

Emerging Market Equity Prices and Chaos: Evidence from Indonesia and Malaysia

**Bahram Adrangi^a, Arjun Chatrath^b, Ravindra Kamath^c, and
Kambiz Raffiee^d**

^a *Pamplin School of Business Administration, University of Portland,
5000 N. Willamette Blvd., Portland, Oregon 97203
adrangi@up.edu*

^b *Pamplin School of Business Administration, University of Portland,
5000 N. Willamette Blvd., Portland, Oregon 97203
chatrath@up.edu*

^c *Department of Finance, Cleveland State University,
1860 E. 18th St., Cleveland, Ohio 44114
ravikamath6@yahoo.com*

^d *Foundation Professor of Economics, College of Business Administration
University of Nevada-Reno, Reno, Nevada 89557
Raffiee@unr.edu*

ABSTRACT

We test for the presence of low-dimensional chaotic structure in the Stock Exchanges of Indonesia and Malaysia. 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 structures.

JEL Classification: G15

Keywords: Chaos; GARCH models; Emerging markets; Financial markets; Malaysia and Indonesia Stock Exchanges

* We thank an anonymous referee for helpful and constructive comments. Remaining

errors are our responsibility.

I. INTRODUCTION

In this paper we investigate nonlinearities and chaos in the stock indices of Jakarta, Indonesia and Kuala Lumpur, Malaysia stock exchanges. The motivation behind the study is to provide information on emerging market equity indices. International investors and money managers may benefit from the findings of this research. Furthermore, chaotic processes may be predictable in the short-run using simple technical analysis. The analysis entails examining the indices for low dimension chaos and other complex nonlinearities.

The Stock Exchange of Indonesia and Malaysia are represented by the Jakarta Stock Exchange Composite Index and the Kuala Lumpur Stock Exchange Composite Index, respectively. The primary role of both Stock Exchanges are: (i) to serve as a center for securities trading, and to provide necessary systems 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 exchanges.

The origins of the Kuala Lumpur Stock Exchange lie in the Singapore Stockbrokers' Association, established in 1930 – the first formal organization in the securities business in Malaysia. In 1961, the Board system was introduced with two trading rooms, in Singapore and Kuala Lumpur, that were linked by direct telephone lines into a single market with the same stocks and shares listed at a single set of prices on both boards.) Malayan Stock Exchange formed and public trading of shares began on May 9th. With the secession of Singapore from Malaysia the common stock exchange continued to function but as the Stock Exchange of Malaysia and Singapore. With the termination of currency interchangeability between Malaysia and Singapore, the Stock Exchange of Malaysia and Singapore was separated into the Kuala Lumpur Stock Exchange Board and the Stock Exchange of Singapore. Malaysian companies continued to be listed on the Stock Exchange of Singapore and vice-versa. The Kuala Lumpur Stock Exchange took over operations of the Kuala Lumpur Stock Exchange Board. In 1994, Kuala Lumpur Stock Exchange became a de-mutualized exchange and was re-named Bursa Malaysia.

The history of Jakarta Stock Exchange may be traced back to 1912 when it was set up under the Dutch Colonial rule in Batavia. It was closed during the first and second world wars and did not open until several years after Indonesia gained its independence from Holland. Prior to the WWII, mainly stocks and bonds of Dutch companies traded on the Batavia stock market. The Stock exchange halted operations again in 1956 and did not come to full operation until 1977 when it reopened under the management of Capital Market Executive Agency of the Ministry of Finance. The exchange was privatized in 1992. Jakarta Stock Exchange has grown and changed as the Indonesian economy has grown through its own development. The market capitalization has increased steadily. Since 1995, the Exchange has utilized computerized trading technology, enhancing both efficiency and transparency of the Exchange.

We chose the Jakarta Stock Index and the Kuala Lumpur Stock Exchange to highlight the role of financial markets in the development of emerging markets. The

study of equity markets and the behavior of equity prices in emerging markets such as Indonesia and Malaysia 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). Analyses of emerging market economies and capital markets promote further developments of these markets and the influx of foreign capital, which has stimulated economic growth.

The behavior of these indices, their volatility, and movements are of interest to international money managers, securities authorities' of the two countries, and their Central Banks. Furthermore, these emerging markets have experienced phenomenal economic growth and have occasionally been dubbed "New Tigers." New tigers have become major exporters of goods and services and a focus of international investors.¹ As discussed in Adrangi et al. (2004), chaotic behavior has piqued the interest of financial researchers because many economic and financial time series appear random. In the short-run, random variables may in fact be deterministic chaos, and thus, predictable. It has been shown that technical analysis is successful in forecasting short-term price behavior of various financial series where series are nonlinear and/or chaotic (see for example, Adrangi et al. (2001a), Adrangi et al. (2001b), Adrangi et al. (2004), (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). The consistency of a number of financial time series with deterministic chaos is reported in studies by Lichtenberg and Ujihara (1988), Blank (1991), DeCoster, Labys, and Mitchell (1992), and Yang and Brorsen (1993).

As shown by Adrangi et al. (2001a), Adrangi et al. (2001b) and Adrangi et al. (2004), nonlinearity in economic and financial series may not necessarily be consistent with chaos. This is evidenced in studies by 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, and Hsieh (1993) for futures contracts.

Our paper applies the methodology and chaos tests employed in Adrangi et al. (2001a), Adrangi et al. (2001b) and Adrangi et al. (2004) to examine the emerging equity market of Indonesia and Malaysia. We find strong evidence that Jakarta Exchange Index (JEI), representing Jakarta Stock Index, and Kuala Lumpur Exchange Index (KLEI), representing Kuala Lumpur Stock Exchange, exhibit nonlinear dependencies which are not consistent with chaos. However, we offer evidence that do not suggest chaotic structure. We make a case that employing seasonally adjusted 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 JEI and KLEI series. These findings are particularly noteworthy in that they demonstrate the power of commonly known nonlinear models in explaining the behavior of equity prices in two emerging markets. Furthermore, with the help of the past data, behavior of indices in the Indonesia and Malaysia markets may be predicted employing a nonlinear model.

The next section presents the test results for the JEI and KLEI series. Section III

closes with a summary of the results. The critical values for the BDS statistic of the standardized residuals are developed by bootstrapping the null distribution and reported in Appendix 1.

II. EVIDENCE FROM THE JEI AND KLEI SERIES

We employ the JEI and KLEI series from January 1990 through October 2005 (2,700 observations).² We focus our tests on daily returns, which are obtained by taking the relative log of indices as in $R_t = (\ln(P_t/P_{t-1})) \cdot 100$, where P_t represents the closing indices value on day t .³

Table 1
Return diagnostics

This Table presents the return diagnostics for JEI (Jakarta Exchange Index) and KLEI (Kuala Lumpur Exchange Index) series over the interval, January 3, 1990 through December 30, 1998 (2205 observations). Returns are given by $R_t = \ln(P_t/P_{t-1}) \cdot 100$, where P_t represents closing price 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 Q²(12) statistics represent the Ljung-Box (Q) statistics for autocorrelation of the R_t and R_t^2 series respectively. The ARCH(6) statistic is the Engle (1982) test for ARCH (of order 6) and is χ^2 distributed with 6 degrees of freedom. *** represents the significance level of .01.

| | Indonesia | Malaysia |
|---------------------|-------------|---------------|
| Mean | 0.052 | 0.013 |
| SD | 1.973 | 1.800 |
| SK | -8.954 | -1.369 |
| K | 268.928 | 66.914 |
| JB | 7988.866*** | 462791.000*** |
| ADF | -45.551*** | -49.803*** |
| ADF(T) | -45.163*** | -49.788*** |
| PP | -45.061*** | -49.761*** |
| PP(T) | -45.050*** | -49.746*** |
| Q(12) | 58.827*** | 41.235*** |
| Q ² (12) | 51.911*** | 341.411*** |
| ARCH(6) | 92.645*** | 39.377*** |

Table 1 presents the R_t diagnostics for the series. The returns series are found to be stationary employing the Augmented Dickey Fuller (ADF) statistics. There are linear and nonlinear dependencies as indicated by the Q(12) and Q²(12) statistics, and Autoregressive Conditional Heteroskedasticity (ARCH) effects is suggested by the ARCH(6) chi-squared statistic. Thus, as expected, there are clear indications that nonlinear dynamics are generating the JEI and KLEI series. 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 JEI and KLEI series.

To eliminate the possibility that the linear structure or seasonalities may be responsible for the rejection chaos by the tests employed, we first estimate autoregressive models for JEI and KLEI series with controls for possible day-of-the-week effects, as in

$$R_t = \sum_{i=1}^p \beta_i R_{t-i} + \sum_{j=1}^5 \gamma_j D_{jt} + \phi D_p + \varepsilon_t, \quad (1)$$

where D_{jt} represent day-of-the-week dummy variables, and D_p represents a dummy that captures the effects of the 1997 Thai Baht and the pursuing financial/political crisis. 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 JEI and KLEI series as indicated by the size of the Q-statistics, which indicates that the residuals are free of linear structure.

Table 2
Linear structure and seasonality

The coefficients and residual diagnostics are from the OLS regressions of returns on prior returns and twelve monthly dummies. The lag-length was selected based on Akaike's (1974) criterion. Statistics in () are t-values. The Lagrange Multiplier statistic of first order autocorrelation (LM(1), Chi-square) tests the null of no autocorrelation of order one in the regression residuals. The Q(6) and Q(12) statistics represent the Ljung-Box (Q) statistics for autocorrelation in the residuals. *, **, and *** represent the significance levels of .10, .05, and .01, respectively.

| | Indonesia | | Malaysia | |
|-----------|-----------|---------|-----------|---------|
| Intercept | 0.216** | (2.24) | 0.175** | (2.02) |
| R_{t-1} | 0.137*** | (7.13) | 0.051*** | (2.68) |
| R_{t-2} | 0.007 | (0.34) | 0.011 | (0.60) |
| R_{t-3} | -0.014 | (-0.74) | 0.007 | (0.37) |
| R_{t-4} | -0.025 | (-1.31) | -0.089*** | (-4.63) |
| R_{t-5} | -0.021 | (-1.11) | 0.049*** | (2.53) |
| Mon | -0.289*** | (-2.41) | -0.281*** | (-2.58) |
| Tue | -0.103 | (-0.87) | -0.116 | (-1.07) |
| Wed | -0.129 | (-1.08) | -0.046** | (-0.43) |
| Thr | -0.157 | (-1.31) | -0.201** | (-1.86) |
| Pol Dummy | -0.057 | (-0.74) | -0.058 | (-0.83) |
| R^2 | 0.023 | | 0.016 | |
| LM(1) | 0.04 | | 1.043 | |
| Q(5) | 0.021 | | 0.079 | |

$Q^2(5)$ 93.703*** 265.34***

A. Correlation Dimension Estimates

Table 3 reports the Correlation Dimension (SC^M) estimates for various components of the JEI and KLEI 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.⁴ An absence of saturation provides evidence against chaotic structure. For instance, the SC^M estimates for the Logistic map stay close to 1.00, even as we increase the embedding dimensions. Moreover, the estimates for the Logistic series do not change meaningfully after AR transformation. Thus, as should be expected, the SC^M estimates are not inconsistent with chaos for the Logistic series.

For the JEI and KLEI series, on the other hand, the SC^M estimates provide evidence against chaotic structure. The estimates for the JEI and KLEI AR(5), AR(5) with-seasonal-correction (AR(5), S), and from the random series (JEI and KLEI series shuffled) are substantially higher than one and show no sign of settling. Thus, the Correlation Dimension estimates suggest that there is no chaotic structure in JEI and KLEI series.

Table 3
Correlation dimension estimates

The Table reports SC^M statistics for the Logistic series ($w = 3.750$, $n = 2250$), daily JEI (Jakarta Exchange Index) and KLEI (Malaysia Exchange Index) series and their various components over four embedding dimensions: 5, 10, 15, 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.

| Indonesia | | | | |
|-------------|------|------|------|-------|
| M= | 5 | 10 | 15 | 20 |
| Logistic | 1.02 | 1.00 | 1.03 | 1.06 |
| Logistic AR | 0.96 | 1.06 | 1.09 | 1.07 |
| Returns | 2.12 | 3.43 | 4.44 | 5.31 |
| AR(5) | 2.15 | 3.45 | 4.45 | 5.29 |
| AR(5),S | 2.16 | 3.50 | 4.55 | 5.43 |
| Shuffled | 2.84 | 5.75 | 8.66 | 11.57 |
| Malaysia | | | | |
| M= | 5 | 10 | 15 | 20 |
| Logistic | 1.02 | 1.00 | 1.03 | 1.06 |
| Logistic AR | 0.96 | 1.06 | 1.09 | 1.07 |
| Returns | 1.99 | 3.29 | 4.39 | 5.40 |
| AR(5) | 2.05 | 3.37 | 4.49 | 5.48 |
| AR(5),S | 2.06 | 3.39 | 4.54 | 5.60 |

| | | | | |
|----------|------|------|------|-------|
| Shuffled | 2.75 | 5.54 | 8.25 | 10.50 |
|----------|------|------|------|-------|

B. BDS Test Results

The BDS statistics, developed by Brock, Dechert and Scheinkman (1987) for a test of independence based on the correlation dimension, are reported in Table 4 for [AR(i),S] series, and standardized residuals (ε/\sqrt{h}) from three of ARCH-type models with their respective variance equations,

GARCH (1,1):

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \quad (2)$$

Exponential GARCH(1,1):

$$\log(h_t) = \alpha_0 + \alpha_1 \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| + \alpha_2 \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_1 \log(h_{t-1}) \quad (3)$$

Asymmetric Component GARCH (1,1):

$$h_t = q_t + \alpha_1 (\varepsilon_{t-1}^2 - q_{t-1}) + \beta_1 (h_{t-1} - q_{t-1}) + \beta_2 (\varepsilon_{t-1}^2 - q_{t-1}) d_{t-1} \quad (4)$$

and

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - h_{t-1})$$

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. As reported in Adrangi et al. (2001a), Adrangi et al. (2001b), and Adrangi et al. (2004), the BDS statistics are evaluated against critical values obtained by bootstrapping the null distribution for each of the GARCH models. The critical values for the BDS statistics are reported in Appendix 1.

The BDS statistics strongly reject the null of no nonlinearity in the [AR(i),S] errors for the JEI and KLEI series. This evidence, that there are nonlinear dependencies in JEI and KLEI 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 Pruitt and White (1988), and stock returns in Scheinkman and LeBaron (1989). BDS statistics for the standardized residuals from the ARCH-type models, however, provide evidence against chaos in KLEI, but no for the JEI series. For instance, in the case of KLEI, the BDS statistics are dramatically lower (relative to those for the [AR(5),S] errors) for all the standardized residuals, and are mostly insignificant at any reasonable level of confidence for the GARCH(1,1) and Asymmetric GARCH models. On the whole, the BDS test results provide compelling evidence that the nonlinear dependencies in and KLEI series arise from ARCH-type effects, rather than from a complex, chaotic structure.⁵

On the other contrary, none of the estimated models explain the nonlinear dependencies in the standardized residuals for the JEI series. The BDS statistics stay statistically significant for model residuals. Thus, for the case of JEI, chaos may not be ruled out.

C. ARCH Effects in Emerging Equity Markets

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

Table 4
BDS statistics

The figures are BDS statistics for [AR(i),S] residuals, and standardized residuals ε/\sqrt{h} from three ARCH-type models. The BDS statistics are evaluated against critical values obtained from Monte Carlo simulation (Appendix 1). ** represents the significance levels of .05.

| Panel A: Indonesia | M | | | |
|--|----------------------|--------|--------|--------|
| | ε/σ | 2 | 3 | 4 |
| [AR(5),S] Residuals | | | | |
| 0.0139 | 16.339 | 21.530 | 26.583 | 32.233 |
| 0.0278 | 17.845 | 21.361 | 23.921 | 25.946 |
| 0.0417 | 18.491 | 21.003 | 23.123 | 24.309 |
| 0.0556 | 18.110 | 20.083 | 21.974 | 22.626 |
| GARCH (1,1) Standard Errors | | | | |
| 0.0147 | 11.465 | 14.734 | 18.272 | 22.203 |
| 0.0294 | 11.728 | 13.660 | 15.071 | 15.765 |
| 0.0441 | 11.995 | 13.562 | 14.443 | 14.414 |
| 0.0588 | 11.571 | 13.001 | 13.675 | 13.483 |
| Exponential GARCH Standard Errors | | | | |
| 0.0155 | 9.898 | 12.136 | 14.374 | 16.354 |
| 0.0311 | 11.113 | 12.506 | 13.336 | 13.488 |
| 0.0467 | 12.251 | 13.382 | 13.938 | 13.675 |
| 0.0622 | 13.006 | 14.151 | 14.632 | 14.270 |
| Asymmetric Component GARCH Standard Errors | | | | |
| 0.0139 | 6.816 | 9.023 | 11.652 | 14.142 |
| 0.0278 | 6.869 | 8.445 | 9.752 | 10.408 |
| 0.0417 | 6.513 | 7.686 | 8.648 | 8.862 |
| 0.0556 | 5.982 | 6.634 | 7.301 | 7.378 |

Table 4 Continued

| Panel B: Malaysia | | | | |
|--|--------|--------|--------|--------|
| ε/σ | M | | | |
| | 2 | 3 | 4 | 5 |
| [AR(5),S] Residuals | | | | |
| 0.0172 | 19.207 | 24.067 | 28.447 | 34.422 |
| 0.0344 | 19.299 | 23.662 | 26.496 | 29.460 |
| 0.0516 | 16.852 | 21.093 | 23.354 | 25.091 |
| 0.0688 | 15.845 | 19.886 | 21.845 | 22.774 |
| GARCH (1,1) Standard Errors | | | | |
| 0.0175 | -0.148 | -0.847 | -1.729 | -2.076 |
| 0.0350 | -0.777 | -1.410 | -2.287 | -2.851 |
| 0.0525 | -1.052 | -1.725 | -2.668 | -3.330 |
| 0.0701 | -1.130 | -1.750 | -2.652 | -3.348 |
| Exponential GARCH Standard Errors | | | | |
| 0.0200 | 9.089 | 11.435 | 13.105 | 15.14 |
| 0.0402 | 9.043 | 11.598 | 13.040 | 14.417 |
| 0.0603 | 9.072 | 11.699 | 12.809 | 13.652 |
| 0.0803 | 9.137 | 11.642 | 12.543 | 13.114 |
| Asymmetric Component GARCH Standard Errors | | | | |
| 0.0169 | 0.356 | 2.079 | 1.870 | 2.302 |
| 0.0339 | -0.291 | 1.807 | 1.815 | 1.944 |
| 0.0508 | -0.653 | 1.517 | 1.668 | 1.737 |
| 0.0678 | -0.672 | 1.126 | 1.222 | 1.248 |

Table 5 reports the maximum likelihood results for the KLEI and JEI series. 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 an Asymmetric Component GARCH(1,1) may successfully explain the returns-generating process in the case of KLEI series. This finding is interesting and useful both for country fund managers, domestic central banks and monetary policy, and exchange authorities. For example, some nonlinear models may be able to explain the behavior of KLEI in the near future.

The behavior of the JEI series on the other hand is more vexing, and not easily explained by known ARCH-type models. Conflicting test results in this case, i.e., neither chaotic nor conducive to known econometric modeling, may suggest that this series is not even predictable in the short-run. While an Asymmetric Component GARCH (1,1) model fits the JEI series well, the remaining nonlinearities in this series may not even be subject to short-term forecasts using various charts.

Table 5
ARCH dynamics in Indonesia and Malaysia equity markets

The maximum likelihood estimates are from Asymmetric Component GARCH(1,1) models fitted to JEI (Jakarta Exchange Index) and KLEI (Kuala Lumpur Exchange Index) series, respectively. The variance parameters estimated are from Equation (4). Statistics in () are t-values. TTM represents time to maturity in days. The Chi-square log-likelihood ratio test (LLR) statistic is given by $2(LL(EGARCH)-LL(OLS))$, where LL represents the log-likelihood function. *** represents the significance level of .01.

| | Indonesia [h _t] | | Malaysia [h _t] | |
|---------------------------------|-----------------------------|----------|----------------------------|----------|
| Constant | 3.926*** | (21.85) | 0.518*** | (2.22) |
| Perm : q(-1)-c1 | 0.955*** | (164.29) | 0.999*** | (608.37) |
| Perm: ARCH(-1)-GARCH(-1) | 0.061*** | (7.89) | 0.014*** | (10.69) |
| Trans: q+c2 | -0.016 | (0.71) | 0.016*** | (3.18) |
| Trans: (RES(-1)<0)*(ARCH-q(-1)) | 0.374*** | (15.43) | 0.155*** | (16.32) |
| Trans: GARCH(-1)-q(-1) | -0.101*** | (54.99) | 0.854*** | (80.99) |
| LL(ACGARCH) | -2779.77 | -4278.42 | | |

The statistical findings also indicate that similar models may not be successful in explaining equity market behaviors, even in a similar geographic area. The behavior of JEI series may be reflecting the repercussions of the political and economic turmoil in Indonesia prior to, and following the Asian financial crisis. It is well known that the Malaysian society and economy were relatively more successful in withstanding the effects of the Asian financial meltdown of the late 1990s.

These finding may also have implications regarding the efficiency of these emerging markets. For instance, if a nonlinear model that is based on historic data is successful in predicting near term KLEI movements and volatility, the weak form of market efficiency may be violated. However, this point requires further research.

III. SUMMARY AND CONCLUSIONS

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 Indonesia and Malaysia.

Employing daily series of the Indonesia Exchange Index (JEI) and the Kuala Lumpur Exchange Index (KLEI) series for a period of fifteen years, we conduct a battery of tests for the presence of low-dimension chaos. The JEI and KLEI series are subjected to Correlation Dimension and BDS tests. While we find strong evidence of nonlinear dependence in the data for both series, the evidence is not consistent with chaos in the case of KLEI. Our test results indicate that ARCH-type processes explain the nonlinearities in this series. For the case of JEI series, we cannot find conclusive evidence against for or against chaos. The correlation dimension and BDS tests produce conflicting results, where BDS test suggests that the JEI series may be chaotic or random.

We also show that employing seasonally adjusted index series enhances the robustness of results via the existing tests for chaotic structure. For the KLEI returns series, we isolate an appropriate ARCH-type model. Thus, analysts may be able to model the behavior of the KLEI series.⁶ While the same model fits the JEI series well, it fails to capture all the nonlinearities in this series.

ENDNOTES

1. The importance of emerging market economies to international financial markets is highlighted in Adrangi et al. (2001a), Adrangi et al. (2001b), and Adrangi (2004).
2. The data are obtained from the Indonesia and Malaysia Stock Exchanges.
3. We do not employ smoothing models to detrend the data, as we feel that the imposed trend reversion may erroneously be interpreted as structure (see Nelson and Plosser (1982)).
4. Yang and Brorsen (1993), who also calculate Correlation Dimension for gold and silver, compute SC^M only up to $M=8$.
5. Similar findings are reported for stock market of Thailand in Adrangi et al. (2004).
6. Similar findings are reported for stock market of Thailand in Adrangi et al. (2004).

REFERENCES

- Aczel, A. D., and Josephy, N. H. 1991, "The Chaotic Behavior of Foreign Exchange Rates," *American Economist*, 35, 16-24.
- Adrangi, B., Chathrath, A., Dhanda, K., and Raffiee, K. 2001a, "Chaos in Oil Prices? Evidence from Futures Markets." *Energy Economics*, 23, pp. 405-425.

- Adrangi, B., Chathrath, A., Kamath, R., and Raffiee, K., 2001b, "Demand for the U.S. Air Transport Service: A Chaos and Nonlinearity Investigation," *Transportation Research Part E*, 37, pp. 337-353.
- Adrangi, B., Chathrath, A., Kamath, R., and Raffiee, K., 2004, "Nonlinearity and Chaos in the Stock Market of Thailand," *International Journal of Business*, 9, 159-176.
- Akaike, H., 1974, "A New Look at Statistical Model Identification," *IEEE Transactions on Automatic Control*, 19, 716-723.
- 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.
- 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., 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*, 13, 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 Futures Markets*, 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.
- Dickey, D.A., and Fuller, W.A., 1981, "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.
- 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, 433-454.
- Mayfield, E. S., and Mizraeh, 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, 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*, 14, 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*, 15, 55-56.
- Scheinkman, J. and LeBaron, B., 1989, "Nonlinear Dynamics and Stock Returns," *Journal of Business*, 62, 311-337.
- Taylor, S. J., 1994, "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 ($\alpha_1 = .10$, $\beta_1 = .80$), the exponential GARCH model ($\alpha_1 = .05$, $\alpha_2 = .05$, $\beta_1 = .80$), and the asymmetric component model ($\alpha = .05$, $\beta = .10$, $\rho = .80$, $\phi = .05$). BDS statistics for four embedding dimensions and $\varepsilon = 0.5, 1, 1.5$ 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.

| M | ε/σ | | | |
|--|----------------------|------|------|------|
| | 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 | 0.93 |
| 4 | 1.62 | 1.28 | 1.22 | 1.00 |
| 5 | 1.82 | 1.40 | 1.31 | 1.07 |