ARE NON-LINEAR DYNAMICS A UNIVERSAL OCCURRENCE? FURTHER EVIDENCE FROM ASIAN STOCK MARKETS

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ABSTRACT

With abounding evidence of non-linearity in stock markets of developed markets, this study attempts to narrow the gap in the literature of Asian countries by providing further empirical evidence to the issue "are non-linear dynamics a universal occurrence?". The results from the Hinich bispectrum test indicate strong evidence of non-linearity in all the Asian stock markets under investigate- Japan, Hong Kong, Singapore and Malaysia. These findings further add to the empirical support that non-linearity is a salient feature in stock market time series data and have important implications for works on market efficiency, modelling and pricing and hedging strategies in derivatives markets.

Key Words: Non-linearity; Data generating process; Hinich bispectrum test; Asian stock markets

JEL classifications: **G12**

I. INTRODUCTION

It is an accepted fact that financial economics has been dominated over the past decade by linear paradigm, which assumes that economic time series conform to linear models or can be well approximated by a linear model. For example, empirical tests of market efficiency, purchasing power parity, tests of causality and many of the empirical models of asset pricing have implicitly assumed that the underlying dynamics are in linear form or can be made linear by a simple transformation.

However, there are ample empirical evidence against the linear paradigm. Theoretically, there is no reason to believe that economic systems must be intrinsically linear (see, for example, Pesaran and Potter, 1993; Campbell *et al.*, 1997; Barnett and Serletis, 2000). Empirically, there are a great number of studies showing that financial time series exhibit non-linear dependencies (see, for example, Hsieh, 1989, 1991; Scheinkman and LeBaron, 1989; De Grauwe *et al*., 1993; Abhyankar *et al*, 1995; Steurer, 1995; Brooks, 1996; Barkoulas and Travlos, 1998; Opong, *et al.*, 1999). With this development, the subject has now moved to a new direction. This new direction is, of course, the study of non-linearity. In the words of Campbell *et al.* (1997: 467), "A natural frontier for financial econometrics is the modelling of non-linear phenomenon". A good testimony of the growing interest in non-linear studies would be the founding of a specialized international journal entitled *Studies in Non-linear Dynamics and Econometrics.*. The main driving force behind this shift is the developments in the mathematical and statistical analysis of dynamics systems, which has the ability to uncover a more complex form of dependencies in a time series that appear to be random.

Over the past decade, numerous studies have documented the existence of non-linear dependencies in stock markets (see, for example, Scheinkman and LeBaron, 1989; Hsieh, 1991; Abhyankar *et al*, 1995, 1997; Barkoulas and Travlos, 1998; Opong, *et al.*, 1999). Much of this evidence has been drawn from the widely traded financial markets of well-developed countries, such as the New York Stock Exchange and London Stock Exchange. Though more efforts are now being directed towards the Asian stock markets in light of their increasing importance to the investment world and the world economy, to the knowledge of the writers, there is no study which utilizes recent advances in non-linear dynamics and chaos to examine the data generating process of the Asian stock markets. Thus, this leads to a number of important questions concerning the universal applicability of those findings from developed markets. Motivated by the above considerations, this study attempts to address the question: "are non-linear dynamics a universal occurrence?" by providing further evidence from major Asian stock markets.

This paper is organized as follows: Section II provides a brief discussion on non-linearity, with a focus on the underlying concept and its relevancy to the world of economics and finance. This is followed by a brief review on the methodology commonly used in non-linear studies. Section IV then describes the data and the Hinich bispectrum test used in this study. Section V presents the empirical results as well as the analysis of the findings. Finally, concluding remarks are given at the end of the paper.

II. A BRIEF DISCUSSION ON NON-LINEARITY

It would be appropriate at this stage to clearly define the terms 'non-linearity'. In the literature, there is no generally agreed definition for 'non-linearity'. From the definition given by De Grauwe *et al.* (1993: 244), a system $X_t = h(\Omega_t, \alpha)$ is called a non-linear system if it is not possible to regenerate X_t by one linear model:

$$X_t = \sum_{i=0}^{\infty} \gamma_i \varepsilon_{t-i} \quad \text{and } \varepsilon \text{ is white noise and}$$

$$\sum_{t=0}^{\infty} \gamma_i \text{ is such that } \sum_{t=0}^{\infty} \left|\gamma_t\right| < \infty \tag{1}$$

According to De Grauwe *et al.* (1993), the definition of non-linearity stems from the negation of linearity. This leaves a lot of other possibilities open for a so-called non-linear system. For example, Hsieh (1989) divides the realm of non-linear dependencies into three categories. Additive non-linearity, also known as non-linear-in-mean, enters a process through its mean or expected value, so that each element in the sequence can be expressed as the sum of zero-mean random element and a non-linear function of past elements[1]. With multiplicative non-linearity, or non-linear-in-variance, each element can be expressed as the product of a zero-mean random element and a non-linear function of past elements, so that the non-linearity affects the process through its variance[2]. The final category is known as hybrid dependence, in which non-linearity enters through both the mean and the variance[3].

Researchers in economics and finance have been interested in testing for non-linear dependence in financial time series data for more than a decade now, though the focus is on financial markets of developed countries. With abounding evidence of non-linearity in these markets, further works on non-linear studies have experienced a tremendous growth. Since this line of study has commanded considerable attention from researchers, one might wonder its significance and relevancy to the world of economics and finance. The motivation for this line of inquiry are at least threefold.

First, the evidence of non-linearity in a retun 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 and Hinich, 1999; McMillan and Speight, 2001).

Second, the test for non-linearity can be viewed as general tests of model adequacy for linear models (Hinich and Patterson, 1989). If there is still dependence in the residuals of linear model (of an albeit more complex form), the original linear models can no longer be viewed as an accurate representation

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[1] The non-linear moving average model, the threshold autoregressive model and the bilinear model are examples of additive dependence.
[2] The ARCH-type models are examples of multiplicative dependence.
[3] The ARCH-in-the-mean and GARCH-in-the-mean are examples of hybrid dependence.

of the data. The prevalence of non-linearity in financial time series data has prompted researchers to consider alternative models that take into account the underlying non-linear dynamics of the data generating process. For example, non-linear models such as Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model and Smooth Transition Autoregressive (STAR) model are widely employed in the literature to explain the dynamics of financial time series. Other related developments along this line are non-parametric cointegration test due to Bierens (1997a), non-linear stationarity test (Bierens, 1997b), non-linear causality test (Baek and Brock, 1992), non-linear adjustments towards purchasing power parity (see, for example, Sarno, 2000). The rationale for the phenomenal growth in this area is that if the underlying process is non-linear in nature, then it would be inappropriate to employ linear methods.

Finally, for finance academics and practitioners involved in the pricing of derivative securities and the development of dynamic hedging strategies, the potential implications of securities following non-linear dynamics are no less dramatic. The assumptions that the stochastic process generating securities returns are of primary importance in designing hedges and pricing derivatives. However, if the assumed stochastic processes do not adequately depict the full complexity of the true generating processes, then any derivatives in question may be mis-priced. This implies that investors and institutions may have imperfect hedges, which expose them to unwanted risks.

III. A REVIEW ON METHODOLOGY

There are wide variety of tests employed in the literature to detect non-linearity, just as there is no commonly agreed definition for non-linear system. According to Barnett and Serletis (2000), those non-linearity tests that are widely employed in the literature are the correlation dimension test (Grassberger and Procaccia, 1983), the BDS test (Brock *et al.*, 1996), 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 popular[4] (see, for example, Scheinkman and LeBaron, 1989; Hsieh, 1991; De Grauwe *et al.*, 1993; Steurer, 1995; Abhyankar *et al*., 1995; Brooks, 1996; Opong *et al.*, 1999; Mahajan and 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, either in finite samples or 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) present 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.

IV. METHODOLOGY

The Data

In this study, the data consist of daily closing prices for four major Asian stock market indices: Tokyo Nikkei 225 (Japan), Hong Kong Hang-Seng (Hong Kong), Singapore Straits Times (Singapore) and Kuala Lumpur Composite Index (Malaysia). The prices covering the sample period from 2 January 1990 to 31 October 2001 are transformed into a series of 3087 continuously compounded percentage returns, using the relationship:

$$r_t = 100 * \ln(P_t/P_{t-1}) \tag{2}$$

where P_t is the closing price of the stock on day t, and P_{t-1} the price on the previous trading day.

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[5], but all of the stationary Gaussian time series are linear. The Hinich bispectrum test involves estimating the bispectrum of the observed time series, which is the double Fourier transform of the third-order cumulant function.

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[4] The growing popularity of the BDS test has witnessed its incorporation into commercial statistical package of E-Views version 4.0.

[5] When the distribution of $\{x(n_1),\ldots\ldots x(n_N)\}$ is multivariate normal for all $n_1,\ldots\ldots, n_N$, then the series is called Gaussian.

In this section, we present 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)} is defined to be $C_{xxx}(m,n) = E[x(t+n)x(t+m)x(t)]$ for each (m,n) when E[x(t)] = 0, in which n $\leq$ m and m = 0, 1, 2,…

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

The bispectrum at frequency pair (f_1, f_2) is the double Fourier transform of $C_{xxx}(m,n)$:

$$B_x(f_1, f_2) = \sum_{n=-\infty}^{\infty} \sum_{m=-\infty}^{\infty} C_{xxx}(m,n) \exp[-i2\pi(f_1 m + f_2 n)] \tag{3}$$

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

Since the spectrum of {x(t)}is $S_x(f) = \sigma_u^2 |A(f)|^2$, it follows that:

$$\psi^2(f_1, f_2) \equiv \frac{|B_x(f_1, f_2)|^2}{S_x(f_1) S_x(f_2) S_x(f_1 + f_2)} = \frac{\mu_3^2}{\sigma_u^6 \sigma} \tag{4}$$

for all f_1 and f_2 in Ω, where $A(f) = \sum_{n=0}^{\infty} a(n) \exp(-i2\pi f n)$. The left hand side of Equation (4) defines the square of the skewness function of {x(t)}, $\psi(f_1,f_2)$. Linearity and Gaussianity of {x(t)} are tested through the null hypotheses that $\psi(f_1,f_2)$ is constant over all frequencies and that $\psi(f_1,f_2)$ is zero over all frequencies respectively using the estimated bispectrum.

The test statistics for both hypotheses are reduced to

$$\hat{S} = 2 \sum_m \sum_n \left| \hat{X}_{m,n} \right|^2 \tag{5}$$

at the frequency pair (*m,n*) where

$$\hat{\boldsymbol{X}}_{m,n} = \frac{\hat{\boldsymbol{B}}_x(\boldsymbol{m},\boldsymbol{n})}{[\boldsymbol{N}/\boldsymbol{M}^2]^{1/2}[\hat{\boldsymbol{S}}_x(\boldsymbol{g}_m)\hat{\boldsymbol{S}}_x(\boldsymbol{g}_n)\hat{\boldsymbol{S}}_x(\boldsymbol{g}_{m+n})]^{1/2}} \tag{6}$$

Under the null hypothesis of Gaussianity, $\hat{S}$ is distributed chi-squared with 2P degree of freedom, with P being the number of squares whose centres are in the principal domain. Hinich (1982) shows that, asymptotically, the transformation of $\hat{S}$ is well approximated by a normal distribution with zero mean and unit variance. Thus, the significance of the test statistics is readily determined from standard normal tables.

On the other hand, if {x(t)} is linear but not Gaussian, the sample dispersion of $2\left|\hat{X}_{m,n}\right|^2$ should not differ significantly from the population dispersion of $\chi^2(2,\hat{\lambda})$, where $\hat{\lambda} = \left\{\hat{S}/P\right\} - 2$. Linearity test statistics examine whether the sample dispersion is significantly different from that of $\chi^2(2,\hat{\lambda})$. The distribution of the standard normal is used to produce a one-sided test, in which the null is rejected if the test statistic is greater than the critical value at the chosen level of significance.

It is important to note that this dispersion can be measured in many ways. We used the 90 percent quantile of the empirical distribution in order to get a more plausible result[6]. Another important consideration in the implementation of the bispectrum test 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 respect, the larger (smaller) the M, the smaller (larger) the finite sample variance and the larger (smaller) the sample bias. Owing to this trade-off, there is no unique M that is appropriate to use. In this study, we set M equal to 30[7].

V. EMPIRICAL RESULTS

[6] In a personal communication, Hinich recommends the use of the 90 percent quantile.
[7] Hinich recommends a frame size of 30 for our sample sizes in order to improve the power of the test.

Table 1 provides summary statistics for all the Asian stock return series. The means are quite small. Most of the return series exhibit some degree of positive or right-skewness, with the exception of Hong Kong Hang-Seng. On the other hand, the distributions 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.

TABLE 1: Summary Statistics

	Tokyo Nikkei 225	**Hong Kong Hang Seng**	**Singapore Straits Times**	**Kuala Lumpur Composite Index**
Sample Period	2/1/1990 31/10/2001	2/1/1990 31/10/2001	2/1/1990 31/10/2001	2/1/1990 31/10/2001
No. of observations	3087	3087	3087	3087
Mean	-0.042852	0.041055	0.005173	0.002107
Median	0.000000	0.000000	0.000000	0.000000
Maximum	12.43033	17.24711	14.86849	20.81737
Minimum	-7.233984	-14.73471	-9.671880	-24.15339
Std deviation	1.498114	1.716575	1.358363	1.715348
Skewness	0.267452	-0.037722	0.201159	0.460844
Kurtosis	6.872794	12.50663	14.07012	36.89786
JB normality test statistic	1965.989	11625.34	15783.51	147907.7
(*p*-value)	(0.000000)*	(0.000000)	(0.000000)	(0.000000)

* denotes extremely small *p*-value.

Subsequently, the Hinich bispectrum test is applied to all the Asian stock return series. Table 2 reports the results for the bispectrum Gaussianity test. It is obvious that the null is strongly rejected in each of the stock return series, which confirms the non-normality of the return series suggested by Jarque-Bera normality test results in Table 1.

Although Gaussianity and linearity tests are linked, a rejection of Gaussianity does not necessarily rule out linearity. If the underlying return series are linear, but not Gaussian, then the sample dispersion of $2\left|\hat{X}_{m,n}\right|^2$ should not differ significantly from the population dispersion of $\chi^2(2,\hat{\lambda})$, where $\hat{\lambda} = \left\{\hat{S}/P\right\} - 2$. The linearity test statistics examine whether the sample dispersion is significantly different from that of $\chi_2{}^2(2,\hat{\lambda})$. Table 2 reports the *p*-value for the 90 percent quantile bispectrum linearity test. The results reject the null hypothesis of a linear generating mechanism at the conventional level of significance. This indicates the existence of non-linear dependencies within the daily return series of the Asian stock market under investigate. 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).

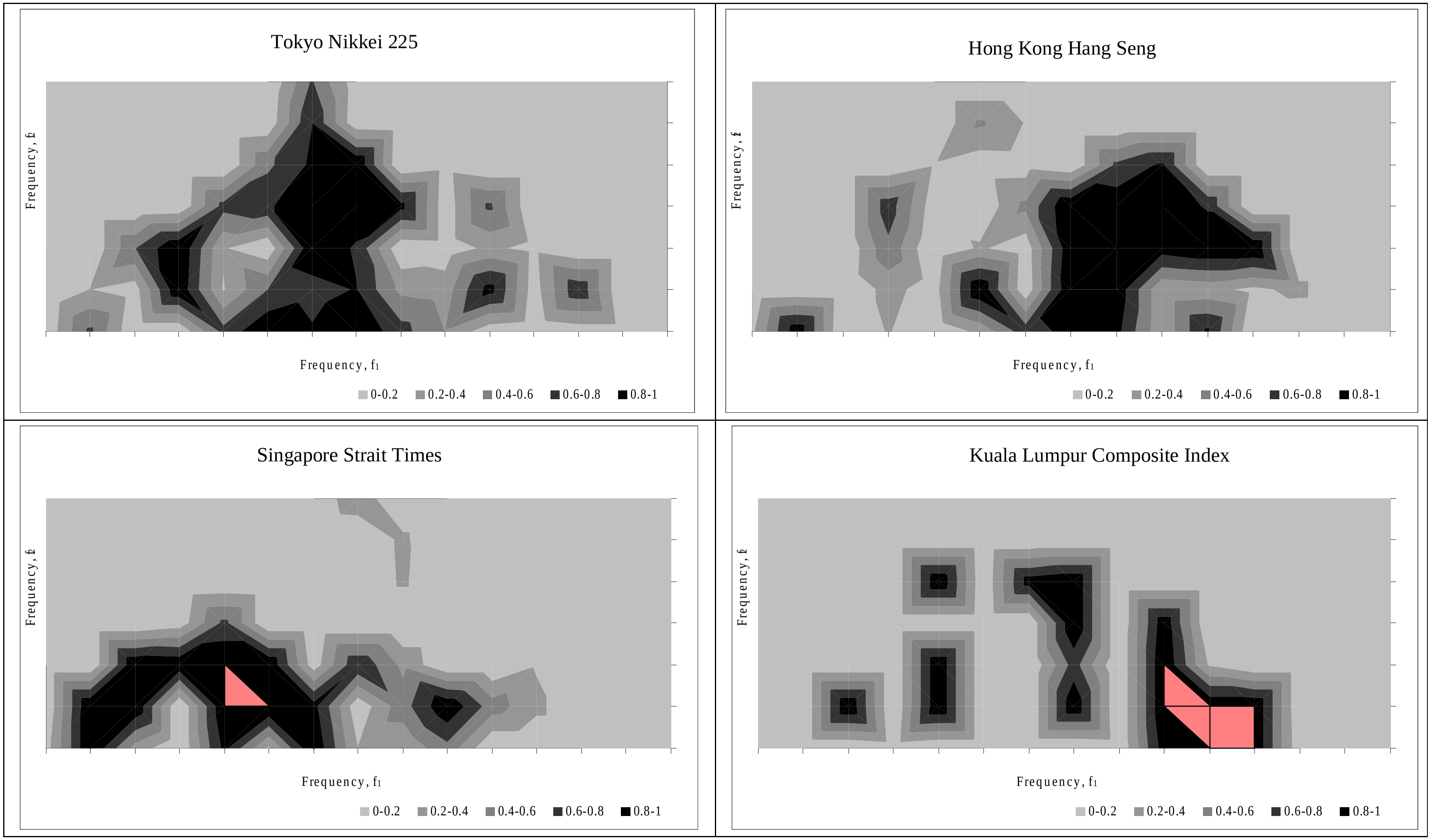
TABLE 2: Gaussianity And Linearity Test Results

Series	**Gaussianity Test Results (*p*-value)**	**Linearity Test Results (*p*-value)**
Tokyo Nikkei 225	0.0000*	0.0192
Hong Kong Hang Seng	0.0000*	0.0074
Singapore Straits Times	0.0000*	0.0064
Kuala Lumpur Composite Index	0.0000*	0.0063

Note: Both test statistics are distributed as N(0,1) and are taken as a one-sided test.
* denotes extremely small value.

Figure 1 illustrates the standardized bispectrum estimates for each of the Asian stock return 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. The horizontal and vertical axes of the plots show the frequencies of points in the principal domain measured in cycles per day. 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 standardized bispectrum estimates are non-zero over its triangular principal domain (observations outside the principal domain are set equal to zero). The findings in Table 2 reflect the rejection of Gaussianity. Although Gaussianity and linearity tests are linked, a rejection of Gaussianity does not necessarily rule out linearity. Thus, linearity tests then examine whether the standardized bispectrum estimates are constant over their principal domain. Since the nulls have been rejected, as reported in Table 2, we would expect to see a number of peaks in the bispectrum, as indeed we do in Figure 1. Furthermore, if the process are linear, we would not find interaction between various frequencies in the sample returns (Hinich and Patterson, 1985). Thus, the plot provides a convenient way to observe that all the Asian stock return series are indeed generated by a non-linear mechanism.

FIGURE 1: Contour Plot of the Estimated Bispectrum for Asian Stock Return Series



V. CONCLUSIONS

The outcomes of our econometric investigation using the Hinich bispectrum test provide strong support for the presence of non-linearity in all the Asian stock market return 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). These results add to the empirical support that non-linearity is a salient feature in stock market time series data.

As we mentioned earlier, the evidence of non-linearity has profound implications on weak-form market efficiency. The validity of market efficiency in these Asian stock markets is questionable since the evidence of statistically significant non-linear components implies the potential for returns predictability. However, it is still an open question whether the detected non-linear structure can be profitably exploited. On the other hand, with the prevalence of non-linearity in stock market series, it is now time to relax the assumption of linearity in our empirical work, which is so dominant in the era of linear paradigm. Future works in Asian stock markets on the area of modelling, market integration, causal relationship, asset pricing, hedging strategies of derivatives, amongst others, should take note of the underlying non-linear dynamics in the data.

To conclude, the prevalence of non-linearity in financial time series, particularly in stock market data of Asian countries, should be taken seriously and not to be neglected. To researchers in developing countries, it is time to embrace the shift to non-linearity, which offers both great excitement and challenges. Though the mathematical ideas involved are more complex than those of linear models, once the complexity is identified, the frontier of these non-linear models is quite fascinating. It is exciting in a sense that it will provide a better understanding of the underlying dynamics of financial time series. On the other hand, they reveal how much work still remains to be done, especially on financial markets of Asian countries.

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