International Journal of Marketing Research and Brand Management
Volume 13 Issue 2, April - June 2025
ISSN: 2995-3758
Impact Factor: 6.92
https://kloverjournals.org/index.php/mrbm

INVESTIGATING LONG MEMORY IN STOCK RETURNS: EVIDENCE FROM EMERGING MARKETS

Chatterjee Ananya Rajiv and Mukherjee Sandeep Alok
Assistant Professor, Army Institute of Management, Bengal, India
DOI:https://doi.org/10.5281/zenodo.15480620

Abstract The present study aimed at investigating the existence of long memory properties in ten emerging stock markets across the globe. When return series exhibit long memory, it indicates that observed returns are not independent over time. If returns are not independent, past returns can help predict future returns, thereby violating the market efficiency hypothesis. It poses a serious challenge to the supporters of random walk behavior of the stock returns. Hurst-Mandelbrot's Classical R/S statistic, Lo's statistic and semi parametric GPH statistic were computed as well as modified GPH statistic of Robinson (1995). The findings suggest existence of long memory in volatility as well as in absolute returns and random walk for asset return series in general for all the selected stock market indices. The study did not support existence of Taylor's effect in the selected emerging markets.

Keywords: Long memory, Rescaled range, Fractional integration, Spectral regression.

Introduction

Presence of stochastic long memory in stock market returns has a direct impact on the world of market efficiency and can pose a serious challenge to the proponents of random walk behavior of the stock returns. Hurst (1951) possibly inspired the development of statistical long-memory processes by introducing a method (rescaled range analysis) for the quantifying of longterm memory. His method involves parameter estimation to capture the scaling behaviour of the range of partial sums of the variable under consideration. Some early studies in long memory process in finance were carried out by Mandelbrot (1971, 1972), Mandelbrot and Wallis (1969) who suggested that in the presence of long memory, arbitrage opportunities may exist as new market information which cannot be absorbed quickly and martingale models of asset prices may not be justified. Studies by Mandelbrot (1997) and Baillie (1996) showed econometric approaches to capture long memory and application of those in financial data series. Robinson (2003) showed the presence of long memory in financial time series of asset returns while Eldera and Serletis (2008) found evidence of long memory in future energy prices. Presence of long memory in financial time series indicates future returns can be predicted from past returns, thus, linear pricing models used for predicting expected returns and statistical inferences about asset pricing models based on standard testing procedures may not be appropriate (Yajima, 1985). Using rescaled range analysis, authors like Mandelbrot (1971), Greene and Fielitz (1977) have claimed that the return from stocks or indices display long memory. However, Lo (1991) pointed that the statistical R/S test used by Mandelbrot and Green and Fielitz is too weak and is unable to distinguish between long and short memory. He proposed a modified R/S test and applied on stock return to conclude that daily stock returns do not display long memory properties. However, Willinger, Taqqu, and Teverovsky (1999) challenged the findings further on the ground that the modified R/S test leads to the rejection of the null hypothesis of short memory when applied to synthetic time series with a low degree of long memory. They claimed Lo's (1991) statistic may not lead to conclusive evidence for financial data of some countries that display low degree of long memory. However, Lo's statistic is well accepted as primary evidence of long memory and is being used by academicians and practitioners to study long memory since last two decades. Long memory process in the volatility of prices is considered to be a stylized fact in finance. It is well known that asset returns contain insignificant serial correlation, in agreement with the efficient markets hypothesis although its volatilities exhibit significant auto correlation. Presently there is considerable evidence from other world markets in support of the long memory stochastic volatility in stock returns and these are well documented in several studies (Andersen & Bollerslev, 1997, 1998; Breidt, Crato, & Lima, 1998; Ding, Granger & Engle, 1993). Harvey (1993) acknowledged the presence of long memory in volatility of currency exchange rates. These findings spawned research into possible explanations and development of alternate models for volatility, such as fractionally integrated generalized autoregressive conditional heteroskedasticity (FIGARCH) model.

The debate on existence of long memory in stock returns still continues since empirical evidences on the topic reported in empirical studies are not strong enough but this fact has important consequences on the capital market theories. Long range dependence generally suggests non linear dependence in average asset returns. The primary implication of this circumstance is that return predictability is possible from past returns. Under such conditions, efficient market hypothesis is clearly rejected because stock market prices do not follow a random walk. Since stock prices behavior will not remain random in presence of long range dependence, models that predict expected returns like Capital Asset Pricing Model (CAPM) (Sharpe, 1964) will no longer be appropriate in predicting returns. Similarly, linear modeling and forecasting of stock returns and applicability of different asset pricing models based on standard statistical and econometric methods may not be apposite.

An area of interest in financial econometrics literature is an evidence of different magnitudes of sample autocorrelations of different power transformations of absolute returns in various financial assets, a property referred to as the 'Taylor effect'. Taylor (1986) observed that the empirical sample autocorrelations of absolute returns are usually larger than those of squared returns. A similar phenomenon is observed by Ding et al. (1993) and Granger and Ding (1995, 1996). Granger and Ding (1995) referred to this phenomenon as the 'Taylor effect.'

The present study aimed at investigating the existence of long memory properties in ten emerging stock markets across the globe. Studies in long range dependence in emerging stock markets are very limited. Mukherjee, Sen and Sarkar (2011) did not find long memory property in raw returns but in absolute and squared returns in Indian stock market while Nath (2001) found evidence of long memory property in the raw returns for Indian market. Disario, Saraoglu, McCarthy, and Li (2008) found evidences of long memory in return volatility in Turkey while Kang, Cheong, and Yoon (2010) find similar evidences in China. However, Sadique and Silvapulle (2001) found evidence for long-term dependence in stock returns in four countries: Korea, Malaysia, Singapore and New Zealand. We have chosen ten leading indices in the ten chosen emerging stock markets. The study also explores the existence of Taylor's effect in emerging stock markets.

Definition of Long Memory

The long memory describes the higher order correlation structure of a series. If a time series y_t is a long-memory process, there is persistent temporal dependence between observations widely separated in time. Such series exhibits hyperbolically decaying autocorrelations and low frequency distributions. If present, long memory has some serious significance into the dynamics of the system; a shock at one point of time which leads to some increased risk and uncertainty in the market does not die down quickly if long memory is present. Rather, it stays on, although in a decaying fashion and affects future outcomes. Mathematically, if $_s$= cov (y_t, y_{t+s}), s=0, ±1, ±2,..., and there exist constants k and , !(0,1) such that limks "# !$_s$s$^-$ $1 then y_t is a long memory process. A long memory process can be regarded as a fractionally integrated process, i.e., between stationary and unit root process. Like a

International Journal of Marketing Research and Brand Management
Volume 13 Issue 2, April - June 2025
ISSN: 2995-3758
Impact Factor: 6.92
https://kloverjournals.org/index.php/mrbm

stationary process, it is also a mean reverting process with a finite memory, i.e., it comes back to equilibrium after experiencing a shock. But unlike an autoregressive stationary process, it shows a much slower hyperbolic rate of decay rather than exponential, and the process takes much larger time to adjust back to equilibrium. When a time series have unit root at level but its first differences are stationary, it is said to be I(1) process (integrated of order one). A stationary process is said to be I(0) process (integrated of order zero). Using the same notation, long memory process is I(d) process, where d lies between 0 and 1 that is a fraction. In the frequency domain, long memory financial time series have typical spectral power concentration near zero or at low frequencies and then it is declining exponentially and smoothly as the frequency increases (Granger, 1966). Long memory has also been called the "Joseph Effect" by Mandelbrot and Wallis (1968), a biblical reference to the Old Testament prophet who foretold of the seven years of plenty followed by the seven years of scarcity that Egypt was to experience. This in general parlance indicates that good times beget good times and bad times beget bad.

Methodology for Testing Long Memory Processes

The empirical determination of the long memory property of a time series is a difficult problem due to strong autocorrelation of long memory processes which decay asymptotically over space and time. The reciprocals of the decay rates are the correlation length and the correlation time and the slow hyperbolic decay rates make statistical fluctuations very large. Thus, tests for long memory tend to require large quantities of data. In this paper, we tested the stationary properties of all the data series using Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test. We have tried to capture the long memory property of financial data using classical rescaled-range (R/S) analysis (Hurst, 1951; Mandelbrot, 1972), modified rescaled-range (R/S) analysis introduced by Lo (1991) and the spectral regression method suggested by Geweke and Porter-Hudak (1983). The above tests were applied on return series, absolute return series and squared return series. The referred methods and the definition of long memory are detailed below.

Rescaled-Range (R/S) Analysis

R/S analysis provides a measure of long range dependence based on the evaluation of the Hurst's exponent of stationary time series introduced by English hydrologist H. E. Hurst in 1951. The Hurst exponent was built on Einstein's contributions regarding Brownian motion of physical particles and is frequently used to detect long memory in time series. R/S analysis in economy was introduced by Mandelbrot (1971, 1972, 1997) who argued that this methodology was superior to the autocorrelation, the variance analysis and to the spectral analysis. Let X(t) be the price of a stock on a time t and r(t) be the logarithmic return denoted by r(t) $ ln(& * X X t% t 1 ')+ . Under the null hypothesis of absence of long memory in the data series, classical R/S analysis is performed by calculating the confidence intervals with respect to generally accepted significance level. The R/S statistic is the range of partial sums of deviations of times series from its mean, rescaled by its standard deviation. Hence, if r(1), r(2),... r(n) denotes asset returns and $\bar{r}_n$ represents the mean return given by r_n $ 1 n ,t$ n 1 r(t) , where 'n' is the time span considered, the rescaled range statistic is given by

(1) &(* RS ')+ $1 /24max1.k.n ,t$k1 (r(t)1r̄n)11min.k.n,t$k1 (r(t)1r̄n)0 5 3
n n

where $-_n$ is the maximum likelihood estimate of simple standard
1,n (r(t)1r̄)^2 deviation: -n $ n t$1 n . The first term in the bracket is the maximum of the partial sums of the first k deviations of r(t) from the sample mean. It is non-negative since sum of all n deviations of r(t)'s from their mean is zero, thus the maximum value with k varying from 1 to n will be zero or a positive number . The second term in the bracket is the corresponding minimum of the same sequence of partial sums and is nonpositive. The difference of these two quantities, called "range" is always

&R' 60. The advantage of non-negative and makes the rescaled range, (* S)+n
the classical R/S analysis is that it does not require the underlying series to follow normal distribution or any other distribution making its finding reliable whether the distribution of the series is known or unknown.

Classical R/S statistic is often criticized for being unable to distinguish between short memory and long memory that may be present in the financial data. This drawback of the classical R/S statistic was removed by modified R/S statistic proposed by Lo (1991).

Modified Rescaled-Range (R/S) Analysis

The modified R/S analysis suggested by Lo (1991) was conducted for long memory that examines the null hypothesis of no long range dependence at different significance levels. Lo's modified R/S statistic, denoted by Q_n is defined as:Q_n $-n1(q) /24max1.k.n 't$k1 (r(t)1ŧn)11min.k.n't$k 1 (r(t)1ŧn)05 3

Where $-_n^2$(q)is the Newey-West (1987) estimate of long run variance of the series defined as:

-n2(q)$ 1n,t$n1 (r(t)1ŧn)2 %2,jq$1 7j (q)8j

Where 8_j represents the sample auto-covariance of order j, and 7_j (q) represents the weights applied to the sample auto-covariance at lag j (1,2,...q). 7_j (q) is defined as: 7_j (q) $11 q%j 1 .

The second term in the long run variance equation intended to capture the short term dependence. Therefore, the estimate of $-_n^2$ (q) involves not only sums of squared deviations of r(t), but also its weighted autocovariances up to lag q. The weights 7_j (q) are the correction factors that help to distinguish between long and short memory. The lag length q obtained from the bandwidth selection procedures suggested by Andrew (1991) have been used to estimate the heteroskedasticity and autocorrelation corrected (HAC) standard deviation and is extremely crucial for modified R/S test of long memory. It is important to note here that if maximum lag length is chosen to be zero, the Equation (2) becomes similar to Equation (1) and gives the classical R/S statistic. The critical values for both classical and modified R/S analysis are obtained from Lo (1991, Table II).

The Spectral Regression Method

A stationary long memory process can be characterized by the behaviour of the spectral density f(!) function which takes the form f(!) c1-e$^{-i!}$ ^{2d} , as !" 0withd 9 0 , where c90, , d is the long memory parameter (or fractional differencing parameter) and 0: d : 0.5.

In order to estimate the fractional differencing estimator d, Geweke and Porter-Hudak (1983) proposed a semi-parametric method of the long memory parameter d which can capture the slope of the sample spectral density through a simple OLS regression based on the periodogram, as follows: log I(!) ="$_0$ 1d log{4sin^2(!$_j$ / 2)}+#$_j$, j$1,...M ,

Where I(!) is the jth periodogram point; ! $_j$ = 2$j/T; T is the number of observations; "$_0$ is a constant; and # $_j$ is an error term, asymptotically independent and identically distributed, across harmonic frequencies with zero mean and variance known to be equal to !^{2} / 6. M $ g;T< T^=$ with 0 < < 1 is the number of Fourier frequencies included in the spectral regression and is an increasing function of T. Geweke and Porter-Hudak (1983) suggested that the inclusion of medium or high periodogram ordinates which is, improper value of M may result in biased estimate of d. Based on available literature on the subject and in absence of any methodology to precisely find the optimum value of M, several values of M are established as M = $T^{0.50}$; $T^{0.55}$; …, $T^{0.7}$. The GPH fractional differencing test is performed on the stock return aiming at a prospective gain in estimation efficiency. The fractional distinction test tends to find out fractal constitution in a time series based on spectral investigation of its low-frequency dynamics.

Data

The series studied in this analysis include ten stock indices, BUX (Hungary), CSI 300(China), IBOVESPA (Brazil), IPSA (Chile), KLSE (Malaysia), KOSPI (Korea), MICEX (Russia), MXX-IPC (Mexico), S&P CNX Nifty (India) and TWII (Taiwan) at daily frequencies. All the above referred countries are in the list of emerging markets as classified by Morgan Stanley Capital International (MSCI). The period of study is from January 2005 to June 2011. The daily closing values of the individual indices were taken and daily index returns were calculated using the relation r;t< = $\ln(p_{t+1})$-$\ln(p_t)$where r(t) is the return on the index on t-th day, $\ln(p_{t+1})$, $\ln(p_t)$ represents natural logarithm of index value on t+1 day and t-th day respectively. We test for long memory on return, absolute return (mod value) and squared return series from the stock markets referred above.

Findings

Descriptive Statistics

The statistical summaries of logarithmic return, absolute return and squared return series of all the indices are reported in Table 1 which shows that average return of four indices BUX, KLSE, MICEX and NIFTY are positive. The returns series of six indices are negatively skewed while other four are positively skewed and all ten return series are leptokurtic. This along with high value of Jarque-Bera statistic clearly suggests that returns series of both the indices cannot be regarded as normally distributed. However, both absolute return series and squared return series of all the indices are positively skewed and leptokurtic, indicating nonnormal distribution.

Table 1: Descriptive Statistics

Indices	Data	Mean	Median	Std. Dev.	Skewness	Kurtosis	JarqueBera
BUX	**RET**	0.000266	0.000584	0.018591	- 0.066128	9.05149	2474.595
	SQR	0.000345	9.39E-05	0.00098	9.667444	129.912	1113116
	ABS	0.01319	0.009688	0.013099	2.899919	17.9075	17281.93
CSI 300	**RET**	- 0.000763	- 0.002119	0.020883	0.467389	6.12087	656.719
	SQR	0.000436	0.000122	0.00098	5.948403	52.6444	161252.3
	ABS	0.014982	0.011037	0.014563	2.088745	9.5515	3735.618
IBOVESPA	**RET**	- 0.000521	- 0.001368	0.019502	0.014333	8.96513	2394.479
	SQR	0.00038	9.95E-05	0.001073	9.158036	118.298	917126.5
	ABS	0.013696	0.009974	0.013889	2.847438	16.8405	15072.81
IPSA	**RET**	- 0.000589	- 0.001158	0.011132	- 0.130255	14.0985	8390.91
	SQR	0.000124	3.35E-05	0.000449	19.68564	559.363	21180054
	ABS	0.007748	0.005789	0.008013	3.661859	32.0325	61038.09
KLSE	**RET**	0.000352	0.000703	0.013165	- 0.142054	102.54	653941.6
	SQR	0.000173	1.58E-05	0.001746	17.92992	349.591	8013138

International Journal of Marketing Research and Brand Management
Volume 13 Issue 2, April - June 2025
ISSN: 2995-3758
Impact Factor: 6.92
https://kloverjournals.org/index.php/mrbm

	ABS	0.006369	0.003971	0.011526	10.5777	149.194	1440134
KOSPI	**RET**	-0.000536	-0.001295	0.014969	0.595335	10.6551	4051.25
	SQR	0.000224	5.48E-05	0.000693	10.85882	162.753	1754501
	ABS	0.010342	0.007401	0.010832	3.111432	20.3854	23015.87
MICEX	**RET**	0.000705	0.001424	0.02564	-0.113932	18.8066	16847.43
	SQR	0.000657	0.00012	0.002772	13.43034	237.46	3754630
	ABS	0.016296	0.010941	0.019803	4.297253	34.1505	70397.65
MXX IPC	**RET**	-0.000621	-0.001322	0.014776	-0.156659	8.35055	1967.77
	SQR	0.000219	5.38E-05	0.000593	8.62413	117.578	919656.7
	ABS	0.01029	0.007332	0.010619	2.680982	14.5286	11073.65
NIFTY	**RET**	0.000612	0.001346	0.017927	-0.031946	10.5801	3840.391
	SQR	0.000322	7.75E-05	0.000994	15.64028	362.037	8680699
	ABS	0.012479	0.008805	0.012882	2.965079	21.6858	25685.68
TWII	**RET**	-0.0002	-0.000816	0.01361	0.395448	6.0569	668.8313
	SQR	0.000185	4.43E-05	0.000415	4.875236	34.2891	72052.64
	ABS	0.009531	0.006657	0.009714	2.059358	8.45865	3136.861

RET – Return Series, SQR – Squared Return Series, ABS – Absolute Return Series.

Unit Root Tests

The results of unit root tests are displayed in Table 2. The null hypothesis of the presence of unit root in ADF test and PP test is rejected at 1% level of significance for logarithmic return, absolute return and squared return series of all ten indices indicating that all the data series are stationary.

Table 2: Unit Root Tests

Indices	**Data**	**ADF**	**PP**
BUX	**Return**	-30.020***	-37.819***
	Squared return	-6.8788***	-38.633***
	Absolute return	-7.2964***	-43.634***
CSI 300	**Return**	-38.288***	-38.288***
	Squared return	-10.521***	-46.133***
	Absolute return	-8.1815***	-57.823***
IBOVESPA	**Return**	-40.673***	-40.673***
	Squared return	-4.2305***	-96.442***

	Absolute return	-5.0850***	-83.298***
IPSA	**Return**	-34.951***	-34.951***
	Squared return	-7.5447***	-49.014***
	Absolute return	-10.050***	-33.856***
KLSE	**Return**	-50.903***	-50.903***
	Squared return	-6.0076***	-35.233***
	Absolute return	-5.9774***	-41.760***
KOSPI	**Return**	-39.644***	-39.644***
	Squared return	-6.1503***	-62.756***
	Absolute return	-6.3731***	-61.622***
MICEX	**Return**	-40.071***	-40.071***
	Squared return	-3.4470***	-188.88***
	Absolute return	-3.6851***	-110.56***
MXX IPC	**Return**	-36.706***	-36.706***
	Squared return	-4.3577***	-114.83***
	Absolute return	-5.7921***	-70.200***
NIFTY	**Return**	-37.745***	-37.745***
	Squared return	-7.6590***	-64.926***
	Absolute return	-7.8657***	-45.155***
TWII	**Return**	-37.881***	-37.881***
	Squared return	-6.3404***	-80.306***
	Absolute return	-5.8534***	-92.787***

a) The critical values are those of Mackinnon (1991).

b) *** Represent the rejection of null hypothesis at 1% level of significance.

Visual Interpretation: Autocorrelation Function (ACF)

The Autocorrelation function was plotted against the time lag for logarithmic return, absolute return and squared return series of all the ten indices. The lag was taken up to thirty five days. The autocorrelation is found to decay quickly and is insignificant in the logarithmic return series of all the indices. However, in case of absolute and squared return series, a slow decay in autocorrelation is observed except for KLSE which shows a complex pattern that calls for further investigation. The ACF of the data series (Figure 1) indicates short memory in return but long range dependence or persistence for absolute and squared return

International Journal of Marketing Research and Brand Management
Volume 13 Issue 2, April - June 2025
ISSN: 2995-3758
Impact Factor: 6.92
https://kloverjournals.org/index.php/mrbm

series in emerging stock markets.

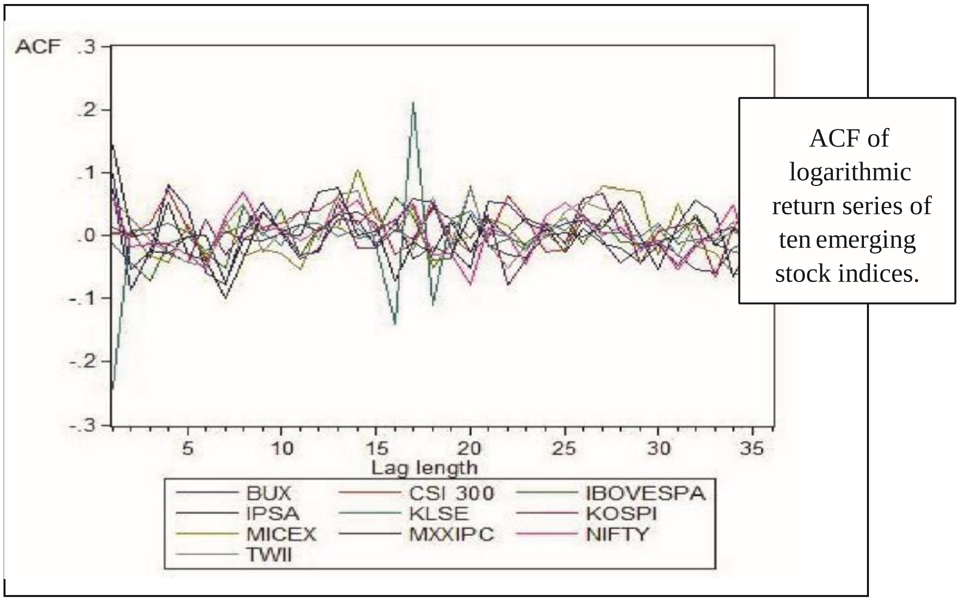
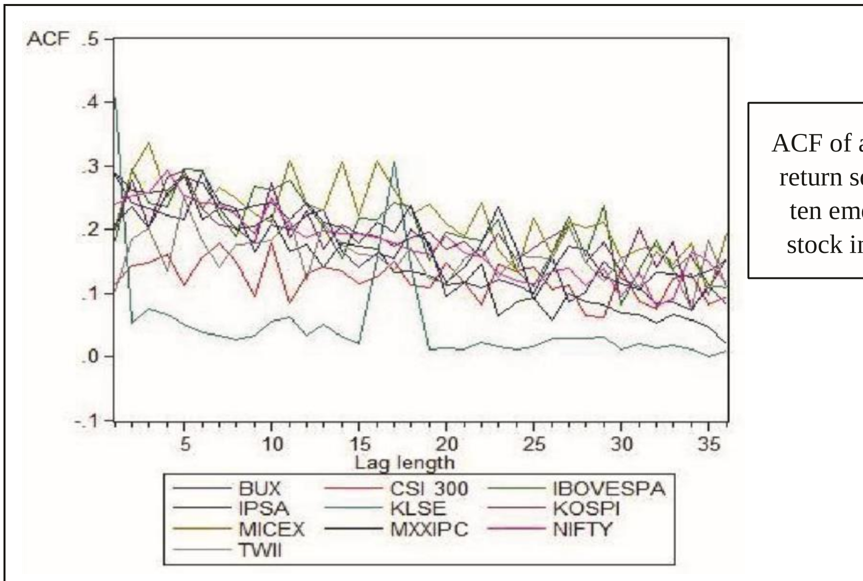
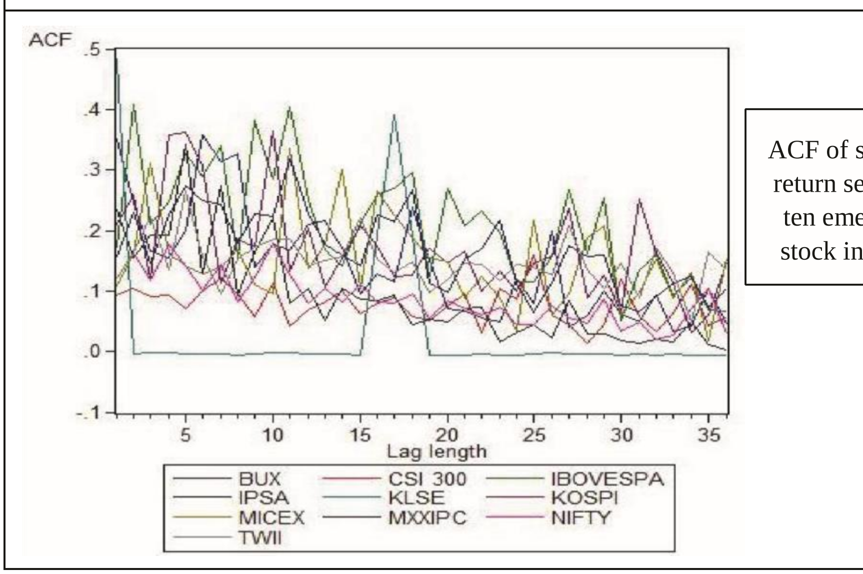


Figure 1: Visual Interpretation: Autocorrelation Function (ACF)

International Journal of Marketing Research and Brand Management
Volume 13 Issue 2, April - June 2025
ISSN: 2995-3758
Impact Factor: 6.92
https://kloverjournals.org/index.php/mrbm



ACF of absolute return series of ten emerging stock indices.



ACF of squared return series of ten emerging stock indices.

Rescaled-Range (R/S) Analysis: Hurst-Mandelbrot's Classical R/S Statistic and Lo Statistic

The results of Rescaled-Range (R/S) Analysis are presented in Table 3 where Hurst-Mandelbrot's Classical R/S Statistic and Lo Statistic are displayed. The estimated value of Hurst-Mandelbrot's Classical R/S

Statistic suggests that the null hypothesis of no long-range dependence in case of return series of all ten indices could not be rejected at a generally acceptable level of significance as estimated value of the statistic falls within the acceptance region. However, for both absolute and squared return, the null hypothesis is rejected at 1% level of significance. The critical values of the statistic are obtained from Lo (Table II, 1991). This clearly indicates that although logarithmic returns may not have long memory, returns without signs as well as volatility as measured by squared returns shows existence of long run dependence in the series. Now, since Classical R/S Statistic is sensitive to short-range dependence and may give biased results in the case of short-range dependence, heterogeneities and non-stationary series, we also computed Lo's statistic which takes care of these shortcomings. The Lo statistic, displayed in Table 3, also shows that the null hypothesis of no long-range dependence in case of return series of all ten indices could not be rejected at a generally acceptable level of significance as estimated value of the statistic falls within the acceptance region. For absolute return series, Lo statistic rejects the null hypothesis at 1% level of significance for all the ten indices but in case of squared return series, the null hypothesis of no long-range dependence is rejected for all the indices at 1% level except for KLSE where value of Lo statistic could not reject the null hypothesis of no long-range dependence. The results of both the tests are consistent and indicate short memory for return series and long memory for volatility in general for the emerging stock markets.

Table 3: Hurst-Mandelbrot's Classical R/S Statistic and Lo Statistic

Indices	Data	Hurst-Mandelbrot's Classical R/S Statistic	Lo Statistic
BUX	Return	1.69	1.68
	Absolute return	5.67	3.17
	Squared return	4.62	2.39
CSI 300	Return	1.98	1.98
	Absolute return	6.01	4.85
	Squared return	4.67	3.98
IBOVESPA	Return	1.24	1.24
	Absolute return	5.64	3.59
	Squared return	4.72	2.92
IPSA	Return	1.55	1.39
	Absolute return	5.41	2.97
	Squared return	3.62	2.22
KLSE	Return	1.32	1.32
	Absolute return	4.28	2.82
	Squared return	2.08	1.53
KOSPI	Return	1.53	1.52

	Absolute return	5.92	3.61
	Squared return	4.62	2.8
MICEX	**Return**	1.52	1.52
	Absolute return	5.98	3.54
	Squared return	4.14	3.19
MXX IPC	**Return**	1.53	1.49
	Absolute return	5.31	3.27
	Squared return	4.5	3.05
NIFTY	**Return**	1.49	1.45
	Absolute return	6.17	3.55
	Squared return	4.33	3.32
TWII	**Return**	1.71	1.63
	Absolute return	6.73	5.31
	Squared return	6.23	4.61

Note:
Critical values:
90% [0.861, 1.747] 95% [0.809, 1.862] 99% [0.721, 2.098]

The Spectral Regression Method (GPH statistic)

Table 4 reports estimates of the fractional differencing parameter (d) for the daily logarithmic return, absolute return and squared return series of all ten indices from ten emerging stock markets. The test examines the null hypothesis of short memory (H_0 :d 0) against long memory alternatives (H_1:d !0) for a range of bandwidth (M $T^{0.50}$, $T^{0.55}$, '', $T^{0.7}$). The estimates of d are statistically significant for all ten indices in absolute and square return series. The null hypothesis of short memory is rejected and the findings show that long memory property exists in absolute return and volatility in emerging markets. However, the findings are mixed in case of logarithmic return series. Estimate of d is found to be statistically significant in two chosen bandwidths in case of Russia, India and Taiwan, whereas it is found significant in one of the chosen bandwidth in case of Hungary, China and Korea. The null hypothesis of short memory in return series is rejected in case of Chile, Brazil, Malaysia and Mexico. The findings did not support existence of Taylor Effect in the selected emerging markets.

International Journal of Marketing Research and Brand Management
Volume 13 Issue 2, April - June 2025
ISSN: 2995-3758
Impact Factor: 6.92
https://kloverjournals.org/index.php/mrbm

Table 4: GPH estimates of fractional differencing parameter (d)

Indices	Data	M=T0. 50	M=T0. 55	M=T0.60	M=T0.65	M=T0.70
BUX	Return	0.18505 (0.0970) [1.9067]	0.2518*** (0.08955) [2.8126]	0.1004 (0.0823) [1.2189]	0.0888 (0.0670) [1.3252]	0.0770 (0.0558) [1.3809]
	Squared return	0.3844*** (0.0555) [6.9249]	0.4990*** (0.0588) [8.4814]	0.5779*** (0.0545) [10.587]	0.5794*** (0.0475) 12.1818	0.5182*** (0.0458) [11.29]
	Absolute return	0.4415*** (0.0853) [5.1750]	0.5143*** (0.0677) [7.5973]	0.5548*** (0.0585) [9.4711]	0.4612*** (0.0499) [9.2404]	0.4190*** (0.0451) [9.2724]
CSI 300	Return	0.2237 (0.1181) [1.8948]	0.2195 ** (0.1056) [2.0793]	0.1479 (0.0817) [1.8092]	0.0931 (0.0678) [1.3739]	0.0222 (0.0526) [0.4227]
	Squared return	0.4143*** (0.0826) [5.0146]	0.3574*** (0.0749) [4.7663]	0.3121*** (0.0632) [4.9373]	0.2993*** (0.0545) [5.4840]	0.2834*** (0.0544) [5.2043]
	Absolute return	0.4456*** (0.0773) [5.7578]	0.4619*** (0.0837) [5.5140]	0.3976*** (0.0699) [5.6816]	0.3722*** (0.0610) [6.0933]	0.2878*** (0.0476) [6.0430]
IBOVESPA	Return	0.1463 (0.0974) [1.5022]	0.0501 (0.0718) [0.6973]	0.0398 (0.0632) [0.6310]	-0.0251 (0.0498) [-0.5018]	-0.0505 (0.0447) [-1.1293]
	Squared return	0.6959*** (0.0710) [9.7974]	0.8277*** (0.0839) [9.8552]	0.7410*** (-0.0668) [11.1134]	0.7109*** (0.5999) [11.8582]	0.5020*** (0.0573) [8.7574]
	Absolute return	0.7223*** (0.1104) [6.5380]	0.6682*** (0.0836) [7.9894]	0.6477** (0.0693) [9.3471]	0.5543*** (0.0579) [9.5683]	0.4520*** (0.5099) [8.8659]
IPSA	Return	0.0331 (0.9267) [0.3572]	-0.0240 (0.0731) [-0.328]	0.017 (0.0811) [0.2100]	0.0057 (0.0637) [0.0910]	-0.0451 (0.0520) [-0.8680]

	Squared return	0.2448*** (0.0622) [3.9307]	0.2872*** (0.0556) [5.1588]	0.4143*** (0.0544) [7.6123]	0.4769*** (0.0429) [11.1105]	0.4893*** (0.0397) [12.3254]
	Absolute return	0.4973*** (0.131) [3.7963]	0.4326*** (0.0969) [4.4649]	0.4546*** (0.0725) [6.2635]	0.4068*** (0.0582) [6.9844]	0.4372*** (0.0508) [8.6055]
KLSE	**Return**	0.1987 (0.1214) [1.6370]	0.1315 (0.0918) [1.4320]	0.0486 (0.0738) [0.6589]	0.0300 (0.0573) [0.5242]	-0.0238 (0.0458) [-0.5206]
	Squared return	0.2540*** (0.0590) [4.3000]	0.4918*** (0.07311) [6.7275]	0.2058*** (0.0682) [3.0175]	0.0244*** (0.0532) [0.4588]	0.1196*** (0.0448) [2.6700]
	Absolute return	0.2032 *** (0.0904) [2.2470]	0.3212*** (0.0792) [4.0511]	0.1739*** (0.0648) [2.6826]	0.0640*** (0.0504) [1.2696]	0.1692*** (0.0479) [3.5277]
KOSPI	**Return**	0.2361** (0.1096) [2.1540]	0.1001 (0.1043) [0.9596]	0.0171 (0.0823) [0.2082]	0.0124 (0.0657) [0.1896]	0.0034 (0.0509) [0.0674]
	Squared return	0.5704*** (0.0535) [10.65]	0.4510*** (0.0471) [9.5731]	0.5731*** (0.0567) [10.0944]	0.5600*** (0.0516) [10.8444]	0.5880*** (0.0464) [12.6716]
	Absolute return	0.7647*** (0.1265) [6.0474]	0.5462*** (0.0979) [5.5768]	0.5006*** (-0.0748) [6.6873]	0.4392*** (-0.06) [7.3206]	0.4237*** -0.0516 [8.2093]
MICEX	**Return**	0.2858*** (0.0899) [3.1792]	0.1766** (0.0822) [2.1484]	0.05241 (0.0700) [0.7486]	-0.0299 (0.0589) [-0.5085]	-0.0007 -0.0483 [-0.0164]
	Squared return	0.7821*** (0.0929) [8.4115]	0.7840*** (0.0681) [11.5029]	0.6987*** (0.0544) [12.8307]	0.3423*** (0.06153) [5.5637]	0.3009*** (0.047) [6.3245]
	Absolute return	0.7207*** (0.0937) [7.6911]	0.7389*** (0.0736) [10.0314]	0.6195*** (0.0617) [10.0416]	0.4365*** (0.0567) [7.6891]	0.4161*** (0.0472) [8.8027]
MXX IPC	**Return**	0.17596 (0.129) [1.3641]	-0.0043 (0.0997) [-0.0433]	0.0624 (0.0799) [0.7810]	-0.0362 (0.0642) [-0.5638]	-0.0731 (0.0507) [-1.4392]

	Squared return	0.6588*** (0.0780) [8.4429]	0.7454*** (0.0727) [10.2522]	0.7686*** (0.0617) [12.4546]	0.6226*** (0.0539) [11.5358]	0.4313*** (0.0467) [9.2281]
	Absolute return	0.5707 *** (0.0958) [5.9531]	0.6293*** (0.0910) [6.9134]	0.6353*** (0.0747) [8.4951]	0.5731*** (0.0624) [9.1345]	0.4856*** (0.0525) [9.2479]
NIFTY	**Return**	0.2049** (0.0949) [2.1582]	0.1426 (0.0786) [1.8144]	0.1688** (.0685) [2.4631]	0.0824 (0.0563) [1.4618]	0.0695 (0.0525) [1.3234]
	Squared return	0.3671*** (0.0982) [3.7377]	0.3707*** (0.0762) [4.8651]	0.4185*** (0.0687) [6.0886]	0.3832*** (0.0565) [6.7741]	0.3018*** (0.0470) [6.4105]
	Absolute return	0.49602*** (0.1005) [4.9373]	0.52033*** (0.0809) [6.4300]	0.55529*** (0.0747) [7.4284]	0.5008*** (0.0597) [8.3854]	0.4249*** (0.0476) [8.9270]
TWII	**Return**	0.2058** (0.0934) [2.2026]	0.1711** (0.0751) [2.2781]	0.1302 (0.0661) [1.9703]	0.0670 (0.0615) [1.0902]	0.0449 (0.0501) [0.8966]
	Squared return	0.6586*** (0.1098) [5.9991]	0.5225*** (0.0874) [5.9761]	0.4748*** (0.0754) [6.2965]	0.3649*** (.063) [5.7932]	0.3291*** (0.0530) [6.2029]
	Absolute return	0.6192*** (0.0953) [6.4983]	0.5191*** (0.0792) [6.5488]	0.5119*** (0.0774) [6.6064]	0.4372*** (0.0671) [6.5107]	0.3375*** (0.0534) [6.3204]

a) ***, ** and ** represents the rejection of null hypothesis at 1%, 5% and 10% level of significance respectively.

b) Standard errors in ( ) and t-statistics in [ ].

To improve the precision of the results we conducted Robinson's (1995) estimate of d and the findings are reported in Table 5. Similar to GPH test the chosen bandwidth ranges from $T^{0.5}$ to $T^{0.7}$. Although similar results are obtained for absolute return and square return series, none of the return series of all the ten indices shows significant estimate of d in the range of bandwidth, suggesting that long-range dependence may not exist in the chosen market indices.

Table 5: Robinson's estimates of fractional differencing parameter (d)

Indices	Data	M=T0. 50	M=T0. 55	M=T0.60	M=T0.65	M=T0.70
BUX	**Return**	0.1524 (0.0990) [1.5396]	0.1574 (0.0879) [1.7892]	0.1098 (0.0817) [1.3436]	0.0884 (0.0668) [1.3224]	0.0724 (0.0553) [1.3079]
	Squared return	0.38821*** 0.0540 [7.1763]	0.4945*** 0.0578 [8.5495]	0.58108*** 0.0539 [10.7746]	0.57814*** 0.0474 [12.1821]	0.51069*** 0.0456 [11.1868]

	Absolute return	0.44650*** (0.0830) [5.3731]	0.5133*** (0.0664) [7.7313]	0.5587*** (0.0579) [9.6466]	0.4599*** (0.0498) [9.2333]	0.4109*** (0.0450) [9.1157]
CSI 300	**Return**	0.2088 (0.1154) [1.8095]	0.2194 (0.1055) [2.0790]	0.1476 (0.0816) [1.8075]	0.0927 (0.0676) [1.3705]	0.0219 (0.0520) [0.4222]
	Squared return	0.4033*** (0.0808) [4.9903]	0.3571*** (0.0749) [4.7653]	0.3117*** (0.0631) [4.9350]	0.2984*** (0.0544) [5.4804]	0.2932*** (0.0549) [5.3383]
	Absolute return	0.4464*** (0.0751) [5.9417]	0.4616*** (0.0837) [5.5137]	0.3970*** (0.0699) [5.6796]	0.3711*** (0.0609) [6.0896]	0.29967*** (0.0489) [6.1207]
IBOVESPA	**Return**	0.1630 (0.0959) [1.6986]	0.0810 (0.0762) [1.0622]	0.0321 (0.0627) [0.5124]	-0.0251 (0.0497) [-0.5058]	-0.0457 (0.0445) [-1.0279]
	Squared return	0.7228*** (0.0734) [9.8412]	0.8235*** (0.0824) [9.9878]	0.7422*** (0.0657) [11.2818]	0.7091*** (0.0598) [11.8525]	0.4908*** (0.0572) [8.5756]
	Absolute return	0.7401*** (0.1087) [6.8090]	0.7006*** (0.0876) [7.9969]	0.6428*** (0.0684) [9.3908]	0.5528*** (0.0578) [9.5611]	0.4435*** (0.0507) [8.7349]
IPSA	**Return**	0.0148 (0.0916) [0.1623]	-0.0195 (0.0718) [-0.2715]	0.0153 (0.0800) [0.1911]	0.0026 (0.0631) [0.0428]	-0.0452 (0.0518) [-0.8734]
	Squared return	0.2683*** (0.0643) [4.1689]	0.3147*** (0.0604) [5.2058]	0.4089*** (0.0538) [7.5880]	0.4860*** (0.043) [11.1707]	0.4872*** (0.0395) [12.3310]
	Absolute return	0.5066*** (0.1276) [3.9682]	0.4481*** (0.09619) [4.6590]	0.4397*** (0.0728) [6.0340]	0.4022*** (0.0577) [6.9685]	0.4351*** (0.0505) [8.6051]
KLSE	**Return**	0.1987 (0.1213) [1.6370]	0.1314 (0.0918) [1.4319]	0.0484 (0.0737) [0.6577]	0.0190 (0.0577) [0.3306]	-0.0241 (.0456) [-0.5290]
	Squared return	0.2539*** (0.0590) [4.3005]	0.4917*** (0.0730) [6.7309]	0.2053*** (0.0681) [3.0134]	0.0214 (0.0526) [0.4080]	0.1190*** (.04460) [2.6681]
	Absolute return	0.2032*** (0.0904) [2.2474]	0.3211*** (0.0792) [4.0526]	0.1736*** (0.0647) [2.6804]	0.0598 (0.0500) [1.1970]	0.1686*** (0.0477) [3.5326]
KOSPI	**Return**	0.2061	0.1194	0.0184	0.0122	-0.0055

		(0.1101) [1.8720]	(0.1039) [1.1491]	(0.0812) [0.2272]	(0.0655) [0.1868]	(0.0504) [-0.1102]
	Squared return	0.5735*** (0.0521) [10.9971]	0.4550*** (0.0463) [9.8071]	0.5788 *** (0.0562) [10.2832]	0.5587 *** (0.0515) [10.8438]	0.5803*** (0.04617) 12.5684
	Absolute return	0.7643*** (0.1229) [6.2169]	0.5579*** (0.0967) [5.7664]	0.4982*** (0.0738) [6.7463]	0.4379*** (0.0598) [7.3145]	0.4189*** (0.0511) [8.1928]
MICEX	**Return**	0.1219 (0.0936) [1.3026]	0.1636 (0.0806) [2.0281]	0.0553 (0.0691) [0.8005]	-0.0303 (0.0587) [-0.5157]	-0.0011 (0.0478) [-0.0240]
	Squared return	0.7835*** (0.0904) [8.6654]	0.7722*** (0.0677) [11.4058]	0.6950*** (0.0537) [12.9228]	0.3406*** (0.0614) [5.5454]	0.2960*** (0.0471) [6.2728]
	Absolute return	0.7191*** (0.0911) [7.8920]	0.7203*** (0.0742) [9.7053]	0.6301*** (0.0618) [10.1935]	0.4350*** (0.0566) [7.6759]	0.4118*** (0.0468) [8.7939]
MXX IPC	**Return**	0.1533 (0.1271) [1.2061]	0.0096 (0.0987) [0.0979]	0.0623 (0.0798) [0.7805]	-0.0364 (0.0641) [-0.5684]	-0.0735 (0.0502) [-1.4637]
	Squared return	0.7071*** (0.0881) [8.0266]	0.7399*** (0.0714) [10.3522]	0.7678*** (0.0616) [12.4587]	0.6209*** (0.0538) [11.5235]	0.4221*** (0.0466) [9.0457]
	Absolute return	0.6271*** (0.1068) [5.8673]	0.6272*** (0.0893) [7.0227]	0.6346*** (0.0747) [8.4957]	0.5717*** (0.0622) [9.1810]	0.4800*** (0.0520) [9.2213]
NIFTY	**Return**	0.1959 (0.0927) [2.1140]	0.1425 (0.0785) [1.8146]	0.1686 (0.0684) [2.4634]	0.0819 (0.0562) [1.4578]	0.0690 (0.0523) [1.3206]
	Squared return	0.3545*** 0.0962 [3.6853]	0.3705*** 0.0761 [4.8655]	0.41818*** 0.0686 [6.0901]	0.3823*** 0.0564 [6.7730]	0.2999*** 0.0468 [6.4000]
	Absolute return	0.4886*** 0.0979 [4.9911]	0.5200*** 0.0808 [6.4309]	0.5546*** 0.0746 [7.4291]	0.4996*** 0.0595 [8.3842]	0.4225*** 0.0474 [8.9150]
TWII	**Return**	0.1998 (0.0911) [2.1946]	0.1803 (0.0742) [2.4301]	0.1300 (0.0661) [1.9691]	0.0666 (0.0613) [1.0861]	0.0444 (0.0499) [0.8909]
	Squared return	0.6312*** (0.1096) [5.7554]	0.5281*** (0.0859) [6.1437]	0.4742*** (0.0753) [6.2942]	0.3637*** (0.0628) [5.7844]	0.3271*** (0.0528) [6.1919]

	Absolute return	0.6051*** (0.0935) [6.4678]	0.5434*** (0.0811) [6.6984]	0.5113*** (0.0774) [6.6050]	0.4359*** (0.0671) [6.5038]	0.3352*** (0.0531) [6.3048]

a) ***, ** and ** represents the rejection of null hypothesis at 1%, 5% and 10% level of significance respectively.

b) Standard errors in ( ) and t-statistics in [ ].

Conclusion

According to the market efficiency hypothesis in its weak form, asset prices reflect all available information and asset prices should fluctuate as random white noise which is satisfied by unpredictable behaviour of asset returns. When return series exhibit long memory, they display significant autocorrelation between distant observations. In such a case, the series observations are not independent over time and past returns can help predict future returns, thus violating the market efficiency hypothesis. Exploring long memory property is appealing to derivative market participants, risk managers and asset allocation decision makers, whose interest is to reasonably forecast stock market movements. The study examined the evidence of long memory in the ten emerging markets – two from Europe, five from Asia and three from Latin America. To test the presence of long memory in asset returns, we computed HurstMandelbrot's Classical R/S statistic, Lo’s statistic, and semi-parametric GPH statistic as well as modified GPH statistic of Robinson (1995). All the tests are consistent with long-range dependence in the absolute return and squared return series. In case of Malaysia (KLSE), Lo statistic could not show long memory in squared return and Robinson’s estimate of d was insignificant in one of the ordinates ($T^{0.65}$) among chosen five ordinates for both absolute return and squared return series. However, HurstMandelbrot's Classical R/S statistic and GPH statistic support the existence of the long memory along with Robinson’s estimates in four ordinates out of five. This support in favour of the existence of long memory is in line with the findings of Beran and Ocker (2001) and Cajueiro and Tabak (2004). We argue that evidence against long memory in KLSE needs further research given the dynamic nature of market movements in Malaysia. Overall findings did not support the Taylor effect as the estimate of the fractional differencing parameter is not higher for the absolute returns than that of squared returns in all the observed bandwidth. However, we find no evidence of long-term memory in chosen emerging stock market returns indicating emerging stock market returns follow a random walk. Absence of long memory in return series of the indices shows no evidence against the weak form of market efficiency in stock returns. Also, the relevance of linear pricing models and statistical inferences about asset pricing models based on standard testing procedures is not questionable in absence of long-range dependence in stock returns. Given the financial economic environment, settlement cycles and market micro-structure in the emerging markets, there may be a lagged adjustment to new information by the security prices. And if this be the cause of autocorrelation in returns, the absence of long-range dependence in stock returns as obtained in our findings should not be surprising. Presence of long memory in squared returns indicates that volatility of asset returns can be modeled using returns from the recent as well as remote past and hence, derivative instruments can now be more efficiently priced. The financial market regulators in these emerging markets may look into the sources of long memory in volatility of stock returns to improve efficiency levels.

References

Andersen, T. G., & Bollerslev, T. (1997). Heterogeneous information arrivals and return volatility dynamics: uncovering the long-run in high frequency returns. Journal of Finance, 52(3), 975-1005.

Andersen, T. G., & Bollerslev, T. (1998). Answering the skeptics: yes, standard volatility models do provide accurate forecasts. International Economic Review, 39(4), 885-905.

Andrews, D. W. K. (1991). Heteroskedasticity and autocorrelation consistent covariance matrix estimation. Econometrica, 59(3), 817-858.

Baillie, R. T. (1996). Long memory processes and fractional integration in econometrics. Journal of Econometrics, 73(1), 5-60.

Beran, J., & Ocker, D. (2001). Volatility of stock market indices - an analysis based on SEMIFAR models. Journal of Business and Economic Statistics, 19(1), 103-116.

Breidt, F. J., Crato, N., & de Lima, P. (1998). On the detection and estimation of long memory in stochastic volatility. Journal of Econometrics, 83(1/2), 325-348.

Cajueiro, D. O., & Tabak, B. M. (2004). The Hurst's exponent over time: testing the assertion that emerging markets are becoming more efficient. Physica A, 336, 521-537.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366), 427-431.

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

Disario, R., Saraoglu, H., McCarthy, J., & Li, H. (2008). Long memory in the volatility of an emerging equity market: the case of Turkey. Journal of International Financial Markets, Institutions and Money, 18(4), 305-312.

Eldera, J., & Serletis, A. (2008). Long memory in energy futures prices.

Review of Financial Economics, 17(2), 146-155.

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

Granger, C. W. J., & Ding, Z. (1995). Some properties of absolute return; an alternativemeasureofrisk.AnnalesD'EconomieetdeStatistique,40,67-91.

Granger, C. W. J. (1966). The typical spectral shape of an economic variable. Econometrica, 34(1), 150-161.

Granger, C. W. J., & Ding, Z. (1996). Varieties of long memory models. Journal of Econometrics, 73(1), 61-77.

Greene, M. T., & Fielitz, B. D. (1977). Long-term dependence in common stock returns. Journal of Financial Economics, 4(3), 339-349.

Harvey, A. C. (1993). Long memory in stochastic volatility. In J. Knight, & S. Satchell (Eds.), Forecasting Volatility in Financial Markets (pp. 307-320). Oxford, UK: Butterworth-Haineman.

Hurst, H. E. (1951). Long-term storage of reservoirs: An experimental study. Transactions of the American Society of Civil Engineers, 116, 770-799.

Kang, S. H., Cheong, C., & Yoon, S. M. (2010). Long memory volatility in Chinese stock markets. Physica A, 389, 1425-1433.

Lo, A. W. (1991). Long-term memory in stock market prices. Econometrica, 59(5), 1279-1313.

Mandelbrot, B. B., & Wallis, J. R. (1968). Noah, Joseph, and Operational Hydrology. Water Resources Research, 4(3), 909-918.

Mandelbrot, B. B., & Wallis, J. R. (1969). Robustness of the rescaled range r/s in the measurement of noncyclic long-run statistical dependence. Water Resources Research, 5(5), 967-988.

Mandelbrot, B. B. (1971). A fast fractional Gaussian noise generator. Water Resources Research. 7(3), 543-553.

Mandelbrot, B. B. (1972). Possible refinement of the lognormal hypothesis concerning the distribution of energy dissipation in intermittent turbulence. In M. Rosenblatt & C. Van Atta (Eds.), Statistical Models and Turbulence, New York: Springer.

Mandelbrot, B. B. (1997). Fractals and scaling in finance: Discontinuity, concentration, risk. New York: Springer-Verlag.

Mukherjee, I., Sen, C., & Sarkar, A. (2011). Long memory in stock returns: Insights from the Indian market. The International Journal of Applied Economics and Finance, 5(1), 62-74.

Nath, G. C. (2001). Long memory and Indian stock market –An empirical evidence. Proceedings of UTI Institute of Capital Markets Conference, India. Retrieved from http://www.utiicm.com/Cmc/PastCMC_2001.asp

Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. Biometrika, 75(2), 335-346.

Robinson, P. M. (1995). Log-periodogram regression of time series with long range dependence. Annals of Statistics, 23(3), 1048-1072.

Robinson, P. M. (2003). Long memory time series. In Peter, M. R. (Ed.), Time series with long memory (pp. 4-32). United Kingdom, UK: Oxford University Press.

Sadique, S., & Silvapulle, P. (2001). Long-term memory in stock market returns: International evidence. International Journal of Finance & Economics, 6(1), 59-67.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under condition of risk, Journal of Finance, 19(3), 425-442.

Taylor, S. (1986). Modelling Financial Time Series. New York, NY: John Wiley & Sons.

Willinger, W., Taqqu, M. S., & Teverovsky, V. (1999). Stock market prices and long-range dependence. Finance and Stochastics, 3, 1-13.

Yajima, Y. (1985). On estimation of long-memory time series models. Australian Journal of Statistics, 27(3), 303-320.