NONPARAMETRIC EFFICIENCY TESTING OF ASIAN STOCK MARKETS USING WEEKLY DATA

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ABSTRACT. The efficiency of speculative markets, as represented by Fama s 1970 fair game model, is tested on weekly price index data of six Asian stock markets - Hong Kong, Indonesia, Malaysia, Singapore, Taiwan and Thailand - using Sherry s (1992) non-parametric methods. These scientific testing methods were originally developed to analyze the information processing efficiency of nervous systems. In particular, the stationarity and independence of the price innovations are tested over ten years, from June 1986 to July 1996. These tests clearly show that all six stock markets lacked at least one of the two required fair game attributes, and, accordingly, Fama s Efficient Market Hypothesis must be rejected for these Asian markets. However, Singapore emerged from these tests as the most efficient regional Asian stock market. A tentative ranking in order of stock market efficiency is: Singapore, Thailand, Indonesia, Malaysia, Hong Kong and Taiwan. Singapore s stock market pricing is closest to the speculative market behavior which can support stock options. Our tests show both Hong Kong and Taiwan to be inefficient markets. Both exhibit non-stationary (likely because of continuing institutional changes) and dependent price innovations, making them particularly unsuitable for stock option pricing. In Taiwan the weekly price innovations show even higher order (Markov) dependencies. Although the price innovations in Malaysia, Thailand and Indonesia are at least stationary at the weekly level, they exhibit regular higher-order transitions and the large sustained movements in both bull and bear markets, which are so characteristic for illiquid emerging markets. All six Asian stock markets exhibit strong price trend behavior, which, perhaps, can be profitably exploited by technical analysis with first-order Markov filters (e.g., Kalman filters) in windows of between a week and more than a month.

1. INTRODUCTION

Efficient stock markets exhibit lower transaction costs and improved transaction speeds compared with inefficient markets. These conditions often act as incentives to increase capital flows and attract international investments, thereby enhancing regional economic growth. In an efficient stock market, prices fully reflect all current information on share values so that no gains from trade can be made with publicly available information. Therefore, stock prices only change in response to new information, which is unpredictable. If such successive price changes are

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stationary (i.e., the underlying pricing processes do not structurally change) and independent, a stock market is said to present a fair game [12].

This importance of efficient and fair stock markets to assist increased capital flows has prompted considerable research in the past two decades on stock markets in developed economies. But as the 1994 Mexican and 1997 Asian financial crises and their astounding mis-valuations demonstrate, still abysmally little is known about how markets truly work in developing countries and about their relative market efficiency. This paper makes a first attempt to resolve that situation by testing for random walk efficiency of the emerging stock markets in six Asian countries: Hong Kong, Indonesia, Malaysia, Singapore, Taiwan and Thailand in the period June 1986 to July 1996 (i.e., before the important structural discontinuity of the Asian financial crisis in 1997).[1]

For example, tested on daily data, the S&P500 Index in the U.S., which is an index containing 500 stocks, appears to follow a random walk [[46], pp. 21-56; 91-92; 113-160; 172-202]. Its price changes, or innovations, appear to be stationary and independent and the S&P500 index may thus follow an efficient and fair market pricing process.[2] In contrast, also tested on daily data, the Dow Jones Industrial Average Index (DJIA), which is an index of only 30 stocks traded on the New York Stock Exchange, is nonstationary, based on the same nonparametric testing approach [[46], pp. 62-64]. The DJIA is maximally uncertain and unpredictable.

This paper attempts thus to answer a very simple question: are the Asian stock markets efficient and fair games, or are they inefficient and unfair games, based on Sherry s nonparametric tests? Sherry s tests were developed for testing information processing by the nervous system. These non-parametric tests were originally developed over a fteen year period by Clifford J. Sherry, a Senior Scientist of Systems Research Laboratories, Inc., to study information processing in the nervous system.

It appears that most of the Asian stock price indices are not entirely efficient, probably since they include relatively small numbers of stocks. In addition, from time to time, noticeable abnormally profitable (or losing) deviations from efficiency exist and regime changes introduce discontinuities and thus nonstationarity. The current institutional characteristics of the developing equities markets of Asia are very different from the ones in the developed ones in North America or Europe. In Asia there have been occasional high investment returns, but there are also very high volatilities and there is small capitalization, limited liquidity, and high

[1]Some early work on the efficiency testing of the stock market in Singapore can be found in [2], although that research was not concerned with testing the random walk hypothesis. When the Spanish stock market is also considered to be an emerging stock market [38], our paper may not be the rst to test the random walk hypothesis for emerging markets *per se*, although it is still the rst for Asian emerging stock markets.

[2]But see the next section where the review of the literature reveals considerable doubt about that nding. Since [46] publishes all his daily and monthly test data, comparative studies using more sophisticated forms of signal processing, like wavelet analysis, can be easily executed.

transaction costs [10], [32].[3] But limited financial liberalization is improving the efficiency of these markets [1].

The remainder of this Introduction briefly reviews the literature relevant to the background, context and objectives of this paper, followed by a discussion of the summary characteristics of the weekly price change data collected from the six Asian stock markets, and is concluded with a detailed discussion of Sherry s overall methodology. In the following sections, Sherry s procedures are presented in the form of easy to follow recipes. Section 2 presents the visualization of the distributions of the weekly price changes together with the all important stationarity tests. Section 3 presents a battery of serial independence tests: tests on differential spectra, on Relative Price Change Transition (RPCT) arrays, on the duration of trading windows, on Category Price Change Transition (CPCT) arrays and on the Markov analysis of the CPCT arrays. Section 4 discusses the (ir)relevance of testing for randomness. The results of all these testing procedures are summarized in Table 12 and discussed in Section 5.

This paper finds that on the basis of a thorough analysis of the weekly price changes all six Asian stock markets are inefficient and do not exhibit random walk behavior. The stock markets of Hong Kong and Taiwan are signi cantly nonstationary, while the stock markets of Indonesia, Malaysia, Singapore and Thailand are stationary, but show significant serial dependencies.

1.1. **Review of the Literature.** The literature of the past three decades also shows that there is very little agreement not only about the form of the data of speculative markets, like stock markets or foreign exchange markets, but also about the pricing mechanisms that generate them. This lack of agreement is due neither to a lack of interest nor to a lack of imagination to analyze these data. The data generating mechanisms are very complex and evolving over time. Still, it is slowly but surely becoming well established that these speculative price data are not randomly generated and contain a lot of structure, actually more than either weak nonparametric tests or (too) constraining parametric tests can reveal.

The most recent statistical evidence, based on highly sophisticated signal processing analysis, shows that the underlying structure of such speculative data is more like that of speech generating mechanisms or that of complex neural information processing mechanisms, as Sherry suggests. The data come in small bursts of energy and show many discontinuities and jumps.

Therefore, the simplifying assumptions of the parametric econometric ARIMA, VAR and ARCH models, like stationarity of unconditional variances and covariances, are clearly violated.[4] The literature on the efficiency of speculative markets largely developed from research on such markets in developed economies, and mostly within the context of violations of parametric correlation analysis or of

[3]In the early 1990s the mistaken impression existed that the emerging markets were always high return markets. However, *The Economist* already reported on February 22, 1997 (before the currency break in July 1997), that since 1994 the stock markets in the developed world, as measured by the MSCI World Index, gained more than 40%, while the emerging stock markets, as measured by the IFC investable Index, lost about 10% in the same period. Emerging markets are highly volatile and exhibit very highly positive *and* negative returns. On average, the returns are moderate.

[4]For an extensive and excellent overview of the parametric approaches to the speculative financial markets, see [6].

Fourier type spectral analysis [7], [37]. In the past three decades, there has emerged a succession of three partially overlapping research questions:

(1) What distributions of the data are generated by these speculative markets? There is now overwhelming evidence that they are clearly not Gaussian, or Student-t, or normal mixtures, or even symmetric, as had been originally hypothesized in, for example, [8], [11], [5]. The evidence appears to argue for mixtures of skewed distributions. Furthermore, the parameters of the proposed distributions tend to vary over time [29]. Thus the next question became:

(2) What is the degree of temporal dependence?[5] There is some evidence for correlation between the first differences of the price data generated by stock markets [12], although not so much for those of foreign exchange markets. This line of research led to more detailed parametric ARIMA analysis [36] and a revaluation of much earlier attempts at power spectral analysis of stock market prices [42], [17], both being forms of linear analysis. Spectral analysis shows the typical spectral shape of financial data: high power at very low frequencies and rapidly declining thereafter, a shape that may be consistent with geometric Brownian motion. However, recent evidence based on nonlinear analysis shows substantial nonlinearities in the speculative pricing data from developed markets [41].[6] This demonstrates that such speculative financial data series cannot be the result from random walks or from geometric Brownian motions, nor from mean reverting processes, i.e., sums of a unit root process and a stationary process [28], [27], [24].

This evidence has led, finally, to the recognition that stationarity of financial time series often has been assumed and not been corroborated and that the possible presence of time localized patterns in the data structure, e.g., the transients, has been ignored. Thus very recent the focus has been on the fundamental statistical research question:

(3) What is the degree of stationarity of the data by speculative markets? It is well known that the variances of stock market prices show heteroskedastic behavior, which originally led to (G)ARCH modeling [40], [4], [26]. However, the legitimacy of the (G)ARCH modeling relies on the existence of unconditional (co-)variance stationarity. Both [39] and [29] demonstrate that such covariance stationarity for stock market and foreign exchange data even over short periods of time is implausible, both at monthly intervals and at daily intervals of sampling. In the current paper we ll show that, based on relatively weakly powered nonparametric analysis, it is also implausible for weekly intervals in at least two out of the six Asian stock markets.

In terms of statistical characteristics, it emerges from the recent literature that the data generated by speculative markets show skewed and leptokurtic (peaked) distributions (i.e., the third and fourth moments are important). Moreover, time windowing shows that the data are highly nonstationary: the skewness changes over time. We find some evidence of these non-Gaussian moment values in our data. But most damaging is , perhaps, that there is very little evidence for almost any frequency (i.e., temporal dependency) to hold over an entire time sequence of data points, although many special day of the week and end of the month quasi-periodicities are apparently observed by financial analysts [9].

[5]This led in the 1970s and 1980s to a whole branch of econometric literature on time-varying parameter estimation, of which I ve thoroughly reviewed and analyzed the econometric theory [31]

[6]See also Chapter 12 Nonlinearities in Financial Data in [6], pp. 467 - 526.

There is also evidence of Dirac delta functions representing impulses, or shocks, to the market systems, that seem to cluster, more than would be expected under the hypothesis of random variation. The bulk of the power of speculative markets appears to be in such chirps. In short, such markets generate highly complex data and show considerable nonlinear structure.[7] These recent statistical ndings clearly violate the assumption of simple random walks. But what about geometric Brownian motion, which underlies such celebrated option valuation models as the Nobel Prize winning Black and Scholes model?

The current conventional wisdom is that stock market prices show some evidence of such exponential motion in their rates of return, based on similar forms of analysis.[8] But several papers indicate that, at various time scales of tick-by-tick, daily, weekly and monthly data, and mostly based on parametric correlation analysis, there are observable differences from the hypothesis of approximately geometric Brownian motion, since the observed data contain more structure than such motion justi es [14], [13], [15], [16], [19],

Because of these peculiar characteristics of speculative markets, two statistical analysis approaches have successively evolved: the non-parametric approach to falsify the hypotheses of the random walk and the geometric Brownian motion, as by [46] and [18], and the most recent approach to establish the precise data characteristics by using wavelet analysis.[9] This latest work is based on work by signal processing engineers and mathematicians.

In this paper we apply the relatively agnostic, primarily falsifying, non-parametric approach of [46] to test for the stationarity of the distributions and for serial independence. The raison d être is that Sherry s approach does not make excessive demands on the data and does not require knowledge of the detailed structure of the data generating pricing processes. This is sufficient for our current purpose of demonstrating that the Asian stock markets are not following random walks, since some show nonstationarity and all show some form of systematic dependencies between the price changes.

1.2. **Data.** In this paper we analyze the weekly pricing in the six Asian stock markets, as measured by their respective market indices in the past ten years, from July 1986 to June 1996. The weekly data for the Jakarta Stock Exchange range actually from January 1988 to June 1996, and the data for the Stock Exchange of Thailand from July 1987 to June 1996.

The weekly data frequencies are the highest frequency data we could obtain on a on a comparable basis and for a sufficiently long period of time, in addition to monthly data. Weekly data are often used by mutual fund (unit trust) managers for investment decisions and trading. Furthermore, when we do monthly tests, we

[7] A wonderful, highly informative and amusing, anecdotal and historical account of such typical market phenomena can be found in [25].

[8] The computation of rates of return from price indices is a stationarity inducing operation, i.e., the rates of return or relative first differences show a more stationary behavior than the direct differences of random walks.

[9] One of the most sophisticated examples of such wavelet analysis in the (very) recent literature was brought to my attention by Professor James Ramsey of New York University. In that paper a matching pursuit algorithm is used to implement dictionaries of Gabor waveforms to decompose the 16384 daily observations Standard and Poor s 500 stock price index from January 3rd, 1928 to November 18th, 1988 [44], [34]. A wave form dictionary is class of transforms that generalizes both windowed Fourier transforms (spectrograms) and wavelets (scalograms).

nd that for the monthly frequency the price changes of ve out of the six Asian stock market show signi cant nonstationarity. Only the monthly Malaysian stock market price changes are stationary. This is in contrast with the weekly data in this paper where only two out of the six Asian stock markets showed signi cant nonstationarity in their price changes. But, the weekly price change data showed more higher order transition and translation dependencies than the monthly data.

The following six price indices are used to conduct the nonparametric efficiency tests:

1. Hong Kong: the Hang Seng Index, which is a capitalization-weighted index of 33 companies, representing approximately 70 percent of the total market capitalization of the Stock Exchange of Hong Kong. This index had a value of 975.45 as of January 13, 1984.

2. Indonesia: the Jakarta Composite Index, which is a capitalization-weighted index of all the stocks listed on the Jakarta Stock Exchange. The index had a base value of 100 as of August 10, 1982.

3. Malaysia: the Kuala Lumpur Composite Index, which is a broad-based capitalization-weighted index of 100 stocks designed to measure the performance of the Kuala Lumpur Stock Exchange. The index had a value of 95.83 as of January 3, 1977.

4. Singapore: the Straits Times Industrial Index, which is a price-weighted index of 30 stocks traded on the Stock Exchange of Singapore, compiled by *The Straits Times* newspaper in Singapore. The index had a base value of 100 as of December 30, 1966.

5. Taiwan: the Taiwan Stock Exchange Index, which is a capitalization-weighted index of all listed common shares traded on the Taiwan Stock exchange. This index had a base value of 100 as of December 30, 1966.

6. Thailand, the Bangkok SET (Stock Exchange of Thailand) Index, which is a capitalization-weighted index of all the stocks traded on the Stock Exchange of Thailand. The index had a base value of 100 as of April 30, 1975.

A summary of the values of the first order differences, or price changes, of these weekly stock market price indices is found in Table 1.

Notice, first, that all price changes have positive means, indicating that, on average over these ten years, stock market prices were rising. All six countries have positive mean innovations on a weekly basis. In particular, the price changes of Hong Kong and Taiwan show substantial positive means, and thus these markets show substantial price index trends. Also notice the mildly negative skewness of all distributions, i.e., with asymmetric tails extending towards negative values, with the exception of Indonesia; and, third, the more than Gaussian positive kurtosis, indicating that these distributions are leptokurtic, i.e., had sharper peaks than Gaussian distributions.[10]

1.3. **Methodology.** As the review of the literature shows, much of the early empirical research on market efficiency revolved around the random walk hypothesis, which has a considerable intellectual history.[11] Under the in uence of the rational expectations literature, Fama organized and presented the empirical evidence in terms of a fair game model, i.e., a conditional expectations model [12]. In contrast

[10] A Gaussian distribution has a kurtosis of 3.

[11] This history, which started with Bachelier s celebrated doctoral dissertation on the Theory of Speculation, [3] is partially reviewed in [33].

Figure 1. TABLE 1. SUMMARY STATISTICS OF PRICE CHANGES

	Hong Kong	Indonesia	Malaysia	Singapore	Taiwan	Thailand
Mean	17.78	1.14	1.77	3.00	10.41	1.99
Std. Dev.	217.16	16.65	20.41	41.30	323.63	36.30
Variance	47160.53	277.32	416.68	1705.80	104735.73	1317.52
Count	521	441	520	521	521	469
Minimum	-1541.51	-41.41	-104.25	-428.85	-1849.23	-224.94
Maximum	933.76	199.59	96.86	121.96	1099.50	166.94
Range	2475.27	241.01	201.11	550.81	2948.73	391.88
Sum	9264.10	501.59	920.97	1560.48	5422.22	932.86
Sum of squares	24688201.95	122590.92	217886.82	891687.70	54519009.10	618455.99
25% Quartile	-49.62	-4.80	-6.71	-16.34	-109.09	-13.76
50% Quartile	13.80	0.65	1.82	4.36	27.93	3.46
75% Quartile	100.40	5.21	10.90	27.40	181.22	18.80
Kurtosis	8.54	50.59	4.00	23.53	4.00	6.11
Skewness	-0.60	4.74	-0.30	-2.55	-0.97	-0.64

to the random walk model, which deals with only the actual sequential price movement over time, Fama s fair game model assumes that the price of an instrument at any point in time would reflect all available information at that point in time.[12] Thus, an efficient market is represented by Fama s model:

$$E(\varepsilon_{j,t+1}|\Phi_t) = E(P_{j,t+1} - P_{j,t}) = E(P_{j,t+1}) - P_{j,t} = 0, \tag{1.1}$$

where $\varepsilon_{j,t+1}$ = price change, i.e., the difference between actual price P at time t and the expected price at time $t+1$ for instrument j; and Φ_t = the set of information assumed to have been reflected into the price P of instrument j at time t. This simple model implies that the market does not produce excess market value for instrument j at time $t+1$ based on the information set Φ_t at time t and therefore the market pricing process represents a fair game .

The interesting question is, of course, what is in the crucial information set Φ_t? In this paper only the historically observed value of stock index j and its observed accumulated distribution at time t is taken as the available and relevant information set Φ_t. Statisticians all too often presume to know the theoretical distribution of the price changes $\varepsilon_{j,t+1}$. For example, they assume that these price changes follow a parametric normal distribution. A normal distribution can be summarized by two parameters only, its mean and its standard deviation.

This paper makes no such parametric distributional assumptions. Sherry s tests are superior to the conventional parametric tests, since they do not require any parametric assumption for the underlying observations generating pricing processes. The only distribution tests used are Chi-square tests, which are nonparametric and

[12] A fair pricing game is, mathematically speaking, a martingale, since the discrete price innovations $\varepsilon_{j,t+1}$ are martingale-differences. Cf. [30], pp 32 - 40 and [45], pp. 18 - 23.

compare observed values with theoretically expected values. Their weakness is their relatively low power.

We test for the stationarity and independence of the observed price changes $\varepsilon_{j,t+1}$ of the selected stock market indices, as summarized in Table 3. All computations were executed in EXCEL spreadsheets.

TABLE 2.	**EFFICIENCY TESTS**
1. Stationarity	**2. Independence**
(i) Cumulative Distributions	(i) Differential Spectra
(ii) Percentile Graphs	(ii) Relative Price Change Transition Arrays
	(iii) Category Price Change Transition Arrays
	(iv) Markow Analysis of CPCT Arrays

For the formal statistical hypothesis testing, we use only the Chi-square test, which compares observed with expected values:[13]

$$\chi^2 = \sum_1^n \frac{(\text{Observed frequency - Expected frequency})^2}{\text{Expected frequency}}, \tag{1.2}$$

Here n is the number of bins in the histogram/2.

It is important to emphasize that the following tests were *not* applied in this paper. In general, they assume stationarity of the underlying time series. Violation of the assumption of stationarity will yield results that are often meaningless. It means that any pattern that you happen to detect is spurious and will not last. In addition, the following tests have their own peculiar shortcomings:

1. Serial and auto-correlation tests, as used, for example, by [12] can test for only linear forms of dependencies, for example sequentialness, periodicity and rhythmicity, and one has to presume the continuity or discreteness of the pricing processes. As Sherry states: ...if the correlation coefficient is low, this does not mean that the time series does not contain signi cant serial depedencies; it merely means that the time series does not contain the type of serial dependencies that correlation tests for. [[46], p. 5]. Tests based on power spectral analysis fall in the same parametric category, since they are essentially Fourier transforms of the correlation tests which are too specific.

2. Runs and persistence tests are confusing, because it is unclear what exactly is tested. There is no agreement whether runs tests test for divergence from randomness or independence (See also Section 4). In addition, often hard to check normality assumptions are introduced *ad hoc*, for example, to test Besson s Coefficient of Persistence.

3. Averaging windows are heavily dependent on subjective preferences for the length or duration of the averaging windows. In contrast, this paper tests for the historically observed durations and attempts to determine such durations directly from the data.

4. Pattern detection by densitograms, periodograms (based on Fourier transforms), triggered categorized price histograms and temporal correlograms, introduce, again, largely subjective judgments or restrictive parametrization. These

[13]It is easy to show that, when this Chi-square test is applied to the analysis of Markov transition matrices, as in Section 3.5, it is essentially independent of the number of observations used.

pattern detection techniques would make sense only after the original tests for stationarity and independence have been applied.

2. STATIONARITY TESTS

A stationary time series is a data series whose statistical properties don t change over time. For stock markets, the trading regime and its resulting pricing process remains consistent. Pattern detection techniques such as moving averages, trend line, serial correlation, work only if the underlying time series is stationary. When time series data are not stationary, the underlying price generating process changes over time and pattern detection techniques yield meaningless results. Any pattern detected would be spurious and would not hold over time.

The following methodology of [[46], pp. 12 - 20], is used to test for stationarity:

Step 1. Each data series is first divided into two equal halves (the chronologically earlier half will be addressed as *half 1* and the successive half as *half 2*).

Step 2. The data in the two halves are then separated into bins of equal interval size.

Step 3. A cumulative graph of both halves is constructed. Initially we use simple visual assessment to assess stationarity.

Step 4. Insert charts with differential spectra include data points in both halves corresponding to percentile increments of 10%, that is, we plotted the $10\%, 20\%$, $30\%, ...$ data value for *half 2* against *half 1*. Using a 45^0 line to indicate equality between the two halves, we test for deviation from the 45^0 line against both halves.

Step 5. Finally, Chi-square tests were conducted on these differential spectra. To do so, the bin intervals for *half 1* were obtained for cumulative percentiles of approximately 10% (i.e., we obtained the intervals for 10%, 20%, $30\%, ..., 90\%$). These bin intervals were then used as reference bins in *half 2* to nd the respective percentiles associated with each of these bin references. The difference between each percentile in *half 1* was then compared with the *half 2* percentile differences using the Chi-square test.

2.1. **Visualization of (Non-)stationarity.**

The cumulative distributions and percentile graphs of the weekly price index changes for the six stock markets are presented in Figures 1 - 6. In the S-shaped cumulative frequency charts the (blue) blocks indicate the observations of the *half 1* bin, while the (red) line represents the observations of the *half 2* bin. When the S-shape is symmetric, the underlying distribution is symmetric. All S-shapes show longer negative tails, i.e. negative skewness, except Indonesia (Fig.2), which shows positive skewness (Cf. also the summary statistics of Table 1.).

When the S-shape shows almost straight angles, the distribution is more leptokurtic. A smoother and more stretched out S-shape indicates less kurtosis. In the case of Hong Kong (Fig. 1), Malaysia (Fig. 3) and Thailand (Fig. 6), the distributions show more leptokurtosis in the 1990s *half 2*, than in the 1980s *half 1*. These markets became more unpredictable. Only in the case of Taiwan, the leptokurtosis decreased over the same period, while simultaneously the volatility decreased and Taiwan s stock market became thus more predictable. Also notice the very irregular and non-smooth S-shape of Taiwan s cumulative distribution. These changes in kurtosis corroborate some of the recent statistical ndings reported in the literature (See Section 1.1).

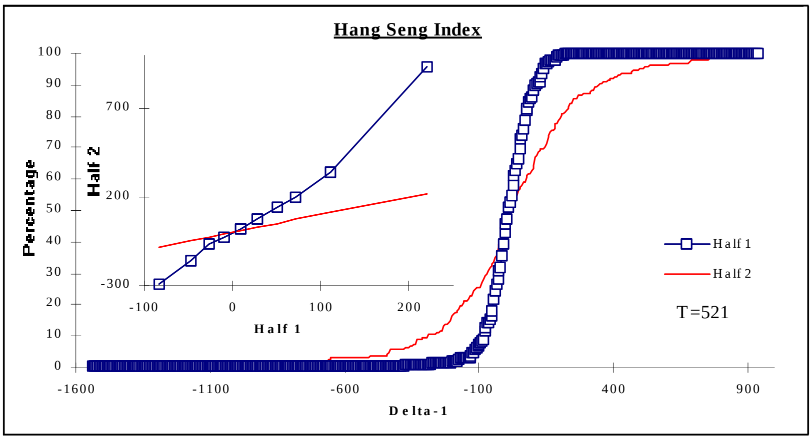

FIGURE 2. Figure 1. Hong Kong - Price Changes, June 1986 - June 1996

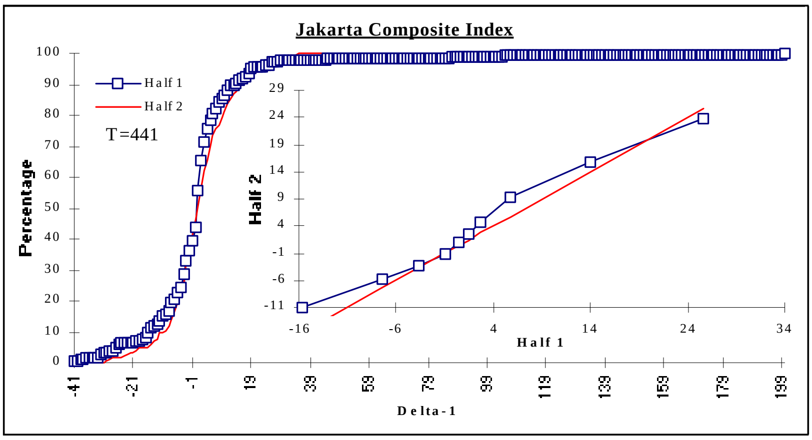

FIGURE 3. Figure 2. Indonesia - Price Changes, January 1988 - June 1996

In the smaller insert charts, the (red) line indicates the 45^0 line, while the (blue) blocks are the 2-dimensional observations on the matched percentiles of the *half 1* and *half 2* bins. When these interconnected blocks deviate from the 45^0 line, the distributional characteristics of *half 2* are different from those of *half 1*. We visually observe that four of the six stock markets exhibit stationarity, except Hong Kong (Fig.1) and Taiwan (Fig. 5), and, perhaps, Malaysia (Fig. 3). If the insert has a plotted line above the 45^0 line it means that the *half 2* bin has price changes that are larger in magnitude than in the *half 1* bin. This means that the stock market price changes in the 1990s were considerably larger in Hong Kong and Taiwan, and, perhaps, Malaysia, than in the 1980s. Their distributional characteristics changed. The pricing mechanisms of these stock markets were nonstationary. In contrast, the charts for *half 1* and *half 2* in Singapore (Fig. 4) and Jakarta (Fig. 2) appear indistinguishable from the 45^0 line, which, as we will see, visually con rms most of the Chi-square test results.

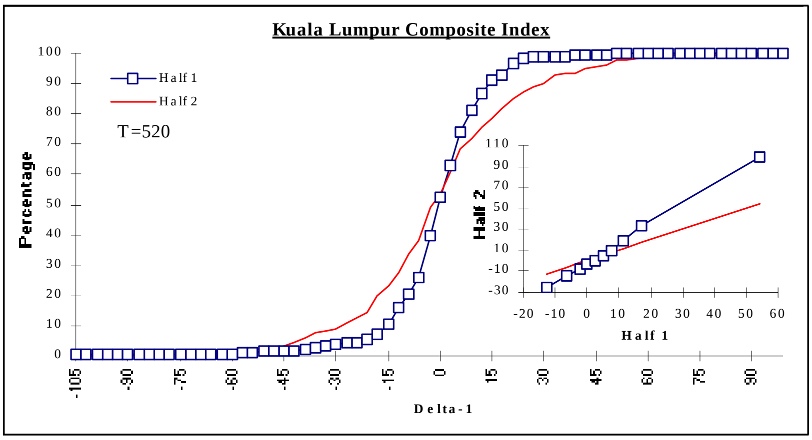

FIGURE 4. Figure 3. - Malaysia - Price Changes, June 1986 - June 1996

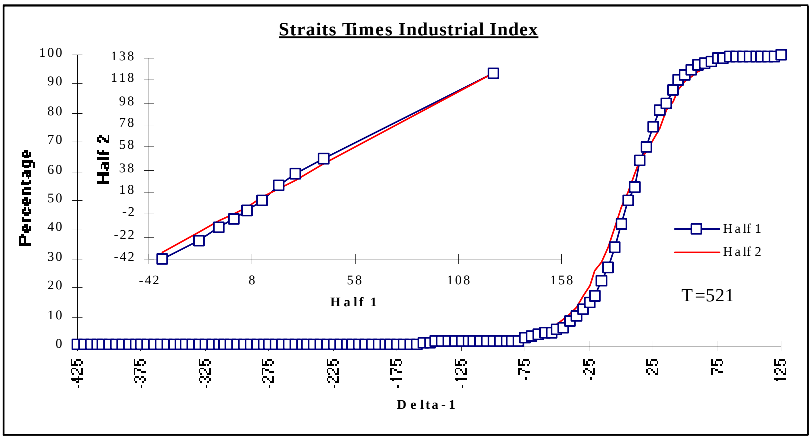

FIGURE 5. Figure 4. Singapore - Price Changes, June 1986 - June 1996

2.2. **Chi-Square Stationarity Tests.** For the weekly data, the Chi-square tests on the weekly price changes cannot reject stationarity for Singapore, Indonesia, Malaysia and Thailand and signi cant non-stationarity for Hong Kong and Taiwan.

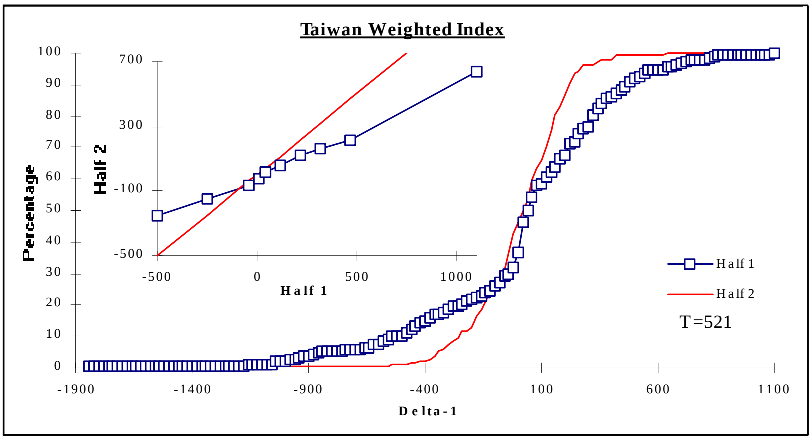

FIGURE 6. Figure 5. Taiwan - price Changes, June 1986 - June 1996

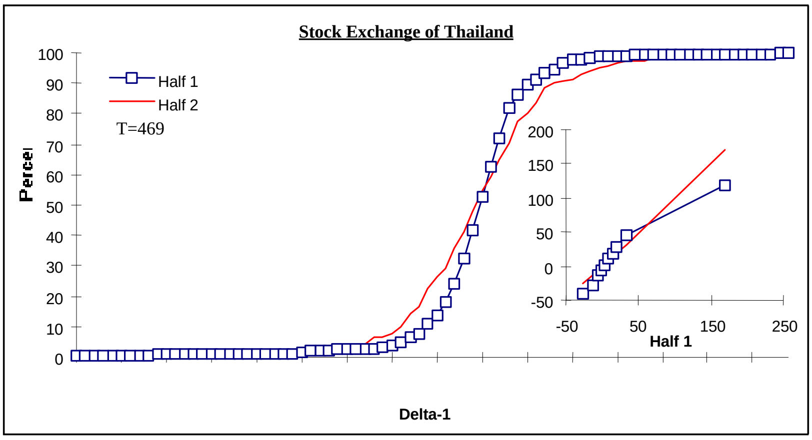

FIGURE 7. Figure 6. Thailand - Price Changes, July 1987 - June 1996

Malaysia s test results proves surprising, given the visual indication of nonstationarity.

TABLE 3.	CHI-SQUARE TEST RESULTS FOR STATIONARITY
COUNTRIES	**For Weekly Price Changes**
Hong Kong	**23.29***
Indonesia	10.53
Malaysia	11.20
Singapore	5.93
Taiwan	**43.64***
Thailand	10.64
* = signi cantly non-stationary	Critical value at the 1% signi cance level is 18.48

3. INDEPENDENCE TESTS

The independence tests attempt to determine if the price changes $\varepsilon_{j,t+1}$ are independent of one another. If these price changes are found to be serially dependent, we can, based on the current stock market index, predict what the near future stock market prices will be. You can use this information to forecast what the index will be next week or next month. Then technical analysis can be applied to identify pro table weekly trading rules. In contrast, when the price changes are independent, such a technical trading strategy will not work (despite the seductive Gambler s Paradox). When the weekly price changes are independent, such trading rules would not produce supra-normal pro ts and losses. The stock markets would be deemed efficient pricing mechanisms, or fair games, like fair roulette wheels or crap games with fair dice.

Because this is such a crucial issue for the determination of the efficiency of the Asian stock markets, and the livelihood of financial analysts in Asia, an extensive battery of tests is employed, since no single scientific test is infallible. This paper discusses the differential spectra, the relative price changes, compute category price change transition (CPTC) arrays and we conduct a Markov analysis of these CPTC arrays.

3.1. **Differential Spectra.** The differential spectrum is a method that allows you to make one pass through the time series and determine if the entire series is independent or not. One has to allocate the data to pre-specified bins. The choice of the bin width is arbitrary, but it affects both the sensitivity and computational effort. In general, as the bin-width increases, the sensitivity of the differential spectrum increases and the probability of detecting divergence from independence increases, but the computational effort increases geometrically.[14] Thus, there is a trade-off between sensitivity of the test and the computational effort involved. Of course, the bin width should not be smaller than the minimum possible price change. In signal processing terms, don t oversample, nor undersample.

Following again the example of [[46], pp. 86 - 91], the following recipe to form differential spectra is used to test for independence :

Step1. The price changes $\varepsilon_{j,t+1}$ are allocated to pre-specified bins.

Step 2. The positive price change bins are paired with the negative price change bins to ensure a symmetric matching of bins. Thus the bin for 0 to 1 is matched with the bin -1 to 0.

Step 3. Using the following Chi-square test based on the frequencies of the items in the bins

$$\chi^2 = \sum_1^n \frac{(\text{Observed frequency-Expected frequency})^2}{\text{Expected frequency}} \tag{3.1}$$

The positive price changes are used as observed values and the negative price changes as the expected values. Here n is half the number of bins in the histogram. The critical value of the test is thus dependent on the number of symmetrical bins used, but not on the number of original data points T. If the price changes $\varepsilon_{j,t+1}$

---

[14]In wavelet analysis, the latest, and more formal, non-parametric approach to data analysis, the bin size, or frequency of observation, depends formally on the resolution scale required. It deploys dyadic multi-resolution of the data where formal links are established between the various scales of resolution by the dilation equation. Here we use only one, subjective, level of resolution at a time.

are independent, the distribution of the weekly price changes around the zero point should be symmetric. But if this distribution is not symmetric, the price changes are not independent and they contain some type of serial dependence.

The differential spectra are collected in Figures 7 - 13, while the Chi-square test results are collected in Table 4. Notice that the bin widths for the price changes of the various indices must differ, since the magnitudes and frequencies of the price changes in the various stock markets are quite different from each other, re ecting the different institutional arrangements and capital liquidities.

No rm conclusion can be drawn from simple visual inspection of Figures 7 - 13, except that the observed price changes for most markets appear to be larger in the range of medium-sized magnitudes, suggesting that not only are the positive weekly price changes larger in magnitude than the negative ones, but that there are more of them in the medium-sized magnitude range. See for example the differential spectra of Hong Kong (Fig. 7) and Singapore (Fig. 10). The observed values of the observed positive price changes in Taiwan (Fig. 11) appear to be larger in magnitude than the expected negative price changes. In Indonesia (Fig. 8) the observed small positive price changes appear to be more prevalent than the expected small negative price changes. All these spectral differences suggest considerable unexpected amount of residual structure and dependence, although these structural dependencies are rather subtle.

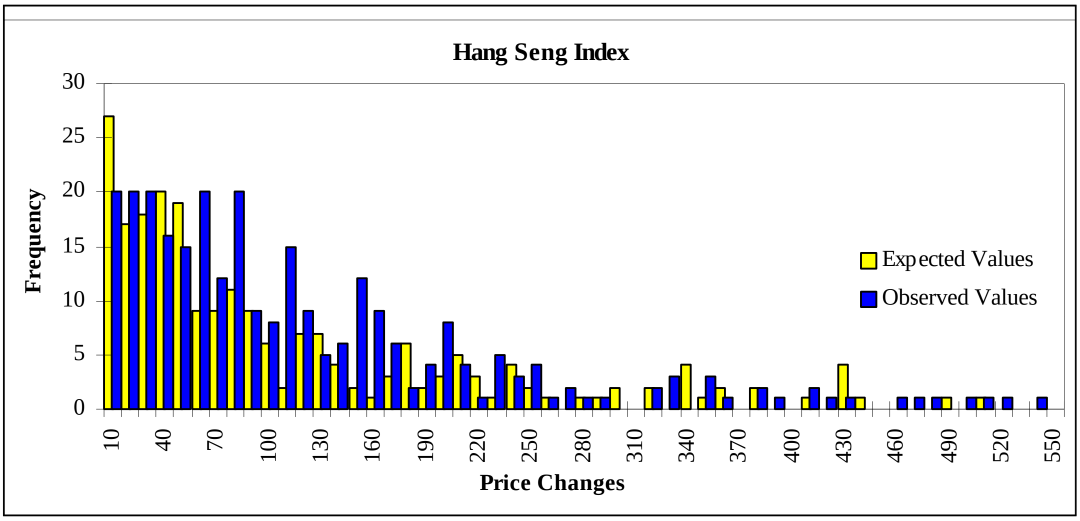

FIGURE 8. Figure 7. Hong Kong - Differential Spectrum, June 1986 - June 1996

3.1.1. *Chi-square Test Results.* The Chi-square test results of comparing the differential spectra are collected in Table 4. The bin widths for the price changes of the various indices differ and thus the number of $bins/2 = n$. Consequently, the critical values against which the Chi-square results are compared must differ from

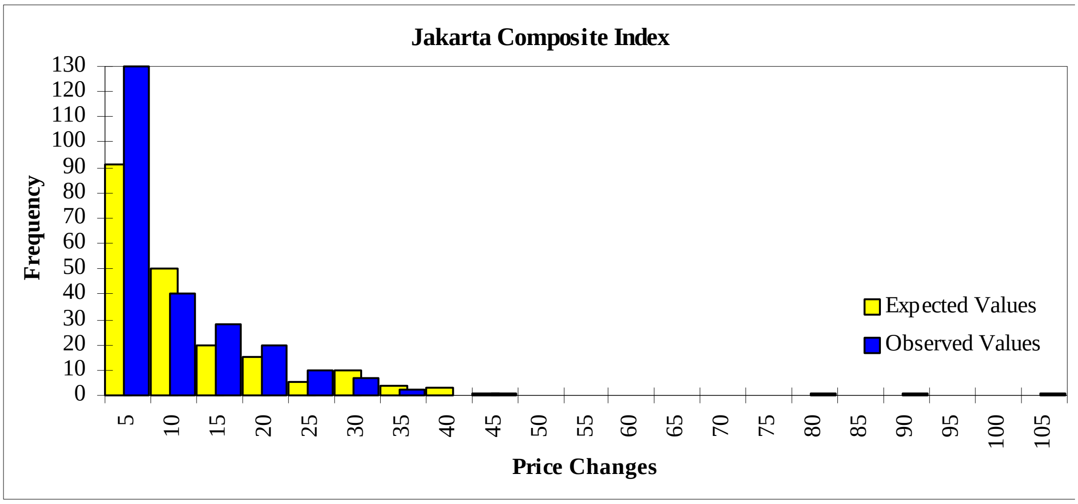

FIGURE 9. Figure 8. Indonesia - Differential Spectrum, January 1988 - June 1996

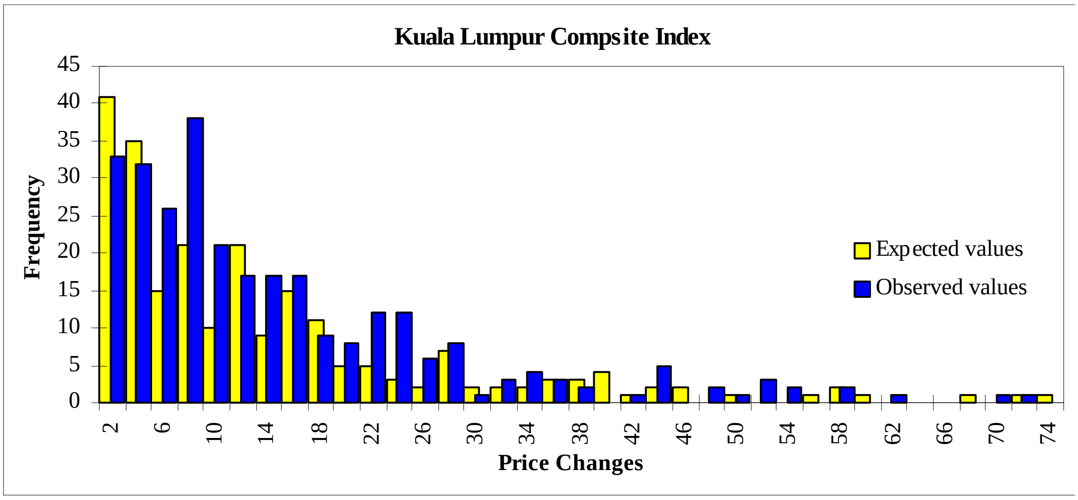

FIGURE 10. Figure 9. Malaysia - Differential Spectrum, January 1986 - June 1996

each other too.

TABLE 4. CHI-SQUARE TEST RESULTS FOR INDEPENDENCE BASED ON DIFFERENTIAL SPECTRA		
COUNTRIES	Critical Value	Weekly Price Changes
HONG KONG	197.74	**308.86***
INDONESIA	66.21	37.48
MALAYSIA	78.62	**120.83***
SINGAPORE	67.46	54.78
TAIWAN	231.54	207.01
THAILAND	149.73	104.97
All critical values are at the 1% signi cance level		

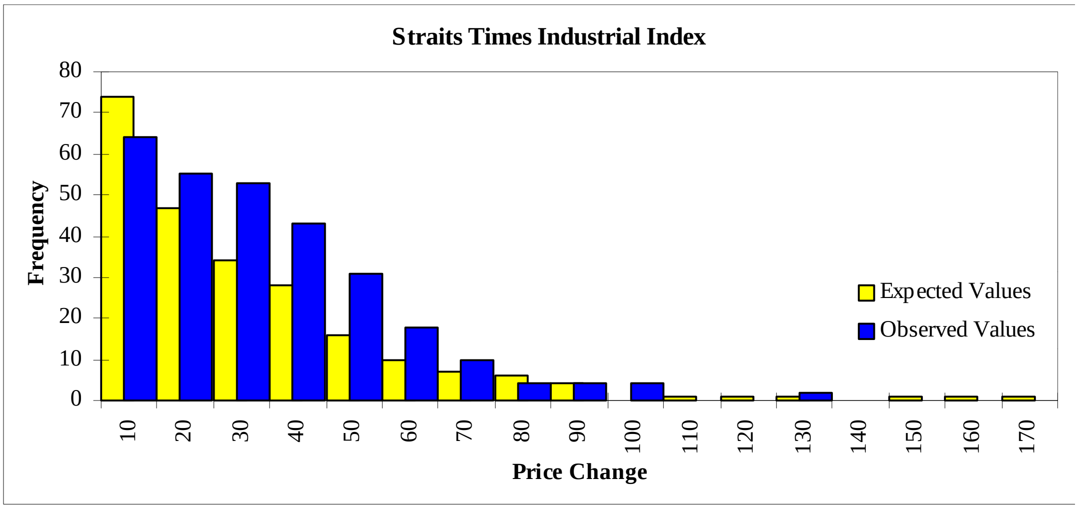

FIGURE 11. Figure 10. Singapore - Differential Spectrum, June 1986 - June 1996

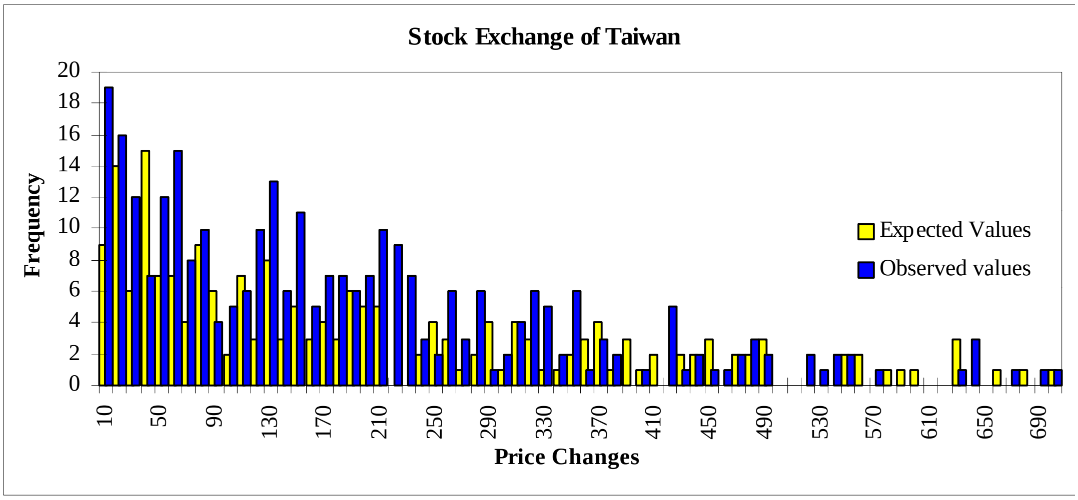

FIGURE 12. Figure 11. Taiwan - Differential Spectrum, June 1986 - June 1996

The weekly stock market price index changes in Hong Kong and in Malaysia exhibit signi cant dependence, whilst the time series underlying the equity markets of Singapore, Taiwan, Thailand and Indonesia are insigni cantly dependent, according to this differential spectrum test. Again, we emphasize the low power, and conservatism, of the Chi-square test, which cannot discriminate between the various subtle visual differences in the differential spectra. This test does not easily reject the hypothesis of independence, so, when it does, it is a signi cant nding.

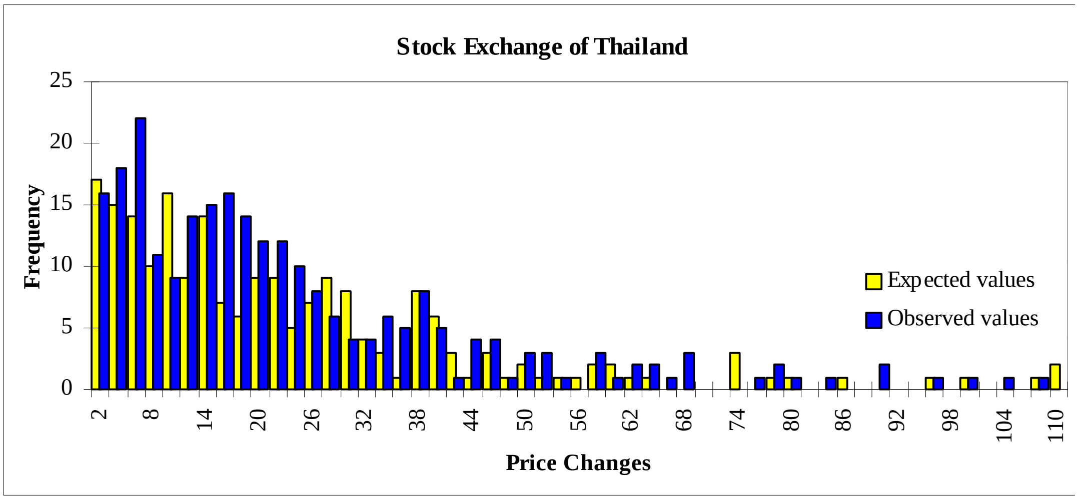

FIGURE 13. Figure 12. Thailand - Differential Spectrum, July 1987 - June 1996

3.2. **Relative Price Change Transition Arrays.** One shortcoming of the differential spectrum is that it only decides whether price changes are independent and fails to identify the type of serial dependence that may be present. The relative price change method assists in determining the type of serial dependence and the duration of the temporal window during which the dependency exists.

The following test recipe is used to form relative price change transition arrays to test for independence, with the theoretical relative frequencies or probabilities of occurrence in Tables 5, 6 and 7 [[46], pp. 93 - 112], which we ll use here and in section 3.4.

Step 1. The price changes $\varepsilon_{j,t+1}$ are translated into a series of arbitrary symbols using an unvarying rule. We adopt the following rule: a sequential increase in the price change is classi ed as 2 , while a sequential decrease in price change is classi ed as 1 . For example, if the string of price changes is 3,5,4,8, the translated symbols would be 2 , 1 , 2 . We exclude ties, when sequential price changes are the same, by then determining the symbol randomly, using the computer s random number generation capability. As a result, the string of symbols will consist solely of either 1 s or 2 s.

Step 2. The string of symbols of 1 s and 2 s are transformed into transition matrices. For the simple 2×2 digram transition matrix, we specify how often a symbol i is followed by a symbol j using the notation ij for a digram (cell) of the transition matrix, where i and j is either 1 or 2. There are four digrams in the 2×2 transition matrix: 11, 12, 21 and 22.

Step 3. The digram series are counted to obtain the relative frequencies of the digrams ij s. The count of the occurring digrams are the observed frequencies for the familiar Chi-square test. The theoretical frequency of occurrence of each digram is given in Table 5,[15] and this probability is multiplied with the total number of

[15]The cells of this theoretical relative frequency of occurrence table, multiplied by the number of different digrams in each row, sum up to unity, i.e. they represent probabilities.

actual price changes to obtain the expected frequency for that digram. For example, a digram 12 has the following expected frequency:

$$\text{expected frequency} = (\text{theoretical probability of digram 12}) \times \times(\text{total number of price changes}) \tag{3.2}$$

TABLE 5.	**THEORETICAL PROBABILITIES OF DIGRAMS**
DIGRAMS	**Probabilities**
11 or 22	2/6
12 or 21	1/6

Step 4. If the obtained Chi-square value is statistically significant, we proceed to generate the $2 \times 2 \times 2$ trigram transition array with eight trigrams, otherwise we stop. For the trigram array, the trigram is ijk , where i , j , or k are either 1 s or 2 s.

Step 5. Again the series of all possible trigrams will be counted and the results are the observed frequencies to be compared with the expected frequencies in the familiar Chi-square test. The expected frequencies are based on the following corresponding theoretical probability Table 6. These probabilities are multiplied by the total number of trigrams in the data to obtain the expected frequency for each trigram.

TABLE 6.	**THEORETICAL PROBABILITIES OF TRIGRAMS**
TRIGRAMS	**Probabilities**
111 or 222	1/24
221, 211, 122 or 112	3/24
121 or 212	5/24

Step 6. If the trigram results are significant, proceed to create a $2 \times 2 \times 2 \times 2$ tetragram transition array with 16 tetragrams. For the tetragram we now examine four consecutive symbols instead of the three of the trigram.

Step 7. The probability table for the tetragrams is as in Table 7.

TABLE 7.	**THEORETICAL PROBABILITIES OF TETRAGRAMS**
TETRAGRAMS	**Probabilities**
1111 or 2222	1/120
1112, 1222, 2111 or 2221	4/120
1121, 1211, 2122 or 2212	9/120
1122 or 2211	6/120
1212 or 2121	16/120
1221 or 2112	11/120

Step 8. In principle one can so proceed until the test results are all insignificant and independence is ascertained. However, for the Relative Price Change Transition (RPCT) arrays, which recognize only two categories per possible transition, the empirical results of this paper based on the weekly stock market price index changes stopped already with the digrams, when almost all the results remained

statistically insignificant. However, we use the same theoretical probabilities for the trigrams and tetragrams in Section 3.4, when we discuss the test results based on the Category Price Change Transition (CPCT) arrays.

3.2.1. *Chi-Square Test Results.* Table 8 shows that the Chi-square tests for the RPCT arrays based on the weekly price levels were significant, but those based on the price index changes (important for the random walk hypothesis) for the digram and beyond were insignificant. This supports the earlier findings that weekly price index levels show de nite serial dependencies because of trend phenomena, which could be pro tably exploited by technical trading. However, such immediate serial dependencies appear not to exist between successive price changes. Immediate weekly changes in the direction of the market pricing are unpredictable also in all six Asian stock markets, despite their apparent institutional inefficiencies.

TABLE 8. INDEPENDENCE CHI-SQ. TESTS BASED ON RELATIVE PRICE TRANSITION MATRICES

DIGRAMS COUNTRIES	Weekly Level	Weekly First Difference
HONG KONG	114.47	0.19
INDONESIA	190.57	9.03
MALAYSIA	128.88	4.27
SINGAPORE	69.15	1.54
TAIWAN	162.47	1.25
THAILAND	126.93	3.61
Note:	Critical value at 1% significance is	11.34

Although the Chi-square test results for the digrams of all six Asian stock markets are insignificant, we ve computed the trigram and tetragram transition matrices for all of them to detect if there were longer transition dependencies. For Hong Kong, Malaysia, Singapore, Taiwan and Thailand, the Chi-square values remained insignificant. But, interestingly enough, Indonesia has signi cant values for the trigram and tetragram transition arrays, despite the insigni cant result for its digram matrix. On closer examination, we discovered that the Jakarta Index has a statistically significant number of 222 trigrams and 2222 tetragrams. This means that in the ten-year period this stock market price index had a signi cant number of price increases with each subsequent price increase usually being higher than the preceding one.

In other words, the Jakarta Index is prone to extreme upswings (This observation is to conform the asymmetric cumulative distribution in Fig. 2, which has an extreme long positive tail). A plausible explanation is that investors in Indonesia are considerably in uenced by previous prices and do not trade primarily on new information. They extrapolate price behavior from the past, in particular when bullish sentiment prevails.

Note that the results for the RPCT arrays and the preceding differential spectra results appear to be in con ict. However, we can resolve this con ict, as follows: differential spectra tests for symmetry about the mean for the underlying (unknown) distribution, whereas transition matrices searches for statistically significant runs in the innovations. Hence, in the context of the two subsequent lines of research in the literature, the first one emphasizing distributional aspects and the second serial dependencies (Cf. section 1.1), it may be entirely possible to encounter a symmetrical distribution of weekly price changes and yet possess a statistically significant number of runs. It also follows that the transition matrix is a powerful test for the detection of *serial* dependencies.

3.3. **Length of Temporal Trading Windows.** Instead of looking at immediately sequential price changes, the relative price change transition (RPCT) arrays can also be used to determine the existence, as well as the duration, of a temporal window during which the price changes exhibit serial dependencies. A lag-n window examines the existence of serial dependencies between a particular price change with the nth price change. This would mean if a temporal window is identi ed, a reasoned trading strategy based on pattern detection methods can be devised within the domain of this window. If we trade outside the domain of this identi ed window, we may become seduced by the Gambler s Paradox, following a winning streak , which means that in the long run we ll depend on luck and ultimately will lose. In addition, if no temporal window can be identi ed, technical analysis is useless.

The following recipe is used to test for such temporal windows:

Step 1. Using the same procedure as in the preceding section, the symbol 1 or 2 is assigned to each price change.

Step 2. A lag-n window is generated by pairing the first symbol with the nth, the second with the $(n+1)$th, and so on.

Step 3. A lag-n temporal window is determined by tabulating the frequency associated with each transition matrix. These frequencies are used as observed values.

Step 4. The observed values are compared to the temporal windows under independence. The theoretical probability of a 1,1 or a 2,2 occurrence is 1/6 and the probability of a 2,1 or a 1,2 is 2/6, as before.

Step 5. The Chi-square test is carried out. If the Chi-square value is significant, the series is not independent and higher order temporal windows will be developed, otherwise the procedure stops. Here we only report the tests for temporal windows of up to and including lag 5, i.e. a temporal window of one and a half months..

3.3.1. *Chi-square Test Results.* The Chi-square temporal window test reveals that the lag-2 digrams for weekly price changes in the first column of Table 9 are all insignificant. But the higher order lags, from lag-3 up to and including lag-5 are significant. A possible explanation is that lags of two weeks (= half a month) do not reveal dependencies, but those around four weeks, or about one month, do. This would indicate an acceptably uncertain monthly periodicity in the stock markets pricing. The periodicity is not precise, perhaps because of different holidays and other trading interruptions.

TABLE 9.	WINDOW	CHI-SQ. TEST	ON WEEKLY	PRICE CHANGES
COUNTRIES	Lag-2	Lag-3*	Lag-4*	Lag-5*
Hong Kong	0.19	66.35	36.45	92.58
Indonesia	9.03	57.8	33.86	47.27
Malaysia	4.27	72.66	71.47	49.66
Singapore	1.54	83.14	56.08	58.20
Taiwan	1.25	78.98	95.36	42.76
Thailand	3.61	34.39	69.95	70.65
Note:	* Critical value for	the digram at	1% significance	is 11.34

3.4. **Category Price Change Transition Arrays.** Using category price change transition (CPCT) arrays, the underlying stock market price change series can be examined in greater detail than with the relative price change transition (RPCT) arrays of the preceding two sections. One determines if relatively large or small price changes deviate from independence, by categorizing these time series according to a set of predetermined criteria. One can have as many categories as one desires and the categories can be in any fashion, as long as some non-varying rule for categorization is used. It is important to emphasize that if a series categorized by one set of criteria is determined to be independent, this does not imply that a categorization by different criteria also leads to independence.

Thus, in principle, there is an infinite number of ways of categorizing time series to test for independence. Considering the demonstration purpose of this paper, we will only show the results for one particular categorization, although these particular results would probably be insufficient evidence. We have not yet found a way to determine what would be a sufficient number of categorizations, but multiresolution theory of dyadic scaling based on wavelet analysis is likely to provide a suitable answer to this vexing research question.[35]

The recipe to form category price change transition matrices to test for independence is again adapted from [[46], pp. 131 - 140]:

Step 1. The cumulative frequency distribution of the price changes $\varepsilon_{j,t+1}$ of Section2. is divided into three parts: the lowest 10% of the series, the next 80% and the highest 10%.

Step 2. Determine in which third each price change $\varepsilon_{j,t+1}$ belongs. If a price change belongs to the ith portion, we encode it with symbol i =1, 2, or 3, i.e. 1 represents the lowest 10% portion, 2 represents the 80% portion, and 3 the highest 10% portion of the cumulative frequency distribution of the series of weekly price changes.

Step 3. The digram category price transition (CPT) matrix is generated by specifying how often a 1 , 2 or 3 is followed by 1 , 2 or 3 . The frequency of occurrence of a symbol i is the number of price changes in the i portion

Step 4. As before, the theoretical probability of occurrence of each component in the digram is computed and the result is multiplied with the total number of price changes to obtain the expected frequency for that digram. In contrast to the RPCT array, the determination of the probability of occurrence of each digram follows the multiplication rule of classical probability theory for assumed independent occurrences. For example, a 13 digram has the following expected frequency:

$$\begin{aligned} \text{expected frequency} &= (\text{theoretical probability of } 1) \times \\ &(\text{theoretical probability of } 3) \\ &\times (\text{total number of price changes}) \end{aligned} \tag{3.3}$$

Thus the theoretical probability of our 13 digram is about $0.1 \times 0.1 = 0.01$.

Step 5. The usual Chi-square test is again carried out by comparing the observed frequencies with the expected values obtained in Step 4.

Step 6. If the Chi-square result obtained is significant, it implies that the series is not digram independent when categorized in a $10\% - 80\% - 10\%$ pattern. Hence, we will continue with the trigram and tetragram transition arrays as in Section 3.2. Again it should be emphasized that the categorization in the $10\% - 80\% - 10\%$ pattern is arbitrary. One could choose another pattern, e.g., $20\% - 70\% - 10\%$ and construct the digram matrices, followed by the trigram, tetragram, etc.

3.4.1. *Chi-square Test Results.* Using category price change transition (CPCT) arrays, Table 10 shows that only Singapore s price changes are insignificant for the digram transition. All the other Asian stock markets show significant dependencies, using the $10\% - 80\% - 10\%$ CPCT arrays.

TABLE 10.	INDEPENDENCE CATEGORY PRICE	CHI-SQARE TESTS TRANSITION	BASED ON ARRAYS
	COUNTRIES	Level (CPT)	First Difference (CPCT)
DIGRAMS*	Hong Kong	836.22	40.98
	Indonesia	712.87	24.96
	Malaysia	817.55	38.61
	Singapore	779.76	**12.13***
	Taiwan	895.75	97.26
	Thailand	677.11	20.93
TRIGRAMS	Hong Kong	7129.95	168.95
	Indonesia	6562.13	275.64
	Malaysia	7471.75	113.07
	Singapore	6610.28	**
	Taiwan	8168.89	436.07
	Thailand	5959.45	75.77
TETRAGRAMS	Hong Kong	59880.36	745.90
	Indonesia	57043.06	456.32
	Malaysia	66302.75	551.78
	Singapore	54924.94	**
	Taiwan	72805.31	1645.89
	Thailand	48884.96	324.64
Notes:	* Critical value for the	Digram at 1% significance	is 20.09
	# Critical value for the	Trigram at 1% significance	is 45.64
	@ Critical value for the	Tetragram at 1% significance	is 112.33
	** No further testing is	required	

For Singapore, using CPCT arrays, the independence of weekly price changes is not rejected. Thus an investor would not be able to predict weekly stock prices in

Singapore, because the price changes are independent, although technical trading based on some extrapolation of trends would still be possible. As Sherry asserts: It is important to realize that you can make money, especially in the short run, with an independent (and stationary) process. Otherwise gambling establishments would have gone long since out of business. [[46], p. 86].

These short term trends are eliminated by taking the first differences. Hence, the fact that a market is independent may not necessarily rule out all possible successful filter rules for very short term windows based on price trends. A Kalman filter, for example, uses Markov transitions and exploits some very simple short term symmetric patterns.[20] But independence of market pricing does mean that if you continue to make buy-sell decisions for a long period of time using the same extrapolation rule, you will lose!

3.5. **Markov Analysis of CPCT Arrays.** Markov analysis was developed by a Russian statistician Andrei A. Markov about a century ago, which permits to specify the level at which serial dependencies exists.[16] While in the preceding section, we looked with the digram transition matrices at zero-order Markov processes, in this section we examine higher order Markov processes. An rth-order Markov process means that the probability of occurrence of a specific price change depends on the immediate preceding r price changes. When the price changes $\varepsilon_{j,t+1}$ follow a Markov process of the first order, their dependence would have the form:

$$P_{j,t+1} - P_{j,t} = \varepsilon_{j,t+1} = A\varepsilon_{j,t} + \eta_{j,t+1}, \tag{3.4}$$

where $\eta_{j,t+1}$ is some form of, unspecified, residual.[17]

Our recipe for the Markov analysis of the CPCT matrices follows again [[46], pp. 140 - 160]:

Step 1: Start with the test for a zero-order Markov process, as in the preceding section. Since their are, in principle, an in nite number of ways of categorizing a time series for non-parametric independence tests, in this section a slightly different categorization is used. Now the time series of the price changes $\varepsilon_{j,t+1}$ is divided in approximately equal thirds, i.e., with three $33.33\% - 33.33\% - 33.33\%$ categories.

Step 2: The category price change transition analysis is performed as before with the Chi-square test to determine if a zero-order Markov process is significant. The degrees of freedom for a zero-order Markov process is $(C-1)^2$, where C is the number of states . For example, digrams have $C = 2$ states so that the degrees

[16]The Russian mathematician Andrei Andreyevich Markov (1856 - 1922) studied sequences of mutually dependent variables, hoping to establish the limiting laws of probability in their most general form. Markov gave particular emphasis to Markov chains sequences of random variables in which the future variable is determined by the present variable, but is independent of the way in which the present state arose from its predecessors. A random walk is a special case of a Markov chain, where the transition matrix is an identity. In 1923, the American mathematician Norbert Wiener (1894 - 1964) became the first to treat rigorously a continuous Markov process (= Wiener process). A special case is the continuous random walk or Brownian motion, which is a continuous-time martingale [Cf. [45], p. 25]. The theoretical foundation of a general theory of stochastic processes was provided during the 1930s by another Russian mathematician, Andrei Nikolaevich Kolmogorov (1903 - 1987), who de ned the (now classical) Kolmogorov probability. Other, non-Kolmogorovian, probability theories exist.

[17]Interestingly, this approach can lead to a seemingly in nite Chinese box approximation, where the next question is if these unspeci ed shocks $\eta_{j,t+1}$ independent of each other, etc., except that there is no self-similarity as in the case of wavelets.

of freedom is $(C-1)^2 = 1$, while trigrams have $C = 3$ states and the degrees of freedom is $(C-1)^2 = 4$.

Step 3: If the value obtained is statistically significant, it means that the price changes $\varepsilon_{j,t+1}$ are not independent and a higher order Markov process (order-1) should be modeled. For an order-1 Markov process, the Chi-square test statistic is calculated as follows:

$$\chi^2 = \sum_{ijk} \frac{(O_{ijk} - E_{ijk})^2}{E_{ijk}} \tag{3.5}$$

, where O_{ijk} is the observed number of occurrences of trigram ijk . E_{ijk} is the expected number of occurrences of the trigram ijk , de ned as follows:

$$E_{ijk} = \frac{O_{.jk}O_{ij.}}{O_{.j.}}. \tag{3.6}$$

In case of $O_{.jk}$ the trigram will begin with any symbol (that is 1, 2 or 3), but will end with a specific digram jk. In case of $O_{ij.}$ the trigram begins with a specific digram ij , but ends with any symbol. Finally, in case of $O_{.j.}$ the trigram begins and ends with any symbol, but has a specific symbol in the middle. The degrees of freedom for this order-1 Markov process test for trigrams is $C(C-1)^2 = 3(3-1)^2 = 12$. If the calculated Chi-square value is still significant, we perform an order-2 Markov analysis.

Step 4: For an order-2 Markov process, the Chi-square test statistic is calculated as follows:

$$\chi^2 = \sum_{ijkl} \frac{(O_{ijkl} - E_{ijkl})^2}{E_{ijkl}}, \tag{3.7}$$

where E_{ijkl}, the expected number of occurrences of the tetragram $ijkl$ is de ned as:

$$E_{ijkl} = \frac{O_{.jkl}O_{ijk.}}{O_{.jk.}}. \tag{3.8}$$

The degrees of freedom for this order-2 Markov process Chi-square test on trigrams is $C^2(C-1)^2 = 3^2(3-1)^2 = 36$. If the calculated Chi-square value is statistically significant, an order-3 Markov process would be performed, etc.

3.5.1. *Chi-square Test Results.* Using category price change transition (CPCT) arrays, Table 11 shows that only the price changes of Hong Kong and Singapore are insignificant for the order-0 Markov transition, but the other stock markets show significant order-0 Markov dependency. Indonesia, Malaysia and Thailand show insignificant order-1 Markov transitions, with Taiwan still showing a significant order-1 Markov transition dependency. Only at the order-2 level Taiwan also shows insignificant dependency.

Thus for Hong Kong and Singapore, using Markov transitions, the independence of weekly price changes is not rejected and Markov transition based predictions would not necessarily show abnormal results. In Indonesia, Malaysia and Thailand buy-sell decisions based on simple Markov models, with a one week serial dependence, could possibly pay off. In other words, the pure random walk is rejected, since there is a detectable minor serial dependence structure in the price changes. In Taiwan the residual serial Markov dependence stretches to two weeks. This clearly shows, again, that there is much more complex, although very subtle, pattern structure in these speculative stock market data than the simple random walk hypothesis suggests.

TABLE 11.	INDEPENDENCE MARKOV ANALYSIS	CHI-SQARE TESTS OF CPT AND CPCT	BASED ON ARRAYS
	COUNTRIES	Level	First Difference
0-ORDER*	Hong Kong	894.18	**0.50***
	Indonesia	682.36	73.39
	Malaysia	958.13	13.42
	Singapore	971.77	**2.03***
	Taiwan	815.56	26.38
	Thailand	790.63	19.64
1-ORDER#	Hong Kong	44.09	**
	Indonesia	50.11	**19.18#**
	Malaysia	68.96	**21.86#**
	Singapore	86.77	**
	Taiwan	57.12	58.67
	Thailand	41.99	**20.44#**
2-ORDER@	Hong Kong	165.12	**
	Indonesia	**29.98@**	**
	Malaysia	**83.85@**	**
	Singapore	**53.54@**	**
	Taiwan	**13.87@**	**33.28@**
	Thailand	113.51	**
Notes:	* Critical value for the 0-order	at 1% significance is 13.28	
	# Critical value for the 1-order	at 1% significance is 26.22	
	@ Critical value for the 2-order	at 1% significance is 112.33	
	** No further testing is required		

4. RANDOMNESS TESTS?

Since we find significant divergences from independence in the weekly price index changes in all six Asian stock markets, these price changes do not behave in the same manner as random events. A random event is one whose outcome is determined purely by chance. For example, like ipping a fair coin (which is an abstraction!), or, the statisticians favorite abstraction, like taking balls from a small urn lled with colored balls. If we assume that all balls are exactly the same except for color, then each ball is, in this abstract model, equally likely to be chosen, so the selection process is random.

However, we find that the current weekly price changes has already been impacted by a number of previous price changes that have occurred. The precise number of these impacts depends on the size of the temporal window that we detected when we found this divergence from independence. Similarly, the current price change will also impact future price changes.

As Sherry states: Therefore, it seems likely that once a particular price change has been determined, this determination limits the size of the frequency histogram of potential future price changes. [[46], p. 202]. The types of nite constraints placed on the frequency histogram of price changes by this selection of a specific price change is not clear at this point and requires considerable future work. Via a different route, using prime numbers, the mathematical system theorist Kalman comes to a similar conclusion that the niteness of the real world eliminates the possibility of actually observing true randomness. [21], [23], [22].

Thus it does not make much sense to test for pure randomness, when true randomness is impossible to observe. The abstraction of the true randomness cannot function even as a nul hypothesis. The observation of particular dependent price changes conditions and limits the observable distribution, which may be random only within the constraints of the new frequency histogram. The observable distribution can only be conditionally and not unconditionally random. [18]

5. CONCLUSIONS

All test results of this paper have been summarized in Table 12. From Table 12, we conclude that, like the Dow Jones Industrial Index of the New York Stock Exchange, the indices of the six Asian stock markets in the region do not pass all the efficiency tests of [46]. For these stock markets the random walk hypothesis of market pricing is soundly rejected. However, these Asian stock markets demonstrate different degrees and dimensions of efficiency. We are therefore tempted to rank the Asian stock markets according to the number of Sherry s efficiency tests each passes.

On that admittedly oversimpli ed score, Singapore appears to be the most efficient of the six Asian stock markets. Qua level of market efficiency, as measured by Sherry s scores, Singapore is followed by Thailand, Indonesia, Malaysia, Hong Kong and Taiwan, respectively.

Since the Hong Kong and Taiwan stock markets show nonstationary distributions for their weekly price changes, their trading regimes and pricing processes are inconsistent over time. Technical analysis is unlikely to work in these stock markets, because the underlying rules that generate the time series of prices change from time to time without warning. For example, this year the government of Hong Kong suddenly threw its previous free-market philosophy to the wind and in August 1998 massively purchased stocks in the Hong Kong stock market. These markets are inefficient, because in these two Asian stock markets investors face both maximum uncertainty (= Dirac delta type discontinuities of regime shifts) and divergence from independence (= unfair games).

In contrast, Indonesia, Malaysia, Singapore and Thailand produce stationary weekly price changes, which are serially dependent. Their underlying trading rules generate price changes which demonstrate both consistency and dependence, meaning, first, that these stock markets are inefficient because of the serial dependencies

[18] In case the reader is curious like we are, all six Asian stock markets show random weekly price changes, using [46] s direct test. His direct test is to divide the data series of the weekly price changes into odd and even changes, the odd half and the even half . Create a frequency table for each half and convert these tables into densities by dividing the frequency of occurrences in each bin by the total number of price changes. Construct cumulative density distributions with the percentile graphs with the 45^o line and conduct the usual Chi-square test, as in Section 3.1, using the odd price changes as expected and the even price changes as observed, or *vice versa*. Of course, these weekly price changes are nonrandom based on the indirect tests which reveal the time-dependencies.

TABLE 12.: CHI-SQUARE TESTS FOR STOCK MARKET DATA
PRICE INDEX CHANGES ∆Pt

WEEKLY DATA	Hong Kong	Indonesia	Malaysia	Singapore	Taiwan	Thailand
1. STATIONARITY	●	✓	✓	✓	●	✓
2. INDEPENDENCE						
Differential Spectra	●	✓	●	✓	✓	✓
Transition Matrices						
Digrams (Lag-2)	✓	✓	✓	✓	✓	✓
Digram Temporal Windows						
Lag-2	✓	✓	✓	✓	✓	✓
Lag-3	●	●	●	●	●	●
Lag-4	●	●	●	●	●	●
Lag-5	●	●	●	●	●	●
Category PT Matrices						
Digrams	●	●	●	✓	●	●
Trigrams	●	●	●		●	●
Quadgrams	●	●	●		●	●
Markov Transition Matrices						
Zero-order	✓	●	●	✓	●	●
First-order		✓	✓		●	✓
Second-order					✓	

~~Note:~~
A black ball ● indicates that the particular data series does NOT exhibit the characteristic
A check mark ✓ indicates that the particular series DOES exhibit the characteristic

FIGURE 14

and, second, that in these stock markets technical analysis likely succeeds in identifying potential low risk/high reward trades.

The degree of uncertainty in these four markets is less than in Hong Kong or Taiwan, although there is divergence from independence of the price changes (= unfair games). But in these markets most of the available information about future price changes can be obtained by studying their past history. The market risk, or price volatility of these markets can thus be properly measured and investment in the detection of financial patterns that might act as signals for buy-sell decisions may pay off. Over time, the arbitrage induced by such technical trading rules will force these four stock markets to function more efficiently. Of course, there is no absolute guarantee that the governments of Indonesia, Malaysia, Singapore and Thailand will not at some future time interfere in their stock markets and cause regime shifts, i.e. cause their stock markets to be nonstationary like in Hong Kong or Taiwan.

In all six Asian stock markets we found significant lag-3, -4 and -5 temporal windows, i.e., trading windows of three, four and ve weeks, or about one-month duration. Specifically, in Indonesia, Malysia and Thailand the price changes followed zero-order Markov processes, while in Taiwan, the price changes followed (non-stationary) first-order Markov processes. These weekly Markov-type price change processes could pro tably have been exploited by Kalman filtering.

The main limitation of Sherry s methodology and therefore of the current paper is the limited frequency of observation on the Asian stock market price indices.

This paper used only weekly price changes and its conclusions hold true for only this data frequency. By focusing on daily or even much higher frequency data, e.g. tick-by-tick, a much more refined picture of the efficiency of the Asian stock markets is likely to be established. Another limitation is the subjective level of resolution of the observations and of the resulting density distributions and tests we are forced to accept by adopting Sherry s nonparametric and nonlinear methods of analysis.

Therefore, efficient (orthogonal) and systematic multi-level resolution by encompassing wavelet analysis of high frequency speculative market data should be the next step in this line of research into the statistical, microstructural characteristics of the pricing mechanisms of Asian stock markets. Wavelet analysis will not give all the answers, but they are likely to force us to ask the right questions. Instead of producing one subjective resolution of the data in time or frequency, as we ve done have done in this paper, it produces a multiresolution visualization of the data, broken down not only qua various localizations in time, i.e., by different dyadically linked time windows, but also qua various frequencies, i.e., by different dyadically linked frequency windows or bandwidths.[19]

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