Full Title: **TESTING THE ASSERTION THAT EMERGING ASIAN STOCK MARKETS ARE BECOMING MORE EFFICIENT**

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Abstract: Testing the assertion that emerging stock markets are becoming more efficient over time has received increasing attention in the empirical literature in recent years. However, the statistical tests adopted in extant literature are designed to detect linear predictability, and hence disregard the possible existence of nonlinear predictability. Motivated by this concern, this study computes the bicorrelation statistics of Hinich (1996) in fixed-length moving sub-sample windows, and found that nonlinear predictability for all returns series follows an evolutionary time path. However, for most indices with the exception of Taiwan SE Weighted, there is no clear trend towards higher efficiency as predicted by the classical EMH.

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I. INTRODUCTION

In conventional market efficiency studies using standard statistical tests, market efficiency is measured as a property that is steady over some predefined period. In other words, these tests lead to the inference that a market either is or is not weak-form efficient for the sample as a whole. However, it is reasonable to expect market efficiency to evolve over time due to factors such as institutional, regulatory and technological changes. To accommodate this possibility, the common approach adopted by earlier studies is to divide the sample periods into sub-periods on the basis of their postulated factors and observe the changes in efficiency test results. For instance, in an effort to identify the impact of regulatory changes on the efficient functioning of the Istanbul Stock Exchange, Antoniou et al. (1997) argued in favour of examining the evolution of the stock market, rather than simply taking a snapshot of the market at a particular point in time. By investigating efficiency on a yearly basis over the period 1988-1993, the results show that the Istanbul Stock Exchange became efficient when the right institutional and regulatory framework is in place. To address the question of whether changes in the regulations governing the direct involvement of banks in the stock market would have any significant effects on market efficiency, Groenewold et al. (2003, 2004) examined market efficiency over three different sub-periods in which banks were subjected to different regulations. Similarly, using sub-periods analysis, Odabaşi et al. (2004) investigated whether the rapid development of the Istanbul Stock Exchange in a decade of existence has rendered the market to become a relatively more efficient market. In the wake of the movement towards financial liberalization in emerging markets, a number of researchers have explored the issue of whether the opening of these markets to foreign investors has caused stock markets to become more efficient, by examining the degree of efficiency before and after the date of liberalization (see, for example, Groenewold and Ariff, 1998; Kawakatsu and Morey, 1999a, b; Basu et al., 2000; Kim and Singal, 2000a, b; Maghyereh and Omet, 2002; Laopodis, 2003, 2004).

The limitation with the above sub-periods analysis is that the movement towards market efficiency is assumed to take the form of a discrete change that occurs at a point in time on the basis of some postulated factors. The possibility of a continuous and smooth change in the behaviour of stock prices over time has only been explored in recent years using more advanced methodologies. The first group of study pioneered by Emerson et al. (1997) applied the Kalman Filter framework that allows for time-varying parameters and a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) structure for the residuals. In this framework, the time-varying autoregressive coefficients were used to gauge the changing degree of predictability, and hence evolving weak-form market efficiency. If the market under study becomes more efficient over time, the smoothed time varying estimates of the autocorrelation coefficient would gradually converge towards zero and become insignificant. This framework was later formalized by Zalewska-Mitura and Hall (1999) as Test for Evolving Efficiency (TEE) to provide an indicator of the degree of market inefficiency and the timing and speed of the movement towards efficiency. Given that the emerging markets in Bulgaria and Hungary were still in the early stages of development, Emerson et al. (1997) and Zalewska-Mitura and Hall (1999) argued that it is not sensible to address the issue of whether the stock markets in these transition economies are efficient or not. The main reason is that when a market first opens, it is hardly credible for the market to be efficient since it takes time for the price discovery process to become known. However, as markets operate and market microstructures develop, within a finite amount of time, they are likely to become more efficient. Hence, the more relevant research question is whether and how these infant markets are becoming more efficient, and this certainly cannot be answered by classical steady-variable approaches that assume a fixed level of market efficiency throughout the entire estimation period. In fact, the early inefficiency would bias the results of these conventional tests and lead to the conclusion that there are profit opportunities simply because of past inefficiencies (see Emerson et al., 1997; Zalewska-Mitura and Hall, 1999). Using the proposed TEE, their results revealed varying degrees of inefficiency in those markets under study and the respective time paths towards efficiency. This framework was subsequently adopted to assess the evolution of efficiency in other stock markets in Central and Eastern European transition economies that have just emerged out of the former communist bloc (see, for example, Zalewska-Mitura and Hall, 2000; Rockinger and Urga, 2000, 2001). Hence, it is not surprising that the TEE literature has been expanding to test a wider set of markets including the Chinese (Li, 2003a, b) and African stock markets (Jefferis and Smith, 2004, 2005). Along the same line, Kvedaras and Basdevant (2004) proposed the time-varying variance ratio statistic that is based on time-varying autocorrelation coefficients estimated using the Kalman filter technique, and applied the methodology to track the changing degree of market efficiency in Estonia, Latvia and Lithuania.

Another strand of study employs fixed-length moving sub-sample windows approach to test the evolution of market efficiency in emerging stock markets. This rolling windows approach computes the relevant test statistic that is capable of detecting serial dependence for the first window of a specified length, and then rolls the sample one point forward eliminating the first observation and including the next one for reestimation of the test statistic. This process continues until the last observation is used. For instance, in a fixed-length rolling windows of 30 observations, the first window starts from day 1 and ends on day 30, the second window comprises observations running from day 2 through day 31, and so on. The last window is built with the last 30 observations. To accommodate the dynamics of the stock price process, Tabak (2003) examined the random walk hypothesis using rolling variance ratio tests with a fixed window of 1024 days, and concluded that the Brazilian stock market has become increasingly more efficient.[1] Besides the popular variance ratio test, the Hurst exponent has been explored by Costa and Vasconcelos (2003) to assess the efficiency of Brazilian stock market using 30 years of daily data from 1968 to 2001. The authors argued that a Hurst exponent (H) of 0.5 for the whole sample period does not necessarily imply the absence of long-range correlations, since this could be due to the averaging of those positive and negative correlations at different time periods.[2] Indeed, the results from the rolling 3-year time windows approach support their conjecture that the Hurst exponent varies considerably over time.[3] In particular, the exponent is always greater than 0.5 before 1990 with the only exception occurring around the year 1986, and drops rapidly towards 0.5 in early 1990. After that, H stays around 0.5 with minor

[1] Yilmaz (2003) has also adopted the rolling variance ratio test to observe whether there is any change in the behaviour of exchange rates over time.

[2] Briefly, there is no evidence of temporal dependence between observations widely separated in time if $H = 0.5$, indicating that the series under examination behaves in a manner consistent with weak-form efficient market hypothesis (EMH). On the other hand, $H > 0.5$ indicates that linear associations between distant observations is somewhat persistent, while there is evidence of long-term dependence with anti-persistent behaviour if $H < 0.5$.

[3] In the foreign exchange market, evidence of time-varying Hurst exponents was documented in Vandewalle and Ausloos (1997) and Muniandy et al. (2001).

fluctuations, suggesting that the market has become more efficient during this period. Cajueiro and Tabak (2004a) formally proposed the calculation of Hurst exponent over time for stock returns using the rolling sample approach as a statistical tool to test the assertion that emerging stock markets are becoming more efficient. The authors argued that stock markets have presented different levels of efficiency over time mainly due to the variation of the effects of (a) speed of information, (b) capital flows, and (c) non-synchronous trading. Using a 4-year time windows, and stock data from eleven emerging markets, plus the U.S. and Japan for comparison, the Hurst exponent is found to be time-varying reflecting the evolution of market efficiency over time in each market under study. The changing degree of long-term predictability is also reported for stock markets in European transition economies by Cajueiro and Tabak (2006). Using similar approach, Cajueiro and Tabak (2004b, c) computed the Hurst exponent over time and build a ranking based on the medians of those computed Hurst exponent to assess the relative efficiency of stock markets. An alternative framework for testing evolving market efficiency was later proposed by Cajueiro and Tabak (2005a, b), in which the Hurst exponent was computed for the volatility of stock returns, measured by absolute and squared returns.

The above discussion clearly demonstrates that it is not sensible for conventional efficiency studies to assume markets are in some kind of steady-state, especially for emerging stock markets. In this regard, those cited statistical tests offer useful framework to capture the evolving dynamics of the detected patterns over time. The test for evolving efficiency (Zalewska-Mitura and Hall, 1999), rolling variance ratio test (Tabak, 2003), time-varying variance ratio test (Kvedaras and Basdevant, 2004) are designed to capture the changing degree of autocorrelation coefficients of lower lag orders over time. On the other hand, the framework of time-varying Hurst exponents (Costa and Vasconcelos, 2003) detects the presence of long-term dependence, in which the autocorrelation function decays at a hyperbolic rate and remains significant even at long lags. As far as financial markets are concerned, the existence of both types of linear dependence, be it short-term or long-term, provides evidence against the weak-form efficient market hypothesis (EMH) which implies unpredictability of future returns based on historical returns. This study focuses on another type of temporal dependence that appears inconsistent with the unpredictable criterion of market efficiency, and has been neglected in this line of empirical inquiry. In particular, given that predictability is assumed to take the form of linear correlations in those cited literature, the main objective of this paper is to demonstrate that detecting nonlinear dependence in a moving time windows provides further insight into the changing degree of market efficiency over time.

There are a number of reasons why nonlinear dependence should not be discarded in the empirical investigation of whether emerging stock markets are becoming more efficient. First, partly due to the development of new statistical tools capable of uncovering any hidden nonlinear structures in time series data[4], overwhelming evidence in support of nonlinear serial dependence has been documented across international stock markets with different market structure mechanisms, indicating that the observed feature is a stylized fact of real financial data. This growing body of research includes the U.S. (Hinich and Patterson, 1985; Ashley and Patterson, 1989;

[4] For a review of those existing non-linearity tests that are widely employed in the literature, see Granger and Teräsvirta (1993), Barnett et al. (1997), Patterson and Ashley (2000) and Kyrtsou and Serletis (2006).

Scheinkman and LeBaron, 1989; Brock et al., 1991; Hsieh, 1991; Kohers et al., 1997; Patterson and Ashley, 2000; Urrutia et al., 2002), U.K. (Abhyankar et al., 1995; Al-Loughani and Chappell, 1997; Omran, 1997; Chappel et al., 1998; Opong et al., 1999; Yadav et al., 1999; McMillan, 2003), and other national stock markets (De Gooijer, 1989; Sewell et al., 1993; Hsieh, 1995; Abhyankar et al., 1997; Pandey et al., 1998; Freund and Pagano, 2000; Sarantis, 2001; Ammermann and Patterson, 2003; Appiah-Kusi and Menyah, 2003; Shively, 2003; Lim and Liew, 2004; Narayan, 2005). Second, the existence of nonlinear dependence implies the potential of predictability, thus posing a serious threat to the weak-form EMH. Brooks and Hinich (1999) argued that if the nonlinearity is present in the conditional first moment, it may be possible to devise a trading strategy based on nonlinear models which is able to yield higher returns than a buy-and-hold rule. Neftci (1991) demonstrated that in order for technical trading rules to be successful, some form of nonlinearity in stock prices is necessary. In testing the primary hypothesis that graphical technical analysis methods may be equivalent to non-linear forecasting methods, Clyde and Osler (1997) found that technical analysis works better on nonlinear data than on random data, and the use of technical analysis can generate higher profits than a random trading strategy if the data generating process is non-linear. The potential of nonlinear predictability generated considerable excitement in the financial econometrics community that led to an explosive growth of nonlinear time series models over the years (see, for example, Tong, 1990; Granger and Teräsvirta, 1993; Franses and van Dijk, 2000). Third, widely applied efficiency tests, such as autocorrelation, variance ratio and spectral tests are not capable of capturing nonlinearity, and may deliver misleading conclusion especially in cases where the underlying series have zero autocorrelation yet possess predictable nonlinearities in mean, such as those generated by bilinear and nonlinear moving average processes.

Motivated by this concern, a number of studies re-examined the weak-form market efficiency using statistical tests that are capable of detecting nonlinear serial dependence (see, for example, Al-Loughani and Chappell, 1997; Antoniou et al., 1997; Kohers et al., 1997; Chappel et al., 1998; Opong et al., 1999; Freund and Pagano, 2000; Appiah-Kusi and Menyah, 2003; Narayan, 2005).

To capture the evolving property of nonlinear predictable patterns, this study adopts the research framework proposed by Hinich and Patterson (1995). In particular, this approach first divides the full sample period into equal-length non-overlapped moving time windows, and then computes the Hinich (1996) portmanteau bicorrelation test statistic that is designed to detect nonlinear serial dependence in each window. This nonlinearity test is the preferred choice for two reasons. First, it has good sample properties over short horizons of data (Hinich and Patterson, 1995, Hinich, 1996). Second, the test suggests an appropriate functional form for a nonlinear forecasting equation. In particular, Brooks and Hinich (2001) demonstrated via their proposed univariate bicorrelation forecasting model that the bicorrelations can be used to forecast the future values of the series under consideration. In the present framework, the evolution of nonlinear predictable patterns can be captured by the moving time windows. Specifically, by plotting the bicorrelation test statistic as a function of time, it permits a closer examination of the precise time periods during which nonlinear serial dependence are occurring. In the literature, this approach has been applied on financial time series data (see, for example, Brooks and Hinich, 1998; Brooks et al., 2000; Ammermann and Patterson, 2003; Lim and Hinich, 2005a, b; Bonilla et al., 2006).

The plan of this paper is as follows. Section II discusses the research framework adopted in this study. Following that, description of the data and discussion on the empirical results are provided. The final section concludes the paper.

II. PORTMANTEAU CORRELATION AND BICORRELATION TEST STATISTICS IN MOVING TIME WINDOWS

The research framework adopted in this study was first proposed by Hinich and Patterson (1995), now published as Hinich and Patterson (2005). It 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. Suppose that a 30-day window length is chosen, the first window comprises the first 30 sample data points, starts from day 1 and ends on day 30. The second window comprises observations running from day 31 through day 60. Subsequent windows will follow in a similar manner until the end of the data series is reached. However, the last window is not used if there are not 30 observations to fill that window. In principle, this approach is similar to the rolling time windows given that the window length in both approaches is fixed. The only difference lies on how the time windows move forward. The data in each window is standardized to have a sample mean of zero and a sample variance of one by subtracting the sample mean of the window and dividing by its standard deviation in each case. Subsequently, two test statistics are calculated for the standardized data in each window. The first one is a portmanteau correlation test statistic, denoted as the *C* statistic, which is a modified version of the Box-Pierce *Q*-statistic. Unlike the Box-Pierce *Q*-statistic that was usually applied to the residuals of a fitted ARMA model, the *C* statistic is a function of the standardized observations and the number of lags used depends on the sample size. The second test statistic is the portmanteau bicorrelation test statistic denoted as the H statistic, which is a third-order extension of the standard correlation test for white noise. The null hypothesis for each window is that the standardized data are realizations of a stationary pure white noise process that has zero correlation and bicorrelation. Under the null hypothesis, the distribution of the C and H statistics are asymptotically chi-squared with degrees of freedom equal to L and $(L-1)(L/2)$ respectively, where L is the number of lags that define the window.[5] Using the two portmanteau test statistics, the proposed research framework looks for those windows in which the time series exhibits behaviour that departs significantly from pure white noise in terms of linear serial dependence (significant autocorrelations detected by C statistic) or nonlinear serial dependence (significant bicorrelations detected by H statistic). In other words, the null hypothesis is rejected if the process in the window has some non-zero correlations or bicorrelations, implying the potential of predictability for the series under consideration. The full theoretical derivation of the test statistics and some Monte Carlo evidence on the small sample properties of both test statistics are given in Hinich (1996) and Hinich and Patterson (1995, 2005).

Mathematical Representation

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 k-th 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 $t_{k+1} = t_k+n$. The null

[5] The proofs for the asymptotic property of C and H statistics are given in Box and Pierce (1970) and Hinich (1996) respectively.

hypothesis for each time window is that $y(t)$ are realizations of a stationary pure white noise process. Thus, under the null hypothesis, the correlations $C_{yy}(r) = E[y(t)y(t+r)]$ and bicorrelations $C_{yyy}(r, s) = E[y(t)y(t+r)y(t+s)]$ are all equal to zero 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 $C_{yy}(r) \neq 0$ or $C_{yyy}(r, s) \neq 0$ for at least one r value or one pair of r and s values respectively.

Define $Z(t)$ as the standardized observations obtained as follows:

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

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

The r sample correlation coefficient is:

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

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:

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

The (r, s) sample bicorrelation coefficient is:

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

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:

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

where $G(r,s) = (n-s)^{\frac{1}{2}} C_{ZZZ}(r,s)$

Empirical Implementation

Since the focus of this paper is to determine whether stock returns contain predictable nonlinearities after removing all linear dependence, we filter out the autocorrelation structure in each window by an autoregressive AR(p) fit. We use the minimum number of lags that ensure there is no significant C statistic in each window at the specified threshold level. It is worth highlighting that the AR fitting is employed purely as a prewhitening 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, and any further rejection of the null hypothesis of pure white noise is due only to significant H statistic. In the time-varying Hurst exponent framework, Cajueiro and

Tabak (2004a) filtered the data in each window by means of an AR-GARCH procedure to account for short-term autocorrelation and time-varying volatility commonly found in financial returns series. However, Brooks and Hinich (2001) argued that this procedure is unnecessary with the bicorrelation test since the presence of GARCH effects will not cause a rejection of the null hypothesis of pure white noise. This is due to the fact that the GARCH process has zero bicorrelation, and hence, the bicorrelation test will have the proper size, asymptotically, even in the presence of GARCH effects (see also Ammermann and Patterson, 2003).[6]

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. All lags up to and including L are used to compute the bicorrelations in each window. Based on the results of Monte Carlo simulations, Hinich and Patterson (1995, 2005) recommended the use of b=0.4 in order to maximize the power of the tests while ensuring a valid approximation of the asymptotic theory even when n is small. 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. This window length is sufficiently long enough to

[6] Nonetheless, Hinich and Patterson (1995, 2005) demonstrated that the presence of ARCH/GARCH effects does not cause false rejection by the H statistic in two different ways. First, a computer simulation of a GARCH model is carried out, and the size of the H statistic is reported. Second, the simulated GARCH data is transformed to a binary series (0, 1), turning the GARCH into a pure white noise process, and then evaluate the size of the H statistic. In both instances, the H statistic has the appropriate size. See also Brooks and Hinich (1998) and Brooks et al. (2000).

validly apply the test and yet short enough for the data generating process to have remained roughly constant.

The *H* statistic for each window in this study is computed using the T23 FORTRAN program.[7] Instead of reporting the test statistics as chi-square variates, the program transforms the computed statistics to *p*-values based on the appropriate chi square cumulative distribution value, since it is a simple and informative way of summarizing the results of statistical test. If the *p*-value for the *H* statistic in a particular window is sufficiently low, then one can reject the null hypothesis of pure white noise that has zero bicorrelation. In this case, the significant *H* statistic indicates the presence of nonlinear dependence in that window. In the present study, a window is defined as significant if the *H* statistic rejects the null hypothesis at the specified threshold level for the *p*-value, which is set at 5% in the empirical analysis. To offer further improvement to the size of the test in small samples, resampling with replacement (Efron, 1979) that satisfy the null hypothesis is used to determine a threshold for the *H* statistic that has a test size to be 5%. Hence, the null hypothesis in each window is rejected when the *p*-value for the *H* statistic is less than or equal to the bootstrapped threshold drawn from 5000 replications that corresponds to the specified nominal threshold level of 5%.

[7] The T23 FORTRAN program can be downloaded from http://www.gov.utexas.edu/hinich/.

III. EMPIRICAL APPLICATIONS

The Data

The present study utilizes indices at daily frequency for ten emerging stock markets in Asia as categorized by Standard & Poor's *Global Stock Markets Factbook 2004*: 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 31/12/2005. 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, and p_{t-1} the price on the previous trading day. This transformation yields 3130 observations for the empirical analysis.

Preliminary Analysis

Table 1 provides the summary statistics for the returns series of all the ten Asian stock indices. Notably, the China stock market exhibits the highest level of volatility. Most of the indices exhibit some degree of right-skewness, with the exception of Pakistan, South Korea and Taiwan. On the other hand, the distributions are highly leptokurtic, in which the tails of their respective distributions taper down to zero more gradually than do the tails of a normal distribution. Not surprisingly, given the non-zero skewness levels and excess kurtosis, the Jarque-Bera (JB) test statistics clearly indicate that all returns series under study significantly deviate from normality.

The lower panel of Table 1 reports the autocorrelation coefficients for the first five lags. In all cases except Taiwan, the first order autocorrelation coefficient is statistically significant, and its magnitude is generally higher than those of longer lags. Even so, there is still evidence of significant autocorrelation at lags higher than one. Moreover, the null hypothesis of autocorrelation for all orders up to lag 10 is strongly rejected by the Ljung-Box *Q*-statistic. Taken as a whole, these results clearly indicate the presence of linear dependence in the daily returns series of all indices.

<<Insert Table 1 about here>>

Evidence of Nonlinearity

To test whether nonlinear serial dependence also plays an important role in the data generating process, in addition to the autocorrelations identified earlier, this study employs a battery of univariate nonlinearity tests outlined in Patterson and Ashley (2000). These tests are selected for two reasons. First, most of the existing tests have differing power against different classes of nonlinear processes and none dominates all others (see, for example, Ashley et al., 1986; Ashley and Patterson, 1989; Hsieh, 1991;

Lee et al., 1993; Brock et al., 1991, 1996; Barnett et al., 1997; Patterson and Ashley, 2000). Second, the estimations can be carried out using the Nonlinear Toolkit provided by Patterson and Ashley (2000), and it been used in the literature by Panagiotidis (2002, 2005), Panagiotidis and Pelloni (2003) and Ashley and Patterson (2006).[8] It is important to note that the main objective is not to determine the precise nature of the nonlinearity but to determine whether or not nonlinearity exists in the full sample of the returns series under study.

The battery of nonlinearity tests included in the toolkit are: McLeod-Li test (McLeod and Li, 1983), Engle LM test (Engle, 1982), BDS test (Brock et al., 1996), Tsay test (Tsay, 1986), bicorrelation test (Hinich, 1996) and bispectrum test (Hinich, 1982).[9] With the exception of the bispectrum test, each of these 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 contrast, the bispectrum test provides a direct test for a non-linearity, irrespective of any linear serial dependence that might be present. Ashley et al. (1986) presented an equivalence theorem to prove that the Hinich bispectrum test is invariant to linear filtering of the data, even if the filter is estimated.

[8] The toolkit can be downloaded from Richard Ashley's webpage at http://ashleymac.econ.vt.edu/ashleyhome.html, while instructions and interpretations of all the tests are given in chapter 3 of Patterson and Ashley (2000).

[9] The descriptions of these tests are deliberately omitted due to space constraint. The reader is to refer to the detailed discussion in Patterson and Ashley (2000).

In this case, the test is robust even if linear pre-whitening model has failed to remove all linear serial dependence in the data.[10]

Given the differing power of these nonlinearity tests against different classes of nonlinear processes, it is not surprising to observe from Table 2 that ‘unanimous’ verdict on the existence of nonlinearity is reached only for six markets. In the case of China, the Mc-Leod-Li test cannot reject the null of linearity even at the 10% level of significance. On the other hand, the bispectrum test cannot reject the null for South Korea, Sri Lanka and Thailand. Taken as a whole, the results indicate that nonlinearity plays a significant role in the returns dynamics for each of the indices. Hence, the present findings provide further support to the main argument of this paper that empirical study on market efficiency should not implicitly disregard the possible existence of this particular type of higher-order temporal dependence.

<<Insert Table 2 about here>>

[10] Given that the size of the bispectrum test is found to be conservative for finite samples, this study utilizes the shuffle bootstrap approach (resampling without replacement) outlined by Hinich et al. (2005) with 1000 replications. The FORTRAN program is available from http://www.gov.utexas.edu/hinich/.

Results from Moving Time Windows Approach

This section proceeds to compute the bicorrelation or *H* statistic for each window to determine whether those detected nonlinear serial dependence is localized in time. As noted by Ammermann and Patterson (2003), it is possible that the significant results of nonlinearity in the full sample are driven by the activity within a small number of sub-periods. To conserve space and for comparison purpose, Figure 1 and 2 plot the *p*-values of the *H* statistic in moving time windows for two selected markets- Taiwan and Sri Lanka.[11] The vertical axis shows the *p*-values, while across the horizontal axis are the starting dates for each time window. In the present framework, a window is defined as significant if the *H* statistic rejects the null hypothesis of pure white noise at the specified threshold level, i.e. when the *p*-value of the *H* statistic is less than or equal to the bootstrapped threshold that corresponds to the nominal threshold level of 5%. Graphically, a window is significant if the *p*-value lies below or on the threshold line. For instance, in the case of Taiwan (Taiwan SE Weighted)) as depicted in Figure 1, there are six windows with strong non-zero bicorrelations and hence move the *H* statistic to cross the bootstrapped threshold for the *p*-value of 0.0677 (dashed line), thus implying the potential of nonlinear predictability during these particular time periods. Table 3 provides the time periods of those windows with significant *H* statistic, making it possible for future research to explore in detail the factors that generate this predictability. It is interesting to note that after removing all short-term linear dependence, the stock returns under study still contain predictable nonlinearities that contradict the unpredictable criterion of weak-form EMH.

[11] Figures for other stock markets are available upon request from the authors.

Some general observations can be drawn from the visual inspection of these figures. First, given that the *p*-value is plotted as a function of time, it is apparent from these graphical plots that the degree of market efficiency follows an evolutionary time path. This is consistent with the findings in extant literature that focused on autocorrelation coefficients and Hurst exponents. In particular, all the returns series follow a pure white noise process for long periods of time, only to be interspersed with brief periods of nonlinear predictability. Hence, the present findings add further empirical support to the argument that it is not sensible for conventional efficiency studies to assume markets are in some kind of steady-state, at least in the context of emerging stock markets. This has implication even for those earlier cited studies that re-examined the weak-form market efficiency using nonlinear tests (see, for example, Al-Loughani and Chappell, 1997; Antoniou et al., 1997; Kohers et al., 1997; Chappel et al., 1998; Opong et al., 1999; Freund and Pagano, 2000; Appiah-Kusi and Menyah, 2003; Narayan, 2005), given that their findings of nonlinear departure from market efficiency in the full sample could masked those time periods when stock returns series are actually moving in a random walk. Second, the assertion that emerging markets are becoming more efficient over time does not hold for most countries in this sample. Taiwan is the only country that exhibit inexorable trend towards higher efficiency, in which no evidence of nonlinear predictability was detected since October 1998. This is not surprising as evidence from time-varying autocorrelation coefficients and Hurst exponents also found that some stock markets do not present clear trend towards efficiency (see, for example, Rockinger and Urga, 2000; Jefferis, K. and Smith, G., 2005; Cajueiro and Tabak, 2004a, 2006). Perhaps, market dynamics is more complex than those predicted by classical EMH. Third, Sri Lanka stands out to be the market with more frequent deviations from market efficiency. It seems natural for us to speculate that market size is responsible for these differences, given that Taiwan is one the largest among these Asian emerging stock markets whereas Sri Lanka has the lowest market capitalization (*Global Stock Markets Factbook 2004*). However, there are a number of possible factors that could contribute to the non-linear burst of dependencies, such as the characteristics of the market microstructure, behavioural biases, the existence of market imperfections, or the occurrence of unexpected events (see Antoniou et al., 1997).

<<Insert Figure 1 and 2 about here>>

<<Insert Table 3 about here>>

VI. CONCLUSION

The literature survey in the present paper has demonstrated that there is a shift of research focus in recent years from the all-or-nothing notion of 'absolute market efficiency' to the more practical version of evolving market efficiency, especially in the context of emerging stock markets. However, there is still a significant gap in extant literature given that predictability is assumed to take the form of linear correlations. The major drawback of this assumption is that the lack of autocorrelation does not imply unpredictability and hence market efficiency. In fact, it has been shown that time series with zero autocorrelations are forecastable from their own past in a nonlinear manner. The application of a battery of nonlinearity tests reveals the existence of nonlinear predictability in all the returns series under study, and hence contradicts the unpredictable criterion of weak-form EMH.

Motivated by the concern that the findings of nonlinear departure from market efficiency in the full sample could actually masked those time periods when stock returns series are in fact pure white noise, bicorrelation or *H* statistics of Hinich (1996) were estimated using fixed-length moving sub-sample windows approach. The results reveal that the detected nonlinear predictability for all returns series is localized in time and follows an evolutionary time path. This adds further support to the argument that market efficiency is not an all-or-none condition but is a characteristic that varies continuously over time. However, for most indices with the exception of Taiwan SE Weighted, there is no clear trend towards higher efficiency as predicted by the classical EMH. All this points to the search for an alternative hypothesis, and the statistical features of our data are very much in line with those postulated by the Adaptive Markets Hypothesis (AMH) of Lo (2004, 2005). According to Lo (2005), the notion that evolving systems must march inexorably towards some ideal stationary state is incorrect. Instead, the AMH implies considerably more complex market dynamics, with cycles as well as trends, panics, manias, bubbles, crashes, and other phenomena that are routinely witnessed in natural market ecologies. Based on the evolutionary perspective, profit opportunities do exist from time to time. Though they disappear after being exploited by investors, new opportunities are continually being created as groups of market participants, institutions and business conditions change. Hence, the present paper provides some interesting insight into this new paradigm that is still in its infant stage of development.

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Table 1
Summary Statistics for Asian Stock Returns Series

	China	India	Indonesia	Malaysia	Pakistan	Philippines	S. Korea	Sri Lanka	Taiwan	Thailand
Mean	0.0521	0.0391	0.0329	0.0114	0.0315	0.0072	0.0090	0.0076	0.0079	0.0026
Maximum	71.9152	16.6409	13.1279	20.8174	12.7622	16.1776	10.0238	18.2869	8.5198	11.3495
Minimum	-17.9051	-10.2722	-12.7321	-24.1534	-13.2143	-9.7442	-12.8047	-13.8969	-9.9360	-10.0280
Standard Deviation	2.8879	1.6803	1.5566	1.6560	1.6425	1.5022	2.0171	1.0613	1.6508	1.7460
Skewness	5.9369	0.2654	0.1325	0.5270	-0.2957	0.7582	-0.0347	1.2297	-0.0080	0.4105
Kurtosis	136.9144	10.5220	13.2909	41.3770	10.0890	14.2506	6.7093	48.7377	5.3344	7.6139
JB Normality	2357156	7415.683	13820.68	192221.4	6599.564	16807.59	1795.049	273612.7	710.751	2864.249
(*p*-value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Autocorrelation Coefficients										
Lag 1	$0.046^{\#}$	0.110*	0.181*	0.058*	0.080*	0.175*	0.056*	0.301*	0.015	0.121*
Lag 2	$0.044^{\#}$	0.027	$0.038^{\#}$	$0.036^{\#}$	$0.043^{\#}$	0.014	-0.012	0.065*	$0.044^{\#}$	$0.041^{\#}$
Lag 3	$0.043^{\#}$	0.029	-0.009	0.025	0.049*	-0.005	-0.009	0.052*	0.035	0.022
Lag 4	0.031	0.050*	-0.032	-0.096*	$0.036^{\#}$	0.033	-0.026	0.076*	-0.050*	0.005
Lag 5	0.027	0.017	0.001	0.061*	0.024	-0.017	$-0.041^{\#}$	0.062*	0.031	0.027
LB-Q(10)	30.486	67.492	141.71	66.163	58.099	112.77	22.413	371.36	34.576	80.516
(*p*-value)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)	(0.000)	(0.000)	(0.000)

Notes: The JB Normality is Jarque-Bera normality test, which is asymptotically distributed as χ^2 (2) under the null hypothesis of normality; LB-Q(10) is a Ljung-Box test for autocorrelation for all orders up to 10 and is asymptotically distributed as χ^2 (10) under the null hypothesis.
$^{\#}$ and * denote significant at 5% and 1% level respectively.

Table 2
Nonlinearity Test Results for Asian Stock Returns Series

	China	India	Indonesia	Malaysia	Pakistan	Philippines	S. Korea	Sri Lanka	Taiwan	Thailand
McLeod-Li Test										
Using up to lag 20	0.112	0.000	0.000	0.000	0.000	0.009	0.000	0.003	0.000	0.000
Using up to lag 24	0.148	0.000	0.000	0.000	0.000	0.011	0.000	0.003	0.000	0.000
Bicorrelation Test	0.002	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	0.043	0.000	0.000	0.000	0.000	0.004	0.000	0.001	0.000	0.000
Using up to lag 2	0.022	0.000	0.000	0.000	0.000	0.005	0.000	0.001	0.000	0.000
Using up to lag 3	0.017	0.001	0.000	0.000	0.000	0.003	0.000	0.001	0.000	0.000
Using up to lag 4	0.018	0.000	0.000	0.000	0.000	0.003	0.000	0.001	0.000	0.000
Using up to lag 5	0.023	0.000	0.000	0.000	0.000	0.005	0.000	0.001	0.000	0.000
Tsay test	0.006	0.000	0.003	0.000	0.000	0.004	0.000	0.001	0.000	0.007
BDS test										
$\varepsilon/\sigma = 1$; m=2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	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
Bispectrum Test	0.0063	0.0516	0.0405	0.0063	0.0442	0.0134	0.1255	0.0063	0.4704	0.1445

Notes: With the exception of the bispectrum test, all the tests are carried out in the Nonlinear 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 minimize the Schwartz Criterion. The statistics reported are 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 reported statistics are the shuffle bootstrap p-values with 1000 replications.

Table 3
Significant *H* Statistics in Moving Time Windows Test

	China	India	Indonesia	Malaysia	Pakistan	Philippines	S. Korea	Sri Lanka	Taiwan	Thailand
Total number of significant *H* windows	13 (20.97%)	9 (14.52%)	7 (11.29%)	11 (17.74%)	18 (29.03%)	9 (14.52%)	7 (11.29%)	23 (37.10%)	6 (9.68%)	8 (12.90%)
Dates of significant *H* windows	3/12/92-5/20/92 7/30/92-10/7/92 7/15/93-9/22/93 11/17/94-1/25/95 8/24/95-11/1/95 3/21/96-5/29/96 3/6/97- 5/14/97 7/24/97-10/1/97 4/30/98-7/8/98 7/9/98-9/16/98 11/11/99-1/19/00 6/8/00-8/16/00 12/5/02-2/12/03	5/21/92-7/29/92 2/10/94-4/20/94 4/6/95-6/14/95 11/2/95-1/10/96 8/8/96-10/16/96 10/2/97-12/10/97 1/20/00-3/29/00 8/17/00-10/25/00 8/2/01-10/10/01	1/2/92-3/11/92 5/6/93-7/14/93 1/26/95-4/5/95 3/21/96-5/29/96 3/15/01-5/23/01 10/11/01-12/19/01 7/18/02-9/25/02	5/6/93-7/14/93 12/2/93-2/9/94 5/30/96-8/7/96 7/9/98-9/16/98 2/4/99-4/14/99 6/24/99-9/1/99 6/8/00-8/16/00 8/2/01-10/10/01 10/11/01-12/19/01 5/9/02-7/17/02 2/13/03-4/23/03	7/30/92-10/7/92 7/15/93-9/22/93 9/23/93-12/1/93 4/21/94-6/29/94 11/17/94-1/25/95 11/2/95-1/10/96 1/11/96-3/20/96 3/21/96-5/29/96 10/2/97-12/10/97 2/19/98-4/29/98 9/17/98-11/25/98 4/15/99-6/23/99 11/11/99-1/19/00 3/30/00-6/7/00 8/2/01-10/10/01 5/9/02-7/17/02 7/18/02-9/25/02 12/5/02-2/12/03	5/6/93-7/14/93 4/21/94-6/29/94 11/17/94-1/25/95 3/6/97-5/14/97 5/15/97-7/23/97 10/2/97-12/10/97 2/19/98-4/29/98 4/30/98-7/8/98 5/9/02-7/17/02	10/8/92-12/16/92 7/15/93-9/22/93 4/21/94-6/29/94 12/26/96-3/5/97 4/30/98-7/8/98 8/17/00-10/25/00 7/18/02-9/25/02	5/21/92-7/29/92 7/30/92-10/7/92 2/25/93-5/5/93 5/6/93-7/14/93 9/23/93-12/1/93 4/21/94-6/29/94 6/30/94-9/7/94 1/26/95-4/5/95 8/24/95-11/1/95 11/2/95-1/10/96 3/6/97-5/14/97 7/9/98-9/16/98 4/15/99-6/23/99 6/24/99-9/1/99 9/2/99-11/10/99 8/17/00-10/25/00 2/28/02-5/8/02 7/18/02-9/25/02 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	1/2/92-3/11/92 2/25/93-5/5/93 9/8/94-11/16/94 3/21/96-5/29/96 7/24/97-10/1/97 7/9/98-9/16/98	5/21/92-7/29/92 8/24/95-11/1/95 8/8/96-10/16/96 10/17/96-12/25/96 7/24/97-10/1/97 4/30/98-7/8/98 6/24/99-9/1/99 8/2/01-10/10/01

Figure 1: Time Series Plots for *p*-values of *H* Statistic (Taiwan)

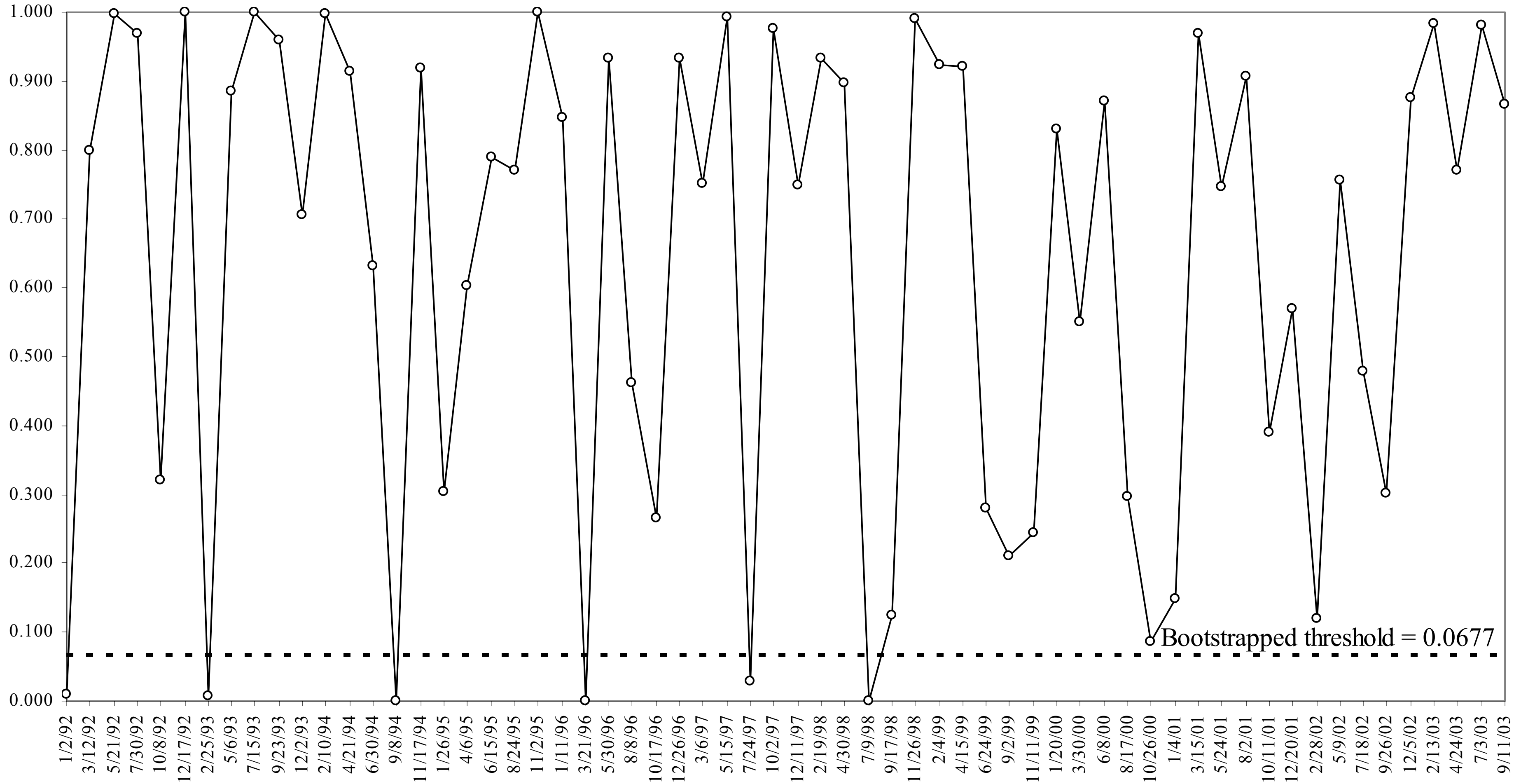

Figure 2: Time Series Plots for *p*-values of *H* Statistic (Sri Lanka)