

NON-LINEAR DYNAMICS IN BILATERAL MALAYSIAN RINGGIT — U. S. DOLLAR SPOT RATES

KIAN-PING LIM

*Labuan School of International Business and Finance
Universiti Malaysia Sabah*

M. AZALI

MUZAFAR SHAH HABIBULLAH
*Faculty of Economics and Management
Universiti Putra Malaysia*

ABSTRACT

This study empirically investigates the presence of non-linearity in the Malaysian exchange rates returns series. Our bispectrum results reveal that the underlying generating process of the Malaysian exchange rates is governed by non-linear dynamics. With this evidence of non-linearity, researchers can no longer take the linear assumption for granted as it has profound implications on the robustness of their empirical results. Thus, this study points to the need to employ formal linearity test as a preliminary diagnostic tool to determine the nature of the data generating process of the series under investigation before any further empirical analysis.

Keywords : Non-linearity, Hinich bispectrum test, Malaysian foreign exchange market.

ABSTRAK

Kajian ini menyelidik secara empirikal kewujudan ketaklinearan siri pulangan kadar tukaran asing di Malaysia. Keputusan dwispektrum menunjukkan bahawa proses penjanaan kadar tukaran asing di Malaysia bersifat tak linear. Bukti ketaklinearan ini memberi implikasi bahawa penyelidik tidak boleh lagi membuat andaian kelinearan terhadap siri ini kerana iaanya akan memberi kesan kepada keteguhan keputusan hasil kajian mereka. Oleh itu, hasil kajian ini telah menunjukkan bahawa penyelidik perlu melakukan ujian formal untuk kelinearan sebagai alat diagnostik awalan untuk menentukan proses penjanaan data terlebih dulu sebelum analisis empirikal seterusnya boleh dilakukan.

Kata kunci : Ketaklinearan, ujian dwispektrum Hinich, kadar tukaran asing pasaran di Malaysia.

INTRODUCTION

This paper empirically investigates the underlying non-linear dynamics in the data generating process of Malaysian exchange rate return series. The study on the foreign exchange markets has attracted the interest of many researchers and it has become even more important in the post-Bretton Woods era. Since the inception of the floating exchange rate regime in 1973, most currency exchange markets have experienced continuous and sometimes dramatic fluctuations and volatility. There is no exception for the Malaysian ringgit, which is the focus of this paper, especially in 1997 when the currency crisis swept the economy of South East Asia.

It is an accepted fact that financial economics has been dominated over the past decade by the linear paradigm. The efficient market hypothesis and the notions connected with it have sparked the interest of financial economists and many papers have been published over the years. Most of the empirical tests of the efficient market hypothesis are based on linear models. Even the empirical exchange rate models are assumed to be in linear form, or can be made linear by the use of a simple transformation.

However, there is no strong reason or convincing empirical evidence to support why economic time series should conform to linear models or even well approximated by a linear model (Pesaran & Potter, 1993; Campbell *et al.*, 1997; Barnett & Serletis, 2000). It is for such reasons that the interest in non-linear studies has in the recent past experienced a tremendous rate of development. Some of the work has been theoretical, attempting to ascertain whether non-linear models can exhibit the kind of fluctuations typically found in exchange rates data (see, for example, Bollerslev, 1986; Bollerslev *et al.*, 1992; De Grauwe *et al.*, 1993; Baillie *et al.*, 1996). Other work has been empirical, examining the presence and nature of non-linearity in the data generating process of exchange rate time series (see, for example, Hsieh, 1989; Steurer, 1995; Brooks, 1996; Vilasuso & Cunningham, 1996; Mahajan & Wagner, 1999). A good testimony of this growing interest in non-linear studies would be the founding of an exclusive international journal entitled '*Studies in Non-linear Dynamics and Econometrics*'.

The main driving force behind the shift to non-linear studies is the developments in the mathematical and statistical analysis of dynamic systems. The richness of these new non-linear tests lies in their ability to uncover a more complex form of dependencies in a time series that appear to be random. This line of research has gain popularity over

the years with substantial literature supporting the presence of non-linearity in the exchange rate returns series (see, for example, Hsieh, 1989; De Grauwe *et al.*, 1993; Steurer, 1995; Brooks, 1996).

The evidence of non-linearity in exchange rate series has profound implications on the three areas that follow:

Model Adequacy: According to Hinich and Patterson (1989), the tests for non-linearity can be viewed as general tests of model adequacy for linear models. The rationale behind this is that if there is still dependence on the residuals of a linear model, the original linear model can no longer be viewed as an accurate representation of the data.

Market Efficiency: The evidence of non-linearity in returns series implies the potential for returns predictability. If investors could have profitably operated a trading rule (net of all transactions costs) which exploits those non-linearity, this would be at odds with the weak-form efficient market hypothesis. Following weak-form efficient market hypothesis, even non-linear combinations of previous prices should not be useful predictors of future prices (Brooks, 1996; Brooks & Hinich, 1999; McMillan & Speight, 2001).

Derivative Markets: The evidence that securities follow non-linear dynamics has strong implications on the pricing of derivative securities and the development of dynamic hedging strategies. Specifically, if the assumed stochastic processes do not adequately depict the full complexity of the true generating processes, then any derivative securities in question may be mis-priced and thus expose investors to unwanted risks due to imperfect hedges.

From the literature survey, most of the studies in the area of non-linearity have been focusing on currencies of developed countries, especially the U.S. dollar, Japanese yen, British pound and German deutschmark, while none has been conducted on the Malaysian ringgit. Though most of the studies acknowledged the prevalence of non-linearity in exchange rate returns data, no conclusion can be inferred for the Malaysian ringgit, which is very likely to exhibit characteristics different from those observed in developed foreign exchange markets. Besides market thinness, investors in the Malaysian foreign exchange market tend to react slowly and gradually to new information, which is in contrast with the highly efficient developed markets. Motivated by the above consideration, this paper would like to fill the gap in the current literature by providing empirical evidence on the underlying dynamics of the Malaysian exchange rates.

Firstly, this paper gives a brief introduction to the development in the Malaysian foreign exchange market. Secondly, a review on the related literature is provided. The following sections then discuss the methodology used in this study and present the empirical results as well as the analysis of the findings. Finally, the concluding remarks are given at the end of the paper.

THE MALAYSIAN FOREIGN EXCHANGE MARKET

This section provides a brief account of the exchange rate regimes in Malaysia for the period 1957-2001. Throughout those 44 years, Malaysia implemented a diverse range of exchange rate regimes, started initially with the pegging of the ringgit to the pound sterling. This was followed by a floating regime, first against the U.S. dollar and later in terms of a composite basket of currencies. Since 1 September 1998, the Malaysian ringgit has been pegged to the U.S. dollar.

In the early days after Independence in 1957, when the value of Malaysian currency was determined in terms of pound sterling, its stability was closely related to the pound sterling in the foreign exchange market. At that time, the foreign exchange was only used to fulfill the needs of exporters. The rate of the Malaysian ringgit was managed by the Malaya Board of Commissioners of Currency and British Borneo (the Currency Board) and fixed at 2s. 4d. sterling. Independence of the foreign exchange market in Malaysia was attained on 12 June 1967 when the Central Bank of Malaysia assumed sole power to issue currency from the Malaya Board of Commissioners of Currency.

With the floating and devaluation of the pound sterling in early 1970, in its place Malaysia later adopted the U.S. dollar as the intervention currency in June 1972. Owing to uncertainty in the international foreign exchange markets, the ringgit was allowed to float upwards from 21 June 1973. Through that floating arrangement, the Central Bank of Malaysia was no longer bound to buy one unit of U.S. dollar with the set floor rate of M\$2.4805.

That floating regime against the U.S. dollar was in place for only two years before the Malaysian Government adopted a new exchange rate regime on 27 September 1975. Henceforth, the rate of exchange of the ringgit was determined in terms of a composite basket, comprising of the currencies of the major trading partners of Malaysia. Under this floating exchange rate regime, Malaysia did not set targets for ringgit exchange rate levels. The Central Bank interventions was only to

ensure the stability of the ringgit, so that the exchange rate reflected the underlying economic fundamentals.

On 2 July 1997, the announcement by the Bank of Thailand to abandon its defence of the Baht caused the collapse of its national currency. What appeared to be a local financial crisis in Thailand quickly escalated into an Asian financial crisis, spreading to other Asian countries including Indonesia, Korea, Malaysia and the Philippines. The Malaysian ringgit came under intense selling pressure and the Central Bank was forced to intervene heavily to defend the value of the ringgit. At the same time, the Malaysian government undertook some corrective measures such as tightening the monetary policy, emphasising fiscal prudence and strengthening the financial system, all aimed to restore confidence and stability in the markets. However, all these efforts were ineffective in curbing the downward pressure on the Malaysian ringgit.

The ringgit continued to experience extreme volatility and reached a historical intra-day low of US\$1 = RM4.8800 on 7 January 1998. The ringgit remained volatile under intense speculative pressure and it traded within the range of US\$1 = RM4.0900 to RM4.2650 during the months of July and August that year. In order to prevent further pressure on the ringgit, the Malaysian government implemented selective exchange control policies on 1 September 1998. This exchange control served to reduce the internationalisation of ringgit through the elimination of speculative activities in the foreign exchange markets, both external and at home. As part of these measures, the ringgit was pegged to the U.S. dollar at RM3.8000. At the time of writing, the ringgit's peg to the dollar has held firm though there have been pressures to re-peg the ringgit at a higher rate following the decline of regional currencies against the U.S. dollar.

REVIEW OF RELATED LITERATURE

Since the inception of the floating exchange rate regime in 1973, major currency exchange markets have experienced continuous and sometimes dramatic fluctuations and volatility. Many different empirical exchange rate models have been developed over the years in an attempt to explain this phenomenon. Most parametric economic models of exchange rate are linear, or can be made linear by use of a simple transformation. However, this class of models does not perform well in explaining movements in exchange rates. The poor prediction quality of these exchange rate models is generally acknowl-

edged after the publication of the influential paper by Meese and Rogoff (1983).

These authors found that a simple random walk outperforms several conventional structural models based on the monetary/asset theories of exchange rate determination. Boothe and Glassman (1987) confirmed these findings for a number of key exchange rates over the period of 1976-1984. Subsequent research along this line have provided empirical evidence against the performance of these linear models. Both Alexander and Thomas (1987) and Wolff (1987) showed that these models were outperformed by the simple random walk forecasting rule, even when time-varying parameters are incorporated in the models to improve their forecasting performance. Wolff (1988) reached a similar conclusion using time-varying autoregressive (AR) models.

Various explanations have been put forward to account for the empirical failures of these linear exchange rate models. Recently, interest has been shown in the possibility that non-linearity accounts for the apparent unpredictability of exchange rates. According to Meese and Rose (1990: 193), non-linear exchange rate effects may provide a potential explanation for the failure of linear exchange rate models. With the uncovering of significant non-linearity in exchange rate data (see, for example, Hsieh, 1989; De Grauwe *et al.*, 1993; Steurer, 1995; Brooks, 1996), attention has been devoted to modelling exchange rates using non-linear procedures.

Schinasi and Swamy (1989), for example, showed that by using a non-linear random coefficient model, exchange rate forecasts can be improved. Engel and Hamilton (1990) and Chinn (1991) provided some evidence in favour of non-linear forecasts of exchange rates. Another recent study by De Gooijer *et al.* (1998) forecasted exchange rates using Time Series Multivariate Adaptive Regression Splines (TSMARS) methodology. The out-of-sample forecasts generated by the TSMARS models are superior to those of a random walk at all forecast horizons. These results suggest that non-linear modelling is a promising line of research.

The above discussions show that the evidence of non-linearity has significant implications on the empirical linear models of exchange rates. Liew *et al.* (2003), among others, advocate the use of formal linearity test as a diagnostic tool to determine the nature of the data generating process before any further empirical analysis. In this regard, a linear

model is only valid when a formal linearity test result fails to provide evidence on the existence of non-linearity.

In the literature, there is wide variety of statistical tests employed to detect non-linearity. According to Barnett and Serletis (2000), those non-linearity tests that are widely employed in the literature are the correlation dimension test (Grassberger & Procaccia, 1983), the Brock-Dechert-Scheinkman test (Brock *et al.*, 1996, hereafter denoted as BDS), the Hinich bispectrum test (Hinich, 1982), the White test (White, 1989) and the Kaplan test (Kaplan, 1994). Among these non-linear tests, the BDS test is by far the most popular¹ (see, for example, Scheinkman & LeBaron, 1989; Hsieh, 1991; De Grauwe *et al.*, 1993; Steurer, 1995; Abhyankar *et al.*, 1995; Brooks, 1996; Opong *et al.*, 1999; Mahajan & Wagner, 1999). However, the BDS test does not provide a direct test for non-linearity because the sampling distribution of the BDS test statistic is not known, neither in finite samples nor asymptotically, under the null hypothesis of non-linearity. The rejection of the null of independent and identical distribution (i.i.d.) in the BDS test can be due to non-white linear and non-white non-linear dependence in the data. Thus, the effects of linear serial dependencies have to be filtered out before the BDS test can be applied to detect any non-linear departure from the i.i.d. null. However, there is always the concern that the rejection of the null by the BDS test could be due to the possibility of imperfect pre-whitening.

Another popular non-linear test is the Hinich bispectrum test. Unlike the BDS test, the Hinich bispectrum test provides a direct test for a non-linear generating mechanism, irrespective of any linear serial dependencies that might be present. Thus, pre-whitening is not necessary in using the Hinich approach. Even if pre-whitening is done anyway, the adequacy of the pre-whitening is irrelevant to the validity of the test. Ashley *et al.* (1986) presented an equivalence theorem to prove that the Hinich linearity test statistic is invariant to linear filtering of the data, even if the filter is estimated. Thus, the linearity test can be applied to the original returns series, or to the residuals of a linear model with no loss of power.

METHODOLOGY

The Data

The daily spot exchange rates for the Malaysian ringgit (MYR/USD) are obtained from the Federal Reserve Statistical Release² over the period 2 January 1990 to 31 August 1998. The sample period after this is

excluded from the current study because Malaysia adopted a fixed ringgit regime from 1 September 1998. At the time of writing, the Malaysian ringgit peg at 3.80 to the U.S. dollar has held firm.

The raw exchange rate data are transformed into the differenced-log returns series (r_t), which is graphically depicted in Figure 1. All subsequent analysis will be performed on these transformed Malaysian exchange rates returns series, which Brock *et al.* (1991) interpreted as a series of continuously compounded percentage daily returns. Formally, it can be written as:

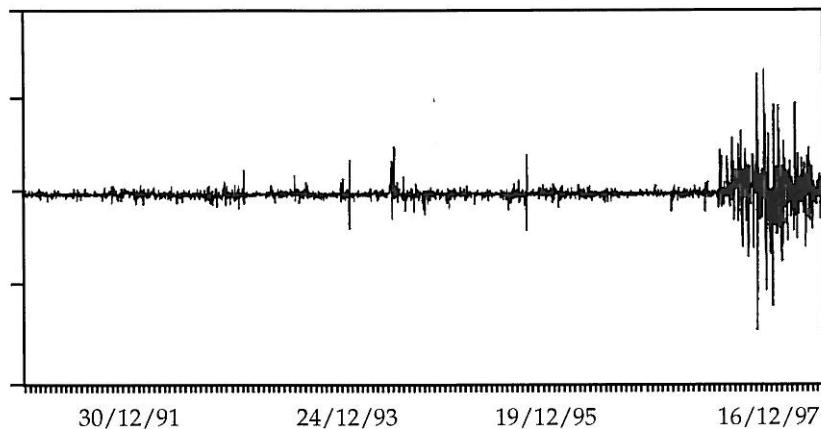
$$r_t = 100 [\ln (E_t) - \ln (E_{t-1})] \quad (1)$$

where E_t is the exchange rate at time t , and E_{t-1} the rate on the previous trading day.

This transformation has become standard in the finance literature (see, for example, Hsieh, 1989; De Grauwe *et al.*, 1993; Steurer, 1995; Brooks, 1996; Mahajan & Wagner, 1999). Thus, this transformation is done to conform to the literature and to allow comparison with other studies in this domain.

Figure 1

Differenced-log Returns of MYR/USD (r_t), 2/1/1990 to 31/8/1998
(2179 observations)



Hinich Bispectrum Test

Hinich (1982) laid out a statistical test for determining whether an observed stationary time series $\{x_t\}$ is linear. It is possible that $\{x_t\}$

is linear without being Gaussian, but all of the stationary Gaussian time series are linear. The Hinich (1982) test involves estimating the bispectrum of the observed time series to test for the null hypothesis of Gaussianity and linearity.

In this section, we provide a brief description of the testing procedures presented by Hinich (1982). Let $\{x_t\}$ denote a third order stationary time series, where the time unit t is an integer. The third-order cumulant function of $\{x_t\}$ in the time domain is defined to be $C_{xxx}(r, s) = E[x_{t+r} x_{t+s} x_t]$ for each (r, s) when $E[x_t] = 0$, in which $s \leq r$ and $r = 0, 1, 2, \dots$

Since third-order cumulants are hard to interpret, and their estimates are even harder to fathom, the bispectrum in the frequency domain is calculated, which is the double Fourier transform of the third-order cumulant (or bicovariance) function.

The bispectrum at frequency pair (f_1, f_2) , denoted as $B_{xxx}(f_1, f_2)$, is the double Fourier transform of $C_{xxx}(r, s)$:

$$B_{xxx}(f_1, f_2) = \sum_{r=-\infty}^{\infty} \sum_{s=-\infty}^{\infty} C_{xxx}(r, s) \exp[-i2\pi(f_1 r + f_2 s)] \quad (2)$$

assuming that $|C_{xxx}(r, s)|$ is summable. The symmetries of $C_{xxx}(r, s)$ translate into symmetries of $B_{xxx}(f_1, f_2)$ that yield a principal domain for the bispectrum, which is the triangular set $\Omega = \{(f_1, f_2) : 0 < f_1 < 1/2, f_2 < f_1, 2f_1 + f_2 < 1\}$.

The use of the bispectrum has an intuitive explanation. If $\{x_t\}$ is linear and Gaussian, the bispectrum is flat at zero over all frequencies $(f_1, f_2) \in \Omega$. However, if $\{x_t\}$ is linear but not Gaussian, then the bispectrum is non-zero, instead it is a constant independent of frequency. Hence, if the bispectrum is non-constant and a function of frequency, then a non-linear process is implied. In this regard, Brillinger (1965) proved that once a consistent estimator of the bispectrum is calculated, linearity and Gaussianity tests can be performed.

Instead of estimating the bispectrum as given in Equation (2), Hinich (1982) provided an equivalent approach that yields a consistent estimator of the bispectrum. Suppose we have a sample of N observations: $\{x_0, x_1, \dots, x_{N-1}\}$. Let $f_c = c/N$ for $c = 0, 1, \dots, N-1$. For each pair of integers j and k , define:

$$F(j, k) = X(f_j) X(f_k) X^*(f_{j+k}) / N \quad (3)$$

where $X(f_c) = \sum_{t=0}^{N-1} \exp[-i2\pi(f_c t)]$ and $*$ denotes the complex conjugate.

A consistent estimator of the bispectrum is formed by averaging the $F(j, k)$ in a square of M^2 points whose centers are defined by the lattice $L = \{(2m-1)M/2, (2c-1)M/2: m = 1, \dots, c \text{ and } m \leq N/2M - c/2 + 1\}$ in the principal domain. For squares that lie completely inside the principle domain, a consistent estimator of the bispectrum is:

$$\hat{B}_{xxx}(f_m, f_n) = M^{-2} \sum_{j=(n-1)M}^{nM-1} \sum_{k=(n-1)M}^{nM-1} F(j, k) \quad (4)$$

If a square has points outside the principal domain, those points are not included in the average. $\hat{B}_{xxx}(f_m, f_n)$ is a consistent and asymptotically complex normal estimator of the bispectrum $B_{xxx}(f_1, f_2)$ in Equation (2) if the sequence (f_m, f_n) converges to (f_1, f_2) .

One important consideration in the estimation of bispectrum is the parameter M , the frame size. The choice of M governs the trade-off between the bias and variance of the estimator. In this regard, the larger (smaller) the M , the smaller (larger) the finite sample variance, but the larger (smaller) the sample bias. Due to this trade-off, there is no unique value for M . Hinich (1982) and Ashley *et al.* (1986) recommended the upper bound value of M should be $M = N^{1/2}$. In this study, we set M equal to 30^3 .

The estimated standardized bispectrum is given by $2 \hat{B}_{xxx}(f_m, f_n) / \hat{S}_{xx}(f_m) \hat{S}_{xx}(f_n) \hat{S}_{xx}(f_{m+n})$, where

$$\hat{X}(f_m, f_n) = \frac{\hat{B}_{xxx}(f_m, f_n)}{[N/M^2]^{1/2} [\hat{S}_{xx}(f_m) \hat{S}_{xx}(f_n) \hat{S}_{xx}(f_{m+n})]^{1/2}}$$

where $f_u = (2u-1)M / 2N$ for each integer u .

The $\hat{S}_{xx}(\cdot)$ in Equation (5) are estimates of the regular power spectrum, which is the Fourier transform of the second-order moment (or autocovariance) and is a function of only one frequency. The power spectrum of $\{x_t\}$ at frequency g is given by:

$$S_{xx}(g) = \sum_{s=-\infty}^{\infty} C_{xx}(s) \exp[-2\pi i g s] \quad (6)$$

where $C_{xx}(s) = E[x_{t+s} x_t]$ is the second-order moment or autocovariance function.

Once again, Gaussianity and linearity of $\{x_t\}$ are tested through the null hypotheses that the estimated standardised bispectrum is zero over all frequencies (f_m, f_n) and that the bispectrum is constant over all frequencies respectively. Though the bispectrum has been understood

for at least 40 years and dates back to the paper by Hasselman *et al.* (1963), the absence of statistical tests for significance of bispectrum estimates was identified as one of the problems that has severely limited its progress. In this regard, Hinich (1982) provided a streamlined and practical procedure that utilises the asymptotic properties of the bispectrum estimator, with the test statistics for both hypotheses reduced to:

$$\hat{Z} = 2 \sum_m \sum_n |\hat{X}(f_m, f_n)|^2 \quad (7)$$

Under the null hypothesis of Gaussianity, the test statistic is distributed asymptotically as a standard normal. On the other hand, under the null of linearity, the test statistic is distributed approximately as a χ^2 random variable with two degrees of freedom. Hinich (1982) and Ashley *et al.* (1986) recommended the use of the 80 per cent quantile of the empirical distribution, scaled by a function of the variance of the series, to provide an asymptotically standard normal variable. However, in this study, we use a 90 per cent quantile to get a more plausible result instead of the 80 per cent⁴.

RESULTS AND ANALYSIS

Before proceeding to the formal non-linear testing with the Hinich bispectrum test, we provide some descriptive statistics for the Malaysian exchange rate returns series in order to get a better view of some of the important statistical features of this series of returns.

Table 1 reveals that the Malaysian exchange rate returns series exhibit some degree of negative or left-skewness. On the other hand, the distributions of these returns series are highly leptokurtic, in which the tails of its distribution taper down to zero more gradually than do the tails of a normal distribution. Not surprisingly, given the non-zero skewness levels and excess kurtosis demonstrated within these series of returns, the Jarque-Bera (JB) test strongly rejects the null of normality.

These results conform to the consensus in the literature that the distributions of exchange rate returns series are non-normal (see, for example, Hsieh, 1988; Steurer, 1995; Brooks, 1996).

Subsequently, the Hinich bispectrum test is applied to the returns series. The result for the bispectrum Gaussianity test for the Malaysian exchange rates returns series is shown in Table 2. The result re-

veals that the null of Gaussianity is strongly rejected, which is consistent with the non-normality of exchange rate returns series suggested by Jarque-Bera (1987) normality test results.

Table 1

Summary Statistics of Differenced-log Returns for MYR/USD (r_t)

	MYR/USD
Sample Period	2/1/1990-31/8/1998
No. of observations	2179
Mean	0.020103
Median	0.000000
Maximum	7.195700
Minimum	-9.156700
Std deviation	0.694546
Skewness	-0.083968
Kurtosis	43.14067
JB normality test statistic	146292.7
<i>p</i> -value	(0.000000)*

* Denotes a very small value.

Although Gaussianity and linearity tests are linked, a rejection of Gaussianity does not necessarily rule out linearity. As mentioned earlier, the null of linearity examines whether the estimated standardised bispectrum is constant over all frequencies, whereas Gaussianity requires constant at zero over all frequencies. The linearity test provided by Hinich (1982) is able to detect a non-constant bispectrum which suggests a non-linear generating process for the returns series. Table 2 reports the *p*-value for the 90 per cent quantile bispectrum linearity test for the Malaysian exchange rate returns series. The result rejects the null hypothesis of a linear generating mechanism even at the 1% level of significance. This indicates the existence of non-linear dependencies within the Malaysian daily exchange rate returns series. It is important to note that the rejection of the null of linearity in the bispectrum test is a strong support for the presence of non-linearity (Barnett *et al.*, 1997).

Figure 2 illustrates the standardised bispectrum estimates for the Malaysian exchange rate returns series, which offer an intuitive account of the Gaussianity and linearity testing procedures. The contour plot displays the estimated bispectrum over the two-dimensional principal domain, viewed from above the surface. Recall that the bispectrum is independent of frequency and is constant if the series conforms to a linear model, and is zero if the series is Gaussian.

Clearly, the standardised bispectrum estimates are non-zero over its triangular principal domain (observations outside the principal domain are set equal to zero), as we observe a number of peaks in the bispectrum displayed in Figure 2. This is reflected in our results in Table 2 where the null hypothesis of Gaussianity is strongly rejected.

Table 2
Gaussianity and Linearity Test Results

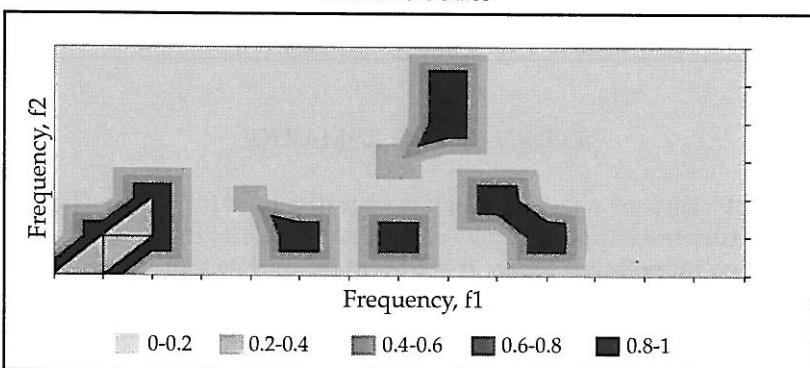
	MYR/USD
Gaussianity Test Results (<i>p</i> -value)	0.0000*
Linearity Test Results (<i>p</i> -value)	0.0063

Note: Both test statistics are distributed as $N(0,1)$ and are taken as a one-sided test.

* Denotes very small value.

Also, the horizontal and vertical axes of the plots show the frequencies of points in the principal domain measured in cycles per day. If the process were linear, we would not find interaction between various frequencies in the sample returns (Hinich & Patterson, 1985). The contour plot in Figure 2 shows the combinations of frequencies where inter-frequency interaction occurs when the input to a non-linear filter is Gaussian white noise, hence, suggesting that the Malaysian exchange rate returns series are indeed generated by a non-linear mechanism. This visual inspection is consistent with the rejection of the null of linearity in Table 2.

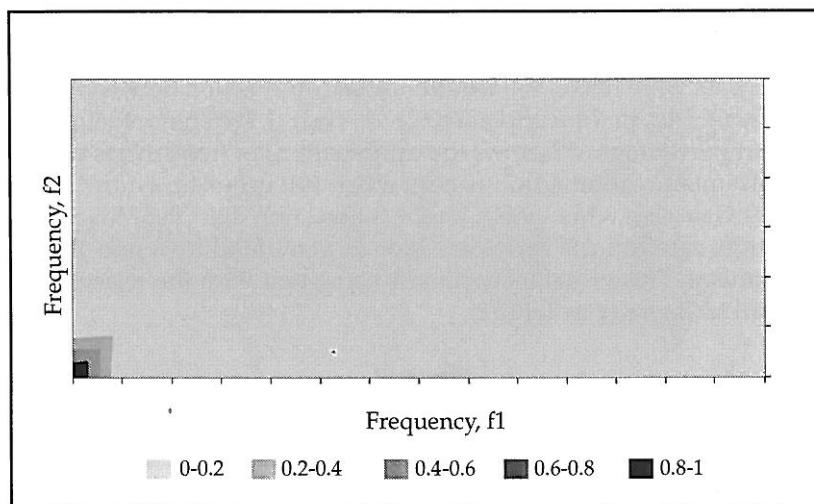
Figure 2
Contour Plot of the Estimated Bispectrum for MYR/USD
Returns Series



To provide a comparison with the non-linear process in Figure 2, a contour view of the standardised bispectrum estimates for a linear process is provided in Figure 3. The model used is a linear autoregressive moving average (ARMA) process, simulated by Barnett *et al.* (1997)⁵.

As mentioned in the earlier section, the bispectrum of a linear process should be constant which is independent of frequency. In Figure 3, the standardised bispectrum estimates are found to be constant at zero with no inter-frequency interaction, only minimum interaction occurs at the lower left corner of the principal domain. The Hinich (1982) test results, though not reported here, show that the null of Gaussianity and linearity cannot be rejected, which is unsurprising given that the simulated data is of linear ARMA process.

Figure 3
Contour Plot of the Estimated Bispectrum for
a Linear ARMA Process



CONCLUDING REMARKS

The outcomes of our econometric investigation using the Hinich bispectrum test support the presence of non-linearity in the Malaysian exchange rate returns series. It is important to note that the rejection of the null of linearity in the bispectrum test is a strong support for the presence of non-linearity (Barnett *et al.*, 1997). This evidence of non-linearity in the underlying data generating process for Malaysian

exchange rates will come as no surprise because the Malaysian foreign exchange market is characterised by abrupt changes traceable to the Central Bank interventions - attempts by the government to control the value of the currency, contrary to natural market forces. To put it differently, by the nature of its intervention, the Central Bank stopped the market from moving freely and reacting completely and immediately to new information.

There are some implications from this study that deserve our attention which might be useful in future work on financial markets. Firstly, most of the widely applied statistical tests like the unit root or stationary tests, the order of integration test, the Granger causality test and the cointegration test are all built on the basis of a linear autoregressive model. This assumption of linearity, which has been made as an approximation of the real world, is now found to be inappropriate, especially with the advancement of research methodology and computer technology. Liew *et al.* (2003) argued that estimating the linear AR(p) model, implicitly disregarding any possible non-linearity in the series under consideration, will yield a mis-specified model and thereby provide wrong clues in policy matters. Specifically, the authors advocate the use of formal linearity test as a diagnostic tool to determine the nature of the data generating process before any further empirical analysis. A linear model is only valid when the formal linearity test result fails to provide evidence of the existence of non-linearity.

In this regard, Taylor and Peel (1997) and Sarno (2000), among others, illustrated that the adoption of linear stationarity tests is inappropriate in detecting the mean reversion if the true data generating process of exchange rate is in fact a stationary non-linear process. On the other hand, the Monte Carlo simulation evidence in Bierens (1997) indicated that the standard linear cointegration framework presents a mis-specification problem when the true nature of the adjustment process is non-linear and the speed of adjustment varies with the magnitude of the dis-equilibrium. Thus, the evidence of non-linearity in this study further strengthens the argument of Liew *et al.* (2003) that researchers can no longer take the linear assumption for granted. In this case, further empirical analysis involving the Malaysian exchange rate returns series should employ tests that are more robust with respect to non-linear generating processes such as the non-parametric cointegration test (Bierens, 1997), non-linear stationarity test (Sarno, 2001; Chortareas *et al.*, 2002; Kapetanios *et al.*, 2003), and non-linear causality test (Baek & Brock, 1992).

Secondly, the validity of market efficiency in the Malaysian foreign exchange market is questionable since the evidence of statistically significant non-linear components from this study implies the potential for returns predictability. Following the weak-form efficient market hypothesis, even non-linear combinations of previous prices should not be useful predictors of future prices. However, it is still an open question whether the detected non-linear structure can be profitably exploited (McMillan & Speight, 2001). In order to assess the economic significance of this non-linearity, it is necessary to consider whether investors could have profitably operated a trading rule which exploits the detected non-linearity. The key message from this is that in an empirical test of market efficiency, the lack of linear dependencies does not necessarily imply an efficient market. There is a possibility of dependencies in the non-linear forms which might be profitably exploited by investors.

Thirdly, the breakdown in the empirical performance of linear models of exchange rate determination during the floating exchange rate period is well documented. It has been suggested that the incorporation of non-linear effects might significantly improve models of exchange rate determination. For instance, recent work in the Purchasing Power Parity (PPP)⁶ literature has attempted to address the issue of non-linearity in mean reversion. Studies by Micheal *et al.* (1997), Sarno (2000), Baum *et al.* (2001) and Liew *et al.* (2002) provided strong support for the validity of long run PPP, in which the real exchange rate adjusts non-linearly towards its equilibrium PPP level.

Lastly, the evidence that exchange rate series follow non-linear dynamics is important to the pricing of currency futures and option contracts and the development of dynamic hedging strategies. This is because the assumption of stochastic process generating security returns is of primary importance in designing hedges and pricing derivatives. The evidence of non-linearity implies that the assumed stochastic processes do not adequately depict the full complexity of the true generating process. Failure to take note of these non-linear dynamics might cause the derivatives in question to be mis-priced. Though at the time of writing, currency futures and option contracts have not been offered in the derivative markets of Malaysia, future launching of these contracts have to take note of the presence of non-linearity so that investors are not exposed to unwanted risks due to mis-pricing and imperfect hedges.

To conclude, this study is conducted with a clear objective of examining the underlying dynamics in the Malaysian exchange rate returns

series. With a strong evidence of non-linearity in the data generating process, it reveals that researchers can no longer take the linear assumption for granted as it has profound implications on the robustness of their empirical results. Thus, it points to the need of employing a formal linearity test as a preliminary diagnostic tool to determine the nature of the data generating process before any further empirical analysis.

NOTES

1. The growing popularity of the BDS test has witnessed its incorporation into commercial statistical package of E-Views version 4.0.
2. These daily data are obtained from the Federal Reserve Board's official website at <http://www.federalreserve.gov/releases/H10/hist> on 18/4/2001. The H.10 release contains daily rates of exchange of major currencies against the U.S. dollar.
3. Hinich recommends a reduction in the frame size to 30 for our sample sizes in order to improve the power of the test.
4. In a personal communication, Hinich recommends the use of 90 percent quantile.
5. We obtained the simulated data from the Barnett web page, <http://wuecon.wustl.edu/~barnett/Papers.html>.
6. The Purchasing Power Parity not only by itself can be viewed as a theory of exchange rate determination, but also serves as a foundation for a more complete theory, namely the monetary approach.

ACKNOWLEDGEMENTS

The authors appreciate the generosity of Professor Melvin J. Hinich of the University of Texas in Austin for sharing his bispectrum codes and some helpful comments in conducting this study. The authors would also like to express their gratitude to the anonymous referee of the journal for constructive comments that greatly improve the final version of the paper. The usual disclaimer applies to any remaining errors or omissions. The first author acknowledges financial support from Universiti Malaysia Sabah (Grant No. A-002-16-ER/U017).

REFERENCES

Abhyankar, A.H., Copeland, L.S. & Wong, W. (1995). Nonlinear dynamics in real-time equity market indices: Evidence from the United Kingdom. *Economic Journal*, 105, 864-880.

Alexander, D. & Thomas, L.R. (1987). Monetary/asset models of exchange rate determination: How well have they performed in the 1980's? *International Journal of Forecasting*, 3, 53-64.

Ashley, R.A., Patterson, D.M. & Hinich, M.J. (1986). A diagnostic test for nonlinear serial dependence in time series fitting errors. *Journal of Time Series Analysis*, 7(3), 165-178.

Baek, E. & Brock, W. (1992). A general test for non-linear Granger causality: Bivariate model. (Working Paper). Iowa State University and University of Wisconsin at Madison.

Baillie, R.T., Bollerslev, T. & Ole Mikkelsen, H. (1996). Fractionally integrated generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 74, 3-30.

Barnett, W.A., Gallant A.R., Hinich, M.J., Jungeilges, J., Kaplan, D. & Jensen, M.J. (1997). A single-blind controlled competition among tests for nonlinearity and chaos. *Journal of Econometrics*, 82, 157-192.

Barnett, W.A. & Serletis, A. (2000). Martingales, nonlinearity, and chaos. *Journal of Economic Dynamics and Control*, 24, 703-724.

Baum, C.F., Barkoulas, J.T. & Caglayan, M. (2001). Nonlinear adjustment to purchasing power parity in the post-Bretton Woods era. *Journal of International Money and Finance*, 20, 379-399.

Bierens, H.J. (1997). Nonparametric cointegration analysis. *Journal of Econometrics*, 77, 379-404.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31, 307-327.

Bollerslev, T., Chou, R.Y. & Kroner, K.F. (1992). ARCH modeling in finance: A review of the theory and empirical evidence. *Journal of Econometrics*, 52(5), 5-59.

Boothe, P. & Glassman, D. (1987). Comparing exchange rate forecasting models. *International Journal of Forecasting*, 3, 65-79.

Brillinger, D. (1965). An introduction to polyspectrum. *Annals of Mathematical Statistics*, 36, 1351-1374.

Brock, W.A., Dechert, W.D., Scheinkman, J.A. & LeBaron, B. (1996). A test for independence based on the correlation dimension. *Econometric Reviews*, 15, 197-235.

Brock, W.A., Hsieh, D.A. & LeBaron, B. (1991). *Nonlinear dynamics, chaos, and instability: Statistical theory and economic evidence*. Cambridge: MIT Press.

Brooks, C. (1996). Testing for non-linearity in daily sterling exchange rates. *Applied Financial Economics*, 6, 307-317.

Brooks, C. & Hinich, M.J. (1999). Cross-correlations and cross-bicorrelations in Sterling exchange rates. *Journal of Empirical Finance*, 6(4), 385-404.

Campbell, J.Y., Lo, A.W. & MacKinlay, A.C. (1997). *The econometrics of financial markets*. Princeton: Princeton University Press.

Chinn, M.D. (1991). Some linear and nonlinear thoughts on exchange rates. *Journal of International Money and Finance*, 10, 214-230.

Chortareas, G.E., Kapetanios, G. & Shin, Y.C. (2002). Non-linear mean reversion in real exchange rates. *Economic Letters*, 77, 411-417.

De Gooijer, J.G., Ray, B.K. & Krager, H. (1998). Forecasting exchange rates using TSMARS. *Journal of International Money and Finance*, 17, 513-534.

De Grauwe, P., Dewachter, H. & Embrechts, M. (1993). *Exchange rate theory: Chaotic models of foreign exchange markets*. Oxford: Blackwell.

Engel, C. & Hamilton, J. (1990). Long swings in the exchange rate: Are they in the data and do markets know it? *American Economic Review*, 80, 689-713.

Grassberger, P. & Procaccia, I. (1983). Measuring the strangeness of strange attractors. *Physica*, 9D, 189-208.

Hasselman, K., Munk, W. & MacDonald, G. (1963). Bispectra of ocean waves. In M. Rosenblatt (Ed.), *Time series analysis* (pp.125-139). New York: John Wiley.

Hinich, M.J. (1982). Testing for gaussianity and linearity of a stationary time series. *Journal of Time Series Analysis*, 3, 169-176.

Hinich, M.J. & Patterson, D.M. (1985). Evidence of nonlinearity in daily stock returns. *Journal of Business and Economic Statistics*, 3(1), 69-77.

Hinich, M.J. & Patterson, D.M. (1989). Evidence of nonlinearity in the trade-by-trade stock market return generating process. In W.A. Barnett, J. Geweke, & K. Shell (Ed.), *Economic complexity: Chaos, sunspots, bubbles and nonlinearity- international symposium in economic theory and econometrics*, (pp.383-409). Cambridge: Cambridge University Press.

Hsieh, D.A. (1988). The statistical properties of daily foreign exchange rates: 1974-1983. *Journal of International Economics*, 24, 129-145.

Hsieh, D.A. (1989). Testing for non-linearity in daily foreign exchange rate changes. *Journal of Business*, 62, 339-368.

Hsieh, D.A. (1991) Chaos and nonlinear dynamics: Application to financial markets. *Journal of Finance*, 46, 1839-1877.

Jarque, C.M. & Bera, A.K. (1987). A test for normality of observations

and regression residuals. *International Statistical Review*, 55, 163-172.

Kapetanios, G., Shin, Y.C. & Snell, A. (2003). Testing for a unit root in the nonlinear STAR framework. *Journal of Econometrics*, 112, 359-379.

Kaplan, D.T. (1994). Exceptional events as evidence for determinism. *Physica D*, 73, 38-48.

Liew, K.S., Chong, T. & Lim, K.P. (2003). The inadequacy of linear autoregressive model for real exchange rates: Empirical evidence from Asian economies. *Applied Economics*, forthcoming.

Liew, K.S., Baharumshah, A.Z. & Lau, E. (2002). Nonlinear adjustment to purchasing power parity: Empirical evidence from Asian exchange rates. *Proceedings of Asia Pacific Economics and Business Conference 2002, 2-4 October 2002, Sarawak, Malaysia*, pp.902-910.

Mahajan, A. & Wagner, A.J. (1999). Nonlinear dynamics in foreign exchange rates. *Global Finance Journal*, 10(1), 1-23.

McMillan, D.G. & Speight, A.E.H. (2001). Nonlinearities in the black market zloty-dollar exchange rate: some further evidence. *Applied Financial Economics*, 11, 209-220.

Meese, R.A. & Rogoff, K. (1983). Empirical exchange rate models of the seventies: Do they fit out of sample? *Journal of International Economics*, 14, 3-24.

Meese, R.A. & Rose, A.K. (1990). Nonlinear, nonparametric, nonessential exchange rate estimation. *American Economic Review*, 80, 192-196.

Micheal, P., Nobay, A.R. & Peel, D.A. (1997). Transactions costs and nonlinear adjustment in real exchange rates: An empirical investigation. *Journal of Political Economy*, 105, 862-879.

Opong, K.K., Mulholland, G., Fox, A.F. & Farahmand, K. (1999). The behavior of some UK equity indices: An application of Hurst and BDS tests. *Journal of Empirical Finance*, 6, 267-282.

Pesaran, M.H. & Potter, S.M. (1993). Nonlinear dynamics, chaos and econometrics: An introduction. In M.H. Pesaran and S.M. Potter (Eds.), *Nonlinear dynamics, chaos and econometrics* (pp.vii-xiii). New York: John Wiley & Sons.

Sarno, L. (2000). Real exchange rate behaviour in high inflation countries: empirical evidence from Turkey, 1980-1997. *Applied Economics Letters*, 7, 285-291.

Sarno, L. (2001). The behavior of US public debt: A nonlinear perspective. *Economics Letters*, 74, 119-125.

Scheinkman, J. & LeBaron, B. (1989). Nonlinear dynamics and stock returns. *Journal of Business*, 62, 311-337.

Schinasi, G.J. & Swamy, P.A.V.B. (1989). The out-of-sample forecasting

performance of exchange rate models when coefficients are allowed to change. *Journal of International Money and Finance*, 8, 375-390.

Steurer, E. (1995). Nonlinear modeling of the DEM/USD exchange rate. In A.P. Refenes (Ed.). *Neural networks in the capital markets* (pp. 199-211). New York: John Wiley & Sons.

Taylor, M.P. & Peel, D.A. (1997). *Nonlinearities in real exchange rate adjustment during the recent float: empirical evidence and Monte Carlo analysis* (Discussion Paper). Institute of Economics and Statistics, University of Oxford.

Vilasuso, J. & Cunningham, S. (1996). Tests for nonlinearity in EMS exchange rates. *Studies in Nonlinear Dynamics and Econometrics*, 1(3), 155-168.

White, H. (1989). Some asymptotic results for learning in single hidden layer feedforward network models. *Journal of the American Statistical Association*, 84, 1003-1013.

Wolff, C.C.P. (1987). Time-varying parameters and the out-of-sample forecasting performance of structural exchange rate models. *Journal of Business and Economic Statistics*, 5, 87-103.

Wolff, C.C.P. (1988) Models of exchange rates: A comparison of forecasting results. *International Journal of Forecasting*, 4, 605-607.