties are then discussed followed by empirical findings. The final section concludes this study with some policy implications of the empirical findings.

Brief Review of Related Literature

Serious empirical research for whether share prices follow a random walk or not can be dated back to 1965. With the objective of testing the random walk hypothesis, Fama (1965) calculated the serial correlations and applied the runs test to daily prices of 30 stocks of the Dow-Jones Industrial Average ($DJIA-30$) for the period of 1957-62. He found a little evidence of linear dependence in daily, 4-, 9-, and 16-day price changes. Fama concluded that the evidence of serial dependence in the $DJIA-30$ stocks is not enough to be exploited by traders to increase expected profits.

Poterba and Summers (1988) conducted an extensive study using various frequencies of data from the New York Stock Exchange (*NYSE*) and 17 other equity markets. Their study consistently showed that returns are positively correlated over short periods but negatively autocorrelated over longer periods. In addition, Poterba and Summers found that for the long horizon, a mean reverting component of stock prices could explain a large portion of variations in stock returns.

Using weekly data of the *NYSE* during 1962-85, Lo and MacKinlay (1988) examined whether stock prices followed the random walk pattern. They found strong evidence of positive serial dependence in successive differences of weekly stock price indexes and individual securities. They rejected the null hypothesis of random walk both for the value and equally weighted portfolios. Using the variance ratio test for size based portfolios, Lo and MacKinlay found that the greatest deviations from market efficiency occurred for small stocks. However, to be appropriate, random walk representation of stock prices requires the variance ratio to fall below unity at the second period difference and to decline as the differencing period grows. However, an important aspect of their study is that neither of these conjectures were supported for the data.

Richardson and Stock (1990) reappraised the evidence of mean reversion in stock prices using the variance ratio and multi-period return autoregression. They challenged the previous findings that variation in 3- to 5-year holding period stock returns is predictable because of the slowly decaying autocorrelation structure. They indicated mean reversion primarily as a phenomenon of the 1926-1946 period, which includes the Great Depression and World War II, when the stock market was highly volatile. On the contrary, post-war data displayed only mean aversion. However, the evidence of mean aversion after World War II was shown to be as strong as that for mean reversion over the whole period. Using the randomization method by shuffling the sample of returns to develop standard error and significance levels for the test statistics free of any distributional assumptions, Richardson and Stock showed that evidence in support of mean reversion uncovered by analysis of the post-1947 data was produced by sampling error.

Huang (1996) used the variance ratio test to examine the random walk hypothesis for nine Asian countries, namely, Hong Kong, Indonesia, Japan, Korea, Philippines, Singapore, Thailand, Malaysia, and Taiwan. Using weekly stock price data from January 1988 to June 1992 of the nine countries, Huang applied both the heteroskedasticity unadjusted and heteroskedasticity adjusted variance ratio test to the data. He found that stock prices of Malaysia and Korea showed positive serial correlation for all the holding periods. whereas, the stock prices of Hong Kong, Singapore and Thailand showed positive serial dependence for some of the holding periods.

Haque *et al.* (1998) examined whether the introduction of automated trading along with the changes in regulatory measures changed the risk return composition and thus improved the market efficiency of the *DSE*. They concluded that the *DSE* at best can be considered as weak-form efficient and the automation and other regulatory measures have done little or nothing at all to change the risk return composition of the market.

In order to compare emerging and developed stock markets in terms of efficiency, Chowdhury (1999) applied Damodaran's (1991, 1993) models to measure the price adjustment coefficients of individual securities over different return intervals. That is, he tested for semi-strong form efficiency of the market. Chowdhury found that information adjusts faster in India and in Malaysia than in other emerging countries (Bangladesh, Pakistan and Indonesia) included in his study during the 1990s.

Methods for Detecting Serial Dependence in Asset Returns

In order to test for serial dependence in the return data, we selected two common statistical techniques: the first one is the runs test, which is a simple non-parametric test. The second one is the variance ratio test proposed by Lo and MacKinlay (1988), which is a direct parametric and much more developed test of serial dependence than other alternative tests (Faust, 1992). In what follows, we provide a brief description of both tests mentioned above.

The Runs Test:

The simplest intuitive way to detect serial dependence in a series is to conduct a runs test, often called Geary's test after its proponent (Geary, 1970). The runs test is based on positive and negative runs from the mean.[5] A run is defined as an uninterrupted sequence of positive/negative values. For example, a sequence of three positive values $(+++)$ would constitute a run. On the other hand, a sequence of four alternative positive and negative values $(+-+-)$ would constitute four runs (for mathematical detail of the test, see Cambell *et al.*, 1997). The expected number of runs, $E(R)$, in a random sequence is given by the following formula:

$$E(R) = \frac{2n_1 n_2}{n_1 + n_2} + 1$$

Where, n_1 = Number of positive observations and

n_2 = Number of negative observations

By comparing the number of runs in the data with the expected number of runs under the $i.i.d.$ random walk increments, a test of identically and independently distributed $(i.i.d.)$ random walk hypothesis may be constructed.[6]

In order to determine whether or not the actual number of runs is significantly different from the expected number of runs, the standard deviations of runs is calculated as follows:

$$S(R) = \sqrt{\frac{2n_1 n_2[2n_1 n_2 - n_1 - n_2]}{(n_1 + n_2)^2(n_1 + n_2 - 1)}} \quad [2]$$

Once the standard deviation of the runs is known, one can compute the normal deviation by dividing the difference between the expected and actual number of runs by the estimated standard deviation.

However, a runs test is limited in scope because it deals with only the direction of a series and with the number of observations that are above or below the average. It does not consider the extent to which the observation of a series differs from the mean value. Parametric procedures of measuring serial dependence, such as the variance ratio test, rely not only on the rank of a series but also on the magnitude of observations and are thus considered as a better measure

The Variance Ration Test:

An important property of a homoskedastic random walk series is that the variance of its increments is a linear function of the time interval over which the increment is computed. If we consider that the continuously compounded returns, that is, $r_t = \ln p_t - \ln p_{t-1}$, are $i.i.d.$, the variance of $r_t + r_{t-1}$ must be twice that of the one period return, r_t, where p_t and p_{t-1} are current and one period lagged stock prices respectively and "ln" indicates natural logarithm. That is, for a random walk with $i.i.d.$ increments, the variance of two-period returns, $Var[r_t(2)]$, where $r_t(2) = r_t + r_{t-1}$, should be twice the variance of one-period return. The ratio of these two variances scaled by the time intervals should be equal to unity, that is, $\frac{Var[r_t + r_{t-1}]}{2 \times Var[r_t]} = 1$. More generally, the variance ratio formed for the k-period returns (relative to 1-period return) is, $VR(k) = \frac{Var[r_t(k)]}{k \times Var[r_t(1)]} = 1$ [7]
[1]
Under the null hypothesis of random walk, the test statistic can be written as: $H_0 : VR = 1$ against the alternative $H_1 : VR \neq 1$. Alternatively, $VR < 1$ indicates mean reversion and $VR > 1$ indicates mean aversion and both indicate forecasting gain (readers interested in mathematical detail of the test may see, Cambell *et al.*, 1997).

Data and the Summary Statistics

In this study, stock return is defined as the difference in the logarithm of prices, that is, $r_t = \ln p_t - \ln p_{t-1}$, where $\ln p_t$ and $\ln p_{t-1}$ are current and one-period back log prices, respectively. Stock returns defined above are nominal only, and do not take into account the effects of dividends, inflation and exchange rates. The data used in this study consists of 522 weekly observations of all share DSE price index from the first week of January 1989 to the last week of December 1998, obtained from various issues of the DSE monthly bulletin and national dailies. The weekly stock returns are calculated from weekly closing prices. If the closing price for a week is not available (due to non-trading, or government holidays), then previous week's closing price is used instead as this week's price (and this occurs only rarely). Weekly share price data are used because one can have many more data points than monthly or yearly series and at the same time can avoid the market microstructure effect present in daily observations.[8]

Before testing for the presence of serial dependence, this study scrutinizes statistical properties of the weekly *DSE* return series in detail. In particular, this study looks at the various descriptive statistics such as the mean, variance, skewness, kurtosis, and normality of the *DSE* stock return series. Table 1 reports various descriptive statistics for the *DSE* return series. The overall weekly *DSE* mean return is positive but statistically insignificant over the entire sample period.[9] The null hypothesis of zero average weekly return can not be rejected at any standard significance level. The median *DSE* return is negative. In large samples of normally distributed data, the estimators of skewness and kurtosis coefficients are normally distributed with means 0 and 3 and variances $6/T$ and $24/T$, respectively. Since the value of the kurtosis coefficient of the normal distribution is 3, the sample excess kurtosis is equal to sample kurtosis minus 2. Sample estimates of skewness and excess kurtosis for weekly *DSE* returns are both large and positive. This indicates that returns have more mass in the tails (skewed to the right) than that of a normal distribution. The standard errors for the sample kurtosis estimate under the null hypothesis of normality is $24/\sqrt{T} = \sqrt{24/522} = 0.214$. Therefore, the sample kurtosis is statistically significant. The standard error for the skewness estimate under null of normality is $\sqrt{6/T} = \sqrt{6/522} = 0.107$. Thus, the skewness estimate of the *DSE* weekly return series is also statistically significant. In other words, the distribution of the *DSE* weekly stock returns is fat or heavy-tailed which also indicates that there are some unusually large numbers of outliers (these outliers occurred during the end of 1996, when the *DSE* crashes). The value of the *Studentdized Range* and the *Jaque-Bera* normality statistics are significant indicating that the weekly return series is not normally distributed.[10] All these results support that the weekly *DSE* return series follows a heavy-tailed non-Gaussian distribution.

In order to investigate the independence of successive log price changes, correlogram of the weekly *DSE* return series are plotted in Figure 3 up to a maximum lag of 60 weeks. The correlation coefficient, ρ_k, of a series measures the amount of linear dependence between observations separated by lag k. If a series is an *i.i.d.* process its sample autocorrelation, ρ_k, will be zero for all values of k and will be approximately distributed as $N\left(0, \frac{1}{T}\right)$. The horizontal lines on the autocorrelation plots are ± 2 standard error band for the sample autocorrelation given the null hypothesis that the data series is serially uncorrelated. The correlogram of the weekly return series, r_t, in Figure 2 has a distinctive shape. The persistent and mainly positive autocorrelations found at distant lags indicate that the *DSE* return series may have a long memory component.[11]

Empirical Findings

By examining how runs behave in a random sequence of observations, one can comment on results of the runs test. If the null hypothesis of no serial dependence is supported by the data, the number of runs obtained from the series r_t should lie between $\left[E(r_t) \pm 1.96 \times \sigma_t\right]$ with 95% confidence. Table 2 shows that we obtain number of positive runs (n_1) equal to 245 and number of negative runs (n_2) equal to 269, whereas, the expected number of runs is 257.44. Hence, the 95% confidence interval is, $[257.44 \pm 1.96 \times 11.30 = 257.44 + 22.148 = 279.588]$. Since the actual number of runs is 197, we can reject the null hypothesis that the weekly *DSE* stock returns are serially independent with 95% confidence. Alternatively, the *DSE* price series has fewer than expected number of runs which indicates that the series' typical run is shorter than a random walk series; that is, the series is trending away from the mean over the sample period.

Table 2 contains the results of the variance ratio test. The main row of Table 2 reports the variance ratios for various values of k ranging from 2 to 54. The second and third rows of the same table contain heteroskedasticity-unadjusted and heteroskedasticity-robust test statistics $Z(k)$ and $Z^*(k)$, respectively. As can be seen in the first row of Table 3, all estimates of the variance ratios are greater than 1 and become larger with the increase in k. This suggests that the riskiness of an investment in the *DSE* index increases with the increment in the return horizon. In particular, the entry 1.175 in the $k=2$ column implies that two-week returns have a variance that is 17.5% higher than twice the variance of one-week returns. Of course, it should be emphasized that this increase in riskiness applies only to return horizons from $k=2$ to $k=30$. For much longer return horizons, for example, $k=36$ or greater, there is some weak evidence that variances grow less than linearly with the return horizon. The empirical evidence that the variance of the *DSE* returns grows faster than linearly demonstrates a gross inconsistency between the "uncorrelated returns" version of the random walk hypothesis and the data.

The $Z(k)$ test statistics provided in the second row of Table 2 are all significant except for $k = 54$, at the conventional 5% significant value of 1.96. On the other hand, the $Z^*(k)$ test statistics are significant for all but $k = 2$ and $k = 54$. The insignificance of the $Z^*(k)$ test statistics for $k = 2$ can be attributed to the fact that the non-randomness in the DSE return series arises mostly from the change in its variance. However, for $k = 4, 6, 12, 18, 24, 30, 36, 42,$ and 48, both the test statistics reject the null hypothesis of no serial correlation in the data. It should be mentioned here that the longer horizon inferences are less dependable than the shorter horizon inferences because they use fewer data points (Campbell *et al.*, 1997). A noticeable feature of the test statistics reported in Table 3 is that the values of the $Z^*(k)$ test statistics are always smaller than the values of the $Z(k)$ test statistics, which supports the empirical findings of Lo and MacKinlay (1988).

However, results of the variance ratio obtained in this study do not indicate that DSE is inefficient or that prices are not rational assessments of fundamental values. Lo and MacKinlay (1988) point out that rational expectations equilibrium prices do not need to form a martingale sequence (of which the random walk is a special case). Hence, without a more explicit model of price generation, a rejection of null hypothesis of random walk has few implications. What our results do imply, though, is that any such model must be able to explain the pattern of positive autocorrelation found in DSE weekly returns.

Conclusions and Policy Implications

This study investigates the serial dependence in the weekly composite stock return index of the Dhaka Stock Exchange. Alternatively, this study tests the "uncorrelated returns" version of the random walk hypothesis. The rejection of the uncorrelated return version of the random walk hypothesis raises the possibility of improving equity returns by active fund management strategies.[13] However, it is difficult to judge what degree of autocorrelation would suggest existence of trading rules with positive expected profits (Fama, 1970).[12]

The results obtained in this study indicate the following characterization of the weekly DSE stock return index:

(a) Returns are mean-averting in the short-run. That is, positive (negative) returns are followed by positive (negative) returns over the short-run. The finding of positive serial dependence over short horizons in the DSE returns indicates that a substantial number of positive feedback traders are present in the market, and arbitrageurs simply fail to eliminate the effects of feedback traders on prices. Positive feedback trading can also rationalize the dramatic price increase over the period of 1994 to 1996, as more and more investors chased the trend. The presence of a substantial number of feedback traders may also cause stock prices to overreact to news.

(b) The weekly DSE returns are mean-reverting over the longer period, as showed by the test results. Weekly DSE returns slowly come back to the long-term mean, and this return occurs only after 30 weeks of the sample period. The return of the stock price to its mean value indicates that the market responds to its fundamental value only after a huge lag. This is an indication of gross informational inefficiency. However, this time lag may be shortened if there is a sufficient number of arbitrageurs in the market.

However, before discussing the policy implications of findings of this study, it would be helpful to consider some major developments at the DSE. The DSE has many peculiarities. The market is more or less captive in the hands of some influential brokers. In addition, sluggish monitoring by the regulatory bodies, political instability, and price manipulation by listed companies either through window-dressing or through direct participation in transactions have made the market more peculiar. During 1994 through 1996, the most eventful period in the history of the DSE, rumors, unethical speculation coupled with disguised demand created simply through transactions among some influential brokers on the very nose of the regulatory bodies, made the DSE a wrong barometer of the country's economic condition. Small and naïve investors without any ability to interpret market signals properly were attracted to the market on the expectation of a continuous uptrend in the share prices. The regulators remained silent to this speculative price hike, which could not be backed by any change in underlying fundamentals. The first regulatory intervention came on October 9, when the SEC imposed a 10% circuit breaker. Later, on November 6, the SEC restricted price movement to 5%. In December 1996, the DSE crashed, leaving the small and naïve investors hopeless and empty handed.

The empirical results of this study and actual condition of the DSE certainly raise some issues to be handled by the policy makers to transform the DSE into a correct barometer of the country's economic condition. To this end, the government and the SEC should take following actions:

- The policy makers first need to introduce more funds managed by professional money managers, so that the hopeless small and naïve investors become more confident about equity investments.

- In order to ensure proper functioning of arbitrageurs, the *SEC* should introduce strictly supervised (so that arbitrageurs cannot manipulate) short selling at the *DSE*. Short selling plays important and constructive roles in the equity markets by providing liquidity and pricing efficiency.

- Like other emerging markets, the *DSE* is also poor in information dissemination. To this end, the listing rules should make companies responsible to disclose all price sensitive information, which has a significant impact on the company's share price.[13] The *SEC* should also ensure that companies are making price sensitive information available to the market as a whole. If companies give any price sensitive information to substantial shareholders or other parties they are dealing with, such "insiders" should not be allowed to deal in a company's securities before the information is made public.

- Finally, tight disclosure requirements accompanied by internationally accepted auditing and accounting standards will certainly create confidence among local and foreign investors to commit their funds to emerging stock markets such as the *DSE*.

Endnotes

1. Campbell *et al.* (1997) distinguish between three versions of the random walk hypothesis - the "IID returns" version (most restrictive), the "independent-returns" version (less restrictive) and the version of "uncorrelated returns" (least restrictive). See Campbell *et al.* (1997) for more detail. The least restrictive version of the random walk hypothesis implies that any process ε_t satisfies $Cov(\varepsilon_t, \varepsilon_{t-k}) = 0$, for all $k \neq 0$ but may not satisfy $Cov(\varepsilon_t^2, \varepsilon_{t-k}^2) \neq 0$, for some $k \neq 0$.

2. Apart form these linear dependencies, asset returns can be nonlinearly dependent with their prior values, which is hard to capture by examining the simple correlation structure of the process.

3. Feedback traders trade on the basis of past behavior of asset returns. Feedback trading includes several well-known trading strategies, such as profit taking, herding, contrarian investment and dynamic portfolio reallocation. A distinction is usually made between the positive and negative feedback trading. Positive feedback traders buy after price increases (similar to herding) and negative feedback traders sell after price increases (similar to profit taking).

4. News about the state of the economy, state of the industry and present and the future earning capacity of the company under consideration are regarded relevant to the stock market.

5. On the other hand, the runs test proposed by Wallis and Moor (1941) is a test based simply on the counts of runs up and down.

6. A series $\{e_t\}_{t=1}^{T}$ is identically and independently distributed $(i.i.d.)$ if all of its terms are independent of the others, and all have the same distribution.

7. The k – period variance ratio statistic, $VR(k)$, satisfies following relation:

$$VR(k) = \frac{Var\left[r_t(k)\right]}{k \times Var\left[r_t(1)\right]} = 1 + 2 \times \sum_{j=1}^{k-1}\left(1 - \frac{j}{k}\right) \times \rho_j$$

   Where $r_t(k) = r_t + r_{t-1} + r_{t-2} + \cdots + r_{t-k+1}$ and ρ_j is the j – th order autocorrelation coefficient of the $\{r_t\}$. Above relation shows that $VR(k)$ is a linear combination of the first $k-1$ autocorrelation coefficients of $\{r_t\}$ with linearly declining weights (Cochrane, 1988). Under the null of random walk, increments for all k, $VR(k) = 1$, since in this case $\rho_j = 0$, for all $j > 1$.

8. The organization of a market may affect the transaction costs and thus net returns available to an investor, the valuation of the asset, allocation of real resources, asset holding patterns, and also the optimal trading strategies. These effects are collectively known as market microstructure effects.

9. The t – test may not be appropriate in this case because of violations of normality and

independence assumption. However, the t – test does give some idea about the mean return on the DSE index. It is worth mentioning that had dividend return been added, the mean return would have been significant. This study only considers the capital appreciation

10. Studentdized Range can be defined as $SR = \frac{(Max-Min)}{Standard\ Deviation}$, which is the range of the data expressed in units of standard deviation, that is, how big is the largest outlier? The value of the SR statistic around 5 or 6 are reasonable if the underlying data come from a normal distribution with a constant mean and variance. Larger SR values indicate either fat-tailed distribution or heteroskedasticity.

11. If a time series is stationary but shows significant autocorrelations even between any two distant observations, it is known as a long memory process.

12. Active fund management strategies include trend analysis, value investing, tactical asset allocation and market timing.

13. Such as major developments, changes in company financial condition, announcements of dividends and other offers of securities, share dealing by directors and substantial shareholders, regular announcement of annual and interim results, etc.

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Figure 1: Weekly DSE Price Index (1st week of Jan'89-last week of Dec'98)

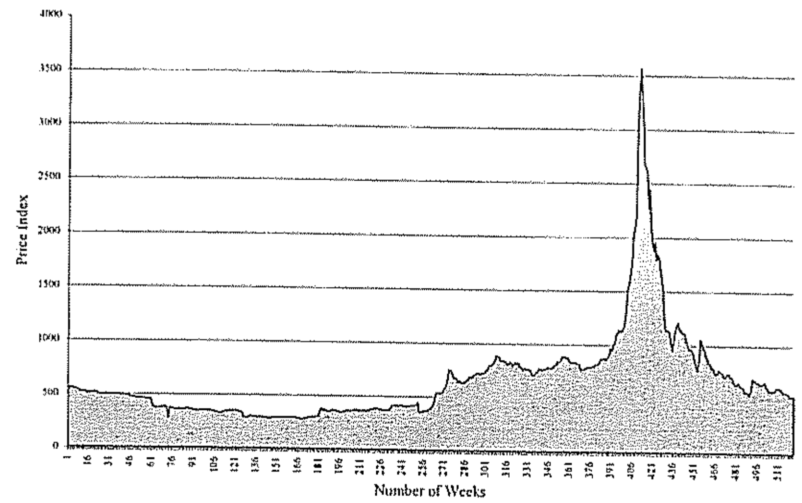

Figure 2: Weekly DSE Returns (1st week of Jan'89-last week of Dec'98)

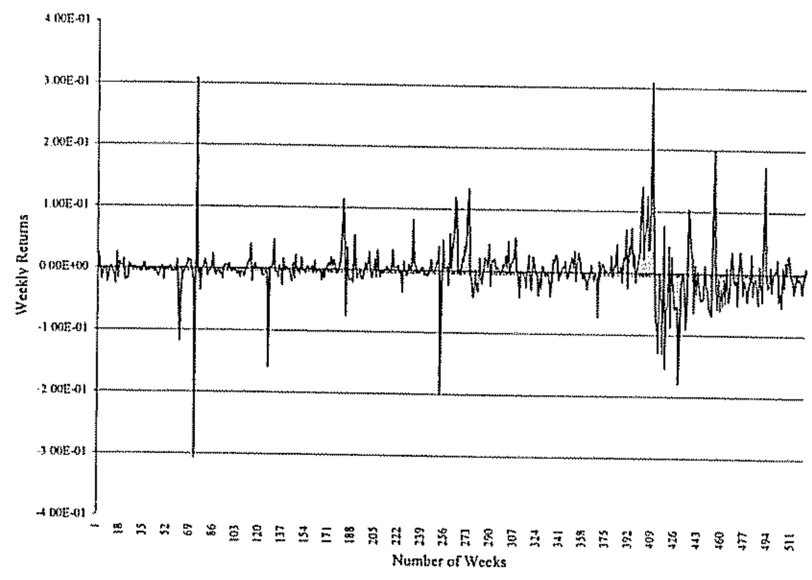

Figure 3: Correlogram of DSE Weekly Returns

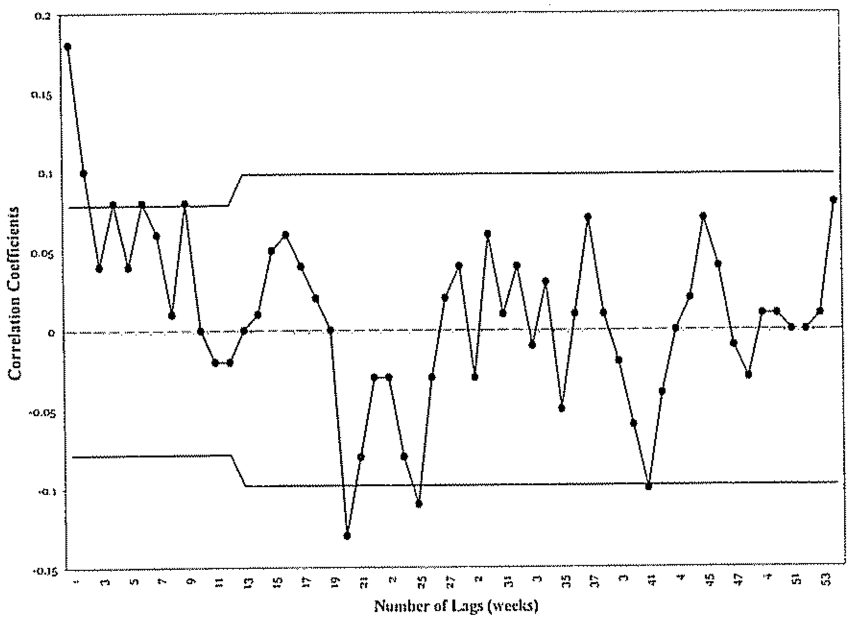

Figure 4:Estimates of Variance Ratios

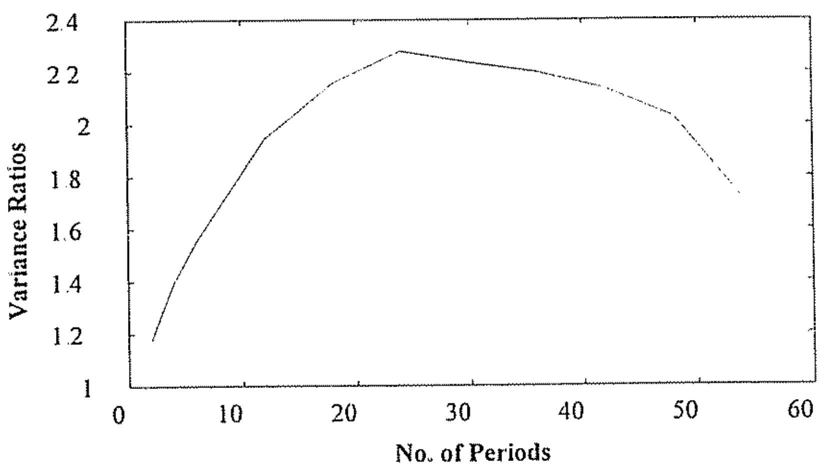

Table 1: Descriptive Statistic of Weekly DSE Returns, $r_t = \log p_t - \log p_{t-1}$

Number of Observations	522
Mean	2.20e-6 (0.00)
Median	-0.307
Standard Deviation	4.38e-2
Skewness	0.712 (6.66)
Excess Kurtosis	16.77 (78.51)
Maximum	0.308
Minimum	-0.307
Normality	6025
Studentdized Range	14.04

Notes: (1) Normality refers to the Jarque-Bera normality test, which follows a χ^2 with 2 degrees of freedom.
(2) In rows 2, 4 and 5 $t-$ values are reported for H_0 : Mean $= 0$, H_0 : Skewness $= 0$, and H_0 : Excess kurtosis $= 0$, respectively.

Table 2: Results from the Runs Test for Weekly DSE Index

Number of Observations	Expected number of runs	Total number of runs	Number of positive runs	Number of negative runs	Normality statistics
522	257.44	197	245	269	-5.35

Table 3: Variance Ratios for Weekly DSE Index for a One-Week Base Observation Period

	Number of Periods k used to estimate variance in the numerator										
	2	**4**	**6**	**12**	**18**	**24**	**30**	**36**	**42**	**48**	**54**
Variance Ratios	1.175	1.396	1.553	1.944	2.156	2.279	2.235	2.198	2.135	2.026	1.709
$Z(k)$	4.01*	4.84*	5.11*	5.75*	5.63*	5.34*	4.58*	4.04*	3.53*	2.98*	1.94
$Z^*(k)$	1.47	2.11*	2.48*	3.27*	3.42*	3.40*	3.02*	2.74*	2.46*	2.13*	1.42

Notes (1) Under the random walk hypothesis, the value of the variance ratio is 1 and the test statistics have an asymptotic standard normal distribution.
(2) Test statistics marked with asterisks indicate that the corresponding variance ratios are statistically different from 1 at the 5% level of significance.