INTERNATIONAL JOURNAL OF BUSINESS, 9(2), 2004 ISSN:1083-4346

Emerging Market Equity Prices and Chaos: Evidence from Thailand Exchange

Bahram Adrangi[a], Arjun Chatrath[b], Ravindra Kamath[c], and Kambiz Raffiee[d]

[a] *School of Business Administration, University of Portland, adrangi@up.edu*
[b] *School of Business Administration, University of Portland, chatrath@p.edu*
[c] *Department of Finance, Cleveland State University, ravi@goodstart.com*
[d] *Department of Economics, University of Nevada, Reno, raffiee@unr.edu*

ABSTRACT

We test for the presence of low-dimensional chaotic structure in the Stock Exchange of Thailand (SET) Index. While we find strong evidence of nonlinear dependencies, the evidence is not consistent with chaos. Our test results indicate that ARCH-type processes generally explain the nonlinearities in the data. We also show that employing seasonally adjusted index series contributes to obtaining robust results via some of the existing tests for chaotic structure.

JEL: *G150, F300*

Keywords: *Stock Exchange of Thailand (SET) Index; Chaos; Equity markets; Emerging market economies*

I. INTRODUCTION

In this paper we investigate the behavior of the Index of the Thailand Stock Exchange Index (SET). This entails examining the index for low dimension chaos and other nonlinearities. The Stock Exchange of Thailand, formerly the Securities Exchange of Thailand, officially started trading On January 1, 1991. The SET's primary roles are: (i) to serve as a center for the trading of listed securities, and to provide the essential systems needed to facilitate securities trading, (ii) to undertake any business relating to the Securities Exchange, such as a clearing house, securities depository center, securities registrar, or similar activities and (iii) to undertake any other business approved by the SEC.

We chose the SET because of the critical role it plays in the development of Thailand's capital market. The behavior of the index, its volatility, and movements are of interest to international money managers, Thailand securities authorities, and the Thai Central Bank. Furthermore, Thailand is one of the three "new tigers" that have experienced phenomenal economic growth. New tigers have become major exporters of good and services and a focus of international investors.[1] The study of equity markets and the behavior of equity prices in emerging markets such as Thailand have become critical as international capital movements among nations have increased. For example, researchers have shown that international investors may benefit from the possibility of diversification in these markets (see Lee, 2003). Emerging market economies and capital markets benefit from the influx of foreign capital, which has stimulated further economic growth.

Chaotic behavior has piqued the interest of financial researchers in the past two decades because many economic and financial time series appear random. Random-looking variables may in fact be deterministic chaos, and thus, predictable, at least in the short-run. It has been speculated that technical analysis may be especially successful in forecasting short-term price behavior of various financial series where series are nonlinear and/or chaotic (see for example, LeBaron (1991), Brock, Lakonishok, and LeBaron (1992), Taylor (1994), Blume, Easley, and O'Hara (1994), Chang and Osler (1995), Bohan (1981), Brush (1986), Pruitt and White (1988, 1989), Clyde and Osler (1997), among others). Furthermore, modeling nonlinear processes may be less restrictive than linear structural systems because nonlinear methods are not restricted by specific knowledge of the underlying structures. Lichtenberg and Ujihara (1988), Blank (1991), DeCoster, Labys, and Mitchel (1992), Yang and Brorsen (1993) have concluded that a number of financial time series exhibit behavior consistent with deterministic chaos.

Clyde and Osler (1997) conclude that it is worthwhile to investigate chaotic behavior because, unlike random processes, nonlinear (including chaotic) ones are more conducive to technical analysis. Therefore, it would be informative to analyze the behavior of various financial data in order to determine the source of nonlinearities, if they exist. If the nonlinearity stems from chaos, then technical analysis may be applicable in the short run for prediction purposes. However, chaos would also imply that while prices are deterministic, long-range prediction based on 'technicals' or statistical forecasting techniques become treacherous, as the slightest errors in function formulation will multiply exponentially.

However, nonlinear patterns in financial and economic time series may not necessarily be consistent with chaos. Some examples may be found in Hsieh (1989), and Aczel and Josephy (1991) for exchange rates; Scheinkman and LeBaron (1989), Hsieh (1991) for stock returns, Mayfield and Mizrach (1992) for S&P index, among others. Hsieh (1993) extends this line of research to futures contracts and shows that nonlinearities in several currency futures contracts are explained by conditional variances and are not necessarily chaotic.

Our paper is distinguishable from other studies on chaos in financial markets in that (i) relatively long index histories are examined; (ii) unlike most prior research, the data are subject to adjustments for seasonalities that may otherwise have led to an erroneous conclusion of chaotic structure; (iii) a wider range of ARCH-type models are considered as explanations to the nonlinearities; (iv) alternate statistical techniques are employed to test the null of chaotic structure; and (v), we consider the emerging equity market of Thailand.

We present strong evidence that SET Index series exhibits nonlinear dependencies. However, we find evidence that is clearly inconsistent with chaotic structure. We make a case that employing seasonally adjusted index series may contribute to obtaining robust results via the existing tests for chaotic structure. We identify some commonly known ARCH-type processes that satisfactorily explain the nonlinearities in the SET Index data. This finding is particularly noteworthy in that it demonstrates the power of commonly known nonlinear models in explaining the behavior of equity prices in an emerging market. Furthermore, with the help of the past data, index behavior in the Thailand market may be predicted employing a nonlinear model.

The next section briefly motivates the tests for chaos and further discusses the implications of chaotic structure in financial price series. Simulated chaotic data is employed to highlight some important properties of chaos. Section III describes the procedures that this paper employs to test the null of chaos. Section IV presents the test results for the SET Index. Section V closes with a summary of the results.

II. CHAOS: CONCEPTS AND IMPLICATIONS FOR FINANCIAL MARKETS

Several definitions of chaos are in use. The following definition is similar to those commonly found in the literature (e.g., Devaney (1986), Brock (1986), Deneckere and Pelikan (1986), Brock and Dechert (1988), Brock and Sayers (1988), Brock, Hsieh and LeBaron (1993), Adrangi and Chatrath (2003)). The series a_t has a chaotic explanation if there exists a system (h, F, x_0) where $a_t = h(x_t)$, $x_{t+1} = F(x_t)$, x_0 is the initial condition at t = 0, and where h maps the n-dimensional phase space, R^n, to R^1, and F maps R^n to R^n. It is also required that all trajectories, x_t, lie on an attractor, A, and nearby trajectories diverge so that the system never reaches an equilibrium or even exactly repeats its path.

Adrangi and Chatrath (2003) discuss the following properties of the chaotic time paths that should be of special interest to financial market observers[2]: (i) the universality of certain routes (such as the period folding over of trajectories) that are independent of the details of the map; (ii) time paths that are extremely sensitive to microscopic changes in the parameters; this property is often termed sensitive dependence upon initial condition or SDIC[3]; and (iii) time series that appear stochastic even though they are generated by deterministic systems; i.e., the empirical spectrum and empirical autocovariance functions of chaotic series are the same as those generated by random variables, implying that chaotic series will not be identified as such by most standard techniques (such as spectral analysis or autocovariance functions).

Here we briefly illustrate some of the above properties in the framework of the Logistic equation, which is commonly presented to demonstrate the chaos phenomenon (e.g., Baumol and Benhabib (1989), Hsieh (1991)). Consider the nonlinear Logistic function with a single parameter, *w*

$$x_{t+1} = F(x_t) = wx_t(1-x_t) \tag{1}$$

Figure 1 graphs the relationship (x_{t+1}, x_t) for w=3.750, x_0=.10.[4] It should be apparent that (x_{t+1}, x_t) oscillations that form a distinctive phase diagram (the bounding parabolic curve). As the oscillations expand, they encounter and "bounce off" the phase curve, moving closer to an apparent equilibrium on the negative slope of the phase curve. However, the convergence towards any equilibrium in that vicinity can only be temporary, since the slope of the phase curve ($\partial x_{t+1}/\partial x_t = w(1-2x_t)$) is less than -1. Figure 1 also illustrates the property of period folding of trajectories in chaotic systems, and demonstrates the concept of low dimension: the chaotic map of x_{t+1} against x_t gives us a series of points in the phase curve. Even in the limit, these points would only form a one dimension set - a curve. On the other hand, had the x_{t+1} and x_t relationship been random, the points would have been scattered about the two-dimensional phase space.

To illustrate the concept of SDIC, we graph in Figures 2 and 3 the time paths (x_t, t = 1.60) for the Logistic Equation with w = 3.750, x_0= .10, and w = 3.753, x_0 = .10 respectively. It is immediately apparent that the Logistic Equation has produced fairly complex time paths. Note that the small change (an 'error') of only .003 introduced in w has caused the time path to be vastly different after only a few time periods. For instance, for the first 9 periods, the time path in Figure 2 'looks' almost identical to that in Figure 3. However, the paths after t=10 diverge substantially. While we employ the Logistic Equation to demonstrate SDIC here, the same sort of behavior holds for a very wide set of chaotic relations.

Figure 1. Logistic Map (xt+1, Xt) for periods 1-60, Xt+1=3.75.x(1-x), x0=0.10

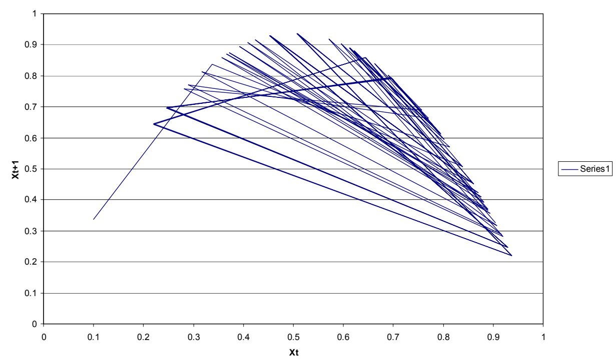


Figure 2. Time Path of Logistic Equation xt+1=3.750.x(1-x), x0=0.10

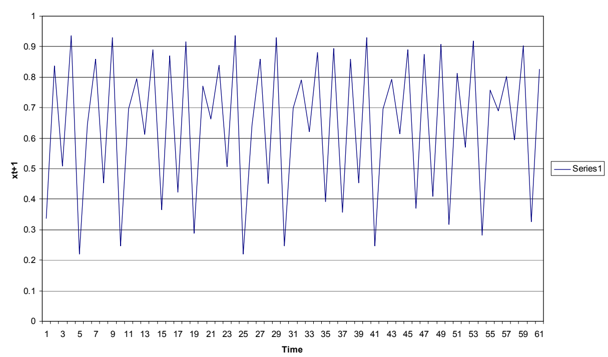
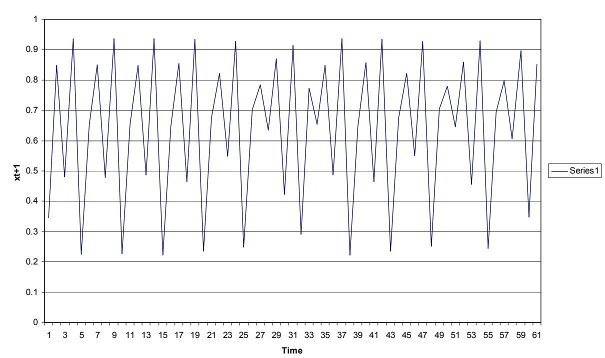


Figure 3. Time Path of Logistic equation xt+1=3.750.x(1-x), x0=0.103



It should be noted that chaotic systems might provide some advantage to forecasting/technical analysis in the very-short run (say a few days when dealing with chaotic daily data). As indicated earlier, a deterministic chaotic system is, in some respects, polar to an instantaneously unpredictable system. For instance, Clyde and Osler (1997) simulate a chaotic series and conclude that the heads-over-shoulder trading rule will be effective in generating profits (relative to random trading) in the presence of a known chaotic system. However, the results in Clyde and Osler also indicate that this property declines dramatically, such that the frequency of 'hits' by this trading rule is not significantly different from a random strategy after just a few trading periods (days).[5]

III. TESTING FOR CHAOS

The known tests for chaos attempt to determine from observed time series data whether h and F are genuinely random. Following Adrangi and Chatrath (2003), we employ three tests: the Correlation Dimension of Grassberger and Procaccia (1983) and Takens (1984), and the BDS statistic of Brock, Dechert, and Scheinkman (1987), and a measure of entropy termed Kolmogorov-Sinai invariant, also known as Kolmogorov entropy.

Among this group, Kolmogorov entropy probably is the most direct test for chaos, measuring whether nearby trajectories separate as required by chaotic structure. However, this and other tests of SDIC (e.g., Lyapunov exponent) often provide relatively fragile conclusions (e.g., Brock and Sayers (1988)), thus, the need for the alternate tests for chaos. We briefly outline the construction of the tests, but we do not address their properties at length, as they have been well established (for instance, Brock, Dechert, and Scheinkman (1987) and Brock, Hsieh and LeBaron (1993)).

A. Correlation Dimension

Imbedding a stationary time series x_t,(t=1...T[6]), in an m-dimensional space by forming M-histories starting at each date t one has: $x_t^2 = \{x_t, x_{t+1}\},.., x_t^M = \{x_t, x_{t+1}, x_{t+2},...x_{t+M-1}\}$. The stack of these scalars are employed to carry out the analysis. If the true system is n-dimensional, provided $M \geq 2n+1$, the M-histories can help recreate the dynamics of the underlying system, if they exist (Takens (1984)). By calculating the correlation integral, one can measure the spatial correlations among the M-histories. For a given embedding dimension M and a distance ε, the correlation integral is given by

$$C^M(\varepsilon) = \lim_{T \to \infty} \{\text{the number of (i,j) for which } \left\| x_i^M - x_j^M \right\| \leq \varepsilon\} / T^2 \qquad (2)$$

where $\|.\|$ is the distance induced by the norm.[7] For small values of ε, one has $C^M(\varepsilon) \sim \varepsilon^D$ where D is the dimension of the system (see Grassberger and Procaccia (1983). The Correlation Dimension in embedding dimension M is given by

$$D^M = \lim_{\varepsilon \to 0} \lim_{T \to 0} \{\ln C^M(\varepsilon) / \ln \varepsilon\} \tag{3}$$

and the Correlation Dimension is

$$D = \lim_{M \to 0} \ln D^M . \tag{4}$$

We estimate the statistic for various levels of M (e.g., Brock and Sayers (1988):

$$SC^M = \frac{\{ \ln C^M(\varepsilon_i) - \ln C^M(\varepsilon_{i-1})\}}{\{ \ln(\varepsilon_i) - \ln(\varepsilon_{i-1})\}} \tag{5}$$

The SC^M statistic is a local estimate of the slope of the C^M versus e function. Following Frank and Stengos (1989), we take the average of the three highest values of SC^M for each embedding dimension.

B. BDS Statistic

Brock, Dechert and Scheinkman (1987) applied the correlation integral to form a statistical test that may be employed to detect various types of nonlinearity as well as deterministic chaos. BDS show that if x_t is IID with a nondegenerate distribution,

$$C^M(\varepsilon) \to C^1(\varepsilon)^M \quad ,\text{as} \quad T \to \text{infinity} \tag{6}$$

for fixed M and ε. Based on this property, BDS show that the statistic

$$W^M(\varepsilon) = \sqrt{T} \; [C^M(\varepsilon) - C^1(\varepsilon)^M] / \sigma^M(\varepsilon) \tag{7}$$

where σ^M, the standard deviation of [·], has a limiting standard normal distribution under the null hypothesis of IID. W^M is known as the BDS statistic. If W^M is significant, then one concludes that a stationary series is nonlinear. If it is illustrated that the nonlinear structure stems from a known non-deterministic system, the absence of chaos is implied. For instance, significant and insignificant BDS statistics, respectively, for a stationary data series and the standardized residuals from an Auto Regressive Conditional Heteroscedasticity (ARCH) model, suggest that the ARCH process explains the nonlinearity in the data, precluding low dimension chaos.

C. Kolmogorov Entropy

Kolmogorov entropy is employed to quantify the concept of sensitive dependence on initial conditions. Consider the two trajectories in Figures 2 and 3. Initially, the two time paths are extremely close so as to be indistinguishable to a casual observer. As time passes, however, the trajectories diverge so that they become distinguishable. Kolmogorov entropy (K) measures the speed with which this takes place.

Grassberger and Procaccia (1983) devise a measure for K as

$$K_2 = \lim_{\varepsilon\to 0} \lim_{m\to \text{infinity}} \lim_{N\to \text{infinity}} \ln\left(\frac{C^M(\varepsilon)}{C^{M+1}(\varepsilon)}\right). \tag{8}$$

If a time series is non-complex and completely predictable, $K_2 \to 0$. If the time series is completely random, $K_2 \to \infty$. That is, the lower the value of K_2, the more predictable the system. For chaotic systems, one would expect $0 < K_2 < \infty$, at least in principle.

Table 1
Return diagnostics

The Table presents the return diagnostics for SET Index (daily data) over the interval, January 3, 1990 through December 30, 1998 (2205 observations). Returns are given by $R_t = \log(P_t/P_{t-1}) \cdot 100$, where P_t represents closing index value on day t. ADF, ADF(T) represent the Augmented Dickey Fuller tests (Dickey and Fuller (1981)) for unit roots, with and with out trend respectively. The Q(12) and $Q^2(12)$ statistics represent the Ljung-Box (Q) statistics for autocorrelation of the R_t and R_t^2 series respectively. The ARCH(1) statistic is the Engle (1982) test for ARCH (of order 1) and is χ^2 distributed with 1 degree of freedom. *** and * represents the significance level of .01 and 0.1, respectively.

	SET Index 1/03/1990-12/30/98
Mean	-0.041
SD	1.99
ADF	-19.99***
ADF(T)	-20.03***
Q(12)	58.13***
$Q^2(12)$	684.11***
ARCH(1)	359.16***

IV. EVIDENCE FROM THE SET INDEX VALUES

We employ The SET Index series from January 1990 through December 1998 (2205 observations).[8] We focus our tests on daily returns, which are obtained by taking the relative log of index as in $R_t=(\ln(P_t/P_{t-1}))\cdot 100$, where P_t represents the closing index value on day t.[9]

Table 1 presents the R_t diagnostics for the series. The returns series is stationary by the Augmented Dickey Fuller (ADF) statistics. There are linear and nonlinear dependencies as shown by the Q(12) and $Q^2(12)$ statistics, and Autoregressive Conditional Heteroscedasticity (ARCH) effects is suggested by the ARCH(1) chi-square statistic. Thus, there are clear signs that nonlinear dynamics are generating the SET Index values. Furthermore, these nonlinearities may be explained by ARCH effects. Whether these dynamics are chaotic in origin is the question that we turn to next. It is clear from these statistics, however, that various ARCH models may be appropriate in the study of the SET Index.

To rule out the possibility that chaos is overshadowed by linear dependencies or seasonalities, we first estimate autoregressive models for SET Index with controls for possible day-of-the-week effects, as in

$$R_t = \sum_{i=1}^{p} \beta_i R_{t-i} + \sum_{j=1}^{5} \gamma_j D_{jt} + \varepsilon_t, \tag{9}$$

where D_{jt} represent day-of-the-week dummy variables. The lag length for each series is selected based on the Akaike (1974) criterion. The residual term (ε_t) represents the index movements that are purged of linear relationships and seasonal influences. Table 2 reports the results from the OLS regressions. There is evidence of the day-of-the-week effect similar to that found in world equities (e.g., Jaffe and Westerfield (1985)). The appropriate linear structure in the return is six lags for SET Index values as indicated by the size of the Q-statistics, which indicates that the residuals are free of linear structure.

A. Correlation Dimension estimates

Table 3 reports the Correlation Dimension (SC^M) estimates for various models of the SET Index returns' series alongside that for the Logistic series developed earlier. We report dimension results for embeddings up to 20 in order to check for saturation.[10] An absence of saturation provides evidence against chaotic structure. For example, the SC^M estimates for the Logistic map stay close to 1.00, even as we increase the embedding dimensions. Furthermore, the estimates for the Logistic series do not change meaningfully after AR transformation. Thus, as one would expect, the SC^M estimates are consistent with chaos for the Logistic series.

Table 2
Linear structure and seasonality

The coefficients and residual diagnostics are from the OLS regressions of returns on prior returns and five day-of-the-week dummies. The lag-length was selected based on Akaike's (1974) criterion. The LM statistic (Chi-Squared) tests the null of no autocorrelation in the regression residuals. The Q(6) and Q(12) statistics represent the Ljung-Box (Q) statistics for autocorrelation pertaining to the residuals up to 6 and 12lags, respectively. *, **, and *** represent the significance levels of .10, .05, and .01 respectively.

SET Index	SET Index	t-statistic
C	-0.270***	(-3.39)
R_{t-1}	0.097***	(4.25)
R_{t-2}	- 0.028	(-1.23)
R_{t-3}	0.025	(1.11)
R_{t-4}	0.015	(0.69)
R_{t-5}	- 0.022	(-0.98)
R_{t-6}	-0.059***	(-2.65)
Mon	$1.17*10^{-7}$	(1.23)
Tue	$3.58*10^{-6}$***	(5.09)
Wed	-0.391***	(-3.63)
Thu	-0.243**	(-2.29)
FR		
R^2	0.048	
Q(6)	1.89	
Q(12)	8.24	
LL	3917.26	

Table 3
Correlation dimension estimates

The Table reports SC^M statistics for the Logistic series (w=3.750, n=2000), daily SET Index and their various components over four embedding dimensions: 5, 10, 15, and 20. AR(p) represents autoregressive (order p) residuals, AR(p), S represents residuals from autoregressive models that correct for day-of-the-week effects in the data.

M =	5	10	15	20
Logistic	1.02	1.00	1.03	1.06
Logistic AR	0.96	1.06	1.09	1.07
SET Returns	4.06	8.26	9.00	10.30
SET AR(6)	4.00	7.41	8.05	16.50
SET AR(6),S	3.97	7.86	7.91	29.58
SET Shuffled	3.71	7.32	7.88	26.91

For the SET Index series, on the other hand, the SC^M estimates provide evidence against chaotic structure. If one examines the estimates for the SET Index returns alone, one could (erroneously) make a case for low dimension chaos: the SC^M statistics seem to 'settle' under 10. However, the estimates for the AR(6), AR(6) with-seasonal-correction (AR(6), S), and from the random series (SET Index shuffled) are substantially higher. Thus, the Correlation Dimension estimates suggest that there is no chaotic structure in SET Index series.

For the SET Index series, on the other hand, the SC^M estimates show evidence against chaotic structure. If one examines the estimates for the SET Index returns alone, one could (erroneously) make a case for low dimension chaos: the SC^M statistics seem to 'settle' under 10. However, the estimates for the AR(6), AR(6) with-seasonal-correction (AR(6), S), and from the random series (SET Index shuffled) are substantially higher. Thus, the Correlation Dimension estimates suggest that there is no chaotic structure in SET Index series.

B. BDS Test results

Table 4 reports the BDS statistics for [AR(6),S] series, and standardized residuals ($\varepsilon/\sqrt{h}$) from three sets of ARCH-type models with their respective variance equations, GARCH(1,1):

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{10}$$

Exponential GARCH (1,1):

$$\log(h_t) = \alpha_0 + \alpha_1 \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| + \alpha_2 \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| + \beta_1 \log(h_{t-1}). \tag{11}$$

Asymmetric Component GARCH (1,1):

$$\begin{aligned} h_t &= q_0 + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta_1 (h_{t-1} - q_{t-1}) + \beta_2 (\varepsilon_{t-1}^2 - q_{t-1}) d_{t-1} \\ q_t &= \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - h_{t-1}). \end{aligned} \tag{12}$$

where $d_{t-1} = 1$ if $\varepsilon_t < 0$; 0 otherwise, and the return equation which provides ε_t is the same as in 9.[11]

Table 4
BDS statistics

The figures are BDS statistics for AR (p), S residuals, and standardized residuals $\varepsilon/\sqrt{h}$ from three ARCH-type models. The BDS statistics are evaluated against critical values obtained from Monte Carlo simulation (Appendix 1). *, **, and *** represent the significance levels of .10, .05, and .01 respectively.

Panel A: SET Index	M			
ε/σ	2	3	4	5
AR(6),S Residuals				
0.50	12.62***	15.62***	18.57***	20.78***
1.00	14.01***	17.02***	19.60***	21.36***
1.50	14.04***	16.82***	18.66***	19.58***
2.00	12.15***	14.80***	16.26***	16.77***
GARCH (1,1) Standard Errors				
0.50	1.48	1.78**	1.67	1.26
1.00	1.44	1.65**	1.72	1.43
1.50	1.32	1.49**	1.60	1.31
2.00	1.26**	1.40*	1.55	1.16
Exponential GARCH Standard Errors				
0.50	12.05***	14.79***	17.47***	19.44
1.00	13.25***	16.11***	18.62***	20.37
1.50	13.44***	16.19***	18.07***	19.07
2.00	11.74***	14.44***	15.99***	16.56
Asymmetric Component GARCH Standard Errors				
0.50	0.58	1.41*	1.73**	1.12
1.00	0.63	1.06	1.49**	1.37*
1.50	0.52	0.95	1.45**	1.38**
2.00	0.46	0.88	1.41***	1.25***

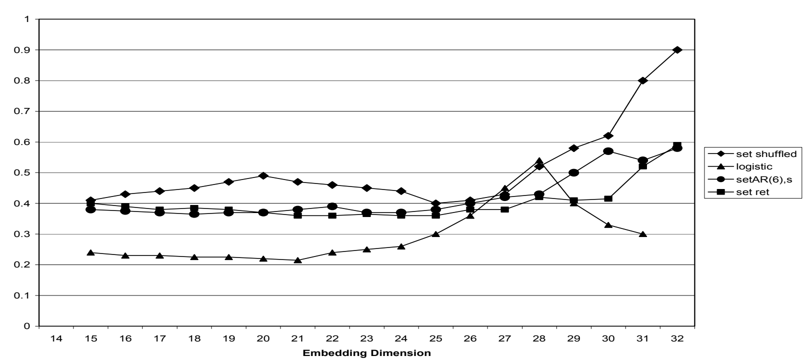
The BDS statistics are evaluated against critical values obtained by bootstrapping the null distribution for each of the GARCH models (see Appendix 1). The BDS statistics strongly reject the null of no nonlinearity in the [AR(6),S] errors for the SET Index values. This evidence, that there are nonlinear dependencies in SET Index series, is consistent with the findings reported for exchange rates in Aczel and Josephy (1991), foreign exchange rates in Hsieh (1989), the CRISMA trading system in Pruit and White (1988), and stock returns in Scheinkman and LeBaron (1989). BDS statistics for the standardized residuals from the ARCH-type models, however, clearly indicate that the source of the nonlinearity *is not* chaos. For instance, the BDS statistics are dramatically lower (relative to those for the

[AR(6),S] errors) for all the standardized residuals, and are consistently insignificant at any reasonable level of confidence for the GARCH(1,1) model. On the whole, the BDS test results provide compelling evidence that the nonlinear dependencies in SET Index series arise from ARCH-type effects, rather than from a complex, chaotic structure.

C. Entropy estimates

Figure 4 plots the Kolmogorov entropy estimates (embedding dimension 15 to 30) for the Logistic map (w=3.75, x_0=.10) and [AR(6),S] SET Index series. The estimates for the Logistic map provide the benchmarks for a known chaotic and a generally random series. The entropy estimates for the [AR(6),S] SET Index series shows little signs of 'settling down' as do those for the Logistic map. There is a general rise in the K_2 statistic as one increases the embedding dimension. The plots in Figure 4 corroborates the Correlation Dimension and BDS test results suggesting no evidence of low dimension chaos in SET Index values.

Figure 4. Kolmogorov Entropy Estimates



D. ARCH Effects in Emerging Equity Markets

It is apparent from the BDS statistics presented in Table 4, that the GARCH (1,1) model may explain the nonlinearities in the SET Index values. The standardized residuals show that after accounting for the nonlinearities in the SET Index by employing a GARCH (1,1) model, BDS statistics become insignificant. Therefore, the GARCH (1,1) model may be an example of a nonlinear model that is successful in capturing and explaining the behavior of the SET Index.

Table 5 reports the maximum likelihood results for the SET Index. In the interest of brevity, we do not present the results from the mean equations. The results indicate strong ARCH effects, as shown by the statistical significance of the lagged variance. The overall significance of the model coefficients shows that a GARCH (1,1) may successfully explain the returns-generating process. Therefore, a well-known econometric model such as GARCH (1,1) may be perfectly capable of explaining SET behavior and its volatility. This finding is interesting and useful both for country fund managers, domestic central bank and monetary policy, and exchange authorities. For example, some nonlinear models may be able to explain the behavior of SET in the near future. This finding may have implications regarding the efficiency of this emerging market. For example, if a nonlinear model that is based on historic data is successful in predicting near term SET movements and volatility, the weak form of market efficiency may be violated. However, this point requires further research.

Table 5
ARCH dynamics SET Index

The maximum likelihood estimates are from GARCH model fitted to SET Index returns. The variance parameters estimated are from equation (11). Statistics in () are t-values. The Chi-square test statistic for SET is LL (GARCH)-LL (OLS)), where LL represents the Log-likelihood function. *** represents the significance level of .01.

	SET [h_t]	
constant	0.126***	(4.58)
ε_{t-1}	0.220***	(7.54)
h_{t-1}	0.780***	(34.13)
LL	-5350.11	
Chi-Squared	610.96	

V. CONCLUSION

Financial researchers have become interested in chaotic time series in the past two decades because many economic and financial time series appear random. However, random-looking variables may in fact be chaotic, and thus, predictable, at least in the short-run.

Many studies have analyzed financial time series for nonlinearities and chaos in the developed markets of the world. The evidence on these issues has been mixed. However, the nonlinearity and chaotic structure of equity prices in emerging markets has rarely been investigated. Some researchers have suggested that the technical analysis may be especially successful in forecasting short-term price behavior of various financial series because these series may be nonlinear and/or chaotic. Furthermore, modeling nonlinear processes may be less restrictive than linear structural systems because nonlinear methods are not restricted by specific knowledge of the underlying structures. This information may enable money managers and analysts to have a better understanding of the equity price movements and sudden volatility patterns in an emerging market equity market such as Thailand.

Employing daily, nine–year series of the Stock Exchange of Thailand (SET) Index, we conduct a battery of tests for the presence of low-dimension chaos. The SET Index series is subjected to Correlation Dimension tests, BDS tests, and tests for entropy. While we find strong evidence of nonlinear dependence in the data, the evidence is not consistent with chaos. Our test results indicate that ARCH-type processes explain the nonlinearities in the data. We also show that employing seasonally adjusted index series enhances the robustness of results via the existing tests for chaotic structure. For SET Index returns, we isolate an appropriate ARCH-type model. Thus, analysts may be able to model the past behavior of the SET Index. Furthermore, relatively common nonlinear econometric models may be employed to gather information and predict futures movements and the volatility of the SET Index. This information maybe valuable for money mangers, global fund managers, country fund investors, as well as local monetary policy and exchange authorities of Thailand. It also suggests that the "weak form" of the Efficient Market Hypothesis may be violated in this emerging market. This is so because an ARCH-type nonlinear model may be employed for possible predictive purposes. This point will be the topic of future research.

NOTES

1. The importance of emerging market economies to international financial markets may be highlighted by the fact that the 1997 currency crisis and the ensuring financial market turmoil began partially due to Thai bath crash.
2. See Brock, Hsieh and LeBaron (1993) for a compete overview of the properties.
3. This property follows from the requirement that local trajectories must diverge; if they were to converge, the system would be stable to disturbance, and nonchaotic.
4. The selection of $w>3$ was not arbitrary. At $w<3$, the series would converge to a single value. At $w=3$, the series fluctuates between two values (or equilibria). The number of solutions continues to double (not infinitum) as w is increased beyond 3, producing a time path that is oscillatory. Also see Baumol and Benhabib (1989), who outline four cases for the value of w.
5. Some short-term forecasting techniques, such as locally weighted regressions, perform better for chaotic data than for random data (e.g., Hsieh (1991)).
6. It is shown in the literature that nonstationary processes can generate low dimensions even when not chaotic (e.g., Brock and Sayers (1988). To avoid confusion, one may difference the original series if it contains a unit root.
7. In practice length of the data length limits T, which in turn puts limitations on the range of the values of ε and M to be considered.
8. The data are obtained from the Thailand Stock Exchange.

9. We do not employ smoothing models to detrend the data, as we feel that the imposed trend reversions may erroneously be interpreted as structure (see Nelson and Plosser (1982)).
10. Yang and Brorsen (1993), who calculate Correlation Dimension for gold and silver, compute SC^M only up to M=8.
11. The return equation from the ARCH-type systems provided coefficients similar to those in Table 2. We also estimated another familiar model, Garch in Mean (GARCHM). The BDS statistics from the GARCHM and GARCH (1,1) models were found to be very similar. In the interest of brevity, we do not provide the results from the GARCHM model. The GARCH model is due to Bollerslev (1986), the exponential model (EGARCH) is from Nelson (1991), and the asymmetric component ARCH model is a variation of the Threshold GARCH model of Rabemananjara and Zakoian (1993).

REFERENCES

Aczel, A. D. and Josephy, N. H., 1991, "The Chaotic Behavior of Foreign Exchange Rates," *American Economist*, 35, 16-24.

Adrangi, B., Chatrath, A., 2003, "Nonlinear Dynamics in Futures Prices: Evidence from the Coffee, Sugar, and Cocoa Exchange," *Applied Financial Economics*, 13, 245-256.

Akaike, H., 1974, "A New Look at Statistical Model Identification," *IEEE Transactions on Automatic Control*, 19, 716-723.

Baumol, W.J., and Benhabib, J., 1989, "Chaos: Significance, Mechanism, and Economic Applications," *Journal of Economic Perspectives*, 3, 77-105.

Blank, S.C., 1991, "Chaos in Futures Markets? A Nonlinear Dynamical Analysis," *Journal of Futures Markets*, 11, 711-728.

Blume, L., Easley, D., and O'Hara, M., 1994, "Market Statistics and Technical Analysis: The Role of Volume," *Journal of Finance*, 49, 153-181.

Bohan, J., 1981, "Relative Strength: Further Positive Evidence," *Journal of Portfolio Management*, Fall, 36-39.

Bollerslev, T., 1986, "Generalized Autoregressive Conditional Heteroskedasticity," *Journal of Econometrics*, 31, 307-327.

Brock, W.A., 1986, "Distinguishing random and Deterministic Systems," *Journal of Economic Theory*, 40, 168-195.

Brock, W.A., and Dechert, W., 1988, "Theorems on Distinguishing Deterministic and Random Systems," in Barnett, W., Berndt, E., and White, H., ed., *Dynamic Econometric Modeling*, Proceedings of the Third Austin Symposium, Cambridge: Cambridge University Press.

Brock, W.A., Dechert, W., and Scheinkman, J., 1987, "A Test of Independence Based on the Correlation Dimension," Unpublished Manuscript, University of Wisconsin, Madison, University of Houston, and University of Chicago.

Brock, W.A., Hsieh, D.A., and LeBaron, B., 1993, *Nonlinear Dynamics, Chaos, and Instability: Statistical Theory and Economic Evidence*, MIT Press, Cambridge, Massachusetts.

Brock, W.A., and Sayers, C.L., 1988, "Is the Business Cycle Characterized by Deterministic Chaos?" *Journal of Monetary Economics*, 22, 71-90.

Brock, W., Lakonishok, J., and LeBaron B, 1992, "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns," *Journal of Finance*, 47, 1731-1764.

Brush, J., 1986, "Eight Relative Strength Methods Compared," *Journal of Portfolio Management*, Fall, 21-28.

Chang, P.H.K., and Osler, C.L., 1995, "Head and Shoulder: Not Just a Flaky Pattern," *Federal Reserve Bank of New York Staff Papers*, No. 4.

Clyde, W.C., and Osler, C.L., 1997, "Charting: Chaos Theory in Disguise?" *Journal of FuturesMarkets*, 17, 489-514.

DeCoster, G. P., Labys, W.C., and Mitchell, D.W., 1992, "Evidence of Chaos in Commodity Futures Prices," *Journal of Futures Markets*, 12, 291-305

Deneckere, R., and Pelikan, S., 1986, "Competitive Chaos," *Journal of Economic Theory*, 40, 12-25.

Devaney, R.L., 1986, *An Introduction to Chaotic Dynamical Systems*, Benjamin/Cummings Publishing, Menlo Park, CA.

Dickey, D.A., and Fuller, W.A., "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root," *Econometrica*, 49, 1057-1072.

Engle, R.F., 1982, "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation," *Econometrica*, 50, 987-1007.

Frank, M., and Stengos, T., 1989, "Measuring the Strangeness of Gold and Silver Rates of Return," *Review of Economic Studies*, 456, 553-567.

Grassberger, P., and Procaccia, I, 1983, "Measuring the Strangeness of Strange Attractors," *Physica*, 9, 189-208.

Hsieh, D.A., 1989, "Testing for Nonlinear Dependence in Daily Foreign Exchange Rates," *Journal of Business*, 62, 339-368.

Hsieh, D.A., 1991, "Chaos and Nonlinear Dynamics: Applications to Financial Markets," *Journal of Finance*, 46, 1839-1876.

Hsieh, D.A., 1993, "Implications of Nonlinear Dynamics for Financial Risk Management," *Journal of Financial and Quantitative Analysis*, 28, 41-64.

Jaffe, J. and R. Westerfield, 1985, "The Week-End Effect in Common Stock Returns: The International Evidence," *Journal of Finance*, 40 (2), 433-454.

LaBaron, Blake, 1991, "Technical Trading Rules and Regimes Shifts in Foreign Exchange," University of Wisconsin, Social Sciences Research Institute Working Paper.

Mayfield, E. S., and Mizrach, B., 1992, "On Determining the Dimension of the Real Time Stock Price Data," *Journal of Business and Economic Statistics*, 10, 367-374.

Lee, S., M., 2003, "Diversification Benefits if Emerging Market Funds: Evidence from Closed-End Country Funds," Paper presented at the American Society of Business and Behavioral Sciences, February 2003.

Lichtenberg, A.J., and Ujihara, A., 1988, "Application of Nonlinear Mapping Theory to Commodity Price Fluctuations," *Journal of Economic Dynamics and Control*, 13, 225-246.

Nelson, D., 1991, "Conditional Heteroskedasticity in Asset Returns: A New Approach," *Econometrica,* 59, 347-370.

Neslon, C., and Plosser, C., 1982, "Trends and Random Walks in Macroeconomic Time Series," *Journal of Monetary Economics*, 10, 139-162.

Pruitt, S.W., and White R.E., 1988, "The CRISMA Trading System: Who Says Technical Analysis Can't Beat the Market?" *Journal of Portfolio Management*, 55-58.

Pruitt, S.W., and White R.E., 1989, "Exchange-Traded Options and CRISMA Trading: Who Says Technical Analysis Can't Beat the Market?" *Journal of Portfolio Management*, 55-56.

Pruitt, S.W., and White R.E., 1988, "The CRISMA Trading System: Who Says Technical Analysis Can't Beat the Market?" *Journal of Portfolio Management*, 55-58.

Rabemananjara, R., and Zakoian, J.M., 1993, "Threshold ARCH models and Asymmetries in Volatility," *Journal of Applied Econometrics*, 8, 31-49.

Ramsey, J., and Yuan, H., 1987, "The Statistical Properties of Dimension Calculations Using Small Data Sets, C.V. Starr Center for Applied Economics," New York University.

Scheinkman, J., and LeBaron, B., 1989, "Nonlinear Dynamics and Stock Returns," *Journal ofBusiness*, 62, 311-337.

Takens, F., 1984, "On the Numerical Determination of the Dimension of an Attractor, in Dynamical Systems and Bifurcations," Lecture Notes in Mathematics, Springer-Verlag Publishing, Berlin.

Taylor, S. J., 994, "Trading Futures Using a Channels Rule: A Study of the Predictive Power of Technical Analysis with Currency Examples," *Journal of Futures Markets*, 14, 215- 235.

Yang, S., and Brorsen, B.W., 1993, "Nonlinear Dynamics of Daily Futures Prices: Conditional Heteroskedasticity or Chaos?" *Journal of Futures Markets*, 13, 175-191.

Appendix 1
Simulated critical values for the BDS test statistic

The figures represent the simulated values of the BDS statistic from Monte Carlo simulations of 2000 observations each. The simulations generated the 250 replications of the GARCH model (α_1=.10, $ß_1$=.80), the exponential GARCH model (α_1=.05, α_2=.05, $ß_1$=.80), and the asymmetric component model (α=.05, ß=.10, ρ=.80, ϕ=.05). BDS statistics for four embedding dimensions and ε = 0.5, 1, 1.5 and 2 standard deviations of the data were then computed for the 250x3 simulated series. The critical values represent the 97.5th and 2.5th percentile of the distribution of the simulated statistics.

		ε/σ		
M	0.5	1.0	1.5	2.0
GARCH (1,1) (97.5% critical values)				
2	1.62	1.53	1.42	1.25
3	1.76	1.63	1.45	1.44
4	2.35	2.21	2.16	1.97
5	2.42	2.28	2.25	2.10
Exponential GARCH (97.5% critical values)				
2	2.75	2.54	2.10	1.83
3	3.30	3.07	2.42	2.38
4	3.48	3.31	2.66	2.56
5	3.66	3.47	2.97	2.61
Asymmetric Component GARCH (97.5% critical values)				
2	1.40	1.13	1.02	0.80
3	1.47	1.27	1.17	093
4	1.62	1.28	1.22	1.00
5	1.82	1.40	1.31	1.07