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Nonlinear serial dependence and the weak-form efficiency of Asian emerging stock markets

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Abstract

The objective of this paper is to re-examine the weak-form efficiency of 10 Asian emerging stock markets. Using a battery of nonlinearity tests, the statistical results reveal that all the returns series still contain predictable nonlinearities even after removing linear serial correlation from the data. The next stage of sub-sample analysis using the Hinich [Hinich, M., 1996. Testing for dependence in the input to a linear time series model. Journal of Nonparametric Statistics 6, 205–221] bicorrelation test shows that the 10 Asian series follow a pure noise process for long periods of time, only to be interspersed with brief periods of strong nonlinear dependence. The exploratory investigation found that the cross-country differences in nonlinear departure from market efficiency can be explained by market size and trading activity, while the transient burst of nonlinear periods in each individual market can be attributed largely to the occurrence of economic and political events.

JEL classification: G15; C49

Keywords: Predictability; Nonlinearity; Market efficiency; Emerging markets; Asia

1. Introduction

In the voluminous literature on the weak-form efficient market hypothesis (EMH), the unpredictability of security returns from past returns has become the most commonly tested criterion in

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empirical studies.[1] However, these short-horizons return predictability studies (commonly known as conventional efficiency studies) have been widely criticized for their focus on linear correlations of price changes. First of all, it is well established in the literature that thin trading would induce spurious autocorrelation in stock returns that is not genuine predictability, but rather a statistical illusion. Another potential source of bias is the imposition of price limits by stock exchanges. Though a number of studies have proposed some adjustment procedures, there is always a concern that the effects of these trading frictions would be underestimated. Since one can never be sure on the degree of these spurious autocorrelations, Hong and Lee (2005) argued that an alternative approach would be to remove all linear serial correlation from the data and determine whether stock returns still contain predictable nonlinearities.

The second criticism launched against the conventional efficiency studies is that a white noise process does not necessarily imply efficiency as returns series can be linearly uncorrelated and at the same time nonlinearly dependent. This was highlighted 24 years ago by Granger (1983) in his appropriately titled "Forecasting white noise", in which the author demonstrated that one could never be sure that a time series with zero autocorrelation is not forecastable. The same decade also witnessed the development of some nonlinear tools that led to subsequent uncovering of hidden nonlinear serial dependency structures in earlier observed random stock market data (see Hinich and Patterson, 1985; Hsieh, 1991). This piece of evidence suggests the potential of predictability, and prompted researchers to re-examine the weak-form market efficiency using statistical tests that are capable of detecting nonlinear patterns in financial time series (for some recent studies, see Panagiotidis, 2005; Saadi et al., 2006).

The present paper straddles different strands of studies in the huge return predictability literature in three significant ways. Firstly, this study applies a battery of nonlinearity tests outlined in Patterson and Ashley (2000) to a broader set of emerging Asian stock markets in order to determine whether or not nonlinearity exists in the full sample of the returns series. Secondly, conventional efficiency studies commonly assume market efficiency is a static characteristic that remains unchanged over different stages of market development. However, the statistical findings of inefficiency in the full sample could have masked those periods when market is indeed efficient and vice versa. Motivated by this concern, a number of recent papers have shifted from the traditional focus of absolute market efficiency to tracking the changing degree of efficiency over time in emerging stock markets (see, for example, Rockinger and Urga, 2000; Cajueiro and Tabak, 2006). Using the autocorrelation coefficient (short-term linear dependence) or Hurst exponent (long-term linear dependence) as indicators of market efficiency, the time-varying framework permits the above studies to identify when and speculate why market inefficiency occurs in a particular stock market.[2] Following this group of emerging studies, the subsequent analysis further examines whether the detected nonlinear dependency structures in the emerging Asian returns series, if any, are localized in time (see Ammermann and Patterson, 2003). The research framework employed was originally proposed by Hinich and Patterson (1995), in which the full sample

[1] Methodologically, the serial correlation tests, runs test, variance ratio tests and unit root tests are the common statistical tools employed (some recent studies include Al-Khazali et al., 2007; Hoque et al., in press).

[2] Rockinger and Urga (2000, p. 458) argued that this approach appears to be the only way of measuring whether market efficiency has increased since there is no observable variable for emerging markets that might be used to quantify improvements in stock market efficiency. Nevertheless, this framework was also adopted for the developed US stock market by Gu and Finnerty (2002), who found that the Dow Jones Industrial Average has slowly evolved towards efficiency in the last 103 years (see also Chordia et al., 2005 for the speed of convergence to weak-form efficiency using intraday data for stocks listed on the New York Stock Exchange).

period is divided into equal-length non-overlapped moving time windows, and the Hinich (1996) portmanteau bicorrelation test statistic is then computed for detecting nonlinear serial dependence in each window.

Thirdly, the above sub-sample analysis not only enables one to gauge the changing degree of market efficiency over time, but also provides a useful approach to assess the relative efficiency of the Asian stock markets by comparing the total number of windows that exhibit nonlinear dependence in each market. This flexible framework also permits us to explore a number of possible factors that might account for the cross-country differences in the level of market inefficiency and the transient burst of nonlinear dependence in each market.[3] It is worth highlighting that the study by Lagoarde-Segot and Lucey (in press) also measured the relative efficiency for seven emerging Middle-Eastern North African (MENA) stock markets and related these cross-country variations to the theoretical underpinnings of market efficiency. However, their aggregate efficiency index based on the results of random walk tests and technical trading rules focuses on the linear departure from market efficiency. On the other hand, though Lim et al. (in press) employed the bicorrelation test for detecting nonlinear predictability in six of our sampled Asian stock markets, their analysis examines within-country efficiency and the impact of the 1997 Asian financial crisis by dividing the sample into sub-periods of pre-crisis, crisis and post-crisis.

The plan of this paper is as follows. Section 2 discusses the methodology proposed by Hinich and Patterson (1995). Following that, Sections 3 and 4 provide a description of the data and discussion on the empirical results, respectively. Concluding remarks are given at the end of the paper.

2. The portmanteau correlation and bicorrelation test statistics in moving time windows framework

The research framework adopted in this study was first proposed by Hinich and Patterson (1995), now published as Hinich and Patterson (2005), to detect epochs of transient dependence in a discrete-time pure white noise process (independent and identically distributed random variates). The framework involves a procedure of dividing the full sample period into equal-length non-overlapped moving time windows, in which the window length is an arbitrary choice, and then the portmanteau correlation and bicorrelation test statistics (denoted as C and H statistics) are computed for each window to detect linear and nonlinear serial dependence, respectively.

Let the sequence $\{y(t)\}$ denote the sampled data process, where the time unit, t is an integer. The test procedure employs non-overlapped time windows, thus if n is the window length, then the kth window is $\{y(t_k), y(t_k+1), \ldots, y(t_k+n-1)\}$. The next non-overlapped window is $\{y(t_{k+1}), y(t_{k+1}+1), \ldots, y(t_{k+1}+n-1)\}$, where $t_{k+1}=t_k+n$. Define $Z(t)$ as the standardized observations obtained as follows:

$$Z(t) = \frac{y(t) - m_y}{s_y} \tag{1}$$

for each $t=1, 2, \ldots, n$ where m_y and s_y are the sample mean and sample standard deviation of the window.

The null hypothesis for each time window is that the transformed data $\{Z(t)\}$ are realizations of a stationary pure white noise process. Thus, under the null hypothesis, the correlations

[3] We thank an anonymous referee for suggesting this exploratory investigation.

$C_{zz}(r) = E[Z(t)Z(t+r)] = 0$ for all $r \neq 0$ and the bicorrelations $C_{zzz}(r, s) = E[Z(t)Z(t+r)Z(t+s)] = 0$ for all r, s except when $r = s = 0$. The alternative hypothesis is that the process in the window has some non-zero correlations or bicorrelations in the set $0 < r < s < L$ where L is the number of lags that define the window. In other words, if there exists second-order linear or third-order nonlinear dependence in the data generating process, then $C_{zz}(r) \neq 0$ or $C_{zzz}(r) \neq 0$ for at least one r value or one pair of r and s values, respectively.

The r sample correlation coefficient is:

$$C_{zz}(r) = (n-r)^{-1/2} \sum_{t=1}^{n-r} Z(t)Z(t+r) \tag{2}$$

The C statistic, which is developed to test for the existence of non-zero correlations (i.e. linear dependence) within a window, and its corresponding distribution are:

$$C = \sum_{r=1}^{L} [C_{zz}(r)]^2 \sim \chi^2_L \tag{3}$$

The (r, s) sample bicorrelation coefficient is:

$$C_{zzz}(r, s) = (n-s)^{-1} \sum_{t=1}^{n-s} Z(t)Z(t+r)Z(t+s) \quad \text{for } 0 \leq r \leq s \tag{4}$$

The H statistic, which is developed to test for the existence of non-zero bicorrelations (i.e. nonlinear dependence) within a window, and its corresponding distribution are:

$$H = \sum_{s=2}^{L} \sum_{r=1}^{s-1} G^2(r, s) \sim \chi^2_{L(L-1)/2} \tag{5}$$

where $G(r, s) = (n-s)^{1/2} C_{zzz}(r, s)$.

Since it is difficult to quantify how much the significant autocorrelation that could be attributed to thin trading or price limits, this study instead focuses on whether stock returns still contain predictable nonlinearities after removing all linear dependence. The autocorrelation structure in each window is removed by an autoregressive AR(p) fit, in which the number of lags is selected such that there is no significant C statistic at the specified threshold level.[4] It is worth highlighting that the AR fitting is employed purely as a pre-whitening operation, and not to obtain a model of best fit. The portmanteau bicorrelation test is then applied to the residuals of the fitted model of each window, so that any further rejection of the null hypothesis of pure white noise is due only to significant H statistic.

The number of lags L is specified as $L = n^b$ with $0 < b < 0.5$ where b is a parameter under the choice of the user. Based on the results of Monte Carlo simulations, Hinich and Patterson (1995, 2005) recommended the use of $b = 0.4$ which is a good compromise between (1) using the

[4] In the literature, in particular those on long-term dependence, pre-filtering by means of an AR-GARCH procedure is commonly adopted to remove short-term autocorrelation and time-varying volatility. However, this procedure is unnecessary since the bicorrelation test relies on the property that the bicorrelation coefficient is equal to zero for a pure noise process, and the null hypothesis is only rejected when there exists some non-zero bicorrelations suggesting nonlinear dependence in the conditional mean (additive nonlinearity), but not the presence of conditional variance dependence (multiplicative nonlinearity).

asymptotic result as a valid approximation for the sampling properties of H statistic for moderate sample sizes, and (2) having enough sample bicorrelations in the statistic to have reasonable power against non-independent variates. Another element that must be decided upon is the choice of the window length. In fact, there is no unique value for the window length. The larger the window length, the larger the number of lags and hence the greater the power of the test, but it increases the uncertainty on the event time when the serial dependence occurs. In this study, the data are split into a set of equal-length non-overlapped moving time windows of 50 observations.[5]

3. The data

The present study utilizes indices at daily frequency for 10 emerging stock markets in Asia as categorized by Standard and Poor's *Global Stock Markets Factbook 2006*: China (Shanghai SE Composite), India (India BSE National), Indonesia (Jakarta SE Composite), South Korea (Korea SE Composite), Malaysia (Kuala Lumpur Composite), Pakistan (Karachi SE 100), Philippines (Philippines SE Composite), Sri Lanka (Colombo SE All Share), Taiwan (Taiwan SE Weighted) and Thailand (Bangkok S.E.T.). All the closing prices of these indices collected from *Datastream* are denominated in their respective local currency units for the sample period 1/1/1992 to 12/31/2005. The data are transformed into a series of continuously compounded percentage returns by taking 100 times the log price relatives, i.e. $r_t = 100\ln(p_t/p_{t-1})$, where p_t is the closing price of the index on day t.

4. Empirical results

4.1. Testing for nonlinear serial dependence using a battery of nonlinearity tests

Patterson and Ashley (2000) has made available a "nonlinearity toolkit" that provides convenient access to a selection of the best tools available for statistically detecting nonlinearity in the generating mechanism of a given time series (some recent applications include Ashley and Patterson, 2006; Panagiotidis and Pelloni, in press).[6] The present analysis utilizes this toolkit that consists of the McLeod-Li test, Engle LM test, Brock–Dechert–Scheinkman test, Tsay test, Hinich bicorrelation test and Hinich bispectrum test, to determine whether or not nonlinearity exists in the full sample of the Asian returns series. With the exception of the bispectrum test, each of the five tests is actually testing for serial dependence of any kind, whether linear or nonlinear. Hence, data pre-whitening is necessary prior to the application of these five tests in order to remove any linear structure from the data, so that any remaining serial dependence must be due to a nonlinear data generating mechanism.

In the "nonlinearity toolkit", the linear dependence is removed from the data by fitting an autoregressive model of order p, i.e. AR(p), for values from $p = 0$–10, and the optimal lag is chosen to minimize the Schwarz's Bayesian Information Criterion. To avoid imperfect pre-whitening operation, this study selects the minimum number of lags for which the Ljung–Box $Q(10)$ statistic

[5] This window length is sufficiently long enough to validly apply the bicorrelation test and yet short enough for the data generating process to have remained roughly constant (see Monte Carlo results in Hinich, 1996; Hinich and Patterson, 1995, 2005).

[6] The toolkit can be downloaded from Richard Ashley's web site at http://ashleymac.econ.vt.edu/. Readers are advised to consult Patterson and Ashley (2000) for detailed descriptions, instructions and interpretations of all the nonlinearity tests.

is insignificant at the 10% level.[7] These white noise residuals are then subjected to further testing using the statistical tests in the "nonlinearity toolkit". On the other hand, since all the tests are only asymptotically justified, this study bootstrapped the significance levels using 1000 replications. The results in Table 1 as a whole provide strong evidence of nonlinearity in all the Asian returns series, though 'unanimous' verdict from all the tests is reached only for seven markets. In the case of China, the McLeod–Li test cannot reject the null of linearity at the 10% level of significance using lags up to 24. On the other hand, the bispectrum test cannot reject the null hypothesis for South Korea and Taiwan.

4.2. Detecting epochs of transient nonlinear dependence

Though the full sample results in the preceding section reveal strong evidence of nonlinearity in all the Asian returns series, it is possible that those significant results are actually driven by the activity within a small number of sub-periods. To address this possibility, the subsequent analysis breaks the whole sample period into equal-length non-overlapped moving time windows of 50 daily observations, and then computes the H statistic of Hinich (1996) to detect nonlinear serial dependence in each time window. In the empirical analysis, a window is defined as significant if the H statistic rejects the null hypothesis at the specified threshold level (or cut-off point) for the p-value, which is set at 5%. To offer further improvement to the size of the test in small samples, bootstrapping with 10,000 replications that satisfies the null hypothesis is used to determine a threshold for the H statistic that has a test size of 5%.

As a preliminary analysis and for comparison purpose, this section first computes the C statistic in all the 73 moving non-overlapped time windows. The second row of Table 2 provides the total number of windows where the null hypothesis of pure white noise is rejected by the C statistic at the specified threshold level of 5% for the p-value, with the corresponding percentage in parenthesis. These empirical results from the Asian markets highlight the importance of testing for statistical dependence using shorter time periods as advocated by Nawrocki (1996), given that the significance of linear correlations varies from period to period. The transient burst of linear dependence is illustrated at the upper graphs of Figs. 1 and 2 for two extreme cases at the opposing end, i.e. Taiwan and Sri Lanka.

However, due to the possibility of spurious autocorrelations, the subsequent investigation filters all linear dependence by means of an AR(p) fit and examines whether the nonlinear dynamics are localized in time. The third row of Table 2 shows the total number of significant H windows, indicating the presence of nonlinear serial dependence in those time periods identified in the final row of the same table. Given that the H statistic is highly significant in earlier full sample analysis, one would expect these nonlinear features to be persistent throughout the data or at least many more of the time windows to exhibit significant H statistic. Instead, the results show that the significant test results in the whole series are actually triggered by the activity within a few relatively short "pockets" of highly nonlinear data. For instance, nonlinear predictable patterns are detected in 6 out of the total 73 windows (equivalent to 8.22%) for Taiwan. Even the market with the highest number of significant H windows, Sri Lanka, the percentage is only 32.88%.

[7] We thank an anonymous referee for highlighting the possibility that the lag length selected based on the Schwarz's Bayesian Information Criterion in the 'nonlinearity toolkit' might not produce white noise residuals, which was confirmed on some of the Asian returns series using the Ljung–Box Q statistic.

Table 1
Nonlinearity test results for Asian stock returns series

	China AR(3)[a]	India AR(10)[a]	Indonesia AR(6)[a]	Malaysia AR(5)[a]	Pakistan AR(3)[a]	Philippines AR(1)[a]	S. Korea AR(1)[a]	Sri Lanka AR(7)[a]	Taiwan AR(4)[a]	Thailand AR(8)[a]
McLeod–Li test										
Using up to lag 20	0.093	0.000	0.000	0.000	0.000	0.004	0.000	0.001	0.000	0.000
Using up to lag 24	0.120	0.000	0.000	0.000	0.000	0.005	0.000	0.002	0.000	0.000
Hinich bicorrelation test	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Engle test										
Using up to lag 1	0.076	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Using up to lag 2	0.039	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Using up to lag 3	0.017	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Using up to lag 4	0.018	0.000	0.000	0.000	0.000	0.002	0.000	0.001	0.000	0.000
Using up to lag 5	0.022	0.000	0.000	0.000	0.000	0.004	0.000	0.001	0.000	0.000
Tsay test	0.008	0.000	0.004	0.000	0.000	0.002	0.000	0.000	0.000	0.001
BDS test										
$\varepsilon/\sigma = 1; m = 2$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\varepsilon/\sigma = 1; m = 3$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\varepsilon/\sigma = 1; m = 4$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hinich bispectrum test	0.0063	0.0454	0.0395	0.0063	0.0366	0.0133	0.1276	0.0065	0.2642	0.0607

Notes: With the exception of the bispectrum test, all the five tests are carried out in the "nonlinearity toolkit" of Patterson and Ashley (2000). These tests are applied to the residuals of an AR(p) model, in which the lag length is chosen to ensure that the Ljung–Box $Q(10)$ statistic is insignificant at the 10% level. The entries are the bootstrap p-values with 1000 replications. On the other hand, the bispectrum test is implemented using the FORTRAN program that has incorporated the shuffle bootstrap approach proposed by Hinich et al. (2005). The BISPEC FORTRAN program can be downloaded from http://www.gov.utexas.edu/hinich/. The entries are the shuffle bootstrap p-values with 1000 replications.

[a] Fitted AR(p) model.

Table 2
Hinich correlation and bicorrelation tests results in moving non-overlapped time windows for Asian stock returns series

	China	India	Indonesia	Malaysia	Pakistan	Philippines	S. Korea	Sri Lanka	Taiwan	Thailand
Total number of significant *C* windows	9 (12.33%)	10 (13.70%)	18 (24.66%)	11 (15.07%)	11 (15.07%)	4 (5.48%)	6 (8.22%)	36 (49.32%)	2 (2.74%)	6 (8.22%)
Total number of significant *H* windows	14 (19.18%)	13 (17.81%)	10 (13.70%)	12 (16.44%)	19 (26.03%)	9 (12.33%)	7 (9.59%)	24 (32.88%)	6 (8.22%)	7 (9.59%)
Dates of significant *H* windows	3/12/92–5/20/92	5/21/92–7/29/92	1/2/92–3/11/92	5/6/93–7/14/93	7/15/93–9/22/93	5/6/93–7/14/93	10/8/92–12/16/92	5/21/92–7/29/92	1/2/92–3/11/92	8/24/95–11/1/95
	7/30/92–10/7/92	2/10/94–4/20/94	5/6/93–7/14/93	12/2/93–2/9/94	9/23/93–12/1/93	4/21/94–6/29/94	7/15/93–9/22/93	7/30/92–10/7/92	2/25/93–5/5/93	8/8/96–10/16/96
	7/15/93–9/22/93	4/6/95–6/14/95	1/26/95–4/5/95	5/30/96–8/7/96	4/21/94–6/29/94	11/17/94–1/25/95	4/21/94–6/29/94	12/17/92–2/24/93	9/8/94–11/16/94	10/17/96–12/25/96
	11/17/94–1/25/95	11/2/95–1/10/96	3/21/96–5/29/96	7/9/98–9/16/98	11/17/94–1/25/95	3/6/97–5/14/97	12/26/96–3/5/97	2/25/93–5/5/93	3/21/96–5/29/96	7/24/97–10/1/97
	8/24/95–11/1/95	8/8/96–10/16/96	3/15/01–5/23/01	2/4/99–4/14/99	11/2/95–1/10/96	10/2/97–12/10/97	4/30/98–7/8/98	5/6/93–7/14/93	7/24/97–10/1/97	4/30/98–7/8/98
	3/21/96–5/29/96	10/2/97–12/10/97	10/11/01–12/19/01	6/24/99–9/1/99	1/11/96–3/20/96	2/19/98–4/29/98	8/17/00–10/25/00	9/23/93–12/1/93	7/9/98–9/16/98	6/24/99–9/1/99
	3/6/97–5/14/97	1/20/00–3/29/00	7/18/02–9/25/02	6/8/00–8/16/00	3/21/96–5/29/96	4/30/98–7/8/98	7/18/02–9/25/02	4/21/94–6/29/94		8/2/01–10/10/01
	7/24/97–10/1/97	8/17/00–10/25/00	4/8/04–6/16/04	8/2/01–10/10/01	10/2/97–12/10/97	5/9/02–7/17/02		6/30/94–9/7/94		
	4/30/98–7/8/98	8/2/01–10/10/01	11/4/04–1/12/05	10/11/01–12/19/01	2/19/98–4/29/98	11/20/03–1/28/04		8/24/95–11/1/95		
	7/9/98–9/16/98	11/20/03–1/28/04	8/11/05–10/19/05	5/9/02–7/17/02	9/17/98–11/25/98			11/2/95–1/10/96		
	11/11/99–1/19/00	4/8/04–6/16/04		2/13/03–4/23/03	4/15/99–6/23/99			3/6/97–5/14/97		
	6/8/00–8/16/00	11/4/04–1/12/05		4/8/04–6/16/04	3/30/00–6/7/00			7/9/98–9/16/98		
	12/5/02–2/12/03	10/20/05–12/28/05			8/2/01–10/10/01			4/15/99–6/23/99		
	8/26/04–11/3/04				5/9/02–7/17/02			6/24/99–9/1/99		
					7/18/02–9/25/02			9/2/99–11/10/99		
					12/5/02–2/12/03			8/17/00–10/25/00		
					6/17/04–8/25/04			2/28/02–5/8/02		
					11/4/04–1/12/05			7/18/02–9/25/02		
					10/20/05–12/28/05			9/26/02–12/4/02		
								12/5/02–2/12/03		
								4/24/03–7/2/03		
								7/3/03–9/10/03		
								9/11/03–11/19/03		
								10/20/05–12/28/05		

Notes: Both the *C* and *H* statistics are computed using the T23 FORTRAN program, which can be downloaded from http://www.gov.utexas.edu/hinich/. This program operates on the transformed variate $U = F(C)$ and $U = F(H)$, which has a uniform (0,1) distribution under the null hypothesis of pure white noise, where F is the cumulative distribution function of a Chi-squared distribution. The p-values for the C and H statistics in each window are $1-F(C)$ and $1-F(H)$, respectively.

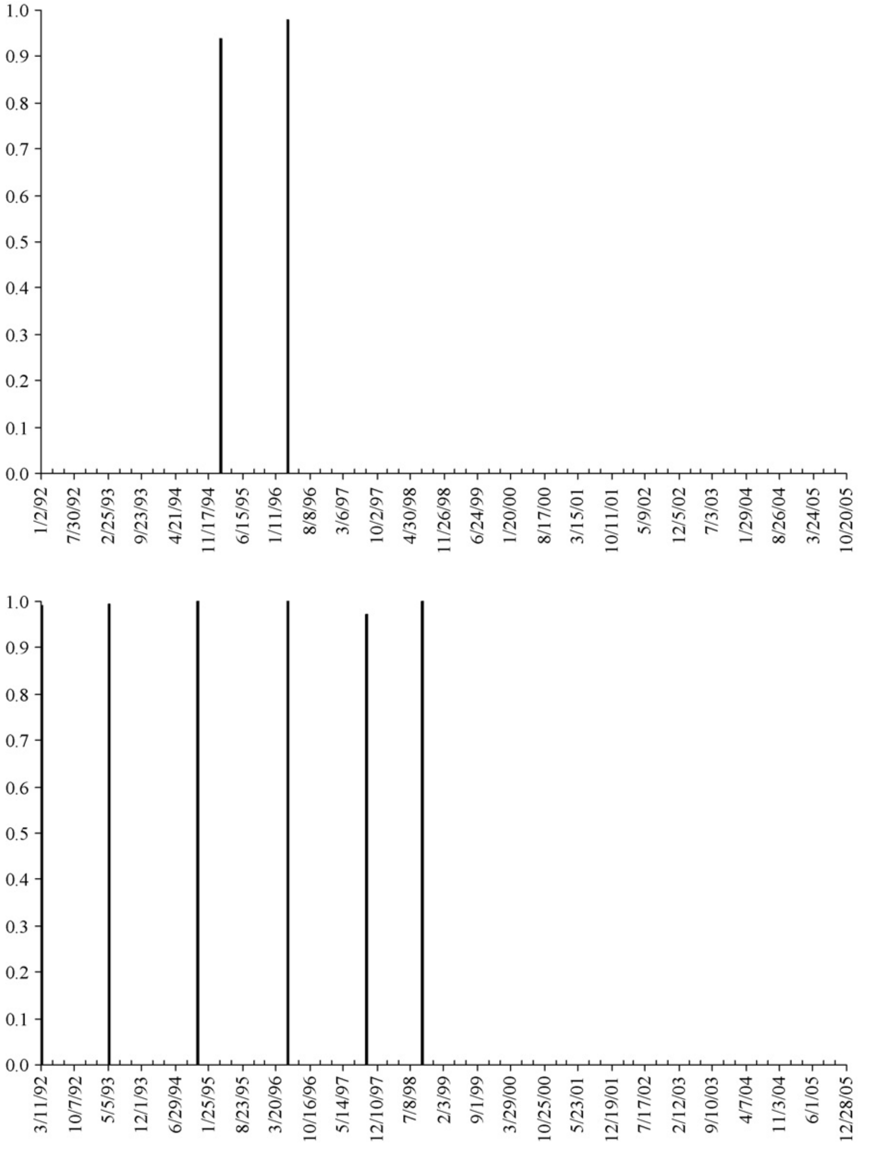

Fig. 1. Time series plots of significant C and H windows for Taiwan. *Notes:* The significant C windows are plotted at the top panel, where the X-axis is labelled with the starting date of the non-overlapped moving time windows. The lower panel plots the significant H windows, with the ending date of the non-overlapped windows at the X-axis. To give an example, the first window starts from 1/2/1992 and ends on 3/11/1992. The vertical axis in both graphs shows the uniform statistics $U = F(C)$ and $U = F(H)$ (or one minus the p-values), respectively.

The transient behaviour of the detected nonlinear dependence is illustrated at the lower graphs of Figs. 1 and 2 for Taiwan and Sri Lanka. It is worth noting that in all cases except Indonesia and Sri Lanka, nonlinear dependence of the returns series occurred more frequently than the linear correlations.

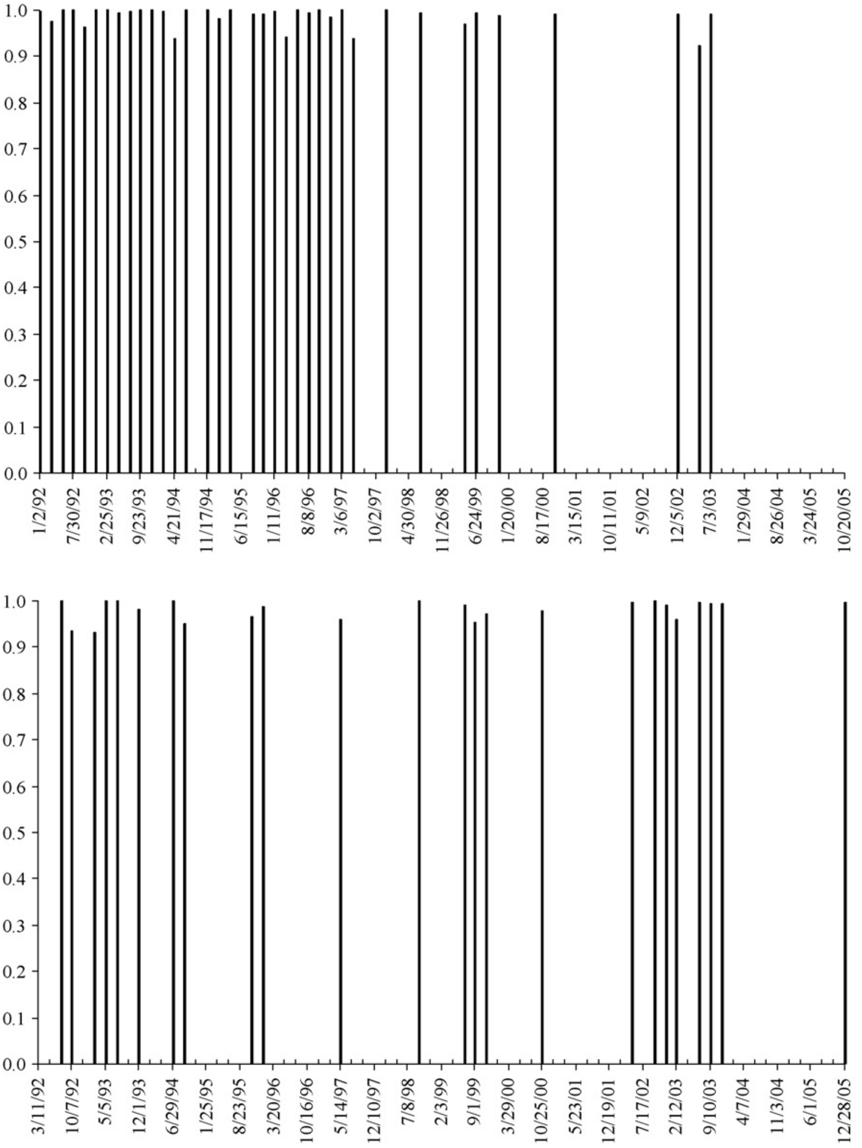

Fig. 2. Time series plots of significant C and H windows for Sri Lanka. *Notes:* The significant C windows are plotted at the top panel, where the X-axis is labelled with the starting date of the non-overlapped moving time windows. The lower panel plots the significant H windows, with the ending date of the non-overlapped windows at the X-axis. To give an example, the first window starts from 1/2/1992 and ends on 3/11/1992. The vertical axis in both graphs shows the uniform statistics $U = F(C)$ and $U = F(H)$ (or one minus the p-values), respectively.

An interesting insight from the present framework is that one is able to assess the relative efficiency of stock markets in the sample. The results from the application of 'nonlinearity toolkit' reveal overwhelming evidence in support of nonlinear serial dependence in all the Asian emerging stock markets, suggesting that these markets are inefficient. It may be of little value to know that a market is inefficient per se, but rather more useful to know the differences in the degree of inefficiency across markets. Campbell et al. (1997, p. 24) argued that the notion of relative efficiency may be a more useful concept than the all-or-nothing view taken by the conventional efficiency studies. In this context, the present findings reveal that over the course of 14 years from 1992 to 2005, Taiwan, South Korea and Thailand are more efficient than Pakistan and Sri Lanka. Specifically, Sri Lanka stands out to be the market with the most frequent deviations from market efficiency.

4.3. *Exploring the determinants for cross-country differences in the total number of significant H windows*

There are a number of studies that associate deviations in returns series from random walks with the degree of financial markets development (see Matteo et al., 2005). To address this possibility, the present paper utilizes three commonly used stock market development indicators: (1) the ratio of stock market capitalization to GDP; (2) the ratio of stock market total value traded to GDP; (3) stock market turnover ratio. The data for the above measures covering our sample period of 1992–2005 are obtained from the World Bank's Financial Development and Structure database compiled by Beck et al. (2000), and updated until 2005 by the authors. The top panel of Table 3 provides the averages of these annual observations for each individual market. The Spearman rank correlation is then performed to determine how well each measure matches the cross-country differences in total number of significant H windows. As shown in the last column of Table 3, all the stock market development indicators have the expected negative sign. Furthermore, market capitalization/GDP and total value traded/GDP are statistically significant with p-values of 0.009 and 0.042, respectively, indicating that the existence of nonlinear dependence can be explained by market size and trading activity, at least in the context of Asian emerging stock markets.

On the other hand, it is commonly hypothesized that short-horizon return predictability should be quickly arbitraged away when the stock market is liquid. This study further explores whether differences in market liquidity is another possible contributing factor. Though the ratio of stock market total value traded to GDP and stock market turnover ratio employed earlier are popular liquidity indicators, Lesmond (2005) argued that accurate measures of liquidity are necessary to more adequately assess market efficiency. This prompted Lesmond (2005) to analyze the efficiency and efficacy of four commonly used proxies for estimating emerging market liquidity. Based on his findings and recommendations, the second panel of Table 3 reproduces from Lesmond (2005, Table 1) the liquidity estimates of Lesmond et al. (1999), Roll (1984) and Amihud (2002). The rank correlation results show that all the three liquidity measures do not match the cross-country differences in market inefficiency. Specifically, none of the correlation coefficient is significant at the 5% level, though they all have the expected positive sign. Hence, the results do not support the conjecture that more liquid markets should exhibit less pronounced return predictability.

It would also be interesting to probe whether the legal and institutional environment of a country matters for the efficiency of the stock market. To measure the institutional characteristics of our sampled stock markets, we follow Lombardo and Pagano (2006) in using the following six regulatory-institutional indicators that are widely employed in the law and finance empirical studies: (1) anti-director rights; (2) judicial efficiency; (3) rule of law; (4) corruption in the government; (5) risk of expropriation; (6) risk of contract repudiation by the government. The data on laws and their enforcement obtained from La Porta et al. (1998, Tables 2 and 5) are reproduced

Table 3
Rank correlation between total number of significant *H* windows and selected indicators of market performance

	China	India	Indonesia	Malaysia	Pakistan	Philippines	S. Korea	Sri Lanka	Taiwan	Thailand	Rank correlation (%)
Stock market development indicators											
Market capitalization/GDP (average)	0.222797	0.341537	0.227983	1.775688	0.167388	0.485642	0.419114	0.143740	0.942790	0.542617	−77.20*
Total value traded/GDP (average)	0.271920	0.394411	0.096067	0.860772	0.340594	0.137048	0.963096	0.024596	2.291887	0.422683	−65.05**
Market turnover ratio (average)	1.476369	1.163120	0.418587	0.437766	2.097739	0.254086	2.157726	0.166253	2.459888	0.818941	−37.08
Liquidity indicators											
LOT measure (%)	2.683	7.618	15.038	4.299	10.299	13.300	4.161	12.165	2.346	8.017	30.40
Roll measure (%)	2.039	3.263	3.748	2.171	2.785	3.209	2.744	2.775	1.981	2.717	27.96
Amihud measure (%)	0.394	2.580	0.009	0.773	2.098	0.850	0.007	1.703	0.035	1.196	57.75
Regulatory-institutional indicators											
Anti-director rights	n/a	5	2	4	5	3	2	3	3	2	60.04
Judicial efficiency	n/a	8.00	2.50	9.00	5.00	4.75	6.00	7.00	6.75	3.25	34.31
Rule of law	n/a	4.17	3.98	6.78	3.03	2.73	5.35	1.90	8.52	6.25	−66.11
Corruption	n/a	4.58	2.15	7.38	2.98	2.92	5.30	5.00	6.85	5.18	−34.31
Risk of expropriation	n/a	7.75	7.16	7.95	5.62	5.22	8.31	6.05	9.12	7.42	−54.39
Risk of contract repudiation	n/a	6.11	6.09	7.43	4.87	4.80	8.59	5.25	9.16	7.57	−67.78**

Notes: The data for stock market development indicators are obtained from the updated World Bank's Financial Development and Structure (see Beck et al., 2000). The entries are the averages of the annual observations for each measure over the sample period 1992–2005. The liquidity estimates are from Lesmond (2005, Table 1), while the data on laws and their enforcement are sourced from La Porta et al. (1998, Tables 2 and 5).

* Significant at 1% level.

** Significant at 5% level.

at the final panel of Table 3.[8] The rank correlation analysis suggests that the degree of market inefficiency in the Asian stock markets is not related to the legal environment in their respective country. Only the variable of risk of contract repudiation by the government is significant at the 5%, where its rank is 67.78% correlated with the rank of market inefficiency. On the other hand, anti-director rights and judicial efficiency have the wrong sign. This evidence is preliminary and a more rigorous analysis is warranted in future research to extend the law and finance literature to include the effects of investor protection on stock market efficiency.

4.4. Are major economic and political events responsible for the transient burst of nonlinear dependence?

As noted in the earlier section, the presence of nonlinear dependence suggests the potential of predictability, and this explains why the bulk of the literature has been devoted to the modelling and forecasting of nonlinear dynamics in financial time series data. In contrast, theoretical work to explain its existence is relatively scarce. Nawrocki (1996) hypothesized that economic events are important in generating temporal dependence in the stock market. While his empirical investigation focused on autocorrelation coefficient, the hypothesis applies equally to the formation of nonlinear dependence. To understand the underlying logic, one has to view the returns generating process in the framework of information arrival and markets reactions to that information. Specifically, when investors do not respond instantaneously to information, the returns series tend to exhibit serial dependence, which can be in linear or nonlinear form, hence challenging EMH for assuming prices adjust without delay to the arrival of new information (for detailed discussion, see Lim et al., 2006 and references cited therein).

Given that informational events are hypothesized to be a source of nonlinear dependence, a logical extension is to identify the major events that are responsible for the transient burst of significant H windows. To explore this possibility, the present section utilizes the chronology of important financial, economic and political events in emerging markets provided by Geert Bekaert and Campbell Harvey, though the archive was updated only until June 2004.[9] The matching procedure shows that the majority of the nonlinear periods correspond to at least one significant event listed in the chronology. Specifically, the proportion for each Asian market is 10/14 (China), 11/13 (India), 6/10 (Indonesia), 8/12 (Malaysia), 12/19 (Pakistan), 9/9 (Philippines), 7/7 (South Korea), 15/24 (Sri Lanka), 5/6 (Taiwan) and 7/7 (Thailand). However, these findings are indicative rather than definitive. A more rigorous analysis is needed in future research to provide empirical support to the hypothesis that the existence of nonlinear dependence is due to events that shook the market. This would require: (1) a thorough search of news archives for extraordinary media events, such as those conducted by Fair (2002); (2) in order to pinpoint precisely the event that generate nonlinear dependence, one should examine the day-to-day changes in the time series behaviour. The use of cross-sectional analysis (see Nawrocki, 1996) or intra-day data (see Lim et al., 2006) provides sufficient number of observations for the estimation of H statistic for each day.

[8] Readers are advised to consult La Porta et al. (1998) for complete description of the variables. Unfortunately, China is not included in the database.

[9] The events archive can be downloaded from Campbell Harvey's web site. The URL is http://www.duke.edu/∼charvey/Country_risk/couindex.htm.

4.5. Exploring the role of market states in generating nonlinear dependence?

The present section further investigates whether the state of the market is a potential source of nonlinearity in the Asian returns series (see Maheu and McCurdy, 2000; Woodward and Marisetty, 2005). To explore this possibility, we need to identify the state of the market for each of the 73 non-overlapped time windows. Given that there is no generally accepted formal definition of bull and bear markets in the finance literature, the analysis proceeds with the "up" and "down" market definitions using two different classifications: (1) a window is defined as up (down) market if the average returns over the 50-day sample period is positive (negative); (2) if the proportion of positive to negative returns in a window is greater (less) than one, then that window is classified as up (down) market.

The upper panel of Table 4 identifies the market states using average returns as the basis of classification. Focusing on those windows with a significant H statistic, it seems to suggest that nonlinearity arises mostly during bear market states in India, Malaysia, the Philippines, South Korea and Thailand. However, it is worth highlighting that there are still many down market windows in the above-mentioned countries that exhibit pure noise behaviour. Hence, the results as a whole do not support the conjecture that market states are responsible for the periods in which nonlinear dependence is detected in the Asian stock markets. To further determine whether the significant H statistic is in the more extreme market state windows, the upper panel of the same table computes the average returns for each market state, covering both cases of significant and insignificant H windows. The results again rule out the state of the market as a key factor in explaining the periods of nonlinear dependence. Using the proportion of positive/negative returns as the basis of classification reaches a similar conclusion on the insignificant role of market states in generating nonlinear dependence, as shown in the lower panel of Table 4.

4.6. Is it possible to predict when the nonlinear dependence would occur?

It is worth noting that it is very unlikely that the nonlinearity detected in the Asian returns series would be useful for out-of-sample forecasting since they are not identifiable for long stretches of time but only in limited sub-samples of the data. For instance, if the nonlinear dependence is not present in the prediction period, then nonlinear time series models cannot be expected to generate more accurate forecasts than their linear counterparts for these series. Nevertheless, it would be interesting to examine whether it is possible to predict when the Asian returns series become nonlinear. Stokes (1997) argued that if the estimated vector of $C(H)$ statistics is autocorrelated, then it may be possible to predict recurring periods of linear dependence (nonlinear dependence) by fitting an ARIMA model. To explore whether it is possible to predict via a linear model when the significant H windows occur, the present analysis computes the autocorrelation coefficients for those earlier computed H statistics in all the 73 non-overlapped time windows.[10]

In all cases except Sri Lanka, there is no significant autocorrelation up to the specified order of five lags, suggesting that the H statistics for these nine markets are not linearly correlated. While the evidence implies the inadequacy of linear model, it would be premature to conclude that the occurrence of those significant H windows is random. We do not rule out the possibility that some nonlinear time series models are capable of predicting the recurring periods of nonlinearity, but this would require detailed model searching through simulations, which

[10] The results are available upon request from the authors.

Table 4
Summary of up and down markets in non-overlapped moving time windows

	China	India	Indonesia	Malaysia	Pakistan	Philippines	S. Korea	Sri Lanka	Taiwan	Thailand
Average returns as the basis of classification										
Total number of significant H windows in up market	7 (0.3138)	4 (0.2464)	5 (0.1864)	4 (0.1106)	11 (0.1668)	2 (0.1784)	2 (0.2796)	12 (0.2588)	3 (0.2159)	0 (0.0000)
Total number of insignificant H windows in up market	30 (0.3091)	39 (0.2362)	39 (0.2293)	35 (0.1910)	27 (0.3221)	35 (0.2165)	43 (0.1861)	26 (0.1656)	38 (0.1833)	35 (0.2534)
Total number of significant H windows in down market	7 (−0.2606)	9 (−0.2708)	5 (−0.1486)	8 (−0.1463)	8 (−0.2186)	7 (−0.2218)	5 (−0.3389)	12 (−0.1948)	3 (−0.1923)	7 (−0.3358)
Total number of insignificant H windows in down market	29 (−0.2378)	21 (−0.2091)	24 (−0.2514)	26 (−0.1925)	27 (−0.1968)	29 (−0.1797)	23 (−0.2284)	23 (−0.1531)	29 (−0.2186)	31 (−0.2109)
Proportion of positive/negative returns as the basis of classification										
Total number of significant H windows in up market	8 (1.57)	5 (1.60)	6 (1.63)	4 (1.35)	10 (1.55)	3 (1.30)	3 (1.33)	10 (1.77)	2 (1.28)	1 (1.14)
Total number of insignificant H windows in up market	24 (1.42)	35 (1.43)	37 (1.43)	31 (1.41)	27 (1.71)	31 (1.38)	36 (1.36)	27 (1.44)	33 (1.31)	26 (1.46)
Total number of significant H windows in down market	6 (0.69)	8 (0.76)	3 (0.84)	8 (0.75)	8 (0.71)	6 (0.64)	4 (0.79)	14 (0.66)	4 (0.74)	6 (0.61)
Total number of insignificant H windows in down market	30 (0.75)	22 (0.77)	24 (0.69)	23 (0.69)	20 (0.70)	29 (0.74)	26 (0.79)	20 (0.60)	32 (0.72)	35 (0.74)

Notes: The upper panel defines a window as up (down) market if the average returns over the 50-day sample period is positive (negative). In parenthesis is the average returns across those identified windows. The lower panel classifies a window as up (down) if the proportion of positive/negative returns is greater (less) than one. The proportion across those identified windows is provided in parenthesis.

is well beyond the scope of the present paper. On the other hand, for the exceptional case of Sri Lanka, the first-order autocorrelation coefficient is statistically significant, but dies off at higher lags, indicating that the H statistics obey a low-order autoregressive process. Moreover, the null hypothesis of autocorrelation for all orders up to lag 10 cannot be rejected by the Ljung–Box Q statistic at 1% level of significance. These results for Sri Lanka reveal a strong positive relation between H statistics in successive periods, indicating that the distribution of the significant windows over time is not random but could be predicted using a simple linear model.

5. Conclusion

Motivated by the possible existence of nonlinear serial dependence in financial time series and the concern that statistical dependence is very much localized in time, the present study re-examines the weak-form efficiency of 10 Asian emerging stock markets. Using a battery of nonlinearity tests, the statistical results reveal that all the returns series still contain predictable nonlinearity even after removing linear serial correlation from the data. The next stage of analysis splits the whole sample into a set of 73 equal-length non-overlapped sub-samples of length 50 observations. The application of the Hinich (1996) bicorrelation test shows that the 10 Asian returns series follow a pure noise process for long periods of time, only to be interspersed with brief periods of strong nonlinear dependence, suggesting that these markets are weak-form efficient most but not all the time. The exploratory investigation found that the cross-country differences in market inefficiency, as proxied by the total number of significant H windows, can be explained by market size and trading activity, but not market liquidity and the legal environment of the country. On the other hand, the transient burst of nonlinear periods in each individual market can be attributed largely to the occurrence of economic and political events, rather than the states of the market. The final analysis found that it is possible to predict the recurring periods of nonlinearity using a simple linear model only for the Sri Lankan returns series. As for the remaining nine markets, the scope of model search has to be expanded to the more complicated nonlinear time series models, which is an avenue for future research.

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