# LONG MEMORY IN STOCK RETURNS: EVIDENCE FROM THE DHAKA STOCK EXCHANGE

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## ABSTRACT

*This study examines the long memory property in the weekly return series and its certain transformations of the Dhaka Stock Exchange over the period of January 1989 to January 2004. Well-known methods for detecting the long memory property of a time series such as the classical rescaled range (originally developed by Hurst, 1951) and its modified version propounded by Lo (1991) are used. Empirical results obtained in this study suggest statistically significant but weak evidence of long memory for weekly stock returns at levels. But for nonlinear transformations of return, such as the absolute and squared returns, the series show strong and significant long memory. The finding that above mentioned transformations of return series contain long memory supports the claim made by Taylor (1986) and Ding et al. (1993).*

## I. INTRODUCTION

The main objective of this study is to examine the presence of long memory in the weekly stock returns of the Dhaka Stock Exchange, the prime stock market of Bangladesh. Well-known methods for detecting the presence of long memory in a time series, such as, the classical rescaled range (originally developed by Hurst, 1951) and its modified version propounded by Lo (1991) are used. In addition, as the transformations of an IID process should have short-memory, this study also intends to test long memory property of certain transformation of returns such as $r_t^2$ and absolute returns, $|r_t|$.

Empirical evidence support that financial time series possess long memory property (see, for example, Goetzman, 1993; Cheung, 1993; Lee and Robinson, 1996; Barkolus and Baum, 1996; and Baillie, 1996). The evidence that asset returns are negatively correlated over the long run (Fama and French, 1988; Poterba and Summers, 1988; Lo and MacKinlay, 1988) supports long term persistence in stock returns. Empirical evidence also support that nonlinear transformations of asset returns, $r_t$, such as squared returns, $r_t^2$, absolute returns, $|r_t|$, and $|r_t|^d$, where value of "$d$" is close to 1, show long range dependence (Taylor, 1986; Ding et al., 1993). Specifically, empirical search for the presence of long memory property or persistence in stock returns has started by Greene and Felietz (1977). Using

classical rescaled range analysis, they find evidence of long memory dependence in the US stock returns. However, their empirical work faces severe criticism on the ground that the classical rescaled range analysis cannot distinguish the short-term dependence from the long-term dependence. The study by Ayodogan and Booth (1998) reveals that the classical rescaled test is sensitive to short-term autocorrelation and non-homogeneity in the data.

Lo (1991) modifies the classical rescaled range technique, making it robust to both autocorrelation and heteroskedasticity in the data. Following Lo's work, several researchers have used modified rescaled range analysis and obtained the results similar to those of Lo (see, for example, Cheung et al., 1993; Ambros et al., 1993; and Mills, 1993; Hiemstra and Jones 1996; Sadique and Silvapulle,2001). Hiemstra and Jones (1996) apply the modified rescaled range to the daily return series of 1952 common stock. Using the asymptotic and bootstrapped critical values, they obtain weak evidence of long memory in returns of few stocks. They provide evidence that Lo's rescaled range analysis is sensitive to the choice of autocovariance truncation lags, to the moment condition failure and to the survivorship bias. Sadique and Silvapulle (2001) use a battery of tests (including traditional and modified rescaled range analysis) to identify the long memory property in the weekly stock returns of seven countries (Japan, Korea, Malaysia, Singapore, Australia, New Zealand and the USA). Their study shows that stock returns of New Zealand and of Korea are long-range dependent whereas other market returns do not show any systematic presence of long memory.

In financial markets, autocorrelation and variance of returns depend on the speed with which traders' incorporate information into stock prices. Despite receiving the same information at the same time, two investors can reach opposite conclusions about its likely effects on prices (Kurz, 1994). Kurze notes that neither investor is irrational but one might be proven wrong. His empirical study shows that accumulation of these mistakes generates endogenous uncertainty, which causes more than two-third of the variability in stock returns. In real markets, often traders may change their opinions or forecasts as a function of those of other traders.

Due to their uncertainty about true state of the economy, market participants like to herd. If some traders forecast an increase in the price of an asset and others follow, resulting demand will drive the price up and thus confirming the prediction. However, the opposite case may bring the market price to its previous level. Such switching back and forth of market price makes it path dependent, that is, history does count in shaping future trading strategies and inject long memory into asset prices. Moreover, feedback traders, whether positive (buying after price increase) or negative (buying after price decrease), are the sources of persistent change in asset prices (Cutler et al., 1990). Such predictable behavior of market traders is considered as a reason for the presence of non-periodic cycles in asset prices (Kaen and Rosenman, 1986).

The theoretical explanation given above for the presence of long memory in stock returns is almost similar to that we see in the Dhaka Stock Exchange (DSE, hereafter). Small and naïve investors often show herd

like behavior and are not responsive to the arrival of new and relevant information. This limitation allows some traders to create disguised demand simply through their transactions. Speculative attacks, price manipulation by company owners, absence of proper government control, and political instability have almost turned the DSE into a wrong barometer of the country's economic condition.

However, despite these limitations, we cannot deny the potential role of the DSE in the country's development. Moreover, as an emerging market, DSE provides foreign investors a great opportunity of risk diversification (Bailey and Stulz, 1990; Classens, 1995). Therefore, the characterization of dynamic behavior of returns of the DSE, a less developed and small equity market, is important not only for the investors but also for the policy makers. The motivation of this study comes from this fact and also from the fact that the DSE has never been examined for long term dependence in its stock returns. In addition, conclusions of tests of efficient market hypotheses or stock market rationality also depend on the presence or absence of long memory in the stock return series (Lo and MacKinlay, 1999)

The remaining study is organized as follows. Section 2 gives a description of common models for modeling long memory property of a time series, traditional and modified rescaled range analysis, as well as the methods to use them in testing long memory. A description of the data used in this study, their statistical properties and the analysis of empirical results constitute Section 3. Finally, Section 4 concludes the study.

## II. ANALYSIS METHODOLOGY

This section starts with a brief introduction to popular long memory models followed by a brief introduction to the classical and modified rescaled range analysis, the methods used in this study to identify long memory property of the DSE weekly returns and of its nonlinear transformations.

### a. Long Memory Models

Time series models such as the Fractional Gaussian Noise (FGN, hereafter) and Fractionally Integrated Autoregressive Moving Average (ARFIMA, hereafter) are suitable for modeling long memory property of a series. This is because the increments of these processes are stationary and their autocorrelation functions decay at an algebraic rate less than one (Beran, 1994). The FGN was introduced by Mandelbrot and Van Nees (1968) and has been widely used to model strongly dependent geophysical phenomena. The FGN model for a time series, $\{r_t\}_1^T$, can be specified in terms of three parameters the mean, variance and the memory parameter, $H$, with

Mean, $= E[r_t] = 0$

Variance $= Var(r_t) = \gamma_0$
and, theoretical autocorrelation function,

$$\rho_k = 0.5\left[(k+1)^{2H} - 2k^{2H} + (k-1)^{2H}\right], \text{ where}$$
$H$ satisfies $0.5 < H < 1$

The index $H$ (often called as self-similarity parameter) in this context, measures the intensity of long memory. The FGN is a unique Gaussian sequence with the property that its partial sums has the probability

distribution same as that of the original series (known as self-similarity).

Granger and Joyoux (1980) and Hosking (1981) proposed the ARFIMA model as an alternative to the FGN to model the long memory property of a time series. A time series, $\{r_t\}_1^T$, can be expressed as an ARFIMA $(p, d, q)$ process defined as, $\varphi(B)(1-B)^d r_t = \theta(B) u_t$, where $\varphi(B)$ and $\theta(B)$ are autoregressive and moving average polynomials in $B$, respectively, and $B$ is the backward shift operator defined as,

$(1-B) r_t = r_t - r_{t-1}$

$(1-B)^2 r_t = (r_t - r_{t-1}) - (r_{t-1} - r_{t-2})$

The values of the fractional integration parameter, "$d$", lies in between $-1$ and $+1$. The ARFIMA model becomes interesting for $-0.5 < d < 0.5$. In particular, $\{r_t\}_1^T$ becomes stationary and shows long-range dependence for $0 < d < 0.5$.

In sum, the slowly decaying autocorrelations of a long memory process are captured by the fractional integration parameter "$d$" of an ARFIMA model. The long memory parameter $H$ in the FGN and "$d$" in the ARFIMA model are related to each other as $H = d + 0.5$. However, one important distinction between these competing time series model is that the FGN has the property of self-similarity, which the ARFIMA models do not possess.

## b. The Rescaled Range Method

The rescaled range statistic (hereafter RS) is the range of partial sums of deviations of a time series from its mean, rescaled by its standard deviation. The traditional RS is defined as:

$$\tilde{Q}_T = \frac{Range}{S_T} = \frac{\underset{1 \le k \le T}{Max} \sum_{j=1}^{k}(r_j - \bar{r}_T) - \underset{1 \le k \le t}{Min} \sum_{j=1}^{k}(r_j - \bar{r}_T)}{S_T} \quad (1)$$

In (1), $r_1, r_2, \cdots, r_t$ represent the return series, $t = 1, 2, \cdots, T$, $\bar{r}_t = 1/T * \sum_j r_j$ and $S_T = \sqrt{1/T * (r_j - \bar{r}_t)^2}$ denote the sample mean and standard deviation, respectively. The first term in the brackets in (1) is the maximum (over $k$) of partial sums of the first $k$ deviations of $r_j$'s from the sample mean and is always non-negative. The second term in brackets in (1) is the minimum (over $k$) of the same sequence of partial sums and is always non-positive. The difference between the two quantities, known as range, is naturally always non-negative; hence $\tilde{Q}_T \ge 0$. The classical RS method does not have an asymptotic distribution theory, so that one can explicitly test the null hypothesis of short memory. Thus, the significance of point estimates that $H = 0.5$ or $H \ne 0.5$ rests on the subjective assessments.

The modified version of the RS method (hereafter, MRS) introduced by Lo (1991) can demarcate the long-range dependence from the short-range dependence in a time series (for more detail, see. Campbell et al. 1997; Lo and MacKinlay, 1999). The major improvement of the MRS method over the traditional RS is in the denominator of (1). In order to capture short-range dependence more accurately, this estimator includes autocovariances along with the variances of the partial sums. Specifically, Lo considered $\{r_t\}_1^T$ as the return series under the null hypothesis as:

$r_t = a + u_t$ \hfill (2)

In (2), "$a$" is a fixed parameter and $\{u_t\}$ is a zero mean random variable. Accordingly, the return series can be considered as a short memory process if we fail to reject the null hypothesis of short memory. Moreover, $\{u_t\}$ satisfies some conditions as restrictions on the maximum degree of dependence and heterogeneity allowable in the data. Lo's modification of RS method was accomplished by the following statistic $Q_T$, where:

$$Q_T = \frac{Range}{\tilde{\sigma}_T^2(q)} \qquad (3)$$

The estimator $\tilde{\sigma}_T^2(q)$ is defined as follows:

$$\tilde{\sigma}_T^2(q) = \frac{1}{T}\sum_{j=1}^{T}(r_j - \bar{r}_T)^2 \qquad (4)$$

$$+ \frac{2}{T}\sum_{j=1}^{q}\left(1 - \frac{j}{q+1}\right)\left\{\sum_{i=j+1}^{T}(r_i - \bar{r}_T)(r_{i-j} - \bar{r}_T)\right\}$$

In (4), $q < T$, by allowing $q$ to increase with the number of observations, $T$, at a rate, $\left(q \sim o(T^{1/4})\right)$, the denominator of $Q_T$ is adjusted appropriately for general forms of short-range dependence. Lo points out that $\tilde{\sigma}_T(q)$ will be nonzero if the series is short-term dependent. Normalizing the statistic $Q_T$ by the square root of the number of observations, Lo derives the MRS test statistic defined as follows:

$$V_T(q) = \frac{1}{\sqrt{T}} * Q_T \qquad [5]$$

The test statistic, $V_T(q)$, has the probability distribution with mean $E[V] = \sqrt{\pi/2}$, and the variance $E[V^2] = \pi^2/6$. On the basis of the ability of the MRS test to detect long run persistence, Lo provides critical values at different, generally accepted significance levels (Lo, 1991; Table II; page 1288).

# III. DATA AND EMPIRICAL RESULTS

This section describes the data and analyzes the statistical properties of the DSE return series in detail.[1] After identifying the basic statistical characteristics of the series, it discusses and analyzes the results of the classical and modified rescaled range methods.
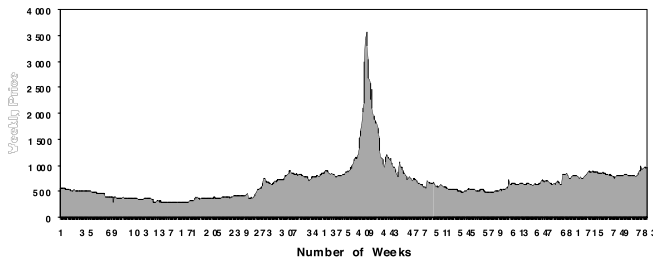
## a. Data Description

The data used in this study consists of 786 weekly observations of all share DSE price index from the first week of January 1989 to the last week of January 2004. The weekly DSE price index series is collected from various issues of the DSE monthly bulletin, national dailies and, also from the DSE computer files. Specifically, in this study, weekly stock return is defined as the logarithmic ratio of this week's closing-price to closing-price of previous week. If 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 (this happens only rarely). Weekly share price data is used because one can have many data points than monthly or yearly series and at the same can avoid market microstructure effect present in daily observations. Stock returns used in this study are nominal only, and do not take into account the effects of dividends, inflation and exchange rates.

## b. Statistical Properties of the Weekly DSE Returns

The all share DSE price index is plotted in Figure 1 against time (in weeks). The

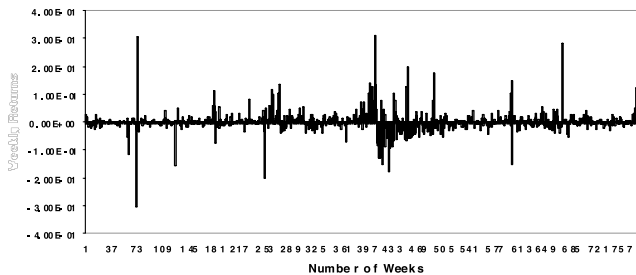plot indicates that the price series is approximately stationary and does not have any significant trend.[2]

**Figure 1: Weekly DSE All Share Price Index  (5/1/1989-29/1/2004)**



The DSE weekly return series looks apparently random and mean reverting as it returns to the mean very often (Figure 2).

Table 1 reports the descriptive statistical

**Figure 2: Weekly All Share Return Index   (12/1/1989-29/1/2004)**



properties of the DSE return series. Firstly, the overall mean return is positive for the DSE stocks. A $t$ test with the null hypothesis that average weekly returns are zero suggests that the null cannot be rejected although at any usual statistical level of significance. This means that the buy-and-hold investment strategy (or any other passive investment strategies) is not suitable over the sample period on average. The weekly return series has statistically significant positive coefficient of skewness, which indicates that the series is skewed to the right. If we look at Table 1, we would find that the coefficient of excess kurtosis is positive and statistically significant. In other words, the probability distribution of the DSE weekly return series is fat or heavy tailed, which also indicates that there are some large outliers. As evident from the coefficients of kurtosis and skewness, the Jarque-Bera normality test is highly significant indicating that the weekly DSE return series does not follow standard normal distribution.

It is often useful to look at the average return and its variance over a year. This is because investors often compare the performance of the market against other investments over a common period of time, which is usually a year. Table 2 of this study provides the yearly average return and its standard deviation for the entire sample period. While the average returns of the DSE are very small, it is changing over time and large positive return in one year cancels out large negative returns in another year, making overall average return small. The standard deviation of DSE yearly returns is always higher than the mean over the sample period. From practitioners' viewpoint the risk-return profile of the DSE indicates investors following the buy and hold investment strategy may not be compensated in terms of risk and returns.

In order to investigate the independence of successive log price changes, correlogram

## Table 1: Summary Statistics of Weekly DSE Returns

The sample period is from January 1989 to the last week of January 2004. Weekly price increments are calculated as $r_i = \ln(p_i) - \ln(p_{i-1})$, where $p_i$ indicates price at time $i$ and $p_{i-1}$ indicates price one period before. In row 2, 4 and 5 absolute $t-$ values reported in parentheses are for $H_0$: Mean $= 0$, $H_0$: Skewness $= 0$, and $H_0$: Excess kurtosis $= 0$, respectively. $*$ indicates significant at the 1% level and $**$ indicates significant at the 5% level. Studentdized range is defined as

$SR = \dfrac{(\text{Max - Min})}{\text{Standard Deviation}}$, which is the range of the expressed in units of standard deviation. For

| | |
|---|---|
| Mean | 0.726e-03 (0.018) |
| Median | − 0.3188e-03 |
| Standard Deviation | 0.395e-01 |
| Skewness | 1.1036 (12.64*) |
| Excess Kurtosis | 20.6138 (118.26*) |
| Maximum | 0.3084 |
| Minimum | − 0.3073 |
| Normality | 13871 (*p*-value=0.00) |
| Studentdized Range | 15.57 |
| No. of Observations | 786 |

## Table 2: Yearly Simple Mean and Standard Deviation of the DSE Return Series

The overall and yearly mean returns and standard deviations are multiplied by 100.

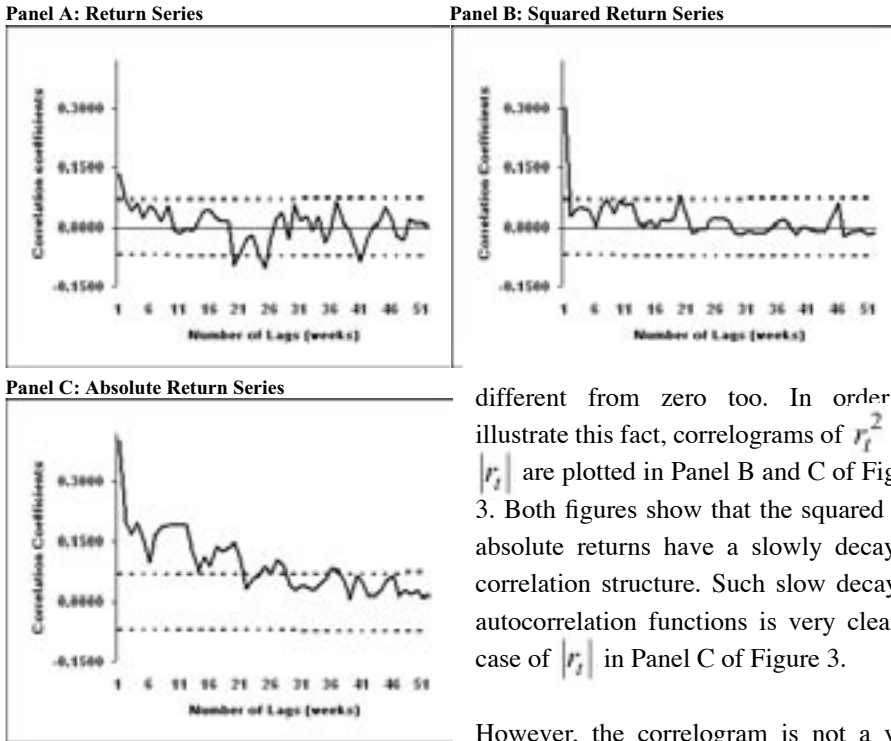| Period | Mean | Standard Deviation |
|---|---|---|
| **1989-2003** | **0.072** | **3.97** |
| 1989 | 0.278 | 1.044 |
| 1990 | 0.551 | 6.423 |
| 1991 | 0.327 | 2.572 |
| 1992 | 0.417 | 2.637 |
| 1993 | 0.112 | 3.415 |
| 1994 | 1.479 | 3.697 |
| 1995 | 0.020 | 1.820 |
| 1996 | 1.918 | 6.720 |
| 1997 | 2.089 | 6.382 |
| 1998 | 0.658 | 3.576 |
| 1999 | 0.196 | 1.614 |
| 2000 | 0.541 | 3.607 |
| 2001 | 0.489 | 4.482 |
| 2002 | 0.055 | 1.709 |
| 2003 | 0.118 | 2.090 |

of the return series in levels and transformed returns are plotted in Figure 3, up to a maximum lag of 52 weeks. The correlogram of the return series in level, $r_t$, in Panel A of Figure 3 has distinctive shape with 1st and 2nd order significant positive autocorrelations followed by positive but insignificant autocorrelations up to 9th lag. The autocorrelation coefficient becomes negative and statistically significant again around the 20th lag, 25th and at 41st lag. Such pattern is indicative of the presence of memory in the series, which can be predicted and can be exploited. However, the nonlinear transformation of an IDD process should also be uncorrelated. Therefore, the ACF of $r_t^2$ and $|r_t|$ should not be significantly

**Figure 3: Correlogram of the Return, Squared Return and Absolute Return Series**

The horizontal lines on the autocorrelation plots are 95% confidence band $\left(\pm 1.96 T^{-1/2}\right)$, where $T$ is the sample size, for the sample autocorrelations given the null hypothesis that the data series is serially uncorrelated.

Panel A: Return Series



Panel B: Squared Return Series



Panel C: Absolute Return Series



different from zero too. In order to illustrate this fact, correlograms of $r_t^2$ and $|r_t|$ are plotted in Panel B and C of Figure 3. Both figures show that the squared and absolute returns have a slowly decaying correlation structure. Such slow decay of autocorrelation functions is very clear in case of $|r_t|$ in Panel C of Figure 3.

However, the correlogram is not a very strong diagnostic for detecting long-range

**Table 3: Results of the Ljung-Box Test Q ($p$)**

The Ljung Box portmanteau test statistic is constructed from the first $J$ squared autocorrelations as $Q = n(n+2)\sum_{j=1}^{J}\frac{1}{n-j}r_j^2$ . Under the null hypothesis that a series is uncorrelated, the L-B test statistic is asymptotically distributed as $\chi^2$ with $P$ = degrees of freedom. $p$-values are in parentheses.

| Data Series | $Q$ (10) | $Q$ (20) | $Q$ (30) | $Q$ (40) | $Q$ (50) |
|---|---|---|---|---|---|
| $r_t$ | 31.00 (0.001) | 42.39 (0.002) | 64.95 (0.000) | 73.18 (0.001) | 84.55 (0.002) |
| $r_t^2$ | 89.41 (0.000) | 101.41 (0.000) | 103.92 (0.000) | 105.17 (0.000) | 109.95 (0.000) |
| $|r_t|$ | 352.77 (0.000) | 510.43 (0.000) | 553.77 (0.000) | 578.20 (0.000) | 589.16 (0.000) |

dependence in a time series. This is because long memory is an asymptotic notion and correlogram at high lags cannot be estimated in a reliable way. In order to provide more evidence about the dependence structure of the successive returns, the Ljung-Box (LB) statistic is calculated. All the LB statistics for $r_t$, $r_t^2$, and $|r_t|$ are statistically significant at all standard significance levels (Table 3). The results of the LB statistic again support our finding that the DSE return series and its transformations do not follow a random walk.

## c. Analysis of Results of the Rescaled Range Method

In Table 4, the results of the traditional rescaled range (RS) and modified rescaled range (MRS) test are reported. The first column of the Table 4 contains results for lag length $q = 0$, that is, without any correction for short-run dependence in data series and thus is similar to the traditional RS analysis. The remaining columns of Table 4 contain the results of the MRS test for various lag lengths. The choice of $q(T)$ influences both actual size of the test, $P(reject\ H_0 | H_1)$, and its power, $P(accept\ H_0 | H_1)$, therefore, the appropriate choice of $q(T)$ in MRS is essential (see, Pagan, 1996). However, there is no final and foolproof formula for the choice of truncation lag $q$ and several rule of thumbs are used. Such rule of thumbs include $_{[int]}$ x $[T^{1/4}]$, $_{[int]}$ x $[T^{1/3}]$, $_{[int]}$ x $[T^{1/2}]$, where indicates integer part and $T$ is the sample size. Often this choice is made on the basis of Andrew's (1991) data dependent formula:

$$q = [k_T],\ k_T = \left(\frac{3T}{2}\right)^{1/3} x \left(\frac{2\hat{\rho}}{1-\hat{\rho}^2}\right)^{2/3}$$

where $[k_T]$ denotes the integer part of $k_T$ and $\hat{\rho}$ is the estimated first-order autocorrelation coefficient of the data series. In this study, we have used all options for truncation lag determination given above and, also calculated MRS statistics for some predetermined lag lengths, such as 7, 12, 15, 20, and 25.

It is well evident that the value of the truncation lag $q$ influences the value of the MRS statistic (Teverovsky et al. 1998 and; Pagan, 1996). The results of the RS and MRS test indicate statistically significant persistence in DSE weekly returns, but only up to 5th lag. However, MRS results show that beyond the 5th lag, such persistence in the series disappears. On the other hand, the value of the RS and MRS test statistics for the transformed return series (squared and absolute return series) are all statistically significant throughout all lags considered in this study. Two major findings of this study are worth noting here:

(a)  The long memory property is uniformly stronger in absolute than in squared returns and squared returns has long memory property greater than the returns in levels. That is, , and

$$RS(|r_t|) \geq RS(r_t^2) \geq RS(r_t),$$

$$MRS(|r_t|) \geq MRS(r_t^2) \geq / MRS(r_t)$$

which confirms the finding of Ding et al., (1993) and, Taylor (1986).

(b)  The strength of statistical significance of the MRS test statistic is highly dependent on the choice of number of lag values included to calculate the short-term dependence in the data, which is in agreement of Teverovsky et al. (1998) and Pagan (1996).

### Table 4: Results of the Rescaled Range Analysis

$\tilde{V}_T$ and $\tilde{V}_T(q)$ denote the classical and modified rescaled range statistics respectively. *, **, and *** indicate significant at the 1%, 5% and 10% level, respectively, for rejection of the short memory null hypothesis. The 99%, 95%, and 90% intervals are [0. 721, 2.098], [0.809, 1.862] and [0.861, 1.747] respectively [Lo (1991), Page, 1288, Table II]. Bias (%) is computed using the formula

$$\left(\frac{\tilde{V}_T}{\tilde{V}_T(q)}-1\right) \times 100$$

and indicates bias of the classical rescaled range statistic in the presence of short-range dependence. For the series, Andrew's optimal lag length $q=4$, for the series $r_t^2$ optimal lag length $q=8$, and for the series $|r_t|$ optimal lag length $q=10$. Using the rule of thumbs, we obtain 3 optimal lag lengths, 28, 8, and 5. Predetermined lag lengths used are 7, 12, 20 and 25.

| Data Series | $\tilde{V}_T$ | $\tilde{V}_T(q)$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | q = 0 | q = 4 | q = 5 | q = 7 | q = 8 | q = 10 | q = 12 | q = 15 | q = 20 | q = 25 | q = 28 |
| $r_t$ | 2.122** | 1.813*** | 1.779*** | 1.718 | 1.694 | 1.6529 | 1.628 | 1.603 | 1.560 | 1.570 | 1.587 |
| % Bias | ------ | (17.06) | (19.28) | (23.52) | (25.20) | (28.38) | (30.31) | (32.41) | (35.97) | (35.15) | (33.72) |
| $r_t^2$ | 5.899* | 4.459* | 4.331* | 4.136* | 4.041* | 3.8729* | 3.718* | 3.537* | 3.315* | 3.141* | 3.053* |
| % Bias | ----- | (32.29) | (36.22) | (42.64) | (45.97) | (52.32) | (58.64) | (66.76) | (77.93) | (87.83) | (93.21) |
| $|r_t|$ | 14.917* | 8.721* | 8.1555* | 7.322* | 6.988* | 6.434* | 5.990* | 5.483* | 4.884* | 4.459* | 4.258* |
| % Bias | ----- | (71.06) | (82.94) | (103.72) | (113.45) | (131.84) | (149.02) | (172.04) | (205.43) | (234.48) | (250.35) |

## IV. CONCLUSION

In this study, we have investigated the long memory property of weekly stock returns of the Dhaka Stock Exchange (DSE) using two popular methods for detecting long memory in the data. The first one is the traditional original rescaled range analysis (RS) proposed by Hurst (1951) and the other one is its improved version propounded by Lo (1991) known as the modified rescaled range analysis (MRS). The tests applied here can be considered as a test of weaker version of the efficient market hypothesis, where the best forecast of today's stock price is yesterday's price. Using the RS and MRS tests, this study finds statistically significant but weak evidence of long memory in the DSE weekly stock return series. In addition to the return series at level, $r_t$, this study also finds that certain transformations of $r_t$, e.g., the absolute return, $|r_t|$, and the squared return, $r_t^2$ show statistically significant and strong evidence of long memory. The finding that above mentioned transformations of return series contain long memory supports the claim made by Taylor (1986), Ding et al., (1993) and is indicative of long memory in return volatility.

Previous study such as Sadique and Chowdhury (2001) has found that stock price dependence of the DSE index varies over time and with the volume of trade. One possibility of this is that increase in volume of trade does indicate that more information is arriving in the market. This increase in information causes uncertainty and trading

at disequilibrium prices. This results in a competence-difficulty (C-D) gap defined as the gap between the investors' competence in analyzing complex information (see, for detail, Heiner, 1983; Kaen and Rosenman, 1986). Consequently, instant dissemination of information is not possible as predicted by the EMH; rather the market absorbs relevant new information in phases. The practical implication for the presence of long memory in market return is that the market participants can devise rules (such higher order moving average) to earn extra profits. That is, active fund management techniques become attractive in presence of long memory in returns. However, whether this inefficiency can be exploited by market participants is an empirical question. Second, long memory in stock returns may increase its volatility and thus increase the riskiness

of portfolio investment opportunities. This study suggests a well-defined public regulation of financial institutions and markets to achieve informational efficiency of the DSE. However, identification of what type of regulation is suitable is an area of further research.

A number of statistical techniques are available to identify long memory property of a time series (see, Beran, 1994; Baillie, 1996). This study has only considered two related and most popular statistical techniques to identify long memory property of weekly DSE stock returns. This can be considered as a limitation of this study. Direct estimation of particular parametric model would surely provide better evidence on the long memory property of a series (e.g., see, Beran, 1994).

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[1] For a brief description of Dhaka Stock Exchange, please see Basher et al. (2003).

[2] The Phillips-Perron (PP) test shows that although the price series is not level stationary, it is first difference stationary. The PP test statistic for first differenced series with constant but no trend is –18.78 (asymptotic critical value at 1% level of significance is –3.43). Whereas the PP test statistic for first differenced series with constant and trend is –18.77 (asymptotic critical value at 1% level of significance is –3.96)

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