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The Comparative Dynamics of Developed and Emerging Stock Markets: A Long Memory Perspective

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Abstract

The paper explores the difference in efficiency between developed and emerging stock market from a long memory perspective for the period 2000 to 2015. Ten developed, and ten emerging countries were selected for the study based on Morgan Stanley Capital International's classification. We used both rescaled range and detrended fluctuation analysis and supplemented the findings with estimates of the fractionally integrated parameter for stock market return, its volatility as well as its absolute return using spectral regression. Findings are supportive of the absence of long memory in returns but support presence of long memory in absolute returns and volatility. We conclude that co-movement and spillover between stock markets have affected the market efficiencies and the efficiency of the emerging stock markets is no longer very different from that of the developed stock markets.

Keywords

Long Memory, Rescaled Range, Detrended Fluctuation Analysis, Fractional Integration, Spectral Regression

1. Introduction

Emerging market finance has attracted the attention of researchers and practitioners since the early nineties. Authors have argued that the emerging markets bring issues that challenge the framework of the neoclassical finance, needing special attention [1]. Comparative analyses of emerging and developed markets highlight the difference in efficiency of the markets [2]. On the other hand, [3] showed that with the rise of global integrations, stock markets exhibited greater co-movement, particularly during the IT bubble. While they found the phenomenon to be temporary and not an indication of permanent global integration of stock markets, [4] found evidence that the correlations across global financial markets had been permanently affected by the financial crisis. In spite of the voluminous literature on the comparative analysis of emerging and developed markets, it is necessary to vouch and authenticate the existing research findings, and we continue to look into the relative market characteristics from different perspectives to understand the effect of global integration.

Long memory in stock returns is a direct comment on the efficiency of the stock market. 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 evidence on the topic reported in empirical studies are not strong enough. Long range dependence generally suggests nonlinear structure in asset returns. Such long-range dependence structure indicates that returns can be predicted, the efficient market hypothesis is violated, and applicability of random walk in stock prices is challenged. It would also raise concern regarding linear modelling, forecasting, statistical testing of pricing models based on standard statistical methods, and theoretical and econometric modelling of asset pricing. We hypothesize that long memory statistics of the emerging and the developed market should reveal how different the markets are. Taking data from stock market indices of ten developed and ten emerging markets we run tests for long memory and find out the comparative scenario. Our findings indicate that while the volatility of returns in both developed and emerging markets exhibit long memory, there is no significant difference in the long memory characteristics of the two sets of markets. The article augments the existing literature by examining the efficiencies of the developed and emerging markets from a different perspective and is one of the early studies to evidence that no significant difference in terms of efficiency exists between the two classes of markets.

In this article, we start in Section 2 with a brief literature review on Long Memory tests of financial markets. The issues and concerns with same are highlighted therein. In Section 3 we give the details of the data and methodology adopted. In the next section, we familiarize the readers with the theoretical background of the methods used to test the long-range dependence of the returns in the financial markets. In Section 5 we discuss the results of our empirical findings. Finally, we present our conclusions in Section 6.2.

2. Studies in Long Memory

Initial works on long memory for stock returns are by [5] and [6]. [7] reported that the rescaled range statistic used by them is less powerful and often fails to distinguish between long and short memory. He proposed a modified rescaled range test using a statistic popularly called Lo statistic and concluded that daily stock returns do not display long-memory properties. [8] criticised the Lo statistic on the ground that it failed to detect a low level of long-range persistence or memory and challenged the inferences drawn from the evidence of long memory when long memory is identified using Lo statistic.

There exists a general consensus among finance community that long-memory is an imperative characteristic of asset price volatility while asset returns, in agreement with the efficient markets hypothesis, contain insignificant serial correlation. [9] provides a decent survey of existing literature on the issue. Early evidence of long-range dependence in currencies is available in [10] while similar evidence in stock prices was provided by [11] and others. [12] provides evidence that international stock markets like Korean, Malaysian, Singapore and New Zealand stock market returns have long memory and therefore are not efficient while Japan, USA and Australia were found to be efficient. The divergent findings on the topic spawned research to include memory characteristics in volatility models and development of popular models like the inclusion of fractionally integrated component in GARCH family of models. More recent studies include [13] [14], and [15] provide assorted results. [13] reported the evidence of long memory in volatility of Chinese stock market. While [14] observed long memory in volatility of returns but not in mean returns for Indian stock market, contrary evidence was reported by [15] where they claimed for the presence of long memory in mean returns for medium and small stocks in India. [16] suggested that portfolios with higher long memory parameter possess higher expected return with lower risk. Absence of long memory in returns was reported by [17] in emerging markets and in developed markets by [18] but both [17] and [18] evidenced presence of long memory in volatility and absolute returns. An excellent review of the literature on long memory beginning from [19] is reported by [20].

3. Theoretical Background of Long Memory

Long memory is a measure of persistence and can be explained both in the time domain and frequency domain. In the time domain, it is generally described as an exhibition of persistent autocorrelations with very slow decay at a hyperbolic rate. For a zero-mean covariance stationary process $\{x_t, t = \cdots, -1, 0, +1, \cdots\}$ with auto covariance function $\gamma_u = E(x_t x_{t+u})$, the time domain explanation of long memory says that $\sum_{u=-\infty}^{\infty} |\gamma_u| = \infty$. In the frequency domain, the long memory is described in terms of rates of explosions of low frequency spectra. The presence of explosions in the spectrum of a process $(x_t)_t$ makes it variable. When x_t has an absolutely continuous spectral distribution with a spectral density function $f(\lambda)$; according to the frequency domain definition of long memory, the spectral density function is unbounded at some frequency λ in the interval $[0, \pi]$, *i.e.*, $f(\lambda) \to \infty$ as $\lambda \to \lambda^*$, where $\lambda^* \in [0, \pi]$. Empirical studies generally consider the case when the singularity or pole in the spectrum occurs at the zero frequency. This basically represents the general fractionally integrated

$I(d)$ models of the form: $(1-L)^d x_t = u_t, t = 0, \pm 1, \cdots$, where $x_t = 0$ for $t \le 0$, and $d > 0$, where L is the lag operator and u_t is a covariance stationary process with a spectral density function that is positive and finite at any frequency. When the spectral power concentration is at very low frequencies near zero and has an exponential decline with an increase in frequency, it is indicative of the existence of long memory.

4. Data & Methodology

We explored the existence of long memory using ten indices from both emerging and developed markets at a daily frequency. For emerging market category, we selected Hungary (BUX), China (SHCOMP), Brazil (IBOVESPA), Chile (IPSA), India (NIFTY), Korea (KOSPI), Malaysia (KLSE), Mexico (MXX-IPC), MICEX (Russia), and TWII (Taiwan). For developed market category we considered Australia (ALL ORDINARIES), Canada (TSX), France (FCHI), Germany (DAX), Hongkong (HANGSENG), Japan (NIKKEI), Netherlands (AEX), Singapore (STRAITS TIMES), United Kingdom (FTSE 100) and United States of America (DJA). We adopted Morgan Stanley Capital International (MSCI) classification for segregating stock markets into emerging and developed which takes into account market accessibility, its size and liquidity and economic development. The daily closing values of the selected indices from January 2000 to September 2015 were considered based on availability, and non-availability of more recent data from all the markets is a limitation of the study. Stock market returns (r_t) are obtained as the natural logarithm of the ratio of the current value of the stock index to the previous price. We considered three forms of return viz., return (r_t), absolute return (modulus value) and return squared series from each index. We used Detrended Fluctuation Analysis, Rescaled range analysis and an estimate of the fractional differencing parameter to explore long memory characteristics as discussed in subsequent sections.

We first investigate the descriptive statistics of all the data series and follow it up with stationarity tests using standard unit root tests. For Hurst exponent estimation, we adopt Detrended Fluctuation Analysis (DFA), Lo (1991) statistic and also estimated the long-memory parameter using the semiparametric log-periodogram regression estimator applying [21] modifications. We discuss the above-referred methods below.

4.1. Detrended Fluctuation Analysis

Detrended fluctuation analysis (DFA) of [22] quantifies fractal-like correlation properties of the time series to investigate long-range power-law Correlations. It is done by detrending the sub-periods and using squared fluctuations around the trend of the signal, measured within observation windows of various sizes and then plotted against window size on a log-log scale $\log \sigma_{DFA} \infty H \log(n)$. The scaling exponent H (Hurst exponent) indicates the slope of this line, which relates log(fluctuation) to log(window size). The linear relationship supports the presence of power-law (fractals) scaling which indicates that there is self-similarity in the series indicating that the fluctuations over small time scales are related to fluctuations over larger time scales. This H is used to identify the long memory properties of the time series. While $H = 0.5$ is indicative of random walk, its value 0 and 0.5 is indicative of anti-persistent behaviour and between 0.5 and 1.0 indicates persistent behaviour.

4.2. Estimation of Lo Statistic

The rescaled range provides a powerful alternative to autocorrelation, the variance analysis and spectral analysis while dealing with long-range persistence. For rescaled range statistic we find the ratio of the range of the sum of the deviations from the local mean divided by the standard deviation from the mean. Lo's (1991) statistic is a stable estimate of the long-range dependence of the time series which avoids sensibility of the general rescaled range statistic to short-term correlations by performing a Newey-West correction. Hence, if "n" is the time span, $\overline{r}_n$ represents the mean return and Lo's modified R/S statistic, denoted by Q_n is defined as:

$$r_n = \sum_{t=1}^{n} r(t) \Big/ n \tag{1}$$

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

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

where γ_j represents the sample auto covariance of order j, and $\omega_j(q) = 1 - (j/q + 1)$ represents the weights applied to the auto covariance at j^{th} lag.

The term $\sum_{j=1}^{q} \omega_j(q) \gamma_j$ is useful in understanding the short-term dynamics. The statistic is sensitive to heteroscedasticity and autocorrelation corrected standard deviation which in itself is sensitive to the lag length q. We applied [23] procedure for obtaining optimal q.

4.3. Estimation of Fractionally Integrated Parameter

Here we use the standard spectral density function $f(\lambda)$ which takes the form $f(\lambda) : c\left|1 - \mathrm{e}^{-i\lambda}\right|^{-2d}$ as $\lambda \to 0$ with $d \ne 0$ where $c \ne 0$, $d \in (0, 0.5)$ is the fractionally integrated parameter that indicates memory. [24] proposed a least-squares estimator of d to understand the slope of the spectral density and is based on the regression equation:

$$\log I(\lambda) = \beta_0 - d \log\left\{4 \sin^2\left(\lambda_j / 2\right)\right\} + \upsilon_j, \ j = 1, \cdots, M, \tag{4}$$

where $I(\lambda)$ is the j^{th} periodogram point, λ_j is the jth Fourier frequency and υ_j is an identically distributed error term. $M = g(T) = T^{\mu}$ with $0 < \mu < 1$ is the number of Fourier frequencies included in the spectral regression and is an increasing function of T. The estimator is known as a semi-parametric estimator since it does not require the AR and MA parameters a priori. We estimated long memory parameter here using [21] innovations that allow for a larger fraction of the ordinates of the empirical periodogram of the series with averaging of the periodogram over adjacent frequencies. On the choice of the number of harmonic ordinates to be included in the spectral regression, we consider $M = T^{0.50}$; $T^{0.55}$; $T^{0.70}$.

5. Empirical Analysis

Table 1 displays the descriptions of all forms of return from all the indices selected for the study. We observed that all emerging nations except Taiwan have positive average return during the period while four developed countries like Japan, UK, France and Netherlands have negative average return during a similar period. Except for two developed European nation like Germany and France and two Latin American emerging nations like Chile and Mexico, all other return series are negatively skewed while all the return series from both developed and emerging nation are leptokurtic. The normality assumption for the logarithmic return was clearly rejected based on Jarque-Bera statistic. Normality is also rejected for absolute return series and volatility series of all developed and emerging indices using Jarque-Bera statistic which display of positive skewness and leptokurtic behaviour.

While testing for time series stationarity using unit root tests, the findings of ADF and PP unit root tests reject the hypothesis of a unit root in all forms of return series for all the markets as presented in Table 2. The primary inference from this is that the data series is stationary.

5.1. Detrended Fluctuation Analysis

The values of Hurst component are displayed in **Annexure 1**. The minimum and maximum Hurst exponent value for return series for developed markets are 0.476 and 0.557 respectively whereas for emerging nations it is 0.506 and 0.609 respectively. In the case of squared return series, the min-max values are 1.05 and 0.96 respectively for developed markets and 1.00 and 0.87 for emerging markets respectively. For absolute return series, the min-max values are 1.00 and 0.89 for developed markets and 0.95 and 0.83 for emerging markets. While applying t-test for the null hypothesis that means of each series is 0.5 we get the following observations:

The findings as reported in Table 3 indicate that the hypothesis of Hurst exponent equaling 0.5 is rejected for all the return series and long memory is weak for return series while squared, and absolute return series shows strong, persistent behaviour. For developed markets squared and absolute return series shows strong, persistent behaviour while the possibility of returns following random walk cannot be ruled out.

Table 1. Data Summary: Return, |Return|, Return Squared.

Indices	Data	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
Developed Nations								
	RET	0.00013	0.00048	0.05360	−0.08554	0.0097	−0.591	9.248
^AORD	SQR	0.00010	0.00002	0.00732	0.00000	0.0002	11.372	211.28
	ABS	0.00685	0.00492	0.08554	0.00000	0.0069	2.8322	17.712
	RET	−0.00011	0.00043	0.10028	−0.09590	0.0147	−0.085	9.210
AEX	SQR	0.00022	0.00005	0.01006	0.00000	0.0006	7.9556	89.015
	ABS	0.01001	0.00680	0.10028	0.00000	0.0108	2.8196	15.219
	RET	0.00010	0.00075	0.10798	−0.07434	0.0154	0.0104	7.130
DAX	SQR	0.00024	0.00006	0.01166	0.00000	0.0005	7.8794	104.66
	ABS	0.01085	0.00758	0.10798	0.00000	0.0110	2.3277	11.796
	RET	0.00009	0.00044	0.10508	−0.08201	0.0119	−0.064	10.934
DJA	SQR	0.00014	0.00003	0.01104	0.00000	0.0004	11.972	220.09
	ABS	0.00804	0.00546	0.10508	0.00000	0.0087	3.0700	19.986
	RET	−0.00007	0.00033	0.10595	−0.09472	0.0150	0.0055	7.661
FCHI	SQR	0.00023	0.00006	0.01123	0.00000	0.0005	8.3195	105.22
	ABS	0.01061	0.00752	0.10595	0.00000	0.0104	2.5061	13.517
	RET	−0.00003	0.00000	0.09384	−0.09265	0.0124	−0.164	9.401
FTSE 100	SQR	0.00015	0.00003	0.00881	0.00000	0.0004	9.910	147.78
	ABS	0.00827	0.00569	0.09384	0.00000	0.0088	2.788	16.406
	RET	0.00006	0.00037	0.13407	−0.13582	0.0154	−0.078	10.868
HANGSENG	SQR	0.00024	0.00005	0.01845	0.00000	0.0007	12.889	243.82
	ABS	0.01060	0.00735	0.13582	0.00000	0.0112	3.061	21.121
	RET	−0.00001	0.00032	0.13235	−0.12111	0.0154	−0.395	9.197
NIKKEI	SQR	0.00024	0.00007	0.01752	0.00000	0.0006	12.442	229.14
	ABS	0.01108	0.00826	0.13235	0.00001	0.0108	2.846	19.544
	RET	0.00003	0.00022	0.07531	−0.09095	0.0117	−0.349	8.986
STRAITS TIMES	SQR	0.00014	0.00003	0.00827	0.00000	0.0003	9.474	136.92
	ABS	0.00810	0.00558	0.09095	0.00000	0.0085	2.751	15.831
	RET	0.00013	0.00070	0.09370	−0.09788	0.0115	−0.653	12.136
TSX	SQR	0.00013	0.00003	0.00958	0.00000	0.0004	11.625	188.18
	ABS	0.00780	0.00549	0.09788	0.00000	0.0085	3.367	22.868
Emerging Nations								
	RET	0.00023	0.00031	0.13178	−0.12649	0.0157	−0.079	8.865
BUX	SQR	0.00025	0.00007	0.01737	0.00000	0.0007	11.971	219.58
	ABS	0.01130	0.00851	0.13178	0.00001	0.0109	2.808	18.55

Continued

	RET	0.00026	0.00048	0.13677	−0.12096	0.0182	−0.070	6.722
IBOVESPA	SQR	0.00033	0.00011	0.01871	0.00000	0.0008	10.042	165.41
	ABS	0.01348	0.01051	0.13677	0.00000	0.0123	2.31	13.634
	RET	0.00031	0.00047	0.11803	−0.07173	0.0100	0.030	11.780
IPSA	SQR	0.00010	0.00003	0.01393	0.00000	0.0003	22.050	803.198
	ABS	0.00714	0.00538	0.11803	0.00000	0.0070	3.225	27.584
	RET	0.00018	0.00040	0.16020	−0.15568	0.0096	−0.509	60.637
KLSE	SQR	0.00009	0.00002	0.02567	0.00000	0.0007	27.99	874.75
	ABS	0.00594	0.00402	0.16020	0.00000	0.0076	7.977	127.10
	RET	0.00016	0.00071	0.11284	−0.12805	0.0161	−0.565	8.941
KOSPI	SQR	0.00026	0.00006	0.01640	0.00000	0.0007	10.269	167.85
	ABS	0.01105	0.00758	0.12805	0.00000	0.0117	2.671	15.47
	RET	0.00059	0.00118	0.25226	−0.20657	0.0219	−0.217	16.540
MICEX	SQR	0.00048	0.00011	0.06364	0.00000	0.0019	17.843	454.25
	ABS	0.01472	0.01057	0.25226	0.00000	0.0163	3.963	34.41
	RET	0.00046	0.00080	0.10441	−0.08267	0.0135	0.027	7.882
MXXIPC	SQR	0.00018	0.00005	0.01090	0.00000	0.0004	8.782	131.78
	ABS	0.00949	0.00671	0.10441	0.00000	0.0096	2.543	13.650
	RET	0.00041	0.00104	0.16334	−0.13054	0.0155	−0.297	11.10
NIFTY	SQR	0.00024	0.00006	0.02668	0.00000	0.0007	17.80	499.24
	ABS	0.01086	0.00791	0.16334	0.00000	0.0110	3.085	23.80
	RET	0.00021	0.00058	0.09401	−0.09256	0.0164	−0.274	7.38
SHCOMP	SQR	0.00027	0.00006	0.00884	0.00000	0.0006	6.532	59.34
	ABS	0.01141	0.00787	0.09401	0.00000	0.0118	2.397	11.60
	RET	−0.00001	0.00035	0.06525	−0.09936	0.0144	−0.23	6.065
TWII	SQR	0.00021	0.00005	0.00987	0.00000	0.0004	6.13	71.806
	ABS	0.01011	0.00694	0.09936	0.00000	0.0102	2.02	8.784

RET—Return Series, SQR—Squared Return Series, ABS—Absolute Return Series (Source: Author).

The box plot figures (**Figures 1-3**) for all the series for both the markets further supports the findings that squared and absolute return series show persistent behaviour. Additionally, returns from emerging markets show weak persistence while evidence for returns from developed markets is inconclusive and ranges between random walk and weak persistence.

However the possibility that these findings being influenced by the presence of short memory cannot be ruled out, and we use rescaled range analysis for the same.

5.2. Rescaled-Range (R/S) Analysis

Rescaled Analysis is based on the premise that range as a measure of dispersion

Table 2. Findings from the Unit Root Tests.

Indices	Data	Unit Root Tests		Indices	Unit Root Tests	
		ADF	PP		ADF	PP
	RET	−64.32	−64.37		−30.43	−59.48
^AORD	SQR	−8.28	−82.39	BUX	−7.61	−68.27
	ABS	−9.28	−85.50		−12.26	−75.93
	RET	−30.39	−64.02		−61.78	−61.86
AEX	SQR	−6.19	−89.96	IBOVESPA	−6.93	−89.84
	ABS	−6.76	−92.77		−9.70	−85.36
	RET	−64.26	−64.37		−52.86	−52.51
DAX	SQR	−6.86	−89.10	IPSA	−11.66	−65.62
	ABS	−8.33	−92.86		−11.52	−70.61
	RET	−48.56	−68.15		−61.87	−61.96
DJA	SQR	−7.96	−93.82	KLSE	−24.93	−36.55
	ABS	−7.02	−92.85		−23.77	−55.35
	RET	−31.31	−66.24		−60.65	−60.69
FCHI	SQR	−7.07	−85.67	KOSPI	−11.05	−76.97
	ABS	−8.76	−90.84		−8.28	−87.61
	RET	−30.87	−67.17		−60.39	−60.37
FTSE 100	SQR	−6.32	−85.51	MICEX	−5.93	−83.97
	ABS	−8.18	−85.96		−6.13	−84.75
	RET	−62.59	−62.64		−44.65	−56.62
HANGSENG	SQR	−8.66	−65.36	MXXIPC	−6.70	−86.23
	ABS	−7.11	−87.09		−9.68	−84.77
	RET	−64.25	−64.38		−44.70	−57.85
NIKKEI	SQR	−10.31	−75.16	NIFTY	−12.85	−65.38
	ABS	−11.23	−82.43		−10.77	−75.43
	RET	−61.53	−61.59		−59.71	−59.75
STRAITS TIMES	SQR	−8.21	−84.72	SHCOMP	−12.46	−70.16
	ABS	−7.03	−88.62		−10.61	−78.57
	RET	−63.77	−64.06		−59.52	−59.51
TSX	SQR	−5.05	−78.36	TWII	−9.36	−79.99
	ABS	−7.60	−86.41		−7.41	−89.24

The null hypothesis of unit root is rejected for mean return, absolute return and squared return for all markets. (Source: Author Calculations).

of the series, follows a scaling law. We estimated Lo statistic for all the series and is reported in **Annexure 1**. We did not find evidence to reject the null hypothesis of absence of long memory in return. Contrary findings are evidenced using

Table 3. Estimates of t statistic (Ho: Mean of each series = 0.5).

	For Developed Markets		
	RET	SQR	ABS
Test statistic	2.004	45.5486	42.5659
Two-tailed p-value	0.075	5.928e−012	1.088e−011
One-tailed p-value	0.037	2.964e−012	5.438e−012
	For Emerging Markets		
Test statistic	3.85108	33.0184	27.5554
Two-tailed p-value	0.0039	1.056e−010	5.298e−010
One-tailed p-value	0.00195	5.278e−011	2.649e−010

Null hypothesis is rejected for all the data series. (Source: Author Calculation).

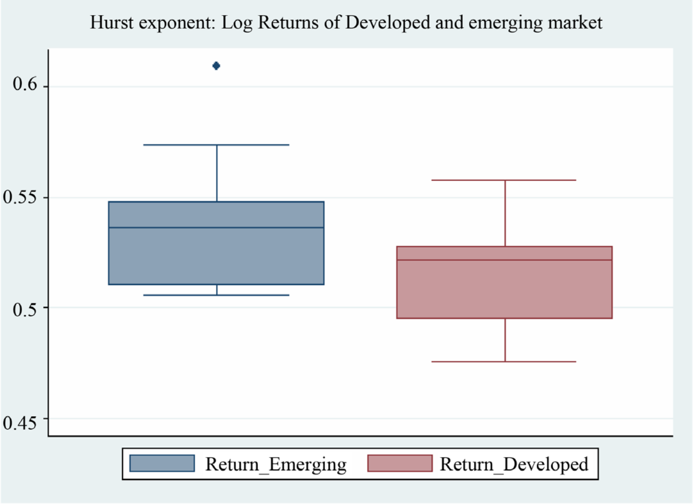

Figure 1. Hurst exponent for returns. Source: Author.

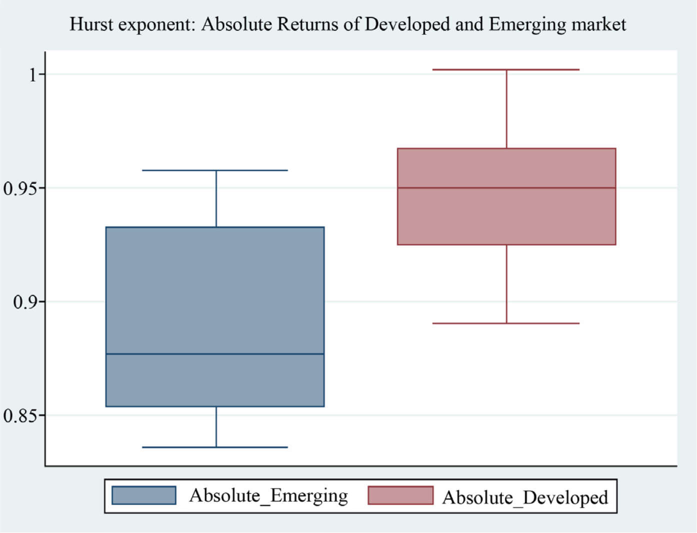

Figure 2. Hurst exponent for absolute returns. Source: Author.

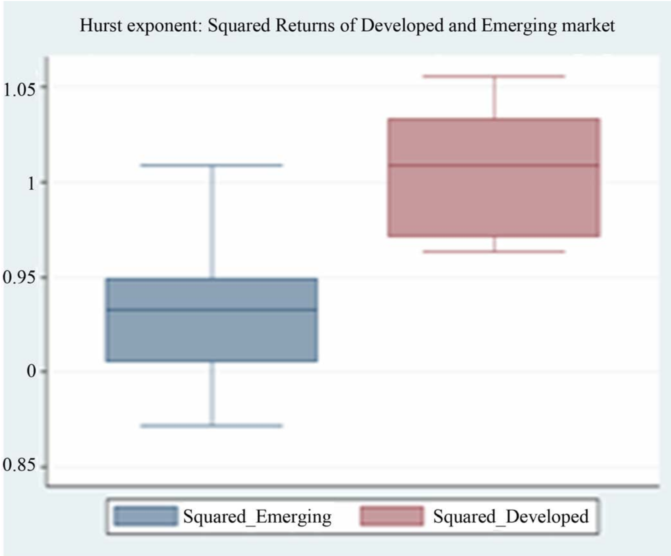

Figure 3. Hurst exponent for volatility. Source: Author.

volatility and absolute return series where the existence of long memory is rejected except for Malaysia, where the null of no long-range dependence could not be rejected at acceptable levels of significance.

5.3. The Spectral Regression Method (Robinson's Estimates)

The estimates of the fractional differencing parameter (d) are reported in **Annexure 2**. The hypothesis of short memory (d = 0) is rejected for absolute return and volatility indicating that fractionally integrated models would be required for modelling these series and similar findings are observed for developed and emerging markets with the exception of Malaysia where the presence of long memory in volatility could not be evidenced. However consistent with earlier findings, the null hypothesis for return series could not be rejected for all the emerging and developed market indices.

6. Conclusions

The comparative dynamics of emerging and developed financial markets is an important area of study, especially to understand the increasing impact of global integration. One aspect that distinguishes a mature market and a young market is the difference in market efficiency. The comparative studies thus focus on the efficiency of emerging and developed stock markets. However, [25] showed that the commonly used measures of weak and semi-strong efficiency have limitations in capturing the efficiency. An alternative way to gauge market efficiency is the use of long memory statistics. In this article, we have extended the literature on the comparative dynamics of emerging and developed stock markets using long memory statistics.

Overall findings did not suggest any significant difference in returns from developed markets and emerging markets in terms of memory as the presence of long memory could not be established in return series of both the groups. This possibly lends support to the view that modern technology-driven equity markets, whether developed or emerging, are either efficient with arbitrage-free pricing or they are similarly immune to information asymmetry. The distinction between emerging and developed markets regarding efficiency needs a relook as we do not find any significant difference between them in terms of persistence. The findings are supportive of the argument that returns of stock markets follow a random walk and have important implications for equity and portfolio investors. The assertion of random walk seemed indisputable not only on empirical justifications but also consistent with the efficient market paradigm. In the case of Malaysia, significant R/S statistic with insignificant Lo statistic for squared return series indicates evidence of short memory in volatility in line with the observations of [26] and [27]. We argue that evidence against long memory in KLSE needs further research considering the market microstructure and the dynamic nature of market movements in Malaysia. Findings also indicate possibilities of speculation in derivatives market as the presence of memory in volatility leaves room for impaired price discovery. In line with [28], the findings support the presence of non-linearity in emerging and developed markets.

We did not find any significant difference in the long memory statistics of the two market groups. We can conjecture that due to global integration the efficiency of the emerging stock markets is no longer very different from that of the developed stock markets. This study has important implications for global investment decisions. For policymakers in emerging market, the lesson from this article is that liberalisation of markets has resulted in improving the efficiency of the markets. The greater the integration with global markets the more is the benefit for the emerging markets. The future research scope would be in finding and establishing the range of the fractional differencing parameter (d) for each of emerging and developed markets.

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Annexure 1

HURST Exponent							
Developed Markets				Emerging Markets			
Indices	RET	SQR	ABS	Indices	RET	SQR	ABS
AORD	0.5278	0.9123	0.9705	BUX	0.5391	0.8535	0.9256
AEX	0.5275	1.002	1.056	IBOVESPA	0.5059	0.8532	0.938
DAX	0.5199	0.9674	1.015	IPSA	0.5355	0.8354	0.9047
DJA	0.4824	0.9675	1.033	KLSE	0.5735	0.8443	0.8754
FCHI	0.4947	0.9512	1.002	KOSPI	0.5068	0.9428	0.969
FTSE 100	0.476	0.9489	1.016	MICEX	0.5262	0.9326	1.009
HANGSENG	0.5145	0.939	0.9788	MXXIPC	0.5103	0.8958	0.9492
NIKKEI	0.5238	0.8902	0.9656	NIFTY	0.537	0.893	0.9269
STRAITS TIMES	0.5577	0.9242	0.9634	SHCOMP	0.6087	0.8612	0.8717
TSX	0.5335	0.9802	1.053	TWII	0.5476	0.9579	0.9397
Lo Statistic							
AORD	1.35	3.44	4.41	BUX	1.36	2.56	3.36
AEX	1.28	2.19	2.78	IBOVESPA	1.58	2.66	3.68
DAX	1.46	2.65	3.48	IPSA	1.59	2.3	2.75
DJA	1.19	2.68	2.69	KLSE	1.18	1.64	3.04
FCHI	1.07	2.61	3.5	KOSPI	1.22	3.27	4.36
FTSE 100	1.12	2.38	2.81	MICEX	1.23	2.83	3.45
HANGSENG	1.31	2.68	3.76	MXXIPC	1.41	2.95	3.56
NIKKEI	1.15	2.01	2.52	NIFTY	1.43	2.92	3.16
STRAITS TIMES	1.49	3.38	3.57	SHCOMP	1.64	3.58	4.09
TSX	1.09	2.49	3.03	TWII	1.16	3.74	4.42

The values of Hurst component and Lo statistic. Note: Critical values: The critical values of the statistic are obtained from Lo (Table II, 1991). 90% [0.861, 1.747]. 95% [0.809, 1.862]. 99% [0.721, 2.098].

Annexure 2

The estimates of the fractional differencing parameter (d)

Indices	Data	$M = T^{0.50}$	$M = T^{0.55}$	$M = T^{0.60}$	$M = T^{0.65}$	$M = T^{0.70}$
			Developed Markets			
^AORD	RET	0.1075	0.1352	0.0768	0.0145	0.0196
^AORD	SQR	0.4394***	0.5112***	0.4784***	0.4439***	0.4416***
^AORD	ABS	0.5437***	0.5347***	0.5199***	0.4787***	0.4732***
AEX	RET	0.0534	0.0587	0.0845	0.0664	0.0462
AEX	SQR	0.3976***	0.5022***	0.5479***	0.6041***	0.4885***
AEX	ABS	0.4480***	0.5352***	0.5844***	0.6039***	0.5236***
DAX	RET	0.0452	0.1057	0.0589	0.0461	0.0188
DAX	SQR	0.4379***	0.4687***	0.4733***	0.5163***	0.4409***
DAX	ABS	0.5092***	0.5557***	0.5075***	0.5206***	0.4617***
DJA	RET	0.0335	−0.0010	−0.0094	−0.0083	−0.0378
DJA	SQR	0.4956***	0.6507***	0.5962***	0.6217***	0.5795***
DJA	ABS	0.5296***	0.5444***	0.5752***	0.5685***	0.5432***
FCHI	RET	−0.0508	−0.0125	−0.0107	−0.0279	−0.0665
FCHI	SQR	0.4471***	0.5002***	0.4672***	0.4760***	0.4020***
FCHI	ABS	0.4772***	0.5456***	0.5104***	0.4913***	0.4583***
FTSE 100	RET	0.0419	0.0181	0.0097	−0.0341	−0.0070
FTSE 100	SQR	0.4772***	0.5546***	0.5040***	0.5209***	0.4349***
FTSE 100	ABS	0.4560***	0.5086***	0.4824***	0.4883***	0.4748***
HANGSENG	RET	0.0305	0.1449	0.0930	0.0497	−0.0007
HANGSENG	SQR	0.3434***	0.4237***	0.4435***	0.4970***	0.3406***
HANGSENG	ABS	0.5276***	0.5577***	0.5535***	0.5292***	0.4257***
NIKKEI	RET	0.0038	−0.0009	−0.0356	0.0009	−0.0398
NIKKEI	SQR	0.2670***	0.3203***	0.4461***	0.5505***	0.4445***
NIKKEI	ABS	0.3399***	0.3556***	0.4705***	0.5189***	0.4235***
STRAITS TIMES	RET	0.1409	0.2116***	0.1364***	0.1302***	0.0772
STRAITS TIMES	SQR	0.3807***	0.4238***	0.4586***	0.5016***	0.4531***
STRAITS TIMES	ABS	0.5001***	0.5068***	0.4954***	0.4840***	0.4357***
TSX	RET	0.1109	0.1539	0.0760	0.0293	−0.0069
TSX	SQR	0.6009***	0.7026***	0.5343***	0.6165***	0.6340***
TSX	ABS	0.6258***	0.6424***	0.5020***	0.5189***	0.5284***
			Emerging Markets			
BUX	RET	0.0717	0.1361**	0.1306**	0.0481	0.0442
BUX	SQR	0.2938***	0.3622***	0.4588***	0.5523***	0.5145***

Continued

BUX	ABS	0.3498***	0.3818***	0.4330***	0.4484***	0.4022***
IBOVESPA	RET	0.0596	0.1052	0.1079**	0.1229***	0.0363
IBOVESPA	SQR	0.3728***	0.6161***	0.6610***	0.5883***	0.5486***
IBOVESPA	ABS	0.4539***	0.5401***	0.5225***	0.4638***	0.4152***
IPSA	RET	0.1293	0.0435	0.0150	0.0403	−0.0081
IPSA	SQR	0.2108***	0.2418***	0.2984***	0.3637***	0.4395***
IPSA	ABS	0.3669***	0.4634***	0.4440***	0.4343***	0.4109***
KLSE	RET	−0.0127	0.0619	0.0056	−0.0025	0.0440
KLSE	SQR	0.0849	0.0054	0.0661	0.0327	0.0084
KLSE	ABS	0.2483**	0.2081**	0.2026***	0.1687***	0.1398***
KOSPI	RET	0.0205	0.1119	0.0366	−0.0414	−0.0365
KOSPI	SQR	0.4226***	0.4773***	0.3778***	0.4072***	0.3728***
KOSPI	ABS	0.6117***	0.6416***	0.4991***	0.4807***	0.4423***
MICEX	RET	0.1642	0.1364	0.0794	0.0360	0.0103
MICEX	SQR	0.4601***	0.6681***	0.6894***	0.6371***	0.2798***
MICEX	ABS	0.5151***	0.5597***	0.6022***	0.5355***	0.3344***
MXXIPC	RET	0.0138	0.0454	0.0538	0.0478	0.0131
MXXIPC	SQR	0.3047***	0.4762***	0.5066***	0.5062***	0.4480***
MXXIPC	ABS	0.4557***	0.5045***	0.4866***	0.4558***	0.4736***
NIFTY	RET	0.0517	0.0998	0.1291	0.1049**	0.0549
NIFTY	SQR	0.2939***	0.3607***	0.3664***	0.3309***	0.2869***
NIFTY	ABS	0.4027***	0.4669***	0.4886***	0.4293***	0.3957***
SHCOMP	RET	0.2145	0.1144	0.0966	0.0355	−0.0136
SHCOMP	SQR	0.5849***	0.4347***	0.3642***	0.2915***	0.3152***
SHCOMP	ABS	0.6049***	0.4882***	0.4515***	0.3825***	0.3666***
TWII	RET	0.1026	0.0505	0.0366	0.0733	0.0250
TWII	SQR	0.5643***	0.4872***	0.3933***	0.3210***	0.2881***
TWII	ABS	0.5742***	0.5030***	0.4609***	0.4233***	0.3413***

*** & ** denotes significance at 1% and 5% level respectively (Source: Author Calculation).