The Chaotic Dynamical Approach To The Analysis of Stock Price Behavior : The case of The Stock Exchange of Thailand.

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Abstract

The concept of the Efficient Market Hypothesis (EMH) is the basis of quantitative capital market theory. Almost every financial model depends on it. However, a wide number of tests have been carried out to test the validity of the EMH, the results of these tests are not conclusive, and as such the EMH is only partially believed. The Efficient Market Hypothesis is based on certain key assumptions ; Fair Price, Rational Investor, No Memory and Random Walk. These assumptions are at best only partially true. This has led to the development of a new approach based on Chaos Theory. It is believed that the Chaos theory will better explain the behavior of a financial asset because of the feedback system. In chaotic dynamics there are three important concepts ; Feed Back System, Phase System, Attractor, Sensitive Dependence on Initial Conditions, Fractal Strucutre. These concepts are important in explaining the behavior of the Stock Prices. In addition, the Chaos theory deals with the random-appearing or chaotic process, which is believed to better reflect the behavior of the financial assets.

A number of empirical studies about the chaotic behavior, covering stocks, commodity and money markets have been carried out in the United States and Europe. The results showed that some financial markets are chaotic, whereas some are not.

In this paper, methodologies based on Chaos theory, particularly Fractal Market Hypothesis will be used to study the behavior of the Stock exchange of Thailand (SET). Hurst Exponent and Lyapunov Exponent will be discussed in relation to the SET index. The paper is divided into five parts, in the first section we discuss the limitations of the EMH and explain an alternative hypothesis based on Chaos theory, in the second part we look at the implications of the Chaos theory in the Stock Market including the different exponents which can be used to study the behavior of the Stock Market. More specifically, we look at the Hurst Exponent(Rescale Range (R/S) Analysis), Lyapunov

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Exponent and the Correlation Dimension. In the third section we look at the Fractal Market Hypothesis (FMH) as an alternative to EMH, in the fourth part we discuss the results of the analysis on the SET and in the last section we draw some conclusions and make recommendations. In this study, we emplyed three techniques mentioned above, and used three frequencies of the data- monthly, weekly and daily data. The data was collected for the period April 30 , 1975 the start of the Stock Exchange of Thailand (SET) to September 30, 1998. The data was whitened and detrended for inflation using the Consumer Price Index. The results indicate the limitations of the Efficient Market Hypothesis. The study also shows that the market has a memory and has at least two dynamical variables.

Key words : chaotic behavior, correlation dimension, EMH, Fractal dimension, Fractal Market Hypothesis, Fractal time series, Hurst exponent, Lyapunov exponent, stock exchange of Thailand, Rescale range analyses.

The Limitations of the EMH

The EMH states that information is widely and cheaply available to investors, and that all relevant and ascertainable information is reflected in security prices (Fama 1970, 1975). If prices always reflect all relevant information, then they will change only when new information arrives. However, new information by definition cannot be predicted ahead of time; otherwise, it would not be new information. Consequently, price changes cannot be predicted ahead of time. If stock prices already reflect all information, which is predictable, then stock price changes must reflect only the unpredictable information. The series of price changes, thus, must be random. In practice, however, this concept may not be followed. The reason, e.g., is that investors may not know how to interpret the available information.

The EMH is based on some few key assumptions: fair price—all information is reflected in prices; rational investor—investors are risk-averse, know what information is important for them and also know how to interpret information; no memory—markets have no memory, or yesterday's events do not influence today's events; and random walk—returns are independent, identically distributed (IID) or normally distributed. However, there are arguments against these assumptions as follows;

Fair Price

In the EMH, an efficient market is one in which assets are fairly priced based on the information available, and neither buyers nor sellers have an advantage over the information. However, in practice, this assumption is not necessarily true. Investors may ignore information, because they might not know how to interpret them, until trends are well in place and then react in a cumulative fashion to all the information previously ignored. In addition, a market is made up of many individuals with many different investment horizons. The behavior of any individual is different from another. Therefore, each individual may interpret information in different ways and at different times.

Rational Investor

Rationality is defined as the ability to value securities on the basis of all available information and to price them accordingly. Rational investors know what information is important and what is not for them. They are risk-averse, require risk/return trade-off. However, there are evidences indicating that investors are not rational. They may not know how to interpret all known information and might react to trends. Also, investors tend to be risk-seeking when losses are involved. They are more likely to gamble, if gambling can minimize their losses. Nevertheless, investors are not accurate and not unbiased at all time. They may have, sometimes, a common tendency to be overconfident of their own predictions.

No Memory

The EMH states that the sequences of past price changes contain no information about future price changes; more concisely, markets have no memory. However, what is missing in the EMH is the qualitative aspect, which comes from human decision making. Investors as human being are influenced by what has happened. Their expectations about the future are shaped by their recent experiences. In fact, if markets have no memory, how can one explain the reluctance of financial managers to issue stocks after a fall in price, or favor equity rather than debt financing after an abnormal price rise.

Random Walk

Following the concepts; prices reflecting all known information, investors being rational and markets having no memory, price changes become random or follow the random walk theory (Alexander.S.1964). If enough price changes are collected, their probability distribution should be a normal distribution. However, a number of empirical studies (Gupta et al 1994, Yong 1990) on probability distribution of price changes indicate that price changes are often negatively skewed. The explanation for this may be because prices fall faster than they rise. Also, many studies indicated that the probability distribution of price changes shows fatter tail and higher peak around the mean than predicted by normal distribution, a condition called "leptokurtosis." These call into question the probability distribution of price changes.

Nevertheless, a number of investment strategies, such as trend analysis, market timing, value investing and tactical asset allocation, do work in practice, even they should not work if markets are efficient(Chou 1989; Sweeney.R.J. 1990). Conversely, strategies which depend on the EMH, such as Capital Asset Pricing Model and most option-pricing theory, become suspect.

Chaotic Behavior

In dynamical system, the distinction between deterministic and probabilistic processes is that the deterministic process is one in which the evolution of behavior is completely determined by initial conditions of motion, while that of probabilistic one is irregular and not determined by any law. Chaotic process, on the other hand, is neither deterministic nor probabilistic. It falls into both categories . It refers to the irregular, unpredictable pattern of deterministic, nonlinear process. Consequently, the presence of chaotic behavior, whether probabilistic or deterministic, may be difficult to distinguish.

However, there is a way to distinguish chaotic from probabilistic processes. Chaotic process, is finite-dimensional, whereas probabilistic process is infinite-dimensional. On the other hand, the distinction between chaotic and deterministic processes, apart from its appearance (chaotic process is defined as random-appearing deterministic process), is that, for chaotic process, the unpredictability cannot be avoided by just making more precise measurement of the initial conditions, even the form and parameterization of the process are perfectly known.

In chaotic dynamics, there are some important terms which are related to this study and are addressed here.

- *Feedback System*: Feedback system is defined as a set of interconnected systems, or the outputs become the inputs in the next iteration.
- *Phase Space*: Typically, the problems involved in chaotic dynamics have no single solution; they have multiple, perhaps, infinite solutions. However, all the solutions are contained in a finite space, called phase space. Consequently, visual inspection of the data in phase space is important and is a powerful tool in chaotic dynamics.
- *Attractor*: Dynamic modelers have often implicitly assumed that a dynamical system will ultimately achieve either an equilibrium, a cyclic pattern or some other orderly behavior. However, the discovery of chaos revealed that the place toward which the system goes can be a bizarre and flit endlessly in a random manner. This place is termed attractor. There are four types of attractor: fixed

point, limit cycle, torus—resembling to the surface of a doughnut and strange (chaotic)—random-appearing—attractors. Only strange attractor has sensitivity to initial condition, or is unpredictable.

- *Sensitive Dependence on Initial Conditions*: In linear dynamics, points, which are close together, would remain close together. But, in nonlinear dynamics, nearby points will diverge quickly with the passage of time. A small error will have great impact. It could dramatically affect the forecasting ability. The further ahead in time one looks, the less certain one is about the validity of the forecasts. This property is called sensitive dependence on initial conditions.
- *Fractal*: There are two terms of fractal which are mostly used in chaotic dynamics: fractal structure and fractal dimension. Fractal structure is defined as the feature of an object in which the parts are in some way related to the whole—the individual components are self-similar, and as an object which reveals more details as it is increasingly magnified. There are also two types of fractal structure: deterministic and random fractals. Deterministic fractal is generally symmetric, mostly generated by deterministic rules. Random fractal, on the other hand, does not necessarily have pieces which look like pieces of the whole. Instead, they are qualitatively related. For fractal dimension, it characterizes how the object fills its space. It describes the structure of the object as the magnification factor is changed, or how the object scales. In other words, fractal dimension describes how dense the system is. Therefore, fractal dimension can be used to measure how chaotic the system is.

The Implications of the Chaos Theory in Stock Market

When analyzing the prices of commodities, securities and financial instruments in a variety of markets, the commonly used assumption is that the probability distribution of price changes is normal distribution. This is a very natural assumption, which is based on the EMH. However, the results of techniques, based on this assumption, are not always reliable. They will be reliable only to the extent that the probability distribution of the system being analyzed is normal, or at least only over a short time period.

Because of the realization of the insufficiency of the EMH, there is new approach. This new approach is based on the Chaos theory. It sets , a priori, no assumptions concerning the probability distribution of the system being analyzed. Thus, it can be used in any situation. (In fact, unless there is sound reason to believe that the probability distribution of the system is normal, it must be viewed as, at least potentially, not-normal.) The diffusion of chaotic dynamics in financial market is because it fits the nature of financial market. More specifically, financial markets do have memory—past prices influencing present and future prices. This is in line with the feedback system of chaotic dynamics. In addition, chaotic dynamics can deal with long memory process, or long-term correlation, of the systems, even if those systems appear to be random.

In stock market, if the stock markets' behavior is chaotic, long-term price prediction is not possible because of the sensitive dependence on initial conditions. However, short-term prediction is still feasible. Furthermore, the advent of chaotic dynamics to financial market has brought new models. These models, such as long memory process and chaotic behavior, have in turn required the calculation of new attributes, such as Hurst exponent, correlation dimension and Lyapunov exponent.

Fractal Time Series

A time series is said to be random only when it is influenced by a large number of events, which are equally likely to occur. In statistical terms, it has a high number of degree of freedom. Yet, a random time series has no correlation with previous points. It will fill up whatever space it is placed in. Unlike random time series, nonrandom time series will clump together to reflect the correlation. In other words, the time series will be fractal. (A fractal time series is characterized as long memory process. Also, it can be called biased random walk time series.) In fractal geometry, a fractal shape shows fractal structure with respect to space, but for a fractal time series, it exhibits fractal structure with respect to time. As aforementioned, there are two types of fractal structure: deterministic and random fractals. In the case of fractal time series, it is random fractal. A series of stock prices is an example of random fractal time series. For instance, if daily, weekly and monthly prices are plotted, all of them will look qualitatively similar.

Hurst Exponent—Rescaled Range (R/S) Analysis

Standard statistical analysis begins by assuming that the probability distribution of the system under study is normal. Yet, if it is not normal, but close enough, standard statistical analysis can still be applied with some modifications. However, if the probability distribution of the system is not normal, or close enough, a nonparametric analysis is needed. In the case of time series, R/S analysis is such a method.

R/S analysis can distinguish fractal from random time series, or find the long memory process. It indicates the long memory process by the Hurst exponent (H), which is defined as:

$$(R/S)_n = a * n^H$$

where $(R/S)_n$ = rescaled range value for a time series of $x_1, x_2, x_3, \ldots, x_n$

n = number of observations

a = constant

H = Hurst exponent

or

$$\ln\,(R/S)_n = H * \ln\,n + \ln\,a$$

where H = derived by regressing $\ln\,(R/S)_n$ against $\ln n$

$\ln\,a$ = derived by regressing $\ln\,(R/S)_n$ against $\ln n$

If the value of H is equal 0.5, the time series is normally distributed, or has no long memory process. If $0 \leq H < 0.5$, the time series is an antipersistent or mean reverting time series. If the time series, i.e., has been up in the previous period, it is more likely to be down in the next period, and vice versa. The strength of antipersistent behavior depends on how close H is to zero. The closer it is to zero, the more strength the antipersistent behavior. When $0.5 < H \leq 1$, the time series is persistent or trend reinforcing time series. If the time series has been up in the previous period, it is more likely to be up in the next period, and vice versa. The strength of trend reinforcing behavior increases as H approaches one. A persistent time series is defined as fractal or biased random walk time series.

R/S analysis can not only indicate the probability distribution and long memory process, but can also estimate the duration of cycle—how long memory process is—of a time series. Duration is the length of time after which knowledge of initial conditions is lost. In other words, the time series will finally converge to the value of H equal 0.5, because the memory effect diminishes to a point at which it becomes unmeasurable. The duration of memory effect can be visualized by plotting the logarithmic of time against R/S value. Furthermore, R/S analysis can be used to measure how jagged a time series is. The lower the H value, the noisier is the time series, the more random-like will be the time series, as a result, the time series will be more jagged. On the other hand, higher the H value, the more apparent will be the trend, and less jagged the time series.

Correlation Dimension

The Chaos theory deals with deterministic process which appears to be random, but whose dimension is finite. Specifically, random process is defined to have high dimension, while deterministic one has low dimension. Consequently, dimension can be used as a rough indicator to distinguish deterministic from stochastic processes. In chaotic analysis, the focus is on fractal dimension. Fractal dimension also gives important information about the underlying system. The next higher integer, i.e., to the fractal dimension tells the minimum number of dynamical variable needed for modeling the dynamics of the system. It places a lower bound on the number of possible degrees of freedom. To find out the fractal dimension, correlation dimension—sometimes called correlation exponent—technique is the most extensively used procedure in chaotic dynamical analysis.

Correlation dimension is based on the Takens' embedding theorem. The Theorem states that the system's phase space can be detected with sufficiently large enough embedding dimension (m). It also states that by using time delay method, the phase space can be constructed from a single time series. In other words, by providing proper time lag and embedding dimension, the reconstructed phase space will have all the characteristics of the real phase space. Because a single time series is affected by all of the relevant dynamical variables; therefore, it contains a relatively complete historical of the dynamics. As a result, it is possible to glean the dynamics from a single time series without reference to other variables. On the basis of reconstructed phase space, then, correlation dimension can be computed by means of the correlation integral, developed by Grassberger and Procaccia (1983).

$$C_m(\varepsilon) = \lim_{N\to\infty} \lim_{\varepsilon\to 0} \frac{1}{N^2} \sum_{\substack{i,j=1 \\ i\neq j}}^{N} Z\left(\varepsilon - \left\| X_i - X_j \right\|\right)$$

where $C_m(\varepsilon)$ = correlation integral for dimension m given the ε value

m = embedding dimension

ε = small value greater than zero

N = number of sets of m - history observations

($N = T - mt + t$; T = original number of observations, t = time lag)

$Z(\bullet) = 1$ if $\varepsilon - \|\bullet\| > 0$; 0 otherwise

$\|\bullet\|$ = Euclidean length (e.g., $\|X_i - Y_i\| = \sqrt{\left[(x_1 - y_1)^2 + (x_2 - y_2)^2 + \ldots + (x_n - y_n)^2\right]}$)

X_i = a set of m - history observations

When the value of ε is increased, $C_m(\varepsilon)$ will increase at the rate of ε^D, and gives the following relation:

$$C_m(\varepsilon) = \varepsilon^D$$

or

$$\ln\ C_m(\varepsilon) = D\ *\ \ln\ \varepsilon + \text{constant}$$

$$\text{where } D = \text{correlation dimension}$$

$$\text{constant} = \text{derived by regressing } \ln\ C_m(\varepsilon) \text{ against } \ln\ \varepsilon$$

By finding the slope of a graph of ln $C_m(\varepsilon)$ with ln ε, the correlation dimension can be estimated. The procedure is repeated for a sequence of increasing values of m. The correlation dimension should initially increase with increasing values of m. However, at some points, it should level off and remain constant for all further values of m. That is, by increasing m, correlation dimension will eventually converge to its true value.

Like R/S analysis, correlation dimension can be used to indicate how jagged a time series is. Higher the value of correlation dimension, the more jagged the time series will be.

Lyapunov Exponent

Lyapunov exponent (λ) is of fundamental importance in studying chaotic dynamics. It provides a measure of the averaged exponential rates of convergence or divergence of nearby points. There are as many exponents as there are degrees of freedom for a system. Lyapunov exponent can be negative or positive. A negative exponent measures the exponential rate of convergence, whereas a positive one measures the exponential rate of divergence. A positive exponent also indicates chaos—implying that the system is sensitive to initial conditions, and sets the time scale on which the state of prediction is possible. For a system to be specified as chaotic, there must be at least one positive Lyapunov exponent.

In time series analysis, by the well-known technique of phase space reconstruction, the full spectrum of Lyapunov exponents may be calculated, but most of the methods for doing so are very complex. However, there is a straight forward algorithm for calculating the largest positive Lyapunov exponent. This exponent measures how quickly linear distances grow, and it places an upper limit on the prediction time for a system. Smaller exponents have less effect but shorten the prediction time. The bigger the largest positive Lyapunov exponent, the more rapid the loss of predictive power, and the less the prediction time for the system.

Wolf et al (1985) give an algorithm for obtaining the largest Lyapunov exponent from a time series. The approach is based on following the divergence of a neighboring orbit from a fiducial orbit as shown in Figure 1.

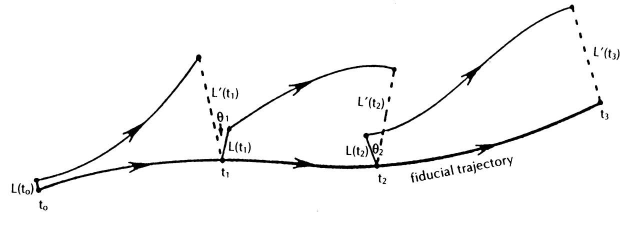

Figure 1: Artist's Sketch of Wolf et al Algorithm for Estimating the Largest Positive Lyapunov Exponent from a Time Series (Reproduced from Peters, 1991).

Over a time interval, t_0 to t_1, the rate of divergence of two points which evolve from $L(t_0)$ to $L'(t_1)$ may be characterized by the quantity:

$$\frac{\log_2\left(\frac{L'(t_1)}{L(t_0)}\right)}{t_1 - t_0}$$

Periodically, when the distance between the two points become large, a new neighbor point must be chosen, because the distance must be kept small. After m repetition of stretching, the rates are weighted by the fraction of time and then added to yield an experimental value for the largest positive Lyapunov exponent:

$$\lambda_l = \sum_{i=0}^{m-1} \left\{ \left[\frac{(t_{i+1} - t_i)}{\sum_{i=0}^{m-1}(t_{i+1} - t_i)} \right] \left[\frac{\log_2\left(\frac{L'(t_{i+1})}{L(t_i)}\right)}{(t_{i+1} - t_i)} \right] \right\}$$

Since $\sum_{i=0}^{m-1}(t_{i+1} - t_i) = t_m - t_o$, the equation becomes

$$\lambda_l = \frac{\sum_{i=0}^{m-1} \log_2 \left[\frac{L'(t_{i+1})}{L(t_i)} \right]}{t_m - t_o}$$

or

$$\lambda_l = \frac{1}{t} \sum_{i=0}^{m-1} \log_2 \left[\frac{L'(t_{i+1})}{L(t_i)} \right]$$

In practice, the calculation of Lyapunov exponent is by numerical experimentation. However, Wolf et al give rules of thumb in dealing with this situation. That is, two nearby points should be at least one mean orbital period apart; the embedding dimension should be larger than just the next higher integer of the correlation dimension; the maximum length of divergence of points should not be greater than 10 percent of the difference between the maximum and minimum values of the time series; and the evolution time should be long enough to measure stretching.

The unit of Lyapunov exponent is bit of information per iteration. Specifically, it is bit of loss of predictive power per unit of time. For instance, if the Lyapunov exponent of a time series is 0.05 bit per day; this means that the predictive power loss is 0.05 bit every day going forward, or the information becomes useless after 1/0.05 or 20 days. It can also be used to estimate the cycle length of a time series. In previous example, e.g., the cycle length is 20 days.

The Fractal Market Hypothesis (FMH)

If the EMH is not applied in practice, what could be the other alternatives. The FMH may be an alternative, because it can explain why market exists—the necessary requirement of market.

Market exists because investors need liquidity. They need a place where they could find a buyer/seller if they want to sell/buy. Nevertheless, market consists of different investment horizon investors. All of them need sufficient liquidity to allow them to trade with one another. Also, they want their transactions to bring a good price, not necessarily fair price. On the other hand, the EMH states nothing about liquidity. It implicitly states that there is always enough liquidity in market.

Market consists of different investment horizons. And, information which is important to each investment horizon could be different, and create different concept of fair price. If information received by market is important to all investment horizons, liquidity can be affected. However, investors are not homogeneous. Liquidity also depend on types of information. The importance of each type of information is different for each time horizon .

The FMH emphasizes the impact of liquidity and investment horizon. It states that market will be stable when many investors participate and have many different investment horizons. When a five-minute trader experiences unaffordable volatility, an investor with a longer investment horizon must step in and stabilize the market. The longer investment horizon investor will do so because, with his/her investment horizon, there is not unusual volatility. As a result, as long as market has different investment horizon investors, market will stabilize itself. The situation in which market has different investment horizon investors, conforms to the Fractal Market Hypothesis because of the fractal—self-similar—structure of the market. (That is, each investment horizon has its own bearable risk level.)

Market becomes unstable when fractal structure breaks down. A breakdown occurs when investors with long investment horizons either stop participating in the market or become short-term investors themselves. Investment horizons are shortened when investors feel that longer-term fundamental information, which is the basis of their market valuations, is no longer important or is unreliable. (Periods of economic or political crisis, when the long-term outlook becomes highly uncertain, probably account for most of these events.) The instability is characterized by extremely high levels of short-term volatility. The end result can be a substantial fall or a substantial rise in a very short time period.

All in all, fractal structure exists because it is a stable structure. As long as investors with different investment horizons participate in market, a panic at one horizon can be absorbed by the other ones as a buying/selling opportunity.

Analysis of the SET Index

In this study, we employed the three techniques described above, and used three frequencies of the data—monthly, weekly and daily data.The data was collected for the period April 30, 1975 the start of the Sock Echange of Thailand (SET) to September 30, 1998. The data was obtained from the program Analyst of Reuters(Thailand) Limited. Daily, weekly(5 day) and monthly were used in this study for the purpose of testing the stability of the tools. For the rescaled range (R/S) analysis the logarithmic returns were used, because the objective is to test whether the returns are normally distributed according to the EMH. Given the amount of data, computer programs were written using Visual Basic on Excel to carry out the computations. There are four programs used in this study, namely, R/S analysis,Correlation Dimension,Lyapunov exponent and the programs for creating the graph of ln(R/S) versus ln(n) used in R/S analysis. We used index numbers directly for correlation dimension and Lyapunov exponent, but used returns for the R/S analysis ,because returns may not be the appropriate time series for nonlinear dynamical system analysis. They whiten the data by eliminating serial dependence. The data was detrended for inflation using the Consumer Price Index .

R/S Analysis

Figure 2 shows the ln/ln plot of the monthly returns. The jagged line represents the ln/ln plot of R/S values vs numbers of observations, whereas the two straight lines represent the H-estimate lines. As shown in the Figure, the R/S values fluctuate along the 0.883-estimate line, meaning that the long memory process is at work. However, after a point, the R/S values deviate from 0.883-estimate line and follow 0.508-estimate line (approximate random walk line), or they become normally distributed. The result indicated that the monthly returns are not normally distributed. They are subject to long memory, but finite, process.

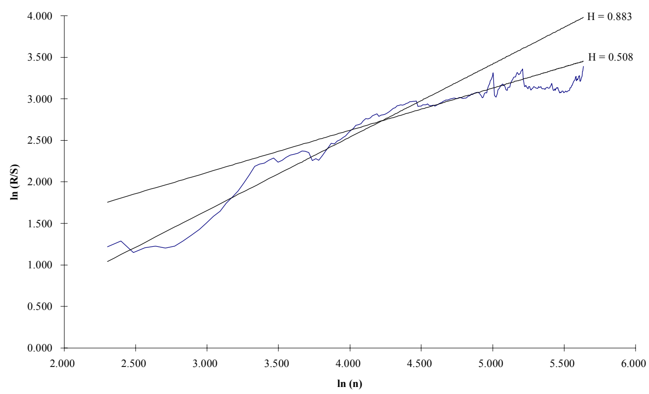

Figure 2: The Hurst Exponent of the SET Index's Monthly Returns.

For the weekly and daily returns, we found that they are also subject to long memory process. The H estimates for weekly and daily returns are 0.746 and 0.704 respectively.

By applying R/S analysis, we found that in each case (monthly, weekly or daily) returns are not normally distributed (the H estimates are not equal to 0.5). The monthly returns have the highest H value, whereas the daily returns have the lowest H value. This is because daily returns have more level of noise than monthly and weekly returns; consequently, they have lower value of H.

To test the validity of the results, we shuffled the data so that the structure of the data would be destroyed. Because the actual observations are all still there, the frequency distribution of the observations remains unchanged. After calculating the H value on the shuffled data, if the series is truly an independent series, the H value should remain virtually unchanged, because there is no memory effect or correlation between the observations.

We shuffled the monthly returns, and measured the H value of the shuffled series. We found that the H value of the monthly returns changed to 0.528, closer to 0.5 (as shown in Figure 3). In other words, the series of the returns is closer to a random walk series. Also, the R/S values of the shuffled returns fluctuate along 0.528-estimate line, and seem not to deviate from this line.

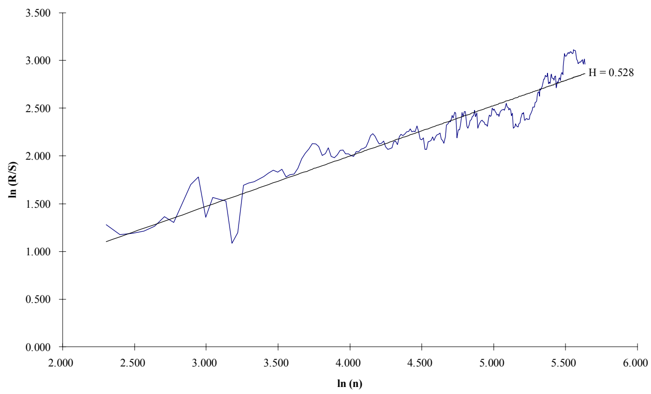

Figure 3: The Hurst Exponent of the Shuffled SET Index's Monthly Returns.

The shuffle test is also applied to the weekly and daily returns. The outcomes are similar to that of the monthly returns. The H values of the weekly and daily returns changed to 0.558 and 0.544 respectively. The shuffled H values are close to 0.5, implying that the shuffled returns are close to normal distribution. As a result, the results tell us that the returns do have a long memory effect, or they are not normally distributed.

The next question is , how long the memory effect or cycle length of the SET Index is? To find out the cycle length, we have to find out from which point the series become random. In the monthly returns, we found that after 86 observations (86 months), the observations become random. It means that the cycle length of the monthly returns is 86 months or about 7.17 years. But for the weekly and daily returns, they last for 350 weeks or about seven years , 1,720 days or about 6.88 years . This is not surprising. Because daily returns have more level of noise than monthly and weekly returns, their correlation or memory effect should diminish at a faster rate than those of monthly and weekly returns, and result in the shorter length of cycle.

As aforementioned, R/S analysis can be used to indicate the jaggedness or riskiness of a time series. The higher the H value, the less jagged the time series. For the monthly returns, we found that they have lowest risk (highest H value) among the three frequencies. In other words, the time series of the monthly returns is less jagged than those of the weekly and daily returns (as shown in Figure 4-6). (Intuitively, we are also agree that long-term investment is less risky than short-term investment.)

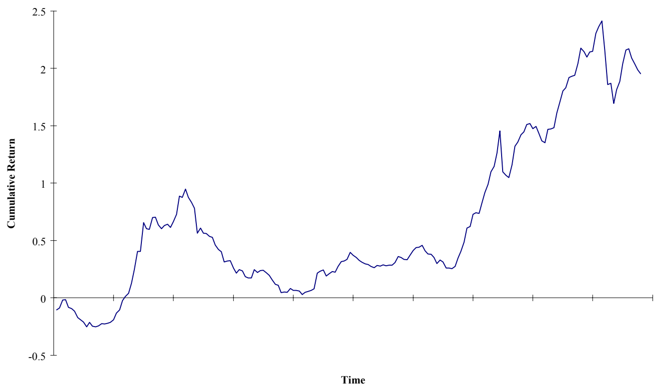

Figure 4: The Cumulative Monthly Returns of the SET Index.

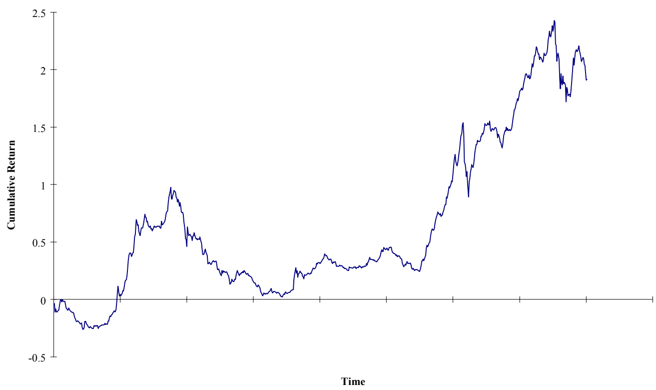

Figure 5: The Cumulative Weekly Returns of the SET Index.

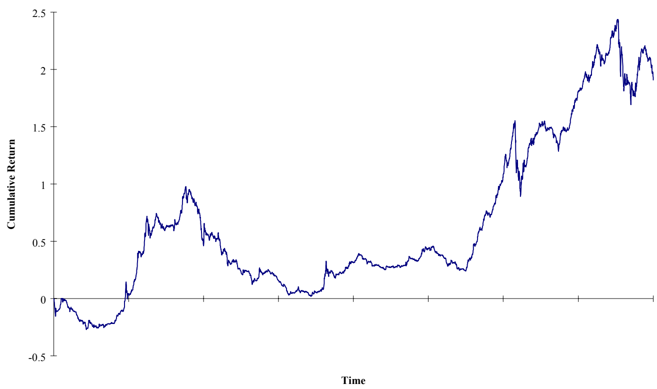

Figure 6: The Cumulative Daily Returns of the SET Index.

Correlation Dimension

In this section, we applied the correlation dimension technique to find out the SET Index's behavior. We used prices (index numbers) directly, because the objective is to forecast the price's behavior, not return's behavior. In Figure 7, we plotted the ln $C_m(\varepsilon)$ versus ln (ε) of the monthly SET Index for a variety of embedding dimensions in order to see their slopes (the slope of ln $C_m(\varepsilon)$ vs ln (ε) is the correlation dimension). If the slopes remain constant for further increasing embedding dimensions after changing at the beginning, it means that the correlation dimension converges to its true value. Unfortunately, the discrepancy of the slopes for various embedding dimensions cannot be visualized in the graph. Therefore, we calculated the slopes and plotted them in Figure 8. In

Figure 8, we can clearly visualize the convergence of the correlation dimensions. It converged to 1.88.

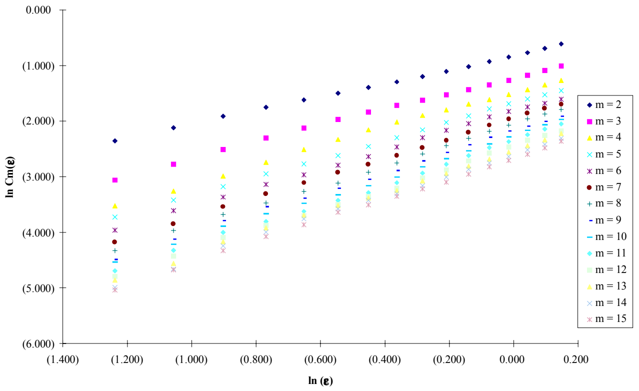

Figure 7: The Correlation Integral of the Monthly Data.

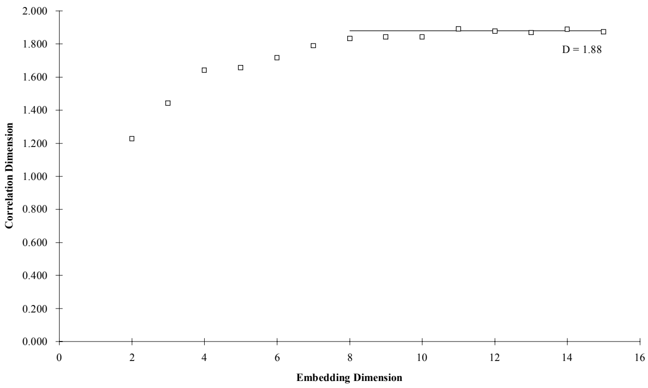

Figure 8: The Convergence of Fractal Dimension of the Monthly Data.

Using the same methodology, we found that the correlation dimension of the weekly SET Index converged to 1.73, whereas that of the daily SET Index converged to 1.69.

Consequently, we can conclude that the SET Index's behavior is deterministic, because its dimension did settle at a point. The correlation dimensions of the monthly, weekly and daily data settled at 1.88, 1.73 and 1.69 respectively. Also, the results told that the minimum factor, which affects the SET Index's behavior, is two.

In order to confirm that the SET Index's behavior is truly deterministic, we also applied the shuffle technique. If the SET Index's behavior is deterministic, by shuffling, the structure will be destroyed. The series of the SET Index will be changed to be random, and its dimension will increase with increasing embedding dimension. In this study, we shuffled only the monthly SET Index. The result confirmed that the SET Index's behavior is deterministic. The shuffled data's dimension, i.e., increased with increasing embedding dimension, and seem not to settle at any point (as shown in Figure 9-10).

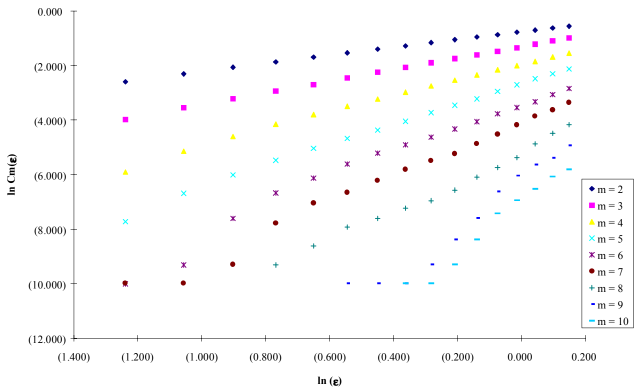

Figure 9: The Correlation Integral of the Shuffled Monthly Data.

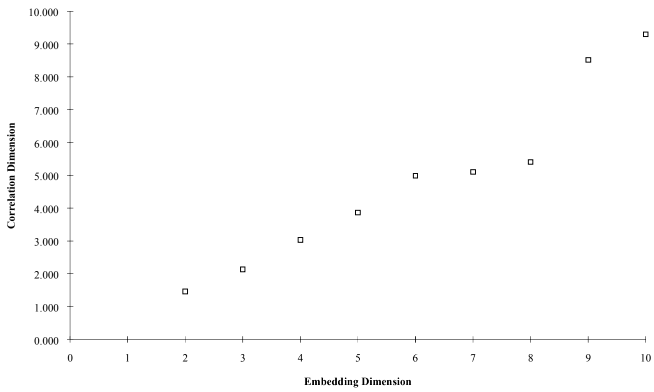

Figure 10: The Convergence of Fractal Dimension of the Shuffled Monthly Data.

Correlation dimension can be used to explain the jaggedness of a time series. The higher the dimension, the more jagged the time series. Unfortunately, the results are not encouraging. The monthly data, have higher dimension than the weekly data, and the weekly data have higher dimension than the daily data. This means that the monthly data is more jagged or riskier than weekly data, and the weekly data is riskier than the daily data, as opposed to the results from R/S analysis.

Lyapunov Exponent

As yet, we found that the SET Index is deterministic. However, to be specified as chaotic, the SET Index needs to have at least one positive Lyapunov exponent. In this study, we used three evolution times—three, six and 12 months to the Lyapunov exponent technique. Consequently, almost all the results gave positive Lyapunov exponents. In other words, the results indicated that the SET Index is chaotic.

In Figure 11, the Lyapunov exponent of the monthly SET Index for three-month evolution time stabilized at 0.040 bits per month after changing at the beginning. Similarly, the Lyapunov exponents of the six- and 12-month evolution times of the monthly SET Index are 0.025 and 0.016 bits per month respectively.

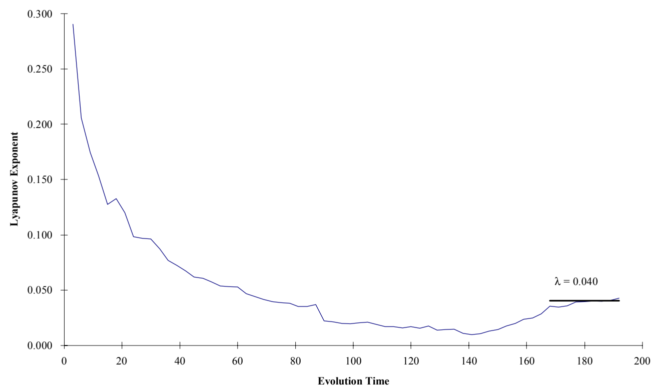

Figure 11: The Convergence of Lyapunov Exponent of the Monthly Data for Three-Month Evolution Time.

For the weekly SET Index, the Lyapunov exponents stabilized at 0.014 and 0.011 bits per week for three- and six-month evolution times. But, there is no convergence of the exponent of the weekly SET Index for the 12-month evolution time. There is, also, no convergence of the Lyapunov exponent of the daily SET Index for the 12-month evolution time. There are only the exponents for three- and six-month evolution times, 0.004 and 0.003 bits per day respectively.

Although Lyapunov exponent can be used to find out the cycle length of a time series, we cannot figure it out in this study. The results, corresponding to each evolution time and frequency of data, are somewhat different. The results gave the length of cycle ranging from one to five years. In addition, the cycle length obtained from Lyapunov exponent technique is rather different from that obtained from R/S analysis technique (about seven years).

Conclusions and recommendations

The results of the study clearly indicated the limitations of the EMH. The SET Index's returns, are not normally distributed. They are biased random walk, or fractal, time series. However, we cannot figure out the exact cycle length, or long memory process of the SET Index, because the results gave the cycle length ranging from one to seven years. The study indicated that the SET Index is chaotic, and is characterized by at least two dynamical variables. However, the study cannot indicate the exact reliable time period of prediction for the SET Index, because we cannot figure out the exact cycle length of the SET Index. Also, it did not show us, what are those two variables.

As a result of this study, we would like to make some recommendations for explaining and/or forecasting the SET index's behavior;

1. In this study, we found that the SET Index is chaotic. It means that the SET Index is random-looking deterministic process. And, we know that the minimum variable for explaining the SET Index's behavior is two. Therefore, we should find out what those two variables are, measure their impact on the SET Index's behavior, and set up the model or equation of motion of the SET Index so that we can explain and/or forecast its behavior more accurately in the future.
2. If we want to improve the efficiency of SET , we have to ensure that its returns(SET Index) follow a stochastic process. Stochastic process is defined to have infinite dimensions or degrees of freedom. This study shows that the SET

Index has only about two dimensions. In other words, it is mostly influenced by only two variables. Therefore, to make the SET Index more efficient , we have to increase the impact of other variables or reduce the impact of those two variables on the returns, so that the level of impact of each variable is about the same. In other words, we have increase the degree of freedom of the SET Index.

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