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Exploring Presence of Long Memory in Emerging and Developed Stock Markets

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According to the market efficiency hypothesis in its weak form, asset prices incorporate all relevant information, rendering asset returns unpredictable. The most considerable economical implication of existence of long memory is the contradiction of the weak-form of market efficiency (Fama, 1970) by allowing investors and portfolio managers to make prediction and to construct speculative strategies. The price of an asset determined in an efficient market should follow a martingale process in which each price change is unaffected by its predecessor and has no memory. When return series exhibit long memory, they display significant autocorrelation between distant observations. Therefore, the series realizations are not independent over time and past returns can help predict futures returns, thus violating the market efficiency hypothesis.

Exploring long memory property is appealing for derivative market participants, risk managers and asset allocation decisions makers, whose interest is to reasonably forecast stock market movements. Generally markets are classified as developed or emerging on the basis of their level of efficiency. Since efficiency levels of developed and emerging stock markets are different, long memory properties displayed by them should be different. Motivated by this we investigate long-memory properties in ten stock exchanges from developed markets (USA, UK, Germany, Australia, New Zealand, Hong Kong, France, Netherlands, Japan and Singapore) and ten from emerging markets (Russia, Hungary, Brazil, Chile, Mexico, Malaysia, Korea, Taiwan, China, and India) using daily return, absolute return and squared return. We compute Hurst exponent, Lo's statistic, semi parametric GPH statistic to test the presence of long-memory in asset returns which would provide evidence against the weak form of market efficiency. We look into developed markets with emerging markets to determine if the returns-generating processes and presence or absence of long memory depends on the degree of market development.

Keywords: *Market efficiency, Emerging Market, Developed Market, Long Memory, Hurst exponent, Lo's statistic, semi parametric GPH statistic.*

1. Introduction

Presence of stochastic long memory in stock market returns has a direct implication about market efficiency and can pose a serious challenge to the legacy of random walk behavior of the stock returns. However, there is a near consensus amongst financial econometricians that the squared returns or volatility of stock prices exhibit long memory. All of this begun with evidence of hyperbolic decay in autocorrelations of the stock indices (Taylor 1986, Ding et al., 1993). In recent years, a large number of financial econometricians studied long memory stylizations in volatility of stock prices. The studies related to long range dependence includes detection of long memory in the data, statistical estimation of parameters of long range dependence, limit theorems under long range dependence, simulation of long memory processes, and many others. Hurst (1951) possibly inspired the development of statistical long-memory processes. He proposed a method (Rescaled Range analysis) for the quantification of long-term memory which is based on estimating a parameter for 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) and Mandelbrot and Wallis (1969) who suggested that in the presence of long memory, arbitrage opportunities may exist as new market information cannot be absorbed quickly and martingale models of asset prices may not be justified. Mandelbrot (1997) summarises many of the early papers that Mandelbrot wrote on the application of the Hurst exponent in financial time series. Since those days, the application of the long memory processes in economy has been extended from macroeconomics to finance. A good survey of the econometric approach to long-memory is given in Baillie (1996). Long-memory properties of financial time series indicates linear pricing models and statistical inferences about asset pricing models based on standard testing procedures may not be appropriate (Yajima, 1985). Several authors have claimed that the time series of stock returns for stock prices or indices display long-memory (Mandelbrot, 1971, Greene and Fielitz, 1977). 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 concluded that daily stock returns do not display long-memory properties. Later, Willinger et al. (1999) in turn, showed 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. Since financial data typically display low degree of long-memory, they claim that the result of Lo (1991) may not be conclusive.

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. There are many studies from developed markets showing that conditional volatility of returns on asset prices displays long memory or long range dependence. Andersen and Bollerslev (1997; 1998), Ding, et al. (1993) and Breidt et al. (1998) find evidence of long-memory stochastic volatility in stock returns, and Harvey (1993) finds evidence for this in exchange rates. These results led to the development of alternate models for volatility, such as Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity (FIGARCH) model.

The debate on stock market returns displaying long memory properties still continues since this fact has important consequences on the capital market theories even though evidences on the topic reported in empirical studies is not strong enough. Long range dependence generally suggests non linear dependence in average asset returns. The primary implication of this phenomenon is that returns can be predicted, efficient market hypothesis is violated and stock market prices do not follow a random walk. It would also raise concern regarding linear modeling, forecasting, statistical testing of pricing models based on standard statistical methods, and theoretical and econometric modeling of asset pricing.

An area of interest in financial econometrics literature is evidences 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 phenomena is observed by Ding et al. (1993) and Granger and Ding (1995, 1996). Granger and Ding (1995) referred this phenomenon as the 'Taylor effect.'

Though we have extensive literature on the long-memory properties of stock market prices in the developed countries, very few researches have been conducted on the long memory properties of stock markets in the emerging economy. The present study aimed at investigating the existence of long memory properties in ten developed stock markets along with ten emerging stock markets across the globe. There is a need for a more comprehensive study to make an attempt to find evidence of long memory or market inefficiency, more particularly, in the context of the emergence of new regulations, changing market micro structures in the developed markets. Moreover, it is also to be noted here that there remains always a natural need to vouch and verify the existing research findings. We have chosen ten leading indices in the ten chosen developed stock markets along with ten emerging markets. The study also explores the existence of Taylor's effect in the stock markets. Our attempt has been to find out whether there exists any significant differences in the long memory characteristics and hence efficiency of the two different categories of markets.

2. 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 in one point of time which leads to some increased risk and uncertainty in the market doesn't die down quickly if long memory is present. Rather, it stays on, although in a decaying fashion and affects future outcomes. Mathematically, if λ_s= cov (y_t, y_{t+s}), s=0, ±1, ±2,..., and there exist constants k and α, $\alpha \in (0,1)$ such that $\lim_{s\to\infty} k\lambda_s s^{-\alpha} = 1$ 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 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, i.e., 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 plain English means that good times beget good times and bad times beget bad.

3. Methodology for testing long-memory processes

The empirical determination of the long-memory property of a time series is a difficult problem. The basic reason for this is that the strong autocorrelation of long-memory processes makes 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 is detailed below.

3.1 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 $r(t)=\ln\left(\frac{X_{t+1}}{X_t}\right)$. 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 $\overline{r_n}$ represents the mean return given by $r_n=\frac{1}{n}\sum_{t=1}^{n} r(t)$, where 'n' is the time span considered, the rescaled range statistic is given by

$$\left(\frac{R}{S}\right)_n=\frac{1}{\sigma_n}\left[\max_{1\le k\le n}\sum_{t=1}^{k}(r(t)-\overline{r_n})-\min_{1\le k\le n}\sum_{t=1}^{k}(r(t)-\overline{r_n})\right] \qquad ...(1)$$

where σ_n is the maximum likelihood estimate of simple standard deviation: $\sigma_n=\frac{1}{n}\sum_{t=1}^{n}(r(t)-\overline{r_n})^2$. 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, which is nonnegative. The second term in the bracket is the corresponding minimum of the partial sums, which is nonpositive. The difference of these two quantities, called "range" is always nonnegative and makes the rescaled range, $\left(\frac{R}{S}\right)_n \ge 0$. The advantage of the classical R/S analysis is that the results are reliable regardless whether the distribution of the series is Gaussian or not. The null hypothesis of the test is that there is no long-range dependence in the series. This test is performed by calculating the confidence intervals with respect to generally accepted significance level, and to see whether the rescaled range statistic lies in or outside the desired interval. The critical values for the above two tests are given in Lo, 1991, table II.

A drawback of the R/S analysis is that its measure of long range dependence is affected by short range dependence that may be presented in the financial data. Hence we consider estimating modified R/S statistic proposed by Lo (1991).

3.2 Modified rescaled-range (R/S) analysis

We conducted the modified R/S analysis suggested by Lo (1991) for long memory that examines the null hypothesis of no long range dependence at different significance levels. Lo's modified version of the statistic takes account of short-range dependence by performing a Newey-West correction (using a Bartlett window) to derive a consistent estimate of the long-range variance of the time series. Lo’s modified R/S statistic, denoted by Q_n is defined as:

$$Q_n = \frac{1}{\sigma_n(q)}\left[\max_{1\le k\le n}\sum_{t=1}^{k}(r(t)-\overline{r}_n) - \min_{1\le k\le n}\sum_{t=1}^{k}(r(t)-\overline{r}_n)\right] \quad .(2)$$

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

$$\sigma_n^2(q) = \frac{1}{n}\sum_{t=1}^{n}(r(t)-\overline{r}_n)^2 + 2\sum_{j=1}^{q}\omega_j(q)\gamma_j \quad (3)$$

where γ_j represents the sample autocovariance of order j, and $\omega_j(q)$ represents the weights applied to the sample autocovariance at lag j (1,2,...q). $\omega_j(q)$ are defined as the following Barlett weights: $\omega_j(q) = 1 - \frac{j}{q+1}$ (4)

The second term in the long run variance equation intended to capture the short term dependence. The lag length q used to estimate the heteroskedasticity and autocorrelation corrected (HAC) standard deviation is extremely crucial for modified R/S test of long memory. We have used bandwidth selection procedures suggested by Andrew (1991) to find the lag length.

3.3 The Spectral Regression Method

A stationary long memory process can be characterized by the behaviour of the spectral density $f(\lambda)$ function which takes the form $f(\lambda) \sim c\left|1 - e^{-i\lambda}\right|^{-2d}$, as $\lambda \to 0$ with $d \neq 0$, where $c \neq 0$, , 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: $\log I(\lambda) = \beta_0 - d \log\{4\sin^2(\lambda_j / 2)\} + \upsilon_j, \qquad j = 1, \ldots M,$ ...(5)

where $I(\lambda)$ is the j^{th} periodogram point; $\lambda_j = 2\pi j / T$; T is the number of observations; β_0 is a constant; and υ_j is an error term, asymptotically i.i.d, across harmonic frequencies with zero mean and variance known to be equal to $\pi^2 / 6$. $M = g(T) = T^{\mu}$ with $0 < \mu < 1$ is the number of Fourier frequencies included in the spectral regression and is an increasing function of T. As argued by GPH the inclusion of improper periodogram ordinates M, causes bias in the regression which result in an imprecise value of d. To achieve the optimal choice of T, several choices can be established in terms of the bandwidth parameter $M = T^{0.45}; T^{0.50}; \ldots, T^{0.7}$. 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.

4. Data

The series studied in this analysis include ten emerging stock market 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) and ten developed stock market indices, AEX (Netherlands), ^AORD (Australia), DAX (Germany), DJA (USA), FCHI (France), FTSE 100 (UK), HANGSENG (Hongkong), NIKKEI (Japan), NZE 50 (New Zealand) and STRAITS TIMES (Singapore).at daily frequencies. The market classification into developed and emerging is based on Morgan Stanley Capital International (MSCI). The MSCI market classification scheme depends on the following three criteria: economic development, size and liquidity, and market accessibility. A market is classified as developed if: i) the country's Gross National Income per capita is 25% above the World Bank high income threshold for 3 consecutive years; ii) there is a minimum number of companies satisfying minimum size and liquidity requirements; and iii) there is a high openness to foreign ownership, ease of capital inflows/outflows, high efficiency of the operational framework and stability of the institutional framework.

To be included in the emerging market category, a market is characterized by size, liquidity and market accessibility criteria that are less tight than those for the developed markets.[§] 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.

5. Findings

5.1 Descriptive Statistics

Table 1: Descriptive Statistics

Indices	Data	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
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
	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

[§] For details one may refer to www.msci.com

Indices	Data	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
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

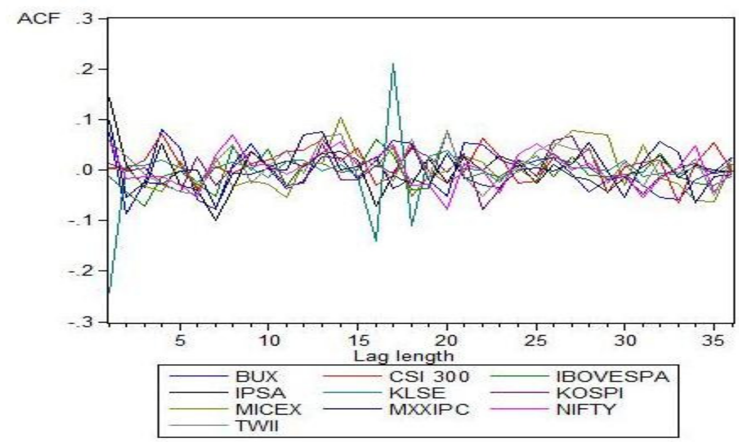
Table 1: Descriptive Statistics

Indices	Data	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
AEX	RET	-0.00003	0.00055	0.014796	-0.159232	12.53456	6336.518
	SQR	0.00022	0.00004	0.000743	8.245191	84.72715	483981.5
	ABS	0.00954	0.00618	0.011309	3.43741	20.35517	24261.88
^AORD	RET	0.00007	0.00055	0.011951	-0.55286	8.137586	1902.147
	SQR	0.00014	0.00004	0.000381	9.038697	126.8836	1079542
	ABS	0.00841	0.00618	0.008491	2.617565	14.66688	11262.62
DAX	RET	0.000311	0.001026	0.014209	0.135695	11.564	5105.45
	SQR	0.000202	0.0000426	0.000656	10.4208	148.5377	1503184
	ABS	0.009551	0.006528	0.010523	3.256275	21.04484	25593.4
DJA	RET	0.00015	0.00075	0.013479	-0.143218	10.73939	4108.639
	SQR	0.00018	0.00004	0.000567	9.299241	122.1793	996647.9
	ABS	0.00893	0.00612	0.0101	3.060672	17.93027	17836.29
FCHI	RET	-0.00002	0.00028	0.014939	0.139911	11.14367	4625.705
	SQR	0.00022	0.00005	0.000711	9.032366	104.5622	741337.5
	ABS	0.01005	0.00685	0.011051	3.228661	19.81492	22602.54
FTSE 100	RET	0.000114	0.000535	0.013306	-0.111072	11.467420	4926.60
	SQR	0.000177	0.000038	0.000573	9.070070	107.669800	774892.40
	ABS	0.008873	0.006156	0.009914	3.286173	19.980070	22764.28
HANGSENG	RET	0.000264	0.000607	0.017637	0.085279	12.02245	5561.239
	SQR	0.000311	0.000058	0.001033	10.60141	151.658	1539892
	ABS	0.011561	0.007613	0.01332	3.215278	20.72255	24273.66
NIKKEI	RET	-0.00009	0.00048	0.01683	-0.57684	12.17072	5695.538
	SQR	0.00028	0.00006	0.00095	10.60768	147.82870	1428364

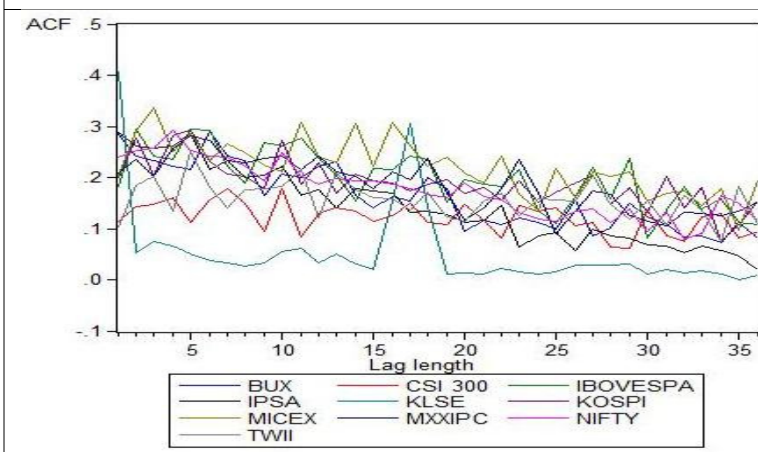
Indices	Data	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
	ABS	0.01131	0.00780	0.01246	3.38563	22.64538	28786.06
NZX 50	RET	0.00006	0.00044	0.00790	-0.31660	7.71956	1540.965
	SQR	0.00006	0.00002	0.00016	10.51878	169.53740	1914881
	ABS	0.00569	0.00413	0.00548	2.51779	15.22086	11872.77
STRAITS TIMES	RET	0.000244	0.000621	0.013286	-0.346848	9.498384	2923.87
	SQR	0.000176	0.0000371	0.000514	8.272209	98.35018	641137.9
	ABS	0.008918	0.006089	0.009849	2.841394	15.48525	12882.18

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

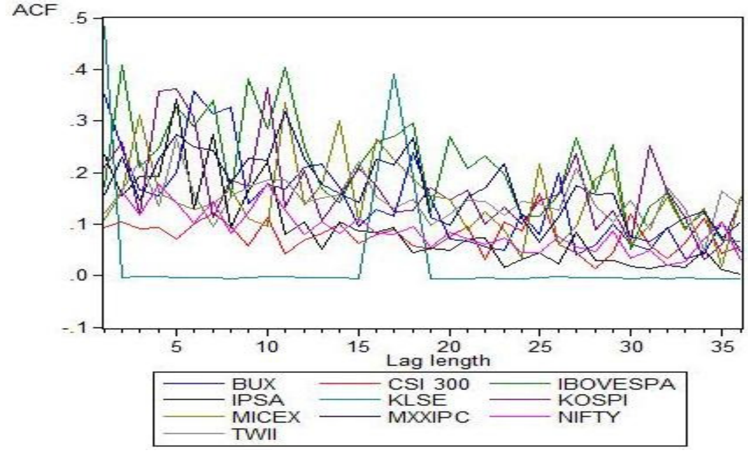
Figure 1: Visual Interpretation: Autocorrelation Function (ACF)



ACF of logarithmic return series of ten emerging stock indices.



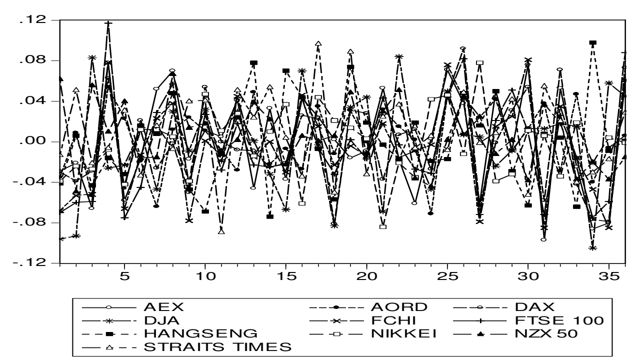
ACF of absolute return series of ten emerging stock indices.



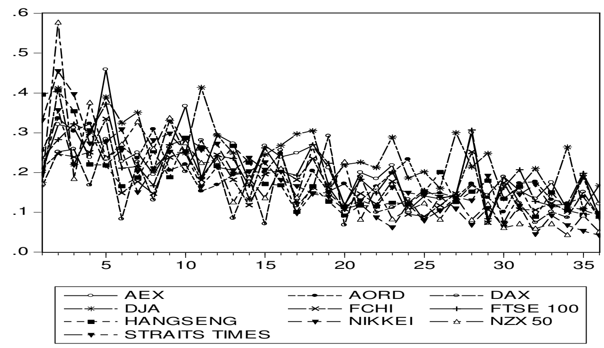
ACF of squared return series of ten emerging stock indices.

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 upto 35 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 series in emerging stock markets.

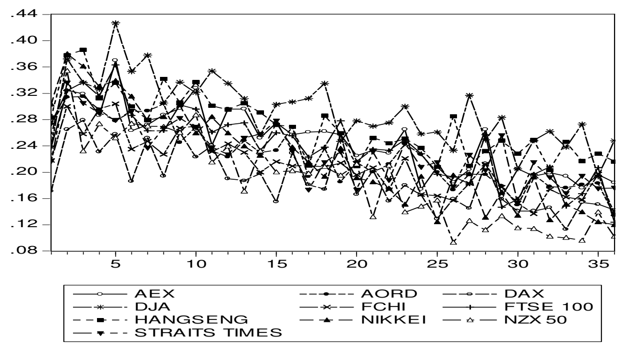
Figure 2: Visual Interpretation: Autocorrelation Function (ACF)
Logarithmic return series of ten developed stock indices



Visual Interpretation: Autocorrelation Function (ACF) of absolute return series of ten developed stock indices.



Visual Interpretation: Autocorrelation Function (ACF) of squared return series of ten developed stock indices.



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 upto 36 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. The ACF of the data series indicates short memory in return but long range dependence or persistence for absolute and squared return series in developed stock markets. The findings also support existence of Taylor Effect in the selected developed markets as autocorrelations of absolute returns are usually larger than those of squared returns.

5.2 Unit Root tests

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.

The results of unit root tests are displayed in **Table 2**. The null hypothesis of 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 all the data series are stationary.

Table 2: Unit Root Tests

Indices	**Data**	**ADF**	**PP**	**Indices**	**Data**	**ADF**	**PP**
AEX	RET	-42.0436 ***	-42.0436 ***	**^AORD**	RET	-42.0522***	-42.0522***
	SQR	-4.4416 ***	-85.5997***		SQR	-7.0459***	-48.3395 ***
	ABS	-5.2382 ***	-69.4831***		ABS	-6.5539***	-50.2863 ***
DAX	RET	-42.0477***	-42.0477 ***	**DJA**	RET	-33.2366 ***	-44.3978 ***
	SQR	-4.4151 ***	-106.7454 ***		SQR	-4.8819 ***	-82.3488 ***
	ABS	-5.5997 ***	-80.7019 ***		ABS	-5.3254 ***	-66.6536***
FCHI	RET	-43.7130 ***	-43.7130***	**FTSE 100**	RET	-19.2083***	-43.6156***
	SQR	-4.5899 ***	-87.9003 ***		SQR	-4.4409 ***	-80.1036 ***
	ABS	-5.9249***	-65.5307 ***		ABS	-7.6952 ***	-42.6195 ***
HANGSENG	RET	-42.1530 ***	-42.1530***	**NIKKEI**	RET	-41.5425 ***	-41.5425 ***
	SQR	-6.8983 ***	-32.5338 ***		SQR	-6.6884 ***	-38.6122 ***
	ABS	-5.2128 ***	-59.0043 ***		ABS	-7.7521***	-37.5714 ***
NZX 50	RET	-37.9154 ***	-37.9154 ***	**STRAITS TIMES**	RET	-41.0268 ***	-41.0268 ***
	SQR	-5.1796 ***	-73.1594 ***		SQR	-6.3265***	-63.0542

Indices	Data	ADF	PP	Indices	Data	ADF	PP
							***
	ABS	-5.6547 ***	-60.0368***		ABS	-5.7316***	-65.8550 ***

c) The critical values are those of Mackinnon (1991).
d) *** represent the rejection of null hypothesis at 1% level of significance.

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

Indices	Data	Hurst-Mandelbrot's Classical R/S Statistic	Lo Statistic
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

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 longrun 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 nonstationary 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 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 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	Indices	Data	Hurst-Mandelbrot's Classical R/S Statistic	Lo Statistic
AEX	RET	1.69	1.69	^AORD	RET	1.67	1.67
	SQR	5.22	3.02		SQR	5.5	2.92
	ABS	6.96	3.8		ABS	6.97	3.66
DAX	RET	1.6	1.6	DJA	RET	1.52	1.52
	SQR	4.73	3.14		SQR	5.55	3.37
	ABS	6.14	3.98		ABS	7.11	3.72
FCHI	RET	1.45	1.45	FTSE 100	RET	1.3	1.3
	SQR	4.64	2.85		SQR	5.08	2.83
	ABS	6.36	3.61		ABS	6.81	3.51
HANGSENG	RET	1.57	1.57	NIKKEI	RET	1.36	1.36
	SQR	5.56	2.64		SQR	4.32	2.09
	ABS	8.26	4.15		ABS	5.73	2.77
NZX 50	RET	1.91	1.85	STRAITS TIMES	RET	1.97	1.97
	SQR	5.19	3.07		SQR	5.79	3.47
	ABS	6.43	3.45		ABS	7.56	4.2

Note:

Critical values:

90% [0.861, 1.747]
95% [0.809, 1.862]
99% [0.721, 2.098]

For developed markets, 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. Despite its popularity, since Classical R/S Statistic is sensitive to short range dependence and may give biased results in the case of short-range dependence and heterogeneities, 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 and findings are similar in case of squared returns as well. The results of both the tests are consistent and indicate short memory for return series and long memory for volatility in general for the selected developed stock markets.

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

Indices	Data	$M=T^{0.50}$	$M=T^{0.55}$	$M=T^{0.60}$	$M=T^{0.65}$	$M=T^{0.70}$
BUX	Return	0.18505 (0.0970)	0.2518*** (0.08955)	0.1004 (0.0823)	0.0888 (0.0670)	0.0770 (0.0558)
	Squared return	0.3844*** (0.0555)	0.4990*** (0.0588)	0.5779*** (0.0545)	0.5794***	0.5182***
	Absolute return	0.4415*** (0.0853)	0.5143*** (0.0677)	0.5548*** (0.0585)	0.4612***	0.4190***
CSI 300	Return	0.2237 (0.1181)	0.2195 ** (0.1056)	0.1479 (0.0817)	0.0931 (0.0678)	0.0222 (0.0526)
	Squared return	0.4143*** (0.0826)	0.3574*** (0.0749)	0.3121*** (0.0632)	0.2993***	0.2834***
	Absolute return	0.4456*** (0.0773)	0.4619*** (0.0837)	0.3976*** (0.0699)	0.3722***	0.2878***
IBOVESPA	Return	0.1463 (0.0974)	0.0501 (0.0718)	0.0398 (0.0632)	-0.0251 (0.0498)	-0.0505 (0.0447)

Indices	Data	$M=T^{0.50}$	$M=T^{0.55}$	$M=T^{0.60}$	$M=T^{0.65}$	$M=T^{0.70}$
	Squared return	0.6959*** (0.0710)	0.8277*** (0.0839)	0.7410*** (0.0668)	0.7109***	0.5020***
	Absolute return	0.7223*** (0.1104)	0.6682*** (0.0836)	0.6477** (0.0693)	0.5543***	0.4520***
IPSA	**Return**	0.0331 (0.9267)	-0.0240 (0.0731)	0.0170 (0.0811)	0.0057 (0.0637)	-0.0451 (0.0520)
	Squared return	0.2448*** (0.0622)	0.2872*** (0.0556)	0.4143*** (0.0544)	0.4769***	0.4893***
	Absolute return	0.4973*** (0.131)	0.4326*** (0.0969)	0.4546*** (0.0725)	0.4068***	0.4372***
KLSE	**Return**	0.1987 (0.1214)	0.1315 (0.0918)	0.0486 (0.0738)	0.0300 (0.0573)	-0.0238 (0.0458)
	Squared return	0.2540*** (0.0590)	0.4918*** (0.07311)	0.2058*** (0.0682)	0.0244***	0.1196***
	Absolute return	0.2032 ***	0.3212*** (0.0792)	0.1739*** (0.0648)	0.0640***	0.1692***
KOSPI	**Return**	0.2361** (0.1096)	0.1001 (0.1043)	0.0171 (0.0823)	0.0124 (0.0657)	0.0034 (0.0509)
	Squared return	0.5704*** (0.0535)	0.4510*** (0.0471)	0.5731*** (0.0567)	0.5600***	0.5880***
	Absolute return	0.7647*** (0.1265)	0.5462*** (0.0979)	0.5006*** (0.0748)	0.4392***	0.4237***
MICEX	**Return**	0.2858*** (0.0899)	0.1766** (0.0822)	0.05241 (0.0700)	-0.0299 (0.0589)	-0.0007 (0.0483)
	Squared return	0.7821*** (0.0929)	0.7840*** (0.0681)	0.6987*** (0.0544)	0.3423***	0.3009*** (0.047)
	Absolute return	0.7207*** (0.0937)	0.7389*** (0.0736)	0.6195*** (0.0617)	0.4365***	0.4161***

Indices	Data	$M=T^{0.50}$	$M=T^{0.55}$	$M=T^{0.60}$	$M=T^{0.65}$	$M=T^{0.70}$
MXX IPC	**Return**	0.17596 (0.129)	-0.0043 (0.0997)	0.0624 (0.0799)	-0.0362 (0.0642)	-0.0731 (0.0507)
	Squared return	0.6588*** (0.0780)	0.7454*** (0.0727)	0.7686*** (0.0617)	0.6226***	0.4313***
	Absolute return	0.5707 ***	0.6293*** (0.0910)	0.6353*** (0.0747)	0.5731***	0.4856***
NIFTY	**Return**	0.2049** (0.0949)	0.1426 (0.0786)	0.1688** (.0685)	0.0824 (0.0563)	0.0695 (0.0525)
	Squared return	0.3671*** (0.0982)	0.3707*** (0.0762)	0.4185*** (0.0687)	0.3832***	0.3018***
	Absolute return	0.49602***	0.52033***	0.55529***	0.5008***	0.4249***
TWII	**Return**	0.2058** (0.0934)	0.1711** (0.0751)	0.1302 (0.0661)	0.0670 (0.0615)	0.0449 (0.0501)
	Squared return	0.6586*** (0.1098)	0.5225*** (0.0874)	0.4748*** (0.0754)	0.3649***	0.3291***
	Absolute return	0.6192*** (0.0953)	0.5191*** (0.0792)	0.5119*** (0.0774)	0.4372***	0.3375***

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 [ ].

The test examine the null hypothesis of short memory ($H_0 : d = 0$) against long memory alternatives ($H_1 : d \neq 0$) for a range of bandwidth ($M = T^{0.50}, T^{0.55}, \ldots, T^{0.7}$). 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 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.

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

Indices	Data	$M=T^{0.45}$	$M=T^{0.50}$	$M=T^{0.55}$	$M=T^{0.60}$	$M=T^{0.65}$	$M=T^{0.70}$
AEX	**RET**	0.1995 (0.1372) [1.4530]	0.2519** (0 .1075) [2.3445]	0.1538 (0.0902) [1.7036]	0.1597 (0.0856) [1.8662]	0.1428** (0.0684) [2.0880]	0.0569 (0.0540) [1.0538]
	SQR	0.5523*** (0.0714) [7.7330]	0.6039*** (0.0614) [9.8341]	0.6348*** (0.05445) [11.6592]	0.7610*** (0.0702) [10.8285]	0.5406*** (0.0571) [9.4552]	0.5244 *** (0.0457)
	ABS	0.6534*** (0.1306) [5.0041]	0.6198*** (0.0930) [6.6641]	0.7218*** (0.0940) [7.6754]	0.6640*** (0.0738) [8.9890]	0.5377*** (0.0612) [8.7781]	0.4414*** (0.0495) [8.9155]
^AORD	**RET**	0.1867 (0.1213)	0.2523** (0.1002)	0.0868 (0.0850)	0.0687 (0.0773)	0.0167 (0.0599)	0.0149 (0.0488)
	SQR	0.4680*** (0.0880)	0.5477*** (0.0735)	0.4886***	0.4849*** (0.0555)	0.4756 ***	0.5199*** (0.0429)
	ABS	0.5197*** (0.1014)	0.6487*** (0.1154)	0.5735*** (0.0956)	0.5455*** (0.0727)	0.5512 ***	0.4811*** (0.0534)
DAX	**RET**	0.2677 (0.1544)	0.1425 (0.1122)	-0.0130 (0.0907)	-0.0297 (0.0729)	0.0184 (0.0630)	0.0061 (0.054)
	SQR	0.5136*** (0.0702)	0.6811*** (0.0913)	0.5549***	0.6034*** (0.0638)	0.4845*** (0.0539)	0.3410*** (0.0465)
	ABS	0.5787*** (0.1534)	0.6394*** (0.1074)	0.5559*** (0.0912)	0.5524*** (0.0821)	0.4850*** (0.0633)	0.3484*** (0.0502)
DJA	**RET**	0.1482 (0.1404)	0.1050 (0.1019)	-0.0171 (0.0858)	-0.0306 (0.0650)	0.0175 (0.0581)	-0.0283 (0.0486)
	SQR	0.7270*** (0.1513)	0.8562 ***	0.6717***	0.7128*** (0.0661)	0.6746 ***	0.5333*** (0.0430)
	ABS	0.6627*** (0.1003)	0.7844***	0.7262 ***	0.7168*** (0.0672)	0.6586 ***	0.5916*** (0.0468)
FCHI	**RET**	0.1027 (0.1328)	0.1965 (0.1059)	0.0448 (0.0901)	-0.00009 (0.0740)	0.0102 (0.0638)	-0.0062 (0.0508)
	SQR	0.6037*** (0.1078)	0.6099*** (0.0863)	0.5536***	0.5943*** (0.0684)	0.4418 ***	0.4085*** (0.0458)
	ABS	0.5637*** (0.1097)	0.5779*** (0.0818)	0.5987 ***	0.5962*** (0.0782)	0.5395***	0.4229*** (0.0502)
FTSE 100	**RET**	0.0217 (0.1521)	0.1173 (0.1136)	-0.0569 (0.0888)	-0.0618 (0.0727)	0.0116 (0.0630)	-0.0160 (0.0508)

Indices	Data	$M=T^{0.45}$	$M=T^{0.50}$	$M=T^{0.55}$	$M=T^{0.60}$	$M=T^{0.65}$	$M=T^{0.70}$
	SQR	0.5387*** (0.0706)	0.6574***	0.5648 ***	0.5966*** (0.0681)	0.4454*** (0.0522)	0.4845*** (0.0441)
	ABS	0.5808*** (0.1167)	0.6638*** (0.0895)	0.6223***	0.5704*** (0.0695)	0.5440*** (0.0581)	0.4328*** (0.0451)
HANGSENG	**RET**	0.1088 (0.1229)	0.3056 (0.1614)	0.1285 (0.1185)	0.0293 (0.0883)	-0.0404 (0.0649)	0.0163 (0.0545)
	SQR	0.3922*** (0.0657)	0.5608*** (0.0970)	0.4852*** (0.0766)	0.5235*** (0.0602)	0.3993*** (0.0512)	0.3010***
	ABS	0.5989***	0.6568***	0.5893 ***	0.6105***	0.5202*** (0.0528)	0.4342*** (0.0460)
NIKKEI	**RET**	0.1359 (0.1442)	0.1358 (0.1071)	0.0331 (0.0820)	0.0679 (0.0657)	0.0413 (0.0559)	0.0088 (0.0480)
	SQR	0.3143*** (0.0581)	0.4148*** (0.0664)	0.4719***	0.6120*** (0.0581)	0.5143*** (0.0518)	0.4568***
	ABS	0.5208*** (0.0955)	0.5242***	0.5949***	0.6369***	0.5575*** (0.0604)	0.5164*** (0.0480)
NZX 50	**RET**	0.0018 (0.1202)	0.1654 (0.0976)	0.1089 (0.0825)	0.1207 (0.0703)	0.1299** (0.0590)	0.0750 (0.0460)
	SQR	0.3001*** (0.0528)	0.3726*** (0.0414)	0.4841*** (0.0500)	0.5531*** (0.0456)	0.6195*** (0.0420)	0.5686*** (0.0453)
	ABS	0.4555*** (0.1193)	0.5075*** (0.0925)	0.6070*** (0.0878)	0.5674*** (0.0655)	0.5749***	0.4598***
STRAITS TIMES	**RET**	0.1831 (0.1404)	0.2477** (0.1046)	0.1655 (0.0833)	0.0729 (0.0635)	0.0599 (0.0615)	0.0769 (0.0506)
	SQR	0.4827*** (0.0707)	0.5487*** (0.0785)	0.5138*** (0.06664)	0.5846*** (0.0609)	0.5000*** (0.0583)	0.4641***
	ABS	0.6988***	0.6692 ***	0.5019*** (0.1014)	0.4883*** (0.0778)	0.4268*** (0.0629)	0.3868 ***

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 [ ].

The test examine the null hypothesis of short memory ($H_0 : d = 0$) against long memory alternatives ($H_1 : d \neq 0$) for a range of bandwidth ($M = T^{0.45}, T^{0.50}, \ldots, T^{0.7}$). 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 the selected stock markets. However the findings are mixed in case of logarithmic return series. Estimate of d is found to be statistically significant at two chosen bandwidths in case of Netherlands(AEX) whereas it is found significant at one of the chosen bandwidth in case of Australia(^AORD), New Zealand (NZX 50) and Singapore (STRAITS TIMES). The null of short memory in return series is rejected in case of Germany, USA, France, UK, HongKong and Japan.

6. Significance of Findings

6.1 Emerging Markets

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 futures returns, thus violating the market efficiency hypothesis. Exploring long memory property is appealing for derivative market participants, risk managers and asset allocation decisions makers, whose interest is to reasonably forecast stock market movements. The study examined the evidence of long memory in the ten emerging markets – 2 from Europe, 5 from Asia and 3 from Latin America. To test the presence of long-memory in asset returns, we computed Hurst-Mandelbrot's Classical R/S statistic, Lo's statistic, semi parametric GPH statistic as well as modified GPH statistic of Robinson (1995). All the tests both 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 5 ordinates for both absolute return and squared return series. However Hurst-Mandelbrot's Classical R/S statistic and GPH statistic supports existence of the long memory along with Robinson's estimates in four ordinates out of five. This support in favour of 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 follows 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 auto correlation 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 volatility of asset returns can be modeled using returns from the recent as sell as remote past and hence derivative instruments can now be more efficiently priced. As an emerging market, a country should undertake economic liberalization and reform measures that ensures and promotes competitive environment and efficient capital market.

6.2 Developed Markets

The study examined the evidence of long memory in the ten developed markets – 4 from Europe, 5 from Pacific and the US. To test the presence of long-memory in asset returns, we computed Hurst-Mandelbrot's Classical R/S statistic, Lo’s statistic and semi parametric GPH statistic. All the tests both are consistent with long range dependence in the absolute return and squared return series. Findings largely support the Taylor effect as autocorrelations of absolute returns are usually larger than those of squared returns and the estimate of the fractional differencing parameter is generally higher for the absolute returns than that of squared returns. Overall findings did not suggest long-term memory in chosen stock market returns indicating developed stock market returns follows 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, strong regulatory authority and market micro structure in the developed markets, a possible explanation for absence of long memory in return series may be based on the grounds that developed markets are informationally efficient, prices tend to reflect all publicly available information and any new information is fully arbitraged away. An alternative explanation was suggested by Lo (1991) when he suggested that "…. we find little evidence of long-term memory in historical U.S. stock market returns. If the source of serial correlation is lagged adjustment to new information, the absence of strong dependence in stock returns should not be surprising from an economic standpoint, given the frequency with which financial asset markets clear. Surely financial security prices must be immune to persistent informational asymmetries, especially over longer time spans". Presence of long memory in squared returns indicates volatility of asset returns can be modeled using returns from the recent as sell as remote past and hence derivative instruments can now be more efficiently priced. The financial market regulators in these developed markets may look into the sources of long memory in volatility of stock returns to improve efficiency levels.

7. General conclusions

Analyzing long memory characteristics of financial time series is a common research agenda undertake by several authors since long. A summary of same may be found in Mukherjee et al (2011). However, the Significance of this study lay in conducting a long memory test on both Developed and emerging markets and compare the same to find if there is any difference in characteristics in that direction. Our findings indicate a presence of long memory in volatility of asset returns in both Emerging and Developed countries. We did not find any significant difference in the long memory statistics of the two market groups. This work may be further refined to test for long memory in pre and post financial crisis periods to see if there is any significant difference in that. The tests may be extended to more markets and one can test for statistical significance of the difference in Long Memory statistics.

References:

ANDERSEN, T.G. and BOLLERSLEV, T. (1997): "Heterogeneous Information Arrivals And Return Volatility Dynamics: Uncovering The Long-Run In High Frequency Returns", *Journal of Finance*, Vol. 52, No.3, pp. 975-1005.

ANDERSEN, T. G. and BOLLERSLEV, T. (1998): "Answering the Skeptics: Yes, Standard Volatility Models Do Provide Accurate Forecasts", *International Economic Review*, Vol.39, No.4, pp.885-905.

ANDREWS, D.W.K. (1991): “Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation”, *Econometrica*, Vol.59, No.3, pp.817-858.

BAILLIE, R.T. (1996): “Long Memory Processes And Fractional Integration In Econometrics”, *Journal of Econometrics*, Vol.73, No.1, pp.5-60.

BERAN, J. and OCKER, D. (2001): “Volatility of stock market indices - an analysis based on SEMIFAR models”, Journal of Business and Economic Statistics, Vol.19, No.1, pp.103-116.

BREIDT, F.J.; CRATO, N. and DE LIMA, P. (1998): “On The Detection and Estimation of Long Memory In Stochastic Volatility”, *Journal of Econometrics*, Vol.83, No.1-2, pp.325-348.

CAJUEIRO, D.O. and TABAK, B.M. (2004): “The Hurst’s exponent over time: testing the assertion that emerging markets are becoming more efficient”, *Physica A*, Vol.336, pp.521-537.

DICKEY, D.A. and FULLER, W.A. (1979): “Distribution of the Estimators for Autoregressive Time Series with a Unit Root”, *Journal of the American Statistical Association*, Vol.74, No.366, pp.427–431.

DING, Z.; GRANGER, C.W.J. and ENGLE, R.F. (1993): “A Long Memory Property Of Stock Market Returns And A New Model”, *Journal of Empirical Finance*, Vol.1, No.1, pp.83-106.

GEWEKE, J. and PORTER-HUDAK, S. (1983): “The Estimation And Application Of Long-Memory Time Series Models”, *Journal of Time Series Analysis*, Vol.4, No.4, pp.221-238.

GRANGER, C. W. J. and DING, Z. (1995): “Some Properties Of Absolute Return; An Alternative Measure Of Risk”, *Annales D’Economie et de Statistique*, Vol.40, pp.67 - 91.

GRANGER, C. W. J. (1966): “The Typical Spectral Shape Of An Economic Variable”, *Econometrica*, Vol.34, No.1, pp.150-161.

GRANGER, C. W. J., and DING, Z. (1996): “Varieties Of Long Memory Models”, *Journal of Econometrics*, Vol.73, No.1, pp:61-77.

GREENE, M. T. and FIELITZ, B. D. (1977): “Long-Term Dependence In Common Stock Returns”, *Journal of Financial Economics*, Vol.4, No.3, pp.339-349.

HARVEY, A.C. (1993): “Long Memory In Stochastic Volatility”, Working Paper 10, London, School of Economics, Department of Statistics.

HURST, H. E. (1951): “Long-Term Storage Of Reservoirs: An Experimental Study”, *Transactions of the American Society of Civil Engineers*, Vol.116, pp.770-799.

KANG, S. H.; CHEONG, C. And YOON, S. M. (2010): “Long memory volatility in Chinese stock markets”, *Physica A*, Vol.389, pp.1425–1433.

Lo, A.W. (1991): “Long-Term Memory In Stock Market Prices”, *Econometrica*, Vol.59, No.5, pp.1279-1313.

MANDELBROT, B.B. and WALLIS, J.R. (1968): “Noah, Joseph, and Operational Hydrology”, Water Resources Research, Vol.4, No.3, pp.909-918.

MANDELBROT, B.B. and WALLIS, J. R. (1969): "Robustness Of The Rescaled Range R/S In The Measurement Of Noncyclic Long-Run Statistical Dependence", *Water Resources Research*, Vol.5, No.5, pp.967-988.

MANDELBROT, B.B. (1971): "A Fast Fractional Gaussian Noise Generator", *Water Resources Research*, Vol. 7, No.3, pp.543-553.

MANDELBROT, B. B. (1972): "Possible Renements Of The Lognormal Hypothesis Concerning The Distribution Of Energy Dissipation In Intermitent Turbulence", in M. Rosenblatt and 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: Insight from the Indian Market", The International Journal of Applied Economics and Finance, Vol. 5, No. 1, pp 62-74

NATH, G. C. (2001): "Long Memory And Indian Stock Market – An Empirical Evidence", Proceedings of UTIICM Conference , India, 2001.

PHILLIPS, P.C.B. and PERRON, P. (1988): "Testing For A Unit Root In Time Series Regression", *Biometrika*, Vol.75, No.2, pp.335–346.

SADIQUE, S. and SILVAPULLE, P. (2001): "Long-Term Memory in Stock Market Returns: International Evidence", *International Journal of Finance & Economics*, Vol.6, No.1 pp.59-67.

WILLINGER, W., TAQQU, M.S. and TEVEROVSKY, V. (1999): "Stock Market Prices And Long-Range Dependence", *Finance and Stochastics*, Vol.3, pp.1-13.

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

YAJIMA, Y. (1985): "On Estimation Of Long-Memory Time Series Models", *Australian Journal of Statistics*, Vol.27, No.3, pp.303-320.

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Abstract:
According to the market efficiency hypothesis in its weak form, asset prices incorporate all relevant information, rendering asset returns unpredictable. The most considerable economical implication of existence of long memory is the contradiction of the weak-form of market efficiency (Fama, 1970) by allowing investors and portfolio managers to make prediction and to construct speculative strategies. The price of an asset determined in an efficient market should follow a martingale process in which each price change is unaffected by its predecessor and has no memory. When return series exhibit long memory, they display significant autocorrelation between distant observations. Therefore, the series realizations are not independent over time and past returns can help predict futures returns, thus violating the market efficiency hypothesis.

Exploring long memory property is appealing for derivative market participants, risk managers and asset allocation decisions makers, whose interest is to reasonably forecast stock market movements. Generally markets are classified as developed or emerging on the basis of their level of efficiency. Since efficiency levels of developed and emerging stock markets are different, long memory properties displayed by them should be different. Motivated by this we investigate long-memory properties in ten stock exchanges from developed markets (USA, UK, Germany, Australia, New Zealand, Hong Kong, France, Netherlands, Japan and Singapore) and ten from emerging markets (Russia, Hungary, Brazil, Chile, Mexico, Malaysia, Korea, Taiwan, China, and India) using daily return, absolute return and squared return. We compute Hurst exponent, Lo's statistic, semi parametric GPH statistic to test the presence of long-memory in asset returns which would provide evidence against the weak form of market efficiency. We look into developed markets with emerging markets to determine if the returns-generating processes and presence or absence of long memory depends on the degree of market development.

Key Words/Phrases: Market efficiency, Emerging Market, Developed Market, Long Memory, Hurst exponent, Lo's statistic, semi parametric GPH statistic.

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