Int. Journal of Economics and Management **6(2):** 278 – 294 (2012) ISSN 1823 - 836X

Multifractality and Efficiency: Evidence from Malaysian Sectoral Indices

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ABSTRACT

This study examines the weak-form efficiency of Malaysian sectoral indices using multifractal detrended fluctuation analysis. The study also uses the rolling window approach to scrutinize the dynamics of weak-form efficiency of Malaysian sectoral stock market. The overall empirical findings revealed that the Malaysian sectoral indices possess multifractality as a result of both fat-tailed probability distribution and long-range correlations. The dynamics of the local Hurst exponents acquired via rolling window approach showed that the Malaysian sectoral efficiency is adversely affected by both Asian and global financial crises, and also negatively impacted by the capital control implemented by the Malaysian government during the Asian financial crisis. The findings suggest that forecasting models that incorporate multifractality might be more appropriate for Malaysian sectoral volatility and crash predictions. Malaysian experience also demonstrates that policy makers should carefully decide on the proper monetary regime as the policy also holds important role in improving the stock market efficiency. A ranking of the sectoral indices according to their relative weak-form efficiency is also presented in this study.

Keywords: Capital control, Financial crisis, Hurst exponent, Rolling window.

JEL Classification: C61, G14

INTRODUCTION

Over the last few decades, concepts and methods developed by physicists have been vigorously applied to elucidate the properties and complex dynamics exhibited in economic and financial time series. The fact that most financial time series possess multifractality has been evidenced in literature and is now widely accepted. One

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of the sources of multifractals is the existence of long-term correlations in the fluctuations of a time series. The presence of multifractals thus could imply the possibility of violation of weak form market efficiency.[1]

A multifractal system is a generalized monofractal dynamic process that involves multiple scaling rules which its dynamics cannot be amply explained by a single fractal dimension. The first Detrended Fluctuation Analysis (DFA) model on monofractal process is proposed by Peng *et al.* (1994). A decade after that, Kantelhardt *et al.* (2002) proposed the Multifractal-DFA (MF-DFA). Since MF-DFA have global detection of multifractal behavior and does not require more effort in programming than the one in DFA, it has become a widely used technique in solving economic and financial problems (e.g. Gu *et al.*, 2010; Chen and Wu, 2011; Wang *et al.*, 2011).

MF-DFA can be applied to investigate the dynamics of weak-form efficiency of financial market by means of Hurst exponent and multifractality degree. For instance, Wang *et al.* (2009) applied the MF-DFA in the analysis of Shenzhen stock market efficiency. By studying the evolution of Hurst exponent and multifractality degree with rolling window, they found that the Shenzhen stock market became more and more efficient over time after the price-limited reform. They also showed the presence of multifractality and long-range correlations in the Shenzhen stock market volatility series. In another study, Wang *et al.* (2010a) also used the MF-DFA to analyze the Hurst exponent and multifractality degree with moving window of Shanghai stock market over time. They concluded that the price-limited reform greatly improved the market efficiency of Shanghai stock market in the long term. Wang *et al.* (2011) have conducted a multifractality study on market efficiency of gold markets. They have proposed a measure of the degree of market inefficiency based on the generalized Hurst exponents. Kumar and Deo (2009) used the same method and discovered that the Indian financial indices possessed multifractality due to the contributions of long-range correlations and the broad probability density function.

In short, there are overwhelming evidence that many stock markets possess multifractality, but the literature has mainly focused on aggregate indices and/or large open economies (e.g. Lee *et al.*, 2006; Zunino *et al.*, 2008; Yuan *et al.*, 2009). Less attention has been devoted for in-depth studies on sectoral indices of emerging market. Although Chin (2008) and Lim (2008) have respectively examined

[1] Weak form market efficient implies that the time series of stock return does not allows for serial correlation, in other words, one cannot use any forms of information available to gain superior investment returns. An inefficient market might provide opportunities for both practitioners and investors to achieve abnormal returns.

the market efficiency of the sectoral indices in Malaysia, to our best knowledge, there is yet any study on the multifractality dimension of market efficiency using MF-DFA. In view of that, this paper analyzes the multifractality dimension of weak-form market efficiency of Malaysia sectoral indices. Specifically, this study employs MF-DFA: (i) to examine the multifractality of the selected sectoral indices; (ii) to investigate the dynamics of the weak-form market efficiency by incorporating the rolling window method; and (iii) to rank the sectoral indices according to their relative weak-form market efficiency.

The preference of Malaysia in this paper is mainly motivated by the interesting insights offered by the country. Malaysia has experienced structural changes throughout the present period of study from 1 November 1993 to 30 June 2011. Malaysia is one of the fast growing emerging countries with open economy and considerably developed stock market. Due to Malaysian economy openness, it had gone through Asian financial crisis (June 1, 1997), the burst of dot-com bubble (March 10, 2000), September 11 attacks on United States (September 11, 2001), and also the global financial crisis (August 1, 2007)[2]. Notably, during the Asian financial crisis, Malaysia had opted distinctive measures to end the speculation on its currency and to bail out its economy through the implementation of capital control policy on September 1, 1998. The regime (pegged of Malaysian ringgit to the US Dollar) continued until Malaysian government announced a new exchange rate regime (de-pegging of Malaysian Ringgit) on July 21, 2005. The remaining of the paper is organized as follows: Section 2 provides the methodology. The data used in this study are detailed in Section 3. Section 4 discloses the empirical results followed by some discussions, and finally, Section 5 concludes the paper.

DATA AND METHODOLOGY

Multifractal detrended fluctuation analysis

We followed the MF-DFA procedure suggested by Kantelhardt *et al.* (2002). The process consists of five steps in which the first three steps are basically analogous to the conventional DFA procedure introduced by Peng *et al.* (1994). Suppose that x_k represents a time series of finite length N with insignificant fraction of zero values and if there is any zero value exist, i.e. $x_k = 0$, it will be interpreted as having no value at k.

[2] The starting date of global financial crisis is as per reference of Rude, C. (2010) The World Economic Crisis and the Federal Reserve's Response to it: August 2007 – December 2008, Studies in Political Economy, 85, 125-148.

Step 1: Establish the "profile" using:

$$Y(i) \equiv \sum_{k=1}^{i} \left[xk - \bar{x}\right], \qquad i = 1, \ldots, N. \tag{1}$$

where $\bar{x}$ denotes the mean of the entire time series.

Step 2: Divide the profile $Y(i)$ into $N_s \equiv \lfloor N/s_{-} \rfloor$ non-overlapping segments of equal length s. Since the length N may not always be the multiple of s where some end part of the profile may remain, the same procedure is repeated starting from the opposite end of the profile so that the remaining data is not ignored. As a result, we obtained a total of $2N_s$ segments altogether.

Step 3: Determine the local trend of each of the $2N_s$ segments by using the least-square fit of the series. After that, determine the variance of each vth segment.

For each segment $v = 1, ..., N_s$, the variance can be obtained by:

$$F^2(v,s) \equiv \frac{1}{s}\sum_{i=1}^{s}\left\{Y\left[(v-1)s+i\right] - y_v(i)\right\}^2 \tag{2}$$

and for each segment $v = N_s + 1, \ldots, 2N_s$, the variance can be found by:

$$F^2(v,s) \equiv \frac{1}{s}\sum_{i=1}^{s}\left\{Y\left[N-(v-N_s)s+i\right] - y_v(i)\right\}^2 \tag{3}$$

where $y_v(i)$ is the fitting polynomial i.e. the local trend in the vth segment. Linear (MF-DFA1), quadratic (MF-DFA2), cubic (MF-DFA3), or higher order polynomials can be used in the fitting procedure. Since the detrending of a time series is done by subtracting the fits from the profile, different degrees of polynomial differ in their capability of eliminating trends in the series. Thus, one can estimate the type of polynomial trend in a time series by comparing the results for different detrending orders of MF-DFA (e.g. Peng *et al.*, 1994; Wang *et al.*, 2009; Kantelhardt *et al.*, 2001).

Step 4: Obtain the qth order fluctuation function by averaging all segments $v = 1, ..., 2N_s$:

$$F_q(s) \equiv \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} \left[F^2(v,s) \right]^{q/2} \right\}^{1/q} \tag{4}$$

where $\{q \in \Re \mid q \neq 0\}$. As q approaches zero, the averaging procedure in Eq. (4) cannot be applied directly because of the diverging exponent. Therefore, the following logarithmic averaging procedure is employed as a substitute for $q = 0$:

$$F_0(s) \equiv \exp\left\{ \frac{1}{4N_s} \sum_{v=1}^{2N_s} \ln\left[F^2(v,s) \right] \right\} \tag{5}$$

Steps 2 to 4 are repeated for numerous time scales s. It is obvious that as s increases, the value of $F_q(s)$ will increase.

Step 5: Analyze the slope of log-log plots of $F_q(s)$ versus s for each value of q to determine the scaling behavior of the fluctuation functions. The value of $F_q(s)$ will increase as a power-law for large value of s if the series x_k are long-range power-law correlated:

$$F_q(s) \sim s^{h(q)} \tag{6}$$

The scaling exponent $h(q)$ in Eq. (6) generally may depends on q. However, in a monofractal time series, $h(q)$ is independent of q since the scaling behavior of the variances in Eqs. (2) and (3) is identical for all segments v. On the contrary, in a multifractal time series, there will be a notable dependence of $h(q)$ on q due to the different scaling behaviors in the small and large fluctuations. The scaling exponent $h(q)$ is known as the generalized Hurst exponent seeing that $h(2)$ is identical to the well-known Hurst exponent.

The relationship between the generalized Hurst exponent $h(q)$ and the classical multifractal scaling exponent $\tau(q)$ can be established by using:

$$\tau(q) = qh(q) - 1 \tag{7}$$

Following Schumann and Kantelhardt (2011), the multifractality degree (or strength of multifractality) in finite limit [$-q$, $+q$]can be described by:

$$\Delta h_q = h(-q) - h(+q) \tag{8}$$

Another quantifier for the multifractality degree for the same limit is:

$$\Delta \alpha = \alpha\big|_{q=-q} - \alpha\big|_{q=+q} \tag{9}$$

Binomial Multifractal Model

Surrogate data serves as an important gauge to validate the apparent scaling behavior and to ensure that the observed multifractal properties are not spurious. In the binomial multifractal model, the kth element $(k = 1, \ldots, 2^{n_{\max}})$ in a time series x_k is defined by (Schumann and Kantelhardt, 2011):

$$x_k = a^{n_{\max} - CS\{(k-1)_2\}}(1-a)^{CS\{(k-1)_2\}} \tag{12}$$

where the parameter $\{a \in \Re \mid 0.5 < a < 1\}$, $CS\left\{(k-1)_2\right\}$ denotes the checksum of the binary representation of (k – 1), e.g. $CS\left\{(23)_2\right\} = CS\left\{10111\right\} = 4$. The binomial multifractal scaling exponents $h(q)$ and $\tau(q)$ can be obtained by (Kantelhardt *et al.*, 2002):

$$h(q) = \begin{cases} \frac{1}{q}\left\{1 - \log_2\left[a^q + (1-a)^q\right]\right\} & ; \quad q \neq 0 \\ -\frac{1}{2}\left\{\log_2\left[a(1-a)\right]\right\} & ; \quad q = 0 \end{cases} \tag{13}$$

and

$$\tau(q) = -\log_2\left[a^q + (1-a)^q\right] \tag{14}$$

The parameter a with a value that is very close to one will generate a series with fat-tailed distribution. Hence, a binomial multifractal series can be used to distinguish the presence of multifractality in a time series is due to a fat-tailed probability distribution (see Kantelhardt *et al.*, 2002).

Data

The selected sectoral indices are construction (CON), consumer product (COP), finance (FIN), industrial product (INP), plantations (PLN), properties (PRP), and trading and service (TAS). The Kuala Lumpur Composite Index (KLCI) is used as the benchmark. In view that some sectoral indices such as construction, consumer product, industrial product, and trading and service are only available since 25 October 1993, we therefore consider daily closing price indices for the sample period ranged from 1 November 1993 to 30 June 2011, or a total of 4609 observations. These data were sourced from Datastream. The data was transformed into series of daily price returns r_t by taking the logarithmic differences:

$$r_t = \log\left(p_t / p_{t-1}\right) \quad (15)$$

where p_t and p_{t-1} are the closing price of an index on day t and $t-1$, respectively.

RESULTS AND DISCUSSION

Multifractal Analysis of the Stock Market

A length s that is too small in the $2N_s$ of non-overlapping segments will result in poor estimates of variances in Eqs. (2) and (3). On the other hand, a length s that is too big will cause poor estimation of fluctuation function in Eq. (4). Hence, following the suggestion of Peng *et al.* (1994) and Wang *et al*. (2009), we set the time scale s to the range of $[10, 15, \ldots, N/5]$. We detrended the series using different degrees of polynomial ranging from first (MF-DFA1) to the fifth order (MF-DFA5), to determine the appropriate detrending order. Similar analyses could be seen in Telesca *et al*. (2009) and Wang *et al*. (2009). The results shown in Figure 1 do not disclose significant difference among the fluctuation curves, and these imply that first order (or linear) detrending is adequate in this study. Therefore, this paper employed MF-DFA1 for subsequent analyses.

The scaling exponent $h(q)$ can be determined from the slope of the fitted straight line in the log-log plot of $F_q(s)$ versus s. In a monofractal series, the values of $h(q)$ are constant over q. As can be evident from the original series shown in Figure 2, the values of scaling exponent $h(q)$ apparently have a nonlinear dependence on q. The findings are supported by the nonlinear relationship between the $\tau(q)$ and q, as presented in Figure 3 (see Kantelhardt *et al.*, 2002). In other words, the results revealed that Malaysian sectoral indices possess multifractality. Subsequently, we carried out a thorough investigation to distinguish the type of multifractality present in the indices. The sources of multifractality in time series generally may be due to: (i) broad probability density function or fat-tailed probability distribution, and/or

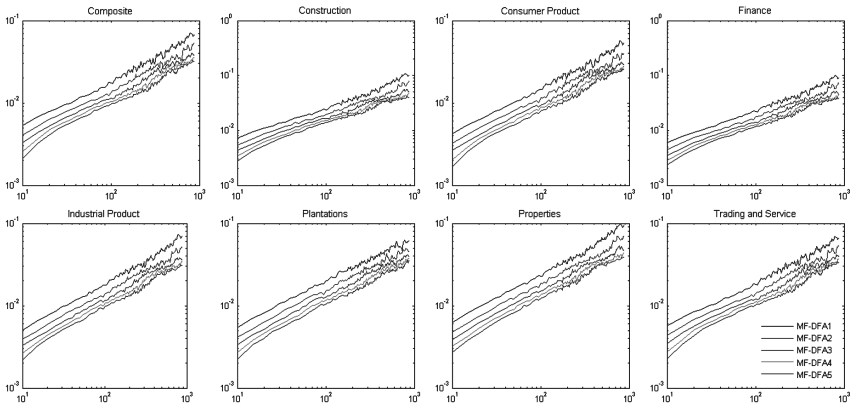

Figure 1 Log-log plots of $F_q(s)$ versus s for q=2 with detrending order from 1 to 5. The results show no significant differences among the linear fluctuation curves for different detrending orders, and indicate that MF-DFA model with first degree polynomial (MF-DFA1) is adequate.

(ii) different long-range correlations of the small and large fluctuations in the values of the time series. The first type of multifractals is not affected by shuffling the series since the multifractality is due to the fat-tailed probability distribution. On the other hand, the second type of multifractals can be distinguished by comparing the original series with those of the shuffled series. In a multifractal series due to the long-range correlations, the scaling exponent $h(q)$ of the corresponding shuffled

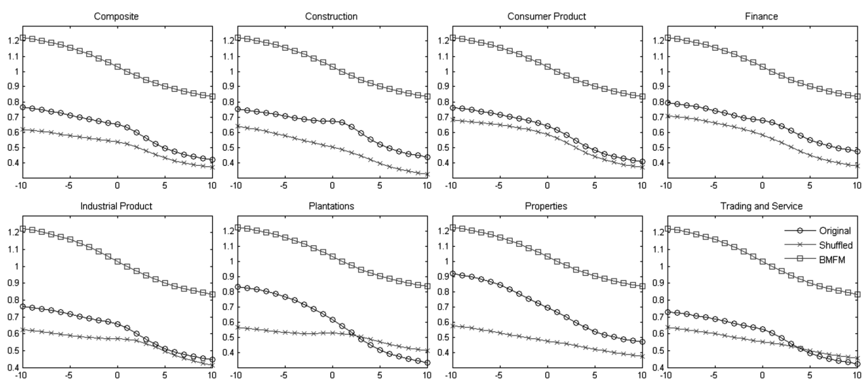

Figure 2 The generalized Hurst exponent $h(q)$ for q from -10 to 10. The dependence of $h(q)$ on q indicates that all indices possess multifractality. A decrease in the slope of shuffled series suggests that both types of multifractals (fat-tailed distribution and long-range correlations) are present.

series will remain constant for all q since all correlations are destroyed by the shuffling procedure. If both types of multifractals are present, the shuffled series will exhibit weaker multifractality than the original series (see Kantelhardt *et al.*, 2002).

We compared our results with the binomial multifractal model's scaling exponents obtained from the Eqs. (13) and (14). Similar to the work of Kumar and Deo (2009), we set the model parameter a = 0.6. From the composite index (KLCI) shown in Figure 2 and Figure 3, we could see that the magnitude of the slopes of the shuffled and the original series have become lower, i.e. the multifractality of the index has become weaker, particularly for $q > 0$. These disclosed the fact that both fat-tailed probability distribution and long-range correlations are the sources of multifractality, in which the latter have greater effect on the index for positive q. Likewise, the results also revealed that the multifractality possessed in the trading and service (TAS), plantations (PLN), properties (PRP), and industrial product (INP) indices are due to both fat-tailed probability distribution and long-range correlations. Conversely, there are no significant variations in the slopes of the original, BMFM and shuffled series of the construction (CON), consumer product (COP) and finance (FIN) indices. These imply that fat-tailed probability distribution has stronger effect on the multifractality of the indices.

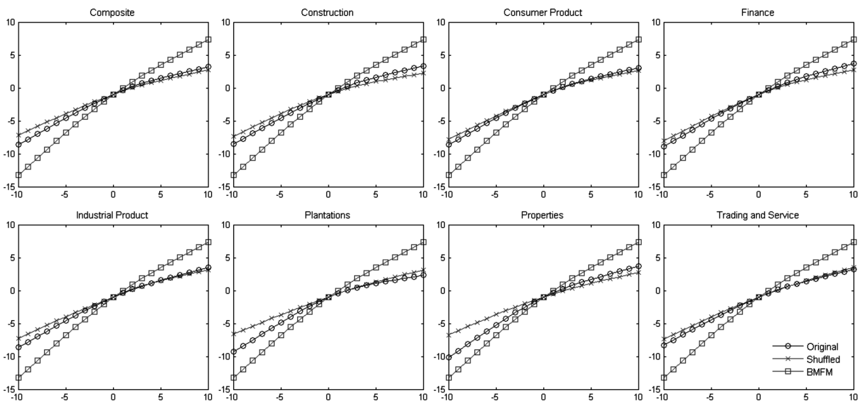

Figure 3 The standard multifractal scaling exponent $\tau(q)$ for q from -10 to 10. The nonlinear dependence of $\tau(q)$ on q indicates that all indices possess multifractality. A decrease in the slope of shuffled series suggests that both types of multifractals (fat-tailed distribution and long-range correlations) are present.

From Figure 4, we evident that the strength of multifractality of both shuffled series and BMFM are weaker than the original plantation (PLN) and properties (PRP) indices. This suggests that both the long-range correlations and fat-tailed probability distribution have essential impacts on the multifractality of plantations and properties indices. The multifractality degrees of the shuffled series of the composite (KLCI), industrial product (INP), and trading and service (TAS) indices are obviously weaker than the corresponding original indices. These indicate that long-range correlations have a strong effect on the multifractality of the indices, in addition to the effect of the fat-tailed probability distribution. There are no significant differences in the multifractality degrees between the original and shuffled series of the construction (CON), consumer product (COP), and finance (FIN) indices. The results show that fat-tailed probability distribution is the main source of multifractals in the series. These findings are noteworthy for their consistency with the results evidenced in Figure 2 and Figure 3.

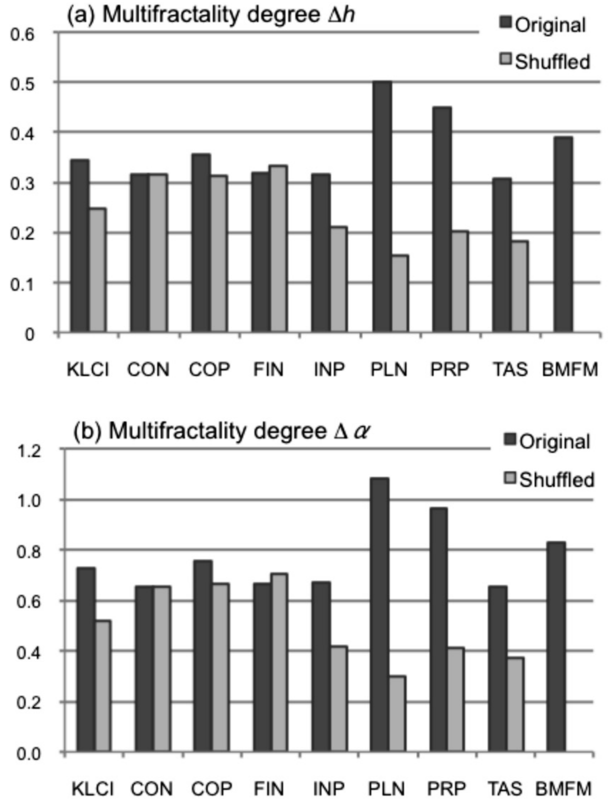

Figure 4 The multifractality degrees Δh and $\Delta \alpha$ for q from -10 to 10. A decrease in the multifractality degree of a shuffled series, as compared to the original series, indicates that both types of multifractals (fat-tailed distribution and long-range correlations) are present.

Efficiency Analysis of the Stock Market

When $q = 2$ $q = 2$, the generalized Hurst exponent $h(2)$ is equal to the well-known Hurst exponent, H. Hurst exponent is widely applied as a measure for long-range correlations and fractality of a time series. Previous studies have demonstrated the utilization of Hurst exponent in quantifying the weak-form efficiency of financial markets (e.g. Matos et al., 2008; Domino, 2011; Onali and Goddard, 2011). If a series is random or uncorrelated, the value of the Hurst exponent is equal to 0.5. A Hurst exponent in the range of $0 < H < 0.5$ corresponds to anti-persistent series which indicates negative long-range dependence, i.e., a positive deviation is generally followed by a negative deviation and vice versa. Conversely, a Hurst exponent in the range of $0.5 < H < 1$ corresponds to persistent series. This implies a series with positive long-range dependence, in which a deviation tends to be followed by another deviation with the same sign.

A number of studies have used the rolling window approach to attain the local Hurst exponent. The rationale of the preference is that a Hurst exponent obtained from the whole series does not necessarily imply presence or absence of long-range correlations. The exponent found could be due to the averaging of those negative and positive correlations. Additionally, the rolling window approach can also disclose the dynamics of market efficiency. The choice of the length of the rolling sample varies for different purposes. Cajueiro and Tabak (2004b), Cajueiro *et al.* (2009) and Wang and Liu (2010) used window length of 1008 business days or around 4 years of data to analyze the evolution of market efficiency. On the other hand, Wang *et al.* (2010b) and Lin *et al.* (2011) employed shorter window length of 250 business days or around 1 year of data in their researches. In this paper, we consider both lengths of the rolling window to investigate the dynamics of the Malaysian sectoral efficiency. The preference is similar to the works of Wang *et al.* (2011), with apprehension that the considered Hurst exponent may lose its locality if the length of the rolling window is too large (Grech and Mazur, 2004). For the window length of 250 trading days, we set the time scale s in the range of [10, 15,…, 250] and the period of the first window is from 2 November 1993 to 31 October 1994. For window length of 1008 trading days, the time scale was set at [10, 15,…, 1008] and the first window interval is from 2 November 1993 to 26 November 1997. Alvarez-Ramirez *et al.* (2008) have showed that the scaling exponent dynamics are retained for different sliding sizes. Following that, the step is fixed at 5 trading days for both cases. As a result, for the window length of 250 and 1008 trading days, we obtain a total of 822 and 671 windows respectively.

The descriptive statistics of the local Hurst exponents for both window lengths are summarized in Table 1. As presented in the panel A of the table, the 250

Table 1 Descriptive statistics, percentage of persistent, Jarque-Bera normality test, and sectoral ranking.

	KLCI	CON	COP	FIN	INP	PLN	PRP	TAS
Panel A: Local Hurst exponents for window length of 250 trading days								
Mean	0.503	0.48	0.497	0.509	0.506	0.498	0.523	0.487
Median	0.497	0.482	0.5	0.514	0.506	0.511	0.529	0.483
Maximum	0.688	0.678	0.729	0.729	0.814	0.704	0.762	0.697
Minimum	0.232	0.223	0.215	0.207	0.207	0.174	0.227	0.207
Std. Dev.	0.088	0.098	0.106	0.095	0.107	0.106	0.095	0.091
Persistent (%)	48.3	43.67	49.88	54.99	52.31	53.28	61.31	44.04
Anti-persistent (%)	51.7	56.33	50.12	45.01	47.69	46.72	38.69	55.96
Jarque-Bera	5.7	22.19	16.45	10.55	4.08	22.27	20.25	3.07
Probability	0.058	0	0.0003	0.0051	0.13	0	0	0.2152
|Median-0.5|	0.0031	0.0182	0.0004	0.0142	0.0062	0.0111	0.0285	0.0172
Ranking	-	6	1**	4***	2***	3***	7	5**
Panel B: Local Hurst exponents for window length of 1008 trading days								
Mean	0.571	0.611	0.571	0.599	0.59	0.52	0.64	0.538
Median	0.543	0.615	0.585	0.597	0.575	0.487	0.641	0.516
Maximum	0.742	0.735	0.654	0.728	0.73	0.691	0.802	0.725
Minimum	0.423	0.487	0.452	0.476	0.446	0.276	0.404	0.38
Std. Dev.	0.082	0.064	0.055	0.072	0.068	0.088	0.078	0.094
Persistent (%)	82.41	97.47	83.31	88.97	92.25	42.18	99.25	55.89
Anti-persistent (%)	17.59	2.53	16.69	11.03	7.75	57.82	0.75	44.11
Jarque-Bera	53.85	21.99	58.84	40.27	15.78	35.22	16.13	43.94
Probability	0	0	0	0	0.0004	0	0.0003	0
|Median-0.5|	0.0433	0.1155	0.0855	0.0965	0.0754	0.0135	0.1407	0.016
Ranking	-	6***	4***	5***	3***	1***	7	2***

Note: *** and ** denote significant at 1% and 5% level of significance respectively. A smaller |Median-0.5| value implies better market efficiency.

trading days rolling local Hurst exponents of financial (FIN), industrial product (INP), plantations (PLN) and properties (PRP) indices exhibited higher percentage of persistency than other indices. In contrast, the trading and service (TAS), construction (CON), and consumer product (COP) indices have greater percentage of anti-persistency. The overall stock market (KLCI) also showed evidence of higher anti-persistency, i.e. negative long-range correlations in the series. In view of the fact that the Jarque-Bera test showed that the local Hurst exponents are not normally distributed, thus, instead of using the mean, we used median to rank the sectoral indices according to their relative weak-form market efficiency. Cajueiro and Tabak (2004a, 2005) also used medians of those computed local Hurst exponents to rank the selected emerging stock markets based on their efficiency level. Since some of the medians fall below $H = 0.5$, thus we made use of the absolute deviation from H, |Median-0.5| to provide a better view of the ranking. The relative ranking showed that the consumer product (COP) is the most efficient sectoral index, followed by the industrial product (INP), plantations (PLN), finance (FIN), and trading and service (TAS) indices. The construction (CON) and properties (PRP) indices are relatively the two least efficient. We also statistically examined the significance of difference between the rankings by using the Mann-Whitney nonparametric test. The results revealed that all the rankings are statistically significant at 1% or 5% level of significance except for the ranking between the construction (CON) and the properties (PRP) indices. Our sectoral efficiency rankings are nearly comparable to the rankings provided by Lim (2008). The results from the panel A also showed that the value of |Median-0.5| for KLCI is relatively smaller than most selected sectoral indices. This suggests that the overall stock market efficiency is comparatively better than others, except the consumer product (COP) sector.

The descriptive statistics of the local Hurst exponents for window length of 1008 trading days are summarized in the panel B of Table 1. From the table, we could see that the percentage of persistency is relatively high in all sectoral indices except for the plantations index. We ranked the sectoral indices using the value of |Median-0.5| seeing that the Jarque-Bera test disclosed that the Hurst exponents are not normally distributed. Relatively, one could see that the plantations (PLN) is the most efficient index, followed by trading and service (TAS), industrial product (INP), consumer product (COP), finance (FIN), and finally tailed by construction (CON) and properties (PRP) indices. Similarly, we used the Mann-Whitney nonparametric test to examine the significance in the rankings. All the rankings are statistically significant at 1% level of significance. The results also showed that the plantations (PLN) and trading and service (TAS) sectoral indices are more efficient than the overall stock market (KLCI).

The dynamics of the local Hurst exponents for the window length of 250 trading days are shown in Figure 5 (a). From the plots, we could see that the local Hurst exponents of all indices fluctuate around $H = 0.5$. Notably, all the Hurst exponents showed significant deviations away from the $H = 0.5$ during the Asian and global financial crises, September 11 attacks, dot-com bubble, as well as when the Malaysian Ringgit was pegged to the US Dollar. These observations are generally in line with the findings of Chin (2008) and Lim (2008), in which the Malaysian sectoral efficiency is adversely affected by the Asian financial crisis and the currency control policy implemented by the Malaysian government during the crisis. On the other hand, only the construction (CON), consumer product (COP), finance (FIN),

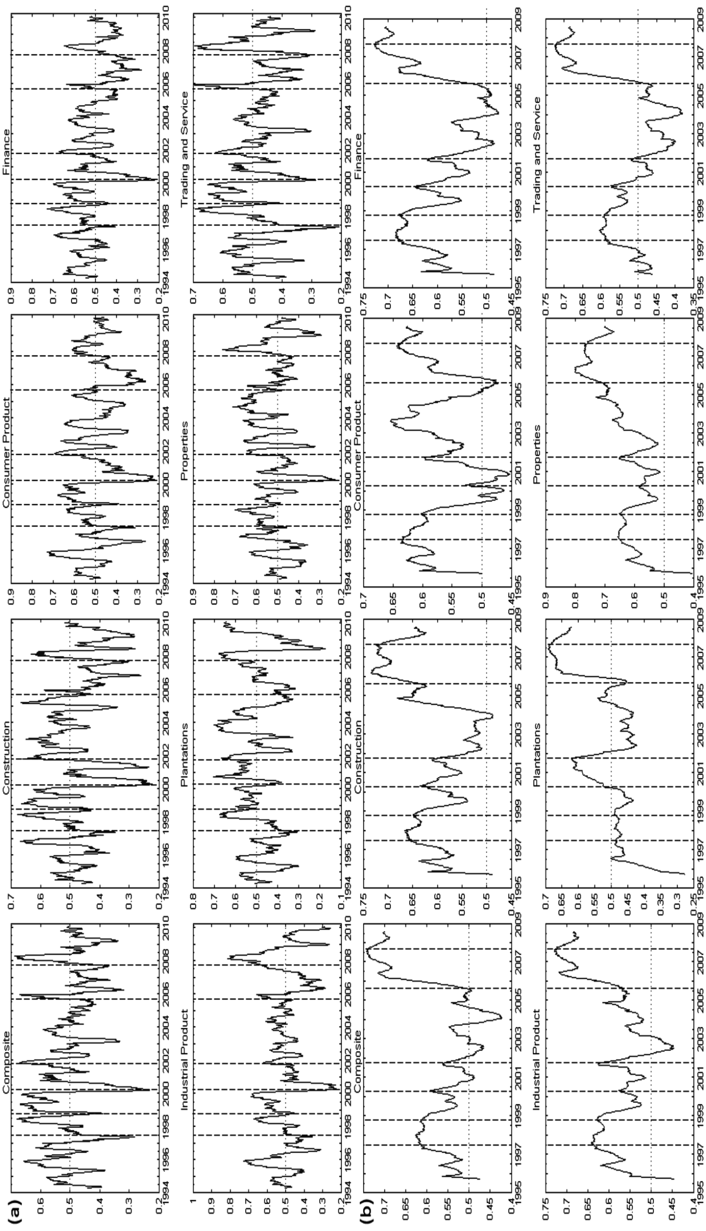

Figure 5. The dynamics of local Hurst exponents for: (a) window length of 250 trading days, and (b) window length of 1008 trading days. The six vertical dashed lines (from left to right) in each plot indicate the date of Asian financial crisis (1 June 1997), Malaysian Ringgit pegged to US Dollar (1 September 1998), dot-com bubble (10 March 2000), September 11 attacks (11 September 2001), de-pegging of Malaysian Ringgit (21 July 2005), and global financial crisis (1 August 2007) respectively. A Hurst exponent that is closer to $H = 0.5$ indicates greater market efficiency.

and plantations (PLN) indices reacted to the de-pegging of Malaysian Ringgit. The reason could be due to the direct involvement of these sectors in international trades and overseas investments, and hence, are relatively more responsive to the appreciation of the Malaysian Ringgit than other sectors.

Figure 5 (b) presents the dynamics of local Hurst exponents for window length of 1008 trading days. As expected, the dynamics of the exponents are relatively smoother than the one obtained from the window length of 250 trading days (Grech and Mazur, 2004). The results disclosed that the weak-form efficiency of the composite (KLCI), construction (CON), finance (FIN), industrial product (INP) and plantations (PLN) indices, gradually improved before the de-pegging of the Malaysian Ringgit. In contrast, the consumer product (COP), trading and service (TAS), and properties (PRP) indices become less efficient during the capital control period. The results also revealed that the burst of the dot-com bubble and September 11 attacks had minimal short-term impact on the weak-form efficiency of the composite and sectoral indices. At the post de-pegging period, most of the sectoral efficiency (except consumer product) deteriorated, and this continues until it reaches the peak when the global financial crisis started. The overall findings suggest that in addition to the exogenous erratic financial crises, exchange rate regime also plays an important role in influencing the stock market efficiency. Hence, policy makers should pay careful consideration to the preference of regulatory factors such as monetary regime in order to improve the stock market efficiency.

CONCLUSION

This paper provides empirical evidence of multifractality in Malaysian sectoral indices by using the Multifractal Detrended Fluctuation Analysis with linear order detrending (MF-DFA1). Thorough analysis on the original and shuffled series revealed that both fat-tailed probability distribution and long-range correlations are the sources of the multifractality in the selected sectoral indices. This could then imply that such indices are inefficient due to the presence of long-range correlations. The findings also suggest that forecasting models that are integrated with multifractals property might be more suitable for Malaysian sectoral volatility and crash predictions. Additionally, the results found via the rolling window lengths of 250 and 1008 trading days disclosed that the sectoral efficiency is adversely affected by the Asian and global financial crises, as well as negatively impacted by the currency control policy implemented by the Malaysian government during the Asian financial crisis.

REFERENCES

Alvarez-Ramirez, J., Alvarez, J., Rodriguez, E. and Fernandez-Anaya, G. (2008) Time-varying Hurst Exponent for US Stock Markets, *Physica A: Statistical Mechanics and its Applications*, **387**, 6159-6169.

Cajueiro, D.O., Gogas, P. and Tabak, B.M. (2009) Does Financial Market Liberalization Increase the Degree of Market Efficiency? The Case of the Athens Stock Exchange, *International Review of Financial Analysis*, **18**, 50-57.

Cajueiro, D.O. and Tabak, B.M. (2004a) Evidence of Long Range Dependence in Asian Equity Markets: The Role of Liquidity and Market Restrictions, *Physica A: Statistical Mechanics and its Applications*, **342**, 656-664.

Cajueiro, D.O. and Tabak, B.M. (2004b) The Hurst Exponent over Time: Testing the Assertion that Emerging Markets are Becoming More Efficient, *Physica A: Statistical Mechanics and its Applications*, **336**, 521-537.

Cajueiro, D.O. and Tabak, B.M. (2005) Ranking Efficiency for Emerging Equity Markets II, *Chaos, Solitons and Fractals*, **23**, 671-675.

Chen, H. and Wu, C. (2011) Forecasting Volatility in Shanghai and Shenzhen Markets based on Multifractal Analysis, *Physica A: Statistical Mechanics and its Applications*, **390**, 2926-2935.

Chin, W.C. (2008) A Sectoral Efficiency Analysis of Malaysian Stock Exchange under Structural Break, *American Journal of Applied Sciences*, **5**, 1291-1295.

Domino, K. (2011) The Use of the Hurst Exponent to Predict Changes in Trends on the Warsaw Stock Exchange, *Physica A: Statistical Mechanics and its Applications*, **390**, 98-109.

Grech, D. and Mazur, Z. (2004) Can One Make Any Crash Prediction in Finance Using the Local Hurst Exponent Idea?, *Physica A: Statistical Mechanics and its Applications*, **336**, 133-145.

Gu, R., Chen, H. and Wang, Y. (2010) Multifractal Analysis on International Crude Oil Markets Based on the Multifractal Detrended Fluctuation Analysis, *Physica A: Statistical Mechanics and its Applications*, **389**, 2805-2815.

Kantelhardt, J.W., Koscielny-Bunde, E., Rego, H.H.A., Havlin, S. and Bunde, A. (2001) Detecting Long-range Correlations With Detrended Fluctuation Analysis, *Physica A: Statistical Mechanics and its Applications*, **295,** 441-454.

Kantelhardt, J.W., Zschiegner, S.A., Koscielny-Bunde, E., Havlin, S., Bunde, A. and Stanley, H.E. (2002) Multifractal Detrended Fluctuation Analysis of Nonstationary Time Series, *Physica A: Statistical Mechanics and its Applications*, **316**, 87-114.

Kumar, S. and Deo, N. (2009) Multifractal Properties of the Indian Financial Market, *Physica A: Statistical Mechanics and its Applications*, **388**, 1593-1602.

Lee, J.W., Lee, K.E. and Rikvold, P.A. (2006) Multifractal Behavior of the Korean Stock-Market Index KOSPI, *Physica A: Statistical Mechanics and its Applications*, **364**, 355-361.

Lim, K.P. (2008) Sectoral Efficiency of the Malaysian Stock Market and the Impact of the Asian Financial Crisis, *Studies in Economics and Finance*, **25**, 196-208.

Lin, X., Fei, F. and Wang, Y. (2011) Analysis of the Efficiency of the Shanghai Stock Market: A Volatility Perspective, *Physica A: Statistical Mechanics and its Applications*, **390**, 3486-3495.

Matos, J.A.O., Gama, S.M.A., Ruskin, H. J., Sharkasi, A.A. and Crane, M. (2008) Time and Scale Hurst Exponent Analysis for Financial Markets, *Physica A: Statistical Mechanics and its Applications*, **387**, 3910-3915.

Onali, E. and Goddard, J. (2011) Are European Equity Markets Efficient? New Evidence from Fractal Analysis, *International Review of Financial Analysis*, **20**, 59-67.

Peng, C.K., Buldyrev, S.V., Havlin, S., Simons, M., Stanley, H.E. and Goldberger, A.L. (1994) Mosaic Organization of DNA Nucleotides, *Physical Review E*, **49**, 1685-1689.

Schumann, A.Y. and Kantelhardt, J.W. (2011) Multifractal Moving Average Analysis and Test of Multifractal Model With Tuned Correlations, *Physica A: Statistical Mechanics and its Applications*, **390**, 2637-2654.

Telesca, L., Lovallo, M., Ramirez-Rojas, A. and Angulo-Brown, F. (2009) Scaling Instability in Self-potential Earthquake-related Signals, *Physica A: Statistical Mechanics and its Applications*, **388**, 1181-1186.

Wang, Y. and Liu, L. (2010) Is WTI Crude Oil Market Becoming Weakly Efficient Over Time? New Evidence from Multiscale Analysis Based on Detrended Fluctuation Analysis, *Energy Economics*, **32**, 987-992.

Wang, Y., Liu, L. and Gu, R. (2009) Analysis of Efficiency for Shenzhen Stock Market Based on Multifractal Detrended Fluctuation Analysis, *International Review of Financial Analysis*, **18**, 271-276.

Wang, Y., Liu, L., Gu, R., Cao, J. and Wang, H. (2010a) Analysis of Market Efficiency for the Shanghai Stock Market Over Time, *Physica A: Statistical Mechanics and its Applications*, **389**, 1635-1642.

Wang, Y., Wei, Y. and Wu, C. (2010b) Cross-correlations Between Chinese A-share and B-share Markets, *Physica A: Statistical Mechanics and its Applications*, **389**, 5468-5478.

Wang, Y., Wei, Y. and Wu, C. (2011) Analysis of the Efficiency and Multifractality of Gold Markets Based on Multifractal Detrended Fluctuation Analysis, *Physica A: Statistical Mechanics and its Applications*, **390**, 817-827.

Yuan, Y., Zhuang, X.T. and Jin, X. (2009) Measuring Multifractality of Stock Price Fluctuation Using Multifractal Detrended Fluctuation Analysis, *Physica A: Statistical Mechanics and its Applications*, **388**, 2189-2197.

Zunino, L., Tabak, B.M., Figliola, A., Pérez, D.G., Garavaglia, M. and Rosso, O.A. (2008) A Multifractal Approach for Stock Market Inefficiency, *Physica A: Statistical Mechanics and its Applications*, **387**, 6558-6566.